National Technical University of Athens
School of Mechanical Engineering
Sector of Industrial Management and Operational Research

OPTIMIZATION TECHNIQUES BASED ON EVOLUTIONARY ALGORITHMS FOR PROBLEMS OF ENERGY SYSTEM MANAGEMENT

PhD Thesis

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Athens, July 2020

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This thesis is dedicated to my mother Susanna, my father Antonis, my sister Katerina, my brother-in-law Lazaros and Anna.

ACKNOWLEDGEMENTS

First of all, I would like to thank my supervisor Associate Prof. Athanasios Tolis for giving me the opportunity to pursue a Ph.D. in the field of Operations Research. His support, guidance and encouragement have significantly helped me towards the completion of my research. I would also like to thank him for the financial support that he provided for my participation in academic conferences.

I would like to thank the other two members of the thesis advisory committee, Prof. Tatsiopoulos I. and Associate Prof. Panagiotou N. for their valuable comments and suggestions, which have improved the Manuscript of the present dissertation. Moreover, I would like to express my gratitude towards Prof. Leopoulos V., Prof. Giannakoglou K., Associate Prof. Kirytopoulos K., and Assistant Prof. Rentizelas A. for honouring me with their participation in the examination committee.

Whatever I write about Constantinos Vrionis will not be enough. We shared the same office for five years and his friendship is invaluable to me. His integrity, intelligence, work ethic, and optimistic attitude are indeed exquisite. I am sure that our friendship will continue after the Ph.D. studies. Moreover, I would like to thank my friends Manoli K., Niko K., Dimitri C., Irene K., Nikola V., Niko L., and Christo P. for their support and their friendship. Discussions with them were a reminder that life goes on despite the problems encountered in the course of a Ph.D..

I would like to dedicate this thesis to my family as a small gesture of appreciation to all those things that they have done for me over the years. To my mother Susanna, for being my 'private' psychologist and encouraging me during all the years of my studies. To my father Antonis who has taught me that hard work and dedication are the virtues that a person needs to do well in life. To my sister Katerina, who always cheered me up when I was in my darkest hours. To my brother-in-law Lazaros, who was always showing me the brighter side of things during my Ph.D. studies, helping me understand that some problems are not as difficult as they seem to be at a first glance. To Anna, who stood by me, supported me and loved me during the hardest days of my life. Sincerely, I feel that there are not enough words to express my gratitude to these people.

Concluding, I would like to gratefully acknowledge the financial support provided to me by Alexander S. Onassis Foundation and Eugene Eugenides Foundation. Their help was literally invaluable, since it would be impossible for me to complete this dissertation without it. Moreover, the scholarships awarded to me by the aforementioned Foundations has been a major reward for my efforts and a demonstration that hard work and dedication are indeed appreciated.

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OPTIMIZATION ALGORITHMS	
CR	Crossover parameter of Differential Evolution
D	Number of objective variables of the problem
F	Scaling factor of Differential Evolution
g	Counter of generations
M	Number of objective functions of the problem
n	Counter of individuals in the population of the Evolutionary Algorithm
$Npop$	Size of the parent population of the Evolutionary Algorithm
$NQpop$	Size of the offspring population of the Evolutionary Algorithm
$Ppop^g$	Parent Population of the Evolutionary Algorithm
$Qpop^g$	Offspring Population of the Evolutionary Algorithm
$\mathbf{x}$	Vector of decision variables

GENERATION EXPANSION PLANNING	
$\alpha_{\alpha,i}$	Availability factor of technology (i). (%)
$\alpha_{c,i}$	Capacity factor of technology (i). (%)
$b(i)$	Learning rate of technology (i).
$C_{i,v}$	Past capacity orders of technology (i) decided in year (v) before the beginning of time counter. (MW)
$Cv_{i,z}$	Operational and maintenance costs of power plant i at year z. (€/MW_{el})
$Cf_{i,z}$	Fuel cost of year (z) and technology (i). (€/MW_{el})
dWt	Wiener (Brownian) differential vector (Normally distributed).
$d_{z,f}$	Total electricity demand of year (z) (simulated projection included losses). (MWh_{el})
D	Vector of diffusion for a generic stochastic process.
D_z	Discounting factor of year (z).
$E_{CO_2 i}$	CO_2 emissions from technology (i). (in CO_2 equivalent tones)
En_i	Natural resources potential from technology (i). (MW_{el})
f_{CO2i}	Emissions factor for unit (i). (in CO_2 equivalent tones / MWh_{fuel})
I	Total number of power generating technologies/ fuel types.
$I_{i,v}$	Capital cost of capacity orders of technology (i) decided in year (v). (€/ MW_{el})
$I_{Dz,i}$	Capital cost repayment (annuity) for capacity orders of technology (i), paid in year (z). (€/MW_{el})
$L_{i,z}$	Installed capacity corresponding to technology (i) in year (z). (MW_{el})
m_r	Reserve margin of peak electricity power. (%)
n_i	Efficiency factor for unit (i). (%)
NPV	Net Present Value. (€)
p_{CO2z}	CO_2 allowance price for year (z). (€/ tones CO_2)
$profits_{i,z}$	Profits for technology (i) in year (z). (€)
pre_z	Fixed electricity price for renewable energy in year (z). (€/ MWh_{el})
PP_i, Py_i	Peak and low production levels annually observed for technology (i). (MW_{el})
Pc_z	Peak power demand in year (z). (MW_{el})
$P_{i,z}$	Total electricity energy production in year (z) from power plants of technology (i). (MWh_{el})

rin_t	Inflation rate of time point t. (%)
r_t	Interest rate of time point t. (%)
RE	Number of energy producing technologies based on Renewable sources
Tl_i	Lead-time (after investing entry) for constructing- commissioning of power plant type (i). $(Years)$
To_i T_{zmax}	Operational life-time of unit type (i). $(Years)$ Total hours of a year.
v	Investment entry time or order decision (specific year).
$X_{i,v}$	Unknown capacity orders of technology (i) decided in year (v). (MW_{el})
Y	Maximum operational life-time of the system. $(Years)$
z	Generic time counter
$\theta_{i,z}$	Unknown load intensity factor: actual operating over total available time for unit (i) during year (z). (%)
SHORT-TERM GENERATION SCHEDULING PROBLEM	
a_i, b_i, c_i	Coefficients of the fuel cost function of thermal generator i, ($\$/h$, $\$/MWh$, $\$/MWh^2$)
$CSUC_i$	Cold start-up cost of unit i, ($)
d_i, e_i, f_i	Coefficients of the emissions function of thermal generator i, (lb/h, lb/MWh, lb/MWh^2)
DR_i	Hourly ramp down limit of thermal generator i, (MW/h)
$EENS^t$	Expected energy not served during hour t, (MWh)
$EENS^{tot}$	Expected energy not served during the scheduling horizon, (MWh)
$EENS^{max}$	Maximum allowable expected energy not served during the planning period, (MWh)
FC_i	Fuel cost function of thermal generator i, ($)
$HSUC_i$	Hot start-up cost of thermal generator i, ($)
i	Index of thermal generators
IN_j^t	Natural water inflow in the reservoir associated with hydro plant j at hour t, (m^3/h)
j	Index of hydro plants
L^t	Expected demanded load at hour t, (MW)
$LOLP^t$	Loss of load probability at hour t
$LOLP^{max}$	Maximum limit of loss of load probability at hour t
LT	Lead time of the system, (h)
MDT_i	Minimum down time of thermal generator i, (h)
MUT_i	Minimum up time of thermal generator i, (h)
NHP	Number of hydro plants
NTG	Number of thermal generators
ORR_i	Outage replacement rate of thermal generator i
P_i^t	Power output of thermal generator i during hour t, (MW)
PE_i^t	Function of emissions produced by thermal generator i at hour t, (lb)
$Pmax_i$	Maximum generation limit of thermal generator i, (MW)
$Pmin_i$	Minimum generation limit of thermal generator i, (MW)
Ph_j^t	Power output of hydro plant j at hour t, (MW)
Pw^t	Expected wind power at hour t, (MW)
Q_j^t	Water discharge of hydro plant j at hour t, (m^3/h)
$Qmax_j$	Maximum limit of water discharge of hydro plant j, (m^3/h)

$Qmin_j$	Minimum limit of water discharge of hydro plant j, (m^3/h)
RSR^t	Spinning reserve requirements at hour t, (MW)
ST_i^t	State of thermal generator i at hour t ($= 1$ if unit is on; $= 0$ if unit is off)
SDC_i^t	Shutdown cost of thermal generator i at hour t, (\$)
SUC_i^t	Start-up cost of thermal generator i at hour t, (\$)
SP_j^t	Water spillage of the reservoir associated with hydro plant j at hour t, (\$)
t	Index of time periods
T	Number of hours within the scheduling horizon, (h)
T_i^C	Amount of time required for generator i to cool down, (h)
$Toff_i^t$	Time interval for which generator i is continually off-line up to hour t, (h)
Ton_i^t	Time interval for which generator i is continually on-line up to hour t, (h)
UR_i	Hourly ramp up limit of thermal generator i, (MW/h)
UHP_j	Number of upstream reservoirs of hydro plant j
V_j^t	Volume of water in reservoir of hydro plant j at hour t, (m^3)
V_j^{final}	Target volume of water in reservoir of hydro plant j at the end of the planning period, (m^3)
V_j^{init}	Volume of water in reservoir of hydro plant j in the beginning of the scheduling horizon, (m^3)
V_j^{min}	Minimum allowable volume of water in reservoir of hydro plant j, (m^3)
V_j^{min}	Maximum allowable volume of water in reservoir of hydro plant j, (m^3)
$\chi_i, \delta_i, \gamma_i$	Coefficients of the exponential start-up cost function of generator i
λ_i	Failure rate of thermal generator i
τ_{lj}	Time delay for water to travel between the cascaded hydro plants l and j, (h)
η_j	Coefficient of the power output function of hydro plant j

EXECUTIVE SUMMARY

Over the years, progress in the industry and the living standards of people have increased electricity demand. Moreover, generation from Renewable Energy Sources (RES) has been deployed to increase the sustainability of power sectors. Due to the recent developments in power systems, system operators and planners have to manage complex decision-making processes to ensure the reliability and quality of power supply at minimal costs over different time horizons. Given the complexity of the efficient management of power systems, the application of advanced optimization tools has become essential for decision-makers in their effort to make optimal decisions. In this context, this dissertation focuses on developing and evaluating optimization tools, which aim at facilitating decision-making in two important problems associated with power system management. The first one is the Generation Expansion Planning (GEP) problem, in which the optimum generating capacity additions to an energy sector over a long term planning horizon are sought to meet the anticipated increase in electricity demand. The second one, is the Short-term Generation Scheduling (STGS) problem, in which the optimal operating schedule of a given set of generators in a power system is determined to efficiently meet the expected load.

A model for GEP of a semi-liberalized energy market is developed. In this model electricity producers are grouped by type of generating technology. The maximization of the power system's Net Present Value (NPV) is the model's objective. The evolution of the average annual System Marginal Price (SMP) and its interaction with the structure of the power sector is simulated. Moreover, energy objectives set by policy makers to promote capacity additions in RES are modelled. The optimal annual capacity orders and the load intensity factors are estimated. The model may allow for an assessment of the impact of energy policies both on the structure of the generating mix and the evolution of the SMP, assisting policy makers during indicative energy planning. A hybrid method based on Evolution Strategies and Interior Point Algorithm is developed to optimize the problem.

Regarding the STGS problem, three variants are examined. The first one is the conventional form of the model. In the second one, the system's reliability is considered. Both models attempt to minimize the operation cost in power systems comprising thermal generators. The last one is a multi-objective model, developed in this dissertation, which considers the emissions of the system as an additional objective. Specifically, it concerns power systems comprising hydro plants and RES besides thermal generators. The model may allow system operators to determine the optimal reserve capacity, considering the unavailability of the units as well as uncertainties related to load and wind power forecasting. A set of solutions is obtained which minimize both operation cost and emissions, each of which corresponds to an optimal operating schedule of the generating units of the power system.

The optimization of all variants of the STGS is implemented using a real-coded Differential Evolution. Moreover, a two-step function is included to determine the operating states (on/off) of the generators. Heuristic repair mechanisms are developed and included within the optimization method to facilitate the obtainment of feasible solutions. Two techniques are proposed allowing an efficient integration of information of the Priority List within the optimization procedure. Moreover, a novel mutation operator and a local search technique are developed to enhance the performance of the single- and multi-objective Differential Evolution, respectively.

The GEP model has been examined on an indicative case and several important conclusions have been reached. The proposed hybrid method has consistently obtained solutions of higher NPV values compared to other optimization methods. This, suggests that the derived capacity orders may increase the producer's probabilities for higher yields. Regarding the examined test case, the future structure of the power sector may be affected due to the integration of energy objectives. Capacity orders in on-shore wind turbines and concentrated solar power are proposed to meet short-term energy targets. Moreover, part of the installed capacity of lignite-fired generators will be replaced by RES as a result of long-term energy objectives. Furthermore, meeting the energy targets, might result in a slight reduction of the SMP in the long run, when present values are considered.

Important conclusions have been derived regarding the optimization of the STGS problem. The proposed mutation operator and the procedure for efficiently integrating information of the Priority List significantly enhance the algorithm's performance. The method for the single objective problems has performed competitively, yielding in some cases generating schedules with approximately 0.8% lower operation cost compared to the previously best reported results, in reduced computational time. Moreover, the developed multi-objective algorithm has efficiently optimized the hydro-thermal-wind STGS model with economic/environmental objectives, deriving sets of solutions that approximate the Pareto fronts of the problem. Therefore, it may potentially assist system operators or generating companies towards efficiently scheduling their generating units. Furthermore, the results reveal that increased load forecasting error and unit's unavailability may require the scheduling of higher reserve capacity, resulting in operating schedules with increased operation cost and emissions. This, however, might not be the case for increased wind power uncertainty as demonstrated by the results of the method.

The main contributions of the thesis regarding the GEP model are the following: i) a stochastic optimization procedure without recourse is developed to determine the best capacity orders towards the optimal compliance with energy objectives, ii) a relaxation factor has been applied on the equality constraints of the energy objectives and its effect on the future generating mix and the optimization procedure is examined and iii) a hybrid algorithm based on Evolution Strategies and Interior Point Algorithm is developed to optimize the GEP model.

Regarding the STGS problem, the main contributions are: i) a method based on a real-coded DE and a two-step function is proposed to optimize the examined variants of the mixed-integer STGS problem, ii) a mutation strategy and a local search technique are developed and combined with the real coded DE to enhance its performance, iii) a new multi-objective formulation of the problem considering system's cost and emissions is developed and may assist system operators to determine the spinning reserve in power systems comprising several generating technologies.

CHAPTER 1
INTRODUCTION

1.1 Context

Electricity is one of the most important commodities in modern societies. It is a key determinant of the well-being of households and of economic growth. Its wide availability and its reasonable cost is the outcome of the proper operation and planning of electric power systems. Power systems consist of several components such as generating units, loads, transmission lines and other ancillary equipment which may spread through large geographical areas [1]. These systems are expected to operate around the clock, aiming to produce the amount of energy that satisfies the demand. Thus, they must operate both efficiently and reliably. Operating failures in such systems may have significant economic implications, translating into economic losses of billions [2]. Therefore, it does not come as a surprise that significant amounts are invested by governments and other authorities, to continuously improve both the components as well as the software used for the operation, analysis and control of a power system.

Over the past few years, the management of power systems has become an increasingly difficult task. This may be attributed to several reasons, such as the increasing integration of renewable sources, the aging of the system's components which calls for management and maintenance, and the changing regulatory environment of the power markets. In fact, it is often argued that power systems are operated close to their capacity limits [3]. In this context, the difficulty of decision-making for the management of power systems has significantly increased. Common decision-making problems addressed by system operators and planners cover several time-frames ranging from seconds to years. For example regarding the operation of the system, short-term generation scheduling problem may be solved several times a day to determine the scheduling of power generators. On the other hand, long-term expansion problems may be solved on an annual basis in order to determine how to upgrade a power system to meet a future increase in demand.

Given the complexity of such problems, the efficient management of power systems requires the application of advanced optimization methods for improved decision-making processes. In fact, optimization has played a key role in almost every aspect of the operation and planning of power systems over the years. Improvements in the algorithms used for solving the different problems encountered in the phase of operation and planning may result in significant economic benefits. For example, millions can be saved by improving the quality of the solutions obtained from algorithms which solve the short-term generation scheduling of the system [4]. Moreover, such tools may improve the system's reliability and efficiency, which is particularly crucial for the new more challenging operating scenarios characterized by increased system complexity, and large-scale renewable energy penetration.

In the planning phase, such tools may allow the System Operator to decide the capacity additions that should be carried out to meet the anticipated electricity demand. Moreover, they may help planners to determine energy objectives regarding the power generating mix that should be achieved in the long run. Concerning the operation phase, efficient optimization tools may allow System Operators to efficiently schedule the generating units which will satisfy the demanded load in the most cost effective manner. Moreover, they may enhance the profitability of generating companies through adequate unit scheduling. It should also be noted that efficient planning and operation of the power system may also indirectly affect the electricity price paid by consumers. Thus, improvements in the algorithms used for solving these different problems are highly desirable since their benefits can be substantial.

1.2 Scope of the present thesis

Operational Research (OR) is a discipline that deals with the application of advanced analytical methods to support the process of decision making, i.e. help make better decisions. In particular, it employs and combines techniques from other mathematical sciences, such as mathematical modeling, statistical analysis, and mathematical optimization to provide optimal or near-optimal solutions to complex decision making problems. OR has contributed in a variety of application areas, including scheduling (of airlines, trains, buses etc.), assignment (assigning crew to flights, trains or buses), facility location (deciding most appropriate location for new facilities such as warehouses), health services (information and supply chain management) and several more. This thesis is motivated by this generic approach, and constitutes the author's attempt to contribute to the research area, which focuses on the applicability of OR in a certain domain of problems, i.e. problems which arise in energy system's management. Consequently, the thesis has been developed following two main research directions, i.e. the development of optimization tools mainly based on Evolutionary Algorithms (EAs) and their application on two problems arising in the area of energy system management, i.e. the Short-Term Generation Scheduling (STGS) problem and the long-term Generation Expansion Planning (GEP) problem. The term 'Evolutionary Algorithms' (which are a subset of Evolutionary Computation methods) concerns optimization methods, in which a set of candidate solutions to the problem at hand (called 'population') is gradually improved by exploiting the Darwinian principles of natural evolution in an iterative procedure to achieve the desired end. The present dissertation is structured in the two following thematic sections:

1. The development and evaluation of optimization methods for the long-term GEP problem, in which, given a set of scenarios of the evolution of the values of variables in a power sector, e.g. CO_2 prices and electricity demand, the optimum capacity orders (time, location, technology type, capacity) are sought.

2. The development and evaluation of optimization methods for the STGS problem. In this problem, the optimal operating schedule of a given set of generating plants in a power sector, to meet the expected demanded load efficiently and reliably is sought. In this dissertation, several realistic variations of the problem have been examined.

The two aforementioned problem categories may display certain characteristics, which increase the difficulty in efficiently applying conventional optimization algorithms. As is the case with many real-world applications, they are complex optimization problems with complicated constraints. The efficient optimization of such problems may be challenging, due to their complexity, non-linearity and potentially high-dimensionality. They may be combinatorial [1] problems and belong to the category of NP-hard problems [2], thus conventional methods may not be able to tackle them efficiently and in reasonable computational time, when the size of the problem is large. The main target of this dissertation, is to provide optimization algorithms which may efficiently optimize problems from the aforementioned groups; the term 'efficiently' concerns both the required computational time and the quality of the provided solutions. To achieve the aforementioned goal, the proposed methods are mainly based on EAs. One of the basic features of EAs is their flexibility, since they can be applied to an optimization problem regardless the characteristics of the objective and constraint functions (linearity, differentiability) or the type of the decision variables (discrete, binary or real-valued variables). Moreover, they may easily incorporate variations in the structure of a problem, thus they are appealing since they may straightforwardly be adapted to the problem at hand. Finally, such methods, due to their population based nature are well suited to deal with optimization problems with multiple objectives. The aforementioned reasons have stimulated a large amount of research on EAs, and have motivated their examination in the present dissertation.

As stated earlier, EAs are optimization methods which follow the principles of Darwinian Evolution. These optimization tools are approximate methods, where heuristic rules are guided by a generic concept in an attempt to tackle a given problem. They may provide near optimum solutions in multi-objective, non-linear, mixed-integer (or combinatorial), highly constrained problems. However, EAs are not a panacea. In complex real-world problems, conventional EAs may require a large time to converge or even converge prematurely. Several studies have shown that the per-

[1] Combinatorial are the problems on which one or more optimal solutions are sought in a finite problem space

[2] Combinatorial problems in which the size of the search space grows exponentially with the instance size leading to exponential increase in the computational time for its solution belong to the category of NP-hard problems

formance of a conventional EA on the optimization of real-world problems, may be significantly enhanced when domain-specific knowledge is incorporated within evolutionary optimization procedure. Domain-specific knowledge is knowledge about the examined domain or geometrical properties of the search space and may be incorporated either implicitly, in the design of data structures, encoding, and handling of constraints, or explicitly, via the design of adequate problem-specific recombination operators [5]. Another way to increase the efficiency of conventional EAs in solving real-world problems is by hybridizing them with other optimization algorithms, in an attempt to exploit the beneficial characteristics of the distinct approaches. Several attempts have been carried out in the relevant literature to combine EAs with mathematical programming methods, local search techniques or other EAs, showing enhanced performance compared to the case where the EA is applied individually. In the present dissertation, the utilization of domain specific-knowledge as well as the combination of EAs with other approaches has been implemented, with an objective of developing methods, which may efficiently optimize problems arising in a power sector.

Regarding the GEP problem, the method proposed in this dissertation belongs to the category of hybrid methods. In particular, it comprises two stages; on the first stage an EA is applied to globally explore the search space, while on the second stage a mathematical programming technique is used, to exploit the area of the search space near the solution provided by the EA. The scope of such a combination is to take advantage of the global explorations abilities of the EAs, while the use of the information of the gradient by the mathematical programming techniques ensures the rapid exploitation of the neighborhood of its initial solution. The proposed formulation attempts to maximize the Net Present Value of the power sector, by deriving optimal capacity additions for the different generating technologies. The model may consider energy objectives set by policy makers to promote capacity orders in Renewable Energy Sources (RES). Modifications on the constraints describing such energy objectives are proposed, which may be justified both with regards to policy as well as algorithmic efficiency. The model may approximate the evolution of the average annual

System Marginal Price [3] (SMP), taking into account its interaction with the generating mix.

Regarding the STGS problem, in the present dissertation two optimization algorithms are developed. In both, conventional EAs have been modified by introducing several novel operators, which may integrate domain-specific knowledge. Moreover, a novel Local Search Technique has been proposed and combined with a conventional EA to solve the STGS problem when multiple objectives are examined. Furthermore, methods to increase the efficiency by adequately including domain specific knowledge within the evolutionary optimization procedure are proposed. In each case, the improvements due to the proposed algorithmic interventions are demonstrated, through series of computational experiments on test systems from the relevant literature and benchmarking with other optimization approaches.

It should be noted that the STGS problem is examined in several forms. In particular, in its 'traditional' form, the system comprises thermal generators, while the minimization of operation cost is the sole objective of the problem. Another form of the problem, where unscheduled generator outages and load forecasting uncertainty have been considered within the conventional form of the problem is also examined. Moreover, given the increasing importance of environmental issues, the environmental factor is included within the problem's formulation as an objective. Then, a form of the problem is proposed, for power system's comprising other types of generating technologies, i.e. hydro plants and RES, in addition to thermal generators.

In general, the notion that EAs should maintain their simplicity, both conceptually and practically, and should be efficient to a large variety of applications without introducing problem-specific knowledge or customized information has prevailed for many years. However in more recent years, the No Free Lunch Theorem (NFLT) [6] has emerged, which states that for any optimization method, an elevated performance over one class of problems is offset by degraded performance over another class. The results of the NFLT suggest that an algorithm cannot demonstrate a su-

[3]The System's Marginal Price is the price paid to the generating companies for producing an additional kW of electricity

perior performance over all the set of problems, rather than it may outperform other approaches if it is customized to the structure of the problem at hand. Following the NFLT, researchers have started proposing more elaborate approaches using EAs, aiming at enhancing their performance for specific classes of problems. In this vein, the present dissertation focuses on the development of optimization methods based on EAs, to be applied on two problems frequently encountered in energy management, i.e. the STGS and the GEP problems, in an attempt to contribute to the following:

- In proposing approaches with increased efficiency, both in terms of time and solution quality, for the aforementioned two problems. For this reason, during the course of the dissertation, new problem customized operators, new local search techniques and new hybrid schemes are proposed. In each case, improvements in the algorithmic performance are demonstrated with adequate computational experiments.

- In the case of the short-term generation scheduling, it is shown that the proposed algorithms may also be adapted to efficiently optimize different forms of the problem, providing flexibility to the user.

The proposed method for the GEP model may assist policy makers, during indicative energy planning, to propose energy policies and incentives towards achieving regulatory objectives. Moreover, it may facilitate the assessment of the impact that specific long term objectives may have on the structure of a power sector and the evolution of the SMP and other variables of a power sector. Regarding the solution of the STGS problem, the proposed method may assist System Operators to determine the operating schedule of the generators that will serve the expected demand. Moreover, they may be utilized by Generating Companies (GENCOS) to determine the schedule of their generators in an attempt to decrease their production costs. The methods proposed in this dissertation may be of interest also for researchers in the field of Evolutionary Computation, since new evolution operators and hybrid schemes are developed, and their efficiency is examined on complex real-world problems.

1.3 Generation Expansion Planning

In recent years, the importance of power systems that perform reliably is ever increasing since nearly all aspects related to the well being of members of modern societies rely on the access to electricity. However, power sectors undergo changes caused by the increasing demand as well as other economical, technical and environmental issues. These, increase the complexity of both generation and delivery of electrical energy. Consequently, the need for an adequate organization of power systems is essential, in an attempt to reliably meet the anticipated increase in the required load. For this reason, the importance of GEP problem has been highlighted over the past years. The optimization of the problem, assists policy makers to make decisions regarding the generation technology type, the time, the capacity and the location of new investments in generating technologies, taking into consideration their techno-economic characteristics as well as scenarios on the evolution of certain commodities in the power sectors.

Investing in RES may mitigate the dependency of power systems on fossil-fueled generating technologies and increase the sustainability of power sectors. Nevertheless, investments in RES are characterized by high investment costs, uncertainty, and usually long return on-investment. For these reasons, the integration of RES technologies within the power industry progress at a relatively slow pace. To promote larger exploitation of RES, governments have utilized several support schemes. Probably the most exploited support scheme, is the so called feed-in-tariff mechanism, according to which electricity produced by RES is compensated on a fix price determined by the state, and does not participate in the electricity market. Moreover, energy produced by RES is given priority in the Merit Order, i.e. if possible all the amount of RES produced electricity is fed to the power system. To further accelerate RES integration within power systems, policy makers set energy objectives related to investments in RES, which should be met by each country. Such objectives may affect the evolution of the power sector's structure. An estimate of the impact of such interventions on certain commodities of the power sectors, i.e. the evolution of the System's Marginal Price or the CO_2 emissions might also be important. However, little work has been dedicated on estimating the effect of such strategic interventions on the evolution of the power sector's variables.

Distinct models have been presented for GEP, each resulting in mathematical problems with different characteristics. Despite the differences, commonly GEP problems are characterized by non-linear and non-differentiable objective and constraint functions as well as a large number of objective variables, which may either be of real or discrete nature. GEP is considered as one of the most complicated types of power system planning problems, and several studies have been dedicated to its solution. To optimize the GEP problem, several solution methodologies have been proposed over the past years. Such methodologies may be based either on mathematical programming techniques or nature inspired meta-heuristics. The former may provide guarantees that the optimal solution is found. However, they may not be able to efficiently handle non-linear and non-differentiable objective and constraint functions of the problem. On the contrary, meta-heuristic techniques may not provide optimallity guarantees, however they demonstrate acceptable performance in reasonable computational time, without posing restrictions on the mathematical formulation of the problem. In the relevant literature, hybrid algorithms which combine approaches from both the aforementioned categories have not been widely examined on the problem. However, such a hybridization might be beneficial since nature-inspired metaheuristics may present global exploration abilities, while with a proper initial point mathematical programming techniques may serve as a local optimizer, which may rapidly exploit the neighborhood of the initial point.

In summary, the main motivation for examining the GEP problem was twofold. Firstly, to propose a model to assess the impact of considering specific energy objectives on the structure of the future generating mix as well as on the evolution of certain commodities of a power sector, such as the SMP. Secondly to examine, whether a hybrid scheme which combines a mathematical programming technique with an Evolutionary Algorithm may provide solutions of better quality to this highly constraint, large scale, non-linear problem compared to the application of each of the aforementioned methods individually.

1.4 Short-term Generation Scheduling Problem

Growing populations and increasing standards of living have triggered a significant increase in the electricity demand over the past few years. In the meantime, during the course of a single day, demand patterns are characterized by variation; commonly demand is higher during the daytime reaching its peak at noon, while a second peak is reached at the early evening. On the contrary, demand is lower at night and early in the morning when human activities are decreased. Moreover, in recent years the introduction of energy from RES within the generation mix has been gradually increased, replacing energy produced by fossil fuels. RES are gaining ground over fossil fuels mainly due to their significantly lower production cost and their beneficial environmental impact (no pollutants are emitted in the atmosphere when energy is produced by RES). Besides, increased utilization of RES reduces the dependency on fossil fuel and the countries which export them. However, their introduction further increases the variability and the uncertainty in the resulting electricity demand, since RES are intermittent and uncontrollable sources of energy, i.e. they deliver energy when the wind blows or the sun shines. The aforementioned, introduce challenges for power system operators in balancing the demanded load with generation and in maintaining system's reliable operation.

One of the most important optimisation problems arising in power systems concerns the determination of the optimal operating state (committed/decommitted) of a given set of generators and the load assigned to each committed unit over a predefined planning horizon, to satisfy the anticipated electricity demand. In the conventional form of the problem, the optimization's objective considers the system's economic output, i.e. the minimization of the operation cost of the system or the maximization of the profits from selling the produced energy. However, environmental awareness has triggered efforts to take into consideration also the impact of energy production in the environment, e.g. by minimizing the emissions produced by fossil-fuel fired generators. The problem is subject to a series of constraints related to the reliable operation of the system as well as to the mechanical and electrical limitations of the operation of individual units. In the relevant literature, the resulting family of models is referred to as the generation scheduling problem or the Unit Commitment Problem. It should be noted that the sub-problem of optimally distributing the load among the units in operation is know as the Economic Dispatch (ED) problem. Due to its significant practical and economic impact, the generation scheduling problem has for long attracted the attention of the research community and a large amount of research work has been devoted for its solution over the years.

The problem may be solved for planning horizons with different lengths, serving each time a different purpose. Specifically, the generation scheduling may be either short-term or long-term, depending on the length of the planning horizon under consideration [7]. Short-term generation scheduling problems have a planning horizon of few hours up to one week and commonly serve production control purposes, i.e. unexpected events that have happened before the beginning of the planning horizon can be taken into consideration within the model. For this reason, a more detailed mathematical form of the model is examined including a large number of constraints. Long-term generation scheduling problems concern periods of one month up to a year, thus some simplifications on the model's formulation may be allowed; such models serve production planning purposes, where the plant performance concerning fuel demand may be analyzed or maintenance scheduling may be examined [7]. In this dissertation, the short-term generation scheduling problem is addressed, focusing on the detailed representation of the operation of individual generators. For a more detailed presentation on the long-term generation scheduling problems and their characteristics the interested reader is kindly referred to [7] and [8].

Despite the significant amount of research that has been carried out, STGS problem still remains a rich and challenging topic for research. It is a large and complex problem, which due to the operational requirements should be solved in a small amount of time and has a significant economic impact [9]. Following the progress of optimization methods, new tools for the solution of the problem emerge, allowing the obtainment of better results in shorter time for existing problem formulations. The economic implications of such improvements should be highlighted since even small reductions on the operation cost of the system may trigger significant savings (in the range of millions) for large economic utilities. A second reason, is the ever-changing environment under which the scheduling should be performed, mainly due to ongoing changes in the generating technologies (introduction of RES) and regulatory environment (transition from a centralized model to deregulated markets), which calls for a continuous adaptation of the models at hand.

The STGS problem is a large scale, non-linear, non-convex, and highly constrained optimization problem, belonging to the category of NP-hard problems [10]. In the relevant literature, the most common approach to solve the problem when only the economic objective is considered is the use of the Branch-and-Bound method. However, to apply the method on the problem, the constraints and the objective functions should be reformulated using linear mathematical expressions. Furthermore, a large number of auxiliary variables is commonly introduced to implement the aforementioned linearization. Many rigorous approaches have been also proposed based on other mathematical programming methods such as Dynamic Programming and Lagrangian Relaxation. However, these methods usually suffer from the 'curse of dimensionality' (the computational time increases exponentially with the size of the system under examination) especially in dealing with modern power systems with large number of generators. Moreover, all the aforementioned methods are single objective problem optimizers and cannot solve efficiently multi-objective problems. A detailed review of such methods will be given on the corresponding Chapters of the dissertation. It should also be noted, that solving STGS considering probabilistic unit outages and uncertainties related to load forecasting is a very challenging task when the aforementioned techniques are considered.

Within the relevant literature, the vast majority of the research works on the STGS problem considers the system operation cost as the sole objective of the problem. Very little work has been carried out on the problem when emissions minimization are considered as a second objective. However, consideration of the environmental impact of energy generation should be more thoroughly examined since the utilities have been pushed towards reducing the contaminants emitted in the atmosphere by fossil-fuel-fired generators. Moreover, commonly the problem is solved under a deterministic environment, without considering the uncertainties inherent in generation scheduling. However, the latter may be subject to uncertainties related to the (unscheduled) outages of thermal generators as well as errors in load forecasting. Solutions to the problem, where such uncertainties are considered may be of importance for system operators. Furthermore, the inclusion of other generating technologies, such as hydro units and renewable energy sources has not received significant attention by the research community except recently. However, hydro plants usually constitute an important component of the energy mix, and their introduction increases the difficulty of optimizing the overall problem, since adequate coordination amongst the thermal and the hydro part of the power system should be achieved.

The methods based on EAs presented in the relevant literature for the optimization of the STGS problem incorporate problem-specific knowledge; heuristic procedures are included within the evolutionary optimization to facilitate the obtainment of feasible solutions. This is because the problem is nonlinear, high-dimensional and highly constrained. Thus, including domain specific knowledge within evolutionary optimization is essential to efficiently solve the problem. Such heuristics take advantage of the Priority List, in which generators are prioritized for commitment according to certain metrics. In the literature, commonly a constant metric is utilized throughout the optimization, which is the unit's average production cost at its maximum operation output. This is commonly based on the assumption that each unit in operation will be fully utilized, since in such a case its average production cost is minimum. However, depending on the variations of the load, units are commonly not fully utilized. It should be noted, that different metrics may lead to prioritizing different generators for commitment, as will be described in a subsequent Chapter of the dissertation. The impact of utilizing a constant metric should be examined, because it may introduce biases towards specific sub-optimal generating schedules leading the algorithm to premature convergence.

The main motivation for the research conducted on the STGS problem in this dissertation, is to propose optimization methods that will efficiently solve the several forms of the problem. The methods are based on a single EA, which is adequately customized depending on the formulation of the generation scheduling problem examined. For this reason, novel evolution operators and heuristic repair mechanisms are included within the evolutionary optimization procedure. To provide near optimal solution to the aforementioned problems, domain specific knowledge is adequately included, utilizing different procedures, especially in non-conventional formulations of the problem. In each case, the improvements resulting from the proposed novelties are demonstrated through computational experiments. Moreover, a multi-objective formulation of the problem taking into consideration several types of generating technologies (including RES), considering several uncertainties related to the power system, is proposed and examined. The main advantage of proposing such a formulation is that a set of trade-off solutions, which balance the economical and environmental factor taking into account several system uncertainties could be provided to the system operator and may be used during decision making.

Despite the ongoing changes in the structure of the electricity market, the role of the basic STGS problem still remains significant for utilities and generating companies. The (Independent) System Operator may execute the STGS program a day-ahead to plan a secure and economical hourly generation schedule based on which the generators in a power sector will operate to satisfy the electricity demand for each hour of the next day. In fact, in such a case the STGS utilizes the market information submitted by the participants of the market (generating companies, the transmission system operator, distribution system operator) such as the characteristics of generating units, generation offers and demand bids, scheduled maintenance etc.. Then the solution of the STGS provides a physically feasible and economically efficient operating schedule, which is made available to the corresponding market participants. The deregulation of the electricity market has given rise also to new forms of the problem. In the context of deregulated markets, the problem's objective may be different, targeting at the maximization of the profits of the individual producer's, considering an expected price for the produced energy. However, the base form of the problem may also be used in that case. For example, before a GENCO submits its bid to the energy market, it will have to decide both the amount of energy and its selling price. The bids may be decided by executing several STGS optimizations for different load curves (representing different supplying alternatives), selecting the one that deriving the best economic results. The basic STGS problem may also be used by a GENCO after auctions close; the company considers the aggregated power that has been assigned to produce as the system's demand and performs a traditional STGS problem to meet obligations at the minimum cost. Moreover, it should be noted that the model may be used in countries in which the electricity market is still regulated, i.e. it has a vertical organisation. For a more detailed analysis on the use of traditional STGS on deregulated markets the interested reader is kindly referred to [11].

1.5 Structure of the dissertation

The present dissertation comprises seven Chapters. In Chapter 1, the objectives of the dissertation are outlined, while the reader is introduced to the basic concepts of the optimization tools that will be used during the dissertation and the problems which will be tackled.

In Chapter 2, the basics of single-objective optimization, multi-objective optimization and EAs are presented, describing in more detail Evolution Strategies and Differential Evolution, which are the two EAs utilized as the base for the development of the algorithms present in this dissertation. Moreover, special emphasis is given to the hybridization of EAs with other optimization methods and local search techniques.

In Chapter 3, the first problem from the field of energy management examined in this dissertation, i.e. the GEP, is introduced. A literature review on the main methods applied to solve the problem and a description of its different forms is carried out. Then, the GEP model with the objective of maximizing the power sector's NPV taking into consideration several constraints related to the system's reliable operation is described in detail. The modelling of energy objectives set by policy makers is also presented. Thereafter, the characteristics of the proposed optimization algorithm, which combines the Evolution Strategies and the Interior Point Algorithm are analyzed. The results of the proposed method are discussed and the improvements compared to other optimization approaches are highlighted.

In Chapter 4, the STGS problem is analytically defined. An extensive literature review is made on the methods applied to solve the conventional form of the problem, by categorizing them into three basic categories: methods based on mathematical programming techniques, methods based on stochastic approaches, and hybrid methods which combine methods from the first two categories. The literature review focuses on presenting the advantages and disadvantages of each method. The Chapter, proceeds with the detailed presentation of the mathematical model of the problem. Subsequently, the solution methodology proposed in this dissertation, including the novel mutation operators and the repair procedure which integrates domain specific knowledge, is described. Thereafter, the improvements due to the integration of the proposed algorithms interventions are demonstrated and the proposed method is benchmarked against the state-of-the-art in solving the problem.

In Chapter 5 the method proposed to solve the STGS problem, considering the reliability of the system, is presented. In particular, the Loss of Load Probability and the Expected Energy Not Served reliability indices are introduced. A literature review of the methods attempting to include the reliability of the system within the problem's formulation is implemented. The methodology to include within the model the uncertainty of load forecasting is described. The proposed solution methodology is given in detail, highlighting the mechanisms proposed in this dissertation to deal with the introduction of the reliability indices within the problems formulation. The validation of the method follows by implementing a comparison of the method's results against other methods of the literature.

In Chapter 6 we describe a novel formulation of the problem, proposed in this dissertation. In particular, the STGS with the additional objective of minimizing the emissions produced by thermal generators is presented, for power systems comprising thermal generators and hydro plants. In this formulation, the wind power and its inherent uncertainty are also considered. Initially a literature review of the different formulations examined is given, while the mathematical formulation of the problem is described in detail. Subsequently, the proposed solution methodology is presented with a special emphasis on the local search technique proposed in this study. The results of a series of computational experiments are then given, which evaluate the efficiency of the proposed method, while the impact of the several uncertainties included on the results of the problem is also assessed.

Finally, in Chapter 7, the conclusions of the present dissertation are drawn. Moreover, the main contributions of the thesis are reviewed and some guidelines for future research are discussed.

CHAPTER 2

OPTIMIZATION AND EVOLUTIONARY ALGORITHMS

2.1 Introduction

Fundamentally, optimization is the process of formulating a single standard of measurement (commonly referred to as a cost function), which summarizes the performance of a decision and iteratively improve this performance by selecting among available alternatives [12]. Most classical methods of optimization generate a deterministic sequence of trial solutions based on the gradient or higher-order statistics of the cost function. Under regularity conditions on this function, these techniques may generate sequences that converge asymptotically to locally optimal solutions; this convergence may be carried out exponentially fast [13]. However, the increasing dimension and complexity of problems found in practice may lead frequently to a situation where classical optimization algorithms may not be able to find a solution within a reasonable amount of time, i.e. in a way that is useful for the decision making process under consideration [14]. Further, converging to locally optimal solutions may be insufficient for real-world engineering problems [12]. The ongoing need for algorithms that are applicable to a wide range of problems, do not need much tailoring for specific problems, and deliver good (not necessarily optimal) solutions within acceptable time, has been a major motivation for the development of the field of Evolutionary Computing (EC) [15]. EC is the branch of computer science concerned with a class of algorithms that are broadly based on the Darwinian principles of natural selection, and that draw inspiration from molecular genetics [15]. The algorithms involved in the field are commonly termed Evolutionary Algorithms (EA).

In this chapter, we start by describing some basic concepts related to single and multi-objective optimization problems. Subsequently, we briefly present EAs focusing on two paradigms, i.e. Differential Evolution and Evolution Strategies, which constitute the base algorithms for the methods proposed in the present dissertation. The Chapter is concluded with a discussion on the hybridization of EAs with other optimization techniques.

2.2 Mathematical form of a constrained optimization (minimization) problem

A constrained minimization problem [1] can be formulated as:

$$min(\mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_M(\mathbf{x})),\ \mathbf{x} = (x_1, x_2, ..., x_D) \in \mathbb{D},\ \underline{x_d} \leq x_d \leq \overline{x_d} \tag{2.1}$$

subject to:

$$g_{l_1}(\mathbf{x}) \leq 0,\ \ l_1 = 1, ..., L_1 \tag{2.2}$$

$$h_{l_2}(\mathbf{x}) = 0,\ \ l_2 = 1, ..., L_2 \tag{2.3}$$

where $\mathbf{F}(\mathbf{x})$ comprises M $(M \geq 1)$ objective functions in the objective function space $\mathbb{F}^M$ ($\mathbb{F}^M \subset \mathbb{R}^M$), $g_{l_1}(\mathbf{x})$ is the l_1-th inequality constraint and $h_{l_2}(\mathbf{x})$ is the l_2-th equality constraint. Moreover, $\mathbf{x}$ is the decision vector, which comprises D decision variables (also called parameters). $\mathbb{D} = \Pi_{d=1}^{d=D}[\underline{x_d}, \overline{x_d}]$ ($\mathbb{D} \subset \mathbb{R}^D$) is the decision variable space, where $\underline{x_d}$ and $\overline{x_d}$ are the lower and upper bound, respectively, of decision variable x_d. A parameter vector which satisfies all the problem constraints is called feasible, otherwise is called infeasible.

When the problem under consideration comprises a single objective function ($M = 1$) then a solution $\mathbf{x_A}$ is optimum when it is feasible and $F(\mathbf{x}_A) <= F(\mathbf{x}_B)$, $\forall \mathbf{x}_B \in \mathbb{D} \backslash \{\mathbf{x_A}\}$. In case the problem comprises multiple conflicting objectives ($M > 1$) no single optimum solution exists. On the contrary, we seek for multiple solutions, which achieve optimum trade-offs among the different

[1] Maximization problems can be tackled as minimization as follows: max F(x) = - min - (F(x))

objectives. Such solutions are called Pareto optimal solutions. The concept of Pareto optimality is defined as follows:

Definition 1: A solution $\mathbf{x_A}$ dominates a solution $\mathbf{x_B}$, denoted as $\mathbf{x_A} \preceq \mathbf{x_B}$, if $F_m(\mathbf{x_A}) \leq F_m(\mathbf{x_B})\ \forall m \in \{1, \ldots, M\}$ and $\mathbf{F}(\mathbf{x_A}) \neq \mathbf{F}(\mathbf{x_B})$.

Definition 2: A feasible solution $\mathbf{x}_A$ is called Pareto optimal, if $\nexists \mathbf{x}_B \in \mathbb{D}$ such that $F_m(\mathbf{x_B}) \leq F_m(\mathbf{x_A})\ \forall m \in \{1, \ldots, M\}$ and $\mathbf{F}(\mathbf{x_A}) \neq \mathbf{F}(\mathbf{x_B})$.

The set of all the Pareto optimal solutions in the objective variable space is called Pareto Set. In multi-objective optimization, in addition to the search space of objective variables, the objective functions constitute a multidimensional space, called the objective function space. Each solution vector $\mathbf{x}$ in the objective variable space, corresponds to a point $\mathbf{F}(\mathbf{x})$ in the objective function space. Thus, the D-dimensional objective variable space is mapped to an M-dimensional objective function space. The image of the Pareto Set on the objective function space is called Pareto Front.

2.3 Evolutionary Algorithms

EA is the general term used to describe optimization algorithms that are inspired by the Darwinian Principles of nature's capability to evolve living beings well adapted to their environment [16]. Several different domains are grouped under the general term EA; such domains include Genetic Algorithms [17], Evolution Strategies [18], Evolutionary Programming [19], Genetic Programming [20], Differential Evolution [21] etc. Despite the differences emerging amongst the aforementioned domains, the principle idea behind them is common; when a population of individuals is within an environment with limited resources, the competition will cause the fittest individuals to survive, triggering a rise in the fitness of the population. In EAs the evolution of individuals is simulated through the processes of selection, recombination, and mutation reproduction.

This aforementioned principle governs the operation of EAs. In particular, given a fitness function to be minimized, a population of candidate solutions, also known as individuals, is created randomly. The fitness function may serve as a measure of the quality of the solutions – the lower the better. At every iteration of the algorithm, commonly referred to as a generation, the population of the candidate solutions is capable of reproducing and is subject to genetic variations, followed by the environmental pressure which causes the survival of the fittest. Individuals of better quality may have a higher chance to be selected for Recombination, during which two or more individuals (known as parents) may be combined to create one or more new solution vectors (known as offspring). Mutation, on the other hand, promotes diversity, since it enables the appearance of new traits in the offspring. The fitness of the offspring population is then evaluated and a selection mechanism is applied to determine which individuals will survive to the next generation. Commonly the procedure terminates after a predefined number of generations (or objective function evaluations) has been carried out. Nevertheless, more complex criteria may also be employed, e.g. the fitness improvement remains below a predefined value for a number of generations, the diversity of the population drops below a threshold value. A flowchart describing the conventional form of an EA is given in Fig. 2.1.

Despite their lack of theoretical foundations, EAs have become common in the solution of difficult, real-world problems in several domains, e.g. engineering, medicine etc. This might be attributed to the practical advantages that EAs exhibit compared to classic methods of optimization. One of their main advantages is that they are conceptually simple and do not require the objective function or the constraints to have specific characteristics, e.g. to be continuous and/or differentiable. In fact EAs can be applied to any problem that can be formulated as a function optimization task [22]. Moreover, they may avoid getting stack in local optimum solutions due to the fact that they rely on stochastic evolution operators for exploring and exploiting the search space [23]. Furthermore, the optimization procedure using an EA may be implemented in parallel. Specifically, the evaluation of each solution can be carried out on distinct processors and only selection requires series processing. As a result, the actual running time of the algorithm may be reduced. Nevertheless, EAs are not a panacea. They may suffer from slow convergence rate and

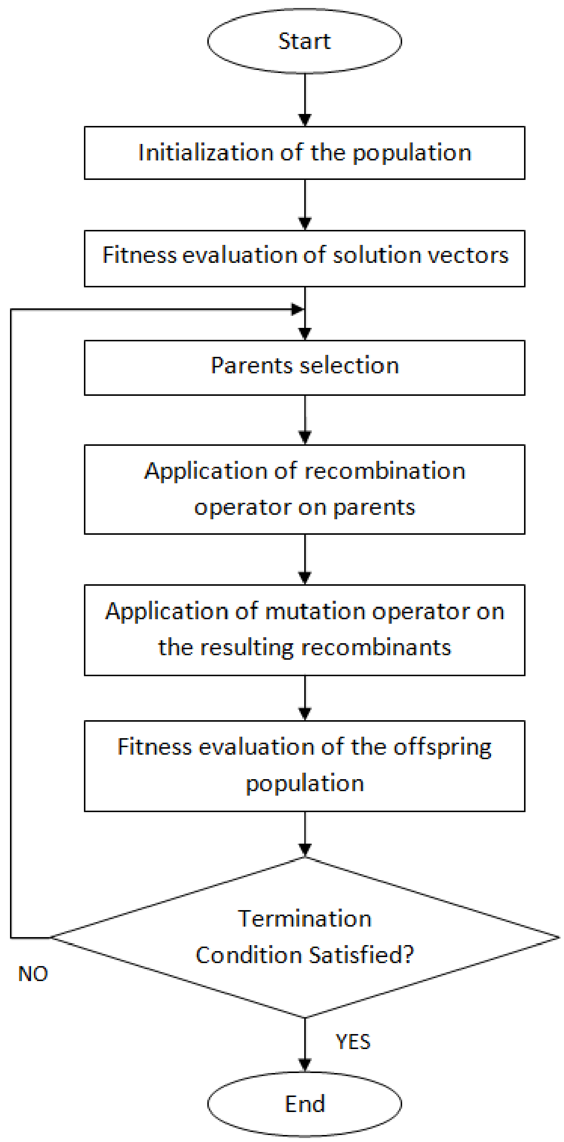


Figure 2.1: General form of a conventional EA

may converge prematurely [24]. Moreover, they may require the utilization of problem-customized operators, which utilize domain-specific knowledge, to converge to optimal solutions in a reasonable computational time. For this reasons, despite the intensive research that has been carried out on increasing the efficiency of EAs, especially when they are applied on real world problems, it still remains a rich and challenging topic for research.

In the following subsections, two of the main paradigms of EAs will be briefly presented, i.e. Evolution Strategies and Differential Evolution. These two EAs have been utilized as base algorithms for the optimization of the two problems examined in this dissertation, i.e. the Short-term generation scheduling problem and the long-term generation expansion planning problem.

2.3.1 Evolution Strategies

Evolution Strategies (ES) were initially proposed by Rechenberg [18] and further developed by Schwefel [25], both working at the Technical University of Berlin. Primarily the method has been proposed as a set of rules for the automatic design and analysis of consecutive experiments. Nevertheless, it has soon emerged as an efficient tool to be applied for optimization tasks. In the initial form of the method, called $(1+1)-ES$, a single offspring was created by adding a (slight) random change to all the parameters of a single parent vector. Then if the offspring is fitter, it becomes the parent for the next generation. Later, Schwefel [26] has introduced two versions of multimembered ES, referred to as $(Npop + NQpop) - ES$ [2] and $(Npop, NQpop) - ES$. In both, the parent population comprises $Npop$ members, which are used to create $NQpop$ offspring individuals at each generation by means of recombination and mutation. The difference amongst the two aforementioned versions lies in the selection of the members of the next generation. In the former, the $Npop$ best out of the $Npop + NQpop$ individuals are selected. In the latter, the best $Npop$ individuals which will survive to the next generation are selected amongst the $NQpop$ offspring. A parameter ρ may also be utilized within the notation used to describe the ES version,

[2] It is noted that in ES the symbols commonly used to describe the parent and offspring populations are μ and λ

which denotes the number of parameters taking part in the creation of a single offspring.

Commonly, in ES the mutation operator utilizes the Gaussian distribution with zero mean and standard deviation σ, which is called the mutation step size. In the simplest form of ES, σ is kept constant during the optimization procedure and is the same for all objective variables. Such a case is commonly referred to as isotropic mutation, and is implemented as follows:

$$\mathbf{x_n^{g+1}} = \mathbf{x_n^g} + \mathbf{z} \tag{2.4}$$

where:

$$\mathbf{z} = \sigma \cdot (N_1(0,1), N_2(0,1), ..., N_D(0,1)) \tag{2.5}$$

In this case, depending on the σ selected different mutation strengths may be applied. The basic advantage of the isotropic mutation operator is that a single parameter should be defined. Alternatively, different mutation step sizes σ_i may be used for each objective variable, as follows:

$$\mathbf{z} = (\sigma_1 \cdot N_1(0,1), \sigma_2 \cdot N_2(0,1), ..., \sigma_D \cdot N_D(0,1)) \tag{2.6}$$

The search might be benefited by the different mutation strengths applied to the different objective variables. In the most general form of mutation a rotation matrix CM may also be utilized to introduce correlations amongst the random variables of the different Gaussian distributions. The aforementioned parameters, control certain statistical properties of the evolution operators (mainly of mutation) and are referred to as strategy parameters. To control the strategy parameters included in the mutation operator, the feature of self-adaptation has emerged. According to it, the strategy parameters of the mutation operator are included within the chromosome of each individual. Then, these strategy parameters may evolve during the course of the optimization by undergoing mutation and recombination similarly to the objective variables. In fact, the mutated strategy parameters are used during the mutation of the objective variables. Moreover, they will survive in the next generation in case the corresponding individual is selected. As a result, strategy parameters that produce better individuals may have higher probabilities of survival.

A recombination operator may also be applied for the creation of the offspring population. In recombination, ρ parents are combined to create a single offspring. The two basic classes of recombination used in ES are the 'discrete recombination' and the 'intermediate recombination'. In discrete recombination, each component of the recombinant vector is selected at random (uniformly) amongst the corresponding components of the ρ parent vectors. On the contrary, in intermediate recombination all the ρ parents are taken into account, since the components of the recombinants are calculated by averaging the values of the corresponding parent components. Two more terms may be introduced regarding the recombination operator. In particular, the recombination is characterized as global, in case the ρ parents to be recombined are selected anew for each component of the recombinant. On the opposite case (i.e. only ρ parents for each offspring), the recombination is called local. Recombination may be used both for the objective variables as well as for the strategy parameters. In fact, different recombination schemes may be used for the objective variables and the strategy parameters.

Between the two main selection schemes used in ES, $(Npop + NQpop)$ selection guarantees that the best individuals found so far will be preserved in the population. Since in $(Npop + NQpop) - ES$, the selection is carried out amongst the combined set of parent and offspring vectors, a parent vector may survive for infinitely large number of generations (even for the entire optimization procedure). Nevertheless, this feature may give rise to some deficiencies. For example, if the fitness function changes over time, the $(Npop + NQpop)$ scheme may cause the premature convergence of the algorithm on outdated solutions. Moreover, it may hinder self-adaptation of strategy parameters, since individuals with relatively good values but poor parameter settings may survive for a large number of generations producing inadequate offspring. Such deficiencies may be avoided when the $(Npop, NQpop)$ scheme is used, since the life time of each individual is limited to a single generation. It is noted that both selection schemes may be more efficient at specific application areas. For instance, the $(Npop + NQpop)$ scheme is recommended when combinatorial problems are tackled, while the $(Npop, NQpop)$ selection may be mainly useful for unbounded search spaces [27].

The steps of a general $(Npop/\rho, \dagger NQPop)$ - ES are summarized in Algorithm 1 [27]. At first the population is initialized, between the corresponding upper and lower bounds. Subsequently, the procedure enters the loop of the main evolution operators. To create each of the $NQpop$ offspring, initially the ρ parents are selected (usually at random) from the $Npop$ parent population ($parent\_selection$ operator in the algorithm). Thereafter, recombination is applied on the strategy parameters ($s\_recombination$) and on the objective variables ($x\_recombination$). Mutation follows, first applied on the strategy parameters ($s\_mutation$) and then on the objective variables ($x\_mutation$). It should be noted that the aforementioned order of mutation should not be changed, to ensure that self-adaptation will work correctly, since the mutated strategy parameters are included within the mutation of the objective variables.

Algorithm 1 Steps of a general $(Npop/\rho, \dagger NQpop)$ - ES

$g \leftarrow 0$
Random initialization of population Pop^0 (objective variables x and strategy parameters s)
Evaluate initial population
while Termination criterion not satisfied **do**
  for $l = 1$ to $NQpop$ **do**
    $C_l = parent\_selection(Pop, \rho)$
    $\tilde{\mathbf{s}}_\mathbf{l} = s\_recombination(C_l)$
    $\tilde{\mathbf{x}}_\mathbf{l} = x\_recombination(C_l)$
    $\mathbf{s}_\mathbf{l} = s\_mutation(\tilde{\mathbf{s}}_\mathbf{l})$
    $\mathbf{x}_\mathbf{l} = x\_mutation(\tilde{\mathbf{x}}_\mathbf{l}, \tilde{\mathbf{s}}_\mathbf{l})$
    Evaluate $\mathbf{x}_\mathbf{l}$
  end for
  Selection of the population of the next generation, Pop^{g+1}
  $g \leftarrow g + 1$
end while

Amongst the several variants of ES proposed, CMA-ES has gained the most attention of the research community. It has demonstrated competitive performance in several global optimization problems [28, 29]. The description of the CMA-ES is beyond the scope of this dissertation, and the interested reader is kindly referred to [30]. Moreover, for a more comprehensive review on the theoretical research carried out to increase the understanding of the Evolutionary Strategies the interesting reader is kindly referred to the several review papers and books on the method, i.e. [15, 18, 27].

2.3.2 Differential Evolution

Differential Evolution (DE) is one of the relatively newest Evolutionary Algorithms. It has been initially presented by Storn and Price in a technical report in 1995 [31]. A journal article has followed afterwards, describing the algorithm in full detail [21]. Since then, DE has emerged as one of the most popular stochastic real-parameter optimization algorithms due to its simplicity, reliability and efficient performance in a variety of applications. In its basic form, DE handles a population of decision vectors which evolves using the computation steps followed by standard EAs. However, compared to the standard EAs, DE does not rely on separate probability distribution to create the population of offspring rather than on the scaled differences of randomly selected individuals of the population.

DE starts with a population of solution vectors which are randomly initialized (utilizing a uniform distribution) within the search space. Subsequently, at each generation, an offspring population is generated utilizing two evolution operators, i.e. mutation and crossover. Specifically, mutation is applied to generate a provisional offspring (in DE called mutant or donor vector) for each parent vector (in DE also called target vector). In its most common form (called the DE/rand/1 mutation scheme), for a parent vector $\mathbf{x_n}$ three distinct vectors $\mathbf{x_{r1}}$, $\mathbf{x_{r2}}$ and $\mathbf{x_{r3}}$ are randomly sampled from the population; r1, r2, r3 are mutually exclusive integers in $\{1, Npop\}/n$. The difference vector of two of them is scaled and added to the third vector to create the donor vector as follows:

$$\mathbf{v_n} = \mathbf{x_{r1}} + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) \tag{2.7}$$

where F is a scale factor (typically $F \in [0.4, 1]$) that controls the amplification of the difference vector. In DE, scaling the difference vector has two main implications [32]; first it ensures that the potential trial vectors are different to each other. Moreover, it may shift the focus of search among local and global optimization reducing thus the probability of entrapment in local minimum solutions. It is noted that, in the mutation of DE the selection of the base vector can be implemented in a variety of ways, from which a random selection or the selection of the best individual in the population is the most common.

After the application of the mutation operator, the crossover operator is implemented to further increase the diversity of the population. During the crossover operator the target vector exchanges its components with the mutant vector to create the trial vector. The crossover operator is controlled by the crossover probability CR which is a user defined parameter. In its most common form, i.e. the binomial crossover, a random number ($rand_d$) is generated anew for each parameter using the uniform distribution. If the random number is greater than CR then the parameter is inherited from the parent vector. Otherwise it is inherited from the mutant vector. Moreover, a single randomly chosen parameter (d_{rand}) is always inherited from the mutant to ensure that the trial will not be a duplicate of the target vector; consequently CR only approximates the probability that a parameter will be inherited by the mutant but it is not equal to it. The binomial crossover operator is implemented as follows:

$$u^g_{d,n} = \begin{cases} v^g_{d,n},\ if\ d = d_{rand}\ or\ rand_d \leq CR \\ x^g_{d,n},\ otherwise \end{cases} \tag{2.8}$$

Another crossover operator used in DE is the exponential crossover. In this crossover, a random parameter index is chosen in $[1, D]$ and the corresponding parameter is inherited to the trial by the mutant. The number of subsequent parameters donated by the mutant to the trial is determined by comparing CR to a uniformly distributed number in [0, 1] generated anew for each parameter. The trial will continue to inherit parameters from the mutant until the first time that the randomly generated number exceeds CR or the number of parameters inherited is equal to D. Several other crossover schemes may be used, i.e. one point crossover, n-point crossover. The interested reader is referred to [32] for a more elaborate explanation of such crossover schemes.

Selection follows, according to which the fittest individual amongst the target and the trial vector survives to the next generation. For unconstrained problems, the selection operator proceeds as follows

$$\mathbf{x}_n^{g+1} = \begin{cases} \mathbf{u}_n^g, \ if \ f(\mathbf{u}_n^g) \leq f(\mathbf{x}_n^g) \\ \mathbf{x}_n^g, \quad otherwise \end{cases} \tag{2.9}$$

As a result, in DE the population is either improved or remains the same with respect to the fitness status. Thus, the selection scheme of DE is elitist since it retains within the population the best-so-far-solutions found in the parent and the trial population. Such a scheme may also provide speed improvements concerning the convergence of the algorithm to the (near) optimal solution. The selection scheme of DE is carried out by implementing $Npop$ binary tournaments where the tournament size is equal to 2. Thus compared to other schemes of tournament selection with larger tournament sizes, the one used in DE introduces a lower selection pressure which may help avoiding premature convergence [32]. Moreover, in each binary tournament, the two vectors that compete are not selected randomly; they are a member of the current population (the target vector) and the corresponding trial, with the provision that the aforementioned vectors are related through crossover. Thus, replacing a vector in the current population, can change the population's composition by a number of parameters depending on the CR value (one in case $CR = 0$ and D in case $CR = 1$). It is noted that, a trial vector might be better than members of the current population but may not survive to the next generation. Nevertheless, one-on-one selection scheme ensures that trial vectors that are worse than the worst member of the current population are discarded. It is noted, that a trial vector replaces the target vector even when both have the same fitness value. This feature may facilitate the population to avoid entrapment in flat regions of the search space.

It is noted that commonly the notation DE/x/y/z is used to distinguish the different variants of the DE algorithm [32], where x represents the base vector, y denotes the number of difference vectors utilized to perturb the base vector and z specifies the crossover scheme used. Thus, for example, the classic DE/rand/1/bin algorithm refers to the DE algorithm in which the base vector is randomly chosen from the current population, a single difference vector is used to perturb it and the binomial crossover is used to generate the trial vector. Given the notation, some of the most common mutation schemes for DE in the relevant literature are the following [33, 34]:

1. **DE/best/1**:

$$\mathbf{v_n} = \mathbf{x_{best}} + F \cdot (\mathbf{x_{r1}} - \mathbf{x_{r2}}) \tag{2.10}$$

2. **DE/rand/2**:

$$\mathbf{v_n} = \mathbf{x_{r1}} + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) + F \cdot (\mathbf{x_{r4}} - \mathbf{x_{r5}}) \tag{2.11}$$

3. **DE/target-to-best/1**:

$$\mathbf{v_n} = \mathbf{x_n} + F \cdot (\mathbf{x_{best}} - \mathbf{x_n}) + F \cdot (\mathbf{x_{r1}} - \mathbf{x_{r2}}) \tag{2.12}$$

4. **DE/current-to-rand/1**:

$$\mathbf{v_n} = \mathbf{x_n} + F \cdot (\mathbf{x_{r1}} - \mathbf{x_n}) + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) \tag{2.13}$$

5. **DE/rand-to-best/1**:

$$\mathbf{v_n} = \mathbf{x_{r1}} + F \cdot (\mathbf{x_{best}} - \mathbf{x_{r1}}) + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) \tag{2.14}$$

where $r1, r2, r3, r4, r5$ are mutually exclusive integers selected at random from $[1, Npop]/n$, $\mathbf{x_{best}}$ is the best solution vector in the population. Each mutation scheme has its own characteristics.

Mutation strategies in which the base and the difference vectors are selected from the population at random, i.e. DE/rand/1 and DE/rand/2, do not introduce biases towards search directions and as a result usually demonstrate enhanced exploration capability combined with slow convergence speed. Mutation schemes which utilize the information of the best individual usually demonstrate an accelerated convergence and perform well in uni-modal problems. However, when applied on multi-modal problems, they may converge prematurely by getting stuck to local optimum solutions. In DE/current-to-rand/1, each target vector learns from a randomly selected individual, thus promoting the diversity. It should be noted that, combinations of the aforementioned mutation schemes may be utilized within the DE framework, to exploit the strengths of the different mutation schemes.

2.4 Handling of constraints

Commonly, optimization problems include a series of constraints (as presented in subsection 2.2). Constraints may cause the focus of the optimization procedure to be shifted towards providing a feasible solution rather than on seeking for the optimal solution. On their original version, EAs are not able to handle constraints. For this reason, over the years several constraint handling techniques have been proposed and coupled with EAs in order to steer the population towards regions of the search space with feasible solutions. The main purpose of a constraint handling technique is to establish a way to compare the parent and the offspring population in the presence of feasible and infeasible individuals. The current most frequently used techniques can be categorized into the following groups [35]:

1. Methods based on penalty functions.

2. Methods based on the distinction among feasible and infeasible solutions.

3. Methods based on the concepts of multi-objective optimization.

Amongst the several constraint handling techniques developed, the most common methods belong to first category [36]. In such approaches, a quantity related to the amount of constraints' violation is added on the objective function value, to 'penalize' individuals violating the problem constraints, in an attempt to favor feasible individuals during the selection process. In the second category, the comparison of individuals is carried out either based on the objective function value or the degree of constraint violations. Usually in such approaches feasible solutions are preferred over infeasible ones. Regarding the methods in the third category commonly the minimization of the total degree of constraint violation is considered as an additional objective of the problem, and the problem is handled as a multi-objective one.

In what follows we will describe in more detail two well-known constraint handling techniques, i.e. the Feasibility Rules and the Stochastic Ranking. The former belongs to the methods which distinguish feasible and infeasible solutions, while the latter is one of the most recent methods based on the penalty function approach. The aforementioned methods will be described since they are used in the constrained evolutionary algorithms developed in the present dissertation. For a comprehensive review over the constraint handling techniques coupled with nature-inspired meta-heuristics the interested reader is kindly referred to the rigorous reviews of Coelo-Coello [37] and Mezura-Montes and Coello Coello [38].

2.4.1 Feasibility Rules

Feasibility Rules constitute one of the most popular techniques for constraint handling. They have been initially proposed by Deb [39]. They belong to the category of techniques which handle the values of constraints separately from the values of the objective function. In particular, when this approach is applied for the case of single objective problems ($M = 1$), the comparison among the individuals in the binary tournament is carried out following three feasibility criteria:

- When both solutions are feasible, the one with the best objective function value is selected.

- When only one of them is feasible, then it is preferred.
- When both solutions are infeasible, the solution with the lower total constraint violation is chosen.

To implement the comparison based on the aforementioned criteria, the total constraint violation, which is the sum of the violations of the individual constraints, of each individual is evaluated as follows:

$$\phi(\mathbf{x}) = \sum_{l_1=1}^{L_1} max(0, g_{l_1}(\mathbf{x})) + \sum_{l_2=1}^{L_2} max(|h_{l_2}(\mathbf{x})| - \epsilon, 0) \tag{2.15}$$

where $g_{l_1}(\mathbf{x})$ is the value of the l_1th inequality constraint ($g_{l_1}(\mathbf{x}) \leq 0 \ for \ l_1 = 1, ..., L_1$), $h_{l_2}(\mathbf{x})$ is the value of the l_2th equality constraint ($h_{l_2}(\mathbf{x}) = 0 \ for \ l_2 = 1, ..., L_2$) and ϵ is a small positive tolerance for relaxing the equality constraints.

One of the basic merits of the method is the lack of user-defined parameters. Nevertheless, the increased pressure towards reaching the feasible region might cause a diversity loss, leading the algorithm to premature convergence. Moreover, since feasible solutions are always preferred over infeasible ones the approach may encounter difficulties when dealing with problems in which the optimum feasible solution lies on the boundary of the feasible region. For this reason, commonly some mechanisms to preserve the diversity of the population have been proposed and applied when the FR method is utilized.

2.4.2 Stochastic Ranking

The Stochastic Ranking method was proposed by Runarsson and Yao in [40] as an attempt to deal with the problem of tuning of penalty parameters. According to [40], an adequate penalty factor should lead on striking a balance between the information exploited from the objective function and the constraints during optimization to steer the search towards feasible regions with optimum solutions of good quality. In particular, if the value of the penalty factor is too large, then the exploration of the infeasible regions during the early stages of the optimization will be discouraged. As a result, the population of solutions may rapidly enter a feasible region, which may contain solutions of poor quality. However, moving from a feasible region to another might be difficult, especially when such regions are distant. The algorithm will probably discard infeasible solutions, which might act as intermediate points towards moving to another feasible region. On the other hand, a small value of the penalty factor might trigger less penalization of the infeasible solutions, making more difficult the finding of feasible regions.

In Stochastic Ranking, binary tournaments among feasible individuals are carried out by comparing their objective function values. If the binary tournament is carried out between two infeasible individuals or a feasible and an infeasible one, then there is a probability equal to P_f of comparing the individuals based their objective function values. In principal, SR was coupled with an $(Npop, NQpop) - ES$. For this reason, ranking was carried out using a bubble-sort-like procedure, as described in Algorithm 2. In this procedure, at least λ sweeps are carried out, to rank individuals of the population by comparing them to their adjacent neighbors. The procedure terminates when the order of individuals does not change during a single sweep of the algorithm. P_f is a parameter introduced in SR, which may adjust the strength of the bias towards feasible solutions. The authors initially suggested $P_f = 0.45$ to slightly bias the search against infeasible individuals. Moreover, within Algorithm 2, the following notation is used: I_i denotes the rank given to individual i, while I_j^{-1} is the individual assigned to rank j. It is noted that SR has been also combined with other EAs, such as DE [41] and EP [42].

2.5 Handling of multiple objectives

As stated in Section 2.2 the main difference of multi-objective optimization compared to the single objective counterpart is that in the former no single optimal solution commonly exists rather than a set of optimal solutions, each of which represents an optimal trade-off among the conflicting objectives. The aforementioned solutions are referred to as non-dominated, efficient or Pareto

Algorithm 2 Stochastic Ranking [40]

$I_j = j,\ \forall j \in \{1, \dots, NQpop\}$
for $i = 1$ to $Npop$ **do**
  for $j = 1$ to $NQpop - 1$ **do**
    Sample $u \in U(0,1)$
    if ($\phi(\mathbf{x}_{I_j^{-1}}) = \phi(\mathbf{x}_{I_{j+1}^{-1}}) = 0$) or ($u < P_f$) **then**
      if ($f(\mathbf{x}_{I_j^{-1}}) > f(\mathbf{x}_{I_{j+1}^{-1}})$) **then**
        swap(I_j^{-1}, I_{j+1}^{-1})
      end if
    else
      if ($\phi(\mathbf{x}_{I_j^{-1}}) > \phi(\mathbf{x}_{I_{j+1}^{-1}})$) **then**
        swap(I_j^{-1}, I_{j+1}^{-1})
      end if
    end if
  end for
end for

optimal solutions. After finding a set of such trade-off solutions the decision maker may use higher-level qualitative considerations to make a decision. Thus, it is important to approximate as many Pareto optimal solutions as possible, because the decision maker will be able to make better decisions when more trade-off solutions are available. It is noted that the search is carried out on the decision variables space; however information from the objective function space may be exploited in the evolution operators of the algorithms. A difference amongst single and multi-objective optimization problems lies on the goals of optimization. In single objective optimization the goal is to find the optimum solution. On the contrary, the goal of approximating the Pareto optimal set of solutions in multi-objective optimization problems may be divided in the following targets [43]:

1. The convergence to the Pareto optimal front should be as close as possible

2. The solutions found should be as evenly distributed as possible

3. The spread of the solutions should also be the maximum possible

Despite the difference in the cardinality of the set of optimal solutions between single and multi-objective optimization problems, in both cases a decision maker would practically require a single solution. In multi-objective optimization, since a set of optimal solutions exists, the user would have to select a single solution among them. However, if a set of trade-off solutions are available, one can evaluate the advantages and disadvantages of each solution utilizing higher-level information to make a choice. Thus, ideally in multi-objective optimization the focus should be concentrated on providing the decision maker with the set of optimal solutions by considering all objective equally important. If a relative preference factor among the objectives is known *a priory* for a specific problem, a composite objective function could be formed as the weighted sum of the objectives, where each weight would be proportional to the preference towards the corresponding objective. The aforementioned procedure is called preference based multi-objective optimization. However, in such a case the single solution obtained would be sensitive to the preference vector used. However, defining a preference vector may be a subjective procedure and is not trivial, since it may require analysis of non-technical, qualitative and experience driven information [43]. Thus, in such a case the optimal solution obtained may be highly subjective to the particular user. On the contrary in the ideal approach, information is utilized to select a solution from a set of obtained solutions. Thus, the ideal approach may be more practical and less subjective.

Based on the aforementioned analysis two main categories of solution methodologies have been proposed to solve multi-objective optimization problems; classical approaches and multi-objective evolutionary algorithms. Both will be described in the following subsections.

2.5.1 Classical approaches for multi-objective optimization

Classical approaches have been proposed to deal with multi-objective problems. In such approaches, usually the multi-objective problem is converted into a single-objective or a series of single objective ones. Then, single objective optimization methods may be employed to tackle the problem. Several runs of the optimization with different parameter settings may be required to obtain a set of solutions which approximates the Pareto-optimal set.

The most common among the classical approaches is the weighted sum approach. In this method, a set of weights is assigned to the different objectives and the weighted objective function values are added to a single scalar fitness function. The aforementioned function is used as a metric of fitness of the different individuals. To find multiple Pareto optimal solutions the weighting parameters must be varied systematically, and the problem should be optimized anew for the different sets of weights. In Figure 2.2, the objective function space of an optimization problem with two objective functions is presented to demonstrate how the weighted sum method proceeds; the Pareto front is shown with dots, while the lines represent solutions of equal cost under a weighted sum. In the left figure 2.2, A is the optimal solution obtained by the method based on the selected set of weights (w_1, w_2). A change to the weights, i.e. $(w_1^{'}, w_2^{'})$ modifies the angle of the lines of equal cost, as shown in the right figure and thus the solution obtained by the method is C. Non-dominated solution B, however, is not optimal for any combination of weights, because it is not on the convex hull of the Pareto Front. This constitutes one of the main disadvantages of the weighted sum approach; the fact that it cannot find which are not on the convex hull of the Pareto Front. [43]. Another disadvantage of the method is that a uniform choice of weight vectors may not necessarily lead to a uniform set of Pareto-optimal solutions. In fact different weight vectors may lead to the same solution depending on each position on the Pareto Front.

Another classical approach, which alleviates the deficiency of the weighted sum approach related to non-convex fronts, is the ε-constrained method. In this method, one of the objectives of the problem is retained, while the other objectives are handled as additional constraints to the problem, by imposing an upper bound on their value (in minimization problems) defined by the parameter ε. Thus, the task of the optimization is shifted towards finding the solution that minimizes the value of the retained objective function within the feasible region. The basic disadvantage of this method is related to the setting of ε. An inadequate setting of ε might lead to problems with no feasible solutions. Moreover, different settings of ε may not necessarily lead to different solution.

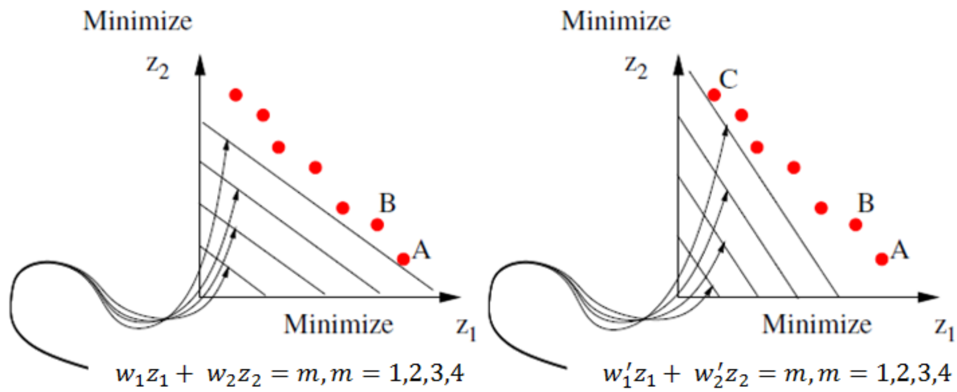


Figure 2.2: Illustration of the operation of the weighted-sum approach

Furthermore, the more the number of objective functions in a problem the more elements in vector of ε should be tuned by the user, increasing the difficulty of adequate tuning.

2.5.2 Multi- Objective Evolutionary Algorithms

In more recent years, Multi-Objective Evolutionary Algorithms (MOEAs) have been proposed as an alternative to classical methods for solving multi-objective problems. EAs seem to be well suited for multi-objective optimization, due to their population-based nature, which enables the approximation of multiple Pareto optimal solutions in a single optimization run. MOEAs share many similar core characteristics to the EAs for single objective optimization; the utilize evolution operators to improve the fitness of a population of solutions for a number of generations. However, since multiple objectives are included on multi-objective problems, fitness assignment and selection of population members for the next generation are not straightforward. Moreover, to achieve the targets of multi-objective optimization, as described in Subsection 2.5, MOEAs may include some additional mechanisms related to fitness assignment and preservation of diversity of solutions, attempting to avoid premature convergence and obtain well distributed Pareto Front approximations.

During the previous years, several research attempts have been published on MOEAs. Most of them follow the principles of the two following algorithmic frameworks: Algorithms which utilize the concept of Pareto Dominance and algorithms based on the concept of Decomposition [44]. In the former, all objectives of the problem are simultaneously optimized, while fitness assignment is carried out based on the concept of Pareto dominance. Furthermore, diversity preservation mechanisms are included within the algorithms to maintain the diversity of the solutions in the population. The second algorithmic framework contains methods in which the problem is decomposed into several scalar objective sub-problems using aggregation based methods. The objective of each sub-problem is a weighted aggregation of the objective functions. Neighborhood relations are established between the different sub-problems, utilizing the distances between the weight vectors and each sub-problem is optimized by using information from the 'neighbor' sub-problems. In such methods, diversity among the population members is usually preserved by using well distributed weight vectors to decompose the problem, thus explicit preservation mechanisms may not be required. It is highlighted that other algorithmic frameworks for developing MOEAs also exist, e.g. preference-based MOEAs and indicator-based MOEAs, and the interested reader is kindly referred to [44], for a detailed discussion on these frameworks.

In the following subsection, we will describe the basic concepts of one of the most popular and efficient MOEA, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [45]. This algorithm has constituted the base for the MOEA developed in this dissertation.

Non-Dominated Sorting Genetic Algorithm (NSGA-II)

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been proposed by Deb et al. [45]. It is an updated version of NSGA [46] and constitutes one of the most widely used MOEAs. Compared to its initial version, in NSGA-II a non-dominated sorting and ranking procedure with lower computational complexity is utilized in an attempt to decrease the computational burden when large population sizes are used. Moreover, elitism is utilized to accelerate the convergence towards the Pareto Front by maintaining the best-so-far solutions found. In particular, the individuals of the parent and offspring populations are combined and sorted using the aforementioned non-dominated sorting and ranking procedure. Furthermore, a mechanism is included, which preserves the diversity of the population, without requiring the tuning of additional parameters by the user. This mechanism does not require the comparison of each solution in the population with all the other solutions, thus it also reduces the computational complexity of the overall algorithm compared to its previous version. The NSGA-II algorithm will be described in more detail in the following paragraphs.

In NSGA-II, a fast non-dominated sorting procedure is used to sort the individuals of the population at different non-domination levels. In this procedure, for each individual i two entities are calculated. The first is the domination count n_i, which is the number of solutions dominating solution i. The second is the set S_i, which contains the solutions that solution i dominates. Thereafter, solutions which have a domination count equal to zero ($n_i = 0$) belong to the non-dominated front of the examined population. For each solution i with $n_i = 0$, each member j within S_i is visited and its corresponding domination count, i.e. n_j, is reduced by one. If for any solution j the domination count becomes zero then this solution is put on a list P'. This procedure is repeated for each solution i having $n_i = 0$, and solutions in P' constitute the second non-dominated front. The procedure is iterated in a similar fashion until all individuals have been assigned to a non-dominated front. An example of the non-dominated sorting procedure for a problem with two objective two be minimized is given in Fig.2.3. Initially, for each solution i the domination count n_i is calculated and the set S_i is filled with solutions that solution i dominates, e.g. for solution 2, $n_2 = 0$ and $S_2 = \{3, 4, 5\}$. Since $n_2 = 0$, solution 2 belongs to the first front (the same holds for solution 1). In the second step (not shown in the left diagramm), solutions 3, 4, 5 are visited since they are contained in S_2 and the corresponding n is reduced by one, e.g. for solution 4 it will become $n_4 = 0$, thus solution 4 belongs in the second front. The procedure is repeated until all solutions have been ranked in a front.

In each generation g of NSGA-II, an offspring population $Qpop^g$ is generated by applying the

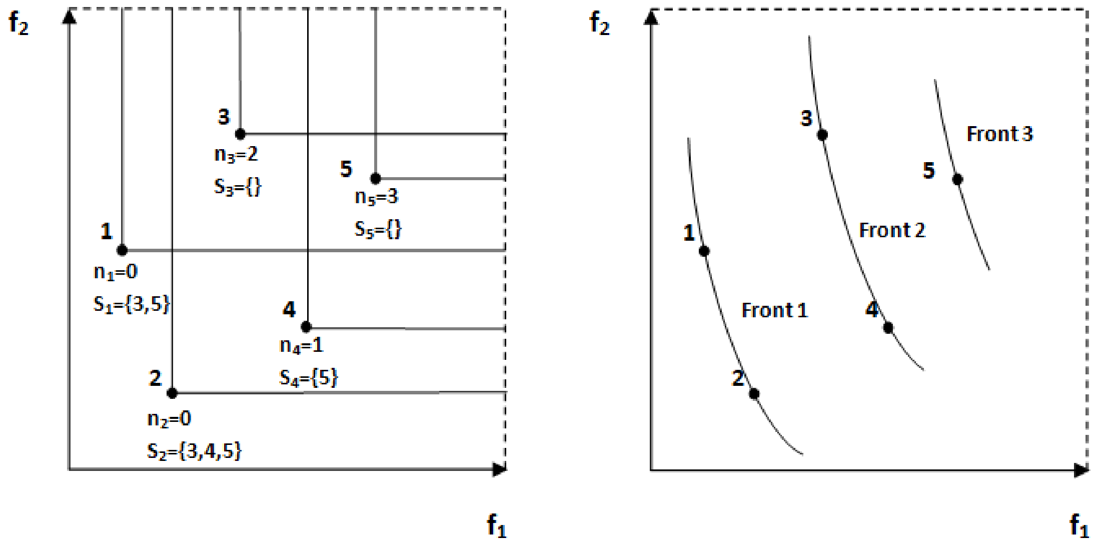


Figure 2.3: Non-dominated sorting procedure of NSGA-II.

evolution operators of a Genetic Algorithm on the parent population $Ppop^g$. The aforementioned two populations are merged to form an intermediate population $Rpop^g (= Ppop^g \cup Qpop^g)$ of size $2 \cdot Npop$. Then, the fast non-dominated sorting procedure, described previously, is applied to rank the individuals of $Rpop$ in different non-dominated fronts. Subsequently, the filling of the parent population of generation $g + 1$ ($Ppop^{g+1}$) begins with the individuals belonging at the best non-dominated front. Since the size of $Ppop^{g+1}$ is $Npop$, while that of $Rpop$ is $2 \cdot Npop$ only the half best individuals of $Rpop$ will be included in $Ppop^{g+1}$. As a result individuals belonging in fronts, which cannot be accommodated in $Ppop^{g+1}$ are discarded. The procedure is elitistic since, the parents of the next generation are selected amongst the best individuals of $Ppop$ and $Qpop$. A case might emerge during which a front, e.g. $FrontL$, can only partially be accommodated within the remaining slots of $Ppop^{g+1}$. To decide which individuals of $FrontL$ will be included in $Ppop^{g+1}$, the crowding distance metric (described in detail in the following paragraph) is calculated. The latter is a metric which estimates the density of solutions in different areas of a non-dominated front. Consequently, solutions belonging to less crowded areas of $FrontL$, are selected to fill the remaining slots in $Ppop^{g+1}$.

The crowding distance metric calculates the average distance between the two points on either side of the examined point along each of the objectives. In particular, for each individual in a front I, this quantity is an estimate of the perimeter of the cuboid formed by using the two neighbor points on either side of it as vertices, as shown in Fig 2.4. A highest value of the crowding distance metric may indicate a less crowded region in the front. The procedure for calculating the crowding distance for solutions belonging in front I is described in Algorithm 3 [45]. Initially, the population is sorted according to each objective function value. Subsequently, the individuals which are the extreme solutions of this front are assigned an infinite distance value. The distance assigned to the intermediate solutions of the front is equal to the absolute normalized difference in the function values of the two neighbor solutions. The procedure is repeated for each of the objectives and the total distance for each point equals the sum of the individual distances. Thus, in some extent, a smaller value of the crowding distance metric indicates that a solution may be located in a more crowded region of the front in comparison to other solutions.

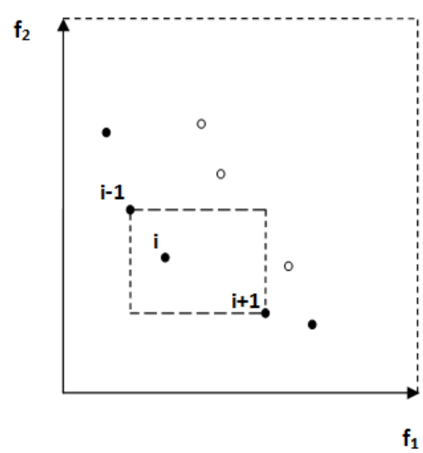


Figure 2.4: The cuboid used to calculate the crowding distance for solution i [45]. It is formed by using the neighbor points of solution i in the same front, i.e. solutions $i-1$ and $i+1$ (solutions in the same front are marked with filed circles).

Algorithm 3 Calculation of the crowding distance metric [45]

$l = |I|$
for $i = 1$ to l **do**
  $I[i]_{distance} = 0$
end for
for $m = 1$ to M **do**
  $I = sort(I, m)$
  $I[1] = I[l] = \infty$
  for $i = 2$ to $l - 1$ **do**
    $I[i]_{distance} = I[i]_{distance} + \frac{I[i+1].m - I[i+1].m}{f_m^{max} - f_m^{min}}$
  end for
end for

2.6 Hybridizing Evolutionary Algorithms with other optimization methods

The elevated difficulty of optimizing real world problems, which are commonly characterized by complex objective functions and large number of objective variables and constraints, calls for optimization methods with increased efficiency. When dealing with real-world and large scale problems, a proper combination of EAs with other optimization techniques (or possibly another EA), called a hybrid algorithm, may result in more efficient algorithmic behavior. Thus, the primary motivation behind hybridization of different algorithms is the obtainment of more efficient approaches that exploit and combine the merits of the individual algorithms, i.e. such hybrid methods may benefit from synergy [47]. Depending on the technique which is hybridized with the EAs, the hybrid algorithms may be distinguished in the following three categories: the first category contains methods in which EAs are combined with other EAs. The second contains algorithms in which EAs have been combined with exact methods from operational research, while the third contains approaches in which EAs are combined with local search techniques. All categories contain a vast variety of methods [48]. In the following subsections, we provide a brief description of the basic notions and some representative methods in each category.

2.6.1 Hybridizing Evolutionary Algorithms with Evolutionary Algorithms

In the context of metaheuristics, several attempts have been carried out to combine the best characteristics of two or more algorithms to obtain an algorithm which may outperform the individual algorithms. Hybridization of EAs is gaining popularity due to their capabilities in tackling real-world problems, which may involve complexity, noisy environment, imprecision, uncertainty, and vagueness [49]. In this subsection, several hybrid algorithms, which combine EAs with other EAs will be reviewed.

An interesting framework for combining Differential Evolution and Particle Swarm Optimization has been developed in [50]. PSO constitutes a nature-inspired metaheuristic proposed by Kennedy and Eberhart in [51], which is inspired by the social behavior of bird flocking and fish schooling. In this framework, at each generation of the algorithm initially the evolution operators of the PSO are implemented to update the positions of the particles in the swarm. Thereafter, DE is applied to evolve the best position found by each particle in the swarm, and if the new best position is better than the current one then it is accepted for the next generation. Thus, DE operates on the best position found in the swarm, aiming to enhance the exploration of the search space during the initial stage of the evolution, while focusing the search on promising regions during the latter generations. The results of the computational experiments, carried out on several multi-modal high-dimensional benchmark functions, indicate that the hybrid method significantly improves the performance of the original algorithms.

In [52], DE with self-adaptive mutation has been hybridized with the PSO algorithm. The main motivation behind this hybridization is to strike a balance between the exploration of the search space and the local exploitation. In the hybrid method, a mutant vector is generated using either a mutation scheme called DE/e-rand/1, which is based on the DE/rand/1 scheme utilizing information from the elite individuals, or the recombination operator of PSO. The probability of utilizing each of the aforementioned schemes is dynamically adjusted according to the number of generations; in the initial stages the DE mutation scheme may be more frequently selected to enhance the exploration, while in the latter stages the PSO scheme has a higher probability of performing mutation, thus enhancing exploitation. Moreover, a method to adapt F and CR is proposed. The method has been evaluated on several benchmark problems demonstrating improved performance compared to the plain DE and PSO and several state-of-the-art approaches.

In [49], a hybrid evolutionary algorithm has been proposed, called Differential Covariance Matrix Adaptation Evolutionary Algorithm (DCMA-EA), in which the mutation, the crossover and the selection schemes of DE are included into the CMA-ES algorithms. The proposed method attempts to exploit the advantage of CMA-ES of avoiding premature convergence in badly scaled high separable functions and also utilizes the DE with the introduction of a difference vector based mutation factor, in order to exploit the capability of DE to adapt to the natural scaling of the fitness landscape. In particular, in DCMA-EA, a mutant is created by utilizing a controlled share of the target vector and the population mean. Moreover, a scaled difference vector and the controlled step-size are added. Subsequently the binomial crossover is applied to create the trial vector. Thereafter, the selection scheme of DE is utilized. It is noted that in the mutation scheme F is uniformly sampled between 0.5 and 1, while in crossover CR is sampled from a Gaussian distribution with mean 0.9 and standard deviation 0.1, to increase populations diversity. The method has been applied on several shifted, rotated and compositional benchmark functions, outperforming the original CMA-ES and DE algorithms, as well as state-of-the-art approaches based on DE and CMA-ES.

In [53], an attempt to exploit the advantages of the two most commonly used models for offspring generations in EAs, i.e. Distributed Model (DM) and Centralized Model (CM), is carried out. The DE (which is based on a DM) constitutes the base algorithm and some key features of a CMA-ES (which is based on a CM) are included into DE. In particular, the cumulative learned Evolution Path of the CMA-ES is utilized, which represents the migration path of the population center. After the trial vector has been generated by mutation and crossover, a differential vector, generated by a Gaussian model along the direction of the EP is added. This additional difference vector contains a factor which takes into consideration the difference in the mean point of a number of best individuals in the population from the previous generation to the current generation. Moreover, the weighted mean of the recent previous center points of the best members of the population is used as an anchor point. The difference vector contains two scaling parameters, which are self-adapted, and control the size and direction of the Evolution Path the step size towards the anchor point. Two DE variants have been considered, i.e. the ED/rand/1 and JADE [54], and the EP has been combined to both of them. The methods have been benchmark on the CEC 2013 test suites and two practical problems, demonstrating improved performance compared to the canonical DE, the original JADE and several state of the art approaches.

2.6.2 Hybridizing Evolutionary Algorithms with exact methods

Exact algorithms commonly provide guarantees to find an optimal solution and to prove its optimality for every instance of an optimization problem. In such category belong methods like the branch-and-bound ($B\&B$), dynamic programming, Lagrangian relaxation, Interior Point Algorithm. Nevertheless, such methods may require increased computational time, especially when the size of the problem under examination increases. In such cases, a trade-off between optimality and run-time may be sought by using heuristic algorithms. When exact methods are hybridized with EAs, the most represented cooperation scheme is the so called High-level Relay Hybrid, in which the different methods are self-contained and are executed in sequence [55]. In particular, in such a sequential scheme commonly the EA (or the meta-heuristic) may be launched first and then the exact algorithm exploits the information from the meta-heuristic. The information may be related to initial bounds, which may speed up the search of the exact algorithm, or an initial solution which facilitates the exploitation of certain sub-spaces of the search space, by the exact algorithm [55]. Some examples of such hybridization schemes are given in the following paragraphs.

In [56] a hybrid algorithm is proposed for the optimal reactive power flow problem, in which the Genetic Algorithm and the Interior Point method are hybridized. The method consists of two stages. In the first stage, the integer variables of the problem are relaxed, and the Interior Point Algorithm is employed to optimize the continuous optimization problem. The values of the relaxed variables are the rounded into discrete numbers, and the discretized solution is introduced in the initial population of the Genetic Algorithm. In the second stage the Genetic algorithm is combined with the Interior Point method to solve the problem. In this stage, the problem is decomposed into two sub-problems. The first is a is a discrete optimization problem in which the real values decision variables are constant and is tackled by the Genetic Algorithm. The values of the discrete variables found in the first problem are introduced into the second problem; it is a continuous optimization sub-problem, in which the discrete control variables are kept constant, and is solved using the Interior Point method. The values of the continuous variables found in the second problem are introduced into the first problem and the procedure is iterated until the termination criterion is met. The efficiency of the proposed method has been demonstrated using several test systems, showing improved performance in finding feasible solutions compared to the individual algorithms as well as a hybrid approach of the relevant literature.

In [57], the Interior Point method is hybridized with the DE in a sequential scheme in order to optimize the Economic Dispatch Problem, when the valve point effect is taken into consideration. In particular, initially the Interior Point method is applied to optimize the model without the inclusion of the valve points. Subsequently, DE is utilized to optimize the problem when valve points are included. The initial population of DE is generated randomly in the vicinity of the solution obtained by the IPA. The proposed method has outperformed several other approaches on two test instances examined.

In [58], Genetic algorithm is combined with Differential Evolution and Sequential Quadratic Programming approach to optimize the ED, when the valve-point effect of the units is considered. In particular, the Genetic Algorithm constituted the main optimization method, while DE and SQP were used to fine tune the solution provided by the Genetic Algorithm. The efficiency of the SQP is enhanced, by approximating the cost function with a smooth and differentiable function based on the maximum entropy principle. The uniform design technique is used to create an initial population, further improving the performance of hybrid algorithm. The efficiency of the method is examined on two test instances consisting of 13 and 40 thermal units, while a benchmarking with other approaches in the literature demonstrates that the hybrid algorithm has a competitive performance.

2.6.3 Hybridizing Evolutionary Algorithms with Local Search Techniques

Amongst the several hybridization schemes presented, the most commonly encountered is the one in which EAs are combined with local search procedures for refining the generated solutions. In such hybrid schemes, the population-based method is utilized to explore the search space, by capturing a global picture of it at the early steps of the optimization and gradually focus the search on promising regions of the search landscape. On the other hand, the strength of local search methods is that they are capable of exploiting and finding better solutions in the vicinity of a given starting solution. Thus, combining the complementary strengths of population-based and local search procedures may lead to highly efficient algorithms. Such hybrid algorithms may also be referred to, in the relevant literature, as Memetic Algorithms (MAs). They are inspired by the Darwinian Evolution theory and the theory of Richard Dawkins on human culture [59], according to which the latter is composed by simple units called memes; memes are 'bricks' of the knowledge that can be duplicated in human brains, modified, and combined with other memes in order to generate a new meme [60]. MAs have demonstrated an efficient performance in a wide range of single and multi-objective optimization problems.

The design of such hybrid algorithms requires the specification of some aspects of the algorithmic configuration, i.e. the population-based method and the local search technique to be used, the number of individuals that will undergo local search, the criteria according to which such individuals will be selected for local search and the frequency of local search implementations. Moreover, in the case of multi-objective optimization problems, the solution evaluation mechanism in the local search procedure should also be defined. Based on the answers given to the aforementioned issues, a large variety of algorithms have emerged.

Population-based methods such as Genetic Algorithms, ES, DE, and Particle Swarm Optimization are utilized in hybrid algorithms for their exploration capabilities; they may provide a reliable estimate of the region of the search space, where the global optimum lies. Such methods may be characterized by their flexibility and ease of application to a variety of problem domains. In one of the earliest attempts in the field [61], a Genetic Algorithm was combined with the Simulated Annealing algorithm, which is a stochastic single-point optimization method, to solve a well studied combinatorial optimization problem, i.e. the Travelling Salesman Problem. Since then, MAs which utilized different population based methods have been developed. For example, in [62], a distributed memetic DE has been proposed. In this approach the population of DE is divided into sub-populations, which evolve independently, while mutually exchanging information. Hook–Jeeves algorithm serves as the local search technique in this approach. It should be noted that the method incorporates both the concepts of Lamarckian and Baldwinian learning. The aforementioned learning concepts concern how learning influences the evolution. In particular, solutions which undergo local search may be improved by modifying the values of the objective variables and thus their fitness values. In Lamarckian learning, the modified solutions are included within the population for subsequent evolutionary processing. On the contrary, in Baldwinian Learning the original solution before the application of the local search is retained, while the value of the fitness function of the modified individual replaces the initial value of the fitness function of the original solution. When multi-objective optimization problems are examined, the more popular approaches utilized are the NSGA-II, Pareto archive Evolutionary Algorithm, MOEA/D.

The local search techniques used in MAs may belong to either deterministic or stochastic approaches [63]. Within the former, methods such as gradient descent, Hooke and Jeeves algorithm and Nelder-Mead simplex may be used in continuous optimization problems, while branch and bound may be utilized for handling combinatorial optimization problems. To deal with the increase in the computational requirements triggered by the increase in the problem's complexity and to enhance the search diversity within the solution's neighborhood in combinatorial optimization problem's, stochastic local search techniques such as the Tabu Search and Simulated Annealing have also been employed. In the context of Multi-objective MAs other methods have been also utilized. For example, in Itschibuschi and Murata [64] which constitutes one of the first attempts to propose an MA for Multi-objective optimization problems, the local search operator modifies the solutions in a randomly selected search direction in an attempt to move the search towards the Pareto front. In Lara et al. [65], the Hill Climber with Sidestep is proposed, where the local search method attempts to increase the convergence towards the Pareto fronts as well as obtain a wider spread of solutions

The problem of frequency of application of the local search procedure and the selection of adequate individuals to undergo local search has also been widely studied. The importance of striking a balance between the local search and genetic search (i.e. the search procedure carried out by the population based methods) has been highlighted both for single objective [60] and Multi-objective MAs [66, 67]. In particular, if local search is applied on a large number of individuals at each generation then the computational time may be largely attributed to local search and the method may not adequately explore regions of the search space with promising solutions. On the contrary, when local search is not frequently applied MA may perform similarly to simple (MO)EAs, lacking local exploitation abilities. To control the computational resources dedicated for local search some parameters may be introduced, e.g. a probability of applying local search to each individual, the number of iterations for which local search is applied to the selected individuals or a frequency parameter which controls the number of generations on which local search is applied. Moreover, selecting adequate individuals to apply the local search is an issue of importance in designing efficient (MO)MAs. In particular, individuals on which the local search is applied may be selected amongst the offspring population the parent population or the combination of the aforementioned populations. In the context of multi-objective optimization, the individuals may or may not belong to the non-dominated front of the current population. Regarding the latter, in the relevant literature it has been demonstrated that selecting adequate individuals, i.e. from the non-dominated front of the current population, to undergo local search may enhance the performance of the hybrid algorithm [68].

When hybrid algorithms combining EAs and Local search techniques are developed for multi-objective optimization, another issue arises, i.e. how to compare solutions within the local search framework. On single objective problems comparison of individuals during the local search is straightforward, since the fitness is related to the corresponding value of the objective function of each individual; in case the problem comprises constraints, a constraint handling technique is used to consider the value of constraint violation during the comparison of the individuals. In multi-objective optimization comparison of solutions may not be straightforward. Two methods have been mainly used to compare individuals in such approaches; comparisons may be implemented using either a scalar fitness function in which the objectives are combined, or the concept of Pareto dominance has been utilized. In the former, commonly the weighted sum approach is utilized, thus an adequate mechanism for the determination of weights is important. In the latter, solutions are compared based on the dominance relationship; since the latter defines a partial order among the compared solutions, commonly archives are utilized to store solutions that are non-dominated with respect to the one undergoing local search.

CHAPTER 3

RELAXATION OF QUANTITATIVE ENERGY OBJECTIVES ON GENERATION EXPANSION PLANNING: A COMPUTATIONAL AND POLICY STUDY

3.1 Introduction

During the past years, significant effort has been concentrated in optimal Generation Expansion Planning (GEP) of power sectors. In an attempt to comprehend the difficulties of long-term planning, several authors have proposed analytical procedures to increase the accuracy of simulating a power sector. Achieving realistic solutions is essential and depends directly on the mathematical formulation of the model. In this vein, limitations concerning several aspects of a power sector, i.e. the profitability of investments, stability of the grid, and diversity of generation mix, have been included in GEP models. Moreover, existing or future strategies, for the development of a power sector, should be taken into consideration in GEP models. Those strategies are a consequence of international and governmental guidelines, based on environmental or economical criteria. For example, the European Union (EU) has conducted Directive 2009/28/EC [69], Energy 2020 [70] and Energy Roadmap to 2050 [71] to set the EU goals for the European Energy System at 2020 and 2050.

The evolution of the power sector's structure might be modified by the adoption of such directives. Compensation schemes, investment motivation, and regulatory policies are applied to promote capacity additions in certain emerging or mature generating technologies. The power sector's economical and environmental viability is dynamically impacted. As a result, the agents of the system, either internal, i.e., producers, consumers, or external, i.e. carbon trading markets, may be influenced. In this context, policy makers would ideally also search for the optimal actions towards the accomplishment of the desired energy targets. Their research could be summarized to the following question: 'Which would be the steps towards an economically and environmentally optimal compliance with the directives?' These steps are related to investment decisions for capacity additions in several generating technologies. Optimal investment decisions may increase the power system's aggregate net present value (NPV), comprising of the financial yields of the system minus the electricity production costs. Moreover, investments occurring at an optimal entry time may also increase producers' chances for higher benefits [72]. Optimal system's NPV may also trigger moderation of the System's Marginal Price (SMP) or enhance the environmental sustainability of the power sector, benefiting electricity consumers. Thus, an estimation of the effect of those strategic interventions on the evolution of the power sector's variables, i.e. SMP and CO_2 emissions, may facilitate the decision-making process of the various system agents.

Electricity market models usually follow one of the main paths in existing literature: optimization, equilibrium, and/or simulation models [73]. An alternative approach might be the replication of system dynamics and the relationship among system agents to extract their dynamic response [74]. In perfect competition though, the required market model might be based either on the minimization of the total cost or on the net benefit maximization of the whole market, as entailed by microeconomic theory [73]. Especially in complex systems with numerous agents, where system dynamics' investigation might be confronted with numerical complexities, optimization-based models might still drive a means of modeling. Moreover, markets under perfect competition, when optimized, might still provide some chances for profitable individual companies, even on the long run. As emerged by Grkan et al. [75], electricity markets might be approximated as operating in a state of perfect competition and as such they might be resolved through optimization models. Although this may depart from the real markets' imperfect state, an insight of the market investment trends might still be provided though optimization at an affordable computational budget.

In this chapter, a decision support model is presented for optimizing the GEP of electricity markets under certain quantitative energy objectives. The market's agents (i.e. electricity producers based on different generating technologies) are considered to be numerous thus they are grouped by type of power producing technology. The optimal annual capacity orders are extracted over-time so that they smoothly comply with the predefined target plans. The optimal annual load intensity factors are also derived. The model is implemented on the case of the Greek power sector, but it can be adjusted to any other semi-liberalized electricity market. Based on the EU Directives mentioned earlier, two energy plans were conducted for this market: the National Renewable Energy Action Plan (NREAP) [76] and the National Energy Planning (NEP) [77]. The energy objectives set in both plans are included to assess their impact on the development of the power sector's structure.

The optimal generation capacity orders are estimated by implementing a non linear Stochastic Programming approach. The Stochastic Programming is implemented through a Monte-Carlo Simulation in order to produce multiple scenarios of evolution of stochastic commodities (electricity demand, CO_2 allowance and fuel prices, interest and inflation rates). These scenarios are further averaged, producing the final input for the GEP model.

Moreover, a hybrid algorithm (ISRES-IPA), consisting of Improved Stochastic Ranking Evolution Strategy (ISRES) and the Interior Point Algorithm (IPA), is employed to optimize the large scale[1] GEP model. ISRES is an Evolutionary Algorithm (EA) accompanied by a constraint handling technique proposed in [79], suitable for non-linearly constrained global optimization problems [80, 81]. Here, ISRES is used to address the selection difficulties of a proper initial vector for IPA. Given an adequate trial vector, IPA may lead to rapid convergence, thus it was selected as the local searcher [82].

In addition, a relaxation factor is applied on the constraints representing the objectives of the examined energy policy. Specifically, the factor defines a percentage of permissible deviation from the energy objectives. This approach is based both on computational and energy policy reasoning, as analysed later.

In this context, three cases with different levels of relaxation are optimized under the same scenario and compared to a base case, where the targets are not embedded in the GEP model.

[1] Number of decision variables ranging between 100 and 1000 [78].

Thus, the impact of energy objectives' integration and relaxation on the evolution of the examined power sector's structure is estimated. For each of the aforementioned cases, five computational experiments are conducted. In the first two, IPA is utilized, under a tight and a more generous computational budget, respectively. In the third, ISRES-IPA is applied on the GEP model. In the remaining two, a commonly used Genetic Algorithm (GA) is employed as a single solver (GA) and in conjunction with IPA (GA-IPA), respectively. Therefore, the efficiency of ISRES-IPA on GEP model's optimization is assessed, revealing improved performance compared to the competing solvers. Moreover, the effect of the objectives and their relaxation on the optimization procedure is analysed.

The rest of this chapter is organized as follows: Section 3.2 presents a review of the relevant literature. In Section 3.3 the GEP model is presented. In section 3.4, ISRES-IPA is presented. Section 3.5 describes the set up of the numerical experiments and the case study power sector. Section 3.6 discusses the results of the GEP model's optimization.

3.2 Literature review

GEP is a complex multiperiod problem, aiming at the determination of the optimal investments in a power sector (timing, generating technology, capacity, and location), under economic criteria, while ensuring that the expected electricity demand is satisfied. The decision criterion is, either the minimization of the total cost or the maximization of the financial benefits, arising from the realization of the proposed investments. Furthermore, GEP models include additional constraints, e.g. grid stability, reserve margin, and plants' operation. Phillips et al. [83], was one of the first attempts on GEP, in which a non-linear static expansion planning model for the all-thermal units system of Great Britain has been developed. On the basis of that work, Ramos et al. [84] present a non-linear static expansion planning model, where costs related to hydro storage and pumped plants are also considered.

After the United Nations Conference on Environment and Development held in Rio in 1992, the awareness about climate change and its consequences has substantially increased. The elevated consideration regarding the environmental factor has triggered the conduction of energy action plans towards the sustainable development of power sectors. The environmental factor has also been included in the latter GEP models.

Karaki et al. [85] develop a GEP model for the estimation of capacity orders foreseen by the Electricity of Lebanon, based on probabilistic production costing, tunnel dynamic programming, and environmental assessment. The environmental factor is included in the objective function as an additional cost for cleaning pollutants emitted by power plants. Hemmati et al. [86] examine the effects of wind power uncertainty on GEP. They propose a model that represents a 2-level deregulated market combined by a pool market model (Cournot model) to determine the clearing prices. More specifically, the method comprises a master and a slave level. In the latter, the optimal investment planning of each generating company within a power sector is determined based on a GEP optimization targeting at maximizing the profits. The optimization is carried out using PSO. Thereafter, in the master level, the reliability of the power system is examined, by checking several constraints related to the system's reserve capacity. The master level is considered as a pool market and the Cournot model is used to approximate the price of electricity in the system. The two stages are iterated until the termination criterion is met. Rajesh et al. [87] use a capacity expansion model to study the impact of wind power's penetration on the generation mix of the State of Tamil Nadu in India. In particular, a simple least-cost model has been employed to assess the long term impact of investments on wind power. Wind power plants are modelled as thermal units with a high forced outage rate, i.e. high probability of not being available for production. To optimize the GEP problem, a simple DE algorithm has been utilized. The analysis implemented has shown that the integration of RES decreases the cost of emissions from fossil fuel fired plants. Nevertheless, the reliability of the power system decreases when wind energy penetration increases, resulting in increased overall cost of the system. In a subsequent work, Rajesh et al. [88] have extended the aforementioned model to examine the impact of solar power's penetration on the generation mix of the State of Tamil Nadu in India. In [89], a multi-objective model has been proposed for the GEP of the Brazilian power system. The three conflicting objectives of the model are the minimization of the total cost of the system, the contribution of non-hydro RES on the total production and the maximization of generation at the peak load. The results of the model highlight the benefits arising from the increased integration of solar power within the future Brazilian power system, especially in terms of CO_2 emissions reduction.

The various uncertainties, related to the evolution of energy demand and commodity prices, e.g., fuel prices, interest rates, and CO_2 emission allowance prices, may have a significant impact on the investment planning. For this reason, several stochastic programming approaches have been implemented for the optimization of GEP [90]. Tangavelu et al. [91] propose a generic methodology to determine an optimal generating mix for a Southeast Asian region, minimizing risks caused due to forward uncertainties. These are related to commodity prices, electricity demand, and the evolution of renewable energy technologies. In particular, the method of scenario tree is utilized to represent future projections of uncertain variables. The model's objective is the minimization of the system's total cost, taking into account the cost due to emissions of Greenhouse Gases. Several constraints are included, related to the reliability of the system as well as the diversity of the generating mix. The resulting non-linear model is solved in GAMS, and the test results demonstrate that taking into account uncertainties in the evolution of the variables of a power sector results in more reliable generation mixes, which are feasible for a large number of scenarios of energy demand evolution. The unpredictability of commodity values is also considered by Kamalinia et al. [92] where a resource planning model integrating transmission network expansion is examined. In their work, an incomplete information noncooperative game-theoretic method is implemented in order each participating generation company to decide its strategic capacity expansion investments. Tolis and Rentizelas [72] propose a GEP model for the investigation of the impact of electricity and CO_2 allowance prices uncertainty on the investment decisions for different forms of market regulation regimes.

The interaction between expansion policies and investment planning has received attention in recent years. In Haller et al. [93] and Shayeghi et al. [94] environmental regulations related to emission constraints are taken into account by imposing a pre-specified cap on the total emissions during the planning horizon. A real options approach is implemented by Reuter et al. [95] for the comparison of different policy measures and an analysis of their effect on the decisions of an electricity producer to invest into new power generating capacity, to select the type of technology and to optimize its operation under price uncertainty. Shrimali et al.[96], use project-level cash flow models to estimate the cost of policy support and thereafter the most cost-effective federal policy to achieve the targets related to renewable energy in India by 2022. The impact of the energy targets set to comply with the EU directives until year 2020 is assessed for Finland [97] and Italy [98] using a static expansion planning approach. In the present work, the necessary investments for complying with EU objectives are dynamically derived. In addition, to the authors' knowledge, the computational impact of including predefined objectives in the GEP has not been examined yet.

Evolutionary algorithms have been extensively used to solve the GEP optimization problem. Kannan et al. [99] have implemented a comparative study of several nature-inspired metaheuristic algorithms on the long-term GEP. Several methods, e.g. GA, DE, ES, PSO, including a hybrid algorithm combining GA with a local search technique have been examined. To enhance the performance of the metaheuristic techniques, a Virtual Mapping procedure has been employed to reduce the size of the parameter vector, by mapping each combination of possible capacity additions into a single integer. Among the examined techniques the hybrid algorithm has performed better in all examined cases. Pereira and Saraiva [100], have proposed a GEP model which utilizes system dynamics to estimate the evolution of electricity demand and the SMP. Specifically, the model consists two stages; in the first, each generating company solves a profit maximization problem to determine the optimal capacity additions. In the second stage, the set of new investments in the power system are considered to determine whether the reliability of the system will be adequate and the dynamic model is used to estimate the evolution of the SMP and electricity demand. The outputs of the dynamic model are then used to determine the investment plants of each generating company. The two stage procedure is iterated until the termination criteria is met. In this model, GA has been utilized for the optimization of the mixed integer expansion planning of the individual agents. The Portuguese/Spanish power system has been employed for the testing of the method. In [101], NSGA-II has been employed to optimize a multi-objective model of GEP where the minimization of the system's cost and CO_2 emissions and the maximization of operational flexibility of the power sector towards dealing with the variability of RES integration are considered. The latter, is represented by a composite flexibility metric, which takes into account technical flexibility characteristics of generating units, such as the ramping capabilities and the minimum up/down times. In [102] a modified DE algorithm, called Information Exchange Based Clustered DE, has been proposed to optimize the GEP considering also the expansion of the transmission system, for power system's comprising solely thermal units. The population of DE is clustered using the k-means method. Different mutation strategies are utilized in the different clusters to allow the algorithm to exploit their different strengths and facilitate adaptation at different topologies of the search space. In an attempt to avoid premature convergence of the algorithm, after a number of iterations, the population of each cluster (except the best solution vector of each cluster) is re-initialized. A local search technique is used, which utilizes the best individual of each cluster to enhance the convergence of the method. The approach had efficiently optimized benchmark functions and two test systems of the relevant literature. In [103], a GEP model is developed, which considers the short-term operation of the power system using a simulation model, i.e. the Clustered Unit Commitment model [104]. To decrease the required computational time, a meta-model assisted DE has been developed; part of the computationally expensive simulations related to the short-term operation of the power system are replaced by computationally cheap cost indicators to reduce the number of simulations required to achieve a near-optimal solution. Several studies have been published in which metaheuristics have been applied on the GEP problem, i.e.

GA,[92, 105, 106, 107], Particle Swarm Optimization,[94, 107, 108, 109, 110], DE [107, 111, 87] and ES [99, 107] Moreover, some hybrid approaches combining GA with simulated annealing [112] GA with generalized Benders decomposition [113] and GA with dynamic programming [114] have been proposed. However, validation of the performance of heuristic approaches in the GEP context should be further researched, as highlighted in the recent review of Sadeghi et al. [115].

It should be noted that, except of models focusing on the expansion of the generating capacity of a power sector, models which deal with the expansion of the transmission network also exist. Since such models are out of the scope of this thesis, the interested reader is kindly referred to the reviews of Koltsaklis and Dagoumas [116] and Dagoumas [117] for a more elaborate analysis of such models.

3.2.1 Contribution to the relevant literature

A decision support model has been developed for the optimization of the generation expansion planning of semi-liberalized electricity markets towards the accomplishment of quantitative energy objectives, related to the integration of RES within a power sector's generation mix. The model maximizes the power sector's NPV, while the annual capacity orders and the occupation factor of the generating technologies constitute the model's decision variables. The quantitative energy objectives were formulated as equality constraints on which a relaxation factor was applied. The contributions of the dissertation to the existing literature regarding the optimization of GEP are the following:

1. A stochastic optimization procedure without recourse has been developed to derive the best capacity additions (time, technology, and capacity) towards the optimal compliance with energy objectives. It takes into consideration several scenarios on the evolution of stochastic variables of a power sector and derives a central averaged scenario, which is introduced as input in the optimization algorithm. Within the relevant literature stochastic optimization

models have been used on researches of generation expansion planning under uncertainties. However, to the authors knowledge, the proposed model is the first that considers a stochastic optimization approach to assess the impact of generating energy objectives on the future structure of a power sector.

2. A relaxation factor is imposed on the equality constraints, which represent the energy objectives. It defines the upper and lower bounds within which the energy targets set by policy makers are considered to be satisfied. This factor is set as a percentage of the specified target. With regards to energy policy reasons the inclusion of a relaxation factor is justified by the fact that the exact achievement of preset values does not reflect the overall aim of the energy objectives. The objectives may be perceived as strict guidelines, which guide the power sector's development towards the energy policy's targets. Moreover, with regards to the optimization procedure, using equality constraints to represent the energy objective may increase the effort required to achieve feasible solutions.

3. A hybrid solver, which combines Improved Stochastic Ranking Evolution Strategy (ISRES), which is a variant of Evolution Strategies for constrained optimization, and the Interior Point Algorithm in a two−stage methodology is proposed. In the first stage, the ISRES steers the search towards the optimal solution from the combined feasible and infeasible region operating as the global solver, which adequately explores the search space. Thereafter, given an adequate trial vector, the Interior Point Algorithm may lead to rapid convergence, operating as the local searcher. To the author's knowledge, it is the first attempt to optimize a Generation Expansion Planning problem using such a hybrid scheme.

3.3 Mathematical formulation of the model

The predefined energy objectives are embedded on a benefit optimization model [118], where the interaction between the generation capacity orders and the evolution of the annual SMPs are formulated. The decision variables comprise of the annual capacity orders $X_{i,v}$ (MW_{el}) of technology i ordered in year v and the dimensionless load intensity factors $\theta_{i,z}$ (%) at year z ($v \neq z$); the latter represents the usage intensity of power plants. Thus, the optimization of the model may indicate the investment entry time and the capacities of each plant category that should be ordered as well as their optimal usage. Consequently, the state may be able to optimally organize the schedule of licensing (annual ordered capacities) in the several available generating technologies. It is noted that, the occupation factor is required only for the fossil fuel fired power generating units. For RES the occupation factor is considered equal to one, since such technologies should be used whenever the power source is available, as is currently the real world practice. Each iteration of the optimization procedure begins with the calculation of the energy produced annually by each generating technology, using the following equation:

$$P_{i,z} = L_{i,z} \cdot \theta_{i,z} \cdot \alpha_{\alpha,i} \cdot \alpha_{c,i} \cdot 8760 \tag{3.1}$$

where

$$L_{i,z} = \sum_{v=1}^{z-Tl_i} X_{i,v} + \sum_{v=-40}^{0} C_{i,v} - \sum_{v=1}^{z-Tl_i} \overline{X_{i,v}} + \sum_{v=-40}^{0} \overline{C_{i,v}} \qquad \forall i, 0 \leq z \leq Y \tag{3.2}$$

and:

$$\overline{X_{i,v}} = \begin{cases} 0, & \text{if } \ v + Tl_i \leq z \leq v + Tl_i + To_i \\ X_{i,v}, & \text{if } \ z \geq v + Tl_i + To_i \end{cases} \tag{3.3}$$

$$\overline{C_{i,v}} = \begin{cases} 0, & \text{if } \ v + Tl_i \leq z \leq v + Tl_i + To_i \\ C_{i,v}, & \text{if } \ z \geq v + Tl_i + To_i \end{cases} \tag{3.4}$$

The dashed symbols denote the capacity additions that have exceeded their operational life time.

In a uniform pricing system the energy produced by each independent producer is remunerated at a price equal to the SMP (in €$/MWh_{el}$), i.e. the price, which equates the load demand and supply curves. In such a pricing system under perfect competition, the bidders bid approximately their unitary cost [119]. Thus, the SMP would normally be equal to the unitary cost of the most expensive unit, dispatched at each hour. In this study, the calculation of the mean annual SMP is based on the previous analysis and the Load Duration Curve. The procedure for approximating the SMP is described in the following subsections.

3.3.1 Produced energy and operational time of each technology

The energy produced annually by each technology is calculated by equation (3.1). The peak load of the examined technologies is calculated using the following equation:

$$PP_i = \begin{cases} \frac{L_i}{1+m_r}\ , & \text{if } i = 1, 2, 3 \\ \frac{P_i}{T_{z,max}}, & \text{if } i = 4, ..., 12 \end{cases} \tag{3.5}$$

Regarding the renewable energy units, their peak and lowest production are considered to be equal since they generate power when their energy source is available. The peak power of conventional fossil-fuel-fired generators is approximated by their installed capacity, taking into account an amount of spinning reserve (m_r) for grid stability.

As stated in Tolis [118], when a yearly averaged model is considered, the generating mix might be approximated using the Load Duration Curve (LDC). In the LDC the hourly aggregate demand ($d(t)$) is sorted in descending order over time. Moreover, the loads dispatched hourly by each technology are depicted in the same sorted order but they are further smoothed. The resulted power lines simulate the merit order, in which the generating technologies are dispatched, beginning from the cheapest and gradually proceed to the most expensive ones. Priority is given to the energy produced from Renewable Energy Sources (RES), since their unitary cost is practically zero. Subsequently, the annual energy production of a conventional technology may be approximated by the area between its power line and the preceding one in the LDC. For this calculation either the trapezoidal formula or the triangle formula may be applied depending on the operating time. Initially the trapezoidal formula is implemented:

$$\frac{PP_i + Py_i}{2} \cdot T_{zmax} = P_{i,z} \tag{3.6}$$

By substituting equations (3.1) and (3.5) at (3.6) we can calculate the minimum load of each conventional technology. Hence:

$$Py_i = L_i \cdot \left(2 \cdot \theta_{i,z} \cdot \alpha_{\alpha,i} \cdot \alpha_{c,i} - \frac{1}{1+m_r}\right) \tag{3.7}$$

If $Py_i \geq 0$, then the technology is in operation for the total hours of the year, thus $t_i = T_{z,max}$. If $Py_i < 0$, then the one side of the trapezoid is negative, which is not acceptable. Therefore, in that case $t_i \leq T_{z,max}$ and the triangular formula is used to approximate the area between the two successive power lines.

$$\frac{PP_i \cdot t_i}{2} = P_{i,z} \tag{3.8}$$

By substituting equations (3.1) and (3.5) at (3.8) we can calculate the operating time of the examined technology as follows:

$$t_i = 2 \cdot \theta_i \cdot \alpha_{\alpha,i} \cdot \alpha_{c,i} \cdot (1 + m_r) \cdot T_{zmax} \tag{3.9}$$

Commonly, the area in the LDC related to the energy produced by the marginal plants is approximated by the triangular formula, due to the fact that they mostly operate during hours of increased demand. On the contrary the base-load units (lignite units in the case study) and the intermediate units (NG-fired plants in the case study), the corresponding area in the LDC is approximated using the trapezoidal formula. It is noted, that the model investigates the appropriate modelling for each technology.

3.3.2 Approximation of the Systems Marginal Price

As stated earlier in a uniform pricing the SMP would normally be equal to the unitary cost of the most expensive unit, dispatched at each hour. In this study, to calculate the mean annual SMP the Load Duration Curve is utilized. In particular, the estimation of the mean annual SMP takes into account the time intervals during which each technology type operates and the unitary cost of the fossil fuel technologies.

Since the pricing of energy is considered uniform, the energy produced hourly by each generating technology during a certain timespan will be compensated at a price close to the unitary cost of the most expensive technology in operation at that timespan. The trapezoidal formula may be used to approximate the respective energy produced. For example, in the timespan during which marginal plants are in operation, the total energy produced by conventional technologies would be:

$$E1_z = \int_{t=t_{oil}}^{t=0} d(t)dt \rightarrow E1_z \cong \frac{t_{oil}}{2} \cdot \Big(\sum_{i=1}^{I-RE} \frac{L_i}{1+m_r} + d_{oil} - PP_{RES} \Big) \tag{3.10}$$

where d_{oil} is the level of production at the intersection of the power line of the marginal plants with the power line of the second most expensive technology. It may be approximated by a linear decrease from $\sum_1^{I-RE-1} PP_i$ to $\sum_1^{I-RE-1} Py_i$. Hence:

$$d_{oil} = \sum_{i=1}^{I-RE-1} \frac{L_i}{1+m_r} - \frac{t_{oil}}{T_{zmax}} \cdot \Big(\sum_{i=1}^{I-RE-1} \frac{L_i}{1+m_r} - \sum_{i=1}^{I-RE-1} Py_i \Big) + PP_{RES} \tag{3.11}$$

Each MWh produced during that time interval, will be rewarded at a price close to the average operational cost of the marginal plans, as follows:

$$SMP1_z = Cf_{oil} + \frac{f_{CO_{2oil}}}{\eta_{oil}} \cdot p_{CO_2 z} + \frac{Cv_{oilz}}{\theta_i \cdot \alpha_{\alpha,i} \cdot \alpha_{c,i} \cdot T_{zmax}} \tag{3.12}$$

The lowest price used for remunerating each technology is assumed to coincide with the higher of the previous cheaper one (e.g.$SMP1_z$:lowest for oil, highest for NG) for diversifying the costs among the units of the same technology. Partly linear segments of SMP were assumed over time for the compensation of the generating technologies, since the load duration curve and the supply-demand curves used are approximated using linear segments. Thus the mean annual SMP is calculated using the following formula:

$$\overline{SMP_z} = \sum_{1}^{k} \int_{t=t_{i-1}}^{t=t_i} SMP(t)dt \tag{3.13}$$

where k is the number of different technologies, which were promoted as the most expensive in operation during that year. For example, if marginal plants are dispatched for t_{oil} and then until T_{zmax} NG units were the most expensive, then the mean annual SMP would be:

$$\begin{aligned} \overline{SMP_z} = \sum_{1}^{2} \int_{t=t_{i-1}}^{t=t_i} SMP(t)dt = \int_{t=0}^{t=t_{oil}} SMP(t)dt + \int_{t=t_{oil}}^{t=T_{zmax}} SMP(t)dt \\ \cong \frac{t_{oil} \cdot \frac{SMP0_z+SMP1_z}{2} + (T_{zmax} - t_{oil}) \cdot \frac{SMP2_z+SMP1_z}{2}}{T_{zmax}} \end{aligned} \tag{3.14}$$

3.3.3 Objective function and constraints

The optimization procedure attempts to maximize the electricity market's NPV, which considers cumulative annual incomes and expenses amortised over operational life-time as follows:

$$
\begin{aligned}
&\mathbf{NPV}(\mathbf{X_{i,v}}, \theta_{\mathbf{i,z}}) = \\
&\quad \sum_{z=1}^{Y}[\overline{SMPz_{1-0}} \cdot E1_z + \overline{SMPz_{2-1}} \cdot E2_z] \cdot D_z + \sum_{i=1}^{RE}\sum_{z=1}^{Y} pre_z \cdot P_{i,z} \cdot D_z \\
&\quad + \sum_{z=1}^{Y} \overline{SMPz} \cdot (d_{z,f} - \sum_{i=1}^{RE} P_{i,z} - E1_z - E2_Z) \cdot D_z - \sum_{v=0}^{Y}\sum_{i=1}^{I} I_{i,v} \cdot X_{i,v} \\
&\quad - \sum_{i=1}^{I-RE}\sum_{z=1}^{Y} P_{i,z} \cdot \frac{f_{CO_{2i}}}{n_i} \cdot p_{CO_2 z} \cdot D_z - \sum_{i=1}^{I}\sum_{z=1}^{Y} Cf_{i,z} \cdot P_{i,z} \cdot D_z \\
&\quad - \sum_{i=1}^{I}\sum_{z=1}^{Y} Cv_{i,z} \cdot L_{i,z} \cdot D_z + \sum_{i=1}^{RE}\sum_{z=1}^{Y} P_{i,z} \cdot \frac{\sum_{i=1}^{I-RE} E_{CO_{2i}}}{\sum_{i=1}^{I-RE} P_{i,z}} \cdot p_{CO_2 z} \cdot D_z
\end{aligned} \tag{3.15}
$$

where D_z is the discount factor, which is calculated using the stochastic interest rate(r_t):

$$D_z = \prod_{t=1}^{z}(1 + r_t)^{-1} \tag{3.16}$$

and $I_{i,v}$ is the investment cost, which gradually decreases based on the Learning rate $b(i)$ and the cumulative installed capacity of technology i at year z:

$$I_{i,v} = I_{i,0} \cdot \left[\frac{\sum_{k=1}^{v} X_{i,k} + \sum_{v=-40}^{0} C_{i,v}}{\sum_{v=-40}^{0} C_{i,v}}\right]^{\log_2(1-b(i))} \tag{3.17}$$

Moreover, $\overline{SMPz_{1-0}}$, $\overline{SMPz_{2-1}}$ denote the SMP derived from the uniform pricing when the marginal plants (e.g. Oil plants in this study) and the intermediate plants (Natural Gas in this study) constitute the price makers, respectively.

The objective function (Eq. 3.15) contains mathematical terms representing the revenues from energy sales (first, second and third term), investment cost (fourth term), cost related to CO_2 emissions trading (fifth term), fuel and O& M costs (sixth and seventh term, respectively) and revenues from CO_2 emissions trading (eighth term). Regarding the last term of Eq. 3.15, it is assumed that emission allowances are generated due to the utilization of RES instead of the conventional technologies, i.e Lignite, Natural Gas and Oil plants. These allowances can be traded through the emission trading system, constituting an additional revenue.

Moreover, the maximization of the objective function is subject to the following constraints:

1. **Non-negativity constraints:**

   The annual capacity orders can not be negative. Moreover, $X_{i,v}$ should not exceed an approximated upper bound $X_{i,max}$, determined based on previous annual investments carried out in the examined electricity market.

$$0 \leq X_{i,v} \leq X_{i,max} \qquad \forall i, v \tag{3.18}$$

2. **Natural Resource Availability:**

   The installed capacity of a generating technology can not exceed its available potential En (in MW_{el}).

$$L_{i,z} \leq En_i \qquad \forall i, z \tag{3.19}$$

3. **Demand:**

   The average electricity production should satisfy the projected demand, including transmission and distribution losses. Moreover, the production should not exceed an upper bound, defined by the demand and a small value e, since excessive electricity is not exploited.

$$d_{z,f} \leq \sum_{i=1}^{I} P_{i,z} \leq (1+e) \cdot d_{z,f} \qquad \forall z,\ e << 1 \tag{3.20}$$

4. **Peak Power Demand:** The annual installed capacity should be able to serve the projected peak power demand plus a reserve capacity. The latter is integrated, using a reserve margin (m_r), in order to account for possible units' outages or other unexpected events affecting the amount of available generating capacity.

$$\sum_{i=1}^{I} \alpha_{\alpha,i} \cdot L_{i,z} \geq Pc_z \cdot (1+m_r) \qquad \forall z \tag{3.21}$$

5. **Producer's Profits**

In order to limit the annual operational time of the marginal plants e.g. oil in this study, an upper bound is imposed on their occupation factor, based on historical data of peak load durations, linearly projected to the future. Otherwise, their operation would be prolonged, since higher profits would be generated by technologies having lower marginal costs, owing to the uniform pricing system. Although these profits would be beneficial for individual producers, electricity consumption would be restricted, since significantly higher SMPs would be transferred to the consumers. Thus, the operation of the marginal plants is limited, using the following constraint:

$$t_{marginal,z} < t_{peakprojectedduration,z} \qquad \forall z \tag{3.22}$$

Each plant should ensure its sustainability, i.e. generate profits. This is related to the minimum operational time of the plants and may be reflected to the minimum occupation factor of each technology group i, $\theta_{imin,z}$; It should lead at least to break even points, as shown in the following inequality constraint:

$$profits_{i,z} = -I_{Dz,i} + [\theta_{i,minz} \cdot \alpha_{\alpha,i} \cdot \alpha_{c,i} \cdot 8760 \cdot (t_{oil} \cdot \overline{SMPZ_{1-0}} + (1 - \delta_{i,j}) \cdot (T_{zmax} - t_{oil}) \cdot \overline{SMPZ_{2-1}} - Cf_{i,z} - \frac{f_{CO_{2i}}}{\eta_i} \cdot p_{CO_{2z}}) - Cv_{i,z}] \geq 0 \tag{3.23}$$

where $\delta_{i,j}, j = j_{oil}$, is the Kronecker delta. Thus, the term $(1 - \delta_{i,j})$ equals zero when the marginal plants are considered. Their profits depend only on $t_{oil} \cdot \overline{SMPZ_{1-0}}$, where t_{oil} is their operating time.

3.3.4 Quantitative energy objectives

Tracing back to late 2009, only 6 out of the 27 EU Member States fully complied with their national targets for 2010 prescribed in Directive 2001/77/EC. An average rate of compliance equal to 85.7% was recorded [120]. This may be attributed to several reasons, e.g. bureaucratic barriers, public acceptance of investments, or even ongoing changes in the financial status of EU Members. Nevertheless, the exact achievement of preset values does not reflect the overall aim of the plans. The objectives may be perceived as strict guidelines, steering the power sector's development towards the energy policy's targets.

Regarding the mathematical model, the representation of the objectives as equality constraints may also impact the optimization procedure. Their addition, may increase the effort of achieving feasible solutions or even affect the efficiency of the solvers. Thus, the aforementioned perspective of allowing limited diversions from the planned targets, could be employed for their mathematical representation. Specifically, in this work, a relaxation factor M is imposed on the equality constraints, which represent the energy objectives. It defines the upper and lower bounds within which the targets are considered to be satisfied. M is set as a percentage of the specified target, i.e. if the required percentage of energy produced by a specific technology j at year t ($P_{j,t}$) over the total production ($\sum_{i=1}^{I} P_{i,t}$) is $lp_{j,t}$, then the constraint related to that target using the relaxation factor M is formulated as follows:

$$(1 - M) \cdot lp_{j,t} \cdot \sum_{i=1}^{I} P_{i,t} \leq P_{j,t} \leq (1 + M) \cdot lp_{j,t} \cdot \sum_{i=1}^{I} P_{i,t} \tag{3.24}$$

By relaxing the target plan constraint, essentially it is transformed from an equality constraint to an inequality one. The ultimate goal is an elaborate broadening of the search landscape in order to obtain more promising results using relatively affordable computational budget. It might be raised as an alternative to set the predefined plans as a lower bound only, disqualifying the upper production constraint (in order to allow economically feasible RES technologies to expand beyond the target limit, and moreover without having to cope with severely restricted search landscapes). However, the scope of this research is not to adversely modify the predefined plans in favour or in the expense of some specific technologies but to estimate a power sector's structure strictly based on existing, predefined energy objectives, as is usually the case.

3.4 Description of the hybrid algorithm

The algorithm proposed for the GEP model optimization combines ISRES[2], an EA capable of solving non-linear constrained global optimization problems, and the IPA[3], a general method for non-linear large scale constrained optimization [121].

ISRES [79] combines an $(Npop, NQpop)$ EA, based on ES with differential variation, and Stochastic Ranking (SR)[40]. SR, as described in Chapter 2, is a bubble-sort like procedure, which balances the objective and constraint functions stochastically. The stochasticity is introduced to abate the difficulty of defining the value of a penalty factor. Hence, SR minimizes the number of additional local optima introduced through inappropriate penalty methods, which may mislead the

[2]Source code was retrieved from T.P. Runarsson's home page.
[3]Source code available at Matlab's optimization package.

search [40].

The IPA employed is proposed in [122]. It combines two distinct methods to compute the steps towards the solution of the barrier function. First, a line search method is used to compute steps by factoring the primal dual equations. If those steps proved to be inefficient, then a conjugate gradient method is employed minimizing a quadratic approximation of the barrier function in a trust region. This mechanism allows IPA to use the computationally expensive iteration of conjugate gradient only if the quality of the steps computed by linear algebra can not be guaranteed.

Due to their amount of decision variables, long term GEP models may be classified as large scale optimization problems [115]. EAs that perform well at low dimensional test functions may encounter difficulties (i.e. curse of dimensionality) in optimizing such problems, raising questions about the appropriateness of ISRES algorithm. However, ISRES is utilized to attain a decent initial point and its effectiveness is researched. Given a proper initial point IPA may be used for local convergence as stated in [121].

A two$-$stage methodology for optimizing the GEP model, using initially a global solver (ISRES) for exploration of the search space and then applying a local solver (IPA) to exploit the attained solution's neighbourhood, is examined in this study. In the first stage (ISRES), SR steers the search towards the optimal solution from the combined feasible and infeasible region [123]. This mechanism is beneficial for handling the constraint functions especially in the early stages of the optimization procedure, when information extracted from infeasible solutions is more valuable for the search [41]. Moreover, ES presents robust convergence velocity and reliability in continuous global optimization problems [124]; the selection scheme $(Npop, NQpop)$ of ES, discards all parents of the population and so can in principle escape (small) local optima [15]. During the second stage, the IPA exploits gradient information and may converge rapidly to feasible local or global optima. In addition, the IPA is suitable for large scale optimization problems [122]. Thus, the exploitation of the aforementioned distinct characteristics during two different stages may be beneficial for the optimization of the examined model. The ISRES and the IPA algorithms are outlined in the following subsections.

3.4.1 Improved Stochastic Ranking Evolution Strategies

The procedure of the improved $(Npop, NQpop) - ES$ included in ISRES is described in Algorithm 4. The basic differences in comparison to the simple ES are the differential variation (line 10) and the exponential smoothing (line 14). Initially, the individuals are ranked using Stochastic Ranking and the best $Npop$ individuals are copied in their ranked order. These are used to produce $NQpop$ individuals for the next generation. Subsequently, differential variation is implemented by performing a single mutation per parent. Briefly, the search directions of $Npop - 1$ individuals, whose step lengths are controlled by parameter γ, are defined by the best individual and the individual ranked one position below the parent i being replaced. For these individuals, the mean step size of the corresponding parent is copied unmodified (line 9). Differential variation is included within the simple ES in an attempt to deal with a deficiency of ES; the search is biased towards a grid aligned with the coordinate system.

For the rest of the offspring population the simple non-isotropic ES is implemented as follows:

$$\sigma'_{k,j} = \sigma_{(i;NQpop),j} \cdot exp(\tau' \cdot N(0,1) + \tau \cdot N_j(0,1)),\ k = Npop, ..., NQpop,\ j = 1, ..., n \quad (3.25)$$

$$x'_{k,j} = x_{(i;NQpop),j} + \sigma'_{k,j} \cdot N_j(0,1),\ k = Npop, ..., NQpop,\ j = 1, ..., n \quad (3.26)$$

where $N(0,1)$ is a normally distributed random variable, with a mean value of zero and variance of one. $N_j(0,1)$ is a random number generated anew for each value of j, while τ and τ' are learning rates, which are set equal to $1/\sqrt{2 \cdot \sqrt{D}}$ and $1/\sqrt{2 \cdot D}$, respectively.

In order to reduce the random fluctuations of the strategy parameters, a method which takes an exponential recency-weighted average of trial step sizes sampled via the lineage, instead of the population is used. This exponential smoothing is shown in line 10 of Algorithm 4 (obtained from [79]). Thus the mean step size is updated according to the mutative rule with a log-normal step-size update and exponential smoothing. It is noted that, if an offspring is generated outside the parametric bounds, the mutation is retried 10 times at most. When these iterations fail to create an individual within the bounds, it returns to its original state, meaning the initial individual.

Algorithm 4 Modified ES included in the ISRES

1: Initialize: $\sigma'_k = (\overline{x_k} - \underline{x_k})/\sqrt{n}, x'_k = \underline{x_k} + (\overline{x_k} - \underline{x_k}) \cdot U_k(0,1)$
2: **while** termination criteria not satisfied **do**
3: evaluate: $f(x'_k), g(x'_k), k = 1, ..., NQpop$
4: rank the $NQpop$ points and copy the best $Npop$ in their ranked order
5: $(x_i, \sigma_i) \leftarrow (x'_{i;NQpop}, \sigma_{i;NQpop}), i = 1, ..., Npop$
6: **for** $k = 1$ to $NQpop$ **do**
7: $i \leftarrow mod(k-1, Npop) + 1$
8: **if** $(k < Npop)$ **then**
9: $\sigma'_k \leftarrow \sigma_i$
10: $x'_k \leftarrow x_i + \gamma \cdot (x_1 - x_{i+1})$ (differential variation)
11: **else**
12: $\sigma'_{k,j} \leftarrow \sigma_{i,j} \cdot exp(\tau' \cdot N(0,1) + \tau \cdot N_j(0,1)), j = 1, ..., n$
13: $x'_k \leftarrow x_i + \sigma'_k \cdot N(0,1)$
14: $\sigma'_k \leftarrow \sigma_i + \alpha \cdot (\sigma'_k - \sigma_i)$
15: **end if**
16: **end for**
17: **end while**

In this problem, a minor modification is applied to the upper limit of the mean step size upper bounds. After a predefined number of generations (50% of the maximum available generations) the limit is reduced to 10% of the initial upper bound to assist exploitation of the region of the search space in which the population may have converged.

3.4.2 Interior Point Algorithm

The IPA used to optimize the proposed GEP model has been initially developed in [122]. It attempts to solve a sequence of approximate minimization problems to the problem at hand. The approximate problems are formulated as follows:

$$minf_{\psi}(x,s) = minf(x) - \psi \cdot \sum_{k} ln(s_k) \tag{3.27}$$

subject to:

$$g(\mathbf{x}) + \mathbf{s} = 0 \tag{3.28}$$

$$h(\mathbf{x}) = 0 \tag{3.29}$$

where $mathbfs$ is a vector with positive slack variables, whose cardinallity equals the number of inequality constraints. The additional logarithmic term is the so called barrier function. Eqs. 3.27, 3.28 and 3.29 define a sequence of equality constrained problems, which are solved using one of the following two types of steps:

- A direct step, which attempts to solve the KKT equations for the approximate problem, via linear approximation.
- If a direct step cannot be made, then a conjugate gradient step is attempted.

To define the direct step $(\Delta x, \Delta s)$, the Hessian H of the Lagrangian function of f_{ψ} is utilized. In particular the following equation is solved:

$$\begin{bmatrix} H & 0 & J_h^T & J_g^T \\ 0 & S \cdot \Lambda & 0 & -S \\ J_h & 0 & I & 0 \\ J_g & -S & 0 & I \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta s \\ -\Delta y \\ -\Delta \lambda \end{bmatrix} = \begin{bmatrix} \nabla f - J_h^T \cdot y - J_g^T \lambda \\ S\lambda - \psi \cdot e \\ h \\ g + s \end{bmatrix} \tag{3.30}$$

where J_g and J_h denote the Jacobian of g and h respectively, S is a diagonal matrix of s, λ and y are the Lagrangian multipliers of constraints g and h respectively, Λ is the diagonal matrix of

λ, and e is a vector of ones with size of the same size as g. If the Hessian is not positive definite matrix then the conjugate gradient step is used

In the conjugate gradient step, the algorithm modifies both x and s, in an attempt to minimize a quadratic approximation of the approximate problem in a trust region, subject to linearized constraints. To adequately describe the conjugate gradient step an extensive list of equations are required; for this reason the interested reader is kindly referred to [122] for a detailed description of this step.

3.5 Setup of the computational experiments

3.5.1 Description of the case study

The Greek power sector currently experiences a transition from a centralized to a semi deregulated market. Electricity derived from conventional technologies is compensated through a day ahead double auction process, while renewable energy prices follow a fixed path. There are several generating companies in Greece, but Public Power Corporation (PPC) holds the lion's share in electricity production, owning more than 60% of the installed capacity. In the beginning of 2015, the total installed capacity[4] was 17598 MW_{el}, comprising of 57% of thermal units (Lignite (LIG), Natural Gas (NG) and Oil units) and 43% of hydro plants and RES. However, electricity generated by RES did not exceed 30% of the total production. The installed capacity in the beginning of 2015 is presented in Table 3.1. The extended exploitation of LIG is a strategic choice of Greece's previous development policies, since the domestic lignite reserves are significant.

The adoption of the Environmental European Policies has gradually altered the Greek power sector, increasing RES penetration during the past few years. This is, partly, a consequence of the policy actions implemented by the former Greek Governments, e.g. the enactment of a Feed in Tariff pricing system. According to the progress report issued by the Greek Ministry of Envi-

[4] Monthly Operations Report of Greek Operator of Electricity Markets.

ronment, Energy and Climate Change [125], the total installed capacity of RES at 2013 exceeded the target set by the NREAP. However, the electricity mix differed significantly from the anticipated one; Solar Photovoltaic (PV) held the largest share of RES installation instead of On-shore Wind Turbines (ONWT). Furthermore, there were no significant investments in emerging technologies, such as Off-shore Wind turbines (OFFWT) and Concentrated Solar Power plants (CSP). This might be attributed to several reasons, e.g. the reduction of PV installation costs and the adoption of favourable support schemes. Consequently, this resulted in impressive increase in PVs' capacity installations. For example, more than 1 GW were installed in year 2012, nearly 3 times larger than the highest investment previously occurred in this market.

Due to the current economical situation of Greece, limitations on the available investment budget arise; these are simulated as upper bounds on the capacity orders of the planning horizon. Moreover, compared to other EU Member States, this market presents relevantly large RES potentials due to its geographical distribution and favourable climatic conditions [120]. Furthermore, Greece has been criticised for not complying with the relevant emission restrictions. Thus, an analysis of the Greek power portfolio's development towards the compliance with the EU targets is of interest.

NREAP and NEP, which describe the short (2020) and long (2050) term energy objectives of Greece, are presented in the following subsections.

National Renewable Energy Action Plan

The development policy towards the compliance of Greece with the European Energy Policy (EEP) set in Directive 2009/28/EC is prescribed in NREAP. EEP mainly involves targets related to energy production and consumption, which are envisaged to be met in the EU by 2020. Initially, a target of 18% RES share on final gross energy consumption at 2020 was established. The Greek Government, by enacting the Law 3851/2010, has increased the desired level of RES penetration to 20%. Concerning electricity production, the target share of RES has been set at 40% of total generation.

Generating Technology	Installed Capacity (MW_{el})	Share of PPC (%)
Natural Gas fired plants	4906	47.6
Lignite fired plants	4456	100
Oil fired plants	698	100
Small Hydro ($\leq 25MW_{el}$)	220	100
Medium Hydro ($> 25MW$)	2473	100
Hydro Pumped and Storage	699	100
Biomass fired plants	48	0
Photovoltaic	2436	0
Concentrated Solar Power	0	0
On-shore Wind Turbines	1662	0
Off-shore Wind Turbines	0	0
Geothermal power plants	0	0
Total	17598	61.8%

Table 3.1: Installed capacity in Greece and the share of PPC in 2015

The accomplishment of this goal requires important investments on generation capacity in several technologies, including ONWT and OFFWT, solar PVs and CSP, Hydro, Biomass and Geothermal power plants. NREAP concludes with the presentation of the required share of each RES in the total electricity production at 2020.

National Energy Planning: Roadmap to 2050

Different development strategies consisting of various policy measures are evaluated in NEP. The aforementioned strategies aim at the fulfilment of the national energy objectives, proposed by EC in [77]. The results revealed that the previous energy strategy would fail to reach the required reduction of GHG emissions. Thus, the adoption of the New Energy Policies Scenarios (NEPS) was essential. According to NEPS, RES penetration in electricity production at 2050 should exceed 85%. Moreover, fossil fuels' exploitation will be mitigated, since the target capacity of Lignite and NG are set at $1\ GW_{el}$ and $3\ GW_{el}$, respectively. Furthermore, the interconnection of the distant islands with the central transmission and distribution system of the mainland obviates the need for oil units. In contrast, significant installed capacity of RES is envisaged at 2050. Thus, the provision for storage units, mainly Hydro pumped storage stations, is highlighted.

3.5.2 Stochastic modelling and inputs

The generation expansion strategy is derived, by optimizing the model using a single scenario of stochastic inputs, acquired by averaging several commodity prices' scenarios. It is assumed that electricity demand[5], CO_2 allowance prices[6], fuel prices[7] and inflation rates[8] evolve following Geometric Brownian Motions (GBM). Their Brownian differentials are correlated in order to endogenously model the existing uncertainties, since the dynamics of their evolution may interact. The required statistical factors of data correlation have been extracted from their historical data. Their mean drift and volatility parameters are derived based on the procedure proposed in [126]. Moreover, the evolution of interest rate[9] is simulated using a Cox-Ingersoll-Ross (CIR) [127] model, suitable for producing non negative values.

The evolution of the corresponding stochastic commodities, using the GBM model, is based on the numerical solution of the Stochastic Differential Equation (SDE):

$$dA_t = \mu_t \cdot A_t \cdot dt + D_{t,A_t} \cdot V_t \cdot dW_t \tag{3.31}$$

where A_t is the instantaneous commodity price at time t, μ_t is the mean drift function, D_{t,A_t} is the diffusion vector, V_t is a matrix$-$valued volatility rate function and dW_t is the differential of a Wiener process.

The evolution of interest rate is simulated using a Cox-Ingersoll-Ross (CIR) model. The form of the CIR model's SDE is the following :

$$dr_t = \mu_t \cdot [L_t - r_t] \cdot dt + D_{t,r^{1/2}} \cdot V_t \cdot dW_t \tag{3.32}$$

where L_t is the expected long run mean function. The non negativity of their solution is guaranteed

[5]Historical Data obtained from the Hellenic Transmission System Operator (HTSO).
[6]Historical data obtained from European Unit Allowance (EUA) of EU-Emission Trading System.
[7]Historical data obtained from the Greek Statistical Service and the International Energy Agency (IEA).
[8]Historical data obtained from National Bank of Greece.
[9]Historical data obtained from the Greek Statistical Service.

by the presence of $r^{1/2}$ in the diffusion vector function D.

Uncertainty is inherent in the investments in the various generation technologies. Here, it is introduced through the aforementioned stochastic variables. Thus, arbitrary assumptions concerning the evolution of the several commodities are avoided [128].

The commodity prices and the interest and inflation rates are derived till 2060, since a period for absorbing the lead-time effect, of the latter investment entries is required [118]. This might had caused abnormal capacity orders i.e. extensive installations of the cheapest technologies, with respect to investment cost. Correspondingly, the model is optimized for the period $2015-2060$ to abate the impact of lead time effects in the period of interest ($2015-2050$).

The technological and economic inputs[10] of the generating technologies are presented in Table 3.2. They can be easily adjusted based on the power sector examined, but also, according to any future progress in generating technologies.

	Natural Gas	Lignite	Oil	Low Hydro	Medium Hydro	Hydro Pumped	Biomass	Solar PV	CSP	Onshore WT	Offshore WT	Geothermy
Investment cost, €/kW_{el}	690	2100	1100	2500	2000	3400	3700	1700	4760	1220	2800	2200
Fixed Cost, €/kW_{el}	14	39	38	30	25	50	19	15	45	23	35	32
Availability factor	0.75	0.85	0.75	0.8	0.85	0.92	0.75	0.9	0.9	0.9	0.9	0.7
Capacity factor	0.65	0.75	0.8	0.45	0.34	0.4	0.8	0.35	0.35	0.25	0.25	0.9
Learning rate	0.01	0.01	0.01	0	0	0	0.15	0.15	0.15	0.1	0.08	0
Commissioning time	2	4	3	9	9	9	3	1	2	1	2	2
Efficiency factor	0.57	0.37	0.31	1	1	1	1	1	1	1	1	1
Emissions factor, tn_{CO_2}/MWh_{fuel}	0.21	0.41	0.3	0	0	0	0	0	0	0	0	0
Operational lifetime, y	35	45	45	45	45	45	20	25	25	25	25	25

Table 3.2: Techno-economic input data

In summary, the numerical algorithm for determining the optimal generation mix comprises the following distinct steps:

1. The techno-economic inputs of the examined technology are retrieved from the respective sources.

2. The evolution of the stochastic variables is simulated using the random walk processes, as described in this subsection.

3. The quantitative energy objectives are drawn from the examined energy plans.

[10]Data retrieved from [72] and IEA.

4. The optimization algorithm is applied on the GEP model.

Table 3.3 summarizes the inputs and outputs of the proposed decision support model.

Inputs of the Model
1. The techno-economic characteristics of the generating technologies (Table 3.2).
2. The historical time series of electricity demand, CO_2 allowance prices, fuel costs, interest and inflation rates.
3. The quantitative energy objectives, described in energy plans.
Outputs of the Model
1. The optimal capacity orders, $X_{i,v}$ (in MW), foreseen for the generating technologies during the planning horizon.
2. The optimal occupation factor, $\theta_{i,z}$, of the conventional technologies.
3. The optimal aggregate NPV of the system.

Table 3.3: Inputs and outputs of the proposed GEP model

3.5.3 Numerical experiments preparation

The capacity orders of 12 generating technologies and the occupation factor of the three fossil fuel technologies, for a 46-year operational life-time of the planned system comprise the optimization problem's 690 decision variables. The NREAP and NEP targets are represented in the model as the short and long term energy objectives, respectively. The Cases under examination are:

- The model containing the constraints presented in subsection 3.3.3, representing the base case (Case 1).
- Two models (Cases 2 and 3) additionally containing the constraints of the energy objectives (subsection 3.3.4) prescribed in the action plans. The relaxation factors are defined at $M_S = 15\%$ for the short term and at $M_L = 10\%$ (Case 2) and at $M_L = 2.5\%$ (Case 3) for the long term energy objectives.
- The model representing the equality constraints case. The relaxation factors are set to $M_S = 15\%$ and $M_L = 0.1\%$ (Case 4); a smaller percentage of the long term relaxation would not serve any practical purpose.

Cases 2, 3 and 4 include the energy objectives with different amounts of relaxation. However, all short term relaxation factors are set at $M_S = 15\%$. Although solar PV installed capacity has surpassed its objective for 2020, concerning other energy objectives this amount is necessary. It is a consequence of the current economical situation and the limited available time for capacity installations required by the NREAP.

In this work, five numerical experiments are conducted (Table 3.4). In each of them, the four Cases are optimized under the same scenario for 25 independent runs. The five numerical experiments denote five different optimization procedures:

Exp. 1: Optimization of the model using IPA under a tight computational budget. The termination criteria are the maximum number of Function Evaluations (FEs) or the minimum Tolerance in the objective Function's improvement (TolFun). These, are set at $7 \cdot 10^5$ and 10^{-6}, respectively. The limited FEs available restrict the optimization procedure. As a result, FEs are the dominant termination criterion, thus, allowing conclusions concerning the impact of the energy objectives' constraints on the Feasibility Rate (FR). The latter indicates the percentage of independent runs, where a feasible solution has been obtained by the algorithm.

Exp. 2: IPA optimizes the model under a more generous computational budget. The maximum number of FEs and the TolFun are set at $7.2 \cdot 10^6$ and 10^{-6}, respectively. Due to the large amount of FEs, TolFun qualifies as the dominant termination criteria. Hence, conclusions regarding the optimization's potentials may be extracted.

Exp. 3: ISRES-IPA is applied for the same FEs as in Exp.2. The termination criteria for ISRES is set at $4.2 \cdot 10^6$ FEs and $(Npop, NQpop) = (30, 210)$. Each optimal solution derived from ISRES is further introduced as an initial vector to IPA. The remaining $3 \cdot 10^6$ FEs and a TolFun equal to 10^{-6}, are IPA's termination criteria.

Exp. 4: The model is optimized using a commonly used EA, e.g. a GA[11] combined with the

[11] Source code available at Matlab's optimization package.

Augmented Lagrangian approach [129]. The termination criteria are the maximum available FEs and TolFun, set at $7.2 \cdot 10^6$ and 10^{-6}, respectively.

Exp. 5: A hybrid GA-IPA is utilized. Similarly to Exp. 3, the available number of FEs for GA are $4.2 \cdot 10^6$. The optimal solution vectors of GA constitute the initial points for the IPA algorithm. The latter terminates either after $3 \cdot 10^6$ FEs or if TolFun is lower than 10^{-6}.

	Exp. 1: IPA-Tight computational budget	Exp. 2: IPA-Generous computational budget	Exp. 3 : ISRES-IPA	Exp. 4 : GA	Exp. 5 : GA-IPA
Case 1	$FEs_{IPA} = 7 \cdot 10^5$ $TolFun = 10^{-6}$ $M_S = -$ $M_L = -$	$FEs_{IPA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = -$ $M_L = -$	$FEs_{ISRES} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = -$ $M_L = -$	$FEs_{GA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = -$ $M_L = -$	$FEs_{GA} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = -$ $M_L = -$
Case 2	$FEs_{IPA} = 7 \cdot 10^5$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 10\%$	$FEs_{IPA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 10\%$	$FEs_{ISRES} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 10\%$	$FEs_{GA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 10\%$	$FEs_{GA} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 10\%$
Case 3	$FEs_{IPA} = 7 \cdot 10^5$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 2.5\%$	$FEs_{IPA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 2.5\%$	$FEs_{ISRES} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 2.5\%$	$FEs_{GA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 2.5\%$	$FEs_{GA} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 2.5\%$
Case 4	$FEs_{IPA} = 7 \cdot 10^5$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 0.1\%$	$FEs_{IPA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 0.1\%$	$FEs_{ISRES} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 0.1\%$	$FEs_{GA} = 7.2 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 0.1\%$	$FEs_{GA} = 4.2 \cdot 10^6$ $FEs_{IPA} = 3 \cdot 10^6$ $TolFun = 10^{-6}$ $M_S = 15\%$ $M_L = 0.1\%$

Table 3.4: Set up of the numerical experiments

3.6 Results and Discussion

3.6.1 Results of the optimization procedure

Observations regarding the optimization procedure, specifically: (i) the effect of the additional constraints representing the energy objectives, (ii) the impact of the level of relaxation and (iii) the efficiency of ISRES-IPA, can be extracted from the examination of Tables 3.5a 3.5b, 3.5c, 3.5d. The results of Exp. 4 are not explicitly presented, since GA failed to produce feasible solutions in all the examined Cases. This may be due to the characteristics of the proposed GEP model (high dimensionality, highly constraint model (Subsection 3.1)).

The inclusion of the additional constraints affects the optimization procedure. Case 1 exhibits higher (or equal) FR compared to Cases 2, 3, 4 (Exp. 1 - 5). However, improvement in FR is observed when relaxation of energy objectives increases. Moreover, higher NPV maxima are attained with elevated relaxation levels. Interestingly, the latter conclusion does not consistently apply to Exp. 2 and 5, (Table 3.5). Possibly, this is a consequence of premature convergence of IPA. This might occur as a result of limited exploration in non feasible regions, which may drive IPA to converge in feasible regions with local minima of lower NPV values. The feasible area expands when looser relaxation is applied, thus premature convergence could be more likely. In contrast, when stricter constraints are applied, IPA requires and utilizes more of the total available FEs budget to achieve feasibility, improving meanwhile the objective function. This might be a justification of the aforementioned contradiction.

The results obtained by the hybrid ISRES-IPA, are presented in Table 3.5c. ISRES-IPA's solutions display higher mean values and lower dispersion, even in stage 1, compared to Exp. 2 and 5. This may indicate the global search capacity of ISRES in non feasible regions. In contrast to ISRES, GA did not derive feasible solutions in any Case in both Exp. 4 and 5. This might be a consequence of stagnation, as the solver failed to reduce the constraint violation after exploiting a low percentage of the available computational budget. However, in stage 2 the FR increases in most Cases (Exp. 3 and Exp. 5), as IPA utilizes gradient information, thus guiding the search to feasible regions. Specifically, ISRES-IPA and GA-IPA reach both 100% FR for Cases 1 and 2 and 100% and 96% for Case 3, respectively. GA-IPA's FR is higher than ISRES-IPA only for lower levels of relaxation (Case 4), where the former reaches 96% and the latter 68%. This may have occurred due to the absence of constraint normalization [130] in ISRES, introducing bias towards some constraints during the first stage, thus, resulting in some improper initial points for Stage 2 of ISRES-IPA. It is noted that IPA (Exp. 2) reaches 100% FR in all Cases. Nevertheless, the overall results indicate that ISRES-IPA achieved robustly plans of higher NPV values compared to the ones derived after dedicating the entire computational budget to IPA, GA or splitting the budget between GA and IPA. This improved performance may be a result of the mechanisms of ISRES-IPA, as described in subsection 3.3.

It should be mentioned that in the final iterations of Exp. 2−5, either stagnation or declination of the convergence rate occurs, resulting in merely slight improvements of the objective function, indicating that the expensive computational budget was sufficient. Taking into consideration their recorded performance, only the solutions obtained by the relatively more efficient ISRES-IPA will be further discussed in the following sections.

IPA (Exp. 1)						
	M_L	**Best**	**Median**	**Mean**	**Std**	**FR**
Case 1	-	104.26	82.18	82.50	6.89	100%
Case 2	10%	89.57	82.93	82.67	4.22	36%
Case 3	2.5%	86.95	84.82	84.90	2.01	12%
Case 4	0.01%	86.38	85.81	83.94	3.74	12%

(a) IPA - Tight computational budget

IPA (Exp. 2)						
	M_L	**Best**	**Median**	**Mean**	**Std**	**FR**
Case 1	-	144.03	113.41	111.69	24.39	100%
Case 2	10%	100.28	88.89	89.89	5.68	100%
Case 3	2.5%	105.53	90.91	91.26	6.82	100%
Case 4	0.01%	116.67	92.12	94.36	10.28	100%

(b) IPA - Generous computational budget

ISRES-IPA (Exp. 3)											
		Stage 1 (ISRES)					**Stage 2 (IPA)**				
	M_L	**Best**	**Median**	**Mean**	**Std**	**FR**	**Best**	**Median**	**Mean**	**Std**	**FR**
Case 1	-	144.84	142.12	142.16	1.75	100%	153.70	153.35	150.76	4.43	100%
Case 2	10%	121.46	116.97	116.82	2.35	88%	129.67	128.30	126.70	3.87	100%
Case 3	2.5%	117.07	113.44	113.41	2.02	84%	127.48	127.05	124.31	5.08	100%
Case 4	0.01%	-	-	-	-	0%	126.63	126.25	120.81	6.47	68%

(c) ISRES-IPA

GA-IPA (Exp. 5)											
		Stage 1 (GA)					**Stage 2 (IPA)**				
	M_L	**Best**	**Median**	**Mean**	**Std**	**FR**	**Best**	**Median**	**Mean**	**Std**	**FR**
Case 1	-	-	-	-	-	0%	81.45	76.09	73.99	5.57	100%
Case 2	10%	-	-	-	-	0%	115.48	87.71	88.01	9.95	100%
Case 3	2.5%	-	-	-	-	0%	127.29	87.92	91.44	12.17	96%
Case 4	0.01%	-	-	-	-	0%	126.23	86.51	90.08	13.13	96%

(d) GA-IPA

Table 3.5: Results of the optimization procedure (NPV in bn€).

3.6.2 Impact of energy objectives on the power sector's formation

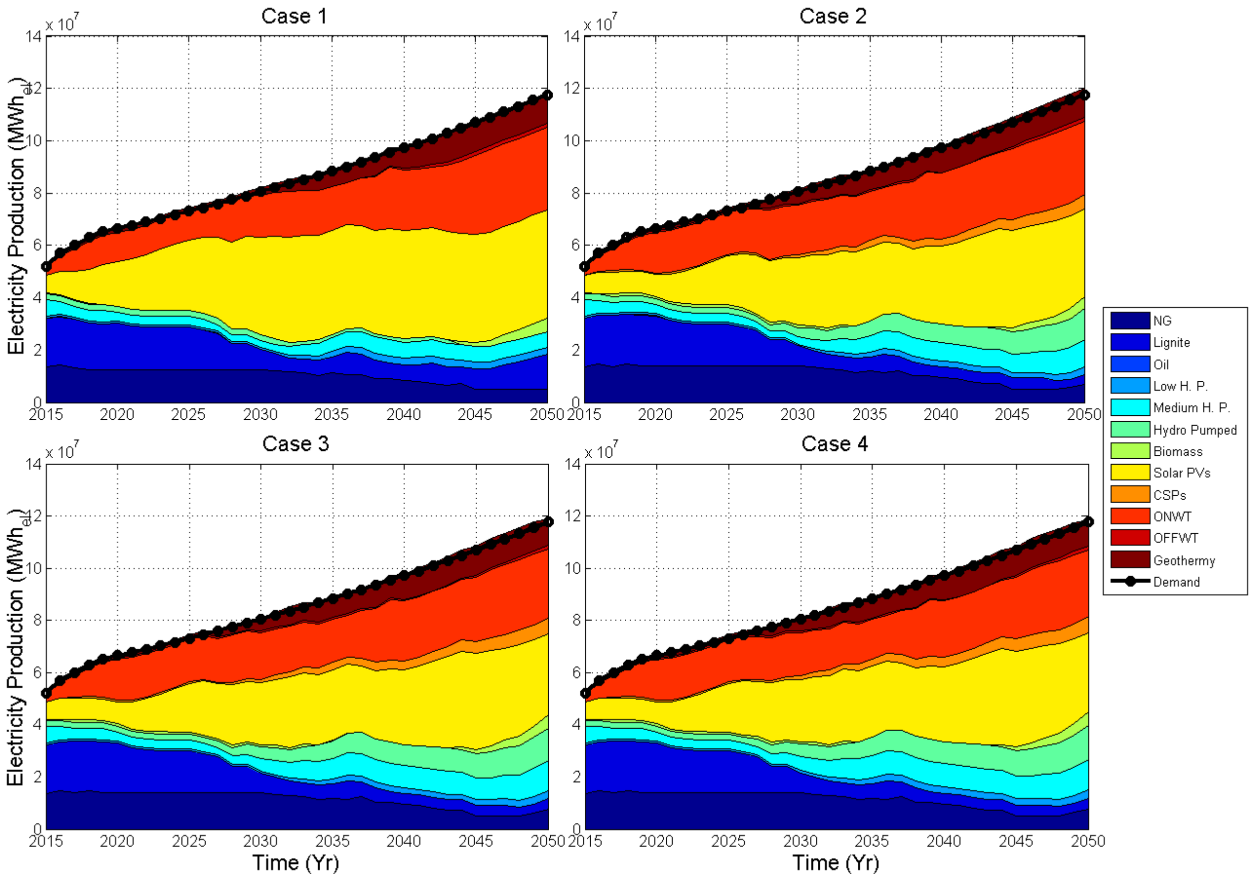


Figure 3.1: Cumulative electricity production of the best solution derived in each Case

Formation of Generation Mix and Installed Capacity

Electricity production (Fig. 3.1) is characterized by increasing utilization of Solar PVs and ONWT (Cases 1, 2, 3 and 4), sharing a major part of power sector breakdown. Their high availability and capacity factors, and lower investment and variable costs, render them efficient investment options. The best and the mean annual installed capacity of the various generating technologies are depicted in Fig. 3.2. Larger investments in Biomass, CSP, ONWT and OFFWT plants are planned until 2020 for Cases 2, 3, 4 compared to Case 1, thus increasing their installed capacity and diversifying the energy mix (Fig.3.1 and 3.2). On the other hand, investments in Solar PV's and Geothermy are expected to be lower until 2020 (Cases 2, 3, 4). This is due to either existing installations of PV's or Geothermy's low energy objective. Moreover, the use of fossil fuels decreases in the long run as seen in Fig. 3.1; part of the energy produced by Lignite in Case 1 is replaced by Hydro technologies in Cases 2, 3, 4. Similarly, part of the installed capacity of Solar PV (Case 1) is replaced by CSP (Cases 2, 3, 4). Therefore, CSP and Hydro orders are driven by the energy objectives at 2050. By examining both Figures 3.1 and 3.2, no significant differences are noted in the breakdown of the generating mix, amongst the Cases with the relaxed energy constraints.

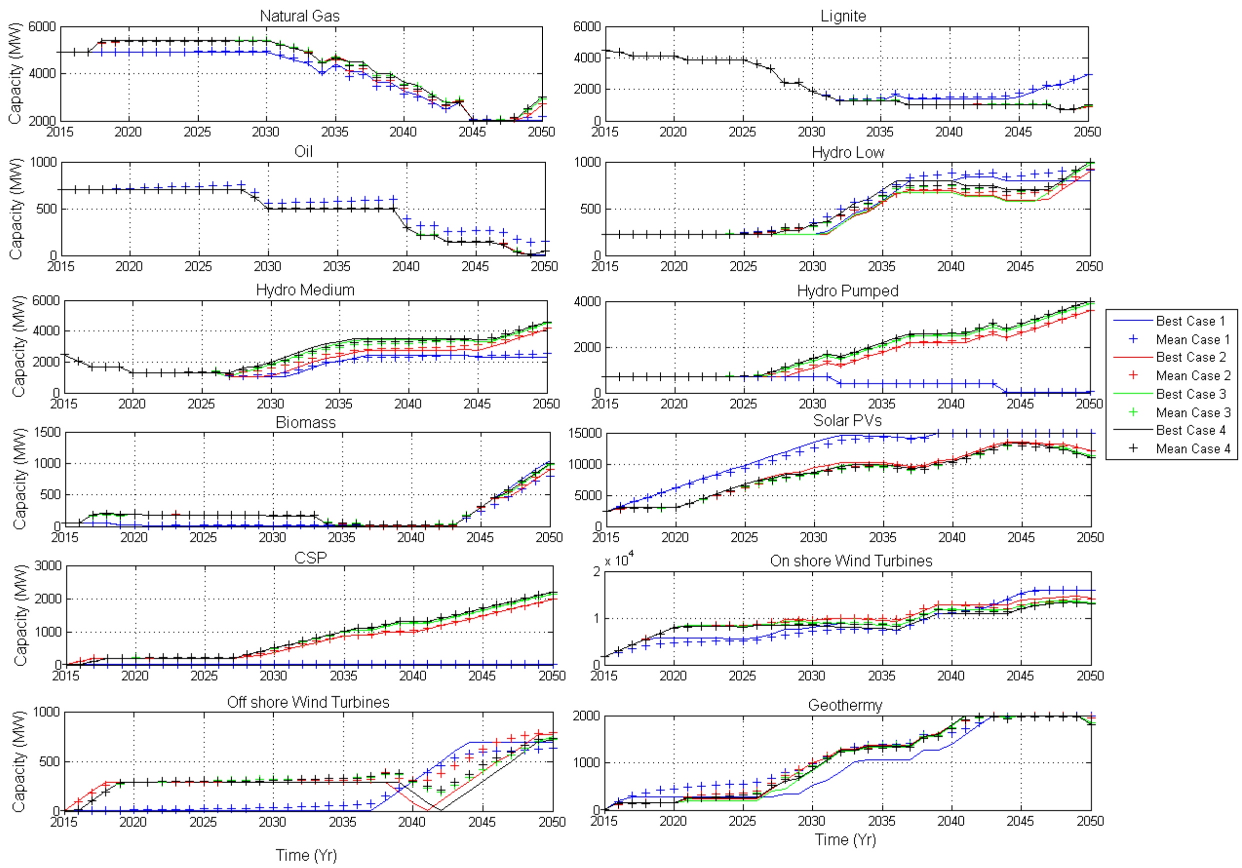


Figure 3.2: Annual installed capacity per generating technology

RES Penetration and CO_2 Emissions

The annual percentage of electricity produced by RES during the period of interest is presented in Fig. 3.3 using a box plot[12]. RES penetration (Case 1) increases rapidly in the early years of the planning horizon (Fig. 3.3), reaching a notable 58% on average at 2020. It is primarily a result of the expanded installations of Solar PVs. The available natural resource of Solar power[13] ($15\ GW$) is suggested to be utilized completely by 2032. Thus, the rate of RES penetration decreases and more capacity orders for Lignite plants are allocated after 2035 in Case 1. As a result, CO_2 emissions (Case 1) do not further decrease after 2035 and follow an upwards trend during $2045-2050$ (Fig. 3.4). In contrast, installations of CSP, OFFWT and Hydro Medium and Pumped technologies further increase RES penetration during $2035-2050$ (Cases 2, 3, 4), reaching 90.8$\%$ on average at 2050. Therefore, CO_2 emissions decrease even after 2035, resulting approximately 57$\%$ lower on average in 2050, compared to Case 1.

SMP and Power Sector's Efficiency

The generation mix interacts with the average annual SMP, depicted in current prices in Fig. 3.5. Case 1 exhibits lower SMP values until 2035 in comparison to Cases 2, 3, 4, when its RES penetration is higher. The same applies for Cases 2, 3, 4 during 2045-2050. By accounting constant prices of base year 2014, SMP tends to slightly reduce in the long run. The evolution of the SMP is relatively smooth in all Cases, despite the differences observed in the financial balance of the market.

The financial balance ($=$ incomes $-$ expenses) and the CO_2 emissions per MWh_{el} annually produced are presented in Fig. 3.6. The power sector was optimized both environmentally and economically in all Cases. Initially, the financial balance of Cases 2, 3 and 4 declines, as a conse-

[12]On each box the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points the algorithm considers to be not outliers and the red crosses represent outliers.

[13]The estimated aggregate potential of the natural resources of each technology is available in [77].

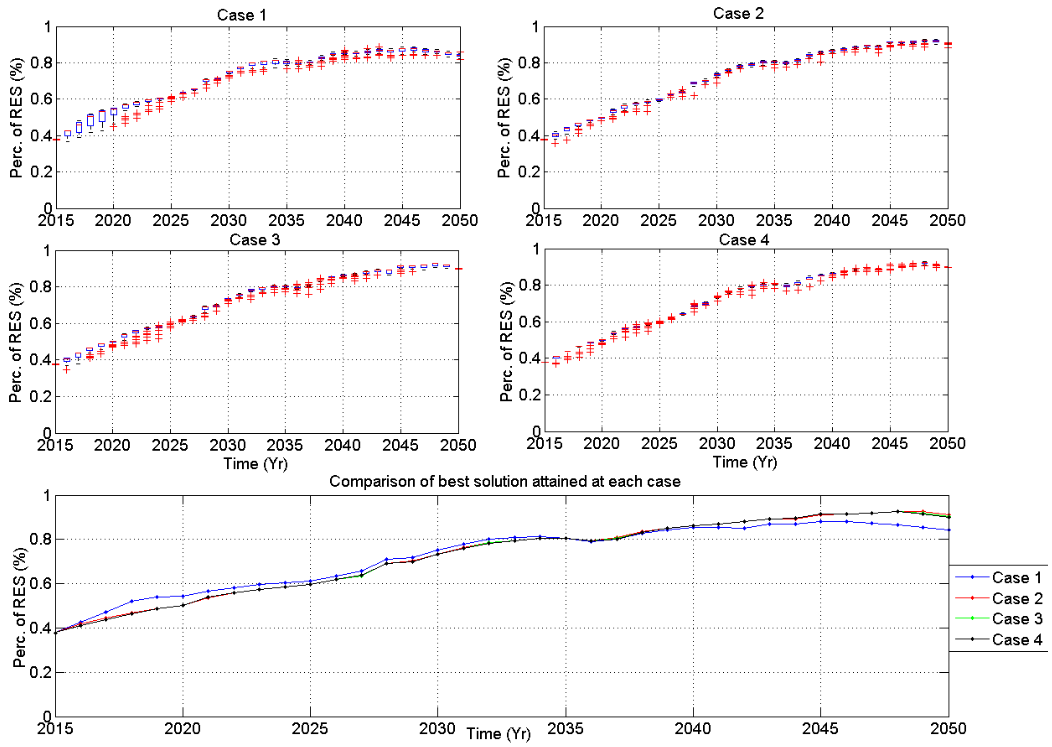


Figure 3.3: Percentage of production from renewable sources

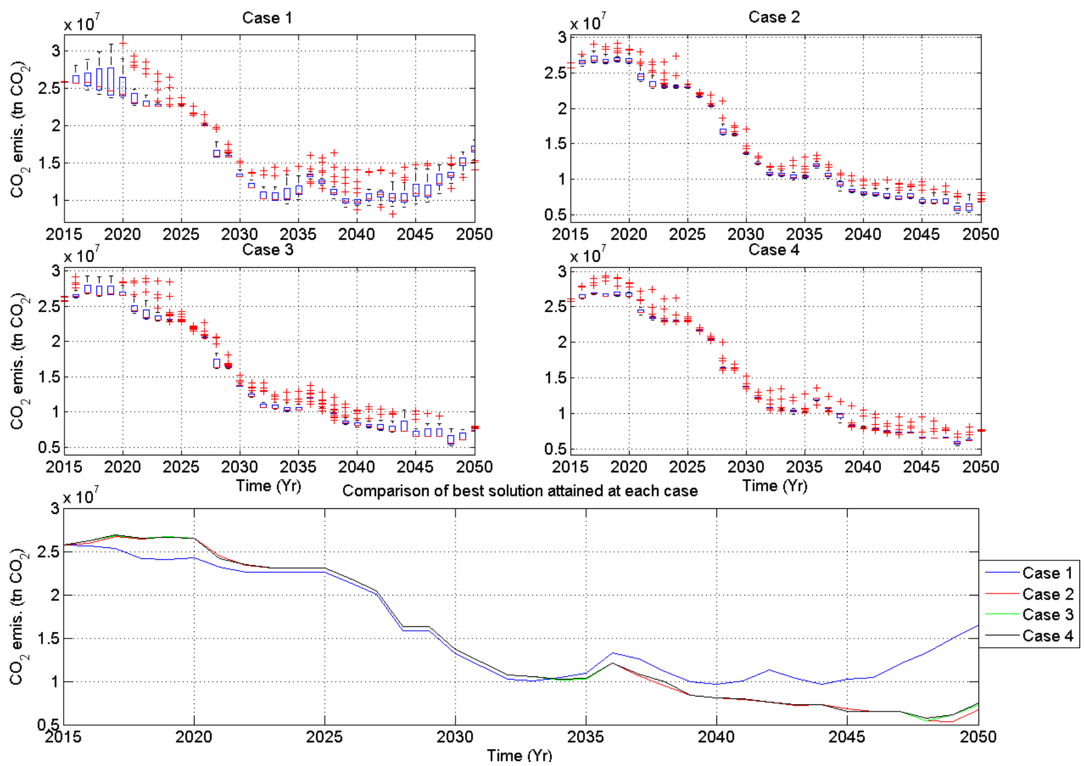


Figure 3.4: Total CO_2 emissions

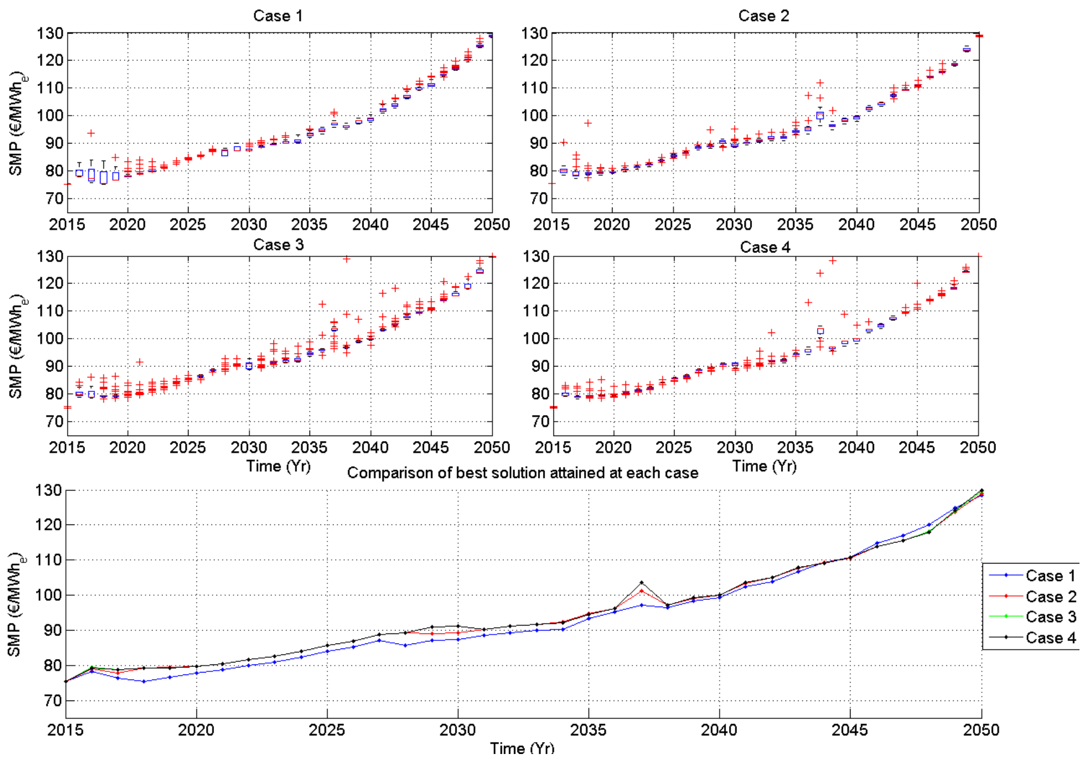


Figure 3.5: System's Marginal Price evolution

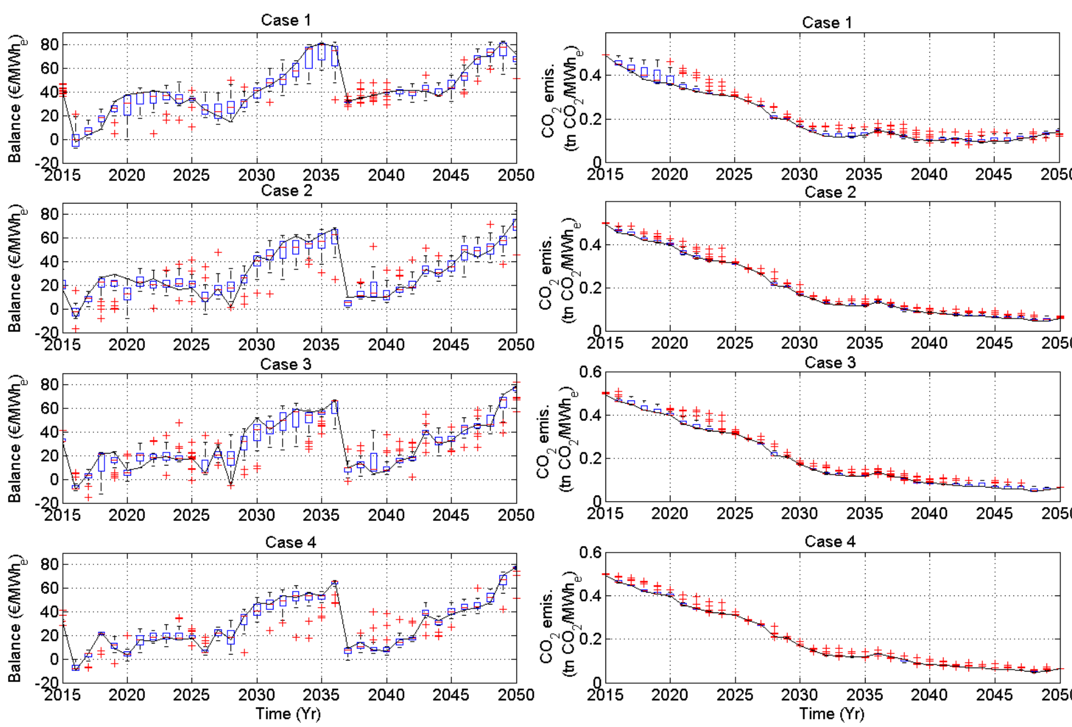


Figure 3.6: Financial balance and average CO_2 emissions evolution

quence of the high investment cost related to expanded capacity installations. This large amount of investments demonstrates the significant effort needed towards the compliance of Greece with its national goals described in NREAP. Investments are required also due to the increasing energy demand, which might justify the smaller nadir observed in Case 1 during the same period.

The financial balance of Case 1 is constantly higher during the planning horizon. However, after the investments in RES, which are proposed for $2034-2037$ (Fig. 3.2), in Cases 2, 3, 4, causing a steep decrease of the balance, the following consequences may emerge: Firstly, the economical growth of the power sector may be enhanced in the long term, resulting in increasing values of financial balance. Secondly, energy may be produced more sustainably as the average CO_2 emissions are further decreased.

3.6.3 Fulfilment of the energy objectives and relaxation's impact

The results regarding the fulfilment of the energy objectives are shown in Table 3.6[14]. The solutions tend to approach either the upper or the lower limit of compliance defined by the relaxation factors. This might indicate the generating technologies in which capacity installations are driven by their economic sustainability or the presence of the energy objectives, respectively. Thus, without the inclusion of the energy objectives, the investments in some technologies, i.e. CSP, Hydro, would have been significantly fewer. This might be confirmed by comparing Cases 2, 3, 4 with the results of Case 1.

Outliers on the power sector's evolving variables emerge, e.g. SMP, CO_2, due to the dispersion of the optimization's solutions noted. These outliers are negatively correlated with relaxation. For example in Fig. 3.5, the amount of outliers observed in the SMP is decreased with higher levels of relaxation. This comparison should be restricted between Case 2 and 3, as Case's 4 data sample is limited by its lower feasibility rate. The negative correlation and solutions' consistency obtained when relaxation factors are utilized, may be of some interest for policy makers and planners.

[14]The target set for solar PV at NREAP was not examined, since it has been already exceeded; it is marked with an asterisk in Table 3.6.

The optimized annual installed capacity of the best solutions of Cases 2, 3, and 4 resulted almost identical for 2020, even though the relaxation of long term energy objectives (NEP) varied, while that of short term (NREAP) remained constant. In addition, their evolution paths, Fig. 3.2, reveal limited differences for the largest part of the planing horizon. Therefore, the short term plan remained relatively unaffected by the relaxed long term plan.

Case 1	NREAP (2020)					NEP (2050)				
Technologies	**Lower Bound (%)**	**Target (%)**	**Upper Bound (%)**	**Mean Result (%)**	**Std (%)**	**Lower Bound (MW)**	**Target (MW)**	**Upper Bound (MW)**	**Mean Result (MW)**	**Std (MW)**
Natural Gas	-	-	-	-	-	-	3000.00	-	2182.58	0.0856
Lignite	-	-	-	-	-	-	1000.00	-	2949.76	0.1821
Oil	-	-	-	-	-	-	50.00	-	148.15	4.6905
Low Hydro	-	1.40	-	1.20	0.0002	-	1000.00	-	913.12	0.1682
Medium Hydro	-	5.70	-	5.03	0.0003	-	4600.00	-	2557.31	0.0890
Hydro Pumped	-	-	-	-	-	-	4000.00	-	44.59	0.0270
Biomass	-	1.80	-	0.21	0.0298	-	1000.00	-	791.77	0.2671
Solar PV*	-	4.30	-	25.38	0.1216	-	11000.00	-	14958.77	0.0110
CSP	-	1.00	-	0.01	0.0357	-	2200.00	-	21.27	0.0293
ONWT	-	23.70	-	13.98	0.1317	-	13000.00	-	15978.97	0.0044
OFFWT	-	1.00	-	0.03	0.0685	-	-	-	-	-
Geothermy	-	1.10	-	3.73	1.1337	-	1800.00	-	1984.96	0.0252

(a) Case 1: No Objectives integrated

Case 2	NREAP (2020)					NEP (2050)				
Technologies	**Lower Bound (%)**	**Target (%)**	**Upper Bound (%)**	**Mean Result (%)**	**Std (%)**	**Lower Bound (MW)**	**Target (MW)**	**Upper Bound (MW)**	**Mean Result (MW)**	**Std (MW)**
Natural Gas	-	-	-	-	-	2700.00	3000.00	3300.00	2702.28	0.0035
Lignite	-	-	-	-	-	900.00	1000.00	1100.00	910.70	0.0382
Oil	-	-	-	-	-	45.00	50.00	55.00	45.05	0.0021
Low Hydro	1.19	1.40	1.61	1.20	0.0009	900.00	1000.00	1100.00	920.18	0.0426
Medium Hydro	4.85	5.70	6.56	5.03	0.0010	4140.00	4600.00	5060.00	4191.34	0.0253
Hydro Pumped	-	-	-	-	-	3600.00	4000.00	4400.00	3600.73	0.0006
Biomass	1.53	1.80	2.07	1.54	0.0152	900.00	1000.00	1100.00	901.46	0.0050
Solar PV*	3.66	4.30	4.95	12.43	0.0094	9900.00	11000.00	12100.00	12095.78	0.0017
CSP	0.85	1.00	1.15	0.85	0.0143	1980.00	2200.00	2420.00	1980.03	0.0000
ONWT	20.15	23.70	27.26	23.11	0.0450	11700.00	13000.00	14300.00	14112.17	0.0363
OFFWT	0.85	1.00	1.15	0.85	0.0048	-	-	-	-	-
Geothermy	0.94	1.10	1.27	1.25	0.0360	1620.00	1800.00	1980.00	1946.32	0.0198

(b) Case 2: $M_S = 15\%, M_L = 10\%$

Case 3	NREAP (2020)					NEP (2050)				
Technologies	**Lower Bound (%)**	**Target (%)**	**Upper Bound (%)**	**Mean Result (%)**	**Std (%)**	**Lower Bound (MW)**	**Target (MW)**	**Upper Bound (MW)**	**Mean Result (MW)**	**Std (MW)**
Natural Gas	-	-	-	-	-	2925.00	3000.00	3075.00	2938.80	0.0111
Lignite	-	-	-	-	-	975.00	1000.00	1025.00	983.98	0.0187
Oil	-	-	-	-	-	48.75	50.00	51.25	49.08	0.0141
Low Hydro	1.19	1.40	1.61	1.20	0.0000	975.00	1000.00	1025.00	982.56	0.0141
Medium Hydro	4.85	5.70	6.56	5.04	0.0000	4485.00	4600.00	4715.00	4500.22	0.0074
Hydro Pumped	-	-	-	-	-	3900.00	4000.00	4100.00	3903.34	0.0029
Biomass	1.53	1.80	2.07	1.53	0.0065	975.00	1000.00	1025.00	980.40	0.0116
Solar PV*	3.66	4.30	4.95	12.44	0.0020	10725.00	11000.00	11275.00	11262.62	0.0041
CSP	0.85	1.00	1.15	0.85	0.0019	2145.00	2200.00	2255.00	2145.29	0.0004
ONWT	20.15	23.70	27.26	23.19	0.0297	12675.00	13000.00	13325.00	13285.95	0.0080
OFFWT	0.85	1.00	1.15	0.85	0.0056	-	-	-	-	-
Geothermy	0.94	1.10	1.27	1.26	0.0062	1755.00	1800.00	1845.00	1840.71	0.0065

(c) Case 3: $M_S = 15\%, M_L = 2.5\%$

Case 4	NREAP (2020)					NEP (2050)				
Technologies	**Lower Bound (%)**	**Target (%)**	**Upper Bound (%)**	**Mean Result (%)**	**Std (%)**	**Lower Bound (MW)**	**Target (MW)**	**Upper Bound (MW)**	**Mean Result (MW)**	**Std (MW)**
Natural Gas	-	-	-	-	-	2999.70	3000.00	3000.30	2999.77	0.0000
Lignite	-	-	-	-	-	999.90	1000.00	1000.10	999.95	0.0000
Oil	-	-	-	-	-	50.00	50.00	50.01	50.00	0.0000
Low Hydro	1.19	1.40	1.61	1.20	0.0004	999.90	1000.00	1000.10	999.94	0.0000
Medium Hydro	4.85	5.70	6.56	5.03	0.0005	4599.54	4600.00	4600.46	4599.68	0.0000
Hydro Pumped	-	-	-	-	-	3999.60	4000.00	4000.40	3999.67	0.0000
Biomass	1.53	1.80	2.07	1.55	0.0448	999.90	1000.00	1000.10	999.96	0.0000
Solar PV*	3.66	4.30	4.95	12.44	0.0028	10998.90	11000.00	11001.10	11001.02	0.0000
CSP	0.85	1.00	1.15	0.85	0.0139	2199.78	2200.00	2200.22	2199.81	0.0000
ONWT	20.15	23.70	27.26	23.19	0.0399	12998.70	13000.00	13001.30	13001.12	0.0000
OFFWT	0.85	1.00	1.15	0.85	0.0059	-	-	-	-	-
Geothermy	0.94	1.10	1.27	1.25	0.0390	1799.82	1800.00	1800.18	1800.14	0.0000

(d) Case 4: $M_S = 15\%, M_L = 0.1\%$

Table 3.6: Fulfilment of the energy objectives

CHAPTER 4

OPTIMIZATION OF THE SHORT-TERM GENERATION SCHEDULING PROBLEM USING DIFFERENTIAL EVOLUTION AND A PLURALITY OF PRIORITY LISTS

4.1 Introduction

In the previous Chapter, a model has been presented for the determination of the optimal investments in a power sector towards the compliance with specific energy targets set by the policy makers. Such GEP models refer to planning horizons which span up to several years. Moreover, a hybrid algorithm combining an EA and a deterministic method has been applied to optimize the aforementioned model. In this and in the following chapters of this dissertation, the interest will shift towards the development of algorithms for the optimization of a problem which is related to the short-term operation of a power system. This problem is commonly known in the relevant literature as the short-term generation scheduling problem (STGS) or the Unit Commitment Problem. It should be noted, that the proposed methods may be used for defining the operating schedule of a power system when the set of generators is predefined. However, it may also be utilized to examine the impact which potential investments in specific generators, may have on the operation of the system, thus facilitating decisions on additions of generators within already existing power systems.

The STGS problem is a complex optimization problem which comprises two interrelated tasks:

- The first is related to the proper scheduling of the operating state of the system's power generators, defining the units that will start up, be in operation or are shut down at each period of the scheduling horizon. This task is known as the Unit Commitment.
- The second concerns the distribution of the demanded load among the generators in operation at an optimum economic fashion, and is known as the Economic Dispatch.

Thus the solution to the problem, in its conventional form, is the operating schedule of the generators which deliver energy to the grid at each hour as well as the energy production of each generator at each hour.

Mathematically, the problem is usually formulated as a mixed integer, non-linear and non-convex combinatorial optimization problem. Commonly, the operating state of the units is represented by binary decision variables, while real valued decision variables are employed for their power output. The problem's non-convexity is caused by the binary nature of the on/off decision. Moreover, the non-linearity emerges due to the non-linear characteristics of the generators cost functions [131]. The aforementioned characteristics and the fact that the search space grows exponentially with the size of the examined power system have rendered the STGS as a very challenging optimization problem. The exact solution of STGS could be achieved by enumerating the possible combinations of the units states. However, for real world power systems, including dozens or hundreds of power generating units, such a method is computationally intractable.

As has been analyzed in Chapter 1, deterministic methods based on mathematical programming techniques may encounter difficulties due to the non-convex and non-linear nature of the problem. For this reason, methods based on EAs have been rendered over the years as adequate alternatives for the optimization of the problem. The method described in this Chapter, is able to deal with the non-convex and non-linear features of the problem. It is based on employing a state of the art DE variant for constrained optimization with advanced evolution operators to determine a near optimum binary operating schedule and load dispatch. The EA approach includes a transformation function, a repair heuristic mechanism and a mutation strategy. The proposed method has managed to derive better or at least competitive solutions compared to recently proposed algorithms for the STGS problem on various forms of power systems examined. Consequently, it might be perceived as a promising alternative for solving the problem.

The rest of the Chapter is structured as follows: Initially, in Section 4.2 the solution methodologies that have been proposed for the optimization of the conventional form of the problem in the relevant literature are described. Thereafter, in Section 4.3 the mathematical formulation of the problem is presented. The variant of DE used for the optimization of the problem is given in Section 4.4. The proposed solution methodology is given in detail in Section 4.5. In the final Section of the Chapter, i.e. Section 4.6, the results of the computational experiments that have been conducted to validate the efficiency of the proposed method are discussed.

4.2 Literature review

The exact solution of the traditional STGS could be achieved by enumerating the possible combinations of the units' states. However, for real world power systems, including dozens or hundreds of power generating units, such a method is computationally intractable. Therefore, over the past years research endeavors have been focused on proposing methods for deriving near optimal solutions in shorter time. As stated in [132], despite the intensive study, STGS still remains a rich and challenging topic for research.

In the relevant literature a wide variety of algorithms has been developed for the optimization of the STGS problem. These methods can be classified in three main groups [133]:

- Deterministic methods, which are mainly based on numerical optimization techniques.
- Stochastic approaches based on methods of Evolutionary Computation.
- Hybrid approaches, which combine techniques from both groups 1 and 2.

Methods belonging in the aforementioned categories will be analyzed in the following subsections. It is noted that comprehensive analysis of the methods applied on the conventional form of the problem can be also found in the surveys of Padhy [4], Yamin [134], and Mallipedi and Suganthan [133].

4.2.1 Deterministic approaches

The first category contains a plethora of solution methodologies. Among these methods are the Priority List method, the Dynamic Programming method, the Lagrangian Relaxation method, the Bender's Decomposition, the methods based on Mixed Integer Linear Programming, the Semi Definite-Programming and the Outer Inner Approximation. The aforementioned techniques are analyzed in the following subsections. Since the focus of this dissertation is on the application of an EA based approach for the short-term thermal generation scheduling, the author by no means attempt to give a full overview of the field of deterministic approaches. For a more comprehensive discussion on such approaches for the thermal STGS problem, we refer to the reviews of [4], [134] and [9].

Priority List method

The utilization of the Priority List of the generators constitutes one of the simplest methods for the short-term thermal generation scheduling problem. In these methods, the generating units are ranked according to a cost criterion (usually their average production cost at maximum or mean generating capacity). The most economic units are then committed until the load demand can be served. Methods based on the Priority List are fast and easy to implement. However, they are highly heuristic and may derive solutions of poor quality [135].

One of the first attempts to apply the Priority List for the solution of the short-term thermal generation scheduling problem is that of Lee et al. [136]. To consider the changes in the load of the system at the different hours of the scheduling horizon the Priority List is created taking into consideration also the production of the units. In [137] the extended Priority List is proposed. The solution procedure consists of two steps. During the first step an initial UC schedule is rapidly created by using a PL based on the maximum capacity of the generators. In case of units having similar maximum capacity their average production cost at their maximum power output is used to rank the units. In the second step, a series of heuristic repair procedures adjust the generating schedules to satisfy the constraints of the problem and improve the final solution. Later the same authors have proposed a method called Stochastic Priority List [135], which also comprises two stages. In the first, an initial solution is created based on the Priority List of the units at their average cost at maximum power output. Then randomly selected committed units exchange states with some decommitted ones to create different solutions. The unit to be committed is selected randomly based on a roulette wheel procedure. Similarly to the previous method, on a second step, the schedules are modified based on heuristics procedures to satisfy the problem's constraints. In [138], the authors propose a heuristic approach to optimize the unit commitment problem which is based on Priority List, enhanced by a heuristic repair procedure. An initial solution is generated using a Priority List based on the middle point of generation of each unit. Then some heuristics are applied to repair the derived schedule in order to satisfy the up/down time constraints. The developed algorithm has managed to provide competitive results compared to a Mixed Integer Linear Programming set up, first on a benchmark system and second on a case where the demand to be satisfied by thermal generators is relatively low. In [139], the authors proposed a method to solve the unit commitment problem, which is based on the Priority List and a modification procedure. Initially a solution based on the Priority List of the units at the middle point of their power output is derived. Thereafter a modification procedure is applied to repair violations of the problem's constraints and improve the final schedule.

Dynamic Programming

Dynamic Programming (DP), initially proposed by Bellman [140], is considered one of the classical approaches to solve the STGS problem. In its basic form, the problem is divided into sub-problems corresponding to each period of the scheduling horizon. The sub-problems are then solved sequentially, beginning from the first period and going towards the last period (forward dynamic programming), or beginning for the last period going towards the first period (backward dynamic programming). For example, in the case of forward dynamic programming, during the first period, all the possible combinations are examined (taking into consideration problem's constraints and the initial state of the units) and the one providing the best cost is selected. Subsequently, the second hour is examined, by considering as known the operating schedule of the first hour. In each hour, each unit should operate in a way that the cost for satisfying the remaining load is the minimum possible. Dynamic Programming methods can handle problems of moderate size and can easily be modified to model the characteristics of specific utilities. Nevertheless, they encounter difficulties in modeling the constraints affecting the operation of a single unit over time, such as the minimum up/down time constraints and the start-up costs. Moreover, examining a large variety of possible unit commitment combinations in each period of the scheduling horizon significantly increases the computational time for large scale systems.

In one of the earliest attempts of DP [141], the commitment of generating units was determined independently for every time period. Such an approach presented a major limitation as it could not take into account the coupling of adjacent time periods, and therefore the time dependent start-up cost was not correctly modeled. Later in [142], a DP method was developed in which each stage represented a particular time period. In every stage the corresponding states represented different combinations of commitment states (on/off) for the generating units in that specific period. However, the approach suffers from the 'curse of dimensionality', since the computational time increases exponentially with the increase in the size of the system. To reduce problem dimensionality, different strategies that truncate the hourly state space have been developed, e.g. DP-Sequential Combination, and DP-Truncated Combination. Additional heuristic procedures have also been combined with Dynamic Programming to achieve a further reduction of the search space and to speed up the execution. In [143], for example, Dynamic Programming is combined with neural networks. Li et al. in [144] have proposed a method to solve the STGS based on Dynamic Programming. The algorithm begins from an operating schedule where all the available units are considered committed. Then, Dynamic Programming is applied to decommit some of the generators based on pre-determined criteria related to the operation cost of each generator. Huse et al. in [145] have presented a method based on Dynamic Programming to simulate the operation of a liberalized electricity market. The start-up cost and the reserve requirements of the system are considered in this approach. More recently, in [146] a fast Dynamic Programming solution algorithm for the STGS problem has been developed by minimizing the number of search paths to be explored and applying a fuzzy logic and simulated annealing based unit selection procedure. To further decrease the computational time of the method priority ordering of the units has been implemented as well as fast economic dispatch procedures based on the priority ordering of the generators. Moreover, the results of the economic dispatch for different combinations of committed units are saved and utilized when the same combinations are encountered during subsequent steps of the method. In [147], an attempt to decrease the computational time of the Dynamic Programming method for the STGS problems has been developed. Two necessary and sufficient conditions were presented, which are used to discard unit combinations that will lead to infeasible generating schedules, therefore unnecessary Economic Dispatch calculations may be avoided. The aforementioned condition may be examined off-line for each combination, i.e. before the start of the optimization algorithm. Consequently, the required computer memory and execution time of the methods may be reduced.

Lagrangian Relaxation method

In Lagrangian Relaxation method a dual optimization procedure is carried out by forming the Lagrangian dual function. This function is formed by relaxing the coupling constraints, i.e. the demand and reserve constraints; the aforementioned constraints are added on the objective function of the problem weighted by Lagrangian Multipliers. Subsequently, the problem can be decomposed into a series of single unit sub-problems, which are independently optimized. Given a set of values of the multipliers, each separated sub-problem is solved considering the constraints representing the operation of the corresponding unit. The entire solution procedure is performed in an iterative manner by successively solving the sub-problems and adjusting the multipliers, according to the extent of violation of system constraints. Lagrangian Relaxation methods can deal with large scale systems without extensive computational burden. Moreover, additional constraints may be easily incorporated. However, the main disadvantage of this method is that due to the non-convex nature of the primal problem the final solution of the dual problem may be infeasible or suboptimal [9].

In [148] one of the first attempts to optimize the STGS problem using the LR method has been proposed. In [149], Baldick proposed a method based on Lagrangian Relaxation to solve the STGS problem taking into consideration several constraints. Such constraints may be related to the fuel consumption of specific generators and limitations on their power output. In [150], the authors propose some modification on the classical Lagrangian Relaxation Algorithm in order to solve the Unit Commitment problem. In particular, to avoid the computational time needed by Dynamic Programming for the single unit scheduling optimization (required in Lagrangian Relaxation) they utilize a formula, which resembles the fictitious payment minus the cost. This formula determines the state of thermal generators, without the need for optimization. Interestingly, the final solution derived by Lagrangian Relaxation is further improved, utilizing a procedure during which some units are either decommitted or replaced by other generators. The efficiency of the method has been validated on several test systems of different sizes. In [151], the authors proposed some improvements on the Lagrangian Relaxation algorithm. After decomposing the dual problem in a way that can be solved by Dynamic Programming, they use a procedure to reduce the search space examining only feasible states combination for each unit. In particular, instead of using Dynamic Programming to define the state of each generator all the feasible on/off state combinations for a unit are determined and then the cost of each state combination is calculated. Among them the state with the lower production cost is kept. The procedure is enhanced by a unit decommitment method to reduce the reserve margin. In [152], a new formulation of the problem is proposed and a solution method based on the Lagrangian Relaxation is developed to solve it. In this approach, for each generator a feasible sequence of on/off operating states is defined which satisfies the minimum up/down time constraints. Each feasible subpath is associated with a binary decision variable which indicated whether this subpath will be selected or not.

Mixed Integer Linear Programming methods

Methods in this category have been mainly proposed to solve linear programming problems. For this reason, when such methods are applied on the Unit Commitment Problem the linearization of the objective and the constraints is required. For example, the fuel cost function of a thermal generator is commonly approximated by utilizing piecewise-linear segments. By increasing the number of the linear segments a better approximation of the original fuel cost function is achieved. However, in such a case for each segment a different objective variable is required. This may cause a significant increase of the computational burden, especially when the size of the system is large, since for each added segment several additional objective variables would have to be introduced to the problem. Thus, as stated in [9], while MILP is a powerful modeling tool, its main drawback is that it may scale poorly when the number of units increases or when additional modeling detail is integrated.

One of the techniques most frequently used to solve Mixed Integer Linear Programming Problems is the Branch and Bound method ($B\&B$). This method searches the integer solution's space using a so called tree search, in order to avoid the exhaustive enumeration of all the possible solutions. While the nodes in the tree increase, the search space is divided into smaller sub-spaces, in which a solution is sought. The steps of the basic $B\&B$ algorithm are briefly described in the following:

1. The algorithm begins by formulating a linear programming problem in which all the variables (either integer- or real-valued) are considered to be real-valued. This problem belongs to the node 0 of the $B\&B$ tree.

2. The problem in node 0 is solved using a method for linear programming problems (commonly simplex). If the solution obtained contains integer values for the integer variables of the initial problem, then this is the problem's optimal solution. However, usually the solution contains real numbers for the integer variables of the initial problem.

3. One of the integer variables is selected (randomly or the variable with the higher decimal value). This variable is then 'branched'. This means that two additional linear problems are created. In the first, a constraint is added to the initial linear problem, which imposes an upper limit to the value of the selected variable; this bound equals the integer part of the initial real-valued number. In the second, a lower limit to the value of the selected variable is added, which equals the closest larger integer number to the initial real-valued number.

4. The two aforementioned problems are nodes of the tree and they are solved using a linear programming method. In fact these sub-problems examine a sub-space of the initial search space of the parent problem.

5. In case an integer solution (i.e. a solution with integer values for the integer variables) is found, which has a better objective function value compared to the current best integer solution, it is saved. In such a case the branch of the tree which connects the node to the parent node is considered as fully searched.

6. If the objective function value of either of the two nodes is worse than the current integer solution, then the procedure of investigating the branch that connects this node with the rest of the tree structure is stopped. The same holds for the case that in a node a feasible solution does not exist.

7. The algorithm ends when all the available nodes have been searched, or a user defined number of nodes have been examined. Among the integer solutions found the one with the best objective function value is kept.

In more recent years, the rise of efficient MILP solvers has increased the interest towards attempts to propose MILP formulations of the STGS problem. In general their efficiency depends on the amount of modeling detail that is integrated in the problem. One of the first attempts to propose a MILP formulation of the problem and solve it with the $B\&B$ algorithm is that in [153]. In the aforementioned formulation three sets of binary variables have been used to model the start-up, shutdown and on/off states for every unit at every hour. The quadratic fuel cost function was modeled using piecewise-linear segments. The problem has been initially tackled with the standard branch-and-bound ($B\&B$), which was proved to be inefficient. As a result, an extended version of the algorithm considering problem-specific characteristics in the branching process was proposed. Results are provided for problems with up to 16 units and 14 time periods. This formulation was later extended in [154] to model the self-scheduling problem faced by a single generating unit in an electricity market. Non-convex production costs, time-dependent startup costs, and inter-temporal constraints such as ramping limits and minimum up and down times were considered. An alternative MILP formulation has been presented in [155]. The main novelty of the aforementioned work, is that a single set of binary decision variables was used, which represented the decision for the operating state of each thermal generator over the examined scheduling period. This lower number of decision variables triggers a reduction in the number of nodes of the search tree used in the branch and cut algorithm, used to optimize the problem. In [132], the authors propose a method to solve the problem based on a MILP solver and iterative linear approximations of the quadratic cost functions of the units. Regarding the solution methodology, the quadratic cost function is iteratively approximated by applying the Kelley's theorem on the convex quadratic cost function of each unit. In particular, the method begins by approximating the cost function using two lines from Pmin and Pmax points. After calculating the cost based on this approximation the difference between the actual cost (in the quadratic cost function) and the one derived by the approximation is calculated and in case that difference is higher than a user defined limit then another line is added to the approximation at the point to which the fuel cost was previously calculated. This goes on until the difference in the actual value and the approximation is lower than the threshold previously mentioned. This way the actual optimal of the STGS can be very closely approximated. In [156], a mixed-integer linear programming reformulation of the thermal unit commitment problem is presented, which is tight and compact. The proposed formulation provides increased tightness and compactness compared to previous MILP models. The tightness is related to the distance between the relaxed and the integer solutions of the problem (relaxed is the solution of the parent node), while the compactness of the model refers to the quantity of data that are processed when the problem is solved. In [157], a novel formulation for the Unit Commitment Problem is proposed. By projecting the power output of a generator in the interval $[0, 1]$ ad using reformulation techniques, a formulation of the problem which utilizes two sets of binary variables is developed. The aforementioned formulation is tighter than previous mixed integer formulations of the problem in terms of the quadratic cost function. Applications of the method on several test system indicate that such a formulation may provide adequate results in less computational time compared to the previous MILP approaches.

Other methods based on deterministic algorithms

A very common class of methods to solve the STGS problem is the approaches based on Bender's Decomposition. Methods belonging in this category commonly decompose the problem into the two following sub-problems: 1) A master problem which is an integer optimization problem dealing with the commitment state of thermal generators, and 2) a sub-problem, which is a non-linear optimization problem which considers the power output of the generators (the integer variables are fixed). The operating states of thermal generators are obtained by solving the integer optimization problem, and the obtained commitment states will be imposed on the non-linear optimization sub-problem, which is solved by applying another routine. After the sub-problem is solved, a set of dual values is returned to the master problems. Then, Bender's cuts are generated based on these dual values which govern the determination of the solution of the master problem. The optimal solutions is achieved by iteratively solve the master problem and the sub-problem. The first attempt to apply the Bender's Decomposition on the STGS problem of a power sector containing thermal generators was that of Turgeon [158]. Several constraints of the problem have been considered. Moreover, an additional cost term has been included within the objective function, which represents the cost of keeping the thermal generators synchronized to the system without providing energy to it. In [159], a new formulation of the STGS problem has been proposed based on Bender's Decomposition. The objective function of the master problem considers the production cost of committed units generating their minimum output powers, the start-up and shutdown cost of generators and the required cuts. In the sub-problem, the power output of the committed units of the main problem is defined based on unit variable costs. Then based on the dual values of the demand constraint and the generation limits constraints in the sub-problem two cuts are formed for the master problem as a function of binary variables, and added to the objective function. The main problem modifies its last iteration results using the updated objective function. Also, a new formulation for the ramp rate constraints has been utilized, which uses only binary variables. The method was tested on systems of up to 100 units and the results reveal the efficiency of the method. In Fu et al. [160], a comparison is carried out between LR and MILP approaches for the optimization of the master problem of Benders' decomposition, in terms of modeling ability, feasibility and optimality, solution stability, computer resource consumption, and application.

Semi Definite Programming is an extension of the Linear Programming. Their basic difference is that in latter, the variables are elements of a vector which is required to be component wise non-negative, while in Semi Definite Programming, the variables form a symmetric matrix which is constrained to be positive semi-definite. An SDP-based solution methodology for the STGS problem has been proposed in [161]. In this procedure the basic constraints have been considered while a simple correction procedure is developed to restore solution infeasibility. The semi-definite program is implemented through a computationally efficient formulation that yields a moderate increase in computational effort with problem size. The method is applied on a real size case-study and demonstrated an efficient performance.

Finally, in [162] a method based on Outer Inner Approximation has been proposed for the thermal generation scheduling problem. In particular, a separable mixed integer formulation has been presented and the Outer Approximation deterministic global optimization method is used to solve it. The method has been implemented on power systems of realistic size providing adequate results.

4.2.2 Approaches based on stochastic algorithms

The second group in the classification regards the EA methods applied on STGS problem. Such techniques can be directly applied on STGS problem offering great modeling flexibility (i.e. easy handling of non-linear objective functions and constraints). Moreover, due to their stochastic nature such methods may avoid getting trap in local minimum solutions providing thus competitive performance.

A common feature in such approaches is that the EA is applied to handle the operating state of the units while the economic dispatch is solved using the Lambda iteration approach. The latter is a well established method for solving the economic dispatch when quadratic cost functions are considered [11]. It is based on the procedure of optimizing the Lagrangian function of the Economic Dispatch problem, in which the power balance constraints are added on the objective function (total fuel cost of the units), using a series of Lagrangian multipliers λ. The Lagrangian multipliers λ are then determined by implementing an iterative procedure. The iterative procedure stops, when the difference between the hourly load and the sum of the power produced by each on-line generator is below a user-defined limit. The procedure is presented in Algorithm 5.

In what follows, we will review some basic methods based on EAs applied on the all thermal STGS problem.

Algorithm 5 Lambda iteration method for economic dispatch

$\lambda_{min} \leftarrow min_{i=1,...,NTG} \frac{dFC_i(Pmin_i)}{dP_i}$
$\lambda_{max} \leftarrow max_{i=1,...,NTG} \frac{dFC_i(Pmax_i)}{dP_i}$
Set the tolerance ϵ
$Diff \leftarrow 10^5$ {Initial value to enter while loop)}
while $|Diff| \geq \epsilon$ **do**
  $\lambda \leftarrow \frac{\lambda_{min}+\lambda_{max}}{2}$
  Calculate P_i by solving $\frac{dFC_i(P_i)}{dP_i} = \lambda$
  $Diff = P_d - sum_{i=1}^{NTG} P_i$
  if $Diff > 0$ **then**
    $\lambda_{min} \leftarrow \lambda$
  else if $Diff < 0$ **then**
    $\lambda_{max} \leftarrow \lambda$
  end if
end while

Genetic Algorithms

One of the first attempts to apply a GA for the solution of the STGS is that of Kazarlis [163]. In this approach, each member of the population comprises ($NTG \cdot T$) binary variables, which represent the state of the thermal generators over the examined scheduling horizon. Except of the recombination operators of the GA algorithm two additional operators, i.e. swap window operator and window mutation operator, are applied to enhance the algorithms performance. The method is tested on test systems comprising 10 to 100 units performing efficiently. In [164], the authors examine a different encoding scheme for the population members of the GA. In particular, each solution vector comprises integer numbers, with a positive number indicating the duration of operating time of the unit, while negative integers represent the duration of the non-operating time of the unit. Lambda iteration is used for the Economic Dispatch. The use of the aforementioned encoding scheme enables the incorporation of the minimum up/down times directly within the model, resulting in reductions of the computational time compared to the method in [163].

In [165], the author proposes a novel representation for the unit commitment problem. In particular, the chromosome comprises the start up and shutdown hours of a unit in the scheduling horizon. To propose such a scheme the two following assumptions are made: 1) The units can start up only when the demand increases and they can shutdown only when the demand decreases. 2) The planning horizon (24 h) can be divided into 5 cycles in which the demand increases and decreases respectively (specifically 3 start up and two shutdown periods). In this approach Lambda iteration is used to optimize the Economic Dispatch. The method is tested on a simple test system comprising 12 units for 24 hours and the results are not benchmarked with competitive methods.

In [166], the authors propose a hybrid biased random key GA (HBRKGA) approach for the optimization of the unit commitment problem with ramp rates. Specifically, the random key GA is a real coded GA where the components of each chromosome consist of random numbers in [0,1]. These numbers are used then to define a rank order in which the units will be used. Moreover, they are used to calculate the power output of each committed thermal generator. A repair mechanism is also utilized to ensure that the decoding procedure derives feasible generating schedules. The recombination and selection operators are modified slightly (hence the term biased), in order to give a higher mating chance to elite individuals. At the end of the method, a local search technique is utilized to further improve the solutions, and operates by swapping the state of two randomly selected units.

Particle Swarm Optimization

One of the first approaches of PSO on the STGS problem is that of [167]. The authors propose a solution methodology based on an Improved PSO algorithm. In particular, they propose the relaxation of the binary variables and the transformation of the MUT/MDT constraints in order to solve the problem by a continuous constrained optimization PSO. The constraint violation is added on the objective function by using the penalty function method. A penalty parameter is also added when the values of the relaxed binary variables are not 1 or 0. Regarding the modification of the PSO, the authors adjust the social cognition term in order the update procedure of the particle to take into account also the position of a number of the best individuals. The method is examined on the system of 10-100 units without the incorporation of the ramp rates.

In [168] a version of the PSO for binary optimization is proposed to optimize the unit commitment problem. In the aforementioned approach, each individual comprises binary variables representing the states of the units. To evolve the population of solutions the classic operators of PSO for updating the velocity and the position of each individual are replaced with operators which can be applied on binary variables; in particular the 'XOR', 'AND' and 'OR' operators are utilized within the proposed scheme. In [169], the same authors attempt to extent the real-valued PSO to handle the binary variables of the STGS problem. In particular, the position of each individual may only take binary variables. The procedure for the velocity update is similar to the common real-coded PSO. The derived velocity is introduced into a sigmoid function which derived values within the range of [0, 1]. The value produced by the sigmoid is compared to a uniformly generated number in [0, 1] to determine the state of the units. In both the aforementioned approaches, heuristic repair operators taking into consideration the Priority Order of the generators at their maximum power output are utilized. Moreover, the Lambda iteration is used to determine the load dispatch amongst the committed generators.

In [170], an approach based on PSO and Expert System Rules is proposed. In particular, an expert system which comprises 8 rules is proposed to handle the problem's constraints; this expert system (consisting of rules which are similar to the procedures of the heuristic repair operators referred previously) is used before the optimization to create an initial population of solutions of adequate quality as well as during the course of the optimization to retain the feasibility of infeasible generating schedules. The well known binary version of the PSO of Kennedy and Eberhart [171] is utilized. To avoid the entrapment of the swarm on local optimum solutions, during the update of the velocity, a group of best positions of each particle, as well as a group of the best positions of the swarm are utilized. Moreover, a mutation is applied occasionally on the best solution, where random bits are selected and flipped according to a certain probability. The economic dispatch for each generating schedule is carried out by a conventional Genetic Algorithm.

In [172], a three stage method is proposed to solve the STGS. Initially the units are committed using a Priority List created based on the production point, where the cost is minimum for each unit. Then, a modified version of the PSO algorithm, called Crazy PSO, proposed by the authors of [172] is applied to optimize the Economic Dispatch. Finally, a restructure method is applied, in which some committed generators are substituted by uncommitted ones based on a series of rules. Thus, the operating schedule is derived by a series of heuristic rules, while the economic dispatch is carried out using the PSO approach proposed by the authors.

In [173] a two layer PSO approach has been proposed for the optimization of the problem. In practice this method combines the binary PSO of [171] with a Simulated Annealing algorithm. The method has been tested on a test system comprising 10 thermal generators.

Differential Evolution

As stated in Chapter 2, in DE the population of candidate solutions evolves based on the following three operators: 1) Mutation, 2) Crossover and 3) Selection. Since conventional DE is used for real parameter optimization, usually binary versions of the algorithm were proposed for STGS.

In Patra et al. [174], two version of DE, a binary and a discrete one, are proposed to solve the STGS problem. In the former, the mutation operator is modified using Boolean logic (XOR and OR/NOT gates) to handle the binary variables. In the latter, a positive (negative) integer in the solution vector indicates the duration of the on (off) state of a power generator. In both approaches, a series of heuristic mechanisms are used to retain the feasibility of the solution vectors, while the Lambda iteration method is applied to optimize the Economic Dispatch of feasible individuals. Both the binary and integer-coded versions of the algorithms have been examined on problems where the number of generators in the power system varies from 10 to 100. The results of the method have been compared to other EA based methods proposed in the literature.

In Jeong et al. [175], a binary DE is proposed for the optimization of the problem. In particular, the structure of the original DE is retrieved; however each solution vector represents the on/off schedule of each unit at each hour. The mutation operator is applied as in the basic DE formulation and based on the sign of each parameter of the mutant vector the binary variable takes a value of zero or one. Moreover, heuristic procedures are employed to repair the violation of the minimum up/down time constraints and spinning reserve constraint, while a unit decommitment procedure is applied to improve the generation scheduling. The Lambda iteration is then applied to economically dispatch the demanded load among the committed units. The method is tested on systems comprising 10-100 generating units and demonstrated an efficient performance.

A binary DE is examined also in Yuan et al. [176], where the authors attempt to expand the notion of the distance to binary search spaces. In this approach, the population of DE comprises binary-valued solution vectors. The rand/1 mutation scheme of DE is modified to handle binary variables. In particular, if the difference vector equals 1, a random number sampled from the uniform distribution is compared to the F value to determine whether a value of 1 or 0 will be added on the base vector. The method is further enhanced by a series of heuristic repair mechanisms, which take into consideration information from the Priority List of the generators, to repair infeasible generating schedules. The optimization of the Economic Dispatch is carried out using the Lambda iteration method. The approach is tested on the system of 10-100 units, having a competitive performance.

An attempt to solve a STGS using a real-coded DE algorithm is that of Uyar et al. [177]. The method utilized the penalty function to handle the constraints related to the on/off state of the units. However, the tuning of the penalty parameters requires extensive computational time especially in real world problems such as a STGS. Moreover, the size of the population used was very large ($500 - 3000$ individuals) and the algorithm required a great number of generations ($1 \cdot 10^{-6}$ - $3 \cdot 10^{-6}$) to converge even for systems of smaller scale, deriving solutions of relatively high operation cost. The method was tested on the system of 10-100 units, however it has not provided efficient performance.

It should be noted that an approach based on Differential Evolution has been also proposed in

[178], where DE is combined with a random search algorithm. Nevertheless, within the aforementioned paper, it is not clearly described how the method handles the constraints of the problem. Moreover, the generating schedules published, violate basic constraints of the problem. For these reasons this method will not be further analyzed.

Approaches based on other EAs

Several other methods have been developed for the optimization of the STGS, based on a large variety of stochastic algorithms. For example, Simopoulos et al. [179] have developed a method based on the Simulated Annealing algorithm for the optimization of the problem. The Simulated Annealing is a single point optimization algorithm which is based on the analogy between the minimization of the objective function of an optimization problem and the procedure of gradually cooling a metal, until it reaches the point, in which the system's energy is minimum. The approach is enhanced by three mechanisms for obtaining feasible solutions in the neighborhood of the current one, and a local optimization technique, to speed up the convergence of the algorithm. A dynamic Economic Dispatch procedure is also proposed, which sequentially solves hourly Economic Dispatch problems in a forward and a backward sweep, attempting to include the ramp rate constraints within the procedure by modifying the generation limits of each unit. The method is tested on power systems comprising up to 100 units taking into consideration the ramp rates of the thermal generators.

Quantum inspired EAs were applied to handle the binary on/off schedule in Lau et al. [180] and Chung et al. [181]. QEA employs a Q-bit as a probabilistic representation, instead of binary or real encoding used by other EAs. In QEAs a rotation gate, which is one of the quantum gates, is used to modify the state of a Q-bit. The rotation gate requires a predefined lookup table to determine the rotation angle. In Chung et al. [181] a simplified rotation gate and a decreasing rotation angle approach are included to enhance the algorithms performance. The simplified rotation gate determines the rotation angle without requiring the lookup table. Moreover, in the decreasing rotation angle approach, the magnitude of the rotation angle is linearly decreased. To further enhance the method's performance, a series of heuristic repair mechanisms are included to handle the problem's constraints. Lambda iteration method is used to optimize the Economic Dispatch. The method has been tested on systems of up to 100 units. In Jeong et al. [182] and Srikanth et al. [183] the evolution operators of PSO and GWO were replaced by the update procedure of Q-bits to derive the on/off schedule, resulting also in efficient approaches for the optimization of the problem.

Binary versions of more recent EAs have been also frequently employed to handle the on/off states of thermal generators in optimization methods for the STGS problem, while the Lambda iteration method is utilized for the Economic Dispatch. Commonly heuristic repair operators are used in such approaches to facilitate the EAs in obtaining feasible generating schedules, since the STGS is a large scale, highly constraint, combinatorial optimization problem. Within this framework methods based on Imperialistic Competition Algorithm [184], Neighborhood Field Optimization Algorithm [185], Gravitational Search Algorithm [186], Artificial Bee Colony Algorithm [187], Grey Wolf Optimizer [188] and Moth Flame Algorithm [189] have been developed. For a detailed description of the aforementioned methods, the interested reader is kindly referred to the reviews of Mallipedi and Suganthan [133] and Abujarad et al. [131].

4.2.3 Hybrid approaches

The third category in the classification of methods applied on the STGS problem contains the hybrid methods, in which the beneficial features of algorithms from both the deterministic and the stochastic methods are combined.

In [190] Lagrangian Relaxation is combined with GA for the optimization of the STGS problem. In the conventional form of the Lagrangian Relaxation approach, commonly some form of sub-gradient algorithm is used to update the Lagrangian Multipliers. However in the approach of [190], GA is incorporated within the Lagrangian Relaxation method to update the Lagrangian

Multipliers. The approach comprises two stages: in the first the minimum of the Lagrangian function under constant Lagrangian multipliers is sought using a Dynamic Programming method. Thereafter, in the second stage, the maximization of the Lagrangian function with respect to the Lagrangian Multipliers is carried out, where the GA is used to update the Lagrangian Multipliers. The method has been examined on systems of up to 100 units and has managed to outperform the individual GA and Lagrangian Relaxation applied on the same systems.

An interesting work in this category is that of Yu and Zhang [191], where the Lagrangian Relaxation method is combined with the Comprehensive Learning PSO algorithm to solve the Unit Commitment problem. The PSO variant is used to update the Lagrangian multipliers in a loop where Lagrangian Relaxation derives the on/off schedule. A reserve repairing heuristic, a unit decommitment heuristic, and an economic dispatch heuristic are also included to obtain feasible individuals during the optimization. The reserve repairing heuristic repairs violations of the spinning reserve and minimum up/down time constraints. Moreover, to reduce the total startup cost, the unit decommitment procedure may decommit thermal generators for a series of consecutive periods. In the initialization phase, each particle of the PSO is initialized using the Lagrangian multipliers obtained from a conventional Lagrangian Relaxation algorithms (which updates the multipliers through a sub-gradient method), in an attempt to begin from a population which will be close to the optimal Lagrangian Multipliers. The efficiency of the method has been validated for systems comprising 10, 20, 40, 60, 80, and 100 units.

In [192] two new solution methodologies have been proposed for the conventional thermal STGS problem. The approaches explore optimization algorithms that hybridize meta-heuristics with mixed integer programming solvers, to accelerate the convergence to near optimal solutions for large scale test instances. The two algorithms developed are the local branching algorithm and a hybridization of Particle Swarm Optimization with a mixed integer programming solver. In the former, firstly the feasible region of the problem is divided into smaller sub-regions and a MILP solver is used to find the best solution in each sub-region. Thus, the MILP approaches are combined with typical meta-heuristic concepts, such as neighborhood definitions and local search. In the second method, PSO is coupled with the MILP solver as follows; first PSO is executed until the maximum number of generations are reached, and the final solution obtained by PSO is used as a high quality initial point for the MILP solver. Both methods have been tested on systems of up to 100 units. The approach where PSO was combined to a MILP solver has provided better results in the majority of the examined systems compared to the local branching method. Nevertheless both methods have demonstrated a very competitive performance on all the examined systems.

Several works have been proposed, where binary stochastic algorithms are employed to determine the optimum on/off schedule while meta-heuristics using real valued representations optimize the ED. In [193] a method which hybridized a real-coded and a binary-coded PSO for the optimization of the STGS is developed. The operating state of each generator is represented by binary variables which are handled by the binary-coded PSO [171]. The power output of the generators is represented by real-valued parameters handled by the real-coded PSO, which is the classical PSO algorithm. Both algorithms are run simultaneously, adjusting their solutions in search of a better solution. The infeasible individuals with respect to the demand constraints and the spinning reserve constraints are handled by using a dynamic penalty function which increases the pressure towards feasible solutions while the number of generations increases. The constraints related to the time interval for which a generator should be in operation are handled by a simple repair mechanism. The method was applied on a system comprising 10 thermal generators and has derived robust solution distributions.

An interesting work on the conventional STGS problem is that of Datta [194], where binary-coded GA and real-coded GA are hybridized to optimize the unit commitment problem. In this case each solution vector comprises ($NTG \cdot T$) binary variables and ($NTG \cdot T$) real-valued variables representing the state and the power output of each committed generator, respectively. On the binary part of each chromosome the two point crossover and the common GA mutation operator (flipping each parameter with a certain probability) are applied, while on the real valued of the chromosome the simulated binary crossover operator and the polynomial mutation operator are applied. A series of heuristic repair mechanisms are utilized to infeasible individuals in an attempt to regain the feasibility of the solutions. The method is applied on the system of 10-100 units with and without the inclusion of the ramp rate constraints demonstrating an efficient performance.

In Datta and Dutta [195], a hybrid binary and real coded DE is applied on a STGS problem. The solution vector comprises of $NTG \cdot T$ binary variables, representing the state of each thermal generator at each hour, and $NTG \cdot T$ real variables representing the corresponding power output. On the real-valued variables the simple DE/rand/1 is applied. On the contrary, the mutation of binary DE is based on a set of rules, which takes into consideration the combinations of $\{0, 1\}$ values between the base and the difference vectors. Thus in this approach, the on/off schedule of thermal generators is handled by the binary-coded DE, while the Economic Dispatch is solved by the real-coded DE. The method is enhanced by PL-based repairing mechanisms. Moreover, a different selection operator is used, where the population of target and trial vectors are combined and then sorted according to their objective function values, to maintain the best individuals in the combined population.

Two approaches in which DE has been hybridized with a GA are proposed in [196] and [197]. In both methods a binary encoded GA is used to determine the optimum on/off schedule, while DE is used to optimize the Economic Dispatch given the set of committed generators. A heuristic initialization scheme and a mechanism based on the Priority List of the units to satisfy the power balance constraints are included in both approaches. Moreover, several mutation schemes of DE have been examined, assessing their impact in the problems optimization. The method has been tested on the system of 10-100 generators providing efficient performance.

In [198], three binary-real coded EAs, i.e. binary-real coded GA, binary real-coded DE, and binary-real coded PSO are applied on the unit commitment problem, taking into consideration the, so called by the authors, wrap around concept, which allows to handle practical scenarios by considering that a planning horizon is the repetition of a production cycle. According to this concept the initial ON/OFF status of the units in such a production cycle will be those at the end in the previous production cycle. The method has provided results for the problem when the wrap-around concept is taken into consideration, demonstrating that among the three examined binary-real coded EAs, the one that performed more efficiently is the binary-real coded GA.

4.2.4 Utilization of the Priority List

The STGS is a large scale, highly constrained and combinatorial problem. Obtaining feasible solutions is a difficult task for any EA. For this reason, heuristic repair mechanisms are commonly used when methods employing stochastic algorithms are applied on a STGS problem. These mechanisms usually take into account domain-specific knowledge in the form of the Priority List of the units, in an attempt to steer the search towards solutions of high quality. When EAs are applied for the optimization of real-world problems incorporation of domain specific knowledge has proved to be beneficial [5]. Repair mechanisms utilize a Priority List, which is created by sorting the units based on their average production cost at a predefined working point. In the vast majority of such approaches, the working point selected to create the Priority List is the maximum power output of the thermal generators, since the Average Production Cost of the generators at that point is minimum. To some extent, this point can be interpreted as the anticipated operating point of a generating unit [138]. However, the use of a Priority List based on the Average Cost of the units at their maximum production point may perform well when the hourly load exhibits small variations, otherwise it may result in increased operation cost schedules [136]. Moreover, utilizing a constant Priority List to repair the generating schedules throughout the optimization may have an impact on the diversity of the schedules examined. Thus, the use of a single Priority List throughout the optimization procedure might have an impact on the quality of the solutions, which should be researched.

4.2.5 Contribution to the relevant literature

In the previous subsections, we have presented the methods that have been proposed in the relevant literature for the optimization of the unit commitment problem; their basic characteristics have been described and several of their variants have been analyzed. As seen, many rigorous approaches have been proposed for the STGS problem based on deterministic and/or numerical methods such as Dynamic Programming and Lagrangian Relaxation. However, these methods may suffer from the 'curse of dimensionality' especially in dealing with modern power systems with large number of generators [133]. Moreover, the generators' cost functions may contain non-convex and non differentiable terms in order to realistically represent the limitations in the operation of a generating unit, such as the prohibited operating zones and the valve point effect [11]. Thus, conventional derivative based methods may encounter difficulties in dealing with such functions.

Based on the above analysis it has been identified that methods based on EAs present several advantages compared to the deterministic methods, the basic of which is their flexibility in handling non-differentiable and non-convex objective functions and constraints. Nevertheless, EAs also present some deficiencies. In fact, they may require large computational time, when the problem contains a large number of objective variables. Moreover, EAs with conventional evolution operators may fail to converge to the optimal solution at affordable computational cost, while in combinatorial problems with a large number of constraints EAs may encounter difficulties in providing feasible generating schedules.

In this framework, further research is needed to increase the efficiency of EAs for solving short-term STGS. This has been the main motivation to propose a solution methodology for this real-world problem, as will be described in the following subsections of this Chapter. It is based on employing a DE variant for constrained optimization, called FROFI, to determine a near optimum binary operating schedule and load dispatch. The EA approach includes a transformation function, a repair heuristic mechanism and a mutation strategy. The proposed method has managed to derive better or at least competitive solutions compared to recently proposed algorithms for the STGS on several test instances examined. The method's salient features, which combined in a computational model managed to lead to promising results, are presented hereinafter:

1. A real-coded variant of DE for constrained optimization, has been utilized to handle both sub-problems of the short-term generation scheduling problem. To determine the binary state of thermal generators a simple parameterless transformation function has been integrated in the optimization procedure. The proposed method allows real-coded EAs to be directly applied on the mixed-integer problem. Thus, in contrast to the majority of the EA-methods applied on the problem, neither sigmoid functions are used nor the operators of the EA are modified to handle the binary states. As discussed in [199], the type of sigmoid function used may have an effect when continuous metaheuristics are applied to binary search spaces, while reformulating the operators may redefine the algebra of the search space. Moreover, the proposed method does not utilize Lambda iteration to optimize the Economic Dispatch which may trigger reductions of the execution time.

2. In an attempt to efficiently incorporate domain specific knowledge within the evolutionary optimization procedure, a series of heuristic optimization mechanisms, have been also proposed. These mechanisms facilitate the obtainment of feasible solutions and steer the search towards adequate generating schedules.

3. A procedure to create a Plurality of Priority Lists has been proposed, which enhances the diversity of the generating schedules examined during the optimization. When heuristics are considered for the repair of individuals commonly a constant Priority List has been used, based on the average fuel cost of the units at their maximum power output. However, the use of a constant PL may bias the search towards sub-optimal generating schedules and cause the premature convergence of the algorithm. On the contrary the proposed Plurality of Priority

Lists procedure, assigns a different PL to each solution vector at each generation, which is used during the repair mechanisms; the Priority Lists are created based on points within the loading range of thermal generators using the uniform distribution anew for each individual at each generation.

4. An Elitist mutation strategy was developed and combined with the DE variant used to improve its performance. The Elitist Mutation attempts to exploit information from the elite member of the population regarding its objective function value, during the stage where the population includes feasible individuals. In particular, a mutant is created by randomly slightly modifying the elite member. This mutant may replace the individual with the worst objective function value in the population, in case the former's objective function value is better. Exploiting information from the elite member may steer faster the individuals towards regions of the search space with solutions of good quality. Moreover, in later stages of the optimization when the population has gradually converged, modifying the elite member may facilitate the population jumping out of basins of attractions with local minimum solutions.

The proposed method is applied on several benchmark test systems frequently examined in the literature. Its performance is compared with the previous DE-based approaches and other advanced deterministic, stochastic and hybrid approaches. The efficiency of the proposed algorithm, both in terms of optimality and consistency, is higher or at least competitive to the ones recorded even in most recent works.

4.3 Mathematical model of the problem

In its basic form, the overall target of the STGS problem is to determine the optimal operating schedule of the thermal generators of a power system to serve the demanded load in the most cost-effective manner. Thus, the thermal generators that will be in service, the number of hours that these generators will operate and the amount of energy that each generator will contribute to the power system at each hour are sought. The decision variables of the problem are the state of the units (denoted as ST) as well as their production level (denoted as P) for each hour of the scheduling period. The former are commonly represented using binary variables; when $ST = 0$ the generator is off-line and does not provide energy to the grid, while when $ST = 1$, the thermal generator is in operation. The energy provided to the grid by a generator is commonly represented by continuous variables and it depends on the state of the generator. In fact, when the state of a thermal generator is zero at hour t then $P = 0$, while when the thermal generators is on-line the production of the thermal generator is between a minimum and a maximum value.

In what follows, it is highlighted that the formulation of STGS examined is the one employed in the vast majority of works in the specific field [163, 200]. Other formulations have also been proposed for the conventional STGS focusing on a more detailed description of some of the problems components, e.g. Liu et al. [201], Pereira et al. [202], Tumuluru et al. [152]. Moreover, models with sub-hourly intervals have also been developed, e.g. [203] and [204]. However, the aforementioned models are not examined in this dissertation.

4.3.1 Objective function

In the conventional form of the STGS (examined in this Chapter), the sole objective function is the minimization of the Total Operation Cost (TOC) of the generators over the examined scheduling period. The TOC takes into consideration the fuel cost, the start-up cost and the shutdown cost of the thermal generators. In the following, we will describe each of the aforementioned terms of the objective function.

- **Fuel cost of thermal generators:** The fuel cost is related to the fuel consumption of the thermal generators and depends on the production level in each period, as well as the type of fuel used in each unit (e.g. lignite, coal, natural gas). In the relevant literature, the fuel cost is represented by quadratic functions of the power output of the thermal generators. Thus, for thermal generator i the fuel cost at hour t is given as follows:

$$FC_i(P_i^t) = a_i + b_i \cdot P_i^t + c_i \cdot (P_i^t)^2 \tag{4.1}$$

where a_i, b_i and c_i are the coefficients of the quadratic fuel cost function of unit i. It should be noted that during the calculation of the fuel cost coefficients, the price of the corresponding fuel is taken into consideration. Moreover, when methods based on Mixed Integer Linear Programming are utilized the fuel cost function is approximated by a series of linear segments. The gradient of each segment ($a_{k,I}$) is multiplied by the corresponding segment of the power output, i.e. P_i^t. In each case, i.e. quadratic or using linear segments, the fuel cost function should strictly increase with the value of the power output of the thermal generator.

- **Start up cost of thermal generators**: The second term of the TOC is the start-up cost of the thermal generators, i.e. the cost associated to the amount of energy expended to bring a decommitted unit 'on-line'. In fact, bringing a generator into operation requires extra cost due to fuel consumption, maintenance and the additional feed of water and energy that are needed for heating. The start-up cost ranges from lower values, if the unit has been recently turned off and the temperature of the boiler is close to the operating temperature, to maximum values, when the unit starts up from a cold state. Thus, the start-up cost primarily depends on the number of consecutive hours for which the unit has not been in operation (denoted as $Toff$), before it is committed. In the relevant literature, two models have been mainly employed for the start-up cost. In the first, the start-up cost is modeled as a two step function [163]:

$$SUC_i^t = \begin{cases} HSUC_i, \; if \;\; MDT_i \leq Toff_i^t \leq MDT_i + T_i^C \\ CSUC_i, \; if \;\; MDT_i + T_i^C < Toff_i^t \end{cases} \tag{4.2}$$

In Eq. 4.2, $HSUC_i$ and $CSUC_i$ are the costs incurred when unit i is brought on-line from a hot and a cold state, respectively. T_i^C is the time needed for the transition of the unit from a 'hot' to a 'cold' state; it is the time required for the boiler of the generator to cool down.

In the second model, start-up costs are modeled by the following exponential function:

$$SUC_i^t = \chi_i + \delta_i \cdot (1 - exp(-\frac{Toff_i^{t-1}}{\gamma_i})) \tag{4.3}$$

where χ_i is the fixed start-up cost, δ_i is the cold start up cost and γ_i is the cooling constant of unit i. Figure 4.1 depicts the two models presented for the start-up cost. In both Eq. 4.2 and 4.3, $Toff$ denotes the duration of unit's i off status, which is calculated using the following formula:

$$Toff_i^t = (Toff_i^{t-1} + 1) \cdot (1 - ST_i^t) \tag{4.4}$$

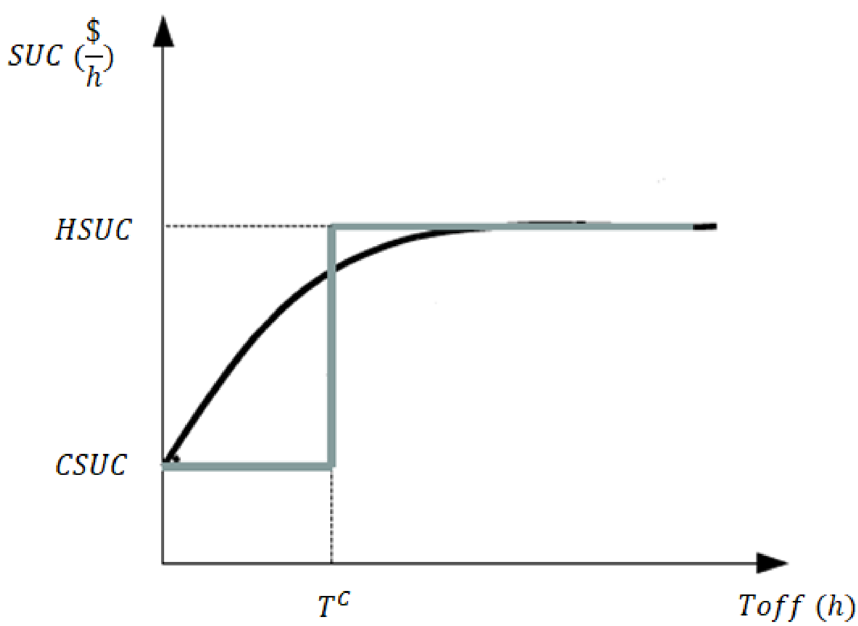


Figure 4.1: Exponential (black color) and two step (grey color) start up cost functions

- **Shutdown cost of thermal generators:** Shutdown costs are commonly considered constant. They are usually considerably smaller than the start-up costs and they represent the labor cost for decommiting a thermal generator. Usually, in the relevant literature such costs are not considered within the model's objective function.

Based on the aforementioned, when the power system comprises NTG thermal generators to be scheduled for T hours, then the objective function of the model is the following:

$$f_1 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} [FC_i(P_i^t) \cdot ST_i^t + SUC_i \cdot ST_i^t \cdot (1 - ST_i^{t-1}) + SDC_i \cdot (1 - ST_i^t) \cdot ST_i^{t-1}] \quad (4.5)$$

As can be seen in Eq. 4.5, the objective function contains both binary and continuous variables and is nonlinear.

4.3.2 Constraints

Any unit commitment procedure must produce a schedule that can be implemented in a real life system [205]. For this reason, it should take into account a number of practical considerations concerning the operation of the system and the generating units. In particular, the derived schedule should be able to satisfy the demanded load in a reliable manner, while the operation of the power units should be limited based on their mechanical and electrical characteristics. The constraints considered in this model are the following:

- **Power Balance constraints:** The power output of the committed thermal generators should satisfy the demanded load P_d^t at each hour $t \in 1, ..., T$ of the planning horizon:

$$\sum_{i=1}^{NTG} ST_i^t \cdot P_i^t = P_d^t, \quad t \in [1, T] \quad (4.6)$$

It is noted that transmission losses can also be included within equation 4.6. Commonly, in the relevant literature the latter are considered as a percentage of the hourly load or are neglected. In the context of the model examined in this dissertation, the transmission losses are not considered.

- **Spinning Reserve constraints:**

  Reserve is the total power available from the committed units minus the hourly load; it is actually a measure of the maximum energy that can be delivered immediately to the grid, without having to bring in operation an additional unit. It should be sufficient to make up for possible unit outages and deviations of the actual load from the anticipated one. Commonly these constraints are formulated as follows:

$$\sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i \geq P_d^t + SRR^t, \quad t \in [1, T] \tag{4.7}$$

  In conventional STGS problems, spinning reserve requirements (SRR^t) are usually taken equal to a certain percentage of the expected demand or equal to the nominal power of the largest committed generator. It should be noted that different types of reserve may be modeled, i.e. primary, secondary and tertiary. However, in this dissertation a single spinning reserve type is considered in line to several works in short-term STGS literature [163, 200].

- **Minimum up time constraints of a generating unit:** When a thermal generator starts up it must remain in operation for at least a number of consecutive periods equal to its Minimum Up Time (MUT_i), before it can be turned off. Mathematically, these constraints are formulated as follows

$$(Ton_i^{t-1} - MUT_i) \cdot (ST_i^{t-1} - ST_i^t) \geq 0, \; i \in [1, NTG], \; t \in [1, T] \tag{4.8}$$

where Ton corresponds to the continuous period for which the unit has remained operational up to hour t:

$$Ton_i^t = (Ton_i^{t-1} + 1) \cdot ST_i^t \tag{4.9}$$

- **Minimum down time constraints of a generating unit:** In case a unit is turned off, it can be brought in operation only after a certain amount of time equal to its Minimum Down Time (MDT_i). These constraints are formulated as follows:

$$(Toff_i^{t-1} - MDT_i) \cdot (ST_i^t - ST_i^{t-1}) \geq 0,\ i \in [1, NTG],\ t \in [1, T] \tag{4.10}$$

- **Ramp Rates of thermal generators:** The power output of a generating unit cannot be adjusted instantaneously without limits. The operating range of all on-line units is restricted by their ramp rates, which impose the coordination of the power generation over consecutive hours. The ramp up constraints restrict the increase in the power output of a generating unit:

$$P_i^t - P_i^{t-1} \leq ST_i^{t-1} \cdot UR_i + (1 - ST_i^{t-1}) \cdot Pmax_i,\ i \in [1, NTG],\ t \in [1, T] \tag{4.11}$$

where UR_i is the ramp up capability of generator i. On the other hand, ramp down constraints restrict the decrease in the power output of a thermal generator among consecutive hours, as follows:

$$P_i^{t-1} - P_i^t \leq ST_i^t \cdot DR_i + (1 - ST_i^t) \cdot Pmax_i,\ i \in [1, NTG],\ t \in [1, T] \tag{4.12}$$

where DR_i is the ramp down capability of generator i. In this dissertation during the start-up and shut-down of a unit the corresponding ramp rates are considered equal to the unit's maximum capacity as in Simopoulos et al. [179], Han et al. [162], Singhal et al. [187].

- **Generation limits of thermal generators:** Thermal units are not technically capable of producing below a minimum production level, nor above a maximum. The power output of each unit is restricted between a maximum and a minimum limit, in order to ensure its stable operation when the unit is committed:

$$ST_i^t \cdot Pmin_i \leq P_i^t \leq ST_i^t \cdot Pmax_i \tag{4.13}$$

  where $Pmin_i$ and $Pmax_i$ are the minimum and maximum permissible power output of the ith generator.

- **Initial conditions of the thermal generators:** The initial commitment state of the ith unit (ST_i^0) as well as the amount of time for which a unit has remained online (Ton_i^0) or off-line ($Toff_i^0$) prior to the beginning of the scheduling period are taken into account. In particular, they are considered when dealing with the on/off decisions during the initial hours of the planning horizon. Moreover, $Toff_i^0$ affects the start-up cost, which will be incurred, in case an initially decommitted unit starts-up.

4.4 Differential Evolution variant used for the optimization of the problem

As stated in Chapter 2, the Feasibility Rules constitute one of the more frequently used constraint handling technique. However, Feasibility Rules is a relatively greedy technique; in order to rapidly steer the population towards the feasible region, the comparison of individuals is mainly based on the total constraints violation, $\phi(\mathbf{x})$, while the information of the objective function is not exploited equally. As a result the method, when applied to complex constrained optimization problems, may encounter difficulties, such as premature convergence to local optimum [38] or infeasible solutions [35]. In this framework, a DE variant for constrained optimization was proposed in [35] called Feasibility Rules with the incorporation of Objective Function Information (FROFI) as an attempt to efficiently balance the exploitation of the information from the objective function and the constraints when the Feasibility Rules technique is used.

In FROFI, the search algorithm coupled with the Feasibility Rules is DE. In particular, two mutation schemes are used on each individual with equal probability to create the mutant vectors. These two mutation schemes are the DE/current-to-rand/1 (Eq. 2.13) and the DE/rand-to-best/1 (2.14). Thereafter the binomial crossover operator (Eq. 2.8) is utilized to create the trial vector, while the selection among the target and the trial vector is carried out based on the Feasibility Rules. FROFI contains some additional modifications to the simple combination of DE and the Feasibility Rules in an attempt to incorporate information of the objective function into the Feasibility Rules. These are based on the following three processes:

- Commonly in constrained optimization problems when the Feasibility Rules and the DE/rand-to-best/1 mutation scheme (2.14) are used, $\mathbf{x_{best}}$ is determined by sorting the population using the Feasibility Rules. Thus, $\mathbf{x_{best}}$ is either the feasible individual with the best objective function value or the individuals with the lowest total constraints violation. However, in FROFI, $\mathbf{x_{best}}$ is the individual with the best objective function value in the current population regardless its total constraints violation. A detailed justification for the aforementioned modification is given in [35].

- FROFI uses an external archive A. In A, trial vectors that cannot survive into the next generation are stored, when their objective function value is better than their corresponding target vector's one. After the selection process, the individuals in A may replace some members of the population, based on a replacement mechanism. During the replacement mechanism, the individuals of the population are sorted based on their objective function value, and the sorted population is divided into MRN parts of equal size. The individual with the maximum total constraints violation, i.e. $\mathbf{x_a}$, in the first part and the individual with the minimum total constraints violation in A, $\mathbf{x_b}$, are selected. If $f(\mathbf{x_b}) < f(x_a)$, then $\mathbf{x_b}$ replaces $\mathbf{x_a}$ in the current population and is deleted from A. The same procedure is carried out for the second part of the sorted population and the individual with the minimum total constraints violation in A. The replacement mechanism is terminated when either all the MRN parts have been updated or A has become an empty set. It should be noted that the replacement mechanism increases the diversity of the infeasible population, and efficiently searches the optimal solution from both the feasible and infeasible areas when the population contains feasible solutions.

- A mutation strategy is applied to avoid the entrapment of the population into local optimums in infeasible regions. Specifically, the individual with the highest total constraints violation ($\mathbf{x_1}$) is replaced by a mutant ($\mathbf{x_2}$), created from a randomly selected individual of the population, if $f(\mathbf{x_2}) < f(x_1)$. It should be highlighted, that this mutation is applied when the population comprises only infeasible individuals.

4.5 Proposed approach

The flowchart describing the overall procedure is depicted in Fig. 4.2, while a detailed description of the main components of the proposed approach is given in the following subsections. As observed in Fig. 4.2, during the first generation ($g = 1$), the population members are initialized within the corresponding bounds. Then, the initial solution vectors undergo the heuristic repair strategies. Thereafter, the objective function value and the total constraints violation of each individual are calculated. Subsequently, the algorithm proceeds as follows:

1. The trial vectors are created based on the operators of DE.

2. The on/off schedule corresponding to each trial vector is determined. Next, each newly generated trial vector undergoes the heuristic repair strategies. The objective function value, and the total constraints violation, of the repaired trial vectors are calculated.

3. The target vectors of the next generation, $g+1$, are selected, based on FR. The trial vectors which are not selected but have better objective function value than the corresponding target vectors are stored in the external archive A.

4. The Replacement Mechanism of FROFI follows, during which some target vectors of the population may be replaced by the individuals in A.

5. The mutation strategy of FROFI is applied if the population comprises only infeasible individuals. On the contrary, if at least one feasible solution vector exists in the population, then the Elitist Mutation strategy (described in section 4.5.3) is applied. It is highlighted that the individuals generated by the above two procedures always undergo the heuristic repair strategies.

6. Then, the termination criterion is checked. In case it is not satisfied the procedure is repeated from step 1.

4.5.1 Representation of solution vectors and determination of the generating schedules

Each target vector, $\mathbf{x_n^g}$, comprises $NTG \cdot T$ real valued variables, $x_{n,i}^{g,t} \in [0, Pmax_i]$, which represent the potential power generated by unit i at hour t. During initialization, each individual is randomly created within the corresponding bounds of each variable using the uniform distribution. Then, the population evolves for a specific number of generations by applying the evolution mechanisms of FROFI.

The vector of binary variables, $\mathbf{ST_n^g}$, defining the operating state (on/off) of each generator at each time period for the corresponding $\mathbf{x_n^g}$, is determined by applying the following two step

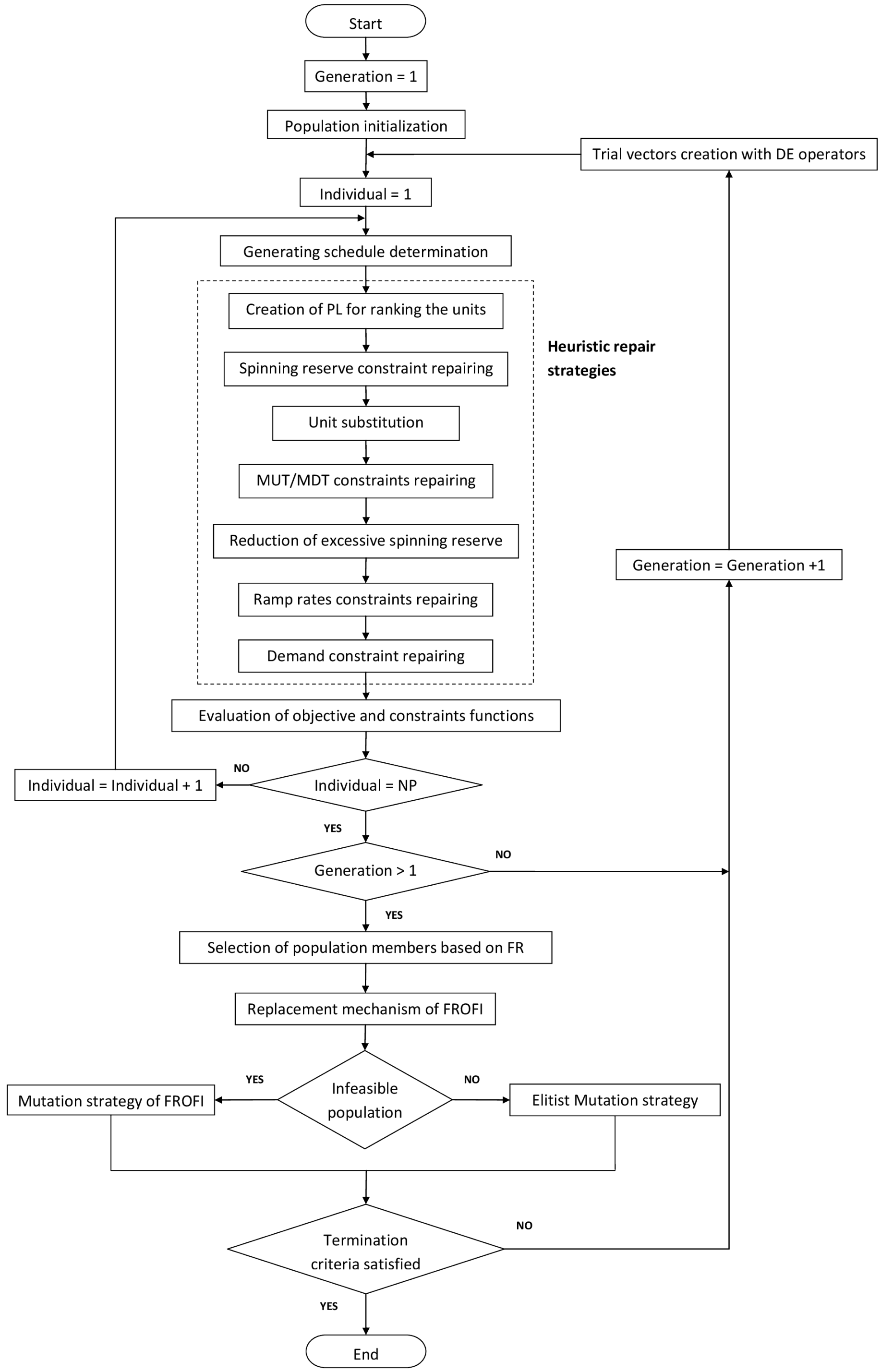


Figure 4.2: The overall procedure of the proposed method

function:

$$ST^{g,t}_{n,i} = \begin{cases} 0, \; if \; x^{g,t}_{n,i} < Pmin_i \\ 1, \; otherwise \end{cases} \tag{4.14}$$

In Eq. 4.14, when $x^{g,t}_{n,i}$ is below the permissible lower limit $Pmin_i$, then unit i is considered 'off-line', thus $ST^{g,t}_{n,i} = 0$. Otherwise, $ST^{g,t}_{n,i} = 1$ and the unit provides energy to the grid. The generating schedule contains the energy generated by the committed units ($x^{g,t}_{n,i}$) to serve the expected demand. It is determined with element by element multiplication of $\mathbf{x^g_n}$ with the corresponding $\mathbf{ST^g_n}$, i.e. Hadamard product. By using the real encoding scheme and the proposed transformation function both sub-problems of a STGS problem can be handled by a single EA, avoiding the use of distinct algorithms for the ED which may lead to a reduction of the algorithm's execution time. Moreover, the transformation function enables real coded EAs to be directly applied for the optimization of the mixed integer STGS without modifications on their basic search mechanisms.

4.5.2 Handling of constraints

A series of heuristic repair mechanisms are utilized in the proposed approach. They are applied to each individual during each generation of the optimization procedure. They modify solution vectors to satisfy the problem constraints and obtain generating schedules with lower operation cost. In case an individual does not satisfy the problem's constraints after undergoing the repair mechanisms, the remaining total constraints violation is handled by the constraint handling mechanisms of FROFI. In the following subsections, the steps of the repair procedure are described in detail.

Creation of Plurality of Priority Lists for ranking the generating units

The fuel cost of a thermal unit is considered as a second order polynomial function of its power output. Hence, the marginal or the average production cost of each unit is also a function of its power output. In the relative literature, when the PL has been used, the units have been ranked according to their Average Cost (AVC) at a certain production point. The maximum or the middle point of the operating range $[Pmin_i, Pmax_i]$ are often used, based on the assumption that they are close to the actual operating points of the units. Nevertheless, any point between the units' maximum ($Pmax_i$) and minimum production ($Pmin_i$) can be used. Depending on the chosen cost metric a different stacking order can be obtained [138]. This may be further explained in Figs. 4.3 and 4.4, where the average cost curves of units 4, 5 and 6 from Table A.1 (Appendix A.1) are depicted. In the former, x-axis contains the power output of the units in MW, while in the latter AVC is plotted versus the percentage of the units' loading in their operating range. As observed, when AVC at the maximum working point (marked with an asterisk in both figures) is opted by the user for ranking the units, unit 4 will have a higher priority followed by unit 5 and unit 6, since it is the most economical. The ranking order changes if the middle point of production (marked with a circle) is chosen, i.e. unit 5 will be preferred over unit 4. In case the minimum point of production (marked with a cross) is selected the order of priority will be as follows: unit 5, unit 6 and unit 4. Therefore, the choice of a constant cost metric to create the PL favours specific generating schedules. To mitigate the possible bias and increase the diversity of the examined schedules, the use of a Plurality of Priority Lists (PPL) is proposed. In particular, for every individual of the population at each generation a different PL is created based on the AVC of the units at a random operating point:

$$AVC_{n,i}^{g} = \frac{a_i + b_i \cdot Pop_{n,i}^{g} + c_i \cdot (Pop_{n,i}^{g})^2}{Pop_{n,i}^{g}} \tag{4.15}$$

where

$$Pop_{n,i}^{g} = Pmin_i + UL_n^g \cdot (Pmax_i - Pmin_i) \tag{4.16}$$

Each Priority List, PL_n^g, is created by sorting the units in ascending order of their $AVC_{n,i}^{g}$ calculated at $Pop_{n,i}^{g}$. Thus, the unit at the top of the list is the one with the highest priority since it is

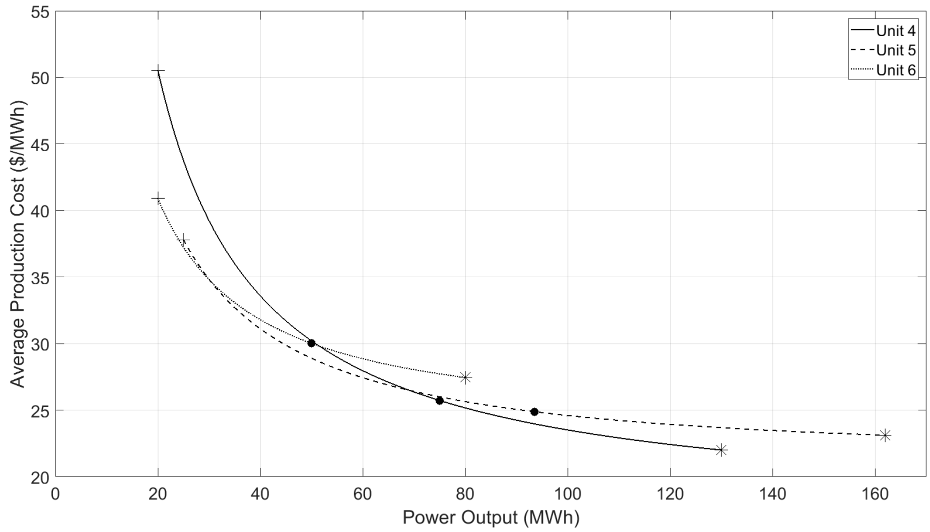


Figure 4.3: Average production cost of thermal units with respect to their power output

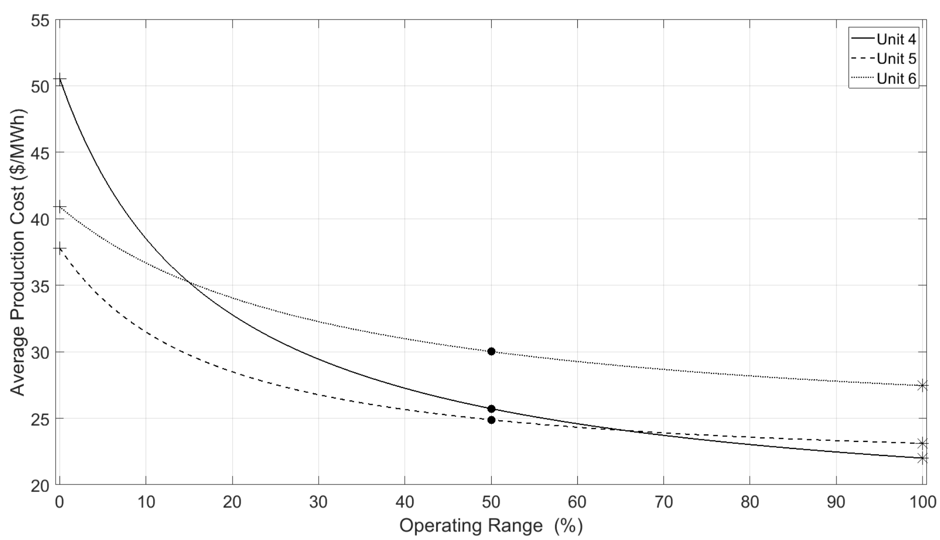


Figure 4.4: Average production cost of thermal units with respect to the loading of the units within their operating range

the most economical at the working point considered. In Eq. 4.16, UL_n^g defines the operating point $Pop_{n,i}^g$, which is used to calculate the AVC of each unit. UL_n^g is a random number drawn from the uniform distribution in [0,1], generated anew for each population member in each generation. By setting stochastically the value of UL_n^g, a different PL_n^g may be assigned to each individual and used during the heuristic repair mechanisms. Consequently, given a different stacking order, different generation schedules can be attained, as in each stage of the mechanism the units prioritized for each individual will be depended on the assigned PL_n^g. Therefore, PPL may affect the repairing process during each part of the heuristic procedure. By adopting the PPL the need of relying on assumptions regarding the expected operating point of the units is mitigated. It is noteworthy, that the amount of different stacking orders depends on the number of intersection points of the AVC curves as a function of the units loading (Fig. 4.4). In particular, the amount of different PL is greater by one compared to the distinct intersection points of the curves in Fig. 4.4. However, when large systems are considered, identifying each different PL might be challenging. Hence, an unbiased PPL is adopted, where the probability of a unit having a higher rank than its preceding in PL_n^g depends on the length of the interval defined by the intersection points of their AVC curves (Fig. 4.4).

Repairing violation of the spinning reserve constraints

Each individual is checked for spinning reserve constraints violations. For each hour of the scheduling period the excess in the spinning reserve is calculated as follows:

$$ESR_n^{g,t} = \sum_{i=1}^{NTG} ST_{n,i}^{g,t} \cdot Pmax_i - P_d^t - SRR^t,\ t \in [1, T] \tag{4.17}$$

In case the spinning reserve is not sufficient ($ESR_n^{g,t} < 0$) the mechanism described in Algorithm 6 is applied to repair the solution vector. Uncommitted units are turned on, beginning from the one with the higher priority, until the spinning reserve constraint is satisfied. Diverse generation schedules might be produced since a different PL may be defined for each population member. To change the status of unit i from 'off' to 'on' ($ST^{g,t}_{n,i} = 0 \longrightarrow ST^{g,t}_{n,i} = 1$), $x^{g,t}_{n,i}$ is set equal to the minimum generation limit ($Pmin_i$) of the unit. It should be clarified that in Algorithm 6, $PL^g_n(pos)$ denotes the unit ranked in the pos place of the PL assigned to the n-th individual at generation g.

Algorithm 6 Repair spinning reserve constraint violations

$pos \leftarrow 1$
while $\sum_{i=1}^{NTG} ST^t_i \cdot Pmax_i - P^t_d - SRR^t < 0$ **do**
  if $ST^t_{PL^g_n(pos)} = 0$ **then**
    $P^t_{PL^g_n(pos)} \leftarrow Pmin^t_{PL^g_n(pos)}$
    $ST^t_{PL^g_n(pos)} \leftarrow 1$
  end if
  $pos \leftarrow pos + 1$
end while

Unit Substitution

Generally, the generating units can be classified into three categories:

1. The base load units, which have low operational cost, high start-up cost and should remain in an operating state (on or off) for a long time-span.

2. The intermediate units, which have medium operational and start-up costs and medium requirements of on/off state durations.

3. The peak load (or marginal) units, which have a high operational cost, low start-up cost and minimum up/down time requirements.

In contrast to the base load and intermediate units, the state of the marginal ones can change more frequently. This property could be used to reduce the operation cost during hours of high demand. In particular, if intermediate units are committed in peak load hours, they cannot be directly turned off when demand declines the following hours, owing to their minimum up time requirement. As a result, excessive spinning reserve may occur during the hours following the peak load, causing an increase in production cost. To avoid this situation, the intermediate units can be replaced by marginal ones, which can be immediately turned off, after peak load hours.

The substitution mechanism utilized in Dieu and Ongsakul [206] was adopted. After repairing the spinning reserve violations, there may be some intermediate units committed for only one hour during the peak load, although their MUT is longer. In this case, the intermediate units should be replaced by marginal ones, which can be immediately turned off in the following hours. When the state of the ith unit at hour t is changed from 'on' to 'off', its corresponding variable, $x_{n,i}^{g,t}$, is randomly reinitialized in the interval $(0, Pmin_i)$ using the uniform distribution. In contrast to the case, where a unit is brought on-line by the heuristic, the corresponding $x_{n,i}^{g,t}$ of a decommitted unit may not be further modified in the following parts of the heuristic. Thus, $x_{n,i}^{g,t}$, is not set to a predefined value, e.g. $x_{n,i}^{g,t} = 0$ or $x_{n,i}^{g,t} = Pmin_i/2$, since that may cause a declination in the population's diversity, as the mutation schemes of DE rely on difference vectors. When a marginal unit is turned on, the parameter vector is modified as described in the previous subsection. The unit substitution procedure is described in the Algorithm 7.

Repairing minimum up and down time constraints

When the minimum up/down time constraints of a unit are violated, the corresponding generating schedule is modified according to the repair mechanism employed from Yuan et al. [176]. The repair procedure is presented in Algorithm 8. In particular, when the up time of a unit is not sufficient the unit is committed for the following hours until the required 'on-line' duration is reached. On the other hand, when unit i remains idle for less than MDT_i hours, then it is brought 'on-line' at these hours. In both cases, when the status of the unit is changed from 'off' to 'on' the corresponding variable, $x_{n,i}^{g,t}$, is set equal to the unit's minimum power output.

Algorithm 7 Unit Substitution

```
t ← 1
while t < T do
    Create a list with committed Intermediate Units (IUL) at hour t, which are off-line the previous
    and the following hour
    Create a list with decommitted Marginal Units (MUL) at hour t
    if (IUL ≠ {}) or (MUL ≠ {}) then
        while IUL ≠ {} do
            Select unit SIU, which is the unit with the lowest priority order in IUL, based on PL_n^g
            if (Total Capacity of Units in MUL is sufficient to cover spinning reserve shortage when
            SIU is decommitted) then
                ESR_n^{g,t} ← ESR_n^{g,t} − Gmax_{SIU}
                Delete SIU from IUL
            end if
        end while
        while ESR_n^{g,t} < 0 do
            Select unit SMU, i.e. the unit with the highest priority order in MUL, based on PL_n^g
            Commit unit SMU
            ESR_n^{g,t} ← ESR_n^{g,t} + Gmax_{SMU}
            Delete SMU for MUL
        end while
    end if
    t ← t + 1
end while
```

Algorithm 8 Minimum up/down time repairing

$t \leftarrow 1$
while $t \leq T$ **do**
  $i \leftarrow 1$
  while $i \leq NTG$ **do**
    if ($ST_i^t = 0$) **and** ($ST_i^{t-1} = 1$) **then**
      if ($Ton_i^{t-1} < MUT_i$) **then**
        $ST_i^t \leftarrow 1$
      else if ($t + MDT_i - 1 \leq T$) **and** ($Toff_i^{t+MDT_i-1} < MDT_i$) **then**
        $ST_i^t \leftarrow 1$
      else if ($t + MDT_i - 1 > T$) **and** ($\sum_{k=t}^{T} ST_i^k > 0$) **then**
        $ST_i^t \leftarrow 1$
      end if
    end if
    $i \leftarrow i + 1$
  end while
  $t \leftarrow t + 1$
end while

Reduction of Excessive Spinning Reserve

After the implementation of the previous heuristic repair mechanisms each solution vector satisfies the spinning reserve and the MUT/MDT constraints. However, excessive spinning reserve may occur owing to the commitment of a number of redundant units at each hour. Excessive spinning reserves may trigger increased total production costs, since more units may operate at suboptimal levels. Hence, each parameter vector is modified by decreasing the number of committed units at each hour to efficiently satisfy the spinning reserve constraints. The procedure described in Algorithm 9 is adopted from [150]. In particular, when excessive spinning reserve occurs, committed units having lower priority order in the PL_n^g are shut down, when the change in their operating status does not cause violation of the MUT and MDT constraints. According to the PL_n^g different units may be prioritized to be decommitted, increasing the diversity of the derived schedules. This procedure is repeated until no further units can be decommitted without causing a violation to the spinning reserve constraints.

Algorithm 9 Reduction of excessive reserve capacity

```
for $t = 1 : T$ do
  for $pos = NTG : -1 : 1$ do
    if $ST^t_{PL^g_n(pos)} = 1$ then
      $ST^t_{PL^g_n(pos)} \leftarrow 0$
      if (The MUT/MDT constraints are violated) then
        $ST^t_{PL^g_n(pos)} \leftarrow 1$
      else if ($\sum_{i=1}^{NTG} ST^t_i \cdot Pmax_i - P^t_d < SRR^t$) then
        $ST^t_{PL^g_n(pos)} \leftarrow 1$
      end if
    end if
  end for
end for
```

Ramp rates constraints repairing

The ramp rates impose restrictions on the drastic change in the power output of a unit in successive hours. The ramp up/down ability of a unit limits its operating range at every time instant taking into account the unit's power output at the previous scheduling periods. In this repair heuristic, when the ramp rate constraints are violated, the units' power output is set on the bound of the restricted operating range, as described in Algorithm 10.

Power balance constraints repairing

The total power provided by the committed units may deviate from the load demand. A heuristic mechanism is developed to adjust the individuals to satisfy the power balance constraints. It takes into account the PL^g_n. The procedure is shown in Algorithm 11. Initially, the difference between the generated energy and the load demand is calculated at each hour:

$$PBV^{g,t}_n = \sum_{i=1}^{NTG} ST^{g,t}_{n,i} \cdot P^{g,t}_{n,i} - P^t_d \tag{4.18}$$

If at hour t, the total generated energy exceeds the hourly load ($PBV^{g,t}_n > 0$), then beginning from the unit with the lowest ranking in the PL^g_n, the power output of the committed units is

Algorithm 10 Ramp Rates constraint repairing

$i \leftarrow 1$
$t \leftarrow 1$
while $i \leq NTG$ **do**
  while $t \leq T$ **do**
    if $(ST_i^t = 1)$ and $(ST_i^{t-1} = 1)$ **then**
      if $P_i^t - P_i^{t-1} > RU_i$ **then**
        $P_i^t \leftarrow P_i^{t-1} + RU_i$
      end if
      if $P_i^t - P_i^{t-1} < -RD_i$ **then**
        $P_i^t \leftarrow P_i^{t-1} - RD_i$
      end if
    end if
    $t \leftarrow t + 1$
  end while
  $i \leftarrow i + 1$
end while

decreased by a quantity GD, which is calculated as follows:

$$GD = min(rand \cdot (P^t_{PL^g_n(pos)} - RPmin^t_{PL^g_n(pos)}), PBV^{g,t}_n) \tag{4.19}$$

where the index $PL^g_n(pos)$ denotes the unit at the pos place of PL^g_n. Moreover, $rand$ is a value sampled from the uniform distribution in $[0, 1]$ and generated anew for each unit examined during this process. Here, GD is set stochastically, based on the uniform distribution, to increase the diversity of the examined schedules. If the total generated energy remains excessive after examining all the committed units, the procedure iterates from the unit at the bottom of PL^g_n, until the energy excess becomes 0. On the other hand, if insufficient total power ($PBV^{g,t}_n < 0$) is the case, the on-line units are considered in descending priority order, and the power output of each unit is increased by GU, which is calculated as follows:

$$GU = min(rand \cdot (RPmax^t_{PL^g_n(pos)} - P^t_{PL^g_n(pos)}), |PBV^{g,t}_n|) \tag{4.20}$$

The procedure is repeated until the total generated power equals the load demand. In the Algorithm, $RPmax_i^t$ and $RPmin_i^t$ are the restricted maximum and minimum generation limit of unit i at hour t, due to the unit's ramping capabilities, calculated as follows:

$$RPmax_i^t = min(P_i^{t-1} + UR_i,\ Pmax_i) \tag{4.21}$$

$$RPmin_i^t = max(P_i^{t-1} - DR_i,\ Pmin_i) \tag{4.22}$$

Note that, the ramping capabilities of the units may not allow the satisfaction of the power balance constraints. In particular, if $P_d^t > \sum_{i=1}^{NTG} ST_i^t \cdot RPmax_i^t$, then $RPmax_i^t$ is set equal to $Pmax_i$. On the other hand, if $P_d^t < \sum_{i=1}^{NTG} ST_i^t \cdot RPmin_i^t$, then $RPmin_i^t$ is set equal to $Pmin_i$. Thus, the satisfaction of demand constraints is prioritized, since the inter-temporal coupling introduced by the ramp rates may be considered relatively weak (Han et al. [207]). Therefore, any remaining constraints violation, after the application of the heuristic repair strategies, is limited to the ramp rates constraints.

4.5.3 Elitist Mutation Strategy

In general, during the optimization process three stages will be inevitably encountered [208]: I) the population contains infeasible individuals only, II) the population comprises both feasible and infeasible individuals and III) the population is entirely composed by feasible solution vectors. FROFI includes a mutation strategy, which is utilized to prevent the entrapment of the population in infeasible regions. It is applied only when all individuals in the population are infeasible (stage I). Nevertheless, in the proposed approach feasible solution vectors could be attained even during the early stages of the optimization procedure owing to the heuristic repairing mechanisms. In this context, an Elitist Mutation (EM) strategy is proposed. It utilizes the information from the elite member of the population, based on the objective function value, during the stages where the

Algorithm 11 Repairing power balance constraints

```
for t = 1 : T do
   PBV^t = \sum_{i=1}^{NTG} ST_i^t · P_i^t − P_d^t
   if PBV^t < 0 then
      pos ← 1
      while PBV^t < 0 do
         if ST^t_{PL^g_n(pos)} = 1 then
            P^t_{PL^g_n(pos)} = P^t_{PL^g_n(pos)} + GU
            PBV^t = \sum_{i=1}^{NTG} ST_t^i · P_i^t − P_d^t
         end if
         pos ← pos + 1
         if pos > NTG then
            pos ← 1
         end if
      end while
   else if PBV^t > 0 then
      pos ← NTG
      while PBV^t > 0 do
         if ST^t_{PL^g_n(pos)} = 1 then
            P^t_{PL^g_n(pos)} = P^t_{PL^g_n(pos)} − GD
            PBV^t = \sum_{i=1}^{NTG} ST_i^t · P_i^t − P_d^t
         end if
         pos ← pos − 1
         if pos < 1 then
            pos ← NTG
         end if
      end while
   end if
end for
```

population includes feasible individuals (stages II, III). The procedure of EM is the following:

1. The individual with the best objective function value in the population at generation g ($\mathbf{x}_{best}^{g}$) is selected, irrespective of its total constraint violation.

2. With equal probability either a single or two dimensions of $\mathbf{x}_{best}^{g}$ are selected randomly and reinitialized within the corresponding bounds using the uniform distribution, creating a mutant vector ($\mathbf{x}_m$). In Fig. 4.5, an example for a system with $NTG = 5$ and $T = 5$ is presented, to illustrate how $\mathbf{x}_{best}^{g}$ is modified to create $\mathbf{x}_m$. In the example, two dimensions of $\mathbf{x}_{best}^{g}$, i.e. x_2^2 and x_4^4 have been selected at random. These dimensions are reinitialized within the corresponding bounds to create $\mathbf{x}_m$. After reinitialization, the corresponding values of the selected parameters in the mutant vector are $\hat{x}_2^2$ and $\hat{x}_4^4$. As shown in Fig. 4.5, the reinitialization of x_2^2 has triggered a change in the on/off schedule of the mutant ($\mathbf{ST}_m$) compared to $\mathbf{ST}_{best}^{g}$, since $ST_2^2 = 0$ while $\hat{ST}_2^2 = 1$. On the contrary, this is not the case for x_4^4, whose reinitialization does not lead to a change in the state of the corresponding unit ($ST_4^4 = \hat{ST}_4^4 = 0$). Subsequently, $\mathbf{x}_m$ undergoes the heuristic repair procedure described in Subsection 4.5.2. It should be noted, that the mutant vector may differ significantly from $\mathbf{x}_{best}^{g}$ as the perturbation could cause a series of alterations forced by the repair heuristic.

3. If $f(\mathbf{x}_m) < f(\mathbf{x}_w^g)$, where $\mathbf{x}_w^g$ is the individual with the worst objective function value in the current generation, then $\mathbf{x}_m$ replaces $\mathbf{x}_w^g$ in the current population. Thus, in some cases feasible individuals may be replaced by infeasible ones within promising regions.

During the early stages of the evolution, the population may benefit by exploiting information of the elite member and thus, be steered faster towards promising regions of the search space. As the population converges, it may be gathered around feasible regions of local minimum [209]. Thus, by randomly perturbing $\mathbf{x}_{best}^{g}$, the population may jump out of basins of attraction with locally minimum values.

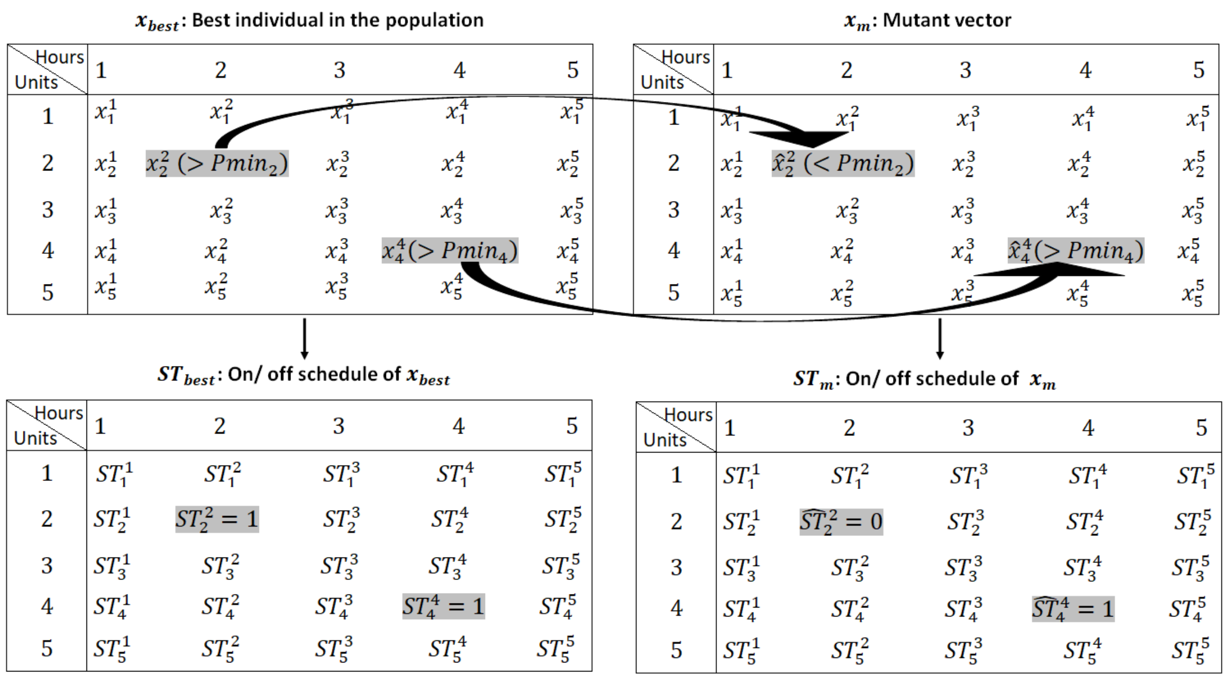


Figure 4.5: Example of the operation of Elitist Mutation Strategy

4.6 Results of the computational experiments and discussion

In this section, the performance of the proposed algorithm is evaluated. The simulation results comprise three parts. In the first part, the impact of adopting the PPL on the algorithm's performance is examined. In the second part, the effectiveness of the proposed EM strategy is demonstrated. In the final part, the proposed approach is benchmarked against other algorithms applied for the optimization of the STGS in four test cases: the 10-100 units system with and without the inclusion of the ramp rate constraints [163], the IEEE RTS system [210] comprising of 26 units and the practical Taiwan Power System of 38 units [211]. The scheduling horizon for each test system is equal to 24 hours. These systems are the most frequently examined, when the performance of an optimization algorithm for the STGS problem is evaluated.

For each of the above cases the proposed approach, i.e. the modified FROFI with Plurality of Priority Lists (mFROFI-PPL), has been applied for 30 independent runs to obtain statistical data of the algorithm's performance. The maximum number of Function Evaluations (MaxFES) has been selected as the termination criteria for each test system, as summarized in Table 4.1. The population's size is set equal to 60 for all the examined cases. In the replacement mechanism of FROFI, MRN is set equal to 15. Moreover, the EA utilizes a pool for the scaling factor and the crossover parameters i.e. $F_{pool} = [0.6, 0.8, 1.0]$ and $CR_{pool} = [0.1, 0.2, 1.0]$, in order to benefit from a range of diverse parameter values. For each individual of the population a random pair of parameter values is chosen from F_{pool} and CR_{pool} at each generation and used during the mutation and crossover operators. The mFROFI-PPL algorithm has been developed on an Intel i7 with 3.07 GHz and 8 GB RAM using Matlab.

	10-100 units system without ramp rates						**IEEE RTS**
Num. of Units	**10**	**20**	**40**	**60**	**80**	**100**	**26**
MaxFES	100000	100000	150000	150000	200000	200000	50000
	10-100 units system with ramp rates						**Tai Power System**
Num. of Units	**10**	**20**	**40**	**60**	**80**	**100**	**38**
MaxFES	150000	150000	200000	200000	250000	250000	20000

Table 4.1: Maximum number of function evaluations (MaxFES) for each test system.

4.6.1 Validating the effect of Plurality of Priority Lists

As analysed in Section 4.5.2, the approaches based on stochastic algorithms usually incorporate domain specific knowledge in the form of PL. The units are ranked based on their AVC_i at a certain working point and this ranking is used during the entire optimization procedure. Usually the working point used is either $Pmax$ ($UL_n^g = 1$) or $Pmean$ ($UL_n^g = 0.5$). To the author's knowledge, it is the first time that a variety of Priority Lists is created based on several operating points. The impact of this approach is examined. The computational experiments have been carried out on the 10-100 units test system [163]. The systems of larger size are obtained by duplicating the characteristics of the basic 10 units system and the daily load demand (the data for the 10 units system are given in Appendix A.1) 2, 4, 6, 8 and 10 times, respectively. The spinning reserve is equal to 10% of the load demand. For each test instance, mFROFI has been applied utilizing three different PL schemes for the heuristic repair algorithm, i.e. PL calculated at $Pmax_i$, PL calculated at $Pmean_i$ and PPL. The distribution of the solutions achieved by the algorithm for each case are depicted in Fig. 4.6. It is evident that the cost metric chosen for the creation of the PL has a significant impact both on the best cost achieved by the algorithm and on the dispersion of the solutions. mFROFI with PPL has obtained solutions with lower total cost for the systems of 40, 60, 80 and 100 units compared to the cases utilizing PL at $Pmax$ or $Pmean$. For the system of 10 units the best solution has been obtained both by mFROFI with PL at $Pmax$ and PPL, while for the system of 20 units the best solution is derived by mFROFI with PL at $Pmax$. Furthermore, the use of PPL has affected the dispersion of the obtained solutions, since mFROFI-PPL derives solutions of lower cost more robustly in all the examined cases, with the exception of the system of 10 units, where mFROFI with PL at $Pmax$ has demonstrated the lower solution dispersion. Thus, overall the use of PPL enhances the algorithm's performance.

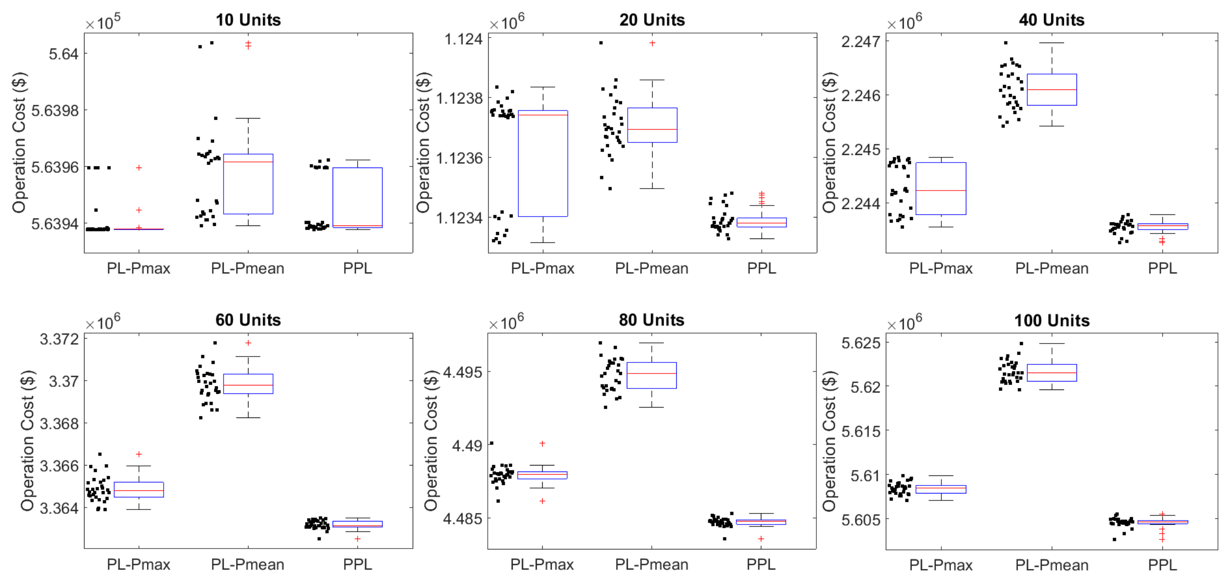


Figure 4.6: Distribution of the solutions obtained by mFROFI for the three different PL schemes in the 10-100 units test system

4.6.2 Validating the effect of Elitist Mutation Strategy

In this section, the effect of the proposed Elitist Mutation (EM) strategy is examined. A series of computational experiments is conducted, where FROFI-PPL without the use of EM is applied on the test systems of 10-100 units, and its results are compared to those of mFROFI-PPL with EM engaged. The results of both approaches are depicted in Fig. 4.7. As observed, mFROFI-PPL has determined solutions with lower cost in all the cases, regardless the size of the system. The dispersion of the solutions is higher for mFROFI-PPL for the systems of larger size, i.e. 40, 60, 80 and 100 units. However, for these systems when EM is used, even the worst solution of mFROFI-PPL is better than the best obtained by FROFI-PPL, which has prematurely converged in all cases. The impact of EM can also be observed when the average convergence curves are examined in Fig. 4.8. The convergence curves of mFROFI are below those of FROFI without EM in all cases examined, indicating that exploiting the information of the best individuals in EM may steer the population towards better regions of the search space even from the initial stages of the optimization. Therefore, the proposed EM has improved the performance of FROFI both in terms of convergence speed and results attained, regarding the STGS.

4.6.3 Comparison with other algorithms

In this section, mFROFI-PPL is benchmarked against state of the art approaches for the optimization of the STGS in several test systems. The comparison is based on the best, average and worst cost yielded by mFROFI and the benchmark algorithms. This kind of comparison has been extensively employed in the STGS literature. Note that the results of the competing algorithms have been obtained from the corresponding research papers.

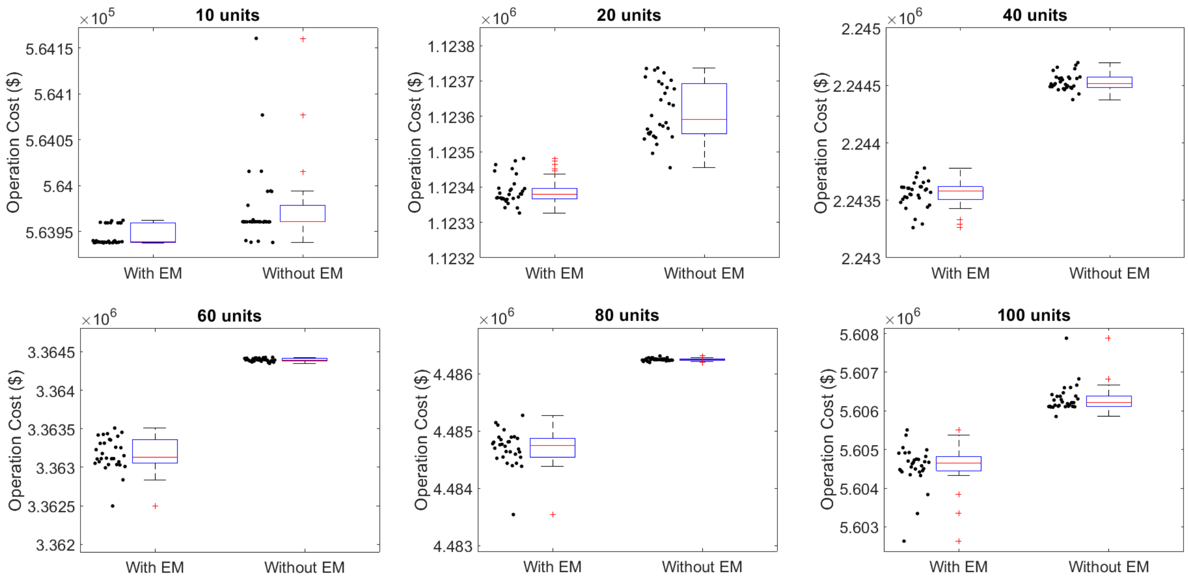


Figure 4.7: Solutions' distribution of FROFI-PPL with and without the use of EM for the 10-100 units test system

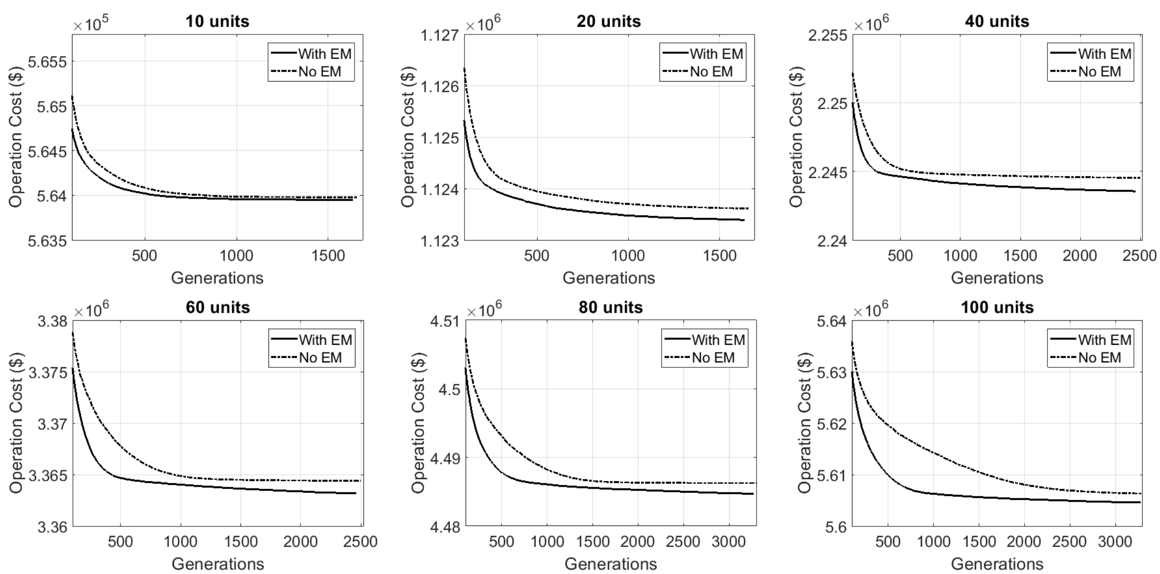


Figure 4.8: Average convergence over 30 runs of FROFI-PPL with and without the utilization of EM for the 10-100 units test system

10-100 units systems without ramp rates constraints

The data for the 10 units system have been retrieved form [163]. The systems of higher order, i.e. 20, 40, 60 ,80 and 100 units are created by correspondingly duplicating the data and the load demand of the basic 10 units system. The spinning reserve is equal to 10% of the load demand. In this case the ramp rate constraints are not examined and shut-down costs are neglected. The mFROFI-PPL algorithm is compared with the previous DE-based approaces (Binary Coded DE (BCDE) [174], Integer Coded DE (ICDE) [174], Enhanced Discrete DE (EDDE) [176], Binary DE (BDE) [175], DE [177], Binary-Real Coded DE (BRCDE) [195], Enhanced hybrid GA-DE (Enh-hGADE) [196] and two hybrid GA-DE schemes, i.e. hGADE/r1 and hGADE/cur1 [197]). Moreover, it is benchmarked against state-of-the-art **deterministic algorithms** (Enhanced LR (ELR) [150], Stochastic PL (SPL) [135], LR [151], Improved Preprepared Demand Table and Muller Method (IPPDTM) [212], SDP method [161], Outer Approximation (OA), Tighter Outer Approximation (TOA) and Outer Inner Approximation (OIA) [162], Cut and Bound (C&B) and CUT& CPLEX [213]), **stochastic approaches** (GA [163], Enhanced SA (ESA) [179], QBPSO [182], Improved QEA (IQEA-UC) [181], ICA [184], Binary Neighbourhood Field Optimization (BNFO) [185], Binary Gravitational Search Algorithm (BGSA) [186], Modified Binary Artificial Bee Colony (MBABC-GC) [187], Binary GWO (BGWO) [188], Quantum Inspired BGWO (QI-BGWO) [183] and Binary Moth Flame Algorithm (BMMFOA) [189]) and **hybrid methods** (Hybrid binary - real coded GA (HGA) [194], hybrid Enhanced LR and PSO (ELRPSO) [191]). Furthermore, a Quadratic Programming (QP) solver is applied to fine tune the final solutions provided by mFROFI-PPL. It should be highlighted that the QP solver does not modify the on/off unit schedule derived by mFROFI-PPL. It is applied only for fine-tuning the allocation of the load demand among the committed units at each hour. Since the ramp rates are not considered in this case, the ED can be implemented separately for each hour and thus the computational time needed by the QP method is low. The overall results and the execution time of each method are shown in

Tables 4.2, 4.3 and 4.4. For each system, the lowest cost in each category is presented in boldface.

In general, mFROFI-PPL and mFROFI-PPL + QP have performed better than the previously proposed DE approaches. Compared to the previous DE based algorithms mFROFI-PPL and mFROFI-PPL + QP have yielded the best cost in the systems of 10, 20, 60, 80 and 100 units. For the system of 40 units BCDE and ICDE have obtained the best cost. However, the execution time of BCDE and ICDE is considerably longer compared to the one of mFROFI-PPL; it is noted that the algorithms have been developed on platforms with different hardware and software configurations, thus a direct comparison of their computational time would not be fair [197]. Nevertheless, it may provide a rough indication of the computational burden of each algorithm as the scale of the problem increases [162]. Moreover, mFROFI and mFROFI + QP have exhibited reduced average and worst cost solutions compared to the other DE based methodologies, indicating that the proposed approach has performed robustly.

The quality of the solutions derived by mFROFI-PPL can be also assessed through a comparison with other solution methodologies. In Tables 4.2, 4.3 and 4.4, it can be observed that the proposed approach has a very competitive performance. For the system of 10 units mFROFI-PPL achieves the minimum best, average and worst cost. For the system of 20 units, it comes first in terms of the average and worst cost compared to the stochastic and hybrid approaches. The same holds for the system of 40 units. For the system of 60 units mFROFI-PPL + QP is ranked second regarding the best, average and worst cost solutions obtained. Furthermore, for the system of 80 and 100 units (large scale systems) mFROFI-PPL + QP achieves the lowest average and maximum costs, which indicates the algorithms robust performance on systems of larger size. Furthermore, the best solution obtained by the proposed method in the large scale systems is only marginally larger compared to those of OIA, which is ranked first regarding the best cost. It should be noted, that the vast majority of the examined cases mFROFI-PPL outperforms the other stochastic approaches, e.g. GA, ESA, QBPSO, IQEA-UC, ICA, BNFO, QIBGWO, BGWO, BMMFOA and the hybrid approaches based on the combination of stochastic algorithms, e.g. HGA. Moreover, the results of the proposed method seem to be similar to that of OIA and ELRPSO which have exhibited excellent performance on solving the STGS. For illustration purposes, the best generating schedule attained by mFROFI-PPL + QP and the corresponding fuel (FC) and start-up (STC) costs are presented in Table 4.5.

Regarding the execution time of the methods some interesting facts can be highlighted. Compared to the previous DE based approaches mFROFI-PPL exhibits solutions of lower cost in shorter computational time. Moreover, compared to the remaining stochastic approaches the execution time is very competitive especially when the systems of larger size are considered. However, in general the computation time of an algorithm may be affected by a variety of factors such as the CPU architecture, memory and frequency and the coding implementation or the operating system, thus the methods' execution times may not be directly comparable. The impact of the size of the system on the execution time of mFROFI-PPL is depicted in Fig. 4.9. It can be observed that the execution time increases almost linearly with the size of the system, which signals that the method is adequate for application on real world large scale power systems.

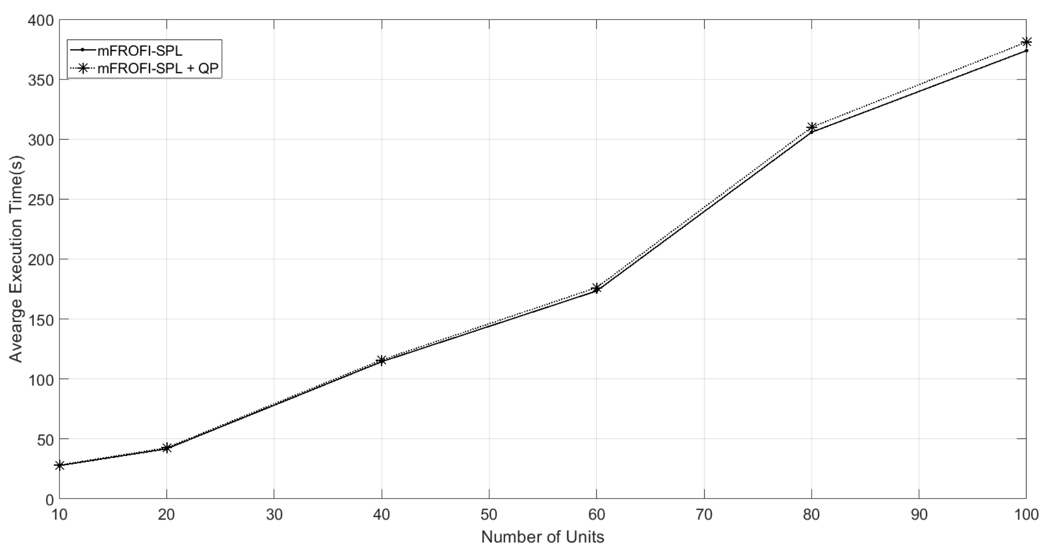


Figure 4.9: Average execution time of the proposed algorithm for the systems of 10 to 100 units

	10 units				20 units			
	Best Cost ($)	**Average Cost ($)**	**Worst Cost ($)**	**Ex. Time (s)**	**Best Cost ($)**	**Average Cost ($)**	**Worst Cost ($)**	**Ex. Time (s)**
DE-based algorithms								
BCDE [174]	563,977	-	-	54.6	1,123,297	-	-	692
ICDE [174]	563,977	-	-	80	1,123,297	-	-	541
EDDE [176]	563,977	564,028	564,241	3.6	1,123,998	1,124,339	1,124,539	71.4
BDE [175]	563,997	563,997	563,997	-	1,123,998	1,124,374	1,124,927	-
DE [177]	565,711	566,070	566,824	-	1,125,735	1,126,121	1,126,651	-
BRCDE [195]	563,938	-	-	27.4	1,124,291	-	-	52.8
Enh-hGADE [196]	**563,938**	563,997	564,261	26	1,123,386	1,124,262	1,124,939	56
hGADE/r1 [197]	**563,938**	564,044	-	24	1,123,383	1,124,436	-	51
hGADE/cur1 [197]	563,959	564,088	-	24	1,123,426	1,124,502	-	48
Other Stochastic algorithms								
GA [163]	565,825	-	570,032	221	1,126,243	-	1,132,059	733
ESA [179]	565,828	565,988	566,260	3.35	1,126,251	1,127,955	1,129,112	16.8
QBPSO[182]	563,977	563,977	563,977	18	1,123,297	1,123,981	1,124,294	50
IQEA-UC [181]	563,938	563,938	563.938	34	1,123,297	1,123,436	1,123,832	98
ICA [184]	563,938	-	-	48	1,124,274	-	-	63
BNFO [185]	563,938	563,938	563,938	4	1,123,297	1,123,431	1,123,563	29
BGSA[186]	**563,937**	564,031	564,241	-	1,123,996	1,124,738	1,125,156	-
MBABC -GC [187]	563,938	563,958	563,977	14.76	1,123,297	1,123,698	1,124,556	36.96
QI-BGWO [183]	**563,937**	**563,937**	**563,937**	62.3	1,123,297	1,123,459	1,123,526	112.12
BGWO [188]	**563,937**	**563,937**	**563,937**	66.15	1,123,294	1,124,215	1,124,379	87.53
BMMFOA [189]	**563,937**	563,950	563,978	35.45	1,124,254	1,124,461	1,124,636	98.78
Deterministic algorithms								
ELR [150]	563,977	-	-	4	1,123,297	-	-	16
SPL [135]	564,950	-	-	7.24	1,123,938	-	-	16.32
LR [151]	563,938	-	-	10	**1,122,637**	-	-	14
IPPDTM [212]	563,977	-	-	0.52	-	-	-	-
SDP [161]	563,938	-	-	25.41	1,124,357	-	-	63.94
OA [162]	563,938	-	-	3.4	1,123,393	-	-	11
TOA [162]	563,938	-	-	3.6	1,123,300	-	-	14
OIA [162]	563,938	-	-	4.5	1,123,297	-	-	17
C&B [213]	563,938	-	-	21	1,123,783	-	-	48.9
CUT&CPLEX [213]	563,938	-	-	1.3	1,123,587	-	-	4
Hybrid algorithms								
HGA [194]	563,938	564,088	564,253	4.31	1,124,290	1,124,678	1,125,103	10.96
ELRPSO [191]	563,938	563,953	563,977	2.46	1,123,297	1,123,502	1,123,637	4.1
mFROFI-PPL	**563,937**	563,945	563,962	27,76	1,123,327	1,123,390	1,123,481	41.76
mFROFI-PPL+QP	**563,937**	**563,937**	**563,937**	28.19	1,123,297	**1,123,297**	**1,123,297**	42.64

Table 4.2: Comparison of the performance of mFROFI-PPL with other algorithms on 10 and 20 units systems

	40 units				60 units			
	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)
DE-based algorithms								
BCDE [174]	**2,242,713**	-	-	1604	3,361,913	-	-	1748
ICDE [174]	**2,242,713**	-	-	811	3,361,913	-	-	1700
EDDE [176]	2,245,631	2,245,877	2,246,457	153.4	3,366,502	3,367,166	3,367,612	257
BDE[175]	2,245,700	2,246,600	2,247,284	-	3,367,066	3,367,405	3,367,783	-
DE[177]	2,249,838	2,255,077	2,251,967	-	-	-	-	-
BRCDE [195]	2,246,274	-	-	161.9	3,365,784	-	-	370.7
Enh-hGADE [196]	2,243,522	2,245,020	2,246,487	147	3,362,908	3,364,538	3,367,820	326
hGADE/r1[197]	2,243,724	2,245,321	-	137	3,363,470	3,365,587	-	227
hGADE/cur1[197]	2,243,522	2,245,020	-	123	3,362,908	3,364,841	-	307
Other stochastic algorithms								
GA[163]	2,251,911	-	2,259,706	2697	3,376,625	-	3,384,252	5840
ESA [179]	2,250,063	2,252,125	2,254,539	88.28	-	-	-	-
QBPSO[182]	2,242,957	2,244,657	2,245,941	158	3,361,980	3,363,763	3,365,707	328
IQEA-UC [181]	2,242,982	2,243,429	2,244,851	146	3,362,507	3,363,458	3,365,270	191
ICA[184]	2,247,078	-	-	151	3,371,722	-	-	366
BNFO[185]	2,242,957	2,243,241	2,244,237	92	3,361,527	3,362,137	3,363,251	193
BGSA[186]	2,246,445	2,247,400	2,247,962	-	3,364,665	3,366,257	3,368,394	-
MBABC -GC [187]	2,243,996	2,244,596	2,245,520	86.52	3,364,076	3,365,357	3,366,928	188.24
QI-BGWO [183]	2,242,947	2,244,071	2,244,279	196.46	3,361,766	3,364,280	3,364,873	355.54
BGWO [188]	2,244,701	2,245,145	2,246,021	153.5	3,362,515	3,366,488	3,367,144	268.2
BMMFOA[189]	2,246,042	2,246,940	2,247,829	118.25	3,365,170	3,366,940	3,367,765	274.45
Deterministic algorithms								
ELR [150]	2,244,237	-	-	52	3,363,491	-	-	113
SPL [135]	2,248,645	-	-	46.32	3,371,178	-	-	113.85
LR [151]	2,243,245	-	-	25	3,363,376	-	-	39
IPPDTM [212]	2,247,162	-	-	6.49	3,366,874	-	-	17.39
SDP [161]	2,243,328	-	-	157.73	3,363,031	-	-	260.76
OA [162]	2,243,386	-	-	17	3,361,814	-	-	21
TOA [162]	2,243,075	-	-	19	3,361,374	-	-	24
OIA [162]	2,242,981	-	-	21	**3,360,820**	-	-	32
C&B [213]	2,243,687	-	-	179.8	3,363,593	-	-	80.2
CUT&CPLEX [213]	2,243,688	-	-	26.7	3,362,951	-	-	39.3
Hybrid algorithms								
HGA [194]	2,246,165	2,246,818	2,247,532	17.45	3,365,431	3,366,178	3,366,995	53.32
ELRPSO [191]	2,243,256	2,243,308	2,243,605	7.19	3,361,573	**3,361,753**	**3,362,157**	9.86
mFROFI-PPL	2,243,262	2,243,555	2,243,781	114.41	3,362,497	3,363,175	3,363,509	173.40
mFROFI-PPL+QP	2,242,957	**2,243,169**	**2,243,256**	115.91	3,361,298	3,361,991	3,362,235	176.23

Table 4.3: Comparison of the performance of mFROFI-PPL with other algorithms on 40 and 60 units systems.

	80 units				100 units			
	Best Cost ($)	**Average Cost ($)**	**Worst Cost ($)**	**Ex. Time (s)**	**Best Cost ($)**	**Average Cost ($)**	**Worst Cost ($)**	**Ex. Time (s)**
DE-based algorithms								
BCDE [174]	4,493,927	-	-	1898	5,615,097	-	-	2020
ICDE [174]	4,493,927	-	-	1821	5,615,097	-	-	2250
EDDE [176]	4,488,225	4,489,253	4,490,252	377.3	5,608,603	5,609,174	5,610,160	485
BDE [175]	4,489,022	4,490,456	4,491,262	-	5,609,341	5,609,984	5,610,608	-
DE [177]	-	-	-	-	-	-	-	-
BRCDE [195]	4,488,450	-	-	568.6	5,607,900	-	-	663.9
Enh-hGADE [196]	4,485,160	4,487,293	4,489,114	404	5,604,787	5,607,487	5,612,131	476
hGADE/r1 [197]	4,486,180	4,489,500	-	368	5,604,787	5,610,074	-	397
hGADE/cur1 [197]	4,485,158	4,487,968	-	343	5,605,075	5,610,336	-	451
Other stochastic algorithms								
GA [163]	4,504,933	-	4,510,129	10036	5,627,437	-	5,637,914	15733
ESA[179]	4,498,076	4,501,156	4,503,987	405.01	5,617,876	5,624,301	5,628,596	696.43
QBPSO [182]	4,482,085	4,485,410	4,487,168	554	5,602,486	5,604,275	5,606,178	833
IQEA-UC [181]	4,484,088	4,485,680	4,488,155	235	5,603,355	5,607,281	5,607,281	293
ICA [184]	4,497,919	-	-	994	5,617,913	-	-	1376
BNFO [185]	4,482,085	4,485,131	4,485,633	331	5,602,433	5,603,120	5,605,678	528
BGSA [186]	4,488,039	4,490,053	4,491,993	-	5,607,838	5,609,585	5,611,188	-
MBABC -GC [187]	4,486,528	4,488,220	4,489,332	323.45	5,605,748	5,607,533	5,609,668	451.78
QI-BGWO [183]	4,481,925	4,486,761	4,487,935	640	5,602,365	5,605,773	5,606,974	912.4
BGWO [188]	4,483,381	4,486,676	4,488,568	469.6	5,604,146	5,607,031	5,607,723	822.23
BMMFOA [189]	4,488,622	4,489,512	4,491,268	398.98	5,608,751	5,609,781	5,610,786	723.567
Deterministic algorithms								
ELR [150]	4,485,633	-	-	209	5,605,678	-	-	345
SPL [135]	4,492,909	-	-	215.77	5,615,530	-	-	374.03
LR [151]	4,484,915	-	-	64	5,604,470	-	-	80
IPPDTM [212]	4,490,208	-	-	31.23	5,609,782	-	-	46.55
SDP [161]	4,484,365	-	-	353.84	5,602,538	-	-	392.56
OA [162]	4,482,784	-	-	39	5,601,581	-	-	48
TOA [162]	4,481,625	-	-	43	5,600,459	-	-	60
OIA [162]	**4,481,611**	-	-	53	**5,600,210**	-	-	87
C&B [213]	4,484,497	-	-	398.9	5,603,976	-	-	276.6
CUT&CPLEX [213]	4,484,497	-	-	90.1	5,602,364	-	-	144.2
Hybrid algorithms								
HGA[194]	4,487,766	4,488,826	4,489,983	87.19	5,606,811	5,609,492	5,612,420	134.47
ELRPSO [191]	4,482,937	4,482,986	4,483,247	12.76	5,601,825	5,601,885	5,602,392	16.18
mFROFI-PPL	4,483,542	4,484,705	4,485,275	305.78	5,602,629	5,604,564	5,605,508	373.89
mFROFI-PPL + QP	4,481,770	**4,482,821**	**4,483,161**	309.99	5,600,226	**5,601,726**	**5,602,386**	381.01

Table 4.4: Comparison of the performance of mFROFI-PPL with other algorithms on 80 and 100 units systems

	Hours																								FC ($)	STC ($)
Units	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**		
1	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
2	245.00	295.00	390.83	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	331.67	281.67	381.67	455.00	455.00	455.00	455.00	411.67	0	189,584	0
3	0	0	0	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	31,810	1,650
4	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	45,771	1.120
5	0	0	0	0	46.67	38.33	45.00	48.33	101.67	162.00	162.00	162.00	162.00	101.67	48.33	25.00	25.00	25.00	48.33	162.00	106.67	0	0	0	37,317	900
6	0	0	0	0	0	0	0	0	20.00	34.67	74.67	80.00	34.67	20.00	0	0	0	0	0	44.67	20.00	20.00	0	0	11,219	510
7	0	0	0	0	0	0	0	0	0	25.00	25.00	25.00	25.00	0	0	0	0	0	0	0	0	0	0	0	4,696	520
8	0	0	0	0	0	0	0	0	0	0	10.00	44.67	0	0	0	0	0	0	0	10.00	0	0	0	0	3,665	120
9	0	0	0	0	0	0	0	0	0	0	0	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	1,876	120
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
12	245.00	295.00	390.83	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	331.67	281.67	381.67	455.00	455.00	455.00	455.00	411.67	383.00	197,210	0
13	0	0	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	40,485	1,100
14	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	48,631	1,120
15	0	0	0	48.00	46.67	38.33	45.00	48.33	101.67	162.00	162.00	162.00	162.00	101.67	48.33	25.00	25.00	25.00	48.33	162.00	106.67	0	0	0	38,722	900
16	0	0	0	0	0	0	0	0	20.00	34.67	74.67	80.00	34.67	20.00	0	0	0	0	0	44.67	20.00	20.00	0	0	11,219	510
17	0	0	0	0	0	0	0	0	0	25.00	25.00	25.00	25.00	0	0	0	0	0	0	0	0	0	0	0	4,696	520
18	0	0	0	0	0	0	0	0	0	10.00	10.00	44.67	10.00	0	0	0	0	0	0	10.00	0	0	0	0	5,504	120
19	0	0	0	0	0	0	0	0	0	0	10.00	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	2,814	120
20	0	0	0	0	0	0	0	0	0	0	0	10.00	0	0	0	0	0	0	0	0	0	0	0	0	948	60
21	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
22	245.00	295.00	390.83	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	331.67	281.67	381.67	455.00	455.00	455.00	455.00	411.67	383.00	197,210	0
23	0	0	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	40,485	1,100
24	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	48,631	1,120
25	0	0	0	48.00	46.67	38.33	45.00	48.33	101.67	162.00	162.00	162.00	162.00	101.67	48.33	25.00	25.00	25.00	48.33	162.00	106.67	65.00	0	0	40,469	900
26	0	0	0	0	0	0	0	0	20.00	34.67	74.67	80.00	34.67	20.00	0	0	0	0	0	44.67	20.00	20.00	20.00	0	12,037	510
27	0	0	0	0	0	0	0	0	0	25.00	25.00	25.00	25.00	0	0	0	0	0	0	0	0	0	0	0	4,696	520
28	0	0	0	0	0	0	0	0	0	10.00	10.00	44.67	10.00	0	0	0	0	0	0	10.00	0	0	0	0	5,505	120
29	0	0	0	0	0	0	0	0	0	0	10.00	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	2,814	120
30	0	0	0	0	0	0	0	0	0	0	0	10.00	0	0	0	0	0	0	0	0	0	0	0	0	948	60
31	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
32	245.00	295.00	390.83	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	331.67	281.67	381.67	455.00	455.00	455.00	455.00	411.67	383.00	197,210	0
33	0	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	43,377	1,100
34	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	48,631	1,120
35	0	0	0	48.00	46.67	38.34	45.00	48.33	101.67	162.00	162.00	162.00	162.00	101.67	48.33	25.00	25.00	25.00	48.33	162.00	106.67	65.00	0	0	40,469	900
36	0	0	0	0	0	0	0	0	20.00	34.67	74.67	80.00	34.67	20.00	0	0	0	0	0	44.67	20.00	20.00	0	0	11,219	510
37	0	0	0	0	0	0	0	0	0	25.00	25.00	25.00	25.00	0.00	0	0	0	0	0	0	0	0	0	0	4,696	520
38	0	0	0	0	0	0	0	0	0	10.00	10.00	44.67	10.00	0	0	0	0	0	0	10.00	0	0	0	0	5,504	120
39	0	0	0	0	0	0	0	0	0	0	10.00	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	2,814	120
40	0	0	0	0	0	0	0	0	0	0	0	10.00	0	0	0	0	0	0	0	0	0	0	0	0	948	60
41	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
42	245.00	295.00	390.83	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	331.67	281.66	381.67	455.00	455.00	455.00	455.00	411.67	383.00	197,210	0
43	0	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	43,377	1,100
44	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	51,492	560
45	0	0	0	48.00	46.67	38.33	45.00	48.33	101.67	162.00	162.00	162.00	162.00	101.67	48.33	25.00	25.00	25.00	48.33	162.00	106.67	65.00	25.00	0	41,414	900
46	0	0	0	0	0	0	0	0	20.00	34.67	74.67	80.00	34.67	20.00	0	0	0	0	0	44.67	20.00	20.00	0	0	11,219	510
47	0	0	0	0	0	0	0	0	25.00	25.00	25.00	25.00	25.00	25.00	0	0	0	0	0	0	0	0	0	0	7,044	520
48	0	0	0	0	0	0	0	0	0	10.00	10.00	44.67	10.00	0	0	0	0	0	0	10.00	10.00	0	0	0	6,424	120
49	0	0	0	0	0	0	0	0	0	0	10.00	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	2,814	120
50	0	0	0	0	0	0	0	0	0	0	0	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	1,896	120
51	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
52	245.00	295.00	390.83	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	331.67	281.66	381.67	455.00	455.00	455.00	455.00	411.67	383.00	197,210	0
53	0	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	0	46,269	1,100
54	0	0	0	0	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	0	0	51,492	560
55	0	0	25.00	48.00	46.67	38.33	45.00	48.33	101.67	162.00	162.00	162.00	162.00	101.67	48.33	25.00	25.00	25.00	48.33	162.00	106.67	65.00	25.00	25.00	43,304	900
56	0	0	0	0	0	0	0	20.00	20.00	34.66	74.67	80.00	34.67	20.00	20.00	0	0	0	20.00	44.67	20.00	0	0	0	12,855	510
57	0	0	0	0	0	0	0	0	25.00	25.00	25.00	25.00	25.00	25.00	0	0	0	0	0	0	0	0	0	0	7,044	520
58	0	0	0	0	0	0	0	0	0	10.00	10.00	44.66	10.00	0	0	0	0	0	0	10.00	10.00	0	0	0	6,424	120
59	0	0	0	0	0	0	0	0	0	0	10.00	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	2,814	120
60	0	0	0	0	0	0	0	0	0	0	0	10.00	0	0	0	0	0	0	0	10.00	0	0	0	0	1,896	120
Total	4200.00	4500.00	5100.00	5700.00	6000	6600.00	6900.00	7200.00	7800.00	8400.00	8700.00	9000.00	8400.00	7800.00	7200.00	6300.00	6000.00	6600.00	7200.00	8400.00	7800.00	6600.00	5400.00	4800.00	3,335,108	26,190
																								Total Operation Cost:	3,361,298	

Table 4.5: Best generating schedule obtained by mFROFI-PPL + QP for the system of 60 units

10-100 units systems with ramp rates constraints

This system is identical to the one examined in the previous subsection. However, in this section the ramp rates of the units are considered, making the problem more realistic. In this case, the attainment of feasible generating schedules becomes more challenging, since ramp rates are dynamic constraints which couple the power output of generating units during successive hours. Their inclusion distinguishes the Dynamic Economic Dispatch from the traditional static Economic Dispatch. In particular, since such constraints involve the evolution of the power output of the generators, the ED can no longer be optimized independently for each scheduling period [207]. For this reason the QP method is not applied in this case, since the computational time would be significantly increased.

In the examined case, the ramp rates of each unit are taken equal to 20% of its maximum power output ($RU_i = RD_i = 20\% \cdot Pmax_i$), while the start-up and shut-down ramps are equal to the unit's maximum power output, as in [179, 162]. The spinning reserve requirements are set equal to 10% of the demanded load and the shut-down costs are not considered. To validate the performance of mFROFI-PPL, it has been benchmarked against deterministic algorithms (C&B, CUT&CPLEX , OA, TOA, OIA, Improved Merit Order - Augmented Lagrangian Hopfield Network (IMO - ALHN) [214]), stochastic -including DE-based - methods (BCDE, ICDE, ESA, and MBABC -GC) and hybrid approaches (HGA). The results are summarized in Tables 4.6 and 4.7.

The results indicate that the method derives solutions of high quality in terms of operation cost for the examined system. Specifically for the systems of 10, 20 and 40 units the mFROFI-PPL achieves the solutions with the lowest operating cost, while it also derives the minimum average and worst cost compared to the other stochastic approaches, revealing a robust performance. For the systems of 60, 80 and 100 units overall mFROFI-PPL is ranked second with respect to the best cost obtained, however it derives solutions distributions with the minimum average and worst cost values compared to the competing algorithms. With regard to the previous stochastic and hybrid approaches mFROFI-PPL derives the lowest best, average and minimum cost for the systems of 10, 20, 40, 80 and 100 units. The only exception is the system of 60 units where the best solution is obtained by BCDE and ICDE. Moreover, compared to the deterministic approaches with respect to the best cost, mFROFI-PPL is ranked first for the systems of 10, 20 and 40 units and second for the systems of 60, 80 and 100. In general, the proposed method performed very competitively in this system. The solution with the lowest cost obtained by mFROFI-PPL for the system of 20 units is shown in Table 4.8.

	10 units				20 units				40 units			
	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)
Stochastic algorithms						-	-					
ESA [179]	-	-	-	-	-	-	-	-	2,255,864	2,256,971	2,258,897	199.55
BCDE [174]	565,540	-	-	-	1,126,385	-	-	-	2,247,999	-	-	-
ICDE [174]	565,540	-	-	-	1,126,385	-	-	-	2,247,999	-	-	-
MBABC -GC [187]	565,671	565,826	565,975	35.49	1,126,634	1,127,075	1,127,545	87.36	2,252,544	2,253,497	2,254,565	212.94
Deterministic algorithms						-	-					
IMO-ALH [214]	565,804	-	-	-	1,127,172	-	-	-	2,249,848	-	-	-
OA [162]	565,601	-	-	-	1,126,876	-	-	-	2,248,697	-	-	-
TOA[162]	565,589	-	-	-	1,126,644	-	-	-	2,248,074	-	-	-
OIA[162]	565,564	-	-	-	1,126,354	-	-	-	2,247,803	-	-	-
C&B[213]	568,863	-	-	31.5	1,135,270	-	-	39.6	2,266,584	-	-	336.6
CUT&CPLEX[213]	565,723	-	-	2.4	1,128,273	-	-	14.6	2,251,134	-	-	33.7
Hybrid algorithms						-	-					
HGA [194]	565,622	565,858	566,073	-	1,127,110	1,127,858	1,128,103	-	2,252,841	2,253,592	2,254,412	-
mFROFI-PPL	**565,195**	**565,289**	**565,487**	41.56	**1,125,667**	**1,125,837**	**1,125,989**	65.80	**2,247,774**	**2,248,592**	**2,249,500**	157.63

Table 4.6: Comparison of the performance of mFROFI-PPL with other algorithms on 10, 20 and 40 units systems with ramp rates

	60 units				80 units				100 units			
	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)	Best Cost ($)	Average Cost ($)	Worst Cost ($)	Ex. Time (s)
Stochastic algorithms						-	-					
ESA [179]	-	-	-	-	-	-	-	-	-	-	-	-
BCDE[174]	**3,367,656**	-	-	-	4,502,186	-	-	-	5,626,162	-	-	-
ICDE[174]	**3,367,656**	-	-	-	4,502,186	-	-	-	5,626,162	-	-	-
MBABC -GC [187]	3,375,368	3,376,642	3,377,977	395.97	4,500,742	4,502,404	4,503,782	614.71	5,626,740	5,628,853	5,630,599	1006.98
Deterministic algorithms						-	-					
IMO-ALHN [214]	3,371,962	-	-	-	4,495,954	-	-	-	5,618,569	-	-	-
OA [162]	3,368,011	-	-	-	4,494,393	-	-	-	5,614,913	-	-	-
TOA [162]	3,367,950	-	-	-	4,495,435	-	-	-	5,613,320	-	-	-
OIA [162]	3,367,816	-	-	-	**4,492,779**	-	-	-	**5,612,105**	-	-	-
C&B [213]	3,399,121	-	-	565.9	4,531,724	-	-	323.5	5,662,294	-	-	336.9
CUT&CPLEX [213]	3,376,480	-	-	88.5	4,501,641	-	-	123	5,625,921	-	-	210.9
Hybrid algorithms						-	-					
HGA [194]	3,375,332	3,376,180	3,377,106	-	4,500,780	4,502,043	4,500,780	-	5,622,688	5,624,623	5,626,737	-
mFROFI-PPL	3,369,320	**3,371,970**	**3,374,724**	238.23	4,494,574	**4,496,343**	**4,497,813**	404.25	5,616,689	**5,620,072**	**5,623,105**	485.31

Table 4.7: Comparison of the performance of mFROFI-PPL with other algorithms on 40, 60 and 100 units systems with ramp rates

	Hours																								FC ($)	STC ($)
Units	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**		
1	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	454.99	203,180	0
2	257.17	276.54	367.54	455.00	455.00	398.12	455.00	387.66	455.00	455.00	455.00	455.00	455.00	410.06	455.00	364.00	303.91	394.80	438.73	455.00	455.00	455.00	408.56	317.85	193,433	0
3	0	0	0	0	0	0	0	128.48	123.39	130.00	130.00	130.00	129.96	127.69	129.72	111.10	129.01	128.52	129.50	130.00	129.90	0	0	0	39,926	1,100
4	0	0	0	0	0	129.71	130.00	129.15	130.00	130.00	130.00	130.00	130.00	128.68	125.15	129.12	129.52	128.44	129.94	130.00	130.00	0	0	0	45,595	1,120
5	0	0	0	38.88	25.00	25.00	49.56	64.61	97.01	129.41	161.81	162.00	129.60	97.20	64.80	32.40	25.00	26.84	59.23	91.63	59.23	58.83	26.45	0	37,622	900
6	0	0	0	0	0	0	0	0	28.94	44.93	60.85	76.66	60.67	44.67	0	0	0	0	0	65.46	49.47	33.50	0	0	13,869	510
7	0	0	0	0	0	0	0	0	0	25.04	25.62	35.46	25.00	0	0	0	0	0	0	0	0	0	0	0	5,005	520
8	0	0	0	0	0	0	0	0	0	28.74	22.02	23.39	12.39	0	0	0	0	0	0	21.06	10.06	0	0	0	7,020	120
9	0	0	0	0	0	0	0	0	0	0	10.01	19.67	0	0	0	0	0	0	0	16.24	0	0	0	0	3,249	120
10	0	0	0	0	0	0	0	0	0	0	0	10.01	0	0	0	0	0	0	0	0	0	0	0	0	948	60
11	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	203,180	0
12	232.83	313.46	397.42	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	455.00	390.64	300.88	217.94	302.84	391.71	455.00	455.00	455.00	454.99	372.16	192,744	0
13	0	0	0	0	0	128.13	130.00	129.97	119.29	130.00	130.00	130.00	130.00	129.93	129.96	116.17	129.66	129.50	129.48	130.00	130.00	0	0	0	45,791	1,100
14	0	0	0	0	129.87	128.99	130.00	129.97	130.00	130.00	130.00	130.00	130.00	129.82	129.93	103.93	129.92	129.92	130.00	130.00	130.00	129.96	0	0	51,021	560
15	0	0	25.04	41.12	25.13	25.05	40.44	65.16	97.53	129.93	162.00	162.00	129.60	97.20	64.80	32.40	25.04	49.14	81.41	113.81	82.32	114.69	0	0	40,453	900
16	0	0	0	0	0	0	0	0	28.84	44.82	60.82	76.72	60.72	44.72	0	0	0	0	0	75.02	59.02	43.02	0	0	14,526	510
17	0	0	0	0	0	0	0	0	25.00	25.20	25.65	37.47	25.01	25.03	0	0	0	0	0	0	0	0	0	0	7,415	520
18	0	0	0	0	0	0	0	0	0	31.93	21.21	28.05	17.05	0	0	0	0	0	0	55.00	0	0	0	0	7,295	120
19	0	0	0	0	0	0	0	0	0	0	10.01	18.50	0	0	0	0	0	0	0	10.87	0	0	0	0	3,070	120
20	0	0	0	0	0	0	0	0	0	0	0	10.07	0	0	0	0	0	0	0	10.91	0	0	0	0	1,923	120
Total	1400.00	1500.00	1700.00	1900.00	2000.00	2200.00	2300.00	2400.00	2600.00	2800.00	2900.00	3000.00	2800.00	2600.00	2400.00	2100.00	2000.00	2200.00	2400.00	2800.00	2600.00	2200.00	1800.00	1600.00	1,117,267	8,400
																							Total Operation Cost:		1,125,667	

Table 4.8: Best generating schedule obtained by mFROFI-PPL for the system of 20 units with ramp rates

IEEE RTS

The practical case of the IEEE - RTS test system comprises 26 thermal units with distinct generating characteristics. The data of the demanded load and the thermal units, including their ramping capabilities, have been obtained from [210] (the data for this system are given in Appendix A.2). In this system the start-up cost is formulated as an exponential function, as in Eq. 4.3. Moreover, the spinning reserve requirements are equal to the capacity of the largest unit, i.e. 400 MW. The results obtained by mFROFI-PPL are compared to those of Artificial Neural Network and DP (ANN-DP) [210], Improved Priority List and Augmented Lagrange Hopfield Network (IPL-ALH) [215] and Binary Real Coded Firefly Algorithm (BRCFF) [216] in Table 4.9. It can be observed that mFROFI-PPL has provided the solution with the minimum cost compared to the previously proposed approaches. In fact, to the author's knowledge, this is the lowest cost reported for the examined system in the literature. The best generating schedule attained by mFROFI-PPL is depicted in Table 4.10.

Algorithm	**Best Cost ($)**	**Average Cost ($)**	**Worst Cost ($)**	**Ex. Time (s)**
ANN-DP [210]	613,653.60	-	-	2.15
IPL-ALH [215]	583,379.50	-	-	0.48
BRCFF [216]	582,938.00	588,874.00	-	473
mFROFI-PPL	**581,764.00**	**582,294.00**	**583,128.00**	26.63

Table 4.9: Comparison of the performance of mFROFI-PPL with other algorithms on the IEEE RTS test system

	Hours																								**FC ($)**	**STC ($)**
Units	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**		
1	0	0	0	0	0	0	0	0	0	2.40	0	2.45	0	0	2.40	0	0	0	0	0	0	0	0	0	259	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	2.40	0	0	0	0	2.40	0	0	0	0	0	0	0	2.40	0	0	0	0	0	0	2.40	0	0	347	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	15.23	15.22	15.20	0	0	15.20	15.20	52.65	76.00	76.00	76.00	76.00	76.00	76.00	70.48	73.64	76.00	76.00	76.00	76.00	76.00	76.00	20.56	15.20	18,790	74
11	0	0	0	0	0	15.21	15.20	53.31	76.00	76.00	76.00	76.00	76.00	76.00	76.00	58.21	76.00	75.94	76.00	76.00	76.00	76.00	15.27	15.23	17,776	91
12	0	0	0	0	0	0	15.23	37.91	76.00	76.00	75.95	76.00	75.95	76.00	63.87	36.39	55.30	50.81	76.00	76.00	76.00	66.83	15.35	15.20	16,026	93
13	0	0	0	0	0	0	0	32.57	71.07	76.00	76.00	76.00	75.99	73.94	41.95	28.86	24.80	39.18	75.67	76.00	76.00	44.78	15.20	15.21	14,263	95
14	0	0	0	0	0	0	25.00	25.00	42.25	86.10	28.12	78.54	27.84	25.05	25.02	25.00	25.00	25.11	38.26	60.53	37.90	25.00	25.00	0	15,131	133
15	0	0	0	0	0	0	0	25.01	25.35	54.56	25.00	51.84	25.17	25.03	0	0	25.00	25.03	25.00	42.55	25.10	25.00	25.00	0	10,831	232
16	0	0	0	0	0	0	0	0	25.29	25.00	25.01	25.28	25.07	0	0	0	0	0	25.17	25.00	25.10	25.04	25.00	0	6,793	255
17	105.26	133.34	111.07	88.64	88.32	117.27	154.66	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	141.40	42,309	0
18	114.46	100.43	54.61	54.59	54.44	91.34	130.76	155.00	155.00	155.00	155.00	155.00	155.00	155.00	154.99	155.00	155.00	155.00	155.00	155.00	155.00	155.00	154.99	118.24	39,866	0
19	65.54	69.90	54.28	54.26	57.09	54.25	106.97	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	103.89	38,203	0
20	58.94	54.46	54.49	54.35	54.25	54.27	94.58	149.58	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	155.00	153.63	75.63	37,466	0
21	0	0	0	0	0	0	0	68.97	69.09	68.99	68.95	68.94	69.03	68.96	68.94	68.95	68.95	68.95	68.95	68.96	68.95	68.95	0	0	27,865	349
22	0	0	0	0	0	0	0	0	68.95	68.95	68.97	68.95	68.95	69.02	68.95	68.95	68.95	68.98	68.95	68.96	68.95	0	0	0	24,245	355
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	270.59	274.25	310.35	298.16	295.89	322.46	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	350.00	96,098	0
25	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	86,814	0
26	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	400.00	87,004	0
Total	1430.00	1450.00	1400.00	1350.00	1350.00	1470.00	1710.00	2060.00	2300.00	2380.00	2290.00	2370.00	2290.00	2260.00	2190.00	2130.00	2190.00	2200.00	2300.00	2340.00	2300.00	2180.00	1910.00	1650.00	580,086	1,678
																								Total Operation Cost:	581,764	

Table 4.10: Best generating schedule obtained by mFROFI-PPL for the IEEE RTS test system

38 units Tai Power System

The fourth case examined is the Tai Power System consisting of 38 units. The generating characteristics (including the ramp rates of the units) and the electricity demand are retrieved from [211] (the data for this system are given in Appendix A.3). The start-up cost is considered constant and the reserve margin is equal to 11% of the demanded load, in line to the recommended instructions. The performance of mFROFI-PPL is compared with the results of the following methods: DP [211], LR [211], SA [211] and Constraint Logic Programming (CLP) [211], Memory Bounded Ant Colony Optimization (MACO) [217], Absolutely Stochastic SA (ASSA) [218], Heuristics and ASSA (HASSA) [219], twofold SA (TFSA) [220], Enhanced Merit Order Augmented Lagrangian Hopfield Network (EMO-ALHN) ([221]), IPL-ALH [215], Augmented Lagrange Hopfield network based LR (ALHN-LR) [206] and BRCFF [216]. In Table 4.11 the best, average and maximum operation cost obtained by each method and their average execution time are presented.

The computational results reveal that mFROFI - PPL obtains the minimum operation cost reported in the literature, to the author's knowledge, for the system of 38 units. Compared to ALHN-LR and IPL - ALHN which are ranked second and third respectively, mFROFI-PPL achieves a cost reduction equal to $1.49M\$$ and $1.99M\$$ (approximately 0.76% and 1%). Moreover, mFROFI exhibits increased robustness since its average cost is the lowest amongst the competing methods. The best generation schedule achieved by mFROFI-PPL is shown in Table 4.12.

Algorithm	**Best Cost (M $)**	**Average Cost (M $)**	**Worst Cost (M $)**	**Ex. Time (s)**
DP [211]	215.20	-	-	199
LR [211]	214.50	-	-	29
SA [211]	215.60	-	-	2589
CLP [211]	213.80	-	-	17
MACO [217]	203.32	205.49	209.61	124.7
TFSA [220]	197.15	198.86	201.53	3.56
ASSA [218]	198.84	199.57	200.73	4.38
EMO-ALHN [221]	198.40	-	-	0.63
HASSA [219]	197.41	-	-	5.34
BRCFF [216]	197.08	199.07	-	603
IPL-ALH [215]	197.05	-	-	2.15
ALHN-LR [206]	196.55	-	-	10.48
mFROFI-PPL	**195.06**	**196.97**	**198.29**	44.57

Table 4.11: Comparison of total production costs and execution time for the systems of 38 units

	Hours																								FC ($)	STC ($)
Units	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**		
1	549.35	540.69	445.85	387.57	405.03	441.94	440.76	532.76	550.00	549.67	549.99	550.00	549.64	550.00	549.97	550.00	550.00	550.00	549.99	550.00	550.00	549.87	547.11	549.95	13,620,929	0
2	549.99	542.24	535.59	539.74	511.21	526.39	536.57	549.99	550.00	549.97	550.00	550.00	548.86	550.00	550.00	550.00	550.00	550.00	546.48	550.00	550.00	550.00	550.00	549.72	14,219,943	0
3	499.81	418.88	386.30	347.82	403.78	319.77	320.10	399.87	483.85	499.99	500.00	500.00	481.90	500.00	499.82	500.00	500.00	499.97	500.00	500.00	500.00	500.00	500.00	499.97	11,974,420	0
4	499.73	494.65	454.60	368.62	331.82	301.83	292.61	376.16	460.10	497.19	499.98	500.00	494.18	500.00	499.99	499.99	500.00	500.00	499.98	500.00	500.00	500.00	500.00	498.41	11,989,419	0
5	499.93	496.79	488.65	431.70	473.98	468.51	435.93	489.11	500.00	499.97	500.00	500.00	499.26	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	12,738,052	0
6	499.94	498.97	485.94	485.14	466.31	383.03	458.06	499.74	500.00	499.99	499.86	499.54	498.78	500.00	500.00	500.00	500.00	500.00	500.00	500.00	499.55	500.00	500.00	500.00	12,730,080	0
7	500.00	497.71	495.56	492.13	496.84	499.90	499.74	499.94	500.00	499.06	499.09	500.00	499.98	500.00	499.71	499.81	499.11	500.00	500.00	500.00	500.00	500.00	500.00	500.00	12,950,568	0
8	500.00	499.84	497.61	443.96	495.44	498.51	499.85	499.99	500.00	499.95	500.00	499.82	499.58	499.99	500.00	499.98	499.97	500.00	500.00	500.00	499.99	500.00	500.00	500.00	12,902,652	0
9	0	0	0	0	0	0	0	0	0	338.35	370.92	345.18	228.66	354.38	324.02	374.54	286.99	0	0	0	0	0	0	0	4,404,847	402,500
10	0	0	0	0	0	0	0	0	0	364.58	441.76	495.77	242.06	368.73	453.79	449.67	432.99	304.75	214.43	340.08	247.75	0	0	0	7,251,620	402,500
11	0	0	0	0	0	0	0	0	0	439.67	438.58	478.70	287.21	412.86	447.96	491.09	460.22	346.82	321.95	428.38	427.55	414.28	339.85	351.79	9,917,769	402,500
12	0	0	0	0	0	0	0	0	498.23	464.62	493.33	498.48	281.44	409.44	499.92	493.58	499.82	465.65	489.45	492.48	499.62	472.37	476.81	494.41	11,964,027	402,500
13	110.88	111.91	110.21	110.33	110.92	110.47	110.64	129.32	228.88	321.03	318.67	395.28	241.98	351.69	392.17	329.56	333.48	203.56	152.35	239.21	303.95	240.25	157.41	166.32	9,381,154	0
14	92.02	91.58	90.32	90.43	90.44	90.27	90.65	100.89	189.45	134.10	183.41	225.91	113.55	204.14	246.23	133.78	120.91	113.56	96.29	188.29	94.79	138.25	141.79	110.86	5,884,601	0
15	82.07	82.25	82.06	82.17	82.33	82.31	82.42	83.14	173.60	151.49	125.94	85.84	82.03	172.15	94.98	108.14	84.84	94.39	88.04	169.57	85.81	94.61	0	0	4534372	0
16	0	0	0	0	0	0	0	0	203.18	160.63	153.78	136.76	121.17	192.94	127.02	178.11	141.61	141.50	0	0	0	0	0	0	2,874,060	575,000
17	0	0	0	0	0	0	0	0	0	0	0	0	0	273.30	225.63	0	0	0	0	0	0	0	0	0	825,724	23,000
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	272.00	272.00	272.00	264.81	271.99	271.98	272.00	272.00	272.00	272.00	272.00	272.00	272.00	272.00	271.99	272.00	272.00	272.00	272.00	272.00	272.00	272.00	272.00	272.00	6,351,704	0
21	272.00	272.00	272.00	271.55	272.00	272.00	267.62	271.90	272.00	272.00	272.00	272.00	272.00	272.00	271.84	271.99	271.36	271.12	272.00	272.00	272.00	272.00	272.00	272.00	6,414,254	0
22	260.00	260.00	259.99	259.90	259.93	259.56	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	260.00	6,281,352	0
23	172.69	91.97	80.79	83.22	81.26	80.90	81.99	127.10	174.73	189.95	189.99	190.00	183.27	190.00	188.11	190.00	190.00	189.39	189.15	190.00	190.00	190.00	190.00	189.94	4,624,206	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	124.75	71.56	60.61	60.34	64.86	60.48	68.66	110.66	124.98	125.00	125.00	125.00	109.04	125.00	125.00	125.00	124.46	121.69	125.00	125.00	125.00	124.75	124.93	124.91	2,969,352	0
26	101.56	55.77	55.52	55.22	55.07	56.32	56.11	82.92	109.85	110.00	109.97	109.91	71.06	99.06	109.16	109.87	110.00	109.77	109.96	110.00	110.00	109.97	106.03	109.73	2,758,223	0
27	51.69	47.80	36.22	35.15	36.12	35.44	35.84	55.54	74.26	74.86	69.74	71.83	37.93	57.93	74.75	74.93	74.44	71.68	74.95	75.00	75.00	74.92	74.99	0	1,829,328	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	32.47	32.67	20.12	20.21	20.24	20.21	20.35	29.66	37.91	37.91	38.00	0	0	0	0	0	0	0	0	0	0	0	0	0	443,635	0
38	29.13	20.72	20.07	20.01	20.42	20.19	20.12	29.33	36.99	38.00	38.00	38.00	24.42	34.40	37.93	37.97	37.82	34.15	37.97	38.00	37.00	36.75	37.09	0	1,019,743	0
Total	5700.00	5400.00	5150.00	4850.00	4950.00	4800.00	4850.00	5400.00	6700.00	7850.00	8000.00	8100.00	6900.00	8150.00	8250.00	8000.00	7800.00	7100.00	6800.00	7300.00	7100.00	6800.00	6550.00	6450.00	192,856,034	2,208,000
																								Total Operation Cost:	195,064,034	

Table 4.12: Best generating schedule obtained by mFROFI-PPL for the system of 38 units with ramp rates

CHAPTER 5

AN APPROACH BASED ON DIFFERENTIAL EVOLUTION FOR THE RELIABILITY CONSTRAINED SHORT-TERM GENERATION SCHEDULING PROBLEM

5.1 Introduction

In the previous Chapter, the basic form of a STGS problem has been examined. An approach which utilizes a DE-based algorithm for constrained optimization has been developed to optimize the problem. A series of modifications to the DE-based algorithm have been proposed to increase the methods efficiency on solving the STGS problem. In particular, a two-step function has been used to determine the state of thermal generators. A series of heuristic repair mechanisms have been included in the optimization procedure to facilitate the obtainment of feasible generating schedules. Moreover, a method has been developed to include a Plurality of Priority orders within the heuristic repair mechanisms in an attempt to increase the diversity of the examined solutions. Furthermore, an Elitist Mutation scheme has been included within the algorithm to accelerate its convergence towards promising regions of the search space. In this chapter, the DE-based approach is extended and applied on another formulation of the STGS problem, which may include uncertainties encountered in the operation of a power sector.

The main goal of a STGS problem is to determine the generating schedule that will provide the demanded load in the most reliable and economic manner. A widely used definition of the term ‘reliability’ is the probability that a system (including all its components) will satisfactorily perform the task for which it was designed or intended, for a specified amount of time and the specified environment [222]. The definition of reliability can be used also for power systems, since such systems should provide power in the most reliable manner [223].

As described in the mathematical formulation of the short-term generation scheduling problem (please see Section 4.3 in Chapter 4), Spinning Reserve is the reserve capacity which is spinning, synchronized and ready to take up load [1]. An appropriate amount of Spinning Reserve is essential for the reliable operation of the power system against unforeseen events, e.g. generator outages and/or deviations of the actual load from the forecasted one. Thus, its availability is crucial because it mitigates the social and economic costs that may rise due to the aforementioned unforeseen events. However, maintaining increased reserve capacity increments the overall operating cost of the system, since additional units have to be committed and operated at suboptimal power output levels [224]. Hence, the system's Spinning Reserve requirements should be carefully assessed.

In the traditional formulation of the STGS problem a fixed amount of Spinning Reserve is scheduled. In practice, power system operators use some deterministic criteria to schedule the amount of required Spinning Reserve. That is the required Spinning Reserve is a given predefined amount. One of the deterministic criteria commonly used, sets the required amount of SR equal to the capacity of the largest generator. This criterion ensures that no load will need to be disconnected in the event of any single unit outage. In fact, it considers that simultaneous outages of two or more generators are so rare compared to the outage of a single unit, that such a case may be ignored. However, the probability of having two or more simultaneous outages might not be that small. Another criterion which is utilized often considers the Spinning Reserve requirements of the system equal to a percentage of the daily forecasted peak load or the hourly demand. While such criteria are easy to implement, they may not consistently define the true risk of the system, as they do not consider the intrinsic reliability of the system's components.

In the relevant literature, some methods have employed probabilistic criteria to determine the required amount of Spinning Reserve. Such methods rely on the inclusion of reliability criteria within the formulation of the STGS problem. Such criteria employ reliability indices, to represent the risk of load loss. In particular, the following two indices are commonly encountered:

[1]Throughout this dissertation, Spinning Reserve is used to refer to the capability of the power system to respond voluntarily to contingencies within the tertiary regulation interval with the already synchronized generation.

1. The Loss of Load Probability (LOLP), which represents the probability (%) that the available committed capacity will not satisfy the load.

2. The Expected Energy Not Served (EENS), which represents the expected amount of energy that will not be supplied by the generating system due to the loss of load.

LOLP and EENS indices may take into consideration several system uncertainties, such as the unavailability of the units, contingencies in transmission lines and load forecast uncertainty. Thus, they may provide a more realistic assessment of the system's Spinning Reserve requirements. It should be noted that such criteria have been initially proposed for reliability assessment studies in long term planning models [222]. Nevertheless in the literature several attempts have been carried out to integrate such reliability criteria within STGS problems as will be described in the following sections. Commonly, upper bounds are imposed on the values of the reliability indices, forming the reliability constraints, which are integrated within the mathematical model of the STGS. In this context, the problem is termed as Reliability Constrained Short-Term Generation Scheduling (RCSTGS) problem.

In this chapter, a method is proposed to include the aforementioned constraints within the DE based methodology as described in the previous Chapter. More specifically, the method integrates a series of heuristic repair mechanisms, proposed in this dissertation, which repair violations of the reliability constraints. These mechanisms take advantage of the Priority List of the generators and steer the search towards adequate generating schedules. The method will be described for the case of systems comprising solely thermal generators. In the following Chapter, it will be extended for the case where, both hydro plants and wind power are also considered within the formulation of the STGS.

Having briefly described the context of this Chapter, the latter is structured as follows: In Section 5.2, a literature review of the methods which examine the integration of the reliability indices within the STGS is described. Then, in Section 5.3 the mathematical formulation of the problem is given. The method for the calculation of the reliability indices will be described in Section 5.4, while the proposed solution methodology is analyzed in Section 5.5. Later, in Section 5.6, the computational experiments carried out to validate the efficiency of the method are described and the results of the method are discussed.

5.2 Literature review

As stated in the introduction of this Chapter, commonly in the relevant literature the required Spinning Reserve of the system is set using deterministic criteria. Nevertheless such criteria do not adequately consider the stochastic nature of the system's components neither the demand forecasting uncertainty. Probabilistic criteria have also been utilized in the STGS formulation for assessing the Spinning Reserve. Such criteria employ reliability indices such as LOLP and EENS to represent the risk of losing load. Thus, they may provide a more realistic assessment of the system's Spinning Reserve requirements. Several approaches have been proposed in the relevant literature, which integrate the reliability criteria into the STGS problem. A review of them will be carried out in the following paragraphs.

In [225], a method is developed to examine the effect of load uncertainty on the risk of losing load, i.e. on the probability of not having sufficient capacity in operation to compensate for failures of unit and deviations of the actual load from the predicted one. The uncertainty in load forecasting is considered using a Gauss-Markov model, which may simulate the correlation between load of consecutive hours. The availability of the units is considered using a Markov model. Nevertheless, the objective of the method is not related to economic criteria; the commitment of generators is carried out using a priority order of generators based on the time a unit requires to start up. Thus, the final solutions provided by this method may have increased operations cost.

In [226], a method is developed to consider the system's risk within the model for STGS. The method is based on a probabilistic reserve assessment, which takes into account the reliability of committed units and the load forecast uncertainty. The aforementioned assessment takes place between the minimization and the maximization of the dual function in a Lagrangian Relaxation algorithm for solving the STGS problem. In particular, in the first step the minimization of the Lagrangian with respect to the unit variables is carried out and then the hourly LOLP is estimated based on the list of committed units. In case the LOLP exceeds a given maximum acceptable system risk value then the Spinning Reserve requirements of the system are increased. Subsequently, the procedure of maximizing the Lagrangian with respect to the Lagrangian Multipliers is implemented. The procedure is repeated from the first step, until a solution that satisfies the required risk levels is found. After the final generating schedule has been obtained a post-processing of the solution is carried out to reduce the excessive reserve capacity if possible. It should be noted that the authors argue that the value of the risk index should be selected on the basis of a trade-off between the system's cost and the expected cost of non-served energy.

In [227], the authors proposed a method to integrate the risk criterion within the optimization procedure of the STGS and avoid the post-processing procedure of [226], which may lead to sub-optimal solutions. The principal difficulty of incorporating probabilistic criteria within a STGS optimization model is that there is no means of incorporating the discrete Capacity Outage Probability Table (COPT) (its calculation will be described later in the Chapter) within the optimization procedure. The authors have developed a system dependent exponential function which approximates the COPT (and thus the LOLP value) for any generation schedule and have included it within a linear constraint. However, the drawback of this approach is that it does not consider the EENS. Although LOLP measures the probability that generating capacity is not sufficient to satisfy the load it does not quantify the extent of the disconnections that might result from such deficits. Moreover, the accuracy of the approximation may deteriorate with increasing LOLP values, and single order contingencies have been considered, i.e. the probabilities of single generators being on outage are taken into account.

Bouffard and Galliana [228] proposed a MILP formulation for the STGS, which incorporates constraints based on the LOLP and EENS reliability indices. In particular, since the LOLP cannot be accurately calculated within a MILP framework, the authors propose a set of additional Bernouli variables and then examine the probabilities of random events of having zero, one or two outages. The probabilities of these events are expressed as a function of the units' states and the new Bernoulli variables. An additional set of binary variables are introduced which signal load loss at a certain outage combination. However, the approach requires a significant number of extra constraints and integer variables that may have a significant impact on the computational speed.

Ortega-Vazquez and Kirschen in [224] propose an approach which calculates the optimal Spinning Reserve requirement for each scheduling period of a power system off-line. In particular this method comprises two distinct steps. In the first step, each period of the scheduling horizon is considered separately and the optimal amount of Spinning Reserve is determined by minimizing an objective function comprising of the sum of operation cost and cost of EENS in each hour of the scheduling period. This is carried out without taking into account the coupling constraints of the STGS problem. Each hour is considered individually and the optimization is carried out using the iterated grid search. After determining the optimal amount of Spinning Reserve for each hour, a traditional short-term generation scheduling problem is optimized and the final derived schedule takes into consideration all the constraints.

One of the first attempts to apply an EA on a RCSTGS which considers the system's reliability is that of Simopoulos [229], where an approach based on the SA algorithm is applied to optimize the problem. In particular, an upper bound is imposed on the values of LOLP and EENS indexes by implementing a series of additional constraints. The SA algorithm generates new solutions by changing the state of randomly chosen generators during randomly selected periods. In case the solutions violate the LOLP constraints they are rejected and the Spinning Reserve requirements of the system are increased. The EENS constrained violation is taken into consideration by applying a quadratic penalty function which increases the value of the fitness of the individual. The method is applied on the IEEE reliability Test System; a series of experiments have been implemented to examine the impact of generators unavailability and load forecast uncertainty on the levels of the required reserve capacity. The method is relatively fast and the reliability indices are accurately calculated. However, SA performance depends on the annealing schedule; a poor tuning of the annealing schedule may inadvertently affect the performance of the SA algorithm.

Wang and Singh [230] included the uncertainty due to unit outage in the STGS problem by revising the Spinning Reserve constraints; specifically, the unavailability of the thermal generators has been taken into consideration in the traditional formulation of the reserve constraint. Moreover, a hybrid binary-real coded PSO has been developed to solve the STGSP problem. However, this approach neglected the uncertainty due to load forecast error and has considered single order contingencies event.

Jalilzadeh et al. [231] have proposed an approach to consider the reliability of the transmission system within the optimization of the reliability constrained unit commitment problem. In particular, for the calculation of LOLP and EENS indices a procedure based on linear programming is proposed, which also minimizes the values of the aforementioned indices. An integer coded GA similar to [164] is applied to optimize the problem. Problem-specific mutation operators such as the swapping operator and the copying operator have been included within the optimization procedure. Similarly, to [229] a dynamic penalty constraint is applied to deal with the violation of the EENS constraint.

In [232], a multi-objective framework has been proposed to consider the reliability of generators within the formulation of the STGS. In particular, the STGS considers two objective functions to be minimized; the first is the system's total operation cost and the second is the sum of the LOLP values over the examined scheduling period. It should be noted that during the calculation of the LOLP, the committed capacity takes into consideration the capacity of the marginal units, regardless their actual operating state (on or off) since, according to the authors, their short-start up time renders them as available for the entire scheduling period. A Genetic Algorithm is developed to solve the problem which makes use of a repair mechanism to repair violations of the minimum up/down time constraint, while the power balance constraints and the ramp constraints are dealt using a penalty function method. Interestingly, the authors apply the weighted sum approach to tackle the multi-objective problem, although their solution method is based on an Evolutionary Algorithm.

An analysis of the trade-offs between the systems reliability and the average production cost in spinning reserve optimization has been carried out in [233]. A new model to optimize the reserve requirements of the system is proposed; the Spinning Reserve is determined by minimizing an objective function which consists of the system's total operation cost and the expected cost of interruptions, which is the EENS multiplied by a Value of Lost Load (VOLL). When calculating the expected cost of interruptions, two different expressions are used. The EENS caused by single outage events of some large units is accurately computed. The EENS of the remaining units is approximately computed, using a piecewise linear function of the system's spinning reserve. The proposed method attempts to strike a balance between model complexity and computation efficiency.

An interesting work has been carried out in [234], where the spinning reserve requirements of a system are optimized by considering a LOLP constrained STGS. In this method, the authors attempt to reformulate the highly nonlinear LOLP constraint into a series of linear constraints to eliminate the combinatorial nature of the LOLP. This problem is then transformed into, a so called, Umbrella Constrained Unit Commitment. Based on a comparison between the LOLP constrained problem and the traditional reserve constrained problem, the authors argue that the former may strike a better balance between reliability and economics compared to the latter. The method is tested on a test system comprising 26 units and their results are compared to previous models in which the LOLP constraints have been approximated with linear segments. Nevertheless the model does not consider the EENS rather the impact of load uncertainty on the formulation of the problem.

In [235] a multi-objective model for the STGS problem is developed, in which the EENS is considered as a conflicting objective to the system's total operation cost. Interestingly, despite the fact that the EENS is considered, the model includes also the spinning reserve constraints. Moreover, to decrease the computational time required single-order contingencies are taken into consideration. A hybrid method, which combines the PSO with the Grey Wolf Optimizer is proposed to optimize the examined formulation. The method has been applied on three test systems, without though examining whether the non-dominated fronts provided by the method may approximate the Pareto fronts.

5.2.1 Contribution to the relevant literature

An approach has been proposed for the optimization of the RCSTGS. In this model an upper bound is imposed on LOLP and EENS forming the reliability constraints, which are included within the problem's formulation. As a result, the spinning reserve requirements of the system are determined implicitly during the optimization based on the values of the LOLP and EENS reliability indexes. A more realistic assessment of the systems reserve requirements may be achieved, since in the calculation of the aforementioned indices possible unit outages as well as the uncertainty in load forecasting are considered. The contributions of this dissertation on the solution of the RCSTGS are the following:

1. A real-coded DE-based method has been proposed for the optimization of the aforementioned problem. It is an extension of the method developed for the conventional form of the problem. To the author's knowledge it is the first time that a real-coded DE has been applied on the RCSTGS.
2. An efficient way to include the calculation of the COPT has been utilized. The latter is required for the calculation of the LOLP and EENS reliability indices (as will be described in section 5.4). The COPT of each commitment pattern of generators encountered during the optimization is stored in an external archive. In case the same commitment pattern is encountered again in subsequent generation of the optimization the COPT is obtained from

the external archive. Thus, the calculation of the COPT is carried out only the first time that a commitment pattern is encountered, reducing repeated evaluations. To avoid extensive RAM memory requirements, the archive is reinitialized after reaching a predefined number of entries. As a result a significant amount of COPT calculations is avoided resulting in savings in computational time.

3. A series of heuristic repair mechanisms has been proposed and included within the optimization procedure. More specifically, the mechanism for the reduction of the excessive reserve capacity has been modified to consider the LOLP constraint. Moreover, two mechanisms has been developed to repair the individuals which violate the EENS and the LOLP constraints, respectively. Both mechanisms make use of domain specific knowledge and thus they may also guide the search towards adequate generating schedules. Compared to the previous method proposed to optimize the problem the inclusion of heuristic mechanisms mitigates the need of using (and setting) penalty parameters to deal with violations of the reliability constraints.

5.3 Mathematical model of the problem

In this Section, the mathematical formulation of the RCSTGS problem is described. It resembles the formulation of the conventional STGS. However, the conventional spinning reserve constraints are replaced by the reliability constraints. Although the equations describing the objective and the majority of the constraints of this model have been analyzed in Chapter 4, for the sake of completeness the equations will be provided also in this Chapter. The objective function of the model is the system's Total Operation Cost, while the constraints are related to the power balance, the minimum up/down time of the thermal generators, the ramping capabilities of the units, the generation limits of the committed generators and the reliability of the system. Thus, the problem is formulated as follows:

Objective function

$$f_1 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} [FC_i(P_i^t) \cdot ST_i^t + SUC_i \cdot ST_i^t \cdot (1 - ST_i^{t-1}) + SDC_i \cdot (1 - ST_i^t) \cdot ST_i^{t-1}] \quad (5.1)$$

The minimization of the objective function is subject to the following constraints:

Power balance constraints

$$\sum_{i=1}^{NTG} ST_i^t \cdot P_i^t = P_d^t, \quad t \in [1, T_{max}] \quad (5.2)$$

Minimum up time constraints

$$(Ton_i^{t-1} - MUT_i) \cdot (ST_i^{t-1} - ST_i^t) \geq 0, \ \forall\, i, t \quad (5.3)$$

Minimum down time constraints

$$(Toff_i^{t-1} - MDT_i) \cdot (ST_i^t - ST_i^{t-1}) \geq 0, \ \forall\, i, t \quad (5.4)$$

Ramp Rate constraints

$$P_i^t - P_i^{t-1} \leq ST_i^{t-1} \cdot RU_i + (1 - ST_i^{t-1}) \cdot Pmax_i \quad for\ i = 1, ..., N,\ t = 1, ...T \quad (5.5)$$

$$P_i^{t-1} - P_i^t \leq ST_i^t \cdot RD_i + (1 - ST_i^t) \cdot Pmax_i \quad for\ i = 1, ..., N,\ t = 1, ...T \quad (5.6)$$

Generation limits of thermal generators

$$ST_i^t \cdot Pmin_i \leq P_i^t \leq ST_i^t \cdot Pmax_i, \ \forall\, i, t \quad (5.7)$$

Reliability Constraints The hourly Spinning Reserve of the system is equal to the amount of committed capacity exceeding the expected load demand:

$$SR^t = \sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i - P_d^t, \ \ t \in [1, T] \tag{5.8}$$

In the RCSTGS, the hourly Spinning Reserve requirements for the system's reliable operation are assessed implicitly, during optimization. Two reliability indices are evaluated, i.e. $LOLP$ and $EENS$. The former expresses the probability that the available generation would not satisfy the load, while $EENS$ represents the expected amount of energy that will not be supplied by the generating system due to the loss of load. The unreliability of generating units and the load forecast uncertainty are explicitly considered during the calculation of LOLP and EENS indices. For each generating schedule, the corresponding LOLP and EENS values are compared to the given maximum acceptable levels [229]:

$$LOLP^t \leq LOLP^{max}, \quad t \in [1, T] \tag{5.9}$$

$$EENS_{tot} \leq EENS^{max} \tag{5.10}$$

where $LOLP^{max}$ is the maximum limit of hourly LOLP, while $EENS^{max}$ is the upper bound of the value of $EENS$ over the entire scheduling period. These designated limits are set by management, based on the desired level of system's reliability [226]. In case, the limits are not satisfied, additional units may be committed to reduce the values of the reliability indices. Consequently, the required Spinning Reserve is implicitly assessed to provide the desired level of reliability.

5.4 Calculation of the reliability indices

The basic modeling approach for the reliability assessment consists of three parts as shown in the Figure 5.1. The generation and load models are convolved to form an appropriate risk model which can be used to calculate the risk of generation capacity to be less than the load. Thus, the reliability evaluation consists of the following steps: 1) create a generation capacity model, 2) create a load model, 3) combine the generation capacity model and the load model to determine the risk model and 4) calculate the reliability indices.

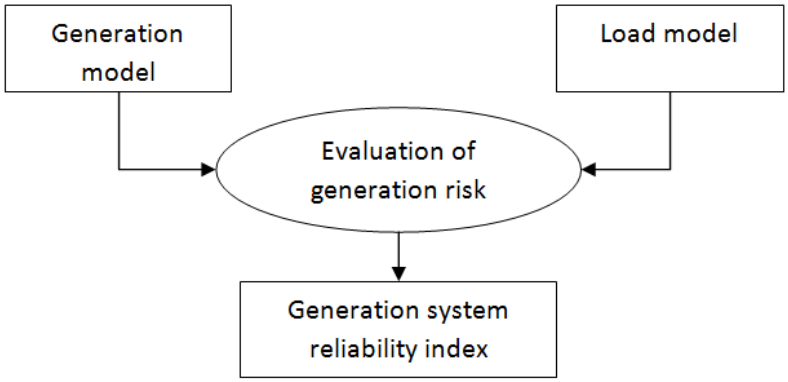


Figure 5.1: Process for the reliability evaluation of generation systems

To evaluate the reliability indices, analytical techniques or Monte Carlo simulation may be used [236]. The analytical techniques represent the power system by analytical models and evaluate the indices from these models using mathematical solutions. On the contrary, Monte Carlo Simulations may simulate the random behavior of the system, by treating the problem as a series of random experiments. The obtained value of the reliability indices indicates the ability of the generating system to satisfy the demanded load. In this dissertation we will focus on the use of analytical methods to calculate the reliability indices, while Monte Carlo simulation may be used in a future extension of our research.

In the analytical method commonly the load model is either the daily peak load or the hourly load [236]. The generation capacity model is the Capacity Outage Probability Table (COPT). The reliability indices can be calculated by convolving the COPT with the hourly chronological load curve of the scheduling period. A COPT is formed for each single scheduling period based on the combination of committed units. Given the list of committed units at each hour, the COPT is created by calculating the probability of losing different levels of generating capacity due to different combinations of generating units being on outage. The procedure for calculating the COPT is described in the following subsections.

5.4.1 Modelling the unavailability of generating units

A basic parameter used in reliability evaluation is the unavailability of a unit, i.e. the probability that the unit will be unavailable to produce power, at some time in the future. To calculate this probability, the simple two-state model is considered in this dissertation to describe the operation of a generating unit [222], as shown in Figure 5.2. According to this model, a generating unit has two possible states, i.e. it may be available to produce its nominal capacity or it may be on (unscheduled) outage, thus unavailable to produce energy. In Fig. 5.2, EFR is the Expected Failure Rate of a unit, while ERR is the expected repair rate. The former is the reciprocal of the mean time to failure of a unit, while the latter is the reciprocal of the mean time to repair.

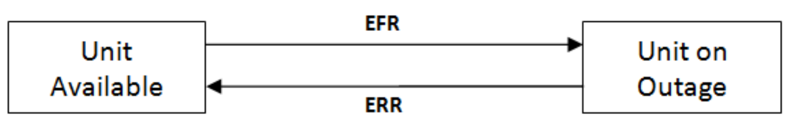


Figure 5.2: The two state model of generating units

Based on this model the probability that generating unit i will be on outage (known also as Forced Outage Rate – FOR) during a short-time interval LT is given by the following formula [222]:

$$FOR_i = \frac{EFR_i}{EFR_i + ERR_i} \cdot [1 - exp(-(EFR_i + ERR_i) \cdot LT)] \tag{5.11}$$

For short-term generation scheduling studies, commonly the time interval LT for which the unit cannot be replaced is considered to be significantly smaller than the mean repair time of a generating unit. In such a case, the repair process can be neglected, i.e. the $ERR_i = 0$. In that case the unavailability of the units is also known as Outage Replacement Rate (ORR) and is calculated as follows:

$$ORR_i = 1 - exp(-EFR_i \cdot LT) \tag{5.12}$$

ORR represents the probability that a unit fails and is not replaced during the short-time interval LT. It should be noted that in order to use the exponentially distributed formula, it is assumed that the failure rate of a unit is constant.

5.4.2 Assembling the COPT

As stated earlier, to calculate the LOLP and EENS indices, the COPT is required. The COPT is formed for each single scheduling period based on the combination of committed units and their corresponding ORR. Given the list of committed units at each hour, each row r of COPT, where $r = 1, ..., Nrows$, contains scenarios of unit outages, the corresponding capacity on outage (C_r^{out}) and in service (C_r^{in}) and the probability of occurrence of these outage level (PR_r), as shown in Fig. 5.3.

$$COPT = \begin{bmatrix} CR_1^{in} & CR_1^{out} & PR_1 \\ \vdots & \vdots & \vdots \\ CR_r^{in} & CR_r^{out} & PR_r \\ \vdots & \vdots & \vdots \\ CR_{Nrows}^{in} & CR_{Nrows}^{out} & PR_{Nrows} \end{bmatrix}$$

Figure 5.3: The Capacity Outage Probability Table

The cumulative probability, i.e. the probability that the capacity on outage is equal to or less than the indicated amount of row r, may also be considered. The capacity that remains in service is given by subtracting the capacity on outage of each row from the total committed capacity at the examined hour.

To assemble the COPT table a recursive algorithm proposed in [222] is used. This algorithm can be utilized using either the individual probabilities (PR_r) of each level or the cumulative probabilities. In this dissertation the former has been used. For a more detailed explanation of the recursive algorithm the reader is kindly referred to [222]. To calculate the probability $PR(C_r^{out})$ that a level of outage C_r^{out} will have, the following formula is iteratively applied for each committed thermal generator:

$$PR(C_r^{out}) = (1 - ORR) \cdot PR'(C_r^{out}) + ORR \cdot PR'(C_r^{out} - Pmax) \tag{5.13}$$

where $Pmax$ and ORR are the capacity and the unavailability of the generator, respectively. Moreover, $PR'(C_r^{out})$ and $PR'(C_r^{out} - Pmax)$ are the individual probabilities that outage levels C_r^{out} and $C_r^{out} - Pmax$ have in the previous step of the procedure, before adding the generator with capacity $Pmax$. It should be noted that, when $C_r^{out} - Pmax < 0$ then $PR'(C_r^{out} - Pmax) = 0$. Moreover, for the case of the first unit of the power system added in the COPT, we have $PR(0) = 1 - ORR_1$ and $PR(Pmax) = ORR$.

5.4.3 Evaluation of LOLP and EENS

As analysed previously, the COPT table, which is assembled for each hour t of the scheduling period based on the list of committed units, contains Nrows. Each row represents a different level of capacity on outage, the capacity that remains in service and the probability of occurrence of the level of capacity on outage. Thereafter, to evaluate the LOLP index, the COPT table is convolved with the load curve as follows [229]:

$$LOLP^t = \sum_{r=1}^{Nrows} (PR_r \cdot LOSS_r), \quad t \in [1, T] \tag{5.14}$$

where $LOSS$ defines the rows of COPT, in which loss of load occurs:

$$LOSS_r \begin{cases} 1, & if \;\; C_r^{in} < P_d^t \\ 0, & otherwise \end{cases} \tag{5.15}$$

Then, the hourly EENS is calculated as follows [222, 229]:

$$EENS^t = \sum_{r=1}^{Nrows} PR_r \cdot LOSS_r \cdot (P_d^t - C_r^{in}), \quad t \in [1, T] \tag{5.16}$$

and $EENS_{tot}$ is the sum of $EENS^t$ over the scheduling horizon:

$$EENS_{tot} = \sum_{t=1}^{T_{max}} EENS^t \tag{5.17}$$

Comment on the assembling of the COPT

The COPT is created using the recursive algorithm presented in [222]. Assembling the COPT is a computationally intense procedure, since all scenarios of possible unit outages are considered. A saving in execution time can be obtained by truncating the outage levels, whose cumulative probability is less than a predefined limit, e.g. 10^{-8} [229], [226]. However, since an EA is employed, a large number of commitment patterns are examined at each generation, increasing considerably the computational burden. In this study, the algorithm's execution time is significantly reduced by utilizing an external archive to store the COPT of each commitment pattern processed during optimization. When identical commitment patterns are encountered in subsequent generations the corresponding COPT is attained from the archive, thus reducing repeated evaluations. The entries of the archive increase in each generation based on the distinct patterns examined. To avoid extensive RAM memory requirements, the archive is reinitialized after reaching a predefined number of entries. While the EA converges and hence less distinct commitment patterns are examined, the external archive consists only relevant COPT matrices. It should be noted that such an approach enables the use of the EA to optimize the problem, otherwise the computational time required would be impractical.

5.4.4 Modelling the load forecast uncertainty

The solution of the STGS largely depends on the value of the expected load for each hour of the scheduling period. Thus, taking into account the inherent uncertainty in load forecasting may affect the scheduling of the thermal generators. In particular, when the forecasted demand is lower compared to the actual value of the load, then the committed capacity which serves as Spinning Reserve may be insufficient to meet the Spinning Reserve requirements of the system. In that case the probability that the committed capacity will not meet the demand if a generator is on outage increases. On the contrary, when the forecasted load exceeds the actual demand then excessive committed capacity may occur and serve as Spinning Reserve. This may increase the system's operating cost since more units will operate on sub-optimal power output levels and unnecessary start-up of generators may be implemented. Thus, the uncertainty in load forecasting should be taken into consideration during the optimization of the problem, since it may affect the results of the method increasing their accuracy.

In this dissertation, following the relevant literature (e.g. [229], [226], [224]), it is assumed that the load forecast uncertainty is adequately approximated by a normal distribution. For each hour, the mean value of the distribution is the expected load (P_d^t), while the standard deviation $\sigma_{P_d}^t$ is commonly expressed as a percentage of the expected load:

$$\sigma_{P_d}^t = s \cdot P_d^t \tag{5.18}$$

The distribution is divided into discrete intervals, the area of which represents the probability the load to be equal to the interval's mid-point [222]. Commonly, a seven step distribution model $(0, \pm\sigma, \pm 2 \cdot \sigma, \pm 3\sigma)$ as presented in Fig 5.4 is used, since it encompasses the 99% of the load uncertainty distribution [226].

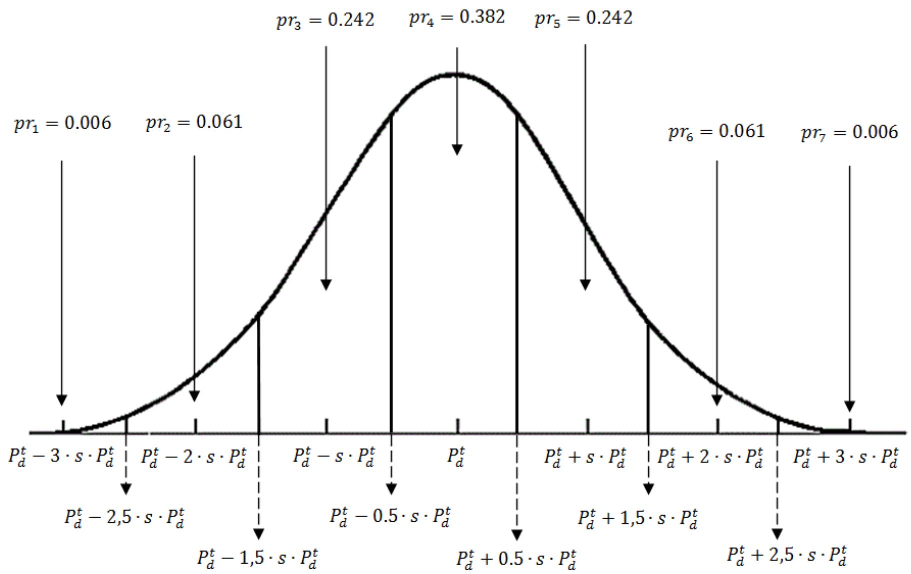


Figure 5.4: Modelling demand uncertainty using a Gaussian Distribution

Thus load forecast uncertainty is taken into consideration by successive convolution of the COPT with the probability distribution function of the demand. Specifically, for each load step m, where $m = 1, ..., 7$, $LOLP_m^t$ and $EENS_m^t$ are calculated based on the corresponding load of the interval at hour t, i.e.:

$$P_d^t(m) = P_d^t + (m-4) \cdot \sigma_{P_d}^t, \forall t \in [1, t], \tag{5.19}$$

The final risk indices are the sum of the products of $LOLP_m^t$ and $EENS_m^t$ with the corresponding interval's probability, $pr(m)$:

$$LOLP^t = \sum_{m=1}^{7} LOLP_m^t \cdot Pr(m), \quad t \in [1, T] \tag{5.20}$$

$$EENS^t = \sum_{m=1}^{7} EENS_m^t \cdot Pr(m), \quad t \in [1, T] \tag{5.21}$$

5.5 Proposed approach to solve the problem

The proposed approach to solve the RCSTGS is based on the FROFI algorithm, the two step function, the EM and the procedure to create a Plurality of Priority Orders. It should be noted that in the DE variant used to optimize the RCSTGS, the DE/current-to-rand/1 scheme has been replaced by the simple DE/rand/1 scheme, in an attempt to further increase the diversity of the population during the different stages of the evolution. A series of new heuristic repair mechanisms are included to deal with the problem when the reliability constraints are considered. The overall procedure is shown in Figure 5.5, where it can be seen that each individual undergoes a series of heuristic repair mechanisms. In case the individual is not fully repaired the constraint handling procedures included in FROFI are utilized. Since the representation of solution vectors, the procedure for the creation of the Plurality of Priority List and the Elitist Mutation scheme have been analytically presented in Chapter 4, they will not be discussed in this Chapter. For this reason, in the following subsections the mechanisms proposed to handle the problem's constraint will be described.

5.5.1 Handling of constraints

In the literature, the methods based on EAs that are applied on the RCSTGS, commonly deal with the violation of the constraints using the penalty function method. However, such a method requires the adequate tuning of the penalty parameters even if dynamic schemes are utilized; the latter increase the value of the penalty taking into account the stage of the optimization procedure. As discussed in the previous Chapter the utilization of heuristic repair procedures may facilitate the optimization of the STGS. For this reason, a series of heuristics have been utilized in the proposed solution methodology and will be described in what follows. The primary unit commitment and the mechanism for the reduction of the excess committed capacity are based on the heuristics described in the previous Chapter, however they have been modified to consider the reliability constraints in their procedure. Moreover, two novel mechanisms have been proposed in this dissertation to repair

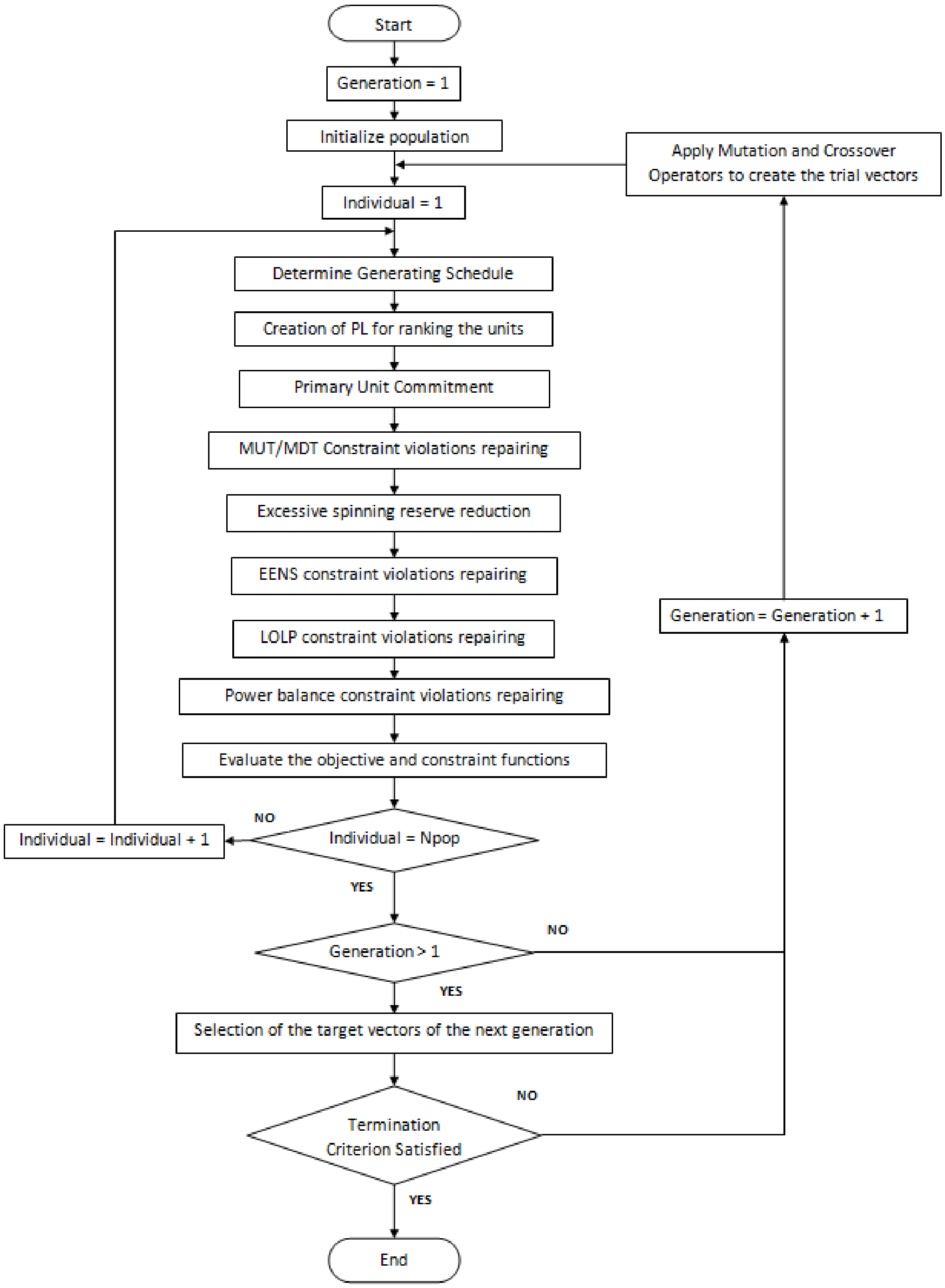


Figure 5.5: Flowchart of the procedure for the optimization of the reliability constrained short term generation scheduling problem

violations of the reliability constraints taking into consideration domain specific knowledge in the form of the Priority List of the generators.

Primary unit commitment to satisfy the expected load

The committed capacity at each hour of the planning horizon should be sufficient to provide the demanded load. Otherwise, uncommitted units having higher priority are committed until the on-line capacity becomes at least equal to the load. For each individual at each generation, this mechanism proceeds as described in Algorithm 12.

Algorithm 12 Primary Unit Commitment to satisfy load

$pos \leftarrow 1$
while $\sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i - P_d^t < 0$ **do**
  if $ST^t_{PL_n^g(pos)} = 0$ **then**
    $P^t_{PL_n^g(pos)} \leftarrow Pmin^t_{PL_n^g(pos)}$
    $ST^t_{PL_n^g(pos)} \leftarrow 1$
  end if
  $pos \leftarrow pos + 1$
end while

During the repair mechanism, when the state of a unit is changed from 'off' to 'on', the corresponding floating point variable is set equal to the unit's minimum generation limit ($Pmin_i$).

Handling of MUT/MDT constraints

MUT/MDT constraint violations are repaired using the procedure described in the previous Chapter. Briefly, this procedure detects hours, where the MUT constraint of a unit is violated. Subsequently, the unit is committed for the hours following this period until the MUT constraint is satisfied. Similarly, in case an uncommitted unit remains off-line for less periods than its MDT, then the unit is brought on-line at these periods.

Reduction of excessive committed capacity

After primary unit commitment and MUT/MDT constraints repairing, the algorithm proceeds with the calculation of the value of the reliability indices as described in subsection 5.4. However, excessive reserve capacity may exist at some hours of the scheduling period. As stated earlier, excessive reserve capacity may trigger an increase in the system's total operation cost. It should be noted that since in the RCSTGS problem we do not consider a lower limit of required reserve capacity, in this case a value of $LOLP^t$ which is significantly lower than the designated limit of LOLP may indicate that hours with excessive reserve capacity exist. This excessive Spinning Reserve should be reduced, without though neglecting the reliability of the system. For this reason the mechanism described in the Flowchart of Fig. 5.6 is applied. The proposed mechanism decreases the excessive reserve as long as the MUT/MDT constraints and the hourly LOLP constraints are not violated. In the flowchart of Fig. 5.6, the index $PL_n^g(pos)$ denotes the unit ranked in the pos position of the PL assigned to individual n at generation g. Moreover, when the state of a unit changes from 'on' to 'off' during the procedure, the corresponding variable is randomly reinitialized below the unit's minimum generation limit. It is noted that during hours, for which the hourly LOLP is below the desired level, no units are shut down.

EENS constraint repairing

$EENS$ constraint considers the total expected loss of energy over the planning horizon. Solution vectors violating constraint (5.10) undergo the procedure described in Fig. 5.7. Specifically, to reduce $EENS_{tot}$, the algorithm detects the hour for which $EENS^t$ is maximum and commits the off-line unit with the highest priority at that hour. The procedure is repeated until $EENS_{tot}$ of the generating schedule reaches the required limit.

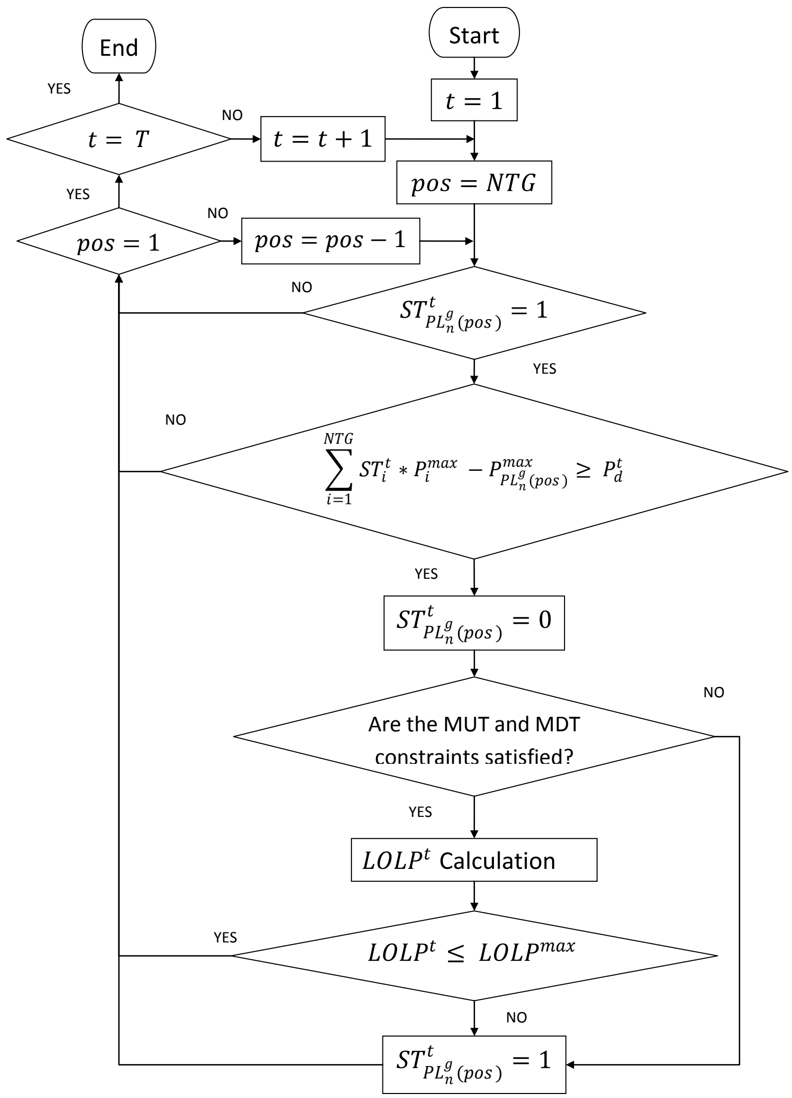


Figure 5.6: Flowchart of the mechanism for reducing excessive reserve capacity

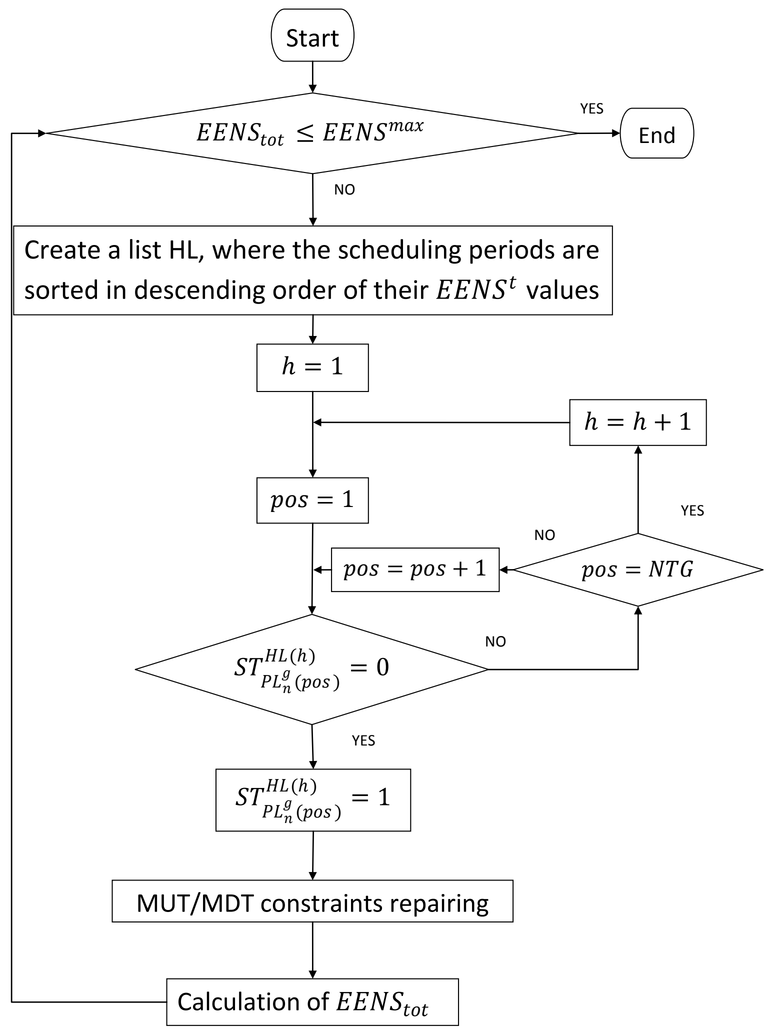


Figure 5.7: Flowchart of the mechanism for repairing violations of the EENS constraint

LOLP constraint repairing

Constraints 5.9 are imposed on every hour of the planning horizon. Thus, even though the EENS constraint is satisfied over the scheduling period, in some hours $LOLP^t$ may exceed the acceptable level. In such cases, the uncommitted units ranked higher in the PL_n^g are committed until the required level ($LOLP^{max}$) is achieved, taking into account and repairing possible violations of the MUT/MDT constraints, as shown in Fig. 5.8.

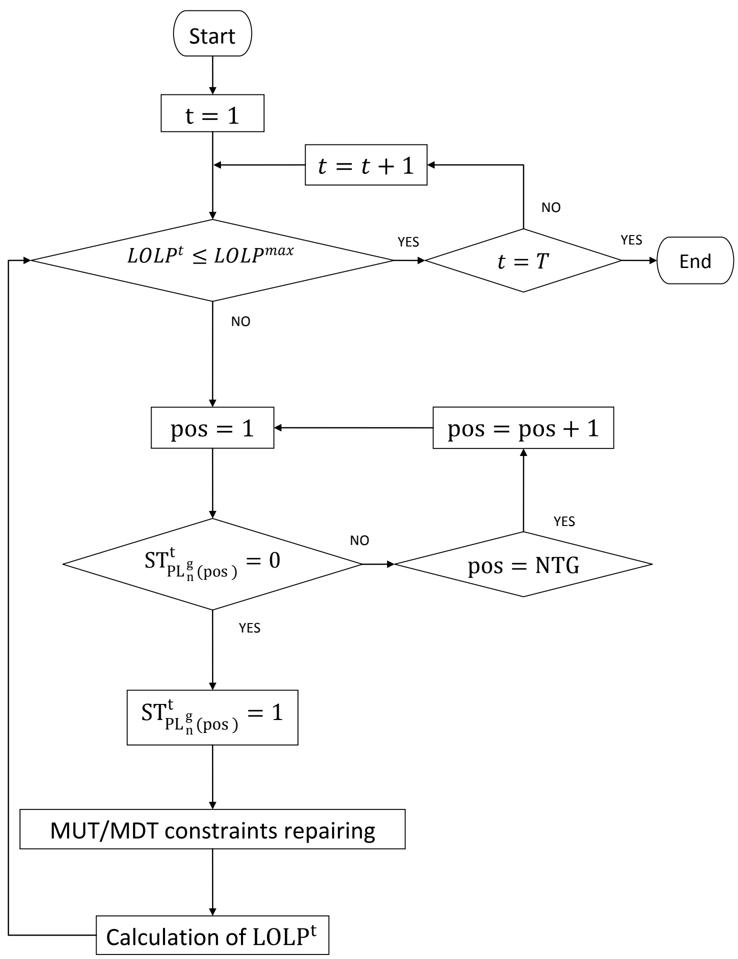


Figure 5.8: Flowchart of the mechanism for repairing violations of the LOLP constraints

Repairing power balance constraints

After implementing the previous mechanisms, some individuals may violate the power balance constraints. Power Balance constraint violations are repaired utilizing Algorithm 11 described in Chapter 4. According to this mechanism, when the hourly generated energy is less than the corresponding load, the power output of the committed units ranked higher in the PL_n^g is increased up to their maximum generation limits, until the total generated power equals the load demand. In contrast, when the generated power is in excess, the units having the lowest rank in the PL are considered, taking one unit at a time and decreasing their power output up to their minimum generation limit, until the power balance constraint is satisfied. It is noted that in this case, the power output of the generators was not modified stochastically (i.e. $rand$ is set equal to 1 in Eq. 4.19 and 4.20), since in the initial implementations of the algorithm on the RCSTGS problem the performance of the method was slightly improved when the power output was deterministically modified.

5.6 Results of the computational experiments

The proposed method is tested on a test system, comprising 26 thermal units for a scheduling period of 24 hours. The data of the operating units are obtained from [210], while the load demand and the units failure rates from [229]. The technical characteristics of the generators of the system are given in Table A.6, while the load demand is given in Table A.8. The performance evaluation comprises the following case studies:

1. The impact of the unavailability of the units on the final operating schedule is assessed
2. The impact of load forecasting uncertainty on the final operating schedule is demonstrated.
3. The applicability of the method on system's of larger size is examined.

It should be noted that in all the assessment procedures the following two combinations of reliability indices upper limits [229] are examined in an attempt to assess the impact of different reliability indices values on the performance of the method and on the examined results:

- Combination 1: $EENS^{max} = 0.01\%$ of the total expected demand and $LOLP^{max} = 1\%$.
- Combination 2: $EENS^{max} = 0.05\%$ of the total expected demand and $LOLP^{max} = 1.5\%$.

Moreover, in each case study the results of the method are compared to the ones obtained by the algorithm in [229]. Regarding the examination of the method on system's of larger size (case study 3), to the author's knowledge this is the first attempt to optimize the RCUCP for such systems. It should be also noted that similarly to [229] the ramp rates have not been considered in the case studies. For this reason, the part of the heuristic related to the ramp rates has not been considered in this chapter of the dissertation. For each case examined 10 independent runs of the algorithm have been implemented. The number of the runs has been set to 10 since the method in [229] is also implemented for a series of 10 runs. In each run, $Npop$ is set equal to 40. The maximum number of generations is selected as the algorithm's termination criterion and is set equal to 300.

5.6.1 Assessing the impact of the units unavailability

The impact of unit's unavailability on the TOC and on the required Spinning Reserve is examined, by varying LT in the range of 2 to 8 hours for both combinations. The load forecast uncertainty has not been considered in this case study, i.e. $s = 0\%$.

First in Table 5.1, we examine the impact of the introduction of the Plurality of Priority Lists and the Elitist Mutation Strategy, within the proposed approach. In particular, we apply the method including both the PPL and the EM and compare the results with the case where the EM is not used while the PL within the heuristic repair procedure is based on the Average Cost (AVC) of the units at Pmax. As can be seen in Table 5.1, the introduction of the PPL and EM may not have a significant impact on the results of the proposed method for the examined case. This might be justified by analyzing the characteristics of the generators of the system under examination. In particular, in the examined system [2], the Average Production Cost curves of the generators with respect to the units loading have very few intersection points. These are presented in Fig. 5.9, where the Average Cost curves with respect to the units loading are given for 6 generators. The Average Cost curves of these generators are the only curves that intersect in the examined system. The last intersection point is between the curves of units 16 and 21, for unit's loading $= 0.6\%$. For the rest of the interval ($= 99.4\%$) of the units loading the priority order of generators is the same to the one created when the AVC at Pmax is used as the metric. Thus, for the vast majority of the individuals undergoing the repair heuristics, the priority order would remain the same regardless of the loading point selected to calculate the Average Costs of the units, resembling the case where a PL at Pmax is used. Thus, in this case the use of the PPL is similar to using a single PL based on the AVC of the units at their maximum power output. Moreover, regarding the EM, the results have demonstrated that the introduction of the heuristic repair procedures facilitates the obtainment of adequate generating schedules (as seen by the case where the EM is not included) within a small number of generations rendering the optimization of this problem easier. Moreover, since the ramp rate constraints have not been included in this case (since the method with which the proposed approach is benchmarked does not consider them) the heuristic repair procedures may fully repair infeasible individuals. As a result the impact of the EM might be less significant in the examined case. Since EM and the PPL do not significantly affect the results of the method for the examined test case, in what follows the results presented have been derived by the DE-based method in which the EM and the PPL have not been considered. These results have been presented in the paper [237]. In the dissertation, we also include the results for Combination 2 to demonstrate the efficient performance of the proposed method in two different sets of examined reliability indices.

In Table 5.1, the results of the proposed method are also compared to the results of the method in [229] for the two sets of different reliability values limits examined. As may be observed, the

[2]The system of 26 units is examined in the vast majority of the studies, which consider the reliability of the system

Combination 1: $LOLP^{max} = 1\%$ - $EENS^{max} = 0.01\%$									
	Proposed approach with PPL and EM			Proposed approach without PPL and EM			Approach of [229]		
	LT=2	LT=4	LT=8	LT=2	LT=4	LT=8	LT=2	LT=4	LT=8
Min. TOC ($)	715575	718072	722223	715620	718078	722149	716083	718574	723300
Avg. TOC ($)	715665	718216	722354	715661	718164	722328	716831	718714	723699
Max. TOC ($)	715700	718274	722616	715699	718244	722607	717965	718827	724253
Avg. Time (s)	39.38	82.73	116.85	37.66	64.09	96.28	135.43	105.71	74.11
Combination 2: $LOLP^{max} = 1.5\%$ - $EENS^{max} = 0.05\%$									
	Proposed approach with PPL and EM			Proposed approach without PPL and EM			Approach of [229]		
	LT=2	LT=4	LT=8	LT=2	LT=4	LT=8	LT=2	LT=4	LT=8
Min. TOC ($)	709009	711773	720263	708873	711842	720150	708791	712067	720718
Avg. TOC ($)	709275	712596	720383	709207	712607	720375	709068	712704	720821
Max TOC ($)	709485	712816	720438	709366	712803	720468	709421	713473	720966
Avg. Time (s)	37.88	70.37	115.25	36.41	47.96	100.63	101.18	98.90	73.20

Table 5.1: Results of the proposed methods with and without the PPL and the EM mechanisms for several LT values

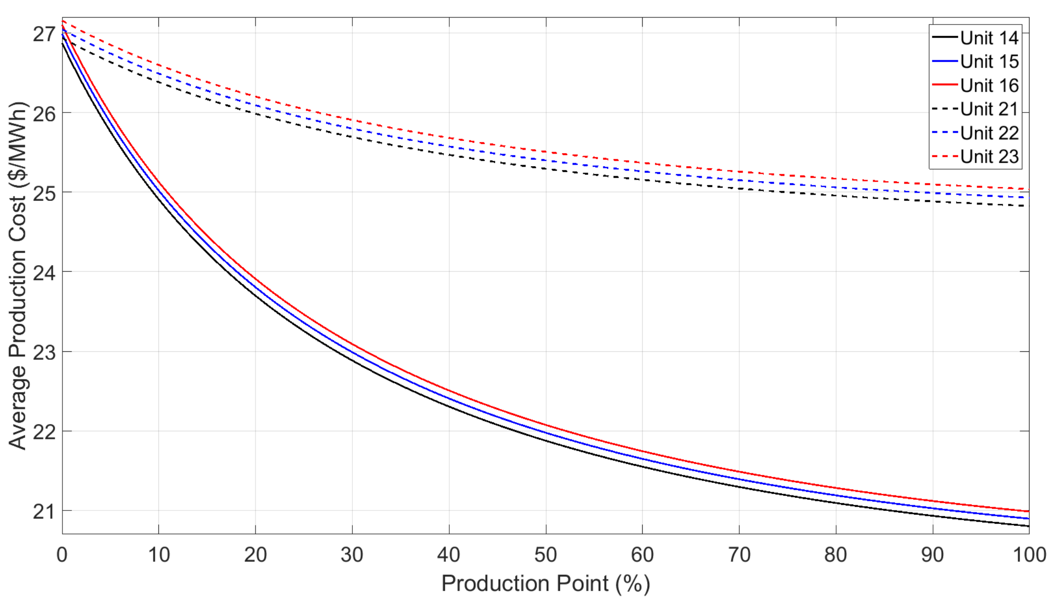


Figure 5.9: Average production cost curves with respect to the units' loading for six units of the system of 26 units

proposed method has managed to obtain generating schedules which demonstrate lower TOC in the vast majority of the examined cases. Specifically, for the case of $LT = 2$ the proposed approach has obtained solution distribution, which exhibit lower minimum, average and maximum cost values compared to the competing algorithms, in Combination 1. On the contrary, when $LT = 2$ in Combination 2 the SA–based approach of [229] has provided solution distributions exhibiting lower minimum and average TOC values compared to the proposed algorithm. When $LT = 4$, the proposed approach manages to achieve solution distributions, which demonstrate significantly lower values of the minimum, average and maximum operation cost, in both combinations of reliability indices values examined. In particular, regarding the average production cost of the obtained solution distributions, the proposed method achieves cost reductions of 0.014% (96.60$) and 0.076% (549.42$) for Combination 1 and 2, respectively. Similarly, for the case of $LT = 8$, the proposed approach demonstrates a better performance compared to the approach of [229]; the minimum, average and maximum operation cost of the solution distributions achieved by the proposed method, are lower compared to the corresponding values of the solution distributions obtained by the SA approach for both Combinations. Regarding the computational time, the proposed method exhibits lower computational time compared to the SA approach for both Combinations when LT = 2 and 4, and higher when LT = 8. The increase in the computational time of the proposed method while the LT value increases may be primarily attributed to the larger number of COPT calculations within the LOLP and EENS repairing mechanisms. Specifically, larger LT increases the units unavailability and as a result a larger Spinning Reserve (and thus more units) is required to satisfy the required reliability. Consequently, the iterations of the LOLP and EENS repair mechanisms are increasing with increased LT, which triggers more COPT calculations and thus the increase in the computational time. It should be noted, that since the configuration of the personal computers used in each case is not the same, a direct comparison of the computational times of the proposed method to the method of [229] may not be fair. However, the computational time may still provide a means to represent the computational burden entailed by each method.

It is noted that when higher LT values are considered, the total operation cost of the system is higher in both Combinations examined as shown in Table 5.1. This was expected since higher LT values increase the unavailability of the generators (as shown in Eq. 5.12) and thus an increased amount of Spinning Reserve is scheduled to obtain generating schedules which satisfy the reliability constraints. The amount of Spinning Reserve for the different LT values for both Combinations are presented in Figure 5.10, confirming the above. Moreover, in Fig. 5.11 the hourly LOLP of the best generating schedules for different LT values for Combinations 1 and 2, respectively, are presented. As shown, the generating schedules satisfy the designated LOLP constraints for both combinations of the reliability indices. The same holds for the EENS values as presented in Table 5.2, where it is shown that the percentage of the obtained EENS values is lower compared to the corresponding upper bounds. In Figure 5.12, the operating schedules of the best solutions found for the different LT values for Combination 1 are shown with bullet points. It can be seen there that when LT increases more units are committed to obtain generating schedules that satisfy the required level of reliability.

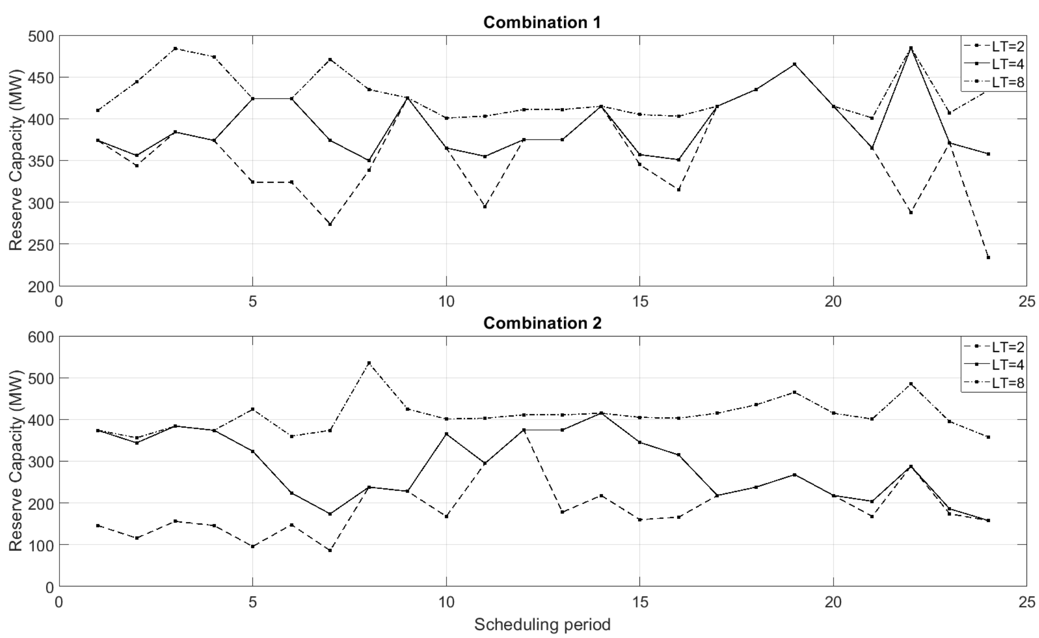


Figure 5.10: Reserve Capacity of the best solutions found for the different LT values of both examined Combinations of reliability indices upper limits

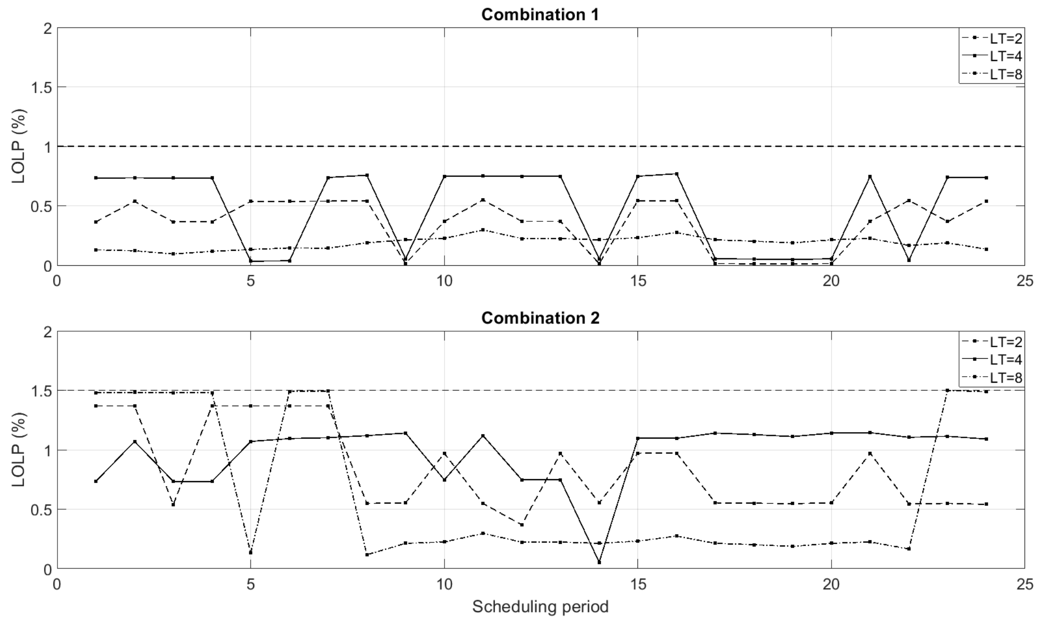


Figure 5.11: Hourly LOLP of the best solutions found for the different LT values of both examined Combinations

	Combination 1	Combination 2
LT = 2	0.009527%	0.049738%
LT = 4	0.009614%	0.049861%
LT = 8	0.009812%	0.041811%

Table 5.2: EENS (in $\%$ of the total load over the scheduling period) of the best solutions found for the different LT values of both examined Combinations

5.6.2 Assessing the impact of demand uncertainty

The standard deviation s of the load forecasting uncertainty is varied from 1% to 5% and the implications on the system's operation cost and the scheduled spinning reserve are examined. During this case study the value of LT is kept constant and equal to 4.

In Table 5.3 the results provided by the proposed algorithm are presented. Moreover, they are compared to the results of the SA in [229]. As observed, the proposed method obtains solutions of lower cost more consistently compared to the benchmark approach for the majority of the

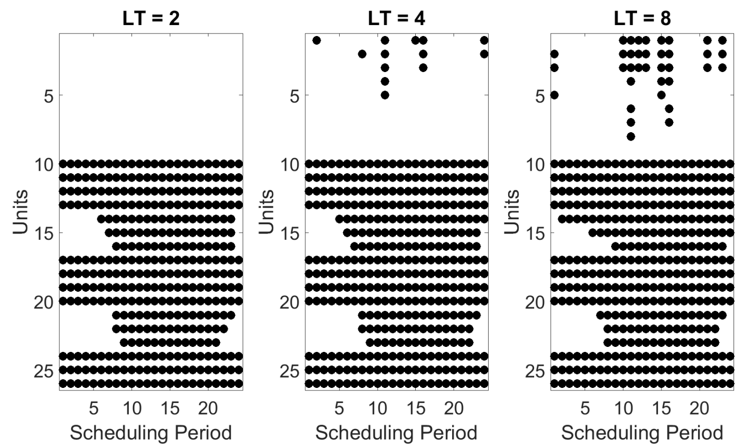


Figure 5.12: Operating schedules of the best solutions for different LT values for Combination 1

examined cases. In particular, when $s = 1\%$, the proposed method has achieved solution distribution with lower minimum, average and maximum TOC compared to the benchmark algorithm for Combination 1. This does not hold, however for Combination 2 ($s = 1\%$), where the SA-based approach has obtained solutions of lower cost compared to the proposed method. For the cases where $s = 3\%$ and $s = 5\%$, the proposed method has managed to obtain solution distributions of lower minimum, average and maximum cost for both Combinations of reliability indices values compared to the SA method of [229]. Thus, it may be indicated that the proposed approach may efficiently optimize the RCUCP, when the load forecast uncertainty is incorporated.

For the two combinations of reliability indices values, the scheduled reserve capacity at each hour of the scheduling period for the different values of s is presented in Figure 5.13. The results confirm, that as expected, an increase of the load forecast uncertainty may lead to increased scheduled reserve capacity in both combinations examined. This may be mainly attributed to the fact that while the uncertainty in load forecasting increases, more reserve capacity is required to guarantee that the system's risk is below the designated reliability indices values. However as seen in the results of Table 5.3, the elevated reserve capacity may trigger increases on the system's TOC, since more units will operate at suboptimal, with respect to their economic efficiency power output levels. While the load forecast uncertainty remains low, economical units will supply most of the

Combination 1: $LOLP^{max} = 1\%$ - $EENS^{max} = 0.01\%$								
	Proposed approach without PPL and EM				Approach of [229]			
	$s = 0\%$	$s = 1\%$	$s = 3\%$	$s = 5\%$	$s = 0\%$	$s = 1\%$	$s = 3\%$	$s = 5\%$
Min. TOC ($)	718078.66	718344.83	721318.66	728601.15	718574.00	718843.00	722544.00	730675.00
Avg. TOC ($)	718164.58	718471.70	721506.43	728660.42	718714.00	719071.00	722859.00	731027.00
Max. TOC ($)	718244.97	718651.50	721546.77	728715.87	718827.00	719334.00	723107.00	731448.00
Avg. Time (s)	64.09	73.75	90.19	137.19	105.71	173.07	172.65	150.21
Combination 2: $LOLP^{max} = 1.5\%$ - $EENS^{max} = 0.05\%$								
	Proposed approach without PPL and EM				Approach of [229]			
	$s = 0\%$	$s = 1\%$	$s = 3\%$	$s = 5\%$	$s = 0\%$	$s = 1\%$	$s = 3\%$	$s = 5\%$
Min. TOC ($)	711842.78	712626.46	713851.26	716664.97	712067.00	712216.00	713855.00	716862.00
Avg. TOC ($)	712607.40	712766.67	713895.45	716775.72	712704.00	712384.00	714119.00	717098.00
Max TOC ($)	712803.54	712809.44	713947.77	716805.67	713473.00	712638.00	714390.00	717318.00
Avg. Time (s)	47.96	59.96	59.45	72.43	98.90	145.28	162.01	146.22

Table 5.3: Results of the proposed method for different s values

load, operating close to their maximum capacity. However, as forecasting uncertainty increases, more expensive units are committed to ensure the required reliability. This is evident, for example in Fig 5.14, where the operating schedule which corresponds to the best solution found by the algorithm for the different values of s in Combination 1 is given.

In Fig. 5.15, the hourly LOLP values of the best solutions achieved by the proposed method for the different values of load forecasting uncertainty are given. It may be observed that the designated LOLP limit is satisfied for each hour of the scheduling period. Moreover, the overall EENS (as a percentage of the total demanded load) is lower compared to the required level, as shown in Table 5.4. Thus, the proposed mechanisms manage to adequately handle the reliability constraints and result into feasible generating schedules.

	Combination 1	Combination 2
s=1%	0.009882%	0.032060%
s=3%	0.009984%	0.047481%
s=5%	0.009996%	0.038373%

Table 5.4: EENS (in % of the total load over the scheduling period) of the best solutions found for the different s values

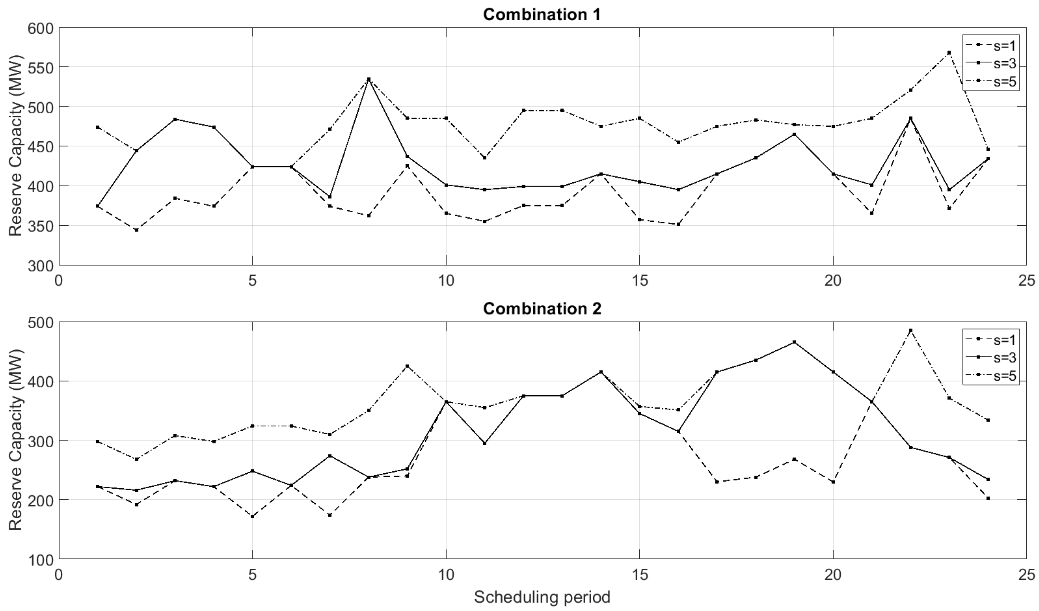


Figure 5.13: Scheduled Reserve of the best solutions found for the different s values

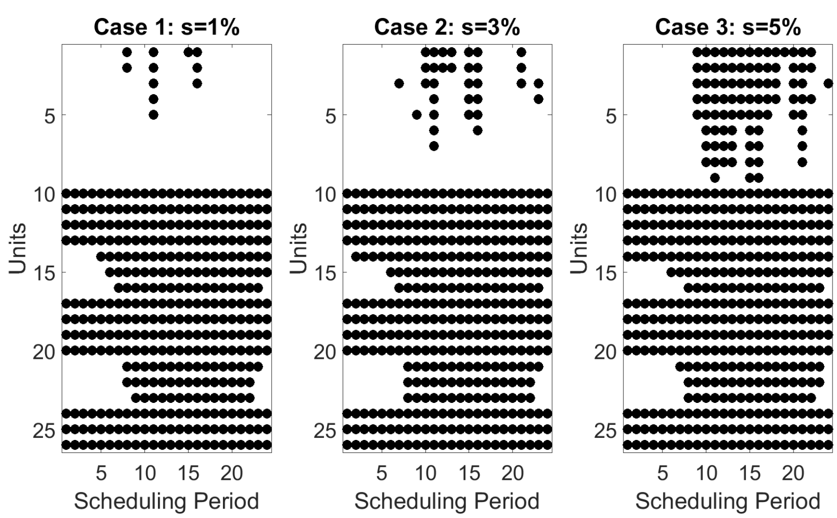


Figure 5.14: Operating schedules of the best solutions found for the different s values for Combination 1

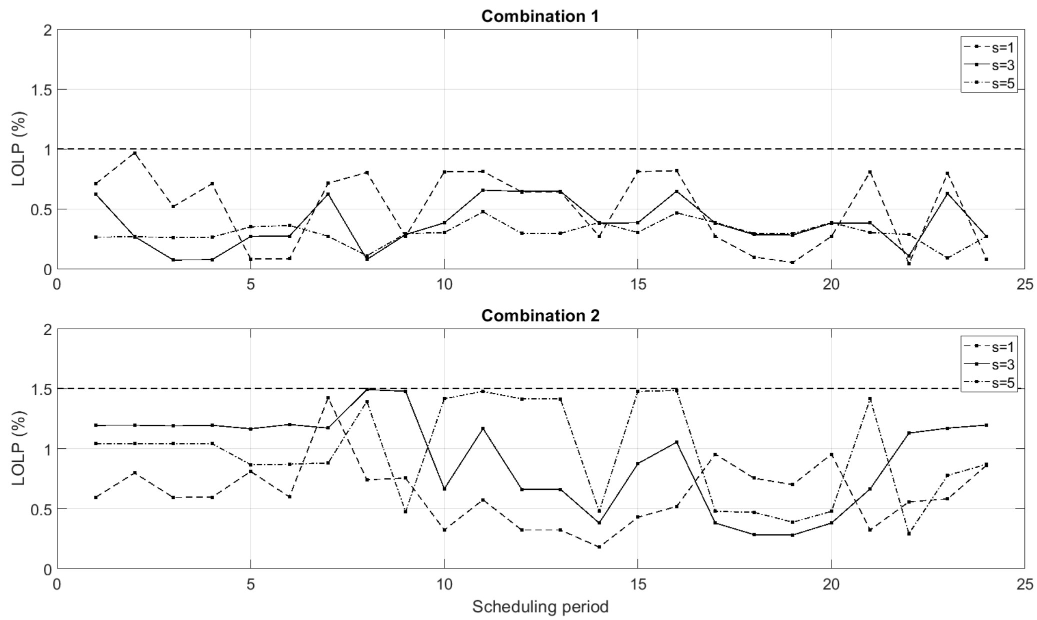


Figure 5.15: Hourly LOLP of the best solutions found for the different s values

5.6.3 Examining the efficiency of the method on system's of larger size

In this subsection, the applicability and efficiency of the method on system's comprising a larger number of units compared to the one examined in the previous subsections is validated. In particular, the basic system of 26 units is duplicated 2 and 3 times, to obtain systems of 52 and 78 units, respectively. The hourly load is scaled proportionally to the system's size, e.g. for the system of 52 units the load at each hour is multiplied by 2. In this subsection the load demand uncertainty is not considered, i.e. $s = 0$ while the LT is taken equal to 2 for each examined case.

In Table 5.6, the results of the method for the systems of different sizes are presented. In particular the minimum, average and maximum cost as well as the Coefficient of Variation (CV) of 10 runs for each examined system are presented. As shown, CV is low for all cases indicating that the method has performed robustly regardless of the system size. Moreover, the average computational time of the method is reasonable as shown in Table 5.6, due to the utilization of the external archive. It is highlighted, that the amount of commitment patterns processed during optimization increases significantly for systems of larger size. It is also noted, that to the author's

	Combination 1	Combination 2
NTG=26	0.009527%	0.049738%
NTG=52	0.003700%	0.032879%
NTG=78	0.000932%	0.003248%

Table 5.5: EENS (in % of the total load over the scheduling period) of the best solutions found for the different s values

knowledge, results for such instances have not been reported in the relevant literature.

Combination 1: $LOLP^{max} = 1\%$ - $EENS^{max} = 0.01\%$					
# of Units	Min. TOC ($)	Avg. TOC ($)	Max. TOC ($)	CV (%)	Av. Time (s)
26	715620	715661	715699	0.003	37.66
52	1418852	1419044	1419308	0.010	262.50
78	2123448	2123603	2123656	0.003	1307.25
Combination 2: $LOLP^{max} = 1.5\%$ - $EENS^{max} = 0.05\%$					
# of Units	Min. TOC ($)	Avg. TOC ($)	Max. TOC ($)	CV (%)	Av. Time (s)
26	708873	709207	709366	0.003	36.41
52	1413490	1413980	1414365	0.023	342.27
78	2121270	2121871	2122492	0.026	1243.32

Table 5.6: Computational results for different system sizes

The hourly LOLP values of the solutions of the minimum cost obtained for all the system sizes of both Combinations are shown in Fig. 5.16. As can be seen in the aforementioned Figure the LOLP constraints are satisfied for each hour of the scheduling period regardless the size of the system. The same holds also for the EENS constraints as shown in Table 5.5. This may indicate that the method may adequately handle the reliability constraints even for systems of larger size.

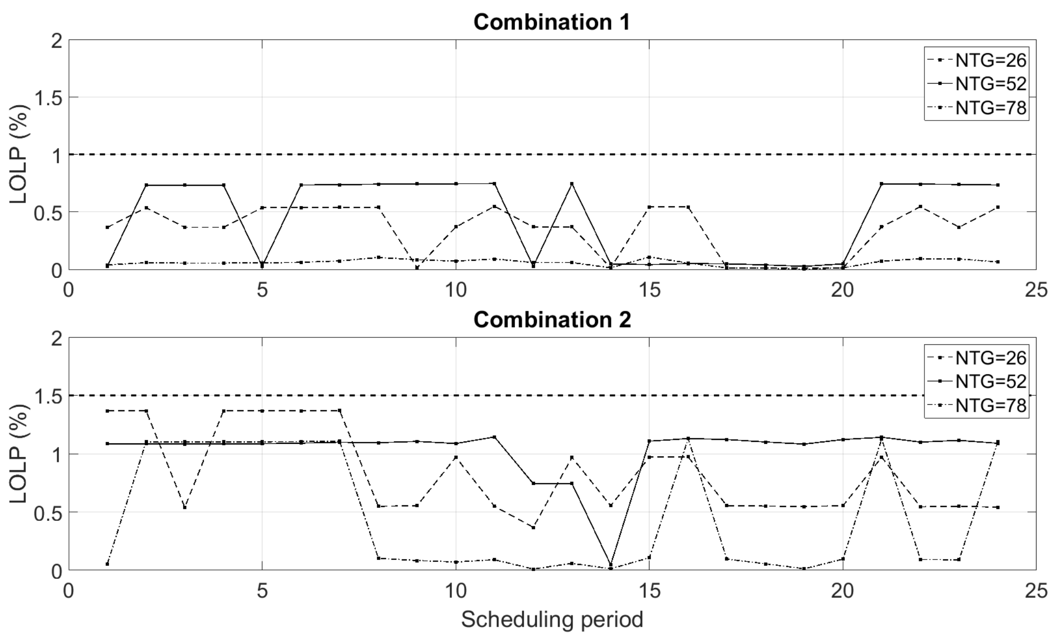


Figure 5.16: Hourly LOLP of the best solutions found for the different system sizes

CHAPTER 6

A HYBRID MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM FOR THE RELIABILITY CONSTRAINED WIND-HYDRO-THERMAL ENVIRONMENTAL/ECONOMIC GENERATION SCHEDULING

6.1 Introduction

In Chapters 4 and 5, the short-term generation scheduling problem has been examined in power systems comprising solely thermal generators, which utilize fossil fuels to produce electricity. However, other energy generating technologies are also available, which use less expensive and more environmental friendly sources of energy compared to fossil fuels. Two major examples of such sources, are the energy of falling or flowing water and the kinetic energy of wind. However, to adequately exploit the energy from those sources, higher level of management and coordination of the several generating technologies is required. In an attempt to assist decision making when other sources of energy are considered within a power system, in this Chapter, we develop a model for short-term generation scheduling which may be applied on power systems comprising thermal generators, hydro plants and wind energy.

Hydro power is derived from the potential energy of water stored in river basins which may be hydraulically coupled. Since this energy is finite, as it is directly related to the amount of water stored, the utilization of water should be adequately scheduled to increase the energy outcome. The scheduling of the hydro system, concerns the determination of the electricity production of each hydro plant, by handling the water flows through each water turbine as well as the levels of stored water within each reservoir. In power systems, comprising both hydro-plants and thermal generators, an adequate coordination should be established to efficiently meet the required demand. This is the context of the short-term hydro thermal coordination problem. In particular, the Short-term Hydro-Thermal Coordination Problem concerns the determination of the optimal operation strategy of hydro and thermal resources during a short period of time, i.e. one day up to one week. Commonly, the optimal operating state of thermal generators, as well as the generated power of the hydro and the thermal plants, are determined to efficiently meet the load demand, subject to a series of constraints [238]. When the production from hydro generators is considered, the difficulty in optimizing the problem may be increased, since additional constraints are included into the problem's formulation related to the limited energy capabilities of hydro reservoirs and the coupling nature of the reservoir constraints [239]. In general, the overall problem comprises three inter-related sub-problems [239, 240]: the Hydro-Thermal Coordination Problem (HTCP), the thermal Unit Commitment Problem (UCP) and the Economic Dispatch Problem (EDP). The latter two have been discussed in the previous chapters of this dissertation (Chapter 4), while the HTCP concerns the determination of the optimal amount of energy produced by the hydro system and the thermal system during the scheduling period [241].

More recently the increasing environmental awareness has gradually shifted the focus of generation scheduling models from purely economic approaches towards models considering the system's emissions within the mathematical formulation of the problem. Generally, base load units, which usually utilize cheaper fuel (thus have lower production cost), e.g. coal or lignite, tend to have increased emissions compared to intermediate and peak load units which may use more expensive fuels, e.g. natural gas, with lower emission factors. Consequently, attempts to minimize the amount of emissions may result in generating schedules that have increased operational cost, rendering the aforementioned two goals as conflicting, e.g. an improvement in one of them results in a degradation in the other. Therefore, not a single solution exists for this problem, rather than a set of solutions which are trade-offs among the operation cost and the emissions of the system for satisfying the demanded load. In the literature, several attempts have been proposed to tackle the problem as a single objective one, either using emissions within constraints, or by converting the emissions into monetary values by using some form of trading schemes, e.g. [242] and [243], and include them within the system's total operation cost. However, both the aforementioned approaches are not able to adequately provide the trade-offs between emissions and operating cost in a single run of the algorithm.

In recent years, the requirement for more sustainable power systems has promoted the deployment of Renewable Energy Sources (RES) [131]. Among them, wind power has been widely exploited to partly replace production from fossil fuel fired power plants and therefore reduce the amount of CO_2 emissions [244]. Wind power is characterized by a low operating cost, negligible emissions and may decrease the dependence of the power sector on fossil fuels [245]. Nevertheless, its variability and limited predictability may significantly affect the scheduling of the operating state of thermal generators as well as the power output of the committed units [246]. Commonly, wind power is given priority in the merit order increasing the uncertainty related to the system's net demand, i.e. the portion of load which is satisfied by dispatchable sources [247]. Deviations of the actual wind power output from the predicted one may cause load shedding (in case of significant unexpected decrease) or spillage of energy (in case of significant unexpected increase) [248]. Thus, the integration of high levels of wind power within future power systems requires a careful assessment of their impact on the operation of the system [131]. System operators attempt to cope with the variability and uncertainty of wind power by scheduling an adequate amount of Spinning Reserve (SR). As discussed in the previous Chapter an appropriate amount of reserve capacity may also protect the system against unforeseen events such as unit outages and/or deviations of the actual net load from the predicted one. In order to adequately represent the inherent uncertainty in wind and its impact on the required reserve of the system the probabilistic criteria examined in the previous Chapter, for the case of the purely thermal generation scheduling problem are here extended and applied on power systems containing also hydro-power plants and wind power. The uncertainty related to the wind power output may result in loosing more frequently energy amounts larger than the largest generator (or a certain percentage of the load), since variations in the wind power output may coincide with outages of generators . Thus, the examination of methods to find the adequate amount of reserve capacity considering the uncertainty of wind power forecasting is of significant importance.

In this Chapter, a multi-objective optimization model is developed for short-term generation scheduling of power systems comprising hydro plants and thermal generators when wind power is integrated. Several uncertainties related to the load and wind power forecasting as well as to the reliability of the generators are considered for the evaluation of the system's SR requirements. In particular, the LOLP and EENS reliability indices are included within the problem's formulation and a designated limit is imposed on their values. Thus, the hourly required SR is assessed during optimization to guarantee that a certain level of reliability is achieved. Moreover, the proposed multi-objective framework enables the examination of the effect of the aforementioned uncertainties on the total operation cost and the emissions of the system as well as on the SR requirements of each solution among the set of trade-off solutions. To optimize the problem, a hybrid Multi-Objective Evolutionary Algorithm (hMOEA) for constrained optimization based on real-valued DE has been developed. A local search technique is utilized to further enhance the performance of the proposed algorithm. The proposed hMOEA has been tested on several systems comprising thermal and hydro plants and has managed to obtain non-dominated fronts that adequately approximate the Pareto Fronts generated by a MILP solver.

The structure of the rest of the Chapter is the following: in Section 6.2 a review of the methods applied to solve the Short-term Hydro-Thermal Generation Scheduling (STHTGS) problem and of approaches assessing the reserve requirements of the system when wind power is considered. In Section 6.3, the mathematical formulation of the multi-objective problem is given. In Section 6.5 the method developed to optimize the multi-objective problem is presented. The validation of the proposed method is carried out in Section 6.6.

6.2 Literature review

6.2.1 Methods applied on the hydro-thermal generation scheduling problem

A variety of methods have been proposed to solve the STHTGS, when the sole objective function of the optimization model is the total operation cost and the system's SR requirements are set in a deterministic manner. These approaches may be categorized into two groups: methods based on mathematical programming (or deterministic methods) and methods based on nature-inspired meta-heuristic approaches. Since the proposed approach is based on EA the review will focus on the methods of the second category. For a detailed review on the methods of the first category the interested reader is kindly referred to the rigorous review of Farhat and El-Hawary [238].

Techniques based on nature-inspired meta-heuristics are attracting the attention of researchers for solving large scale hydro-thermal coordination problems. Zoumas et al. [249] have proposed an approach based on GA for the optimization of the STHTGS. More specifically, a GA enhanced by problem-specific genetic operators optimizes the scheduling of hydro units, while the Priority List (PL) method is applied for the scheduling of thermal generators. The results have demonstrated that the enhanced GA has performed better compared to a plain GA. Troncoso et al. [250] considered a modified GA including a special initialization technique, a crossover operator adapted to the features of the problem and sparsity techniques to reduce the required computational time. The method has been tested on a case based on the Spanish power system and has outperformed an IPA algorithm. In Simopoulos et al. [251], a Simulated Annealing approach has been utilized to solve the thermal sub-problem, while the scheduling of the hydro units is carried out by an enhanced peak shaving method. The algorithm has been tested on a modified version of the Greek Power System. Zhang et al. [252] have developed a hybrid binary and real coded Particle Swarm Optimization with small population size for the STHTGS. To handle binary variables, PSO is extended by modified mutation and migration operators and a DE acceleration procedure, while a series of heuristic repair procedures are included to handle the constraints of the problem. In [253], Simulated Annealing is coupled with Evolutionary Programming to solve the STHTGS. The optimization procedure is mainly carried out by Evolutionary Programming, while Simulated Annealing acts as a local search assisting the algorithm to avoid converging prematurely in local minimum solutions. Yuan et al. [240] have developed an algorithm in which a chaotic embedded Backtracking Search Algorithm is applied on the scheduling of hydro plants, while a Binary Charged System Search Algorithm optimizes the thermal generation scheduling. The algorithm is enhanced by a series of heuristic repair mechanisms, which handle the several system constraints. The method has outperformed two competing algorithms based on binary-real coded Particle Swarm Optimization and binary-real coded Gravitational Search Algorithm.

6.2.2 Assessment of the Spinning Reserve requirements considering wind power

In the relevant literature, several approaches have been proposed utilizing probabilistic criteria within the short-term generation scheduling problem to assess the SR requirements of the system, when wind power is included. We will briefly examine them in the following paragraphs.

Doherty and O'Malley [254] have proposed a methodology to estimate the required SR considering generator outages and wind and load forecast uncertainty. The SR requirements are adjusted so that the number of load shed incidents per year does not exceed a certain value. The use of the aforementioned criterion may quantify the likelihood of failure, but it does not provide an estimate for the magnitude of the average lost load.

Black and Strbac [255] have proposed a method to evaluate the impact of wind uncertainty on the amount of energy stored by hydro pumped generation plants. In their approach, the SR requirements of the examined system have been set equal to β times the standard deviation of the net demand forecast error. Although this method considers the uncertainty in wind power forecasting, it does not take into account either the probability or the extent of contingency events.

Bouffard and Galiana [256], have developed an algorithm in which an upper limit has been posed on the values of both the EENS and the LOLP indices. In their method, the net demand forecasting error has been modelled as a normally distributed random variable. The normal distribution is then discretized into several representative intervals, which are used during the construction of a scenario tree; in the latter each scenario represents a trajectory of possible realizations of net demand forecasting errors over the periods of the scheduling horizon. Subsequently, the unit scheduling is carried out by examining a finite number of such scenarios. The method may accurately represent the influence of sequential fluctuations of wind power. Nevertheless, the number of scenarios grows exponentially with respect to the periods in the scheduling horizon, increasing significantly the method's computational burden. Thus, despite the use of scenario reduction techniques the method is computationally intensive when systems of realistic size are examined.

Ortega-Vazquez and Kirschen [257] have presented a method to estimate the required SR of a system comprising thermal generators and wind turbines using a cost/benefit analysis. Initially, the hourly SR requirements are calculated by optimizing single-period UC optimization problems in which the sum of operating costs and expected cost of interruptions is minimized. Then, the hourly required SR is posed as a constraint in a short-term generation scheduling problem, in which the inter-temporal constraints of the thermal generators are considered. The utilization of a time-decoupled UC problem for the estimation of the reserve requirements of the system, though, might lead to sub-optimal solutions [258].

In [245], a probabilistic model for the security constrained UCP has been presented. The model's objective was the minimization of the operation cost, the cost of spinning reserve provision as well as the expected cost of load shedding. The hourly reserve provision from each unit is considered as an objective variable, thus the spinning reserve requirements are derived based on a cost benefit analysis. Single order contingency events have been assumed, to reduce the computational time required.

In [200] and [259], a multi-objective GA and a MOEA based on Decomposition have been developed, respectively, for the short-term generation scheduling problem considering power systems with only thermal generators. Both approaches consider the uncertainty in load and wind power forecasting as well as the reliability of the system's generators. Moreover, the Cost of Expected Energy Not Served (CEES) has been considered as one of the problem's objectives in both cases; CEES is the product of EENS and Value of Lost Load (VOLL). Thus, the SR requirements may be implicitly assessed. Nevertheless, in both cases the amount of SR is sensitive to the value of VOLL, whose estimation is a rather subjective procedure [237, 226].

In [260], a non-dominated sorting Backtracking Search Optimization algorithm has been developed to solve a bi-objective probabilistic risk and cost short-term scheduling problem. The risk index is represented by the probability of the residual demand to fall within an up and down spinning reserve interval imposed by the $n-1$ criterion.

It should be noted that, in the aforementioned approaches the sub-problem related to the coordination of the hydro and thermal system has not been examined. Nevertheless, hydro production usually constitutes an important component of the energy mix of a power system [252]. Moreover, their introduction increases the difficulty of optimizing the generation scheduling problem compared to the purely thermal system due to the larger number of objective variables and the constraints related to the limited energy storage capability of water reservoirs [239]. To the author's knowledge, the only approach in which the reliability of a hydro-thermal system is examined is that of Zheng et al. [261]. In particular, the spinning reserve requirements of the system are set equal to the sum of the peak load and the value of EENS at each hour. Moreover, a method has been developed to optimize the single objective short-term generation scheduling based on Self-Learning Group Search Optimizer [262]. However, the impact of the load and wind forecasting uncertainty as well as the emissions of the system have not been considered.

6.2.3 Contribution to the relevant literature

In this chapter, a multi-objective formulation of the short-term generation scheduling problem for power system comprising thermal generators, hydro plants and wind power is proposed. It considers the unreliability of thermal generators as well as uncertainties related to the forecast of load and wind power output. The aforementioned have been considered during the LOLP and the EENS reliability indices calculation. Upper bounds on the values of LOLP and EENS are imposed as constraints in the model's formulation. As a result, the hourly reserve capacity of the generating schedule may be implicitly assessed during optimization ensuring that the final schedule maintains the desired reliability level. A multi-objective EA is proposed to optimize the examined formulation. The contributions of the dissertation regarding this model were the following:

1. The multi-objective model considers thermal generators, hydro plants and wind power. Moreover, the reliability of the thermal generators and the hydro units as well as uncertainties in load and wind power forecasting are integrated within the model, during the calculation of the LOLP and EENS reliability indices. Thus, the required reserve of the system may be assessed implicitly during optimization. The proposed formulation may provide trade-off solutions of the system's operation cost and produced emissions, taking into account the impact of inherent uncertainties within the power system. Moreover, it may allow for an impact assessment of the latter on both problem objective functions, as well as on the reserve requirements of the system. To the author's knowledge, it is the first attempt to develop a model combining all the aforementioned characteristics in a multi-objective framework.

2. The real-coded DE based approach is extended to be applied on the aforementioned multi-objective, mixed integer optimization problem. Basic characteristics of the approach applied on the single objective problem, i.e. the two step function and a series of heuristic repair procedures, are retained also in the multi-objective version of the algorithm, while the selection procedure of single objective DE is replaced by the non-dominated sorting and ranking procedure initially proposed for the NSGA-II algorithm.

3. A Local Search technique has been developed in this dissertation and combined with the multi-objective DE to accelerate the convergence of the population towards the Pareto Front of the problem. It combines two local search paradigms, local search based on Pareto dom-

inance and local search based on weighted scalar fitness function, in an attempt to exploit their distinct advantages. Moreover, an adaptive control mechanism for the local search has been developed, which attempts to strike a balance between the global exploration of the MOEA and the local exploitation by taking into consideration the number of non-dominated individuals in the population.

4. A method is proposed to create several Commitment Priority Orders of generators, to be utilized during the heuristic repair mechanisms. The integration of hydro-plants and wind power, may cause low residual load in some hours or drastic changes of the load between successive hours. In such cases, the flexibility of marginal units may be beneficial, since such units may start up of be shut down faster than base or intermediate load units. However, although the Plurality of Priority Lists method manages to increase the diversity of the examined generating schedules, it may not allow marginal units to be prioritized over intermediate or base load ones. For this reason, a method is developed based on a Tournament Selection procedure, which assigns a different commitment priority order to each solution vector at each generation. This method may further enhance the diversity of the schedules examined during optimization, enabling marginal or intermediate units to be prioritized over base load ones.

6.3 Formulation of the problem

The system's total operation cost and the amount of pollutants emitted in the atmosphere by thermal generators comprise the problem's conflicting objective functions to be minimized. The optimization of the aforementioned objectives is subject to a series of constraints, which model the limitations in the operation of individual generating units and the power system. The examined scheduling horizon comprises a single day divided into hourly periods. The proposed formulation is based on the one examined in the majority of studies in the field of applications of EAs on the generation scheduling problem when thermal units are considered and the system's reliability is included [263, 200, 229]. We extend this formulation by considering the hydro-plants to analyze the coordination amongst the aforementioned generation technologies. Moreover, we integrate wind power and the corresponding uncertainty to examine its impact on the system's reserve requirements. In what follows, the mathematical model of the problem will be presented. Since the Total Operation Cost and the constraints of the thermal system have been already described in previous Chapters, in the following subsections the model for hydro units and the second objective function, i.e. the emissions of the system, will be described in detail.

6.3.1 Model of the hydro units

In hydro-power plants, electricity is produced from generators driven by turbines that convert the potential energy of falling or flowing water into mechanical energy. Water is collected or stored at a higher elevation level and led downward through large pipes or tunnels (penstocks) to a lower elevation level; the difference in these two levels is known as the head. The hydro plants may be categorized into the following three types [14]:

1. Run-of-river plants (or continuous flow hydro plants) where the water is not stored into a reservoir rather than it is directly channeled into the water turbine.

2. Hydro plants with water reservoir (or controlled flow hydro plants), where the water may be stored into a reservoir and used when required in the future.

3. Pump-storage hydro plants, which are hydro plants with a reservoir where the water turbines may also operate as water pumps, and used to pump water from a low point to a higher reservoir.

In this dissertation the focus is on the second type of hydro units, i.e. hydro plants with larger reservoirs where water may be stored. The inclusion of the other types of hydro plants within the mathematical formulation of the problem, is a future research direction.

Compared to thermal generators, hydro units have negligible operation costs since their operation is not based on fossil fuels. Moreover, they are emission free and they are able to rapidly modify their production levels. On the other hand, an adequate management of the available water is required throughout the scheduling period, since the water resources are limited. For example, if the available water within the reservoirs is not adequately utilized, a lack of water may occur during periods of drought, or spillage of water may be required if the water inflows in the reservoir are high. In the former case, thermal generation will have to be increased to satisfy the required demand increasing the operating cost of the system as well as the amount of CO_2 emissions. On the other hand, in the case of water spillage, energy which could have been utilized is wasted. Consequently, in systems with both thermal generators and hydro plants an adequate coordination of the technologies is important.

Assuming an hourly resolution, the power output of a hydro plant is a function of the water discharge at the water turbines at each hour (Q_j^t) and the head of the dam ($head_j^t$), taking into consideration also the hydraulic losses due to the transition of water within the penstock. In the relevant literature several non-linear functions have been proposed to represent the function of the power output with respect to the water discharge and the head of the reservoir. However, commonly linear functions are used to model the function of power output. In Figure 6.1, a typical input-output curve of a hydro-electric unit is given for a constant value of the head; it may be observed that up to the rated capacity of the unit the input-output curve is practically linear [11]. After this point, the water volume requirements increase significantly since the unit's efficiency is decreased. Thus, by taking into consideration different head values several similar curves are used to describe the input-output characteristics of the hydro unit.

In this dissertation, the following assumptions have been made regarding the operation of a hydro plant. The hydro plants are considered to be providing energy to the grid at each period of the scheduling horizon as in [240, 252]. This assumption may be partly justified by the fact that hydropower plants are assigned as much load as possible, due to their low production cost and emissions.

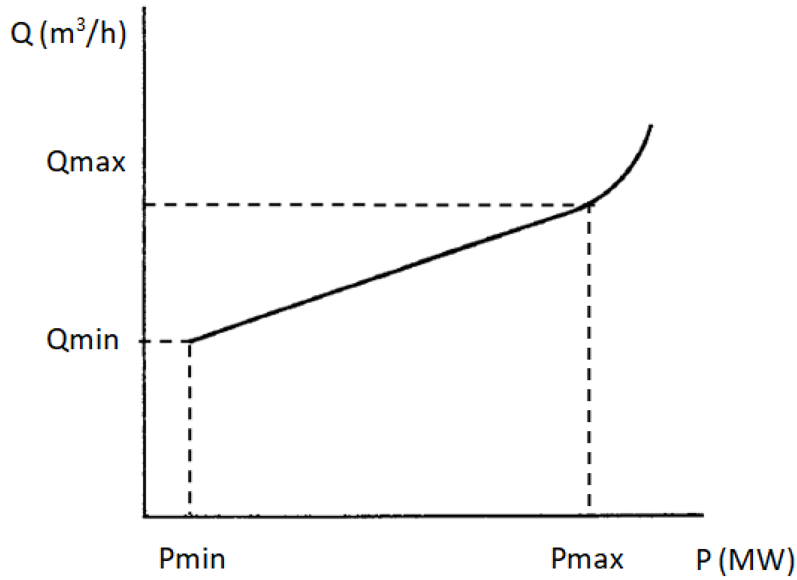


Figure 6.1: Input-Output curve of a hydro-power plant

Moreover, the proposed method focuses on fixed head hydro plants, i.e. it is assumed that the upstream reservoir levels are almost invariant over the examined short-term period. Furthermore, hydraulic losses are neglected. Thus, the power generated by each hydro-power plant j at each hour t is modeled as a linear function of the plant's water discharge rate Q_j^t [251]:

$$Ph_j^t = \eta_j \cdot Q_j^t,\ j \in [1, NHP],\ t \in [1, T] \tag{6.1}$$

where η_j denotes the coefficient of the power output function of hydro-power plant j. It should be noticed, that the modelling methodology can be extended to take into consideration the head effect on the power production of the hydro plants as well as their operating state. In contrast to thermal units, individual generators in a hydro plant commonly present similar operational characteristics [264]. For this reason, in this dissertation, the model of the hydro system considers hydro-plants as aggregated units (i.e. in the reservoir level), and not as individual hydro generators, reducing the number of required objective variables.

6.3.2 First objective function: Total operation cost of the system

The first objective function is the system's total operation cost, as described in Chapter 4. It is the sum of the fuel cost, the start-up cost and the shutdown cost of the thermal generators over the examined scheduling period. The operation cost of the hydro unit's is commonly neglected in the relevant literature, since their marginal cost is considered negligible [265]. Thus, the first objective function is given as follows:

$$f_1 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} [FC_i(P_i^t) \cdot ST_i^t + SUC_i \cdot ST_i^t \cdot (1 - ST_i^{t-1}) + SDC_i \cdot (1 - ST_i^t) \cdot ST_i^{t-1}] \quad (6.2)$$

6.3.3 Second objective function: Total produced emissions

According to the guidelines provided by the European Commission in [266], the amount of CO_2 emitted by thermal generator i at hour t is given as follows:

$$PE = Fuel\,Consumption \cdot Net\,Calorific\,Value \cdot Emission\,Factor \cdot Oxidation\,Factor \quad (6.3)$$

where the $Fuel\ Consumption(tn)$ is a function of the generators' active power output, i.e. P_i^t. Moreover, the $Net\ Calorific\ Value(TJ/tn)$ and the $Emission\ Factor\ (tnCO_2/TJ)$ depends on the type of the fuel used. It is noted that incomplete oxidation of the carbon within the fuel may occur due to inefficiencies in the combustion process. As a result part of the carbon within the fuel may be either partly oxidised or not oxidised at all. The unoxidized or partially oxidized portion of the carbon is considered by utilizing the oxidization factor within Eq 6.3, which is expressed as a number between 0 and 1.

As described in Chapter 4, the fuel cost curve, i.e. $FC(\$/h)$, of each thermal generator is derived by multiplying the fuel consumption of the generator by the price of the fuel, i.e.

$FPR(in\$/tn)$ as follows:

$$FC = Fuel\ Consumption \cdot FPR \tag{6.4}$$

By combining Eq. 6.3 and 6.4 the produced emissions may be expressed as a function of the fuel cost of each generator as follows:

$$PE = FC \cdot (\frac{Net\ Calorific\ Value \cdot Emission\ Factor \cdot Oxidation\ Factor}{FPR}) \tag{6.5}$$

In Eq. 6.5 the terms within the parenthesis depend on the type of fuel and represent the amount of CO_2 emitted per monetary unit, i.e. $tnCO_2/TJ$. If the quadratic function of Eq. 4.1 is used, then the amount of total CO_2 emitted in the atmosphere may also be modelled as a quadratic function of the power output of a thermal generator:

$$PE_i(P_i^t) = d_i + e_i \cdot P_i^t + f_i \cdot (P_i^t)^2 \tag{6.6}$$

where d_i, e_i and f_i are the emission coefficients of thermal generator i which are derived for each generator as follows:

$$d = a \cdot (\frac{Net\ Calorific\ Value \cdot Emission\ Factor \cdot Oxidation\ Factor}{FPR}) \tag{6.7}$$

$$e = b \cdot (\frac{Net\ Calorific\ Value \cdot Emission\ Factor \cdot Oxidation\ Factor}{FPR}) \tag{6.8}$$

$$f = c \cdot (\frac{Net\ Calorific\ Value \cdot Emission\ Factor \cdot Oxidation\ Factor}{FPR}) \tag{6.9}$$

It is assumed that the energy produced by hydro plants does not increase the emissions of the system, since such plants do not use fossil fuels. After the above analysis, the second objective function of the system is related to the total emissions of the power system and is formulated as follows:

$$f_2 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} ST_i^t \cdot PE_i(P_i^t) \tag{6.10}$$

6.3.4 Constraints of the problem

Constraints of thermal generators

Since the constraints of the thermal generators have been described in detail in Chapters 4 and 5, here the corresponding equations will only be provided for the sake of completeness.

Minimum up time constraints:

$$(Ton_i^{t-1} - MUT_i) \cdot (ST_i^{t-1} - ST_i^t) \geq 0,\ i \in [1, NTG],\ t \in [1, T] \tag{6.11}$$

Minimum down time of a thermal generator:

$$(Toff_i^{t-1} - MDT_i) \cdot (ST_i^t - ST_i^{t-1}) \geq 0,\ i \in [1, NTG],\ t \in [1, T] \tag{6.12}$$

Ramp up constraints of a thermal generator:

$$P_i^t - P_i^{t-1} \leq ST_i^{t-1} \cdot UR_i + (1 - ST_i^{t-1}) \cdot Pmax_i,\ i \in [1, NTG],\ t \in [1, T] \tag{6.13}$$

Ramp down constraints of a thermal generator:

$$P_i^{t-1} - P_i^t \leq ST_i^t \cdot DR_i + (1 - ST_i^t) \cdot Pmax_i,\ i \in [1, NTG],\ t \in [1, T] \tag{6.14}$$

Generation limits of thermal generators:

$$ST_i^t \cdot Pmin_i \leq P_i^t \leq ST_i^t \cdot Pmax_i \tag{6.15}$$

Constraints of the hydro system

Water discharge rate limits: The water discharge rate should be limited between a maximum and a minimum bound, which depend on the operating characteristics of the unit. These constraints are formulated as follows:

$$Qmin_j \leq Q_j^t \leq Qmax_j,\ j \in [1, NHP],\ t \in [1, T] \tag{6.16}$$

where $Qmin_j$ and $Qmax_j$ are the minimum and maximum water discharge rate of the hydropower plant j, respectively.

Upper and lower reservoir volume limits: The volume of water stored at the reservoir of each hydropower plant during each period of the examined scheduling horizon is restricted between upper and lower bounds:

$$Vmin_j \leq V_j^t \leq Vmax_j,\ j \in [1, NHP],\ t \in [1, T] \tag{6.17}$$

where $Vmin_j$ and $Vmax_j$ are the minimum and maximum allowable water volume in reservoir of hydro plant j, respectively

Initial and final reservoir storage volumes: The total amount of water that can be used during the scheduling period depends on the initial volume of water in the reservoir and the required final reservoir volume. The latter is set as a target level which should be attained during the scheduling of the hydro system. The initial and final volume of water stored in each reservoir is limited by the following constraints:

$$V_j^0 = V_j^{init} \tag{6.18}$$

$$V_j^T = V_j^{final} \tag{6.19}$$

where $j \in [1, NHP]$; V_j^{init} and V_j^{final} are the initial and final target storage volumes for the reservoir of hydro plant j. It is highlighted that the target bound values are provided by mid-term planning to control the trajectories of water levels, to ensure the availability of water in the long run [11].

Water balance constraints: The structure of a hydro system depends on the water flows and the number and the location of the hydro plants developed. Commonly, to increase the efficiency and take better advantage of the potential power of water, more than one hydro plants may be built on a single river, forming a so called cascade system (see Figure 6.2). Such hydro plants are hydraulically coupled. In such cases, the water discharged from a reservoir 'travels' along the river to the subsequent downstream reservoir. Thus, the latter's production may depend both on the discharge of the upstream reservoirs as well as on the time required for the water to travel from one reservoir to another. Consequently, the structure of the hydro system should be considered during hydro scheduling, increasing the overall complexity of the problem. Constraints 6.20 are used to model the conservation of water volume at reservoir j at each hour t:

$$V_j^t = V_j^{t-1} - Q_j^t - SP_j^t + IN_j^t + \sum_{l=1}^{UHP} (Q_l^{t-\tau_{lj}} + SP_l^{t-\tau_{lj}}),\ j \in [1, NHP],\ t \in [1, T] \tag{6.20}$$

According to Eq. 6.20 the water volume in reservoir j at hour t depends on the water volume in reservoir j the previous hour, the water discharge of hydro plant j, the water spillage SP_j^t of hydro plant j at time period t and the expected external inflows IN_j^t. The discharge and the spillage of the upstream reservoirs are also considered (summation term in Eq. 6.20) taking into account the time delay for water to travel between the cascaded hydro plants l and j, i.e. τ_{lj}. It should be noted that, commonly, spillage of water is avoided due to midterm planning and may only occur in flood seasons [267]. In the proposed model spillage is formulated as follows:

$$SP_j^t = \begin{cases} V_j^t - Vmax_j,\ if\ \ V_j^t > Vmax_j \\ \\ 0,\ otherwise \end{cases} \tag{6.21}$$

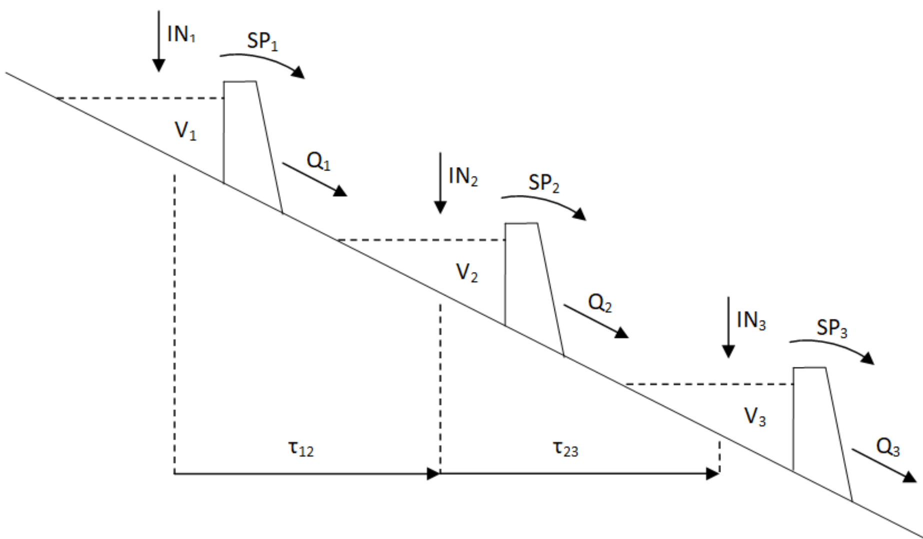


Figure 6.2: Hydro-power plants in cascade

System constraints

Power balance constraints: At each hour of the scheduling period, the energy generated by thermal generators, hydro plants and wind turbines should meet the expected load demand:

$$\sum_{i=1}^{NTG} ST_i^t \cdot P_i^t + \sum_{j=1}^{NHP} Ph_j^t + Pw^t = P_d^t,\ t \in [1, T] \tag{6.22}$$

where Pw^t is the expected wind generation at hour t.

Reliability constraints: As stated in the previous Chapter the hourly SR of the system is equal to the committed capacity of thermal generators exceeding the net demand (it is assumed that hydro units do not contribute to the spinning reserve of the system following [251, 252]):

$$SR^t = \sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i - TGL^t, \ t \in [1, T] \tag{6.23}$$

where TGL^t is the load to be served by thermal generators at hour t, calculated as follows:

$$TGL^t = P_d^t - Pw^t - \sum_{j=1}^{NHP} Ph_j^t, \ t \in [1, T] \tag{6.24}$$

When deterministic criteria are used to set the SR requirements of the system, commonly a lower bound is imposed on the hourly SR^t, as follows:

$$SR^t \geq SRR^t, \ t \in [1, T] \tag{6.25}$$

where SRR^t are the system's reserve requirements. In traditional generation scheduling approaches, SRR^t is set equal to a percentage of the peak load or to the capacity of the largest committed thermal generator at each time period. Nevertheless, such deterministic criteria do not take into consideration the intrinsic unreliability of the power system's components, neither the inherent uncertainty in the forecast of the load or the wind power.

To consider the stochastic nature of the problem in the proposed formulation the reliability constraints are included:

$$LOLP^t \leq LOLP^{max}, \quad t \in [1, T] \tag{6.26}$$

$$EENS_{tot} \leq EENS^{max} \tag{6.27}$$

according to which, the required reserve capacity of the system will be implicitly estimated to maintain a certain level of reliability. Particularly, to satisfy the reliability constraints, additional units may be committed during optimization to decrease the values of reliability indices.

6.3.5 Evaluation of the system's reliability indices

Modelling the unavailability of thermal generators and hydro plants

Each thermal generator is represented by a two-state Markov model according to which the unit may be either available or on (forced) outage as described in Chapter 5. It should be noted that the ORR of hydro units are much lower compared to that of the thermal generators; outages in hydro stations are so infrequent that in comparison to thermal power plants their outage rates can be assumed equal to zero [268].

Calculation of LOLP and EENS reliability indices

The evaluation of the $LOLP$ and $EENS$ reliability indices requires the assembling of the Capacity Outage Probability Table ($COPT$) for each period of the examined scheduling horizon based on the list of committed units using their corresponding ORR values, following the procedure described in Chapter 5. Subsequently, the reliability indices are evaluated as follows [226]:

$$LOLP^t = \sum_{r=1}^{Nrows} PR_r \cdot LOSS_r, \ t \in [1, T] \tag{6.28}$$

where:

$$LOSS_r = \begin{cases} 1, & if\ C_r^{in} < TGL^t \\ 0, & otherwise \end{cases} \quad (6.29)$$

The $EENS$ at each period is then calculated as follows:

$$EENS^t = \sum_{r=1}^{Nrows} PR_r \cdot LOSS_r \cdot (TGL^t - C_r^{in}),\ t \in [1, T] \quad (6.30)$$

Consequently, $EENS^{tot}$ for the examined scheduling period is given by:

$$EENS_{tot} = \sum_{t=1}^{T} EENS^t \quad (6.31)$$

Uncertainty due to load forecasting error

Similarly to the previous Chapter, the uncertainty incurred due to errors in load forecasting is assumed to be normally distributed. In particular, it comprises the expected load and an error; the latter follows the Gaussian distribution with zero mean and a standard deviation ($\sigma_{P_d}^t$) equal to a percentage (s) of the expected demand [226, 229]:

$$\sigma_{P_d}^t = s \cdot P_d^t,\ t \in [1, T] \quad (6.32)$$

Uncertainty due to wind power forecasting error

In [257] it has been noted that wind power forecast errors may not follow a Gaussian distribution rather than a beta distribution. However, the assumption of normally distributed wind power forecasting errors is commonly utilized in the relevant literature. The large number and the geographical dispersion of wind turbines allows the application of the central limit theorem to justify the aforementioned assumption. Thus, the wind power production forecast may be assumed to comprise of the actual wind power production plus a forecasting error, which follows Gaussian distribution. This error may be approximated as follows [257]:

$$\sigma_W^t = \frac{Pw^t}{5} + \frac{W_I}{50},\ t \in [1,T] \tag{6.33}$$

where W_I is the total installed wind power capacity.

Uncertainty due to net load forecasting error

The expected net load is the difference between the expected demand and the expected wind power production:

$$NL^t = P_d^t - Pw^t,\ t \in [1,T] \tag{6.34}$$

The errors in load forecast and wind power forecast are assumed to be uncorrelated stochastic variables [257, 245]. As a consequence the standard deviation of the net demand forecasting error can be approximated as follows:

$$\sigma_{NL}^t = \sqrt{(\sigma_{P_d}^t)^2 + (\sigma_W^t)^2},\ t \in [1,T] \tag{6.35}$$

Since both load and wind power are considered independent normally distributed variables, the net load forecast uncertainties may also be represented by the Gaussian distribution with mean value equal to NL^t and standard deviation equal to σ_{NL}^t. This distribution may be approximated by a seven-step model [222], according to which it is divided into seven discrete intervals $(0, \pm\sigma_{NL}, 2\cdot \pm\sigma_{NL}, 3 \cdot \pm\sigma_{NL})$. The area of each interval represents the probability that the net demand will be equal to the interval's mid-point, NL_m^t. Such a model encompasses the 99% of the net load forecast uncertainty distribution [226].

To evaluate $LOLP$ and $EENS$ for each interval $m, m = 1, ..., 7$, the load to be covered by thermal generators is calculated:

$$TGL_m^t = NL_m^t - \sum_{j=1}^{NHP} Ph_j^t,\ t \in [1,T], m \in [1,...7] \tag{6.36}$$

Subsequently, $LOLP_t^m$ and $EENS_t^m$ are calculated based on the corresponding TGL_m^t utilizing Eq. (6.28) and (6.30), respectively. Then, at each hour the final values of the reliability indices are calculated, taking into consideration the probability $Pr(m)$ of each interval m, as follows:

$$LOLP^t = \sum_{m=1}^{7} LOLP_t^m \cdot Pr(m),\ t \in [1,T] \tag{6.37}$$

$$EENS^t = \sum_{m=1}^{7} EENS_t^m \cdot Pr(m),\ t \in [1,T] \tag{6.38}$$

6.4 Differential Evolution variant used for the optimization of the multi-objective problem

To optimize the multi-objective STHTGS problem a plain Multi-objective DE (MODE) is utilized. In this algorithm, the DE/rand/1 mutation scheme is used in combination with the binary crossover. Moreover, to handle the multiple objectives, the selection scheme of the single objective DE has been replaced by the non-dominated sorting and ranking procedure of NSGA-II [45],as described in Chapter 2. It should be noted that the individuals are compared based on the constraint domination principle, according to which solution x_1 dominates solution x_2, if one of the following applies:

1. Solution x_1 is feasible while solution x_2 is infeasible.

2. Both solutions are infeasible and x_1 has a smaller overall constraints violation.

3. Both solutions are feasible and x_1 dominates x_2.

6.5 Proposed optimization approach

A hybrid MOEA has been developed to optimize the reliability constrained short-term wind-hydro-thermal scheduling problem with multiple objectives. The hybrid MOEA is based on the real coded MODE, while the two step function presented in Chapter 4 is also used here to derive the state of the thermal generators. Moreover, a series of heuristic procedures are included in an attempt to repair individuals violating the constraints of the problem. To increase the diversity of the generating schedules examined during the repair procedure a method is presented to derive the priority order based on which generators might be brought on-line or shut down during the heuristics. Moreover, to further enhance the performance of the proposed method and accelerate the convergence towards the Pareto optimal front, a Local Search algorithm is proposed and combined with the MODE. It combines two methods based on Pareto dominance and weighted scalar fitness function. An overview of the procedure followed at each generation g of the algorithm is given in Fig. 6.3. At each generation, the proposed local search (described in subsection 6.5.5) is applied on $Ppop^g$; $Ppop'^g$ is the population, in which individuals of $Ppop^g$ have been replaced by improved solutions found during the Local Search and $Lpop^g$ is a population formed during the Local Search. Subsequently the evolution operators of MODE and a problem customized recombination operator are applied on $Ppop'^g$ to create the offspring population $Qpop^g$. Then, the non-dominated sorting and ranking procedure is applied on the combined population of $Ppop'^g$, $Lpop^g$ and $Qpop^g$ to determine the parent population of the next generation $Ppop^{g+1}$.

6.5.1 Encoding of parameter vectors and calculation of the operating state of thermal generators

The final operating schedule should consider the operating state (on/off) and the production level of the thermal generators as well as the water discharge rate of the hydropower plants for each scheduling period. In the proposed method, a solution vector $\mathbf{x}$ consists of $(NTG + NHP) \cdot T$

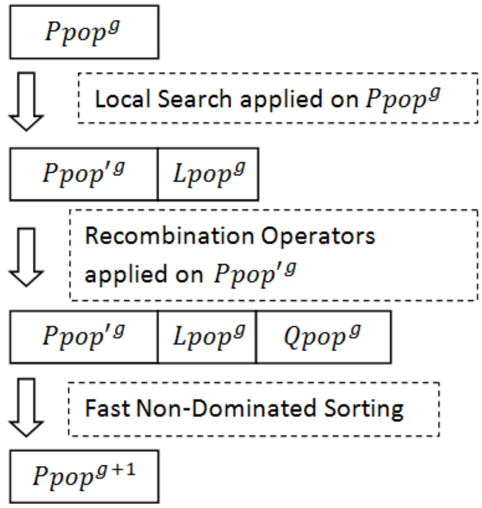


Figure 6.3: Overview of the proposed hybrid MOEA

real-valued parameters as follows:

$$\mathbf{x} = \{\mathbf{p}, \mathbf{Q}\} \tag{6.39}$$

where

$$\mathbf{p} = [p_1^1, p_1^2, ..., p_i^t, ..., p_{NTG}^T] \tag{6.40}$$

and

$$\mathbf{Q} = [Q_1^1, Q_1^2, ..., Q_j^t, ..., Q_{NHP}^T] \tag{6.41}$$

with $i = 1, ..., NTG,\ j = 1, ..., NHP$, and $t = 1, .., T$. Moreover, $Q_j^t \in [Qmin_j,\ Qmax_j]$ and $p_i^t \in [0,\ Pmax_i]$. Based on $\mathbf{p}$, vector $\mathbf{ST}$ containing the operating states of thermal generators is derived using the two step function described in Chapter 4.

6.5.2 Domain-customized mutation operator

The performance of EAs may be significantly enhanced when domain specific knowledge is incorporated [5]. Such knowledge may be explicitly represented within EAs by utilizing problem-specific mutation operators. In this context, the Window Mutation operator [163] is included into the proposed MOEA, as presented in Fig. 6.4. This scheme operates by selecting at random i) a thermal generator i, ii) a time window of size TW in $[1, T]$ and iii) a window position WP in $[1, T-TW+1]$. Subsequently, unit i is either committed or de-committed in all periods within the time window with equal probability. Thermal generator i is shut-down or brought 'on-line' at hour t by uniformly sampling p_i^t in $[0, Pmin_i)$ or $[Pmin_i, Pmax_i]$, respectively. The Window Mutation scheme and the $DE/rand/1$ are applied with equal probability on the part of $\mathbf{x_n^g}$ related to thermal generators, i.e. $\mathbf{p_n^g}$, in an attempt to increase the diversity of operating schedules examined during optimization. On the other hand, the $DE/rand/1$ is applied on the $\mathbf{Q_n^g}$.

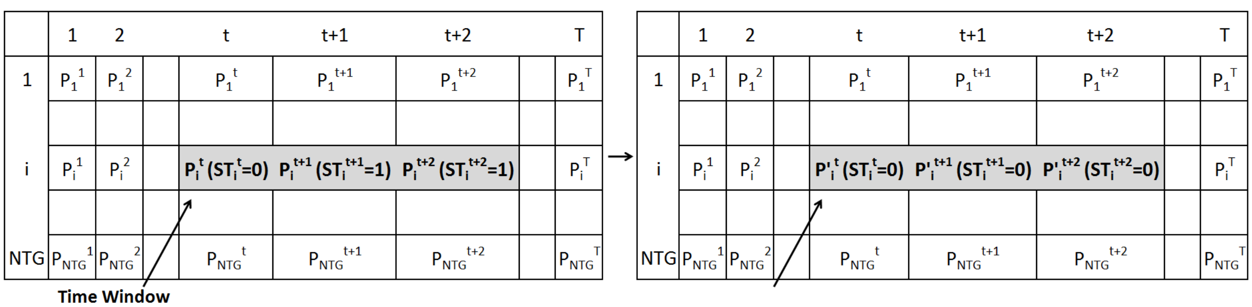


Figure 6.4: Window Mutation Operator

6.5.3 Tournament selection for obtaining the priority order of thermal generators

The priority commitment order of the generators is usually determined by ranking them in ascending order according to the unit's Average Full Load Cost (AFLC); when the objective of emissions is also considered a second priority List may be defined by using the Average Full Load Emissions (AFLE) of thermal generators. However, the optimal Commitment Priority Order may differ significantly from the one based on the two aforementioned Lists, especially regarding the commitment of the intermediate or marginal units [269]. Moreover, the optimal CPO may depend on the shape of the load curve as well as the peak load [269]. In Chapter 2, it has been demonstrated that the utilization of a constant priority order of generators during optimization may introduce biases towards specific generating schedules resulting in sub-optimal solutions. Moreover, a method was proposed to create a Plurality of Priority Lists (PPL) during optimization, according to the Average Cost (AVC) of the generators at distinct operating points chosen randomly for each member of the population at each generation. Although the aforementioned method manages to increase the diversity of the examined generating schedules, it may not allow units with higher AVC to be prioritized over units with lower AVC values. This may emerge clearer in Fig. 6.5, where the AVC curves of five units of the system of 10 units (see Table A.1 in Appendix A.1) are presented versus the percentage of the generator's loading within its operating range. Unit 1 is a base load unit, units 4 and 5 are intermediate load units, while units 9 and 10 are marginal units. As observed, the possible commitment priority orders are two, depending on the operating point selected to estimate the units AVC (the unit ranked first is the one having the highest priority), i.e. 1, 4, 5, 8, 9 and 1, 5, 4, 8, 9. Nevertheless, depending on the shape of the load curve the optimal commitment schedule may differ significantly from the two aforementioned. For example, in normal load situations base load units, which commonly have the largest capacity (and are the least flexible) are continuously used. In case, additional units are required commonly intermediate load units are committed since they are the second cheaper type of units, while marginal units are rarely used to satisfy peak loads when the committed capacity is not sufficient. Nevertheless, when a power sector comprising other types of plants, i.e. hydro units, and the volatile energy from RES is also integrated, hours with low demand or cases where the load drastically changes between successive hours become more frequent. In such cases, the flexibility of marginal units may be beneficial, since such units may start up or shut down faster than base or intermediate load units. Thus, in such cases, guiding (through the plain Priority List or the PPL schemes) the optimization towards cheaper and less flexible power plants will increase the difficulty in finding the optimal generating schedule [138].

Thus, the use of Tournament Selection to create the CPO of the units is proposed, in an attempt to further enhance the diversity of the schedules examined during optimization. The procedure is described in Algorithm 13.

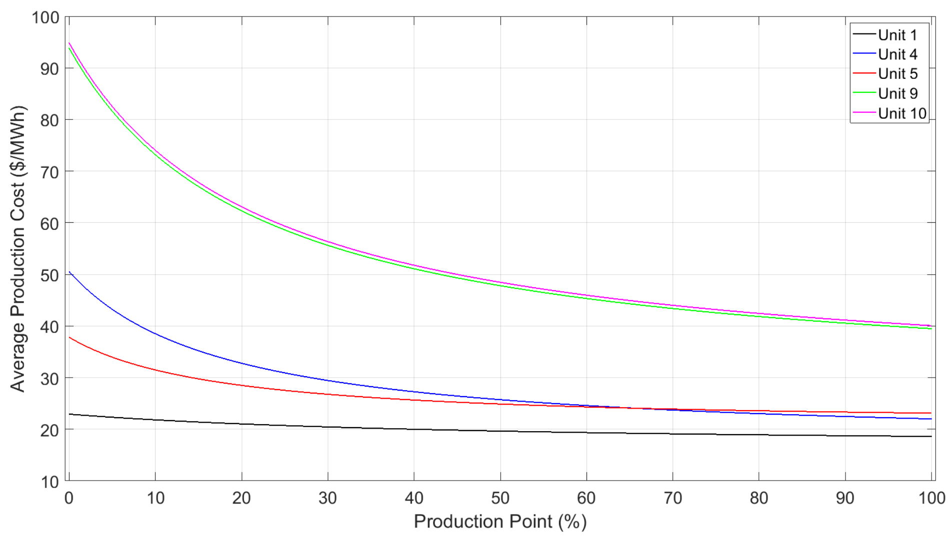


Figure 6.5: Average fuel cost curves as a function of the generators loading point within its operating range

Initially, the metric according to which the priority order will be created is selected with equal probability among the $AFLC$ and the $AFLE$. Then, the CPO is formed by running several tournaments based on the selected metric; in particular TS units are chosen at random and the winner of the Tournament is placed on a higher rank on the CPO compared to the competing units. The procedure is implemented at each generation and may assign a different CPO at each individual. This priority order will be utilized during the heuristic repair mechanisms. As a result, different commitment schedules may be encountered during optimization since, different thermal units may be prioritized for each individual depending on the derived list. It is highlighted, that the number of different stacking orders depends on the tournament size TS. In particular, as the size of the tournament increases, the generators having better values of the selected metric will have a higher chance to be prioritized over units with worse values of the selected metric. Thus, the CPO for

Algorithm 13 Tournament selection procedure for creating the CPO

```
for n = 1 : Npop do
  if rand < 0.5 then
    SM ← AFLC
  else
    SM ← AFLE
  end if
  UPL ← {1, ..., NTG}
  CPO ← ∅
  for rank = 1 : NTG − TS do
    Select TS units from UPL
    SU ← the unit having the best value of SM among the TS units
    SU is placed on the rank position of CPO
    UPL ← UPL \ SU
  end for
  The TS units in UPL are placed in the remaining slots of the CPO in descending order of
  their SM values
end for
```

larger values of TS may resemble the PL based on the selected metric.

6.5.4 Handling of constraints

Heuristic repair mechanisms are included within the hMOEA to facilitate the obtainment of feasible generating schedules. These procedures are applied to the newly generated individuals followed by the evaluation of the objective functions. The flowchart of Fig. 6.6 summarizes the repair process. A case might emerge, in which an individual might not satisfy the problem's constraints even after the repair procedure. Such cases are handled using the constraint domination principle. A detailed description of each step of the heuristic repair procedure is given in the following subsections.

Repairing the final reservoir volume constraint violation

Algorithm 14, describes the procedure applied on parameter vectors to repair the violations of the reservoir volume constraints. At first, the final volume of water in the reservoir of hydro plant j, i.e.

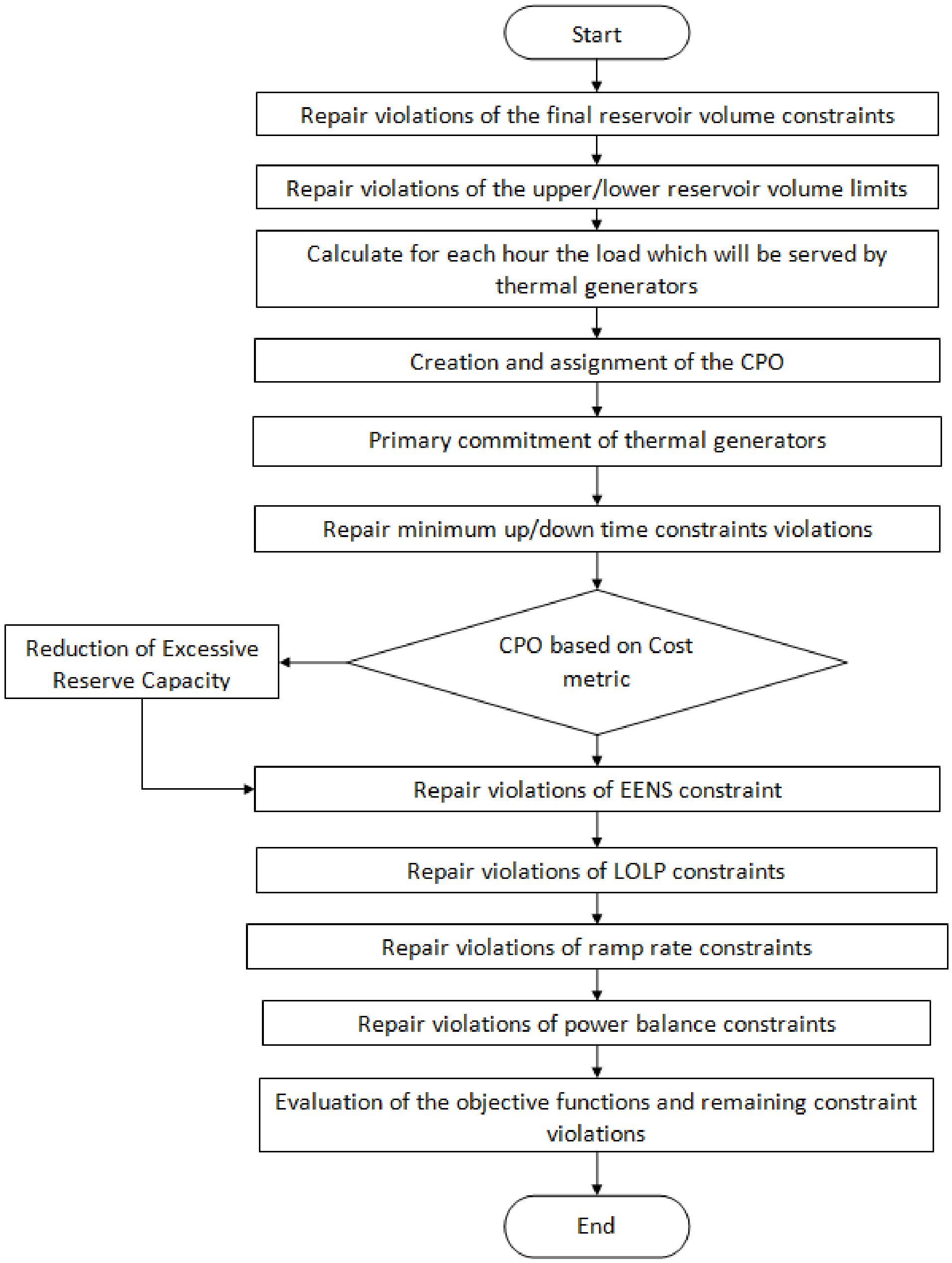


Figure 6.6: The series of heuristic repair mechanisms

V_j^T, is evaluated using the volume of water within the reservoir in the beginning of the scheduling period, the expected inflows, the plant's water discharge as well as the water discharged from the upstream reservoirs. If V_j^T is not equal to the target final reservoir storage volume, the constraint violation is repaired. In particular, an hour within the scheduling period is selected at random and the water discharge of the hydro plant at that hour is adjusted; the procedure is repeated until the deviation of the final reservoir volume from the target volume is equal to zero. When the water discharge during an hour is adjusted the corresponding upper and lower discharge limits are taken into consideration. It should be noted that, in case of hydro plants in cascade the procedure of Algorithm 14 is carried out serially, i.e. beginning from the hydro plant at the top of the cascade configuration and applied sequentially to the downstream plants.

Algorithm 14 Repairing of final reservoir volume constraints

for $j = 1 : NHP$ **do**
  $DQ = V_j^{init} - V_j^{final} + \sum_{t=1}^{T} IN_j^t - \sum_{t=1}^{T} Q_j^t + \sum_{t=1}^{T} \sum_{l=1}^{UHP} Q_l^{t-\tau_{lj}}$
  $PDQ \leftarrow \frac{DQ}{T}$
  while $DQ_j \neq 0$ **do**
    $rt \leftarrow \lfloor U(1, T+1) \rfloor$
    if $(Q_j^{rt} + PDQ \leq Qmax_j)$ **and** $(Q_j^{rt} + PDQ \geq Qmin_j)$ **then**
      $Q_j^{rt} \leftarrow Q_j^{rt} + PDQ$
      $DQ = V_j^{init} - V_j^{final} + \sum_{t=1}^{T} IN_j^t - \sum_{t=1}^{T} Q_j^t + \sum_{t=1}^{T} \sum_{l=1}^{UHP} Q_l^{t-\tau_{lj}}$
    end if
  end while
end for

Repairing the upper and lower reservoir volume limits violations

The upper/lower reservoir volume limits of a hydro plant might be violated at some periods of the scheduling horizon. To repair such violation the procedure from [240] is adopted. In this procedure, when the water volume in the reservoir of hydro plant j at period t violates the corresponding lower limit, the water discharge at previous periods is decreased by a total quantity equal to the violation, while the water discharge at subsequent periods is increased by the same quantity.

The mechanism proceeds correspondingly in case of violation of the upper reservoir limit. It is highlighted that since the total water discharge over the scheduling period has not been modified the final reservoir volume constraint will not be violated. Moreover, during this procedure, the corresponding upper and lower limits of the water discharge of the hydro plants are taken into consideration.

Primary commitment of thermal generators

Algorithm 15 describes the procedure of the primary unit commitment of thermal generators. This procedure is similar to the algorithm described in Chapter 5, with the exception that the load quantity to be satisfied in this case is equal to TGL^t, i.e. the expected load to be satisfied by thermal generators. Thus, when the reliability constraints are examined, SRR^t is set equal to zero since the required reserve capacity will be implicitly assessed during the optimization. On the other hand, when the spinning reserve requirements of the system are defined using deterministic criteria (see Eq. 6.25), then SRR^t is set equal to the value of the required reserve, and units are committed until the capacity in excess of TGL^t is greater equal to SRR^t. In Algorithm 15, $CPO_n^g(pos)$ represents the unit that is ranked in the pos position of the commitment priority order assigned to individual n at generation g. Moreover, when a thermal generator is brought 'on-line', the corresponding real-valued parameter, i.e. $p_{i,n}^{t,g}$, is set equal to $Pmin_i$.

Algorithm 15 Primary commitment of thermal generators

$pos \leftarrow 1$
while $\sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i - TGL^t < SRR^t$ **do**
  if $ST_{CPO_n^g(pos)}^t = 0$ **then**
    $p_{CPO_n^g(pos)}^t \leftarrow Pmin_{CPO_n^g(pos)}^t$
    $ST_{CPO_n^g(pos)}^t \leftarrow 1$
  end if
  $pos \leftarrow pos + 1$
end while

Repairing of minimum up/down time constraints

The procedure described in Algorithm 9 of Chapter 4 is applied to repair violations of the minimum up/down time constraints.

Reducing the excess of reserve capacity

As described in Chapter 4, from an economic point of view, when excessive reserve exists it should be reduced. For this reason, the mechanism described in Algorithm 9 of Chapter 4 is applied on individuals assigned a priority order created based on the AFLC index. During this procedure, thermal generators are shutdown if decommitting them does not trigger a violation of the minimum up/down time constraints and the remain reserve capacity is equal to or larger than SRR^t.

Repairing violations of the EENS constraint

In case the solution vector n violates the EENS constraint (Eq. 6.27), the procedure described in Figure 5.7 (Chapter 5) is applied to repair the violation. In this case the CPO_n^g assigned to each individual at each generation is used to prioritize the uncommitted generators that have higher priority for commitment. Since different generators (based on the corresponding CPO_n^g) may be given priority for commitment for each individual at each generation the diversity of the examined operating schedules is increased. In this mechanism the minimum up/down time constraints of the generators brought on-line are repaired, if the commitment of a generator triggers their violation.

Repairing violations of the LOLP constraints

After the implementation of the previous part of the heuristic repair procedure the $LOLP^t$ constraints are checked. Violations of the LOLP constraints (Eq. 6.26) are repaired using the procedure described in Figure 5.8 (Chapter 5). When a unit is brought on-line in this procedure, possible violations of the MUT/MDT constraints are repaired as described in subsection 6.5.4.

Repairing violations of the ramp rate constraints

When the ramp rate constraints (Eq. 6.13 and 6.14) are violated the procedure described in Algorithm 10 (Chapter 4) is applied, to set the power output of the thermal generators within the range defined by the ramping capabilities of the units.

Repairing violations of the power balance constraints

The load to be served by thermal generators, i.e. TGL^t, may deviate from their total power output at some periods of the scheduling horizon. In such a case, the mechanism described in Algorithm 11 (Chapter 4) is employed to repair the violations of the power balance constraints. During this procedure, COP_n^g is utilized.

6.5.5 Local Search algorithm

A common practice when MOEAs are applied on complex multi-objective problems is the utilization of LS techniques either in hybrid frameworks or as part of their evolution operators [270]; in such combined approaches, the Local Search may accelerate the convergence to the Pareto front. Local Search techniques for multi-objective optimization follow one of the two main search paradigms, i.e. they may be dominance-based or scalarization-based [271]. The former utilize some form of Pareto dominance relationship for comparing the solution vectors. In the latter, the multi-objective optimization problem is transformed into a set of substitute single-objective ones. By solving a series of such single objective problems, the methods based on scalarized fitness function may obtain the solutions of the original multi-objective problem. It is noted that more recently, various studies have demonstrated that combining methods from the two aforementioned Local Search paradigms may result in high performing approaches [271, 272].

In dominance-based approaches solution vectors are compared based on some sort of Pareto dominance relationship. Generally, such methods utilize a set of solutions and define a neighborhood structure[1]. Since Pareto dominance may only define a partial order among individuals commonly an archive is used, where non-dominated solutions are stored. The archive of non-dominated solutions is maintained and iteratively improved by examining parts of the neighborhood of solutions within the archive. A representative method in this category is the Pareto Local Search (PLS) method [273]. In PLS an archive of non-dominated solutions is maintained. The neighborhood of the solutions within the archive is explored and any solution which is not dominated by the solutions in the archive is stored. PLS finishes when a Pareto local optimum set has been found. In [274], if PLS converges to a Pareto local optimum, different neighborhood operators are applied in an attempt to search for a better set of non-dominated solutions. Another well known local search method is the Pareto Archived Evolution Strategies [275], in which an offspring solution is obtained by applying the mutation operator of ES on a solution from the current archive. The offspring might be included within the archive in case it is not dominated by the solutions within it. The size of the archive is kept limited by utilizing a diversity metric, which maintains the solutions in the less crowded regions of the non-dominated front. It is noted that, the basic advantage of methods belonging in this category is that since they maintain an archive of solutions they may return quickly multiple non-dominated solutions. Thus, they may allow a better exploration along the non-dominated front in case they are adequately driven towards the front. Nevertheless, approaches utilizing dominance based comparisons may progress rather slowly towards the Pareto Front.

The second category of Local Search paradigms concerns methods which rely on combining the multiple objective functions into a single scalar fitness function and solve several single-objective optimization problems. Since the solutions are compared based on the value of the single fitness function a total ordering of solutions is defined, thus such methods do not require external archives. Several ways exist in the relevant literature to scalarize multi-objective problems (the interested

[1] A neighbour is a solution that is derived by modifying part of a given solution x. The set of neighbours that can be generated from x constitute the neighbourhood of x.

reader is kindly referred to [276] for an analysis of the methods for scalarizing multi-objective problems). In the context of local search, the most commonly used method is the linear aggregation, where a weighted sum of the several objectives is determined based on a set of weights. A representative method in this category is the Two-Phase Local search approach [277], which comprises two phases. In the first phase, a high quality solution is obtained for each of the objectives of the problem. Then a series of single objective problems is optimized. In each problem a different scalarization is used. Moreover, the starting point for each problem is the solution obtained for the previous scalarization. For the first problem tackled the initial point is one of the solutions found in the first step of the algorithm. This method is used also when local search techniques are hybridized with MOEAs, e.g. Itschibuschi and Murata [64] and Jaszkiewicz [278].

To exploit the advantages of the methods in the aforementioned categories, attempts to combine both search paradigms have been made. Generally, to the author's knowledge, such methods are combined sequentially, i.e. a scalarization based and a dominance based component are combined by applying one method after the other in sequence. In this case, the scalar algorithm may be commonly used to provide some non-dominated supported solutions and then a Pareto based local search methods is applied for finding non-dominated non-supported solutions. An example of such methods is the TP+PLS method [272], in which the Two Phase Local Search [277] is applied on a first step to find supported solutions while then PLS [273] is implemented to find non-supported ones.

Here, a Local Search is proposed which combines two distinct methods from the aforementioned paradigms, i.e. the weighted scalar fitness function method and a Pareto dominance based approach. It is applied at each generation of the optimization procedure. The individuals which undergo the Local Search are selected among the feasible non-dominated solutions of the parent population $Ppop^g$, since it has been demonstrated that selection of proper individuals for applying the Local Search, e.g. from the parent population, may significantly increase the algorithm's efficiency [66, 68]. The method applied on each individual depends on its position on the current

Non Dominated Front (NDF). Specifically, individuals belonging on the endpoints of the current NDF, will undergo the LS based on the Pareto dominance. The rest of the non-dominated population members may undergo the LS based on the weighted scalar fitness function. The members of $Ppop^g$ may be replaced by improved solutions (in the context of Lamarckian learning) during the LS, forming the improved population $Ppop'^g$. The proposed LS is described on the following subsections.

Local Search based on Pareto dominance

Maximizing the spread of the obtained NDF, i.e. the range of values covered by the non-dominated solutions for each objective, constitutes a main objective of multi-objective optimization [279]. In this context, a Local Search technique is proposed to increase the spread of the obtained NDF. Each individual corresponding to the extreme points of the NDF at each generation is used as an initial solution for the LS. This method employs Pareto dominance as an acceptance criterion and it is described in Algorithm 16; note that an external archive H is utilized to store non-dominated solutions obtained during the LS, since Pareto dominance may only define a partial order among solutions. The LS is repeated p_{PD} times for each extreme solution. At each iteration, a single dimension of the current solution CS is randomly selected and re-initialized within the corresponding upper and lower bounds using the uniform distribution, creating a new solution NS. Subsequently, NS undergoes the heuristic repair mechanisms (see subsection 6.5.4) before the evaluation of the objective functions. Then, NS is compared to CS based on the constrained domination principles. Based on the domination status of NS with respect to CS the following three different cases may arise:

1. NS is dominated by CS, as shown in Figure 6.7. In this case, NS may be either also dominated by (some) solutions in H (Figure 6.7 (a)) or only by CS (Figure 6.7(b)). In any of the aforementioned situations NS is discarded. It is noted, that a situation where NS dominates solutions in H is not possible, since the Pareto dominance relation is transitive.

2. NS and CS are non-dominated with respect to each other (Figure 6.8). In this case, NS will be compared to the solutions in H based on the constraint domination principle and three possible situations may occur; In the first two, NS either dominates some solutions in H (Figure 6.8(a)) or NS and solutions in H are mutually non-dominated 6.8(b)). In the aforementioned situations NS will enter the archive, while solutions in H dominated by NS will be discarded. In the third possible situation 6.8(c)), NS is dominated by (some) solutions in H. In that case, NS is discarded.

3. NS dominates CS, as shown in Figure 6.9. In that case, NS will replace the current solution C. Moreover, NS will be compared to solutions in H and may either be mutually non-dominated with them (6.9(a)) or dominate some of them (6.9(b)). In the latter case, solutions in H dominated by NS will be discarded.

Based on the aforementioned analysis, solutions contained in H and CS are mutually non-dominated in any case.

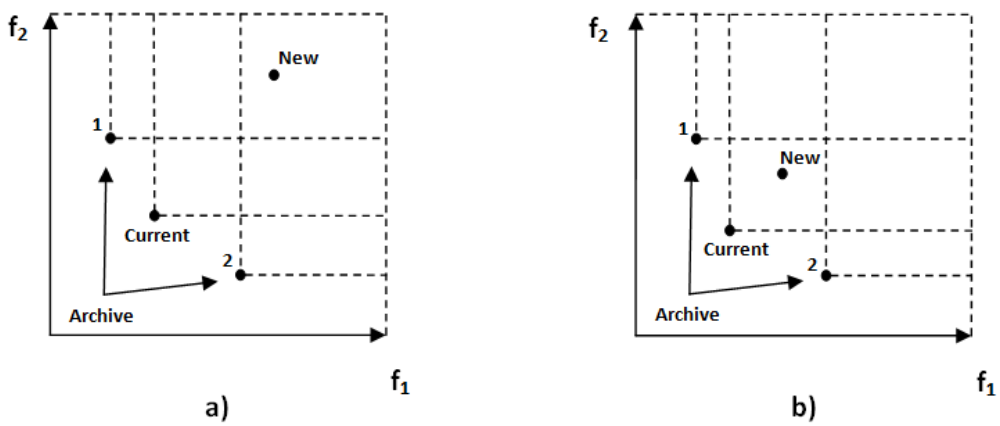


Figure 6.7: Case 1: CS dominates NS. Two subsequent cases may emerge: a) NS is dominated by (some) solutions in the archive, and b) NS is dominated only by CS

After implementing the LS technique, CS enters $Ppop'^g$, while solutions in H form population $Lpop^g$. The latter is combined with $Ppop'^g$ and $Qpop^g$ and undergoes the selection process.

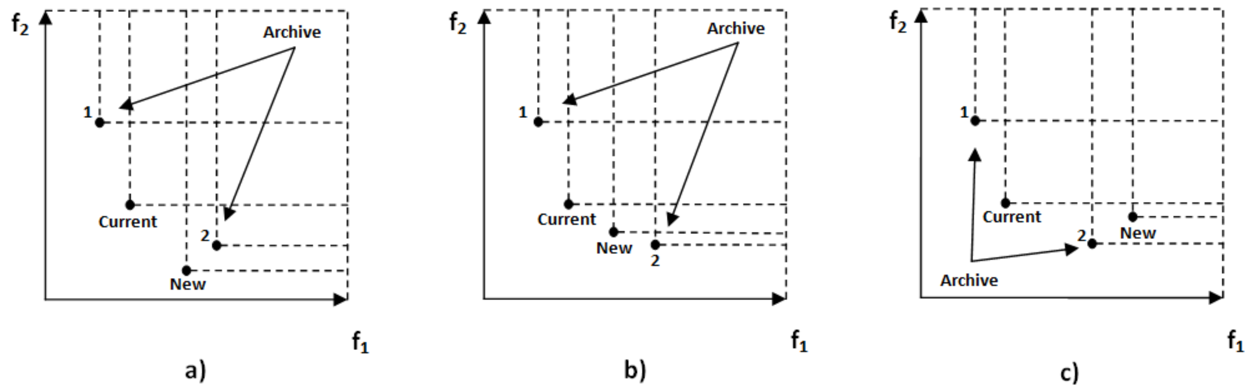


Figure 6.8: Case 2: CS and NS are mutually non-dominated. Three subsequent cases may emerge: a) NS dominates (some) solutions in the archive, b) NS and solutions in the archive are mutually non-dominated, and c) NS is dominated by (some) solutions in the archive

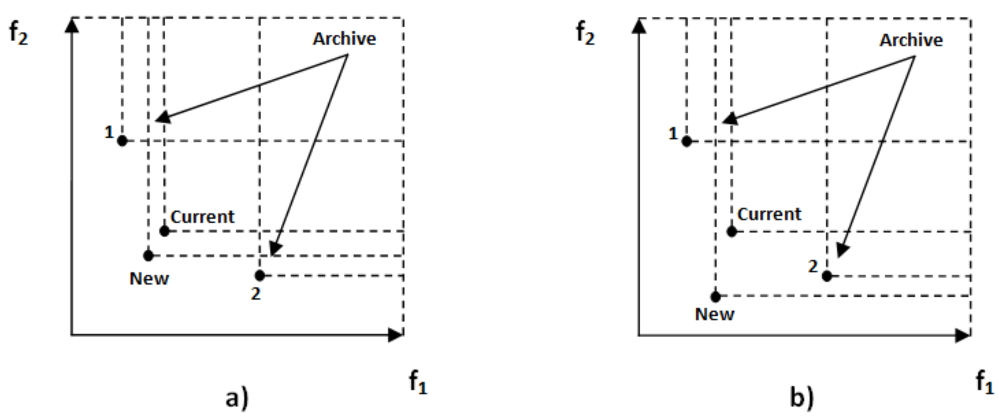


Figure 6.9: Case 3: NS dominates CS. Two subsequent cases may emerge: a) NS and solutions in the archive are mutually non-dominated, and b) NS dominates (some) solutions in the archive

Algorithm 16 Local search based on Pareto dominance

```
Lpop^g ← ∅
for Extreme solution = 1 to 2 do
    CS ← Extreme solution
    H ← ∅
    for iteration = 1 to p_PD do
        Create NS by perturbing CS
        if (NS is feasible) then
            if (NS dominates CS) then
                Compare NS with solutions within H
                Delete from H solutions dominated by NS
                NS becomes the current solution CS
            else if (NS and CS are non-dominated to each other) then
                Compare NS with the solutions in H
                if (NS is not dominated by any solution in H) then
                    Store NS in H
                    Delete from H solutions dominated by NS
                else
                    Discard NS
                end if
            else
                Discard NS
            end if
        else
            Discard NS
        end if
    end for
    Lpop^g ← Lpop^g ∪ H
end for
```

Local Search based on weighted scalar fitness function

Approaches based on scalar fitness function aggregate the multiple objectives of the problem into a single objective function. The most common scalarization approach is the weighted scalar fitness function (or weighted sum) [278, 66], in which a linear aggregation of the objectives is implemented as follows;

$$y(\mathbf{x}|\lambda) = \lambda_1 \cdot f_1(\mathbf{x}) + \lambda_2 \cdot f_2(\mathbf{x}) \tag{6.42}$$

where $\lambda = [\lambda_1, \lambda_2]$, with $\lambda_1, \lambda_2 \geq 0$ and $\lambda_1 + \lambda_2 \geq 1$. Commonly, normalized objective function values are used in Eq. 6.42. The local search based on the weighted scalar fitness function is applied on the set of feasible non-dominated population members which are not extreme solutions of the NDF. Let us denote the set of these solutions as S. The overall procedure is described in Algorithm 17. Initially, the current solution, CS, that will undergo the weighted sum approach is selected based on the value of $y((\mathbf{x})|\lambda)$ from the set S. Then, NS is created by CS. If NS is infeasible, it is discarded. Otherwise, NS and CS are compared based on the values of the weighted scalar fitness function. If NS has a better value, then it replaces CS. The procedure is iterated p_{WS} times and the final solutions enter $Ppop'^{g}$. It is noted that, CS is not degraded in the sense of Pareto dominance, i.e. CS may not move to any dominated solution. This is a consequence of the weight setting, i.e. $\lambda_1, \lambda_2 \geq 0$. Moreover, since the minimization of the two objectives is sought, $-\lambda = [-\lambda_1, -\lambda_2]$, may be interpreted as the direction of the steepest improvement of the objective functions values in the objective space. Thus, an appropriate local search direction for each offspring depends on its position on the objective function search space. For this reason, here the individual with the best fitness function value based on the set of randomly generated weights is selected, since it may have the highest chance of producing better individuals with respect to the examined fitness function and thus steer the search faster towards the actual Pareto Front. This is illustrated in Figure 6.10, where it is shown that for two different combinations of weights the individuals having the best value of the corresponding fitness function are selected, since when the local search is applied on them new solutions may be closer to the actual Pareto Front.

Algorithm 17 Local search based on scalar fitness function

Sample $\lambda = [\lambda_1, \lambda_2]$ using the uniform distribution, such as $\lambda_1, \lambda_2 \geq 0$ and $\lambda_1 + \lambda_2 = 1$.
Select CS from S; it will be the solution vector with the lowest value of $y(\mathbf{x}|\lambda)$.
for $iteration = 1$ to p_{WS} **do**
  Create NS by perturbing CS
  Calculate $y(NS)$
  if (NS is feasible) **and** $(y(NS) \leq y(CS))$ **then**
    NS becomes the current solution CS
  end if
end for

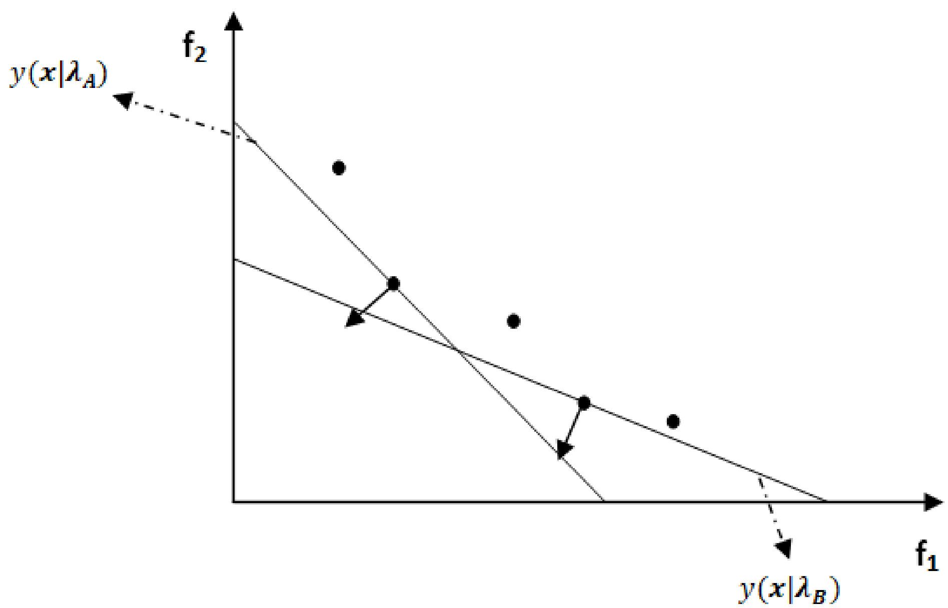


Figure 6.10: The individuals with the best value of the corresponding scalarized fitness function are selected to undergo the local search procedure

Control Mechanism for the application of local search

Balancing the genetic search and the local search is of significant importance when hybrid meta-heuristics are utilized [66]. In this context, the number of individuals undergoing local search is controlled by the cardinality of the set of non-dominated solutions $FNS(Ppop^g)$, as described in Algorithm 18. In the initial stages of the optimization, the population is guided towards the Pareto front mainly by the evolutionary search, as the number of non-dominated solutions is low. The Local Search technique will be applied more frequently in subsequent generations, as the cardinality of $FNS(Ppop^g)$ increases, enhancing local exploitation. In the control mechanism p_{ls} is a percentage, which defines the number of non-dominated individuals that will undergo LS. Moreover, $|FNS(Pop^g)|$ denotes the cardinality of the set of non-dominated solutions and $\lfloor . \rfloor$ is the floor operator.

Algorithm 18 Control the number of individuals for local search

if $(\lfloor p_{LS} \cdot |FNS(Ppop^g)| \rfloor < 1)$ **then**
  LS is not applied
else if $(1 \leq \lfloor p_{LS} \cdot |FNS(Ppop^g))| \rfloor \leq 2)$ **then**
  Apply the LS based on Pareto dominance on the extreme points of the NDF
else if $\lfloor p_{LS} \cdot |FNS(Ppop^g)| \rfloor > 2$ **then**
  Apply LS based on Pareto dominance on the extreme points of the NDF
  Apply LS based on scalar fitness function on $\lfloor p_{LS} \cdot |FNS(Ppop^g)| \rfloor - 2$ non-dominated individuals
end if

6.6 Results of the computational experiments

The efficiency and applicability of the proposed hMOEA is examined in this section. The computational results are divided into three parts. In the first, the impact of creating the CPO utilizing the Tournament Selection procedure is assessed. In the second, the effect of including the proposed LS and the Window Mutation operator on the performance of the MOEA is demonstrated. In both the aforementioned case studies, the method is applied on hydro-thermal systems in which the SR requirements are set using deterministic criteria. In the third case study, the hMOEA is applied on the reliability constrained generation scheduling formulation; in particular, a system comprising thermal generators, hydro plants, and wind power is examined, considering the uncertainty in wind power and load forecasting as well as the reliability of thermal generators.

For each case examined, 20 independent runs of the proposed method have been implemented to assess its robustness. The two pools of values used in the algorithms of Chapters 4 and 5 are also utilized in the proposed hMOEA. Thus, for each target vector at each generation, a value for F and CR is uniformly sampled from F_{pool} and CR_{pool}, respectively, and utilized during the evolution operators. An assessment of the algorithm's performance for different settings of the LS parameters has been carried out using the hypervolume indicator (described in the following subsection). Thereafter, the values of the parameters of the LS algorithm have been selected as follows: $p_{PD} = 5$, $p_{WS} = 5$ and $p_{LS} = 0.1$.

6.6.1 Assessing the quality of approximation sets

The Hypervolume (I_H) indicator [280] has been employed to assess the quality of the approximation sets obtained by the multi-objective stochastic optimizers. This unary indicator measures the hypervolume of the portion of the objective space that is weakly dominated by an NDF; the setting of a reference point which is dominated by all points in the NDF is required for the calculation of I_H. A larger value of I_H indicates a better approximation set. The procedure described in [281] is utilized for the calculation of I_H. In particular, the objective function values of the approximation sets are normalized within $(0, 1)$. Then, the hypervolume of each approximation set is calculated utilizing $[1.1, 1.1]$ as the reference point.

6.6.2 Examining the efficacy of the tournament selection procedure for creating the CPO

The impact of utilizing the Tournament Selection procedure on the performance of the proposed algorithm is examined. In this case study, the ramp rates of the units are not considered and the spinning reserve requirements of the examined systems are set using deterministic criteria. Moreover, the shutdown costs are neglected. The computational experiments have been carried out on four test systems comprising different numbers of thermal generators and hydro plants. The first system comprises 10 thermal generators and 2 hydro units (Test Instance 1). The data of the thermal generators have been obtained from [163], while the coefficients of the emission's function of the thermal generators have been obtained from [282]. The data of the hydro plants have been obtained from [283]. To balance the production from the hydro plants the load has been increased by $100\ MW$ at each period compared to the initial load demand of the system presented in Table A.2. The data of this system are provided in Appendix A.1. Based on the system of 10 thermal generators and 2 hydro plants two more systems are created. The former comprises 20 thermal generators and 4 hydro plants (Test Instance 2) and the latter 40 thermal generators and 8 hydro plants (Test Instance 3). The specifications of the aforementioned systems are obtained by replicating the characteristics of the basic system 2 and 4 times, while the load demand is correspondingly increased. In each system, the spinning reserve requirements at each period are considered equal to 10% of the hourly load [163]. The fourth test system comprises 26 thermal generators and a cascade of 4 hydro plants (Test Instance 4). The thermal part of the system is the well known IEEE-RTS [210], while the coefficients of the emissions function have been obtained from [223]. The data of the hydro system are obtained from [240]. In this case, to balance the production from hydro units the demand of the system is increased by 25% at each hour of the scheduling period compared to the demand presented in Table A.8. The specifications of the thermal generators and the hydro plants, as well as the configuration of the hydro system are presented in Appendix A.2. The spinning reserve requirements are equal to the capacity of the largest committed thermal generator at each hour [210]. It is noted that, the algorithm is terminated after implementing a predetermined number of Function Evaluations (FES). The maximum number of FES (FES^{max}) and the population size utilized for the different systems examined are presented in Table 6.1.

Examining the impact of tournament size

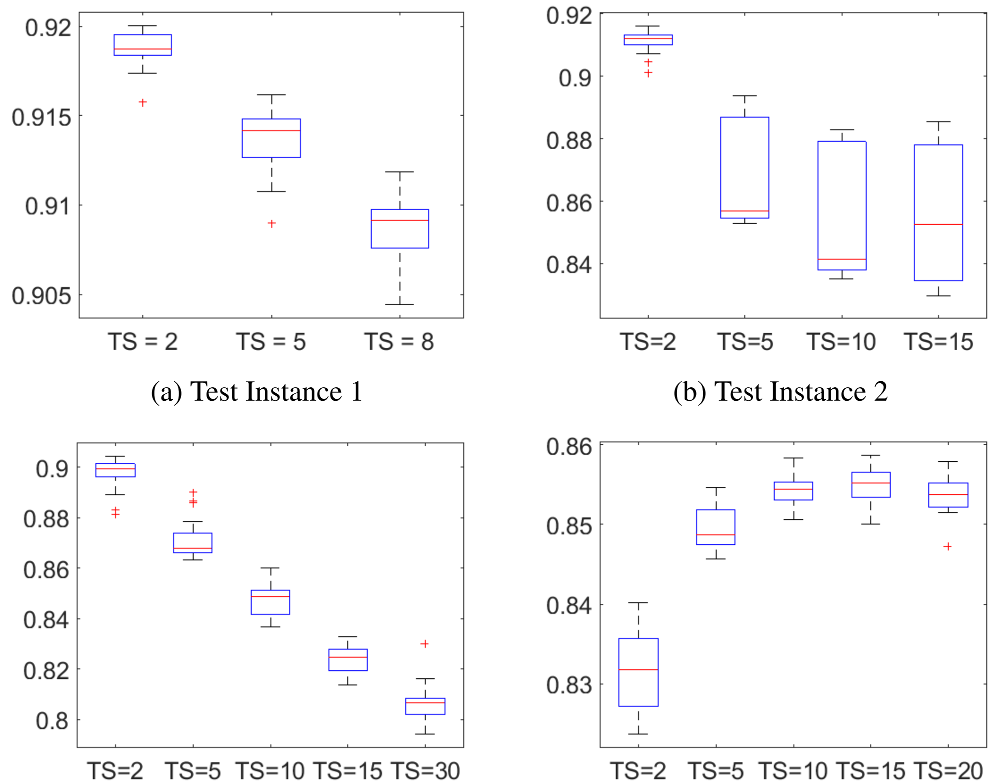
To examine the impact of the size of the Tournament, several computational experiments have been implemented, in which the value of the TS parameter has been varied for each test system. The

	Test Instance 1	Test Instance 2	Test Instance 3	Test Instance 4
NTG	10	20	40	26
NHP	2	4	8	4
FES^{max}	1,000,000	2,000,000	6,000,000	1,000,000
Np	200	200	300	200

Table 6.1: Number of thermal generators and hydro plants, maximum number of function evaluations and population size of the examined test instances

results, i.e. the values of the hypervolume indicator of the approximation sets obtained for each case, are presented in Fig. 6.11 using box plots [2]. It can be observed, that the performance of the algorithm varies with different values of the TS parameter. In Test Instances 1, 2, 3 the algorithm has obtained approximation sets demonstrating a better median value of the hypervolume metric for $TS = 2$. Moreover, the performance of the algorithm, with respect to the I_H, is improved while the value of the TS parameter decreases. However, this does not hold for Test Instance 4, where the algorithm has provided approximation sets with higher median of the hypervolume metric with increased values of the TS parameter. To examine the statistical significance of the aforementioned outcomes Wilcoxon rank sum test is implemented at a significance level of 0.05, i.e. $\alpha = 5\%$, as suggested in [281]. For each test instance, the configuration that has provided the highest median value of the I_H metric is compared to the remaining configurations. The results of the test are summarized in Table 6.2. For Test Instances 1, 2, 3 the p-values are below α for all pairwise comparisons. Thus, the performance of the algorithm is significantly better, with respect to the hypervolume metric, for $TS = 2$ compared to the remaining TS values. Regarding Test Instance 4, when $TS = 15$ the performance of the algorithm, with respect to the hypervolume metric, is significantly better compared to the cases where $TS = 2$ and $TS = 5$. For the cases, where $TS = 10$ or $TS = 20$, the difference in the algorithms performance is not significant, compared to the case where $TS = 15$.

[2] In the box plots the central mark indicates the median, while the top and bottom edges indicate the 25^{th} and 75^{th} percentile, respectively



(a) Test Instance 1

(b) Test Instance 2

(c) Test Instance 3

(d) Test Instance 4

Figure 6.11: Assessment of the impact of different values of TS on the hypervolume of the obtained approximation sets

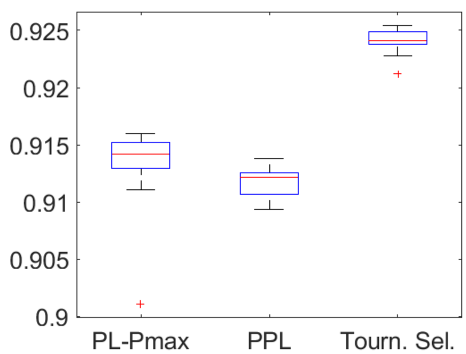
Table 6.2: Results of Wilcoxon Rank Sum test $(\alpha = 5\%)$ on I_H for different values of TS parameter

Test Instance 1		Test Instance 2		Test Instance 3		Test Instance 4	
	$TS = 2$		$TS = 2$		$TS = 2$		$TS = 15$
$TS = 5$	6.80E-08	$TS = 5$	6.80E-08	$TS = 5$	6.80E-08	$TS = 2$	6.80E-08
$TS = 8$	7.90E-08	$TS = 10$	6.80E-08	$TS = 10$	6.80E-08	$TS = 5$	1.58E-06
		$TS = 15$	6.80E-08	$TS = 15$	6.80E-08	$TS = 10$	2.22E-01
				$TS = 30$	2.96E-07	$TS = 20$	1.02E-01

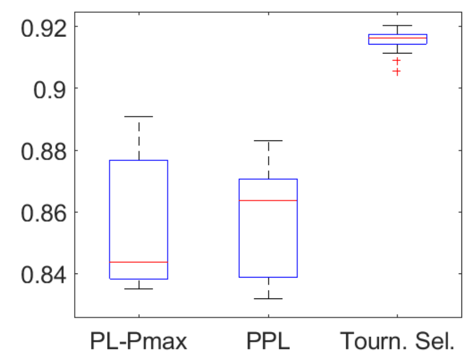
Comparing tournament selection procedure to the conventional priority list method and the plurality of priority lists approach

To validate the efficiency of the proposed Tournament Selection procedure for the creation of the CPO, we implement two variants of the hMOEA. In the former, the Tournament Selection procedure has been replaced by the conventional Priority List, i.e. PL-Pmax; in particular, each individual at each generation is assigned a PL based on either the AFLC or AFLE. In the second, the PPL is included in the hMOEA; for each individual at each generation a different operating point is selected and the corresponding PL is created with equal probability based on the AVC or the Average Emissions of the generators at this point.

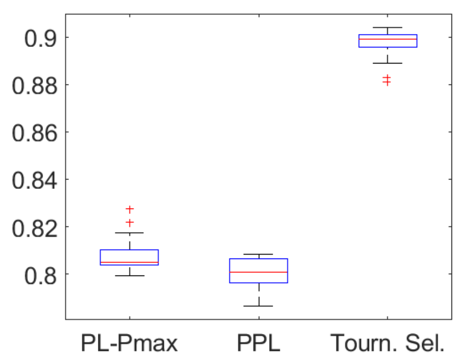
The distribution of the I_H of the approximation sets obtained by each algorithm are presented in Fig. 6.12. The results of hMOEA with Tournament Selection, presented for Test Instances 1, 2, 3 are for the case of $TS = 2$, since this parameter setting has provided the best I_H values. Regarding Test Instance 4, the results of the case $TS = 15$ are included in Fig. 6.12; although the algorithm has not performed significantly better, with respect to I_H, for $TS = 15$ compared to the cases of $TS = 10$ and $TS = 20$, it has obtained a distribution of I_H with higher median value. As shown in Fig. 6.12, in Test Instances 1, 2, 3 the utilization of the Tournament Selection procedure has increased the performance of the hMOEA, since it has obtained approximation sets exhibiting higher I_H compared to the corresponding approximations sets obtained when the hMOEA utilizes PL-Pmax or PPL. Moreover, for the aforementioned test instances the dispersion of the I_H values of the approximation sets obtained when the Tournament Selection is included is also lower compared to both the cases of PL-Pmax and PPL. Regarding Test Instance 4, the distribution of I_H when Tournament Selection is included has higher median value compared to both the cases of PL-Pmax and PPL, while demonstrating similar dispersion compared to the PPL variant. To test the statistical significance, the Wilcoxon rank sum test has been conducted and the results are presented in Table 6.3. For Test Instances 1, 2, 3 the $p - values$ are less than α, which indicates that the algorithm including the Tournament Selection has significantly outperformed, with respect to the hypervolume metric, the competing algorithms. Regarding Test Instance 4, the results of the Wilcoxon reveal that non of the approaches has statistically performed significantly better compared to the others. Based on the aforementioned analysis, the use of Tournament Selection for creating the CPO has enhanced the algorithm's performance in the majority of the examined test instances, while it has performed statistically similarly compared to the other cases at a single test instance.



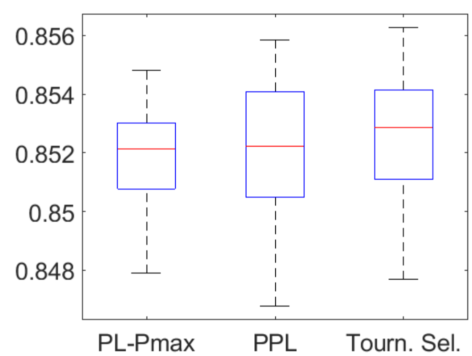
(a) Test Instance 1



(b) Test Instance 2



(c) Test Instance 3



(d) Test Instance 4

Figure 6.12: Distribution of I_H of the approximation sets obtained by i) hMOEA with conventional PL method (PL-Pmax), ii) hMOEA with the PPL approach (PPL) and iii) hMOEA with the Tournament Selection procedure (Tourn. Sel.)

Test Instance 1		Test Instance 2		Test Instance 3		Test Instance 4	
	Tourn. Sel		Tourn. Sel.		Tourn. Sel.		Tourn. Sel.
PL-Pmax	6.80E-08	PL-Pmax	6.80E-08	PL-Pmax	6.80E-08	PL-Pmax	2.62E-01
PPL	6.80E-08	PPL	6.80E-08	PPL	6.80E-08	PPL	6.36E-01

Table 6.3: Results of Wilcoxon Rank Sum test ($\alpha = 5\%$) on I_H for PL-Pmax, PPL and Tournament Selection

6.6.3 Assessing the effectiveness of the local search technique

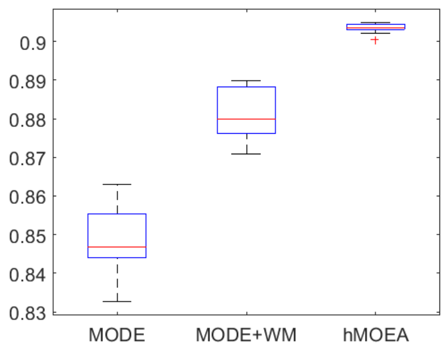
In this subsection, the hMOEA is benchmarked against two MOEAs; the conventional MODE, and the MODE combined with the Window Mutation operator (MODE+WM). In both the aforementioned algorithms, the F_{pool} and CR_{pool}, the parameter vector encoding and the heuristic repair procedures are utilized. Moreover, the Tournament Selection procedure has been employed in all algorithms, with $TS = 2$ for Test Instances 1, 2, 3 and $TS = 15$ for Test Instance 4. The population size and the maximum number of function evaluations used for each algorithm are as presented in Table 6.1.

The distribution of the I_H of the approximation sets obtained by each algorithm are presented in Fig. 6.13. It can be observed that, when LS is included, the distributions of the I_H of the obtained approximation sets exhibit higher median values in all Test Instances examined. Moreover, the approximation sets derived by hMOEA have lower dispersion of the hypervolume value compared to MODE in all test systems and compared to MODE+WM in Test Instances 1 and 3. The statistical significance of the differences is examined using the Wilcoxon rank sum test and the results are demonstrated in Table 6.4. The $p - values$ of all pairwise comparisons are less than the α value signalling that when the LS is included the algorithm's performance is significantly better, with regards to the hypervolume metric, compared to the performance of MODE and MODE+WM.

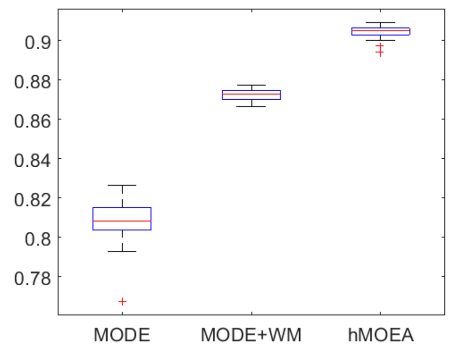
In Fig. 6.14, the NDF of the independent runs with the highest I_H value obtained by each algorithm for each test instance are presented. Moreover, in the same figure a number of points of the Pareto optimal front for each examined test instance are also included[3]. As shown the

[3]The points of the Pareto Front are derived by solving the MO-STHTGS using a MILP formulation and the

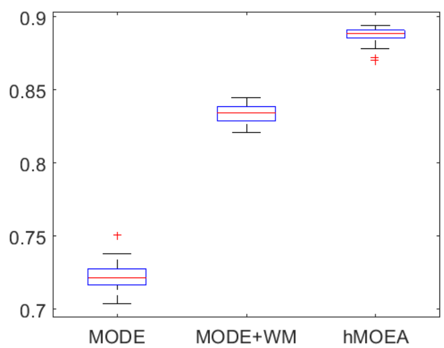
proposed hMOEA has managed to obtain better approximation sets compared to both MODE and MODE+WM for all test instances examined with respect to the convergence to the Pareto Front. Furthermore, the NDFs obtained by the hMOEA adequately approximate the Pareto Fronts of the examined test instances. Thus, the inclusion of the local search technique has significantly improved the performance of the proposed method.



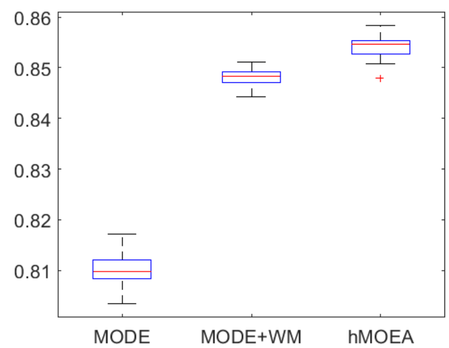
(a) Test Instance 1



(b) Test Instance 2



(c) Test Instance 3



(d) Test Instance 4

Figure 6.13: Distribution of hypervolume values of the approximation sets obtained by i) MODE, ii) MODE with Window Mutation (MODE+WM) and iii) the proposed hMOEA

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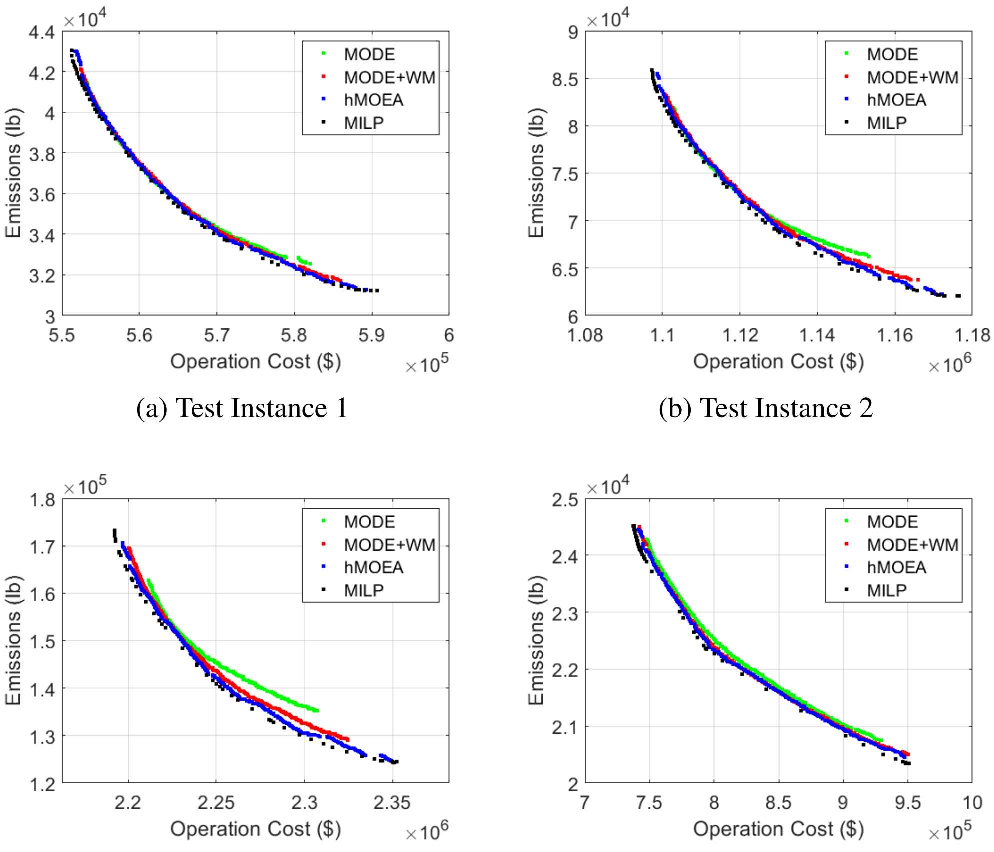
weighted sum approach for the following pairs of weight values (λ_1, λ_2) = [(1, 0), (0.99, 0.01), (0.98, 0.02), ..., (0, 1)].

Test Instance 1		Test Instance 2		Test Instance 3		Test Instance 4	
	hMOEA		hMOEA		hMOEA		hMOEA
MODE	6.80E-08	MODE	6.80E-08	MODE	6.80E-08	MODE	6.80E-08
MODE+WM	6.80E-08	MODE+WM	6.80E-08	MODE+WM	6.80E-08	MODE+WM	4.54E-07

Table 6.4: Results of Wilcoxon Rank Sum test ($\alpha = 5\%$) on I_H for MODE, MODE+WM and the proposed hMOEA



(a) Test Instance 1 (b) Test Instance 2

(c) Test Instance 3 (d) Test Instance 4

Figure 6.14: NDF with the best I_H for MODE, MODE+WM and the hMOEA for each test Instance

6.6.4 Application of proposed hMOEA on the reliability constrained wind-hydro-thermal MO generation scheduling problem

In this subsection, the efficacy of the proposed hMOEA on the reliability constrained multi-objective generation scheduling problem is demonstrated. The impact of several uncertainties on the system's TOC, total emissions and required spinning reserve is assessed. The computational experiments are carried out on a power system comprising Test Instance 4 and an ensemble of wind farms with a total installed capacity of $W_I = 620$. The data of the expected wind power are shown in Table A.10 of Appendix A.2. The data of installed wind capacity and expected wind power have been obtained from [257]. In all the cases examined, $LOLP^{max} = 1\%$ and $EENS^{max}$ is set equal to 0.01% of the expected total demand of the scheduling period.

Impact of thermal generators reliability on the obtained solutions

The effect of the thermal generators reliability is evaluated by varying LT from 2 to 8 hours, while $s = 1\%$. The NDF that has exhibited the highest I_H value amongst the 20 runs for each examined value of LT is depicted in Fig. 6.15. As shown, when the value of LT decreases the provided NDF are closer to the origin of the axis. This is mainly attributed to the increased reserve capacity that is scheduled when the LT value increases; for example the hourly SR of the solutions having the lowest cost in each NDF of Fig. 6.15 is depicted in Fig. 6.16a. When LT increases the probability that a generator will be on outage increases. As a result, to obtain commitment schedules which satisfy the designated limits of the reliability indices, an increased amount of SR is required. However, the latter leads to an increment on both the TOC and the emissions of the system, since more thermal generators are committed and operated on sub-optimal power output levels. Moreover, the hourly LOLP values of generating schedules of the aforementioned solutions are presented in Fig. 6.16b. It can be seen that the generating schedules satisfy the desired LOLP limit for each value of LT. The EENS constraints are also met, since the $EENS^{tot}$ are equal to 0.00996%, 0.00998% and 0.00910% of the total load when LT is 2, 4 and 8 respectively. In summary, the results verify that the generators' reliability may affect the solutions obtained by the proposed approach.

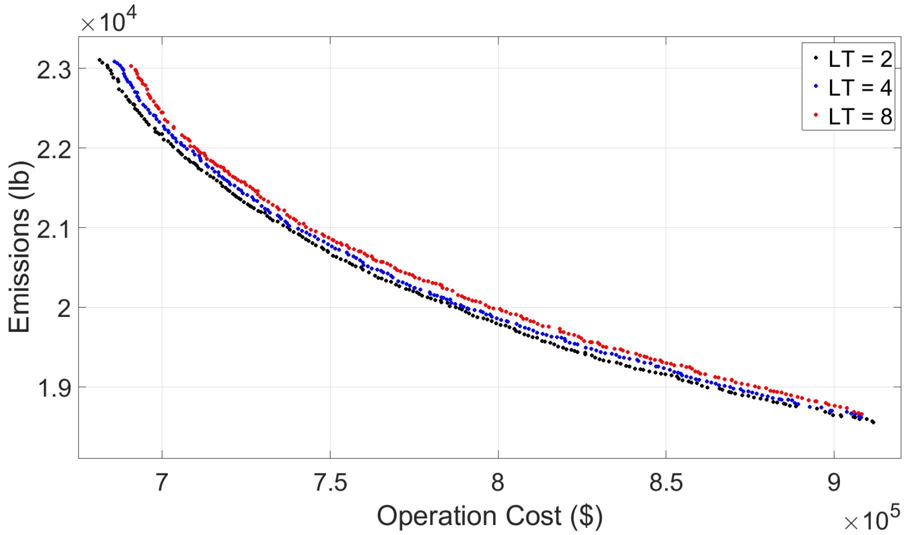
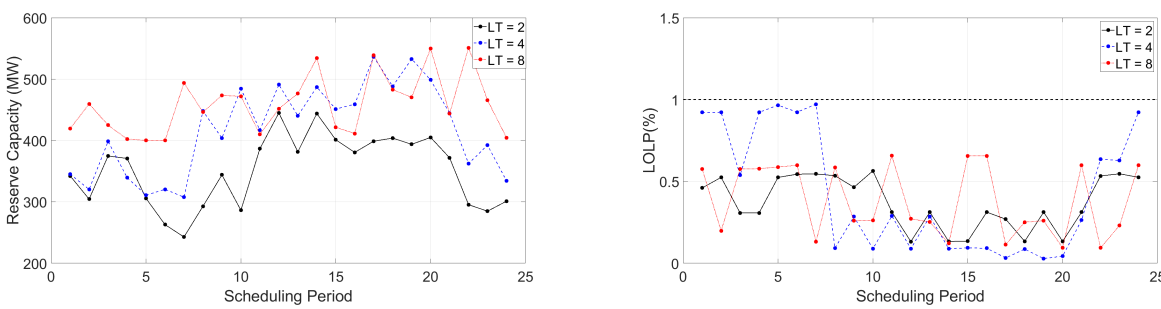


Figure 6.15: NDF of the independent run with the best I_H for each different LT value



(a)

(b)

Figure 6.16: (a) Hourly Reserve Capacity and (b) Hourly $LOLP$ values of the solutions exhibiting the lowest cost in the NDFs of the run with the best I_H for each LT

In Table 6.5, the hydro-thermal generating schedule for the case where $LT = 4$ is examined. It may be observed that the constraints of the thermal generators are satisfied. Moreover, as shown in Fig. 6.17, the schedule is feasible with respect to the constraints related to the volume of water in the reservoir. Thus, the proposed algorithm is able to derive adequate generating schedules which satisfy the complex constraints of the reliability constrained multi-objective wind-hydro-thermal generation scheduling problem.

	Hours																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Thermal																								
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	15.2	15.2	15.2	15.5	15.3	18.0	46.4	76.0	76.0	76.0	76.0	76.0	76.0	74.9	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	15.3
11	15.2	15.2	15.2	15.2	15.3	15.4	42.5	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	72.4	15.3
12	15.2	15.2	15.2	15.2	15.2	15.2	39.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	75.9	76.0	76.0	76.0	76.0	76.0	71.8	15.2
13	15.2	15.2	15.2	15.2	15.2	15.2	20.1	58.6	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	76.0	74.8	76.0	76.0	74.9	44.4	15.4
14	0	0	0	0	0	25.1	25.4	47.4	83.0	89.5	100.0	86.2	100.0	68.2	87.2	95.8	74.0	88.5	72.2	77.1	92.9	74.6	25.0	25.0
15	0	0	0	0	0	0.0	25.0	52.6	44.0	60.4	88.3	58.6	76.6	63.9	77.8	75.6	45.2	73.6	54.1	61.4	82.8	79.9	25.0	0
16	0	0	0	0	0	0	0	25.0	25.0	49.6	78.5	47.9	67.1	65.6	68.0	53.3	28.7	33.7	26.2	46.9	63.9	40.2	25.2	0
17	142.8	155.0	147.6	136.3	149.2	151.8	152.9	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0
18	129.1	137.4	113.5	133.0	142.2	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	154.9
19	134.7	128.5	90.8	122.4	144.8	154.8	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	143.3
20	116.4	122.0	112.7	131.5	116.0	153.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	155.0	150.2
21	0	0	0	0	0	0	0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.1	69.0	69.0	69.0	69.0	69.0	0
22	0	0	0	0	0	0	0	69.5	69.3	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	69.0	0	0
23	0	0	0	0	0	0	0	0	0	69.0	69.3	69.3	69.1	69.4	69.0	69.2	69.0	69.0	69.0	69.0	69.0	0	0	0
24	345.1	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0	350.0
25	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0
26	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0	400.0
Hydro																								
1	46.4	71.7	54.3	49.4	63.3	46.4	46.4	46.4	129.2	113.9	105.0	85.4	46.4	117.0	78.4	128.6	109.1	53.3	61.8	73.7	91.9	97.6	46.4	46.4
2	34.7	34.8	34.7	34.7	34.7	34.7	34.7	34.7	64.6	63.8	67.3	48.2	34.9	74.9	73.2	69.4	57.8	34.8	63.2	51.4	83.8	34.7	34.7	34.7
3	52.5	33.9	39.9	33.5	35.5	41.0	47.5	95.1	82.6	82.4	82.5	95.8	87.1	54.0	65.6	85.8	66.0	77.4	76.5	77.0	33.5	33.5	33.5	33.5
4	138.6	144.4	181.0	142.9	173.0	222.1	287.2	420.4	425.9	407.1	426.1	413.3	420.5	333.5	420.0	411.3	420.4	421.0	398.4	425.0	421.1	423.1	345.1	240.3
Total	2001.0	2038.5	1985.4	1994.8	2069.7	2197.8	2382.2	2916.6	3066.5	3147.7	3229.0	3116.6	3113.5	3057.3	3151.0	3200.9	3082.1	3063.3	3032.0	3093.3	3150.8	2994.6	2638.4	2194.6

Table 6.5: Power output (MWh) of thermal generators and hydro plants of the best cost solution in the NDF with the highest I_H value when $LT = 4$

Examining the impact of demand uncertainty on the obtained solutions

In the previous subsection, the standard deviation of the load forecasting error has been considered equal to 1% of the expected load at each hour. In this subsection, we examine the impact of load forecast uncertainty on the solutions. In particular, s is varied from 1% to 5% and the implications on the obtained NDFs and on the reserve requirements of each generating schedule are assessed. In all examined cases LT has been considered equal to 4.

In Fig. 6.18, the NDF of the independent run with the highest I_H for each different value of s is presented. As observed, while the uncertainty of load forecasting decreases the NDF obtained by the proposed MOEA are closer to the origin of the axis, thus resulting to generating schedules with lower cost and lower emissions. The reserve capacity of the generating schedules that have

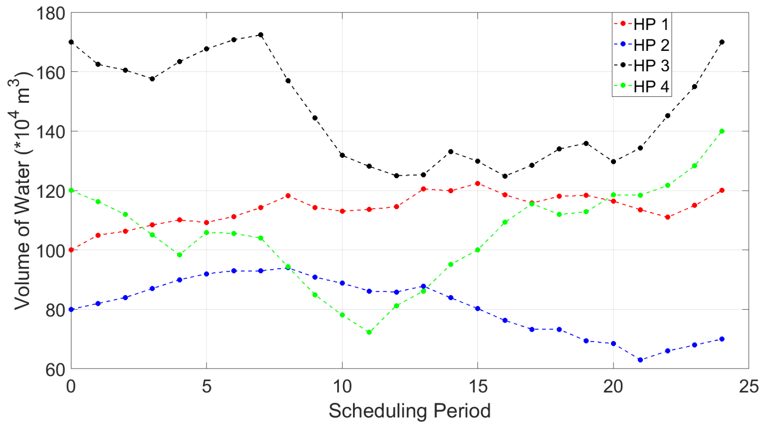


Figure 6.17: Volume of the water in the reservoir ($\cdot 10^4 m^3$) of the schedule of best cost for the NDF with the highest I_H value for $LT = 4$

exhibited the lowest cost and the lowest emissions on the aforementioned NDFs are provided in Fig. 6.19a and 6.19b, respectively. In general, while the standard deviation of load forecasting error increases, the reserve requirements of the system are increased and a larger number of thermal generators should be committed to maintain the values of the reliability indices below the desired levels. The latter is illustrated in Fig. 6.20a, where the schedules of lowest cost of the NDF with the best I_H value for $s = 1\%$ and $s = 5\%$ are presented. As observed, when the volatility of load forecasting increases marginal units are brought on-line to attain the desired reliability, triggering an increase of the TOC by approximately 0.75% ($687,778.95$\$ to $692,858.95$\$) and of the amount of emissions by 0.41% ($23,043$ lb to $23,147$ lb). Correspondingly, in Fig. 6.20b the schedules of lowest emissions are depicted. When $s = 5\%$, generators $10 - 13$ are brought on-line more frequently. These generators are more reliable than marginal units, however they are less efficient with respect to the amount of pollutants emitted, triggering an increase in the system's emissions by 1.08% ($18,626$ to $18,827$ lb). Thus in summary, as the error in load forecasting increases the system's TOC as well as the systems' emission increment.

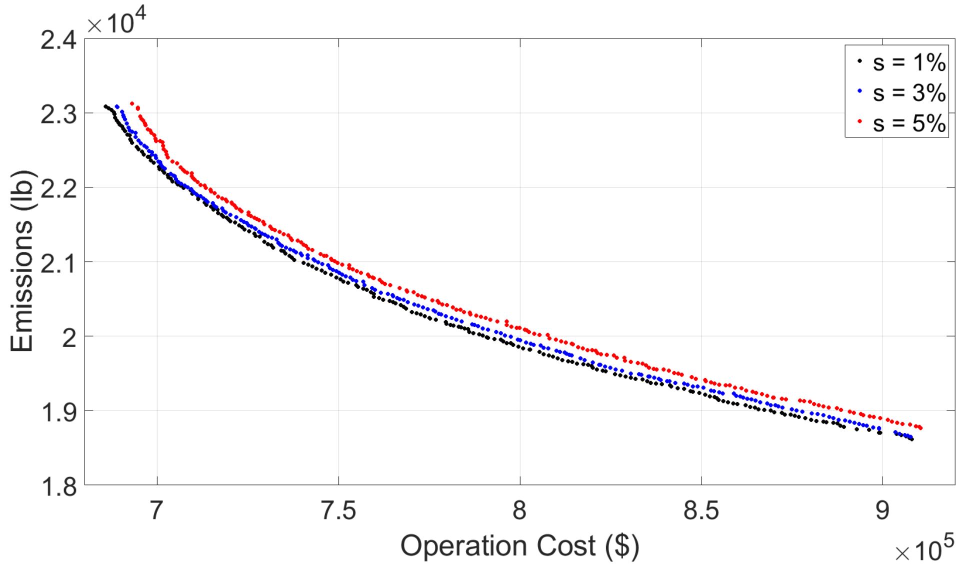
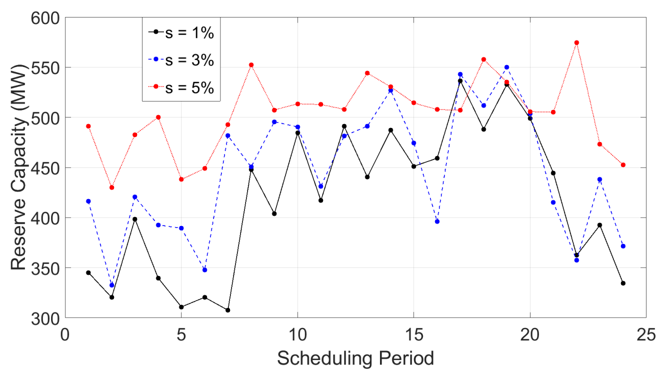
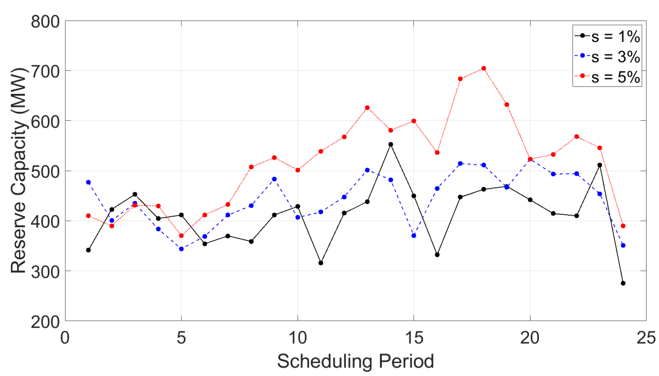


Figure 6.18: NDF of the independent run with the best I_H for different values of s

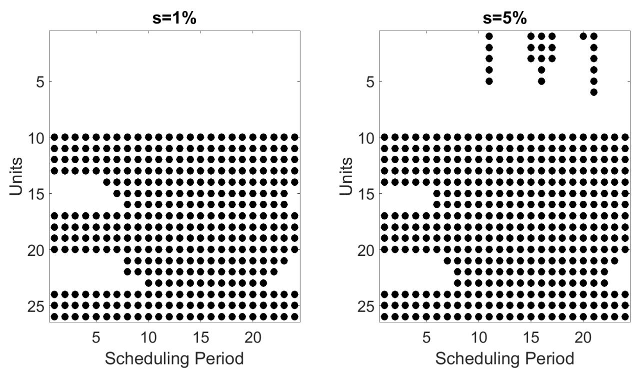


(a)

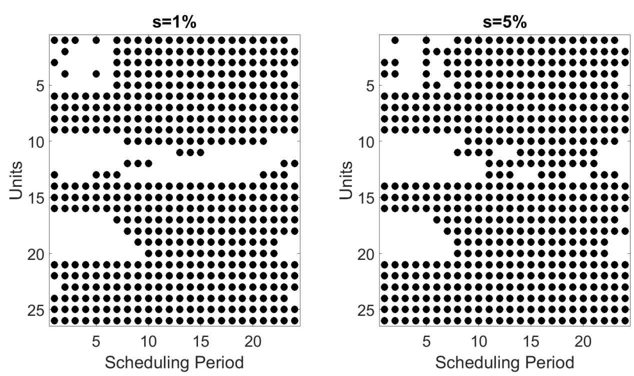


(b)

Figure 6.19: Hourly Reserve Capacity of (a) the lowest cost solutions and (b) the lowest emissions solutions of the NDFs with the best I_H for each s



(a)



(b)

Figure 6.20: Operating schedules of thermal generators for (a) the solutions of lowest cost and (b) the solutions of lowest emissions of the NDFs with the best I_H for $s = 1\%$ and $s = 5\%$

Assessing the impact of wind power uncertainty on the derived NDF

In this subsection, the effect of wind power integration on the NDF obtained by the proposed algorithm and on the reserve capacity of the system is discussed. More specifically, three cases are examined in which the wind power is considered equal to 70%, 100% and 130% of Pw^t (as presented in Table A.10), respectively. In all the examined cases, $LT = 4$ and $s = 1\%$.

In Fig. 6.21, the NDF with the best I_H value for each examined case is presented. As shown, an increased wind power penetration triggers considerable reductions both to the system's operation cost and the emissions, due to the reduced reliance on fossil fuel fired generators. The latter is shown in Fig. 6.22, where the schedules of the solution with the lowest cost in the aforementioned NDFs are demonstrated, for the cases of $70\% \cdot Pw^t$ and $130\% \cdot Pw^t$. It can be seen that fewer generators are brought on-line when the wind power output is increased, resulting in a decrease of system's total operation cost by approximately 4.87% ($702,711$\$ to $670,060$\$) and emissions by approximately 3.3% ($23,396$ lb to $22,648$ lb). Moreover, as shown in Fig. 6.23 the increase in the wind power included in the system has not triggered an increase in the spinning reserve requirements of the system. For the system under examination, this might be partly justified as follows; when increased wind power is considered within the system the standard deviation of net load forecasting error increases. Nevertheless the value of the expected net load demand decreases. As a result, the latter may be satisfied by utilizing solely base and intermediate load units. Such generators have commonly a low probability to be on (forced) outage. Thus for the lower net demand they may provide adequate reliability.

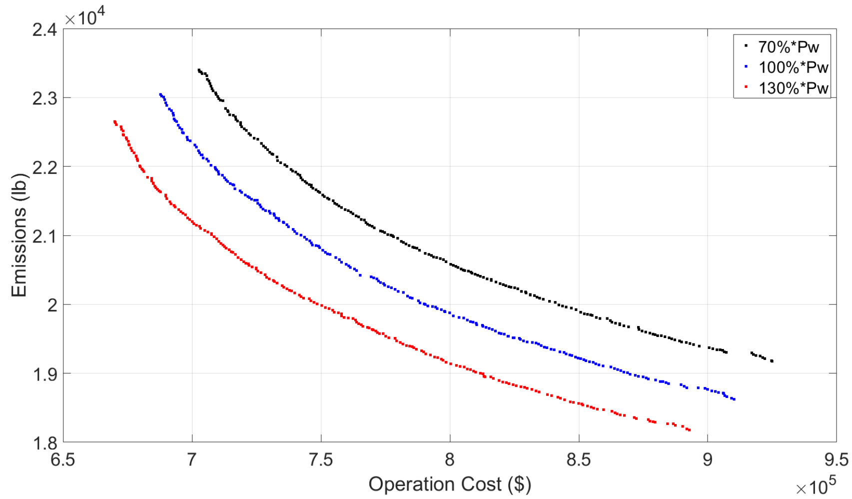


Figure 6.21: NDF of the independent run with the best I_H for the different cases of wind power integration

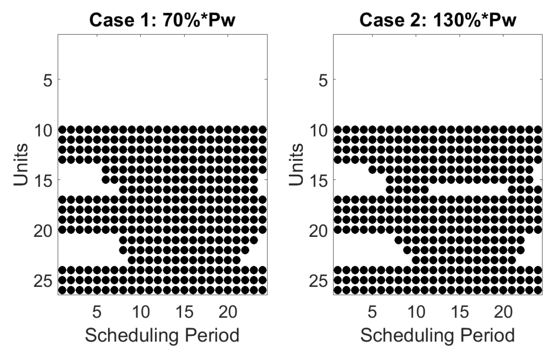


Figure 6.22: Operating schedule of thermal generators of the lower cost solution for the independent run with the best I_H for the cases of 70% and 130% wind power integration

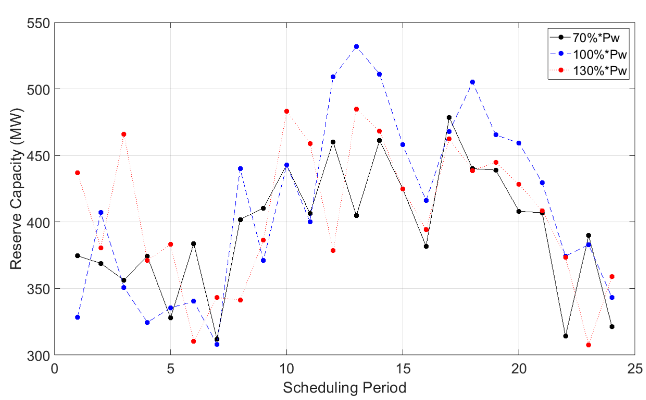


Figure 6.23: Reserve capacity of the solutions of lowest cost for the NDF with the highest I_H for the different cases of wind power integration

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

The basic objective of the present dissertation was to propose, develop and evaluate optimization methods based on Evolutionary Algorithms for two important optimization problems encountered in energy system's management. The proposed methods are based on two Evolutionary Algorithms, i.e. the Differential Evolution and the Evolution Strategies. A series of modifications have been proposed to enhance the performance of each of the aforementioned algorithms when they are applied on the following two real-world problems:

1. The short-term generation scheduling problem, in which the optimal scheduling of the generating units in a power system is sought, to efficiently meet the expected load. Several variants of the problem have been tackled taking into consideration uncertainties related to errors in load and wind power forecasting and unscheduled outages of the generating units, different types of generating technologies and economic/environmental objectives.

2. The generation expansion planning problem, in which the optimum long-term investment planning (technology type, capacity, and investment time) is determined for a power sector with the purpose of reliably meeting the anticipated electricity demand growth as well as satisfy specific energy objectives related to the integration of Renewable Energy Sources within the generation mix.

The aforementioned problems have several characteristics (large number of objective variables and constraints, non-linear and non-differentiable objective and constraint functions) which may pose challenges for their efficient optimization by general purpose EA algorithms. For these reasons, a series of algorithmic interventions have been proposed to increase the efficiency of Differential Evolution and Evolution Strategies for the optimization of the examined problems. These modifications enable the obtainment of solutions of better quality in a shorter time by the algorithms. Moreover, in the case of Short-term generation scheduling it is shown that the algorithm may be easily adjusted to optimize different forms of the considered problem. Thus, the proposed tools may facilitate possible decision makers of the corresponding fields during the decision making process. The proposed method for the GEP model may assist policy makers to assess the impact that specific energy objectives may have on the structure of a power sector and the evolution of the SMP. The proposed method for the STGS problem may assist System Operators and GENCOS towards determining the optimal schedule of generators in an attempt to decrease their production costs.

In what follows, the problems tackled in this dissertation, the algorithms developed and the corresponding contributions are presented.

7.1 Contribution on the optimization of the Generation Expansion Planning problem

A decision support model has been developed for the optimization of the generation expansion planning of semi-liberalized electricity markets towards the accomplishment of quantitative energy objectives, related to the integration of RES within a power sector's generation mix. The power sector's NPV constitutes the objective function of the model while the annual capacity orders and the occupation factor of the generating technologies are the model's decision variables. The quantitative energy objectives were formulated as equality constraints on which a relaxation factor was applied. In summary the contribution to the existing literature consists of the following:

1. A stochastic optimization procedure without recourse has been developed to derive the best capacity additions (time, technology, and capacity) towards the optimal compliance with energy objectives.

2. An assessment of the impact of including the energy objectives in the GEP model is implemented, both on the power sector's evolution and on the optimization procedure.

3. A relaxation factor has been applied on the equality constraints representing the energy objectives and an analysis of its effects has been made, both on the power sector's structure and on the optimization procedure.

4. A hybrid algorithm has been proposed, which combines Improved Stochastic Ranking Evolution Strategy (ISRES) and the Interior Point Algorithm (IPA) to optimize the non-linear, large-scale GEP model.

Five numerical experiments were conducted, where the GEP model was optimized. In the first two, only IPA was used for limited and large number of Function Evaluations, respectively. In the third, ISRES-IPA was used. In the remaining two, the model was optimized by a commonly used GA and a hybrid GA-IPA. In each numerical experiment different values of the relaxation factor were examined for a series of optimization runs. The results were compared with those derived from the optimization of the same model without the additional constraints related to the energy objectives. The results indicate that:

- A higher Feasibility Rate and lower solutions' dispersion were achieved, when the relaxation factor's value increases. However, elevated levels of relaxation drive IPA to premature convergence.

- The ISRES-IPA achieved solutions of higher best and mean NPV values and lower dispersion compared to the IPA, the GA, and the GA-IPA, revealing improved performance of the proposed algorithm in the large-scale optimization problem examined. Hence, depriving computational budget from the early stages of optimizing with IPA and dedicating it to ISRES may result in producing an adequate initial solution vector, facilitating IPA's convergence.

- When relaxation is negligible, the Feasibility Rate of ISRES-IPA decreases. This may be attributed to the absence of constraint normalization in the original ISRES. In this context, the impact of normalizing the model's constraints may be assessed in future works.

Moreover, the relaxed constraints have led to conclusions regarding the structure of the power sector:

- Capacity orders of Off-shore wind turbines, Concentrated Solar Power, On-shore wind turbines, and biomass are proposed for meeting the short-term targets.

- The estimated installed capacity of Lignite plants is decreased on the long run and mainly replaced by hydro and Concentrated Solar Power units as a result of the long-term objectives.

- Differences emerge in the anticipated generating mix of the cases including the energy constraints compared with the base case. As a consequence, the evolution of the core indicators of the electricity market is affected. The accomplishment of the energy objectives is expected to result in higher SMP values, for the largest part of the planning horizon. However, if present values are considered, a slight reduction of SMP might be expected in the long run. This may be of some interest for the final users, since social cost might be reduced.

- The proposed capacity expansion plans may lead to increasing financial balance in the long run irrespective of the investigated case. This also holds, when the examined policy's targets are implemented, despite the higher investment cost, required for the planned investments in RES.

Interestingly, higher levels of relaxation led to lower solution's dispersion. Thus, the robustness of the optimization procedure and the reliability of the derived expansion plans increase. In addition, the results derived for various relaxation levels exhibited relatively small differences regarding the power sectors breakdown. As a consequence, relaxation factors, when properly adjusted, may facilitate the attainment of optimal plans towards accomplishing energy objectives. The GEP model and the corresponding results have been published in a journal paper [284].

7.2 Optimization of the short-term generation scheduling problem

The short-term generation scheduling problem is considered as one of the most important problems in the power industry. Its main objective is the determination of the optimal operating schedule of available generators in a power system to meet the anticipated demand. The problem is large scale, non-linear, mixed-integer, highly constrained and belongs to the category of NP hard problems. In this dissertation, a solution methodology of the problem based on Differential Evolution has been developed to tackle the several variants of the problem.

7.2.1 Contribution on the single-objective short-term generation scheduling problem for power systems comprising only thermal generators

Initially, the conventional form of the problem is tackled, in which the power system comprises only thermal generators. The problem's objective function is the minimization of the system's operation cost. For the optimization of the problem, an efficient method for solving a short-term generation scheduling problem is proposed based on DE with enhanced evolution operators, that exploits domain specific knowledge through adequate heuristic procedures. In particular the method's salient features are:

1. The suggested method optimizes both sub-problems of UCP using a single DE variant. Each population member comprises solely real valued variables, which represent the power output of the units. Moreover, a simple transformation function determines the binary on/off state of the units.

2. The proposed method includes heuristic repair mechanisms, which exploit the information provided by the PL of the units. The impact of the cost metric chosen to form the PL on the performance of the algorithm is examined. Moreover, a method for the creation of a Plurality of PL (PPL) is proposed to enhance the diversity of generating schedules examined during optimization.

3. An Elitist Mutation (EM) operator is introduced to strengthen the performance of the DE-based solver. In EM, the information from the population member with the best objective function value is exploited to drive the population towards promising regions of the search space and avoid the premature convergence of the algorithm.

The beneficial impact of the proposed algorithmic interventions has been demonstrated on a series of computational experiments on the system of 10-100 units; In particular, it has been shown that:

- The use of a Plurality of Priority Lists enhances the algorithm's performance compared to the case, where Priority Lists based on constant metrics have been used. The integration of the Plurality of Priority Lists has led to solutions of lower cost more consistently, especially for system's of larger size. On the contrary as shown by the results, utilizing a single priority list during the heuristic repair procedures may cause the premature convergence of the algorithm.
- The algorithm performs better, with the inclusion of the Elitist Mutation strategy. When the Elitist Mutation Strategy is included, the method obtains solutions of lower cost more consistently, especially in systems of larger size, i.e. 60, 80 and 100 thermal units. As shown in the convergence curves, the use of the Elitist Mutation may accelerate the convergence of the algorithm, steering the population to solutions of lower cost from the initial stages of the optimization.

Furthermore, the proposed method was benchmarked against other advanced approaches on several power systems and exhibited a quite competitive performance. In particular:

- Regarding the system of 10-100 units without ramp rates the method has managed to derive better results compared to all the previous DE-based approaches and the majority of methods based on other stochastic optimization algorithms and hybrid methods based on combination of stochastic optimization algorithms. Moreover the computational time required by the method is considered reasonable. Regarding the system of 10-100 units with ramp rates, the method achieved considerable cost reductions compared to the various competing algorithms, for the systems of 10, 20 and 40 units.

- For the practical cases of IEEE RTS test system and the 38 units Tai Power System the method yielded generating schedules which reduced the operating cost by $1,291\$$ (0.21%) and $1.49M\$$ (0.76%) compared to the previously best reported results. Besides, the proposed method performed quite robustly, since in most of the examined cases it obtained solution distributions with the lowest average and maximum costs amongst other stochastic, conventional or hybrid, approaches.

Thus, it may be concluded that the proposed method may be a promising alternative for the the conventional Short-term Generation Scheduling problem, since it has performed efficiently in all the examined test systems. It is noted that the method and the corresponding results have been presented on a conference paper [285] and a journal publication [286].

7.2.2 Contribution on the single-objective problem when the system's reliability is integrated

A method has been developed to solve the short-term generation scheduling problem when the reliability constraints are considered within the formulation of the problem; in this case, the spinning reserve requirements of the system are not set based on deterministic criteria, rather than they are implicitly derived during the optimization based on the values of the LOLP and EENS reliability indexes. During the calculation of the latter the probabilities of (unscheduled) outages of thermal generators as well as uncertainties in load forecasting are considered. In such a case a more realistic assessment of the systems reserve requirements may be achieved. The contributions of this dissertation on the solution of the problem are the following:

1. The real-coded DE-based method developed for the conventional form of the problem is extended to handle the RCSTGS.

2. An external archive is used to store the COPT tables of the commitment patterns encountered during optimization. When such patterns are encountered again during subsequent stages of the optimization the COPT is obtained from the external archive. As a consequence considerable savings in computational time may be achieved.

3. Two mechanisms have been developed to repair the individuals which violate the EENS and the LOLP constraints, respectively. Moreover, the mechanism for reducing the excessive reserve capacity is modified to consider the constraints of the LOLP reliability index. Thus, the use of penalty parameters to deal with violations of the reliability constraints is avoided.

The performance of the method has been evaluated on the test case used in the bibliography when the reliability of a power system is taken into consideration. Three case studies have been implemented. For each one of the aforementioned, two combinations of reliability indices have been examined. More specifically:

- The impact of the unavailability of the units on the total operation cost and on the reserve capacity of the system has been examined. The computational results demonstrate that as expected, an increase of the unavailability of generators, triggers an increase in the operation cost of the obtained solutions. This is mainly attributed to the increased reserve capacity required to meet the designated reliability limits, when the unavailability of the units is higher. Moreover, the results of the method have been compared with those of the SA approach in [229]. In the majority of the examined cases the proposed method has managed to derive solution distributions with lower minimum, average and maximum cost compared to the SA method. Moreover, the computational time of the proposed method is competitive compared to the benchmark approach.

- The impact of the load forecasting uncertainty on the operation cost and the reserve capacity has been assessed. The results confirm that increased load forecast uncertainty triggers an increase in the required reserve capacity of the system as well as its operation cost. In this case study, the results of the proposed method are also compared to the results of the SA approach, demonstrating better solution distributions in the majority of the cases examined.

- The method has been applied on systems of higher number of units performing robustly and requiring reasonable execution time.

It should be noted that the proposed heuristics have adequately repair individuals violating the reliability constrains leading to feasible solutions. Thus, it may be concluded that the proposed method may be a promising alternative for optimizing the RCSTGS, providing an adequate method for determining the spinning reserve requirements taking into consideration the unavailability of generators and the load forecast uncertainty. The DE-based method to solve the RCSTGS and the corresponding results have been demonstrated in a conference paper [237].

7.2.3 Contribution on the multi-objective problem for power systems comprising thermal generators, hydro plants and wind power

A multi-objective formulation of the short-term generation scheduling problem for power systems comprising thermal generators, hydro plants and wind power has been proposed. The LOLP and EENS reliability indices are considered as constraints within the formulation of the problem. During the calculation of the LOLP and EENS, the unreliability of thermal generators as well as uncertainties related to the forecast of load and wind power output are considered. The hourly reserve requirements of the system are estimated during the optimization ensuring that the final schedule maintains the designated reliability levels. The problem is optimized by a hybrid multi-objective DE method. The contributions of the dissertation regarding this model are summarized as follows:

1. The multi-objective formulation of the STGS considers thermal generators, hydro plants and wind power as well as the reliability of generators and uncertainties in load and wind power

forecasting. To the best of the author's knowledge, a model combining the aforementioned features in a multi-objective framework has not been proposed in the literature.

2. A multi-objective real-coded DE approach, in which the selection procedure of NSGA-II is integrated, has been developed to optimize the aforementioned problem. The method considers the two step function and several repair mechanisms and constitutes an extension of the DE method applied on the single objective STGS models examined in the thesis.

3. A Local Search technique has been combined with the multi-objective DE to enhance the algorithms performance. The latter combines two local search paradigms, a local search based on Pareto dominance and a local search based on weighted scalar fitness function, while an adaptive control mechanism has been also proposed, to balance the global exploration and the local exploitation during the optimization.

4. A method is proposed to create the CPO of generators, which is utilized during the heuristic repair mechanisms. It is based on a Tournament Selection procedure, during which generators are compared based on an economic or an environmental metric. The method may increase the diversity of the schedules examined during optimization, improving the performance of the proposed algorithm.

The beneficial impact of the proposed algorithmic interventions has been validated by implementing several computational experiments, in power systems comprising different numbers of hydro-plants and thermal generators. In particular, it has been shown that:

- In the tournament selection procedure, the Tournament Size may have a considerable impact on the algorithm's performance. In fact, depending on the characteristics of the generators in the power system, the optimal performance of the algorithm may be exhibited for different values of the TS.

- Engaging the proposed Tournament Selection procedure within the hybrid MOEA has significantly improved the algorithm's performance, compared to the cases where the conventional Priority List and the Plurality of Priority Lists have been considered.

- The method performs significantly better, when the local search technique is included compared to the cases of the simple MODE and the MODE combined with the Window Mutation operator.

- The hybrid MOEA has managed to consistently provide non-dominated fronts which adequately approximate the Pareto Fronts of the examined test instances.

Besides, the effect of several uncertainties, such as the unavailability of the generating units and load and wind power forecasting errors, on the trade-off solutions of total operating cost and emissions has been assessed. The results reveal that:

- When the unavailability of the units decreases, then the NDF obtained are closer to the origin of the axis. This is mainly attributed to the increased reserve capacity required in order the system to maintain the designated reliability level when the unavailability of the units is higher. Higher reserve capacity triggers increases both in the operation cost and the emissions of the system.

- When the uncertainty of load forecasting decreases, the NDF are closer to the origin of the axis. Examination of the reserve capacity of the schedules of minimum cost and minimum emissions for the several values of demand uncertainty has revealed an increase in the reserve capacity with increased load forecasting uncertainty. The latter causes an increase in both the system's cost and emissions.

- The impact of wind power forecasting uncertainty is examined, by varying the power output of wind generators. As expected an increase in the wind power has led the obtained NDF closer to the origin of the axis. With increased wind power output, the load to be satisfied by thermal generators decreases, leading to lower operating cost and emissions. Interestingly, the increase in the wind power included in the system has not triggered an increase in the spinning reserve requirements of the system.

In conclusion, the proposed hybrid MOEA has efficiently optimized the reliability constrained economic/environmental short-term wind-hydro-thermal generation scheduling problem. Moreover, the proposed model may provide a systematic framework for estimating the required SR in systems with hydro-plants, thermal generators and wind power. It is noted that part of the research on the multi-objective problem has been published on a conference paper, i.e. [287].

7.3 Discussion on the limitations of the proposed models

Regarding the Generation Expansion Planning model, the obtained results may provide some insight on planners and policy makers regarding the impact that certain energy objectives may have on the structure of a power sector. However, the approach has a series of limitations that should be taken into account, when its results are examined:

- The first is related to the level of detail of the approximation of the short term operation within the GEP model. In fact, the GEP model approximates the short-term operation of the power system by utilizing the load duration curve. Thus, the dispatch of the technologies is approximated using the demand and the variable costs of each technology, simulating the merit order effect. Such an approach may encounter difficulties in preserving the chronological information of the load. The latter may render capturing the thermal unit operating limitations challenging especially in cases of increased RES penetration. However, due to the computational efficiency of such a model it may still provide a useful framework for examining prices and the dispatch in different market models.

- It was assumed that the examined power system is represented as a single zone and thus the location of the capacity orders derived by the model has not been examined. It should be stated, that the model may take into consideration the location of the derived capacity orders by altering the objective variables of the method.

- Interconnections with other power markets have not been examined. The latter may affect the profile of load demand to be satisfied by domestic generating technologies, which may further impact the SMP of the system. Their examination is left as a future research direction.

- As stated in Chapter 3, the proposed model focuses on the expansion of the generating capacity of the examined power sector, without considering the transmission network and its possible expansion. The combination of the proposed model with a Transmission Expansion Planning model may constitute a direction for future research.

The following limitations should be considered when the results of the short-term generation scheduling model are examined:

- Regarding the operating state of the hydro units, the proposed model adopts a common practice in the literature, which considers that the hydro units are in operation at every hour of the scheduling period. Since hydro plants have practically negligible operation cost (and emissions) compared to the thermal generators they are commonly prioritized in the merit order, justifying partly the aforementioned assumption. Moreover, in the examined formulation the hydro production is modelled in the level of hydro-plants, assuming to comprise of identical hydro units.

- Within the examined model, the assumption that the hydro units do not contribute to the system's reserve has been made. Such an assumption, as stated within the relevant literature may not hold for systems where the hydro plants are the primary electricity provider. Thus, in that case, modifications of the reserve constraints and on the calculation of the reliability indices should be made, to account for the capacity of hydro plants within spinning reserve constraints.

- The thermal generating units, the hydro plants as well as the wind turbines are considered to be connected on a single bus, thus the transmission system has not been examined. Considering the transmission network constraints may pose challenges on satisfying the load in the several buses of the system, and should be considered in a future research.

- The examined models of STGS, do not consider interconnections with other power systems.

7.4 Directions for future research

In what follows some directions for future research are given for the optimization methods developed as well as for the problems tackled in this dissertation:

- Regarding both EA algorithms considered, i.e. Differential Evolution and Evolution Strategies, some modified evolution operators may be included into the proposed EA-based frameworks, to research possible improvements in the algorithm's performance for solving the problems examined in this dissertation.

- Regarding the Short-term Generation Scheduling problem, constraints related to the transmission system may be included.

- Within the Short-term Generation Scheduling, the model for hydro-pumped plants should be examined. Such plants provide flexibility to the system enabling the system operator to cope with sudden deviations in the demand or the production from RES.

- The reliability constrained model may be extended to integrate the transmission system taking into consideration the reliability of the transmission lines.

- The traditional model of a generator used in reliability studies consists of two states; the unit is available for operation or on unscheduled outage. Nevertheless, a more accurate modelling may be integrated regarding the units that operate in peak periods. Due to the frequent start ups and shut downs such units are subject to additional stress compared to based load units. This additional stress has been reported as starting failure outage and may be taken into account in future extensions of the proposed model.

- Other types of dispatchable generators should be modeled and included into the formulation of the Short-term Generation Scheduling problem, e.g. combined cycle units. Such technologies have attracted the interest of generating companies, since they combine two or more thermodynamic cycles resulting in improved overall efficiency, and reduced fuel costs. Moreover, investments costs in such technology are relatively low. Compared to conventional thermal generators combined cycle units may present different operating states depending on the number of gas turbines, on which they comprise.

- The proposed approach for the optimization of the short-term generation scheduling problem may be combined with a method for load and wind power forecasting, e.g. based on Deep Learning Artificial Neural Networks, in an attempt to propose a holistic approach for the optimization of the problem.

- Regarding the Generation Expansion Planning problem, the integration of the transmission system within the model as well as its possible expansion should be examined.

- More recently, approaches which integrate the short-term generation scheduling models within Generation Expansion Planning models have been examined. Such approaches, utilize utilize models to simulate the short-term operation of the system in the long run, when the generating plants are added within the power sector. The GEP model used in this dissertation may be extended to take into consideration the short-term operation of the system with increased detail.

- The model has been developed for the expansion of semi-liberalized energy markets. In such markets, the prices for renewable energy are regulated by the state. In the model, the Feed-in-Tariff (FIT) scheme has been modeled, according to which the price for RES energy does not depend on the SMP, rather than it is fixed by the state. The FIT scheme is the most widely used compensation scheme for energy from RES. Nevertheless, there exist other compensation schemes, such as the feed-in-premium (FIP), according to which the price used to compensate energy from Renewable Energy Sources depends on the SMP. The GEP model may be extended to take into consideration different compensation schemes for energy from RES and assess their impact both on the integration of Renewable Energy Sources within the future generating mix as well as on the SMP.

7.5 List of Publications

During the preparation of the present dissertation, a series of publications have been made. They are presented in the following.

Scientific Journals:

1. V. A. Tsalavoutis, C. G. Vrionis, and A. I. Tolis, "Relaxation of quantitative energy objectives on generation expansion planning: A computational and policy study", International Transactions on Electrical Energy Systems, vol. 27, no. 12, e2427, 2017.

2. V. A. Tsalavoutis, C. G. Vrionis, and A. I. Tolis, "Optimizing a unit commitment problem using an evolutionary algorithm and a plurality of priority lists", Operational Research, pp. 1–54, 2018.

3. C. Vrionis, V. Tsalavoutis, and A. Tolis, "A generation expansion planning model for integrating high shares of renewable energy: A meta-model assisted evolutionary algorithm approach", Applied Energy, vol. 259, 114085, 2020.

4. S. Sengupta, S. Basak, P. Saikia, S. Paul, V. Tsalavoutis, F. Atiah, R. Vadlamani and A. Peters, "A review of deep learning with special emphasis on architectures, applications and

recent trends”, Knowledge-Based Systems, vol. 194, 105596, 2020.

5. V. A. Tsalavoutis, and A. I. Tolis, ”A hybrid multi-objective evolutionary algorithm for the reliability constrained wind hydro- thermal environmental/economic generation scheduling”, Journal of Global Optimization (under review).

International Conferences:

1. V. Tsalavoutis, C. Vrionis, and A. Tolis, “An enhanced real coded approach for the optimization of the unit commitment problem”, in 2016 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, 2016, pp. 1–8.

2. V. Tsalavoutis, C. Vrionis, A. Tolis, and D. Plataniotis, “A differential evolution approach for the reliability constrained unit commitment problem”, in 2018 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, 2018, pp. 2329–2339.

3. V. Tsalavoutis, C. Vrionis, and A. Tolis, “A hybrid multi-objective evolutionary algorithm for economic-environmental generation scheduling”, in Proceedings of the Genetic and Evolutionary Computation Conference, 2019, pp. 1338–1346.

4. V. Tsalavoutis, C. Vrionis, and A. Tolis, ”Optimization of the hydrothermal generation scheduling problem using an enhanced multi-objective evolutionary algorithm”, in Proceedings of the 8th International Symposium and 30th National Conference on Operational Research (HELORS 2019).

Appendices

APPENDIX A

DATA OF THE EXAMINED SYSTEMS

A.1 System of 10 units

The first system comprises 10 thermal generators; their techno-economic characteristics are given in Table A.1 [163]. The initial state of the units is presented in the last column of Table A.1; a positive (negative) integer represents the number of hours for which a unit has been on (off) prior to the first hour of the scheduling period. The load demand for each hour of the scheduling period is given in Table A.2.

Unit	Pmax (MW)	Pmin (MW)	a $(\$/h)$	b $(\$/MWh)$	c $(\$/MWh^2)$	MUT (h)	MDT (h)	HSUC (\$)	CSUC (\$)	T^C (h)	Init. state
1	455	150	1000	16.19	0.00048	8	8	4500	9000	5	8
2	455	150	970	17.26	0.00031	8	8	5000	10000	5	8
3	130	20	700	16.6	0.002	5	5	550	1100	4	-5
4	130	20	680	16.5	0.00211	5	5	560	1120	4	-5
5	162	25	450	19.7	0.00398	6	6	900	1800	4	-6
6	80	20	370	22.26	0.00712	3	3	170	340	2	-3
7	85	25	480	27.74	0.00079	3	3	260	520	2	-3
8	55	10	660	25.92	0.00413	1	1	30	60	0	-1
9	55	10	665	27.27	0.00222	1	1	30	60	0	-1
10	55	10	670	27.79	0.00173	1	1	30	60	0	-1

Table A.1: Techno-economic characteristics of the generators of the system of 10 units

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Demand (MW)	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Hour	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Demand (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

Table A.2: Hourly load demand for the system of 10 units

In Chapter 6 the multi-objective short-term generation scheduling problem is examined. The base system, i.e. Test Instance 1, comprises the thermal generators as given in Table A.1. The coefficients of the produced emissions function for each thermal generator are given in Table A.3 and taken from [282]. For the same system two hydro plants are included. The technical characteristics of the hydro plants and the natural water inflows in the reservoirs have been obtained from [283] and are given in Table A.4 and Table A.5, respectively.

Unit	d (lb/h)	e (lb/MWh)	f (lb/MWh^2)
1	42.9	-0.5112	0.0046
2	42.9	-0.5112	0.0046
3	40.27	0.5455	0.0068
4	40.27	-0.5455	0.0068
5	13.86	0.3277	0.0042
6	13.86	0.3277	0.0042
7	330	-3.9023	0.0465
8	330	-3.9023	0.0465
9	350	-3.9524	0.0465
10	360	-3.9864	0.047

Table A.3: Coefficients of the emission's function of the generators of the system of 10 units

Unit	$Qmax$ $(\cdot 10^3 m^3/h)$	$Qmin$ $(\cdot 10^3 m^3/h)$	$Vmax$ $(\cdot 10^3 m^3)$	$Vmin$ $(\cdot 10^3 m^3)$	$Vinit$ $(\cdot 10^3 m^3)$	$Vend$ $(\cdot 10^3 m^3)$	η $(\cdot MW/10^3 m^3/h)$
Hydro Plant 1	125	0	1000	350	750	400	0.6
Hydro Plant 2	100	0	750	250	600	300	0.6

Table A.4: Technical characteristics of hydro plants of the system of Test Instance 1

Hours	1	2	3	4	5	6	7	8	9	10	11	12
Hydro Plant 1	100	90	80	70	60	70	80	90	100	110	120	100
Hydro Plant 2	80	80	90	90	80	70	60	70	80	90	90	80
Hours	13	14	15	16	17	18	19	20	21	22	23	24
Hydro Plant 1	110	120	110	100	90	80	70	60	70	80	90	100
Hydro Plant 2	90	90	90	80	70	60	70	80	90	90	80	80

Table A.5: Natural water inflows $(\cdot 10^3 m^3)$ for Test Instance 1

A.2 System of 26 units - IEEE RTS

The second system comprises 26 thermal generators and is referred as the IEEE Reliability Test system (IEEE-RTS). It is commonly used for studies concerning the reliability evaluation of a power system. The techno-economic characteristics of the thermal generators are given in Table A.6 and A.7. In the last column of Table A.6, the failure rates (EFR) of the generators are given. The latter are used, when the reliability of the system is considered. These data have been obtained from [223]. The hourly demand of this system comprises two cases, i.e. the case of high demand (shown in Table A.8) and the case of low demand (shown in Table A.9).

Units	$Pmax$ (MW)	$Pmin$ (MW)	RU (MW/h)	RD (MW/h)	a $(\$/h)$	b $(\$/MWh)$	c $(\$/MWh^2)$	MUT (h)	MDT (h)	χ $(\$)$	δ $(\$/h)$	γ (h)	Init. State	EFR
1	12	2.4	48	60	24.3891	25.5472	0.02533	0	0	0	0	1	-1	0.00034
2	12	2.4	48	60	24.411	25.6753	0.02649	0	0	0	0	1	-1	0.00034
3	12	2.4	48	60	24.6382	25.8027	0.02801	0	0	0	0	1	-1	0.00034
4	12	2.4	48	60	24.7605	25.9318	0.02842	0	0	0	0	1	-1	0.00034
5	12	2.4	48	60	24.8882	26.0611	0.02855	0	0	0	0	1	-1	0.00034
6	20	4	30.5	70	117.755	37.551	0.01199	0	0	20	20	2	-1	0.00223
7	20	4	30.5	70	118.108	37.6637	0.01261	0	0	20	20	2	-1	0.00223
8	20	4	30.5	70	118.458	37.777	0.01359	0	0	20	20	2	-1	0.00223
9	20	4	30.5	70	118.821	37.8896	0.01433	0	0	20	20	2	-1	0.00223
10	76	15.2	38.5	80	81.1364	13.3272	0.00876	3	2	50	50	3	3	0.00051
11	76	15.2	38.5	80	81.298	13.3538	0.00895	3	2	50	50	3	3	0.00051
12	76	15.2	38.5	80	81.4641	13.3805	0.0091	3	2	50	50	3	3	0.00051
13	76	15.2	38.5	80	81.6259	13.4073	0.00932	3	2	50	50	3	3	0.00051
14	100	25	51	74	217.895	18	0.00623	4	2	70	70	4	-3	0.00084
15	100	25	51	74	218.335	18.1	0.00612	4	2	70	70	4	-3	0.00084
16	100	25	51	74	218.775	18.2	0.00598	4	2	70	70	4	-3	0.00084
17	155	54.25	55	78	142.735	10.694	0.00463	5	3	150	150	6	5	0.00105
18	155	54.25	55	78	143.029	10.7154	0.00473	5	3	150	150	6	5	0.00105
19	155	54.25	55	78	143.318	10.7367	0.00481	5	3	150	150	6	5	0.00105
20	155	54.25	55	78	143.597	10.7583	0.00487	5	3	150	150	6	5	0.00105
21	197	68.95	55	99	259.131	23	0.00259	5	4	200	200	8	-4	0.00106
22	197	68.95	55	99	259.649	23.1	0.0026	5	4	200	200	8	-4	0.00106
23	197	68.95	55	99	260.176	23.2	0.00263	5	4	200	200	8	-4	0.00106
24	350	140	70	120	177.058	10.8616	0.00153	8	5	300	200	8	10	0.00087
25	400	100	50.5	100	310.002	7.4921	0.00194	8	5	500	500	10	10	0.00091
26	400	100	50.5	100	311.91	7.5031	0.00195	8	5	500	500	10	10	0.00091

Table A.6: Technical characteristics of thermal generators of the system of 26 units

The data of the wind power used during the examination of wind power forecasting uncertainty

Units	d (tn/h)	e (tn/MWh)	f (tn/MWh^2)
1	0.49095	0.51427	0.00051
2	0.49139	0.51684	0.00053
3	0.49597	0.51941	0.00056
4	0.49843	0.52201	0.00057
5	0.50100	0.52461	0.00057
6	0.94204	0.30041	9.59E-05
7	0.94487	0.30131	0.00010
8	0.94766	0.30222	0.00011
9	0.95056	0.30312	0.00011
10	4.51118	0.74099	0.00049
11	4.52017	0.74247	0.0005
12	4.52940	0.74396	0.00051
13	4.53840	0.74545	0.00052
14	4.38623	0.36234	0.00013
15	4.39508	0.36435	0.00012
16	4.40394	0.36637	0.00012
17	7.93605	0.59459	0.00026
18	7.9524	0.59578	0.00026
19	7.96848	0.59696	0.00027
20	7.98400	0.59816	0.00027
21	5.21631	0.46299	5.21E-05
22	5.22673	0.46500	5.23E-05
23	5.23734	0.46702	5.29E-05
24	9.84440	0.60390	8.51E-05
25	0	0	0
26	0	0	0

Table A.7: Coefficients of the emissions function of thermal generator of the system of 26 units

Hours	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	1700	1730	1690	1700	1750	1850	2000	2430	2540	2600	2670	2590
Hours	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	2590	2550	2620	2650	2550	2530	2500	2550	2600	2480	2200	1840

Table A.8: Expected hourly load for system of 26 units - High demand case

Hours	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	1430	1450	1400	1350	1350	1470	1710	2060	2300	2380	2290	2370
Hours	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	2290	2260	2190	2130	2190	2200	2300	2340	2300	2180	1910	1650

Table A.9: Expected hourly load for the system of 26 units - Low demand case on the reliability of the system are given in Table A.10. They have been obtained from [257].

Hours	1	2	3	4	5	6	7	8	9	10	11	12
Wind Power (MW)	124	124	127.1	130.2	117.8	114.7	117.8	120.9	108.5	102.3	108.5	120.9
Hours	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	124	130.2	124	111.6	105.4	99.2	93	94.24	99.2	105.4	111.6	105.4

Table A.10: Expected Wind power output for Test Instance 4

The system of 26 units constitutes the thermal part of Test Instance 4 in Chapter 6. In this system 11 units ($1-5$, $14-16$ and $21-23$) are oil-fired, 9 units ($10-13$, $17-20$ and 24) are coal-fired, units 25, 26 are nuclear plants and units $6-9$ utilize NG as their fuel. The technical data of the four hydro plants of the system are given in Table A.11. The natural water inflows in the reservoirs and the configuration of the reservoirs are presented in Table A.12 and Figure A.1, respectively. Moreover, in Table A.13, the number of upstream reservoirs and the time required for the water to travel to the immediate downstream reservoirs are given.

	$Qmax$ $(\cdot 10^4 m^3/h)$	$Qmin$ $(\cdot 10^4 m^3/h)$	$Vmax$ $(\cdot 10^4 m^3)$	$Vmin$ $(\cdot 10^4 m^3)$	$Vinit$ $(\cdot 10^4 m^3)$	$Vend$ $(\cdot 10^4 m^3)$	η $(\cdot MW/10^4 m^3/h)$
Hydro Plant 1	15	5	150	80	100	120	9,273
Hydro Plant 2	15	6	120	60	80	70	5,789
Hydro Plant 3	30	10	240	100	170	170	3,352
Hydro Plant 4	20	6	160	70	120	140	21,322

Table A.11: Technical characteristics of hydro plants of the system of Test Instance 4

A.3 System of 38 units - Tai power system

The third system examined in this dissertation is the practical Tai power system, which comprises 38 thermal generators. In Table A.14 the generating characteristics of the units are listed. In this system, the start up costs are considered constant, thus they do not depend on the amount of time for which the unit has remained out of operation. For this reason a single start up cost is given in Table A.14, i.e. SUC. The hourly load for this system is presented in Table A.15. the data for this system have been obtained from [211].

Hours	1	2	3	4	5	6	7	8	9	10	11	12
Hydro Plant 1	10	9	8	7	6	7	8	9	10	11	12	10
Hydro Plant 2	8	8	9	9	8	7	6	7	8	9	9	8
Hydro Plant 3	8.1	8.2	4	2	3	4	3	2	1	1	1	2
Hydro Plant 4	2.8	2.4	1.6	0	0	0	0	0	0	0	0	0
Hours	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Hydro Plant 1	11	12	11	10	9	8	7	6	7	8	9	10
Hydro Plant 2	8	9	9	8	7	6	7	8	9	9	8	8
Hydro Plant 3	4	3	3	2	2	2	1	1	2	2	1	0
Hydro Plant 4	0	0	0	0	0	0	0	0	0	0	0	0

Table A.12: Natural water inflows $(\cdot 10^4 m^3)$ for Test Instance 4

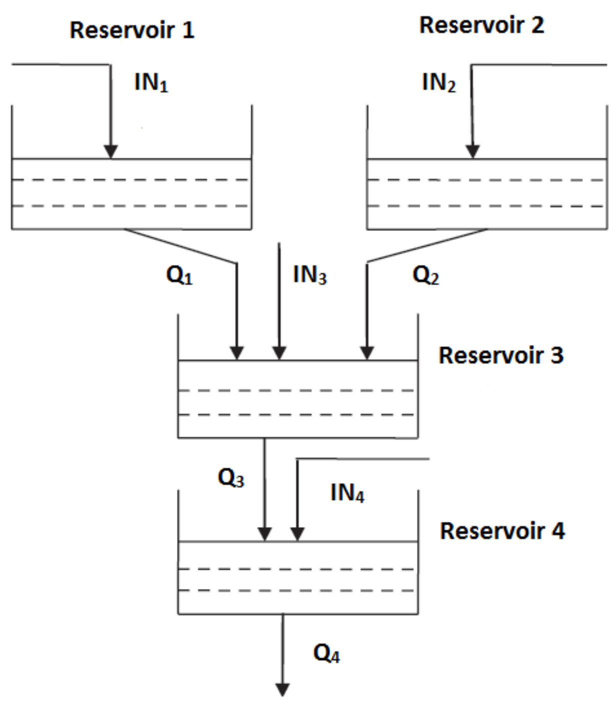


Figure A.1: Configuration of the hydraulic system network of Test Instance 4

Hydro Plant	1	2	3	4
# Upstream Reservoir	0	0	2	1
τ_{lj}	2	3	4	0

Table A.13: Number of upstream reservoirs and water time delay to the immediate downstream reservoir for the hydro system of Test Instance 4

Units	$Pmax$ (MW)	$Pmin$ (MW)	a ($\$/h$)	b ($\$/MWh$)	c ($\$/MWh^2$)	SUC ($)	MUT (h)	MDT (h)	RU (MW/h)	RD (MW/h)
1	550	220	64782	796.9	0.3133	805000	18	8	92	138
2	550	220	64782	796.9	0.3133	805000	18	8	92	138
3	500	200	64670	795.5	0.3127	805000	18	8	84	120
4	500	200	64670	795.5	0,3127	805000	18	8	84	120
5	500	200	64670	795.5	0.3127	805000	18	8	84	120
6	500	200	64670	795.5	0.3127	805000	18	8	84	120
7	500	200	64670	795.5	0.3127	805000	18	8	84	120
8	500	200	64670	795.5	0,3127	805000	18	8	84	120
9	500	200	172832	915.7	0.7075	402500	7	7	128	256
10	500	114	172832	915.7	0.7075	402500	7	7	128	256
11	500	114	176003	884.2	0.7515	402500	7	7	128	256
12	500	114	173028	884.2	0.7083	402500	7	7	128	256
13	500	110	91340	1250.1	0.4211	575000	9	8	110	170
14	365	90	63440	1298.6	0.5145	575000	12	8	92	125
15	365	82	65486	1298.6	0.5691	575000	12	8	92	125
16	325	120	72282	1290.8	0.5691	575000	10	8	82	125
17	315	65	190928	238.1	2.5881	23000	1	1	320	70
18	315	65	285372	1149.5	3.8734	23000	1	1	320	70
19	315	65	271376	1269.1	3.6842	23000	1	1	320	70
20	272	120	39197	696.1	0.4921	575000	9	8	55	91
21	272	120	45576	690.2	0.5728	575000	9	8	55	91
22	260	110	28770	803.2	0.3572	460000	11	8	53	132
23	190	80	36902	818.2	0.9415	92000	14	7	48	98
24	150	10	105510	33.5	52.123	23000	1	1	460	20
25	125	60	22233	805.4	1.1421	115000	8	8	42	60
26	110	55	30953	707.1	2.0275	287500	14	7	28	56
27	75	35	17044	833.6	3.0744	253000	14	14	20	38
28	70	20	81079	2188.7	16.765	5750	1	1	70	30
29	70	20	124767	1024.4	26.355	5750	1	1	70	30
30	70	20	121915	837.1	30.575	5750	1	1	70	30
31	70	20	120780	1305.2	25.098	5750	1	1	75	30
32	60	20	104441	716.6	33.722	7670	1	1	70	30
33	60	25	83224	1633.9	23.915	7670	1	1	70	30
34	60	18	111281	969.5	32.562	7670	1	1	70	20
35	60	8	64142	2625.8	18.362	7670	1	1	70	20
36	60	25	103519	1633.9	23.915	7670	1	1	75	30
37	38	20	13547	694.7	8.482	69000	11	8	10	20
38	38	20	13518	655.9	9.693	69000	11	8	10	20

Table A.14: Data for the system of 38 units

Hours	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	5700	5400	5150	4850	4950	4800	4850	5400	6700	7850	8000	8100
Hours	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	6900	8150	8250	8000	7800	7100	6800	7300	7100	6800	6550	6450

Table A.15: Hourly load for the system of 38 units

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Εθνικό Μετσόβιο Πολυτεχνείο
Σχολή Μηχανολόγων Μηχανικών
Τομέας Βιομηχανικής Διοίκησης και Επιχειρησιακής Έρευνας

ΤΕΧΝΙΚΕΣ ΒΕΛΤΙΣΤΟΠΟΙΗΣΗΣ ΒΑΣΙΖΟΜΕΝΕΣ ΣΕ ΕΞΕΛΙΚΤΙΚΟΥΣ ΑΛΓΟΡΙΘΜΟΥΣ ΓΙΑ ΠΡΟΒΛΗΜΑΤΑ ΔΙΑΧΕΙΡΙΣΗΣ ΕΝΕΡΓΕΙΑΚΩΝ ΣΥΣΤΗΜΑΤΩΝ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

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Αθήνα, Ιούλιος 2020

ΠΕΡΙΕΧΟΜΕΝΑ

ΕΠΟΨΗ

Η βελτίωση του βιοτικού επιπέδου και η οικονομική ανάπτυξη, αύξησαν τη ζήτηση για ηλεκτρική ενέργεια. Παράλληλα, η διείσδυση των Ανανεώσιμων Πηγών Ενέργειας (ΑΠΕ) εντείνεται, αυξάνοντας τη βιωσιμότητα του τομέα ηλεκτροπαραγωγής. Οι διαχειριστές του συστήματος και οι φορείς που σχετίζονται με το σχεδιασμό του συμμετέχουν σε πολύπλοκες διαδικασίες λήψης αποφάσεων για να εξασφαλίσουν την αξιόπιστη παραγωγή ηλεκτρικής ενέργειας στο ελάχιστο κόστος σε διάφορους ορίζοντες προγραμματισμού. Η εφαρμογή εργαλείων βελτιστοποίησης έχει καταστεί απαραίτητη για την λήψη κατάλληλων αποφάσεων στα προβλήματα διαχείρισης των συστημάτων ηλεκτροπαραγωγής. Στο πλαίσιο αυτό, η παρούσα διατριβή προτείνει και αξιολογεί μεθόδους βελτιστοποίησης, για την επίλυση δύο προβλημάτων διαχείρισης ενεργειακών συστημάτων. Το πρώτο είναι το πρόβλημα του μακροχρόνιου προγραμματισμού επέκτασης του δυναμικού παραγωγής ισχύος (Generation Expansion Planning, GEP), που καθορίζει τις βέλτιστες προσθήκες δυναμικού σε τομέα ηλεκτροπαραγωγής για να ικανοποιηθεί η αναμενόμενη αύξηση της ζήτησης. Το δεύτερο είναι ο βραχυπρόθεσμος προγραμματισμός παραγωγής ηλεκτρικής ενέργειας (Short-term generation scheduling, STGS), που καθορίζει το βέλτιστο πρόγραμμα παραγωγής των μονάδων για να ικανοποιηθεί το φορτίο του συστήματος.

Αναπτύχθηκε μοντέλο GEP για ημι-απελευθερωμένη αγορά ηλεκτρικής ενέργειας. Στο μοντέλο αυτό οι παραγωγοί ηλεκτρικής ενέργειας ομαδοποιούνται ανά τύπο τεχνολογίας παραγωγής. Η μεγιστοποίηση της Καθαρής Παρούσας Αξίας (ΚΠΑ) του τομέα είναι η συνάρτηση στόχος του προβλήματος. Στο μοντέλο προσομοιώνεται η εξέλιξη της μέσης ετήσιας Οριακής Τιμής Συστήματος (ΟΤΣ) και η αλληλεπίδραση της με το μείγμα ηλεκτροπαραγωγής. Παράλληλα, μοντελοποιούνται ενεργειακοί στόχοι, που καθορίζονται από την ενεργειακή πολιτική, για την προώθηση επενδύσεων σε ΑΠΕ. Οι βέλτιστες ετήσιες προσθήκες δυναμικού και ο ετήσιος βαθμός χρήσης των τεχνολογιών υπολογίζονται. Το μοντέλο μπορεί να συμβάλλει στην εκτίμηση του αντίκτυπου των ενεργειακών πολιτικών στην εξέλιξη του μείγματος ηλεκτροπαραγωγής και της ΟΤΣ. Για τη βελτιστοποίηση του προβλήματος προτείνεται υβριδικός αλγόριθμος που συνδυάζει τις Στρατηγικές Εξέλιξης και τον Αλγόριθμο Εσωτερικού Σημείου.

Τρεις παραλλαγές του **STGS** εξετάζονται. Η πρώτη είναι το κλασικό μοντέλο του προβλήματος. Στη δεύτερη λαμβάνεται υπόψη η αξιοπιστία του συστήματος. Στα δύο μοντέλα η συνάρτηση στόχος είναι η ελαχιστοποίηση του λειτουργικού κόστους, σε συστήματα θερμικών μονάδων. Η τρίτη, είναι ένα πολυκριτηριακό μοντέλο, που αναπτύχθηκε στην παρούσα διατριβή, στο οποίο η ελαχιστοποίηση των εκπομπών ρύπων αποτελεί τη δεύτερη συνάρτηση στόχο. Αφορά συστήματα που περιλαμβάνουν, εκτός από θερμικές μονάδες, υδροηλεκτρικούς σταθμούς και ενέργεια από ΑΠΕ. Το μοντέλο παρέχει πλαίσιο καθορισμού της απαιτούμενης στρεφόμενης εφεδρείας, λαμβάνοντας υπόψη τη μη διαθεσιμότητα των μονάδων και την αβεβαιότητα στην πρόβλεψη του φορτίου και της παραγόμενης ενέργειας από αιολικά πάρκα. Παρέχει σύνολο λύσεων -προγραμμάτων παραγωγής των μονάδων του συστήματος- στις οποίες ελαχιστοποιείται ταυτόχρονα το λειτουργικό κόστος και οι εκπομπές ρύπων του συστήματος.

Για τη βελτιστοποίηση των παραλλαγών του **STGS** χρησιμοποιείται η Διαφορική Εξέλιξη σε συνδυασμό με μία βηματική συνάρτηση για τον προσδιορισμό των καταστάσεων λειτουργίας των μονάδων. Ευρετικοί μηχανισμοί επιδιόρθωσης εντάσσονται στον αλγόριθμο για την επιδιόρθωση μη εφικτών υποψηφίων λύσεων. Προτείνονται δύο τεχνικές για την ένταξη πληροφορίας από τη Λίστα Προτεραιότητας στη διαδικασία της βελτιστοποίησης. Ένας τελεστής μετάλλαξης και μία τεχνική τοπικής βελτίωσης αναπτύσσονται για να βελτιώσουν την απόδοση της Διαφορικής Εξέλιξης στα μονοκριτηριακά και το πολυκριτηριακό πρόβλημα, αντίστοιχα.

Το μοντέλο **GEP** εξετάστηκε σε μελέτη περίπτωσης από την οποία προέκυψαν σημαντικά συμπεράσματα. Η υβριδική μέθοδος παρείχε συστηματικά λύσεις υψηλότερης ΚΠΑ σε σύγκριση με άλλες μεθόδους βελτιστοποίησης. Επομένως, οι προσθήκες δυναμικού μπορεί να αυξήσουν τις πιθανότητες για κερδοφορία των παραγωγών. Σχετικά με την εξεταζόμενη περίπτωση, η επίτευξη των ενεργειακών στόχων επηρεάζει το μελλοντικό μείγμα ηλεκτροπαραγωγής. Προσθήκες δυναμικού σε χερσαίες ανεμογεννήτριες και σε συγκεντρωτικά ηλιακά συστήματα προτείνονται για την επίτευξη των βραχυπρόθεσμων ενεργειακών στόχων. Επίσης, μέρος της εγκατεστημένης ισχύος σε λιγνιτικούς σταθμούς παραγωγής αντικαθιστάται από ΑΠΕ, ως συνέπεια των μακροπρόθεσμων ενεργειακών στόχων. Παράλληλα, η επίτευξη των ενεργειακών στόχων, μπορεί μακροπρόθεσμα να οδηγήσει σε μικρή μείωση της ΟΤΣ, σε παρούσες τιμές.

Σημαντικά συμπεράσματα εξάγονται και από τη βελτιστοποίηση του STGS. Ο προτεινόμενος τελεστής μετάλλαξης και η τεχνική ένταξης πληροφορίας από τη Λίστα Προτεραιότητας βελτίωσαν την απόδοση του αλγορίθμου. Η απόδοση της μεθόδου στα μονοκριτηριακά προβλήματα κρίνεται ανταγωνιστική, παράγοντας σε ορισμένες περιπτώσεις προγράμματα παραγωγής χαμηλότερου κόστους της τάξης του 0.8% σε σχέση με τα αποτελέσματα της βιβλιογραφίας, σε μειωμένο υπολογιστικό χρόνο. Παράλληλα, ο πολυκριτηριακός ΕΑ βελτιστοποίησε αποτελεσματικά το πολυκριτηριακό μοντέλο, παρέχοντας σύνολα λύσεων που προσεγγίζουν τα μέτωπα Pareto του προβλήματος. Επομένως, μπορεί δυνητικά να βοηθήσει τον διαχειριστή του συστήματος ή εταιρείες ηλεκτροπαραγωγής στον αποδοτικό προγραμματισμό των μονάδων. Από τα αποτελέσματα συνάγεται ότι υψηλότερη αβεβαιότητα στην πρόβλεψη φορτίου ή μη διαθεσιμότητα των μονάδων αυξάνει την απαιτούμενη στρεφόμενη εφεδρεία, αυξάνοντας το κόστος και τις εκπομπές ρύπων του συστήματος. Αντίθετα, αυτό δεν προκύπτει για την περίπτωση υψηλότερης αβεβαιότητας στην πρόβλεψη της παραγόμενης ενέργειας από τα αιολικά πάρκα.

Οι κύριες συνεισφορές της διατριβής για το GEP είναι οι εξής: i) προτείνεται διαδικασία στοχαστικής βελτιστοποίησης για να καθοριστούν οι προσθήκες δυναμικού για τη βέλτιστη συμμόρφωση με τους ενεργειακούς στόχους, ii) μία παράμετρος χαλάρωσης εφαρμόζεται στους περιορισμούς ισότητας των ενεργειακών στόχων και εξετάζεται η επίδρασή της στο μελλοντικό μείγμα ηλεκτροπαραγωγής και στη διαδικασία βελτιστοποίησης, iii) προτείνεται υβριδικός αλγόριθμος βασιζόμενος στις Στρατηγικές Εξέλιξης και στον Αλγόριθμο Εσωτερικού Σημείου για τη βελτιστοποίηση του GEP.

Για το STGS οι κύριες συνεισφορές είναι: i) προτείνεται μέθοδος βασιζόμενη στη Διαφορική Εξέλιξη και σε βηματική συνάρτηση για τη βελτιστοποίηση των παραλλαγών του STGS, ii) αναπτύσσονται ένας τελεστής μετάλλαξης και μία τεχνική τοπικής βελτίωσης για να ενισχύσουν την απόδοσή της Διαφορική Εξέλιξης, iii) προτείνεται πολυκριτηριακό μοντέλο για το STGS, που περιλαμβάνει το λειτουργικό κόστος και τις εκπομπές ρύπων του συστήματος και παρέχει πλαίσιο καθορισμού της στρεφόμενης εφεδρείας σε συστήματα με διάφορες τεχνολογίες παραγωγής.

ΚΕΦΑΛΑΙΟ 1

ΕΙΣΑΓΩΓΗ

1.1 Στόχος της διατριβής

Η παρούσα διατριβή επικεντρώνεται στην ανάπτυξη και στην εφαρμογή μεθόδων βελτιστοποίησης σε προβλήματα διαχείρισης συστημάτων ηλεκτρικής ενέργειας. Οι τεχνικές βελτιστοποίησης που αναπτύσσονται βασίζονται στους Εξελικτικούς Αλγόριθμους, οι οποίοι είναι μέθοδοι βελτιστοποίησης που διαχειρίζονται ένα πληθυσμό υποψηφίων λύσεων του υπό εξέταση προβλήματος. Με την εφαρμογή τελεστών που προσομοιάζουν τις αρχές τις βιολογικής εξέλιξης, σε μία επαναληπτική διαδικασία, ο πληθυσμός σταδιακά βελτιώνεται με την εύρεση λύσεων με καλύτερες τιμές για την αντικειμενική συνάρτηση του προβλήματος, με σκοπό την επίτευξη της βέλτιστης λύσης για το υπό εξέταση πρόβλημα. Η παρούσα διδακτορική διατριβή δομείται με βάση τους εξής δύο θεματικούς πυλώνες:

1. Την ανάπτυξη και αξιολόγηση τεχνικών βελτιστοποίησης για τον βραχυπρόθεσμο προγραμματισμό παραγωγής ηλεκτρικής ενέργειας. Στο πρόβλημα αυτό αναζητείται το βέλτιστο πρόγραμμα παραγωγής των ηλεκτροπαραγωγικών μονάδων τομέα παραγωγής ηλεκτρικής ενέργειας, για να καλυφθεί αξιόπιστα το αναμενόμενο φορτίο του συστήματος. Στην παρούσα διατριβή, διάφορες ρεαλιστικές παραλλαγές του προβλήματος εξετάζονται.

2. Την ανάπτυξη και αξιολόγηση τεχνικής βελτιστοποίησης για τον βέλτιστο μακροχρόνιο προγραμματισμό επέκτασης δυναμικού παραγωγής ισχύος (χρονικό σημείο επένδυσης, τοποθεσία, τεχνολογία παραγωγής, παραγωγική ισχύ) τομέα παραγωγής ηλεκτρικής ενέργειας, με δεδομένα σενάρια για την εξέλιξη των τιμών διαφόρων παραμέτρων του τομέα κατά τη διάρκεια του χρονικού ορίζοντα προγραμματισμού, όπως για παράδειγμα της ζήτησης ηλεκτρικής ενέργειας και της τιμής πώλησης δικαιωμάτων CO_2.

Τα παραπάνω προβλήματα παρουσιάζουν ορισμένα ιδιαίτερα χαρακτηριστικά, όπως είναι οι μη γραμμικές και μη διαφορίσιμες αντικειμενικές συναρτήσεις και περιορισμοί του προβλήματος και το μεγάλο πλήθος αντικειμενικών μεταβλητών, που μπορεί να δυσχεράνουν την αποτελεσματική βελτιστοποίησή τους από τις συμβατικές μεθόδους βελτιστοποίησης. Για αυτό το λόγο στην παρούσα διατριβή γίνεται προσπάθεια για ανάπτυξη αλγορίθμων που βελτιστοποιούν αποδοτικά τα παραπάνω προβλήματα. Ο όρος «αποδοτικά» μπορεί να αφορά και τις απαιτήσεις σε υπολογιστικό χρόνο αλλά και την ποιότητα των λύσεων του προβλήματος. Για να επιτευχθούν οι δύο αυτοί στόχοι οι τεχνικές βελτιστοποίησης βασίζονται στους ΕΑ. Βασικό πλεονέκτημα αυτών των μεθόδων είναι η ευελιξία τους καθώς μπορούν να εφαρμοστούν σε προβλήματα βελτιστοποίησης ανεξαρτήτως της μαθηματικής μορφής της αντικειμενικής συνάρτησης ή των περιορισμών του προβλήματος. Οπότε μπορούν να αντιμετωπίσουν, με σχετικά μικρές μετατροπές, παραλλαγές των προβλημάτων υπό εξέταση. Παράλληλα τέτοιες μέθοδοι, λόγω και του πληθυσμού των λύσεων που διαχειρίζονται είναι καταλληλότερες για την αντιμετώπιση προβλημάτων πολλαπλών κριτηρίων.

Οι ΕΑ παρουσιάζουν όμως και ορισμένα σημαντικά μειονεκτήματα. Σε προβλήματα βελτιστοποίησης του «πραγματικού κόσμου», οι γενικής φύσεως ΕΑ μπορεί να έχουν αυξημένες απαιτήσεις σε υπολογιστικό χρόνο ή ακόμα να συγκλίνουν πρώιμα σε μη βέλτιστη λύση. Σε αρκετές εργασίες της σχετικής βιβλιογραφίας έχει επισημανθεί ότι η απόδοση των ΕΑ για τη βελτιστοποίηση τέτοιων σύνθετων προβλημάτων μπορεί να βελτιωθεί αν εισάγουμε στο διαδικασία της βελτιστοποίησης πληροφορία σχετική με το υπό εξέταση πρόβλημα (**domain-specific knowledge**) [1]. Παράλληλα, η απόδοση των ΕΑ μπορεί να βελτιωθεί περαιτέρω με τον συνδυασμό τους με άλλες μεθόδους βελτιστοποίησης, όπως είναι οι συμβατικές (ή αιτιοκρατικές) μέθοδοι, άλλοι ΕΑ ή οι διαδικασίες τοπικής βελτίωσης των λύσεων. Στην παρούσα διατριβή, πραγματοποιείται η χρήση πληροφορίας σχετικής με το υπό εξέταση πρόβλημα καθώς και ο συνδυασμός των ΕΑ αλγορίθμων με άλλες μεθόδους βελτιστοποίησης, ώστε να βελτιωθεί η απόδοσή τους στα δύο προβλήματα που αφορούν τη διαχείριση ενεργειακών συστημάτων, το βραχυπρόθεσμο προγραμματισμό παραγωγής ηλεκτρικής ενέργειας καθώς και τον μακροχρόνιο προγραμματισμό επέκτασης δυναμικού παραγωγής ισχύος τομέα ηλεκτρικής ενέργειας, συμβάλλοντας:

- Στην ανάπτυξη αποδοτικότερων μεθόδων, όσον αφορά τις ανάγκες σε υπολογιστικό χρόνο καθώς και την ποιότητα των παρεχόμενων λύσεων. Για το λόγο αυτό προτείνονται νέοι τελεστές μετάλλαξης, νέες μέθοδοι τοπικής αναζήτησης καθώς και νέοι υβριδικοί αλγόριθμοι. Οι βελτιώσεις στην απόδοση των αλγορίθμων λόγω των προτεινόμενων αλλαγών αναδεικνύονται μέσα από κατάλληλα υπολογιστικά πειράματα.
- Στην ανάπτυξη ευέλικτων μεθόδων για την επίλυση των προβλημάτων. Για παράδειγμα στο πρόβλημα του βραχυπρόθεσμου προγραμματισμού παραγωγής ηλεκτρικής ενέργειας, μικρές μετατροπές στον αλγόριθμο βελτιστοποίησης επιτρέπουν την επίλυση των παραλλαγών του προβλήματος.

1.2 Βραχυπρόθεσμος προγραμματισμός παραγωγής ηλεκτρικής ενέργειας

Η αύξηση του πληθυσμού παγκοσμίως καθώς και η βελτίωση του βιοτικού επιπέδου προκάλεσαν την αύξηση της ζήτησης για ηλεκτρική ενέργεια. Κατά τη διάρκεια της ημέρας η ζήτηση ηλεκτρικής ενέργειας παρουσιάζει σημαντικές μεταβολές ανάλογα με την ώρα της ημέρας. Για παράδειγμα, τις πρωινές ώρες η ζήτηση είναι υψηλή, φτάνοντας στην υψηλότερη τιμή συνήθως τις μεσημεριανές ώρες. Αντίθετα τις βραδινές ώρες η ζήτηση είναι χαμηλότερη καθώς οι ανθρώπινες δραστηριότητες είναι μειωμένες. Παράλληλα η διείσδυση των Ανανεώσιμων Πηγών Ενέργειας (ΑΠΕ) έχει αυξηθεί σημαντικά τα τελευταία χρόνια, λόγω του χαμηλότερου κόστους παραγωγής και των χαμηλότερων ρύπων που τέτοιες τεχνολογίες παρουσιάζουν έναντι των μονάδων που χρησιμοποιούν συμβατικά καύσιμα. Η διείσδυση των ανανεώσιμων πηγών ενέργειας παρόλα αυτά αυξάνει την αβεβαιότητα όσον αφορά το τελικό φορτίο που θα κληθούν να καλύψουν οι συμβατικές μονάδες, καθώς η ποσότητα ηλεκτρικής ενεργείας που παράγεται από τις ΑΠΕ δεν είναι ελεγχόμενη. Όλα τα παραπάνω διαμορφώνουν μία νέα κατάσταση όσον αφορά τον τρόπο λειτουργίας του τομέα ηλεκτρικής ενέργειας, εγείροντας προκλήσεις για τους διαχειριστές των συστημάτων και δημιουργώντας νέες απαιτήσεις αναφορικά με την οικονομική διαχείρισή τους.

Το πρόβλημα του προγραμματισμού ηλεκτρικής ενέργειας αποτελεί ένα από τα σημαντικότερα προβλήματα που σχετίζονται με την κατάλληλη διαχείριση των μονάδων παραγωγής σε ένα τομέα παραγωγής ηλεκτρικής ενέργειας. Περιλαμβάνει την ταυτόχρονη επίλυση δύο επιμέρους προβλημάτων: το πρώτο αφορά τον καθορισμό των μονάδων που θα ενταχθούν στο σύστημα, ενώ το δεύτερο σχετίζεται με την κατανομή του φορτίου στις μονάδες που λειτουργούν. Στην κλασική μορφή του προβλήματος η αντικειμενική συνάρτηση αφορά κυρίως την ελαχιστοποίηση του συνολικού κόστους παραγωγής των μονάδων ή το κέρδος από την πώληση του ρεύματος. Πιο πρόσφατα, η ποσότητα των εκπεμπόμενων ρύπων από την ηλεκτροπαραγωγή έχει αρχίσει να λαμβάνεται υπόψη στο πρόβλημα, συνήθως σαν μία επιπλέον αντικειμενική συνάρτηση. Αξίζει να σημειωθεί ότι με κριτήριο τον χρονικό ορίζοντα του προγραμματισμού, μπορεί να γίνει η διάκριση του προβλήματος σε βραχυπρόθεσμο (αφορά ορίζοντες μερικών ωρών έως μίας εβδομάδας) ή μακροπρόθεσμο προγραμματισμό παραγωγής (αφορά ορίζοντες μερικών εβδομάδων έως συνήθως ενός χρόνου). Στην παρούσα διατριβή, εστιάζουμε στον βραχυχρόνιο προγραμματισμό παραγωγής ηλεκτρικής ενέργειας. Λόγω των σημαντικών επιπτώσεων, τόσο σε οικονομικό όσο και σε περιβαλλοντικό επίπεδο, που πηγάζουν από την κατάλληλη επίλυση του συγκεκριμένου προβλήματος, το τελευταίο έχει κεντρίσει το ενδιαφέρον ενός μεγάλου αριθμού ερευνητικών προσπαθειών. Παρόλα αυτά λόγω της προόδου στις τεχνικές βελτιστοποίησης που έχει πραγματοποιηθεί τα τελευταία χρόνια, γίνονται προσπάθειες να προταθούν αλγόριθμοι οι οποίοι θα παρέχουν καλύτερες λύσεις σε λιγότερο χρόνο. Παράλληλα, οι συνεχείς αλλαγές στους τομείς ηλεκτρικής ενέργειας (νέες τεχνολογίες, αλλαγές στα θεσμικά πλαίσια), απαιτούν τη δημιουργία κατάλληλων μοντέλων που να προσομοιώνουν με όσο το δυνατόν καλύτερη ακρίβεια τον τρόπο λειτουργίας των συστημάτων.

Στη συγκεκριμένη διατριβή αναπτύσσονται μέθοδοι που βασίζονται στους ΕΑ για την αποδοτική επίλυση των διαφόρων μορφών του προβλήματος. Για αυτό το λόγο προτείνονται νέοι τελεστές μετάλλαξης καθώς και αποδοτικότεροι τρόποι για να εισάγουμε κατά τη διαδικασία βελτιστοποίησης με τους ΕΑ, πληροφορία σχετική με το υπό εξέταση πρόβλημα. Η βελτίωση στην απόδοση των προτεινόμενων αλγορίθμων που προκαλούνται από τις προτεινόμενες αλλαγές, αναδεικνύεται μέσα από κατάλληλα υπολογιστικά πειράματα. Επίσης, προτείνεται μία νέα μορφή του προβλήματος, κατά την οποία επιλύεται το πρόβλημα βραχυπρόθεσμου προγραμματισμού για τομείς παραγωγής ηλεκτρικής ενέργειας, που περιλαμβάνουν υδροηλεκτρικές μονάδες παραγωγής καθώς και ενέργειας παραγόμενης από αιολικά πάρκα. Ένα από τα βασικά πλεονεκτήματα αυτού του νέου μοντέλου είναι ότι η επίλυση του παρέχει ένα σύνολο βέλτιστων λύσεων, στις οποίες επιτυγχάνεται ταυτόχρονη βελτιστοποίηση τόσο του συνολικού κόστους λειτουργίας του συστήματος όσο και της ποσότητας των εκπεμπόμενων ρύπων. Παράλληλα, κατά την επίλυση του συγκεκριμένου προβλήματος λαμβάνεται υπόψη η στοχαστική φύση των στοιχείων του συστήματος. Πιο συγκεκριμένα, γίνεται χρήση των δεικτών αξιοπιστίας της πιθανότητας απώλειας φορτίου και της αναμενόμενης μη εξυπηρετούμενης ενέργειας, κατά τον υπολογισμό των οποίων λαμβάνονται υπόψη πιθανές διακοπές λειτουργίας των μονάδων καθώς και η αβεβαιότητα στην πρόβλεψη φορτίου και στην παραγωγή ενέργειας από τα αιολικά πάρκα.

1.3 Προγραμματισμός επέκτασης της δυναμικότητας παραγωγής ισχύος

Οι συνεχείς μεταβολές στις όποιες υπόκειται η δομή των τομέων παραγωγής ηλεκτρικής ενέργειας αυξάνει την πολυπλοκότητα τόσο της παραγωγής όσο και της διανομής της ενέργειας. Επομένως, η κατάλληλη οργάνωση των τομέων παραγωγής ηλεκτρικής ενέργειας κρίνεται απαραίτητη, ώστε η μελλοντική αναμενόμενη αύξηση της ζήτησης να καλυφθεί με ασφάλεια. Στα πλαίσια αυτά, τονίζεται η σημασία της επέκτασης της δυναμικότητας παραγωγής ισχύος σε ένα τομέα παραγωγής ηλεκτρικής ενέργειας μέσω του μακροχρόνιου προγραμματισμού επενδύσεων στις διάφορες παραγωγικές τεχνολογίες. Η βελτιστοποίηση του προβλήματος μπορεί να βοηθήσει τους φορείς και τις ρυθμιστικές αρχές που λαμβάνουν τις αποφάσεις σχετικά με τις πολιτικές που θα ακολουθηθούν για την επέκταση του τομέα παραγωγής ηλεκτρικής ενέργειας, υποδεικνύοντας τις τεχνολογίες στις οποίες πρέπει να γίνουν επενδύσεις, την παραγωγική ικανότητα των νέων επενδύσεων, καθώς και τον χρόνο επένδυσης.

Οι επενδύσεις σε ΑΠΕ μπορούν να αυξήσουν την βιωσιμότητα ενός τομέα παραγωγής ηλεκτρικής ενέργειας. Λόγω όμως κυρίως του υψηλού κόστους επένδυσης σε τέτοιες τεχνολογίες η διείσδυση των ΑΠΕ προχωράει με ποιο αργό, από τον επιθυμητό, ρυθμό. Για να αυξηθεί ο ρυθμός διείσδυσης των ΑΠΕ, συνήθως οι φορείς που καθορίζουν τις ενεργειακές πολιτικές μίας χώρας προτείνουν ενεργειακούς στόχους, σχετιζόμενους με την εγκατεστημένη ισχύ ή την ηλεκτρική παραγωγή των τεχνολογιών παραγωγής που βασίζονται σε ΑΠΕ. Αυτοί οι ενεργειακοί στόχοι μπορούν όμως να επιδράσουν τόσο στην εξέλιξη της δομής του τομέα ηλεκτρικής ενέργειας αλλά και στην εξέλιξη των διαφόρων παραμέτρων του, όπως είναι η Οριακή Τιμή του Συστήματος.

Βασιζόμενοι στα παραπάνω, αναπτύσσεται μοντέλο βελτιστοποίησης της επέκτασης της δυναμικότητας παραγωγής ισχύος το οποίο επιτρέπει την εκτίμηση της επίδρασης των ενεργειακών στόχων στην δομή ενός τομέα ηλεκτρικής ενέργειας αλλά και στην εξέλιξη ορισμένων μεγεθών του τομέα παραγωγής ηλεκτρικής ενέργειας όπως είναι η Οριακή Τιμή του Συστήματος ή οι εκπομπές CO_2. Ένα τέτοιο μοντέλο θα επιτρέψει στους φορείς που καθορίζουν τις ενεργειακές πολιτικές να προτείνουν ενεργειακούς στόχους που να οδηγούν σε μακροχρόνιο επίπεδο σε συγκράτηση της οριακής τιμής συστήματος όσο και των εκπομπών CO_2, ευνοώντας έτσι τους τελικούς καταναλωτές. Παράλληλα, για την αποδοτική επίλυση του μοντέλου, χρησιμοποιείται υβριδικός αλγόριθμος ο οποίος συνδυάζει την Στρατηγική Εξέλιξης (που είναι ΕΑ) μαζί με τον Αλγόριθμο Εσωτερικού Σημείου (που είναι αιτιοκρατική μέθοδος). Μέσα από μία σειρά υπολογιστικών πειραμάτων προκύπτει ότι η προτεινόμενη μέθοδος μπορεί συστηματικά να παράγει καλύτερες λύσεις για το πρόβλημα σε σχέση με την περίπτωση κατά την οποία εφαρμόζεται μόνο ο Αλγόριθμος Εσωτερικού Σημείου.

ΚΕΦΑΛΑΙΟ 2
ΕΞΕΛΙΚΤΙΚΟΙ ΑΛΓΟΡΙΘΜΟΙ ΚΑΙ ΒΕΛΤΙΣΤΟΠΟΙΗΣΗ

2.1 Ορισμός προβλήματος βελτιστοποίησης

Βελτιστοποίηση είναι η διαδικασία κατά την οποία δημιουργείται ένα ενιαίο μέτρο αξιολόγησης, με το οποίο εκτιμάται η απόδοση μίας απόφασης, και στη συνέχεια η απόδοση αυτή βελτιώνεται μέσω μίας επαναληπτικής διαδικασίας, κατά την οποία γίνεται επιλογή μεταξύ διαθέσιμων εναλλακτικών αποφάσεων.

Ένα πρόβλημα βελτιστοποίησης έχει την εξής μορφή:

$$min(\mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), ..., f_M(\mathbf{x})),\ \mathbf{x} = (x_1, x_2, ..., x_D) \in \mathbb{D},\ \underline{x_d} \leq x_d \leq \overline{x_d} \tag{2.1}$$

υπό τους περιορισμούς:

$$g_{l_1}(\mathbf{x}) \leq 0, \quad l_1 = 1, ..., L_1 \tag{2.2}$$

$$h_{l_2}(\mathbf{x}) = 0, \quad l_2 = 1, ..., L_2 \tag{2.3}$$

όπου $\mathbf{F}(\mathbf{x})$ είναι το διάνυσμα που περιλαμβάνει τις τιμές των M ($M \geq 1$) αντικειμενικών συναρτήσεων, $g_{l_1}(\mathbf{x})$ ειναι ο l_1 περιορισμός ανισότητας και $h_{l_2}(\mathbf{x})$ είναι ο l_2 περιορισμός ισότητας. Το διάνυσμα αντικειμενικών μεταβλητών $\mathbf{x}$ περιλαμβάνει D αντικειμενικές μεταβλητές. $\mathbb{D} = \Pi_{d=1}^{d=D}[\underline{x_d}, \overline{x_d}]$ ($\mathbb{D} \subset \mathbb{R}^D$) είναι το πεδίο τιμών των αντικειμενικών μεταβλητών, όπου $\underline{x_d}$ και $\overline{x_d}$ συμβολίζουν τα κατώτατα και ανώτατα όρια της αντικειμενικής μεταβλητής x_d. Ένα διάνυσμα αντικειμενικών μεταβλητών (υποψήφια λύση του προβλήματος) που ικανοποιεί όλους τους περιορισμούς του προβλήματος ονομάζεται εφικτό.

Στην περίπτωση που το πρόβλημα βελτιστοποίησης έχει περισσότερες της μίας αντικειμενικές συναρτήσεις, τότε κατά την βελτιστοποίηση αναζητούνται πολλαπλές λύσεις, οι οποίες ονομάζονται βέλτιστες λύσεις κατά Pareto και έχουν ως βασικό χαρακτηριστικό ότι δεν κυριαρχούνται από άλλες λύσεις. Μία λύση $\mathbf{x_A}$ κυριαρχεί μίας λύσης $\mathbf{x_B}$, $\mathbf{x_A} \preceq \mathbf{x_B}$, όταν $F_m(\mathbf{x_A}) \leq F_m(\mathbf{x_B})$ $\forall m \in \{1,\ldots,M\}$ και $\mathbf{F}(\mathbf{x_A}) \neq \mathbf{F}(\mathbf{x_B})$. Μία εφικτή λύση $\mathbf{x}_A$ ονομάζεται βέλτιστη κατά Pareto, όταν $\nexists \mathbf{x}_B \in \mathbb{D}$ τέτοιο ώστε $F_m(\mathbf{x_B}) \leq F_m(\mathbf{x_A})$ $\forall m \in \{1,\ldots,M\}$ και $\mathbf{F}(\mathbf{x_A}) \neq \mathbf{F}(\mathbf{x_B})$.

2.2 Εξελικτικοί Αλγόριθμοι

Οι Εξελικτικοί Αλγόριθμοι είναι μέθοδοι βελτιστοποίησης, των οποίων οι αρχές λειτουργίας βασίζονται στη θεωρεία της εξέλιξης του Δαρβίνου. Υπάρχουν διάφοροι ΕΑ στη βιβλιογραφία όπως είναι οι Γενετικοί Αλγόριθμοι [2], οι Στρατηγικές Εξέλιξης [3] και ο αλγόριθμος Διαφορικής Εξέλιξης [4]. Η βασική αρχή πίσω από τους ΕΑ είναι η εξής: αν ένας πληθυσμός βρεθεί σε ένα περιβάλλον με περιορισμένους πόρους, ο ανταγωνισμός θα οδηγήσει στην επιβίωση αυτών που προσαρμόζονται καλύτερα στο περιβάλλον, προκαλώντας τη βελτίωση του πληθυσμού.

Η προαναφερθείσα αρχή διέπει τη λειτουργία των ΕΑ. Έχοντας θέσει μία συνάρτηση στόχο (fitness function) προς ελαχιστοποίηση, η αρχικοποίηση του πληθυσμού πραγματοποιείται με τυχαίο τρόπο, χρησιμοποιώντας συνήθως την ομοιόμορφη κατανομή με όρια το πεδίο τιμών της κάθε μεταβλητής. Σε κάθε επανάληψη του αλγορίθμου, που ονομάζεται γενιά, ο πληθυσμός των λύσεων αναπαράγεται δημιουργώντας «απογόνους» οι οποίοι αξιολογούνται με χρήση της συνάρτησης στόχου. Συνήθως χρησιμοποιούνται δύο τελεστές για τη δημιουργία των απογόνων. Ο πρώτος είναι ο τελεστής διασταύρωσης κατά τον οποίο δύο ή περισσότερες υποψήφιες λύσεις (ονομάζονται και άτομα του πληθυσμού στους ΕΑ) συνδυάζονται για την παραγωγή ενός ή περισσοτέρων απογόνων. Ο δεύτερος είναι ο τελεστής μετάλλαξης κατά τον οποίο κάποιες τιμές αντικειμενικών μεταβλητών των απογόνων μπορούν να υποστούν τυχαίες αλλαγές. Ο μηχανισμός επιλογής εφαρμόζεται στη συνέχεια κατά τον οποίο γίνεται επιλογή των ατόμων που θα αποτελέσουν την επόμενη γενιά, συνήθως συγκρίνοντας τις τιμές της συνάρτησης στόχου που παρουσιάζουν. Συνήθως η διαδικασία ολοκληρώνεται με τη συμπλήρωση ενός συγκεκριμένου αριθμού γενεών ή υπολογισμών της τιμής της συνάρτησης στόχου.

Ένα από τα βασικά πλεονεκτήματα των EA είναι ότι μπορούν να εφαρμοστούν σε μεγάλο εύρος προβλημάτων χωρίς να εξαρτώνται από το αν η αντικειμενική συνάρτηση ή οι περιορισμοί πληρούν συγκεκριμένα χαρακτηριστικά, όπως για παράδειγμα να είναι συνεχείς ή παραγωγίσιμες συναρτήσεις. Επιπρόσθετα λόγω του πληθυσμού λύσεων και της στοχαστικότητας κατά την εξερεύνηση του χώρου αναζήτησης λύσεων, μπορεί να αποφύγουν τον εγκλωβισμό σε τοπικά ακρότατα. Επίσης, μπορούν να διαχειριστούν σχετικά εύκολα προβλήματα πολλαπλών κριτηρίων. Παρόλα αυτά παρουσιάζουν και σημαντικά μειονεκτήματα, όπως το γεγονός ότι μπορεί να απαιτούν μεγάλο χρόνο σύγκλισης, ή να χρειάζονται την χρησιμοποίηση γνώσης σχετικής με το υπό εξέταση πρόβλημα για να συγκλίνουν σε βέλτιστες λύσεις. Για αυτό το λόγο η έρευνα για τη βελτίωση της απόδοσης τους σε δύσκολα προβλήματα του πραγματικού κόσμου, είναι συνεχής. Παρακάτω παρουσιάζονται οι δύο EA που χρησιμοποιήθηκαν ως βάση για την ανάπτυξη των αλγορίθμων της συγκεκριμένης διατριβής.

2.2.1 Στρατηγικές Εξέλιξης

Οι Στρατηγικές Εξέλιξης προτάθηκαν από τον Rechenberg [3] και αναπτύχθηκαν περαιτέρω από τον Schwefel [5]. Στη βασική τους μορφή διαχειρίζονται ένα πληθυσμό $Npop$ γονέων οι οποίοι παράγουν $NQpop$ [1] απογόνους με χρήση των τελεστών μετάλλαξης και διασταύρωσης.

Στις Στρατηγικές Εξέλιξης ο τελεστής μετάλλαξης χρησιμοποιεί μία κατανομή Gauss με μέση τιμή 0 και τυπική απόκλιση σ. Η τιμή του σ μπορεί είτε να είναι σταθερή για όλες τις αντικειμενικές μεταβλητές είτε να διαφέρει από μεταβλητή σε μεταβλητή. Στην τελευταία

[1] Στις Στρατηγικές Εξέλιξης ο συμβολισμός που χρησιμοποιείται για τον πληθυσμό γονέων είναι συνήθως μ και για τον πληθυσμό απογόνων είναι λ. Στη διατριβή χρησιμοποιήθηκε ενιαίος συμβολισμός με την Διαφορική Εξέλιξη

περίπτωση ο τελεστής μετάλλαξης εφαρμόζεται ως εξής:

$$\mathbf{x_n^{g+1}} = \mathbf{x_n^g} + \mathbf{z} \tag{2.4}$$

όπου

$$\mathbf{z} = (\sigma_1 \cdot N_1(0,1), \sigma_2 \cdot N_2(0,1), ..., \sigma_D \cdot N_D(0,1)) \tag{2.5}$$

Εκτός από τις διαφορετικές τυπικές αποκλίσεις σ, στην γενικότερη μορφή των Στρατηγικών Εξέλιξης χρησιμοποιείται και πίνακας CM που εισάγει συνδιακυμάνσεις μεταξύ των αντικειμενικών μεταβλητών. Οι δύο παραπάνω ομάδες παραμέτρων ονομάζονται στρατηγικές παράμετροι, και επηρεάζουν τα χαρακτηριστικά των στατιστικών κατανομών των τελεστών των Στρατηγικών Εξέλιξης. Μία συνήθης πρακτική στις Στρατηγικές Εξέλιξης, είναι οι στρατηγικές παράμετροι να αποτελούν μέρος του διανύσματος των αντικειμενικών μεταβλητών και να λαμβάνουν καλύτερες τιμές, καθώς εξελίσσονται μαζί με τον πληθυσμό των λύσεων.

Όσον αφορά τους τελεστές διασταύρωσης των Στρατηγικών Εξέλιξης, συνήθως εφαρμόζεται ο τελεστής ενδιάμεσης διασταύρωσης, κατά τον οποίο ρ γονείς επιλέγονται, και η τιμή της αντίστοιχης αντικειμενικής μεταβλητής ενός απογόνου προκύπτει ως ο μέσος όρος των αντίστοιχων τιμών της αντικειμενικής μεταβλητής των ρ γονιών:

$$r_d = \frac{\sum_{k=1}^{\rho}(x_k)_d}{\rho}, \tag{2.6}$$

Όσον αφορά τον τελεστή επιλογής, στις Στρατηγικές Εξέλιξης, η επιλογή τον γονέων της επόμενης γενιάς γίνεται είτε μεταξύ του συνδυασμένου πληθυσμού των $Npop$ γονέων και των $NQpop$ απογόνων, είτε μόνο μεταξύ των $NQpop$ απογόνων. Όταν χρησιμοποιείται το πρώτο οι Στρατηγικές Εξέλιξης συμβολίζονται ως ($Npop$ + $NQpop$)- ES, ενώ στην περίπτωση που χρησιμοποιείται το δεύτερο οι Στρατηγικές Εξέλιξης συμβολίζονται ως ($Npop$, $NQpop$)- ES.

2.2.2 Διαφορική Εξέλιξη

Η Διαφορική Εξέλιξη αποτελεί ένα από τους σχετικά καινούργιους ΕΑ. Προτάθηκε από τους Storn και Rainer [6]. Στη βασική της μορφή η Διαφορική Εξέλιξη διαχειρίζεται ένα πληθυσμό λύσεων τον οποίο βελτιώνει με την επαναληπτική εφαρμογή τελεστών εξέλιξης, που βασίζονται σε διανύσματα διαφορών μεταξύ τυχαία επιλεγμένων σωματιδίων του πληθυσμού.

Ο τελεστής μετάλλαξης της Διαφορικής Εξέλιξης εφαρμόζεται για τη δημιουργία ενός προσωρινού διανύσματος απογόνου (στη Διαφορική Εξέλιξη γνωστό και ως μεταλλαγμένο διάνυσμα - mutant vector) για κάθε ένα διάνυσμα γονέα (στη Διαφορική Εξέλιξη γνωστό και ως διάνυσμα στόχος - target vector). Στην πιο απλή μορφή του τελεστή, για κάθε γονέα $\mathbf{x_n}$ επιλέγονται τυχαία τρία άτομα του πληθυσμού $\mathbf{x_{r1}}$, $\mathbf{x_{r2}}$ και $\mathbf{x_{r3}}$, όπου r1, r2, r3 είναι τρεις τυχαίοι ακέραιοι αριθμοί στο $[1, Npop]/n$. Ο τελεστής μετάλλαξης εφαρμόζεται ως εξής:

$$\mathbf{v_n} = \mathbf{x_{r1}} + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) \tag{2.7}$$

όπου F είναι ο συντελεστής κλίμακας (scaling factor), ο οποίος πολλαπλασιάζεται με τη διανυσματική διαφορά και ελέγχει το μέτρο της. Το σχήμα μετάλλαξης που περιγράφηκε παραπάνω ονομάζεται DE/rand/1. Οι τυπικές τιμές για την παράμετρο F είναι στο διάστημα [0.4, 1].

Μετά την εφαρμογή του τελεστή μετάλλαξης εφαρμόζεται ο τελεστής διασταύρωσης για τη δημιουργία του δοκιμαστικού διανύσματος (trial vector). Συνήθως χρησιμοποιείται ο τελεστής διωνυμικής διασταύρωσης (binomial crossover) που έχει την ακόλουθη μορφή:

$$u_{d,n}^{g} = \begin{cases} \mathrm{v}_{d,n}^{g}, \ if \ d = d_{rand} \ \ rand_d \leq CR \\ x_{d,n}^{g}, \ otherwise \end{cases} \tag{2.8}$$

Η παράμετρος CR ονομάζεται και πιθανότητα διασταύρωσης και ελέγχει τον αριθμό των τιμών των παραμέτρων, τις οποίες το δοκιμαστικό διάνυσμα θα «αντιγράψει» από το μεταλλαγμένο διάνυσμα.

Ο τελεστής επιλογής της Διαφορικής Εξέλιξης ακολουθεί, σύμφωνα με τον οποίο επιλέγεται αν το διάνυσμα στόχος ή το αντίστοιχο δοκιμαστικό διάνυσμα θα επιβιώσουν στην επόμενη γενιά ως εξής (για προβλήματα χωρίς περιορισμούς):

$$\mathbf{x}_n^{g+1} = \begin{cases} \mathbf{u}_n^g, \ if \ f(\mathbf{u}_n^g) \leq f(\mathbf{x}_n^g) \\ \mathbf{x}_n^g, \quad otherwise \end{cases} \tag{2.9}$$

Αξίζει να τονίσουμε εδώ ότι έχει προταθεί μία πληθώρα από σχήματα μετάλλαξης καθένα από τα οποία παρουσιάζει συγκεκριμένα πλεονεκτήματα. Ορισμένα από τα πιο συνήθη σχήματα μετάλλαξης δίνονται παρακάτω:

1. DE/best/1:

$$\mathbf{v_n} = \mathbf{x_{best}} + F \cdot (\mathbf{x_{r1}} - \mathbf{x_{r2}}) \tag{2.10}$$

2. DE/current-to-rand/1:

$$\mathbf{v_n} = \mathbf{x_n} + F \cdot (\mathbf{x_{r1}} - \mathbf{x_n}) + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) \tag{2.11}$$

3. DE/rand-to-best/1:

$$\mathbf{v_n} = \mathbf{x_{r1}} + F \cdot (\mathbf{x_{best}} - \mathbf{x_{r1}}) + F \cdot (\mathbf{x_{r2}} - \mathbf{x_{r3}}) \tag{2.12}$$

όπου $r1, r2, r3$ είναι ακέραιοι αριθμοί διαφορετικοί μεταξύ τους που επιλέγονται τυχαία από το $[1, Npop]/n$, ενώ $\mathbf{x_{best}}$ είναι το καλύτερο άτομο στον πληθυσμό. Τα σχήματα που χρησιμοποιούν πληροφορία από το $\mathbf{x_{best}}$ συνήθως παρουσιάζουν αυξημένη ταχύτητα σύγκλισης. Παρόλα αυτά, σε προβλήματα με πολλαπλά τοπικά ακρότατα μπορούν να συγκλίνουν πρόωρα σε τοπική λύση. Στο σχήμα DE/current-to-rand/1, το διάνυσμα στόχος λαμβάνει πληροφορία από τυχαία άτομα του πληθυσμού αυξάνοντας έτσι την ποικιλομορφία (**diversity**) του πληθυσμού.

2.3 Διαχείριση των περιορισμών

Στην αρχική τους μορφή, οι ΕΑ δεν διαθέτουν μηχανισμούς για να διαχειριστούν τους περιορισμούς ενός προβλήματος. Για το λόγο αυτό διάφορες μέθοδοι έχουν προταθεί και συνδυαστεί με τους ΕΑ, ώστε οι τελευταίοι να βρίσκουν εφικτές λύσεις. Οι μέθοδοι διαχείρισης περιορισμών πρακτικά επιτυγχάνουν τη σύγκριση μεταξύ του πληθυσμού των γονέων και των απογόνων, σε περιπτώσεις που υπάρχουν εφικτά και μη εφικτά διανύσματα λύσεων στον πληθυσμό. Παρακάτω θα παρουσιαστούν δύο πολύ γνωστές τεχνικές διαχείρισης των περιορισμών οι οποίες χρησιμοποιήθηκαν στη διατριβή.

2.3.1 Κανόνες Εφικτότητας

Η μέθοδος των Κανόνων Εφικτότητας (**Feasibility Rules**) προτάθηκε από τον **Deb** [7] και αποτελεί μία από τις πιο διαδεδομένες μεθόδους διαχείρισης των περιορισμών. Όταν η μέθοδος εφαρμόζεται σε προβλήματα ενός στόχου, η σύγκριση μεταξύ δύο υποψηφίων λύσεων γίνεται εφαρμόζοντας τους εξής κανόνες:

1. Όταν και οι δύο υποψήφιες λύσεις είναι εφικτές τότε επιλέγεται εκείνη με την καλύτερη τιμή της αντικειμενικής συνάρτησης.

2. Όταν μία από τις δύο υποψήφιες λύσεις είναι εφικτή τότε επιλέγεται εκείνη.

3. Όταν και οι δύο υποψήφιες λύσεις είναι ανέφικτες τότε επιλέγεται εκείνη που έχει την χαμηλότερη συνολική παραβίαση των περιορισμών.

Η συνολική παραβίαση των περιορισμών υπολογίζεται ως εξής:

$$\phi(\mathbf{x}) = \sum_{l_1=1}^{L_1} max(0, g_{l_1}(\mathbf{x})) + \sum_{l_2=1}^{L_2} max(|h_{l_2}(\mathbf{x})| - \epsilon, 0) \tag{2.13}$$

2.3.2 Μέθοδος Stochastic Ranking

Η μέθοδος Stochastic Ranking προτάθηκε από τους Runarsson και Yao [8]. Στη μέθοδο αυτή η σύγκριση μεταξύ εφικτών λύσεων γίνεται βάση της τιμής της αντικειμενικής. Αν όμως τουλάχιστον μία από τις δύο λύσεις είναι μη εφικτή τότε η πιθανότητα η σύγκριση να γίνει βάση της τιμή της αντικειμενικής είναι P_f. Συνήθως αυτή η μέθοδο χρησιμοποιείται σε συνδυασμό με τις Στρατηγικές Εξέλιξης. Στη βασική διαδικασία γίνονται τουλάχιστον NQpop περάσματα, κατά τα οποία τα άτομα του πληθυσμού κατατάσσονται μέσω της σύγκρισής τους με άτομα που βρίσκονται σε γειτονικές θέσεις του πληθυσμού. Η πιθανότητα P_f, προσαρμόζει κατά κάποιο τρόπο την προτίμηση προς επιλογή εφικτών σωματιδίων. Όσο πιο μικρή είναι τόσο μικρότερη είναι και η πιθανότητα να επιλεγεί ένα μη εφικτό σωματίδιο έναντι ενός εφικτού. Αυτό γίνεται σε μία προσπάθεια να χρησιμοποιηθεί η χρήσιμη πληροφορία που μπορεί να παρέχουν μη εφικτά άτομα κατά τη διάρκεια της βελτιστοποίησης.

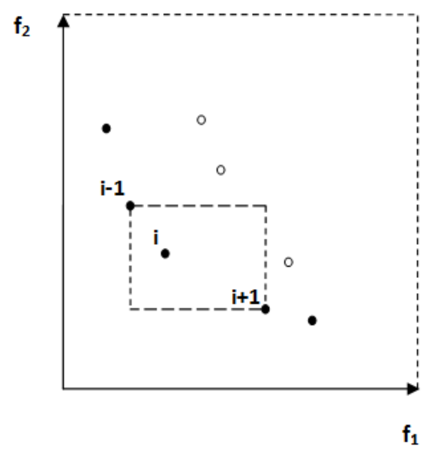
2.4 Διαχείριση Πολλαπλών Κριτηρίων

Δύο είναι οι βασικές κατηγορίες μεθόδων που έχουν εφαρμοστεί για την επίλυση τέτοιων προβλημάτων: οι κλασικές μέθοδοι και οι ΕΑ. Θα περιγραφούν παρακάτω συνοπτικά.

Στην πρώτη κατηγορία, ανήκουν οι μέθοδοι που συνήθως μετατρέπουν το πρόβλημα από πολυκριτηριακό σε μονοκριτηριακό. Έπειτα, για την επίλυση αυτού του προβλήματος μπορεί να εφαρμοστεί αλγόριθμος βελτιστοποίησης για προβλήματα ενός κριτηρίου. Η πιο γνωστή από τις κλασικές μεθόδους μετατροπής προβλημάτων πολλαπλών κριτηρίων σε προβλήματα ενός κριτηρίου περιλαμβάνει την κατασκευή ενός σταθμισμένου γραμμικού αθροίσματος των αντικειμενικών συναρτήσεων. Κατά τη μέθοδο αυτή ορίζονται βαθμωτά σταθμά (weights) για το κάθε προς βελτιστοποίηση κριτήριο, και στη συνέχεια αυτά συνδυάζονται σε μια συνάρτηση που μπορεί να επιλυθεί από ένα αλγόριθμο βελτιστοποίησης μονού κριτηρίου. Για να βρεθούν πολλαπλά σημεία του μετώπου θα πρέπει να οριστούν πολλαπλοί συνδυασμοί βαθμωτών σταθμών και το πρόβλημα να βελτιστοποιηθεί για κάθε συνδυασμό. Ενώ η προσέγγιση αυτή επιτρέπει την χρήση βελτιστοποιητών μονού κριτηρίου δεν μπορεί ωστόσο να βρει όλες τις μη κυριαρχούμενες λύσεις, παρά μόνο εκείνες που βρίσκονται στο κυρτό τμήμα του μετώπου Pareto. Επίσης, διαφορετικοί συνδυασμοί βαρών μπορούν να οδηγήσουν στην ίδια τελική λύση του προβλήματος ανάλογα με τη θέση της στο μέτωπο Pareto.

Πιο πρόσφατα οι ΕΑ άρχισαν να χρησιμοποιούνται για την επίλυση προβλημάτων πολλαπλών στόχων. Λόγω της διαχείρισης πληθυσμού υποψηφίων λύσεων μπορούν να προσεγγίσουν το σύνολο των βέλτιστων κατά Pareto λύσεων σε μία μόνο εκτέλεση του αλγορίθμου. Οι ΕΑ για επίλυση προβλημάτων πολλαπλών κριτηρίων παρουσιάζουν αρκετές ομοιότητες με τους ΕΑ για προβλήματα ενός κριτηρίου. Η βασική διαφορά τους έγκειται στον τρόπο με τον οποίο υπολογίζεται η καταλληλότητα ενός ατόμου, καθώς και στον τρόπο με τον οποίο πραγματοποιείται η επιλογή των ατόμων της επόμενης γενιάς. Επίσης οι πρώτοι περιλαμβάνουν μηχανισμούς έτσι ώστε να διατηρείται η καλή διασπορά των μη-κυριαρχούμενων λύσεων στον χώρο των αντικειμενικών συναρτήσεων. Παρακάτω θα περιγραφεί η μέθοδος **NSGA-II** [9] η οποία αποτελεί ένα από τους αποτελεσματικότερους ΕΑ για επίλυση προβλημάτων πολλαπλών κριτηρίων, και χρησιμοποιήθηκε ως βάση για τον ΕΑ που αναπτύχθηκε στην παρούσα διατριβή.

Ο **NSGA-II** περιλαμβάνει μία διαδικασία ταξινόμησης και κατάταξης των λύσεων ενώ η επιλογή των ατόμων που θα αποτελέσουν την επόμενη γενιά γίνεται από το συνδυασμένο πληθυσμό γονιών και απογόνων, επομένως πρόκειται για ελιτιστική μέθοδο. Κατά τη διαδικασία αυτή για κάθε άτομο i του πληθυσμού υπολογίζεται ο αριθμός των λύσεων που κυριαρχούν της λύσης i (n_i) και το σετ των λύσεων επί των οποίων η λύση i κυριαρχεί (S_i). Έπειτα με χρήση αυτών των δύο τιμών ακολουθείται μία διαδικασία κατά την οποία τα οι υποψήφιες λύσεις ταξινομούνται σε διάφορα μέτωπα λύσεων, με το μέτωπο 1 να περιλαμβάνει τις μη-κυριαρχούμενες λύσεις στον πληθυσμό. Στη συνέχεια, επιλέγονται οι υποψήφιες λύσεις της επόμενης γενιάς, ξεκινώντας από τις λύσεις που ανήκουν στο μέτωπο 1 έπειτα στο μέτωπο 2 και ούτω καθεξής έως ότου συμπληρωθεί ο αριθμός των απαιτούμενων ατόμων. Σε περίπτωση που όλες οι υποψήφιες λύσεις ενός μετώπου δεν μπορούν να συμπεριληφθούν στον πληθυσμό της επόμενης γενιάς, επιλέγονται εκείνες που βρίσκονται σε ποιο αραιοκατοικημένες περιοχές του μετώπου (στο χώρο των αντικειμενικών συναρτήσεων). Για να βρεθούν αυτές οι λύσεις, χρησιμοποιείται το μέγεθος **crowding distance**. Σε πρόβλημα δύο στόχων ($M = 2$), για κάθε σημείο i του μετώπου, το μέγεθος αυτό είναι ενδεικτικό της περιμέτρου του ορθογωνίου που σχηματίζεται με εκατέρωθεν κορυφές τα δύο γειτονικά σημεία του i στο ίδιο μέτωπο, όπως φαίνεται στο Σχήμα 2.1



Σχήμα 2.1: Το ορθογώνιο που χρησιμοποιείται για τον υπολογισμό του μεγεθους **crowding distance** για τη λυση i.

2.5 Υβριδικοί αλγόριθμοι βασιζόμενοι στους ΕΑ

Για να βελτιωθεί η απόδοση των ΕΑ αλγορίθμων για την επίλυση προβλημάτων αυξημένης δυσκολίας, μπορούν να προταθούν συνδυασμοί των ΕΑ με άλλες μεθόδους, δημιουργώντας του λεγόμενους υβριδικούς αλγορίθμους. Ανάλογα με το είδος της μεθόδου βελτιστοποίησης με την οποία συνδυάζεται ο ΕΑ προκύπτουν τρεις κατηγορίες υβριδικών μεθόδων που αναλύονται παρακάτω.

Η πρώτη κατηγορία περιλαμβάνει τις υβριδικές μεθόδους στις οποίες οι ΕΑ συνδυάζονται με αιτιοκρατικές μεθόδους βελτιστοποίησης. Οι τελευταίες συνήθως χρησιμοποιούν πληροφορία από την παράγωγο της αντικειμενικής συνάρτησης, ενώ μερικές από αυτές παρέχουν και πληροφορία σχετικά με την απόκλιση της τελικής λύσης από τη βέλτιστη λύση του προβλήματος. Σε αυτή την κατηγορία ανήκουν μέθοδοι όπως ο Δυναμικός Προγραμματισμός, και ο Αλγόριθμος Εσωτερικού Σημείου. Συνήθως οι διάφορες μέθοδοι εφαρμόζονται αυτούσιες η μία μετά την άλλη. Πιο συγκεκριμένα, συχνά οι ΕΑ εφαρμόζονται στην αρχή για την ολική εξερεύνηση (global search) του πεδίου ορισμού των αντικειμενικών μεταβλητών, παρέχοντας μία λύση για το πρόβλημα. Έπειτα, χρησιμοποιώντας την λύση που παρέχει ο ΕΑ, ως αρχική λύση, εφαρμόζεται η αιτιοκρατική μέθοδος βελτιστοποίησης, για να επιτευχθεί η τοπική βελτίωση (local search) της λύσης, εστιάζοντας την αναζήτηση στην υποσχόμενη περιοχή του χώρου αναζήτησης.

Η δεύτερη κατηγορία περιλαμβάνει τις υβριδικές μεθόδους στις οποίες οι ΕΑ συνδυάζονται με μεθόδους τοπικής βελτιστοποίησης. Σε αυτές τις μεθόδους οι ΕΑ χρησιμοποιούνται για την ολική εξερεύνηση του χώρου ενώ οι μέθοδοι τοπικής βελτιστοποίησης χρησιμοποιούνται για την εξερεύνηση της γειτονιάς των λύσεων. Αυτοί η αλγόριθμοι ονομάζονται και Μιμητικοί Αλγόριθμοι. Για το σχεδιασμό τους απαιτείται η απάντηση σε μία σειρά ερωτημάτων, όπως ποιος ΕΑ και ποια τεχνική τοπικής βελτιστοποίησης θα χρησιμοποιηθεί, ποιος θα είναι ο αριθμός των ατόμων στα οποία θα εφαρμοστεί η τοπική βελτίωση, ποιά τα κριτήρια με τα οποία θα επιλέγονται αυτά τα άτομα, και ποιά η συχνότητα με την οποία θα εφαρμόζεται η τοπική βελτιστοποίηση. Σε προβλήματα πολλαπλών στόχων πρέπει να καθοριστεί και ο τρόπος με τον οποίο θα πραγματοποιείται η σύγκριση των σωματιδίων κατά την τοπική βελτιστοποίηση.

Στην τρίτη κατηγορία περιλαμβάνονται μέθοδοι στις οποίες οι ΕΑ συνδυάζονται με άλλους ΕΑ. Στην κατηγορία αυτή, είτε οι ΕΑ εφαρμόζονται σειριακά (όπως στην περίπτωση συνδυασμού των ΕΑ με τις κλασικές μεθόδους) είτε τελεστές του ενός αλγορίθμου μπορούν να ενταχθούν στη δομή του άλλου.

ΚΕΦΑΛΑΙΟ 3
ΠΡΟΓΡΑΜΜΑΤΙΣΜΟΣ ΕΠΕΚΤΑΣΗΣ ΔΥΝΑΜΙΚΟΥ ΙΣΧΥΟΣ ΜΕ ΕΝΕΡΓΕΙΑΚΟΥΣ ΣΤΟΧΟΥΣ

Η εξέλιξη του μείγματος παραγωγής ενός τομέα παραγωγής ηλεκτρικής ενέργειας επηρεάζεται από τις Κοινοτικές Οδηγίες ή από Εθνικά Σχέδια δράσης που θέτουν τους μελλοντικούς ενεργειακούς στόχους, σχετικά με την ανάπτυξη του τομέα. Οι φορείς που καθορίζουν την ενεργειακή πολιτική ιδανικά θα ήθελαν να γνωρίζουν τις βέλτιστες αποφάσεις σχετικά με την επέκταση του δυναμικού ισχύος, οι οποίες θα οδηγήσουν στην επίτευξη των προαναφερθέντων ενεργειακών στόχων με το βέλτιστο από οικονομικής ή/και περιβαλλοντικής απόψεως τρόπο. Η επέκταση του δυναμικού ισχύος αφορά τις αποφάσεις για επένδυση σε τεχνολογίες παραγωγής ενέργειας (παραγωγική δυναμικότητα, τεχνολογία παραγωγής, χρόνος επένδυσης). Η λήψη των βέλτιστων αποφάσεων θα αυξήσει την Καθαρή Παρούσα Αξία του τομέα παραγωγής ηλεκτρικής ενέργειας, αυξάνοντας τις πιθανότητες κερδοφορίας για τους συμμετέχοντες στον τομέα. Παράλληλα, οι φορείς που καθορίζουν τις ενεργειακές πολιτικές ενδιαφέρονται για την επίδραση των επενδύσεων σε τεχνολογίες παραγωγής ενέργειας στην εξέλιξη ορισμένων μεγεθών του τομέα παραγωγής ηλεκτρικής ενέργειας όπως είναι η Οριακή Τιμή του Συστήματος ή οι εκπομπές CO_2. Οι βέλτιστες επενδύσεις στον τομέα ηλεκτρικής ενέργειας μπορεί να οδηγήσουν σε ελεγχόμενη αύξηση της Οριακής Τιμής Συστήματος καθώς και σε ένα πιο βιώσιμο τομέα ηλεκτροπαραγωγής, ευνοώντας έτσι τους τελικούς καταναλωτές.

Στο παρόν κεφάλαιο αναπτύσσεται ένα εργαλείο για την υποστήριξη αποφάσεων όσον αφορά τον μακροχρόνιο προγραμματισμό επέκτασης δυναμικού παραγωγής ισχύος, όταν έχουν τεθεί συγκεκριμένοι ενεργειακοί στόχοι. Οι προσθήκες στο παραγωγικό δυναμικό που πρέπει να πραγματοποιηθούν ετησίως στις διάφορες τεχνολογίες παραγωγής υπολογίζονται για να επιτευχθεί η ικανοποίηση των ενεργειακών στόχων. Επίσης ο βέλτιστος βαθμός χρήσης της κάθε τεχνολογίας εξάγεται. Η αντικειμενική συνάρτηση του μοντέλου είναι η Καθαρή Παρούσα Αξία του τομέα ηλεκτροπαραγωγής. Για την επίλυση του μοντέλου χρησιμοποιείται ένα σενάριο εξέλιξης της ετήσιας τιμής διαφόρων μεταβλητών του τομέα παραγωγής ενέργειας όπως είναι η ζήτηση ηλεκτρικής ενέργειας, οι τιμές αγοράς δικαιωμάτων εκπομπών CO_2, οι τιμές καυσίμων, το επιτόκιο αναγωγής καθώς και ο πληθωρισμός. Για την παραγωγή αυτού του σεναρίου χρησιμοποιήθηκε στοχαστική διαδικασία Monte Carlo κατά την οποία δημιουργήθηκε πληθώρα σεναρίων που περιγράφουν την εξέλιξη των παραπάνω μεγεθών. Έπειτα για κάθε μεταβλητή του τομέα ηλεκτροπαραγωγής υπολογίζεται ο μέσος όρος των τιμών των σεναρίων για κάθε έτος δημιουργώντας έτσι το σενάριο που χρησιμοποιήθηκε κατά την βελτιστοποίηση του μοντέλου μακροχρόνιου προγραμματισμού επέκτασης του δυναμικού παραγωγής ισχύος. Επίσης, για τη βελτιστοποίηση αυτού του μοντέλου αναπτύχθηκε υβριδικός αλγόριθμος ο οποίος συνδυάζει τις Στρατηγικές Εξέλιξης με τον Αλγόριθμο Ενδιάμεσου Σημείου. Παράλληλα μία παράμετρος χαλάρωσης προτείνεται και εφαρμόζεται στους περιορισμούς που αναπαριστούν τους ενεργειακούς στόχους, που καθορίζει το ποσοστό της επιτρεπτής απόκλισης από τους ενεργειακούς στόχους.

3.1 Μαθηματική διατύπωση του προβλήματος

Οι αντικειμενικές μεταβλητές του μοντέλου είναι οι προσθήκες δυναμικού παραγωγής ισχύος $X_{i,v}$ (MW_{el}) κάθε τεχνολογίας i για κάθε έτος του εξεταζόμενου ορίζοντα παραγωγής v, καθώς και ο ετήσιος βέλτιστος βαθμός χρήσης του εγκατεστημένου δυναμικού παραγωγής ισχύος των τεχνολογιών που χρησιμοποιούν ορυκτά καύσιμα $\theta_{i,z}$ (%). Για τις τεχνολογίες παραγωγής ενέργειας από ΑΠΕ γίνεται η υπόθεση ότι παράγουν όσο τους επιτρέπει η παραγωγική τους δυνατότητα, καθώς η παραγωγή τους δεν είναι ρυθμιζόμενη. Το μοντέλο ακολουθεί τα εξής βήματα για να προσεγγίσει την μέση ετήσια οριακή τιμή του συστήματος:

- Αρχικά βάση των $X_{i,v}$ (MW_{el}), υπολογίζεται σε κάθε χρόνο το συνολικά εγκατεστημένο δυναμικό ισχύος κάθε τεχνολογίας καθώς και η παραγόμενη ενέργεια από κάθε τεχνολογία.

- Έπειτα προσεγγίζεται για κάθε τεχνολογία η μέγιστη φόρτισή της σε κάθε έτος. Για τις τεχνολογίες ορυκτών καυσίμων αυτό γίνεται βάση της εγκατεστημένης ισχύος τους λαμβάνοντας υπόψη ένα περιθώριο στρεφόμενης εφεδρείας. Για τις υπόλοιπες τεχνολογίες γίνεται η υπόθεση ότι το μέγιστο και ελάχιστο φορτίο θεωρείται ότι συμπίπτουν, μιας και παράγουν όποτε η πηγή τους είναι διαθέσιμη.

- Χρησιμοποιώντας μία προσέγγιση της καμπύλης Διάρκειας Φορτίου, το φορτίο κάθε ώρας του έτους τοποθετείται σε φθίνουσα σειρά. Το ωριαίο φορτίο που παράγεται από κάθε τεχνολογία μπορεί επίσης να τοποθετηθεί σε φθίνουσα σειρά, και να προσεγγιστεί από μία γραμμή ισχύος (power line). Αξίζει να σημειωθεί ότι οι τελικές γραμμές προσεγγίζουν τη Σειρά Εντάξεως (Merit Order Effect) των τεχνολογιών στην παραγωγή, κατά την οποία στο σύστημα εντάσσεται η ενέργεια που παράγεται πρώτα από τις φθηνότερες μονάδες συνεχίζοντας σταδιακά προς την ενέργεια των πιο ακριβών μονάδων. Έτσι η ενέργεια που παράγεται από κάθε τεχνολογία μπορεί να προσεγγιστεί από το εμβαδόν της περιοχής που καθορίζεται μεταξύ της δικής της γραμμής ισχύος και της γραμμής ισχύος της τεχνολογίας που εντάθηκε στο σύστημα πριν από αυτήν. Πρακτικά, στο μοντέλο υπολογίζεται ο ετήσιος αριθμός ωρών λειτουργίας μία μονάδας. Αν αυτός είναι ίσος με 8760 τότε η μονάδα δουλεύει όλο τον χρόνο και άρα η παραγόμενη ενέργειά της μπορεί να υπολογιστεί χρησιμοποιώντας εμβαδόν τραπεζίου, αφού πρώτα υπολογιστεί το ελάχιστο φορτίο που καλείται να καλύψει η μονάδα. Σε περίπτωση που δεν είναι 8760, τότε χρησιμοποιείται το εμβαδόν τριγώνου για να προσεγγιστεί η παραγόμενη ενέργεια της μονάδας.

- Αφού, υπολογιστούν τα παραπάνω προσεγγίζεται η μέση ετήσια οριακή τιμή συστήματος, χρησιμοποιώντας τον αριθμό ωρών για τον οποίο κάθε τεχνολογία καθόρισε τιμή στο σύστημα, δηλαδή εντάχθηκε τελευταία στο σύστημα. Θεωρείται για αυτές τις ώρες ότι το μέσο κόστος παραγωγής της τεχνολογίας προσεγγίζει την Οριακή Τιμή του Συστήματος.

Η μέση ετήσια Οριακή Τιμή του Συστήματος προκύπτει ως ο σταθμισμένος μέσος όρος των διαφορετικών Οριακών Τιμών του Συστήματος επί τον αντίστοιχο χρόνο.

Η αντικειμενική συνάρτηση του μοντέλου αφορά την μεγιστοποίηση της Καθαρής Παρούσας Αξίας του τομέα ηλεκτρικής ενέργειας και περιλαμβάνει όρους οι οποίοι είναι σχετικοί με τα έσοδα από την πώληση της παραγόμενης ενέργειας, τα έξοδα επένδυσης, τα λειτουργικά έξοδα κα τα έξοδα συντήρησης της εγκαταστημένης ισχύος κάθε τεχνολογίας, καθώς και τα έσοδα που προκύπτουν από τη μείωση των δικαιωμάτων εκπομπών CO_2 που θα πρέπει να αποκτηθούν λόγω της παραγωγής ενέργειας από ΑΠΕ. Το ετήσιο επιτόκιο αναγωγής χρησιμοποιείται για να ανάγει τους όρους σε παρούσες αξίες.

Οι περιορισμοί του μοντέλου αφορούν τα όρια στο δυναμικό παραγωγής ισχύος που μπορεί να εγκατασταθεί ετήσια καθώς και την μέγιστη εγκατεστημένη ισχύ που μπορεί να έχουμε από κάθε τεχνολογία. Επίσης υπάρχει ο περιορισμός ικανοποίησης της ζήτησης, και ο περιορισμός που εξασφαλίζει ότι η συνολική εγκατεστημένη ισχύς θα μπορεί να παρέχει την απαραίτητη στρεφόμενη εφεδρεία για την ασφαλή λειτουργία του δικτύου. Τέλος, υπάρχει και ο περιορισμός που εξασφαλίζει ότι κάθε τεχνολογία θα λειτουργεί τουλάχιστον για ένα αριθμό ωρών που θα εξασφαλίζει ότι η παραγωγή δεν θα είναι ζημιογόνα.

Όσον αφορά τους ενεργειακούς στόχους που μπορεί να θέτονται από τις ρυθμιστικές αρχές ή τους αντίστοιχους φορείς που καθορίζουν την ενεργειακή πολιτική μίας χώρας, μαθηματικά περιγράφονται από περιορισμούς ισότητας. Στο μοντέλο προτείνεται η εφαρμογή ενός παράγοντα χαλάρωσης αυτών των περιορισμών, που πρακτικά καθορίζει ένα μικρό εύρος τιμών μέσα στο οποίο οι στόχοι θα θεωρούνται επιτυχημένοι. Από μαθηματικής απόψεως αυτό μπορεί να διευκολύνει την εύρεση εφικτών λύσεων, μιας και η εφικτή περιοχή του χώρου αναζήτησης διευρύνεται. Επίσης, συνάδει και με το γεγονός ότι οι ενεργειακοί στόχοι εκλαμβάνονται από το κράτος ως οδηγίες για να ενισχυθεί η επένδυση σε συγκεκριμένες παραγωγικές τεχνολογίες και όχι ως απόλυτοι αριθμοί που πρέπει να επιτευχθούν.

3.2 Ο προτεινόμενος υβριδικός αλγόριθμος

Για τη βελτιστοποίηση του μοντέλου μακροχρόνιου προγραμματισμού επέκτασης της δυναμικότητας παραγωγής χρησιμοποιήθηκε υβριδικός αλγόριθμος στον οποίο συνδυάζεται ένας ΕΑ με μία αιτιοκρατική μέθοδο. Ο ΕΑ που χρησιμοποιήθηκε αποτελεί ένα συνδυασμό της μεθόδου διαχείρισης περιορισμών Stochastic Ranking και μίας μεθόδου βασισμένης στις Στρατηγικές Εξέλιξης. Ο αλγόριθμος αυτός έχει την ονομασία Improved Stochastic Ranking Evolution Strategies (ISRES) και προτάθηκε στην εργασία [10]. Η αιτιοκρατική μέθοδος που χρησιμοποιήθηκε είναι ο Αλγόριθμος Ενδιάμεσου Σημείου (Interior Point Algorithm - IPA) [11]. Ο συνδυασμός των δύο μεθόδων γίνεται ως εξής: Αρχικά εφαρμόζεται η μέθοδος ISRES για την ολική εξερεύνηση του χώρου. Η λύση που παράγεται από τον αλγόριθμο ISRES τροφοδοτείται ως αρχική λύση του αλγορίθμου IPA, ώστε να πραγματοποιηθεί τοπική βελτίωση της λύσης εκμεταλλευόμενος την υποσχόμενη περιοχή λύσεων που έχει βρει ο ISRES.

3.3 Αποτελέσματα της μεθόδου

Το προτεινόμενο μοντέλο εφαρμόζεται στον τομέα παραγωγής ηλεκτρικής ενέργειας της Ελλάδας, λαμβάνοντας υπόψη την εγκατεστημένη ισχύ το 2015. Οι ενεργειακοί στόχοι που τέθηκαν σε δύο σχέδια δράσης λαμβάνονται υπόψη και εξετάζεται η επίδρασή τους στην εξέλιξη της δομής του ελληνικού τομέα παραγωγής ηλεκτρικής ενέργειας. Το πρώτο σχέδιο είναι το Εθνικό Σχέδιο Δράσης για τις Ανανεώσιμες Πηγές Ενέργειας (National Renewable Energy Action Plan - NREAP) [12], που εκπονήθηκε στο πλαίσιο εφαρμογής της Ευρωπαϊκής Ενεργειακής Πολιτικής σε σχέση με την διείσδυση των ΑΠΕ, όπως αυτή περιγράφεται στην Κοινοτική Οδηγία 2009/28/ΕΚ. Στα πλαίσια του NREAP τέθηκε ως στόχος η συνολική παραγωγή ηλεκτρικής ενέργειας από ΑΠΕ να είναι ίση με το 40% της συνολικής παραγωγής. Επίσης για κάθε τεχνολογία ΑΠΕ θέτονται επιμέρους στόχοι που καθορίζουν το ποσοστό ενέργειας που πρέπει να παράγει κάθε τεχνολογία στο σύνολο της παραγωγής. Το δεύτερο σχέδιο δράσης που λαμβάνεται υπόψη σκιαγραφεί το ενεργειακούς στόχους της Ελλάδας για το 2050 (National Energy Plan - NEP) [13]. Σε αυτό το σχέδιο ορίζεται ότι η παραγωγή από ΑΠΕ πρέπει το 2050 να υπερβαίνει το 85% της συνολικής παραγωγής. Παράλληλα, θέτονται στόχοι που ορίζουν την εγκατεστημένη ισχύ σε κάθε τεχνολογία για το 2050.

Όπως προαναφέρθηκε ένα σενάριο εξέλιξης των τιμών των διάφορων μεταβλητών του τομέα ηλεκτρικής ενέργειας χρησιμοποιείται. Για το σενάριο αυτό, δημιουργήθηκε ένας μεγάλος αριθμός σεναρίων (1000 σενάρια) των οποίων ο μέσος όρος των τιμών για κάθε έτος βρέθηκε για να προκύψει το εξεταζόμενο σενάριο. Για τη δημιουργία των σεναρίων υποτέθηκε ότι η ζήτηση ηλεκτρικής ενέργειας, η τιμή αγοράς δικαιωμάτων εκπομπών CO_2, οι τιμές των καυσίμων καθώς και ο πληθωρισμός, εξελίσσεται ακολουθώντας γεωμετρική κίνηση Brown (Geometric Brownian Motion). Επιπρόσθετα, η εξέλιξη των επιτοκίου αναγωγής προσομοιώνεται με τη χρήση μοντέλου Cox-Ingersoll-Ross, καθώς το τελευταίο είναι κατάλληλο για παραγωγή μη αρνητικών τιμών.

Στα υπολογιστικά πειράματα εξετάζονται τέσσερις διαφορετικές περιπτώσεις του μοντέλου. Στην πρώτη (Case 1) οι ενεργειακοί στόχοι δεν λαμβάνονται υπόψη και αυτό αποτελεί το μοντέλο βάσης. Στις υπόλοιπες τρεις περιπτώσεις λαμβάνονται υπόψη οι ενεργειακοί στόχοι (Cases 2,3,4). Για τους βραχυπρόθεσμους στόχους, ο συντελεστής χαλάρωσης λαμβάνει ίδια τιμή και στις τρεις περιπτώσεις. Διαφορετικά επίπεδα χαλάρωσης θέτονται για τους μακροχρόνιους ενεργειακούς στόχους του 2050, έτσι ώστε να μελετηθεί η επίδραση της χαλάρωσης στο μοντέλο.

Παράλληλα, 5 διαφορετικοί αλγόριθμοι εξετάζονται στο μοντέλο:

- Ο IPA, στον οποίο ο μέγιστο αριθμός υπολογισμών αντικειμενικής συνάρτησης (maximum number of function evaluations - FEs) είναι $7 \cdot 10^5$. Αυτό το πείραμα μπορεί να μας δώσει πληροφορίες σχετικά με το πόσο εύκολα μπορεί ο αλγόριθμος να βρει εφικτή λύση.

- Ο IPA, στον οποίο ο μέγιστο αριθμός υπολογισμών αντικειμενικής συνάρτησης είναι ίσος με $7.2 \cdot 10^6$.

- Ο ISRES-IPA, στον οποίο ο ISRES τερματίζει μετά από $4.2 \cdot 10^6$ FEs. Η τελική λύση που παρέχει ο ISRES, εισάγεται στον IPA, ο οποίος τερματίζει μετά από $3 \cdot 10^6$ FEs.

- Εφαρμόζεται ένας Γενετικός Αλγόριθμος (GA) για $7.2 \cdot 10^6$ FEs.

- Εφαρμόζεται ένας υβριδικός αλγόριθμος GA-IPA. Ο GA εφαρμόζεται για $4.2 \cdot 10^6$ FEs. Η καλύτερη λύση που παράγεται από τον GA, εισάγεται σαν αρχική λύση στον IPA για $3 \cdot 10^6$ FEs.

Κάθε ένας από αυτούς του 5 αλγορίθμους εφαρμόζεται και στις 4 προαναφερθείσες περιπτώσεις.

Μετά από ανάλυση των αποτελεσμάτων προκύπτουν τα εξής:

1. Η χρήση των ενεργειακών στόχων επηρεάζει τη διαδικασία βελτιστοποίησης. Όταν οι επιπλέον περιορισμοί εισάγονται στο μοντέλο η διαδικασία εύρεσης εφικτών λύσεων δυσχεραίνεται.

2. Καθώς αυξάνεται η τιμή της παραμέτρου χαλάρωσης, οι λύσεις που βρίσκονται από τους αλγορίθμους παρουσιάζουν μεγαλύτερη Καθαρή Παρούσα Αξία.

3. Όσον αφορά τον ISRES-IPA, τα συνολικά αποτελέσματα αναδεικνύουν ότι ο αλγόριθμος παράγει καλύτερες λύσεις πιο συστηματικά σε σχέση με τον IPA υψηλού αριθμού FES, καθώς και τον GA-IPA. Αξίζει να σημειωθεί ότι όσον αφορά τον GA υψηλού αριθμού FEs, δεν κατάφερε σε καμία από τις εκτελέσεις του να παράγει εφικτή λύση, αναδεικνύοντας την δυσκολία του συγκεκριμένου προβλήματος.

Όσον αφορά τώρα την επίδραση των ενεργειακών στόχων στην εξέλιξη του τομέα παραγωγής ηλεκτρικής ενέργειας, η εισαγωγή των στόχων οδηγεί στην μείωση της παραγόμενης ενέργειας από τεχνολογίες που χρησιμοποιούν ορυκτά καύσιμα. Αξίζει να σημειωθεί ότι λόγω της ύπαρξης των μακροχρόνιων στόχων οι επενδύσεις σε ανανεώσιμες πηγές ενέργειας συνεχίζονται έως το τέλος του χρονικού ορίζοντα προγραμματισμού, σε κάθε μία από τις τρεις περιπτώσεις και αυτό έχει ως αποτέλεσμα οι εκπομπές CO_2 να είναι σημαντικά μειωμένες σε αυτές τις περιπτώσεις σε σχέση με την περίπτωση χωρίς τους μακροχρόνιος στόχους. Όσον αφορά της τιμή της ετήσιας Οριακής Τιμής συστήματος, στο τέλος του ορίζοντα παραγωγής, φαίνεται να υπάρχει μία ελαφριά μείωσή της στις περιπτώσεις όπου έχουμε μεγαλύτερη διείσδυση ανανεώσιμων. Τέλος όσον αφορά την επίτευξη των στόχων η εισαγωγή της παραμέτρου χαλάρωσης φαίνεται να διευκολύνει την εύρεση λύσεων χωρίς να επηρεάζει σημαντικά τις τελικές λύσεις της μεθόδου.

ΚΕΦΑΛΑΙΟ 4
ΒΕΛΤΙΣΤΟΠΟΙΗΣΗ ΠΡΟΓΡΑΜΜΑΤΙΣΜΟΥ ΠΑΡΑΓΩΓΗΣ ΣΥΣΤΗΜΑΤΟΣ ΘΕΡΜΙΚΩΝ ΜΟΝΑΔΩΝ

Στο κεφάλαιο αυτό παρουσιάζεται μία μέθοδος για την επίλυση του προβλήματος βραχυπρόθεσμου προγραμματισμού παραγωγής ηλεκτρικής ενέργειας. Το πρόβλημα περιλαμβάνει την ταυτόχρονη επίλυση δύο επιμέρους προβλημάτων: τον καθορισμό των μονάδων που θα ενταχθούν στο σύστημα, και την οικονομική κατανομή του ωριαίου φορτίου στις μονάδες που λειτουργούν. Πρόκειται για ένα πρόβλημα μικτού ακεραίου μη γραμμικού προγραμματισμού, το οποίο περιλαμβάνει ένα μεγάλο αριθμό περιορισμών ισότητας και ανισότητας, γραμμικών και μη γραμμικών. Συνήθως η κατάσταση λειτουργίας των μονάδων περιγράφεται από δυαδικές μεταβλητές, ενώ συνεχείς μεταβλητές χρησιμοποιούνται για να περιγράψουν την ωριαία φόρτιση κάθε μονάδας η οποία βρίσκεται σε λειτουργία.

Η μέθοδος που αναπτύχθηκε στα πλαίσια της παρούσας διατριβής, βασίζεται σε μία παραλλαγή του αλγορίθμου της Διαφορικής Εξέλιξης για τον προσδιορισμό τόσο της κατάστασης λειτουργίας όσο και της φόρτισης των μονάδων. Πιο συγκεκριμένα, περιλαμβάνει μία βηματική συνάρτηση για τον προσδιορισμό της κατάστασης των μονάδων, μία σειρά από μηχανισμούς που επιδιορθώνουν τυχόν παραβιάσεις των περιορισμών από μη εφικτά άτομα καθώς και έναν νέο τελεστή μετάλλαξης. Η απόδοση της μεθόδου εξετάστηκε σε διάφορα συστήματα παραγωγής που υπάρχουν στη σχετική βιβλιογραφία και κατάφερε να βρει λύσεις οι οποίες να είναι ανταγωνιστικές σε σχέση με σύγχρονες μεθόδους της βιβλιογραφίας εξεταζόμενες στα ίδια συστήματα.

4.1 Μαθηματική διατύπωση του προβλήματος

Η αντικειμενική συνάρτηση του προβλήματος αφορά την ελαχιστοποίηση του συνολικού κόστους λειτουργίας των μονάδων παραγωγής για τον υπό εξέταση χρονικό ορίζοντα (Οι συμβολισμοί που χρησιμοποιούνται δίνονται στη αρχή της διατριβής):

$$f_1 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} [FC_i(P_i^t) \cdot ST_i^t + SUC_i \cdot ST_i^t \cdot (1 - ST_i^{t-1}) + SDC_i \cdot (1 - ST_i^t) \cdot ST_i^{t-1}] \quad (4.1)$$

όπου το κόστος καυσίμου των μονάδων είναι τετραγωνική συνάρτηση της φόρτισης της μονάδας ($FC_i(P_i^t)$), ενώ το κόστος εκκίνησης των μονάδων (SUC_i) δίνεται συνήθως από μία βηματική ή μία εκθετική συνάρτηση λαμβάνοντας υπόψη τον χρόνο για τον οποίο μία μονάδα παραμένει εκτός λειτουργίας. Το κόστος σβέσης της μονάδας (SDC_i) είναι συνήθως σταθερό.

Οι περιορισμοί του προβλήματος αφορούν την κάλυψη της ωριαίας ζήτησης του συστήματος (Εξίσωση 4.2), την εξασφάλιση της απαιτούμενης στρεφόμενης εφεδρείας για την ασφαλή λειτουργία του συστήματος (Ανισότητα 4.3), τα όρια της ενεργού παραγωγής των θερμικών μονάδων (Ανισότητα 4.4), τους περιορισμούς που επιβάλλουν τον ελάχιστο χρόνο για τον οποίο μία μονάδα πρέπει να παραμένει σε λειτουργία μετά την εκκίνησή της (Ανισότητα 4.5) ή εκτός λειτουργίας μετά τη σβέση της (Ανισότητα 4.6), και του περιορισμούς ανάληψης (Ανισότητα 4.7) και απόρριψης φορτίου (Ανισότητα 4.8).

$$\sum_{i=1}^{NTG} ST_i^t \cdot P_i^t = P_d^t, \quad t \in [1, T] \quad (4.2)$$

$$\sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i \geq P_d^t + SRR^t, \quad t \in [1, T] \quad (4.3)$$

$$ST_i^t \cdot Pmin_i \leq P_i^t \leq ST_i^t \cdot Pmax_i \quad (4.4)$$

$$(Ton_i^{t-1} - MUT_i) \cdot (ST_i^{t-1} - ST_i^t) \geq 0,\ i \in [1, NTG],\ t \in [1, T] \tag{4.5}$$

$$(Toff_i^{t-1} - MDT_i) \cdot (ST_i^t - ST_i^{t-1}) \geq 0,\ i \in [1, NTG],\ t \in [1, T] \tag{4.6}$$

$$P_i^t - P_i^{t-1} \leq ST_i^{t-1} \cdot UR_i + (1 - ST_i^{t-1}) \cdot Pmax_i,\ i \in [1, NTG],\ t \in [1, T] \tag{4.7}$$

$$P_i^{t-1} - P_i^t \leq ST_i^t \cdot DR_i + (1 - ST_i^t) \cdot Pmax_i,\ i \in [1, NTG],\ t \in [1, T] \tag{4.8}$$

4.2 Παραλλαγή της Διαφορικής Εξέλιξης που χρησιμοποιήθηκε

Για τη βελτιστοποίηση του προβλήματος ο αλγόριθμος βάσης που επιλέγεται ονομάζεται Feasibility Rules with the incorporation of Objective Function Information (FROFI). Πρόκειται για ένα αλγόριθμο βασιζόμενο στη Διαφορική Εξέλιξη και τους Κανόνες Εφικτότητας. Στο FROFI χρησιμοποιούνται τα σχήματα DE/current-to-rand/1 και DE/rand-to-best/1 με ίση πιθανότητα σε κάθε άτομο του πληθυσμού, καθώς και ο τελεστής διωνυμικής μετάλλαξης. Η επιλογή των ατόμων της επόμενης γενιάς γίνεται με την χρήση των Κανόνων Εφικτότητας. Για να χρησιμοποιηθεί η πληροφορία από την αντικειμενική συνάρτηση, στο σχήμα DE/rand-to-best/1 το $\mathbf{x_{best}}$ είναι το άτομο με την καλύτερη τιμή της αντικειμενικής στον πληθυσμό ανεξάρτητα από το αν είναι εφικτό ή μη εφικτό άτομο. Επίσης, χρησιμοποιείται ένα αρχείο A, στο οποίο αποθηκεύονται τα δοκιμαστικά διανύσματα που δεν επιβιώνουν στον κύριο πληθυσμό αλλά παρουσιάζουν καλύτερη τιμή αντικειμενικής σε σχέση με τα αντίστοιχα διανύσματα στόχους. Μέσω μίας διαδικασίας, αυτά μπορεί να αποτελέσουν μέρος του πληθυσμού. Τέλος χρησιμοποιείται μία στρατηγική μετάλλαξης για να αποφευχθεί η παγίδευση του πληθυσμού σε περιοχές του χώρου αναζήτησης με μη εφικτές λύσεις.

4.3 Η προτεινόμενη μέθοδος

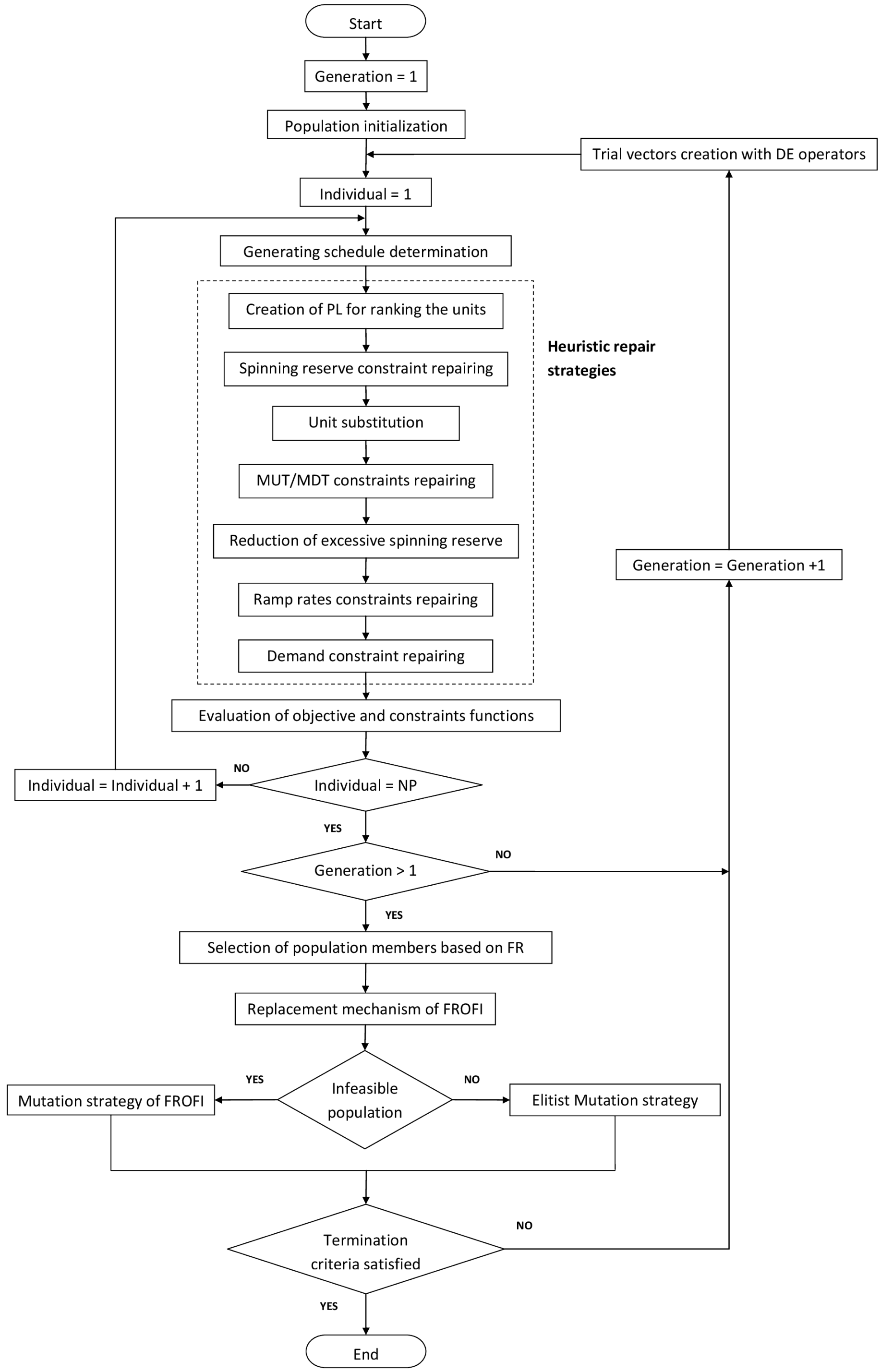
Η προτεινόμενη μέθοδος χρησιμοποιεί τον αλγόριθμο **FROFI**, στον οποίο εντάσσει μία βηματική συνάρτηση για τον προσδιορισμό της κατάστασης λειτουργίας των μονάδων, μία σειρά από μηχανισμούς επιδιόρθωσης των περιορισμών, καθώς και ένα νέο τελεστή μετάλλαξης. Η συνολική διαδικασία παρουσιάζεται στο διάγραμμα ροής του σχήματος 4.1

Κάθε άτομο του πληθυσμού $\mathbf{x_n^g}$ αποτελείται από $NTG \cdot T$ πραγματικούς αριθμούς όπου $x_{n,i}^{g,t} \in [0, Pmax_i]$. Για την εξαγωγή του διανύσματος $\mathbf{ST_n^g}$ με τις καταστάσεις λειτουργίας της κάθε μονάδας χρησιμοποιείται η εξής βηματική συνάρτηση:

$$ST_{n,i}^{g,t} = \begin{cases} 0, \ if \ x_{n,i}^{g,t} < Pmin_i \\ \\ 1, \ otherwise \end{cases} \tag{4.9}$$

Έπειτα υπολογίζεται η φόρτιση κάθε μονάδας με πολλαπλασιασμό σημείο προς σημείο του διανύσματος $\mathbf{ST_n^g}$ με το διάνυσμα $\mathbf{x_n^g}$. Άρα σε περίπτωση που η μονάδα είναι κλειστή η φόρτισή της είναι 0.

Διαχείριση των περιορισμών του προβλήματος Ευρετικοί μηχανισμοί επιδιόρθωσης εντάσσονται στον αλγόριθμο βελτιστοποίησης ώστε να επιδιορθώσουν τα μη εφικτά άτομα του πληθυσμού των λύσεων. Οι μηχανισμοί αυτοί χρησιμοποιούν μια Λίστα Προτεραιότητας των μονάδων παραγωγής, στην οποία οι μονάδες κατατάσσονται από την φθηνότερη στην πιο ακριβή βάσει οικονομικού κριτηρίου. Αυτή η λίστα χρησιμοποιείται για την ένταξη των μονάδων στο σύστημα ξεκινώντας από τη φθηνότερη και καταλήγοντας στην πιο ακριβή μονάδα. Στις μεθόδους της βιβλιογραφίας όταν παρόμοιοι μηχανισμοί επιδιόρθωσης χρησιμοποιούνται συνήθως γίνεται χρήση μίας Λίστα Προτεραιότητας, η οποία δημιουργείται βάσει του μέσου κόστους των μονάδων



Σχήμα 4.1: Ο προτεινόμενος αλγόριθμος

στο $Pmax$ ή $Pmean = (Pmax + Pmin)/2$. Παρόλα αυτά οποιοδήποτε επίπεδο λειτουργίας των μονάδων στο εύρος λειτουργίας τους μπορεί να χρησιμοποιηθεί για να δημιουργηθεί αυτή η Λίστα. Αξίζει να σημειωθεί ότι για διαφορετικά σημεία λειτουργίας, μπορεί να προκύψουν διαφορετικές κατατάξεις των μονάδων. Αντιθέτως η χρήση μίας μόνο Λίστας Προτεραιότητας βασιζόμενη σε ένα μόνο σημείο μπορεί να προκαλέσει την πρόωρη σύγκλιση του αλγορίθμου καθώς συγκεκριμένες μονάδες θα έχουν συνεχώς προτεραιότητα για ένταξη στο σύστημα. Για αυτό το λόγο προτείνεται η χρήση πολλαπλών Λιστών Προτεραιότητας κατά τη διάρκεια τη βελτιστοποίησης. Αυτό γίνεται με τον καθορισμό για κάθε άτομο του πληθυσμού διαφορετικού τυχαία επιλεγμένου σημείου λειτουργίας των μονάδων το οποίο χρησιμοποιείται για να υπολογιστεί το μέσο κόστος βάσει του οποίου δημιουργείται η Λίστα Προτεραιότητας PL_n^g που αντιστοιχεί στο άτομο.

Έπειτα σε κάθε δοκιμαστικό άτομο εφαρμόζονται οι μηχανισμοί επιδιόρθωσης ως εξής:

1. Σε κάθε άτομο, ελέγχεται αν για κάθε ώρα πληρούνται οι περιορισμοί Στρεφόμενης Εφεδρείας. Αν σε κάποια ώρα παραβιάζεται ο περιορισμός, πραγματοποιείται ένταξη των μονάδων, ξεκινώντας από την οικονομικότερη στην PL_n^g, έως ότου η συνολική ισχύ σε λειτουργία ικανοποιεί τον περιορισμό στρεφόμενης εφεδρείας.

2. Μέσω ενός μηχανισμού αντικατάστασης μπορεί να πραγματοποιηθεί αλλαγή μερικών ενδιάμεσων μονάδων σε λειτουργία από ορισμένες μονάδες αιχμής, αν η αντικατάστασή τους δεν οδηγεί σε παραβίαση του περιορισμού στρεφόμενης εφεδρείας.

3. Έπειτα για κάθε μονάδα ελέγχονται οι περιορισμοί ελάχιστου χρόνου λειτουργίας/κράτησης των θερμικών μονάδων. Αν μία μονάδα δεν παραμένει σε λειτουργία για τον απαιτούμενο ελάχιστο χρόνο λειτουργίας τότε η μονάδα εντάσσεται στο σύστημα για ένα αριθμό ωρών έως ότου ικανοποιηθεί ο περιορισμός. Σε περίπτωση που παραβιάζεται ο ελάχιστος χρόνος κράτησης μία μονάδας, τότε η μονάδα εντάσσεται στο σύστημα για εκείνες τις ώρες που αρχικά ήταν εκτός λειτουργίας.

4. Χρησιμοποιείται ένας μηχανισμός ο οποίος σε κάθε ώρα που υπάρχει περίσσεια ποσότητα στρεφόμενης εφεδρείας θέτει εκτός λειτουργίας μονάδες, ξεκινώντας από την ακριβότερη προς τη φθηνότερη βάσει της PL_n^g, έως ότου η περίσσεια στρεφόμενης εφεδρείας μειωθεί στο ελάχιστο. Η ικανοποίηση των περιορισμών ελάχιστου χρόνου λειτουργίας/κράτησης των θερμικών μονάδων ελέγχεται προτού η μονάδα τεθεί εκτός λειτουργίας.

5. Ελέγχεται αν για τις μονάδες που βρίσκονται εντός λειτουργίας παραβιάζονται οι περιορισμοί ανάληψης/απόρριψης φορτίου. Σε περίπτωση παραβίασής τους, η ενεργός παραγωγή των μονάδων τίθεται στα όρια του επιτρεπόμενου εύρους παραγωγής που καθορίζεται βάσει της ενεργού ισχύος της προηγούμενης ώρας και της ικανότητας ανάληψης και απόρριψης φορτίου της μονάδας.

6. Τέλος, επιδιορθώνεται ο περιορισμός του ισοζυγίου ισχύος για τις ώρες που η συνολική παραγόμενη ισχύς διαφέρει από τη ζητούμενη. Ο μηχανισμός εντοπίζει τις ώρες κατά τις οποίες παραβιάζεται ο περιορισμός και μεταβάλλει την ενεργό παραγωγή ορισμένων μονάδων βάσει της PL_n^g, έως ότου ικανοποιηθεί ο περιορισμός. Αξίζει να σημειωθεί ότι κατά την αλλαγή της φόρτισης των μονάδων λαμβάνονται υπόψη οι περιορισμοί ανάληψης/απόρριψης φορτίου.

Σε όλους τους παραπάνω μηχανισμούς όταν μία μονάδα εντάσσεται στο σύστημα η τιμή της αντίστοιχης παραμέτρου $x_{n,i}^{g,t}$ τίθεται ίση με την ελάχιστη επιτρεπόμενη ισχύ της μονάδας.

Ελιτιστικός τελεστής μετάλλαξης Στον αλγόριθμό εντάσσεται Ελιτιστικός τελεστής μετάλλαξης, ο οποίος εφαρμόζεται όταν ο πληθυσμός περιέχει (και) εφικτές λύσεις. Ο συγκεκριμένος τελεστής εφαρμόζεται ως εξής:

- Επιλέγεται το άτομο του πληθυσμού με την καλύτερη τιμή της αντικειμενικής συνάρτησης, $\mathbf{x_{best}^g}$.

- Με ίση πιθανότητα επιλέγεται τυχαία μία ή δύο παραμέτροι του $\mathbf{x}^{\mathbf{g}}_{\mathbf{best}}$ και επαναρχικοποιούνται εντός του πεδίου ορισμού τους, δημιουργώντας το $\mathbf{x}_m$. Το $\mathbf{x}_m$ επιδιορθώνεται βάσει των μηχανισμών επιδιόρθωσης.

- Αν το $\mathbf{x}_m$ έχει καλύτερη τιμή αντικειμενικής από το άτομο του πληθυσμού με την χειρότερη τιμή αντικειμενικής τότε το αντικαθιστά στον πληθυσμό.

Ο μηχανισμός αυτός κατά τα αρχικά στάδια της διαδικασίας μπορεί να βοηθήσει τον πληθυσμό να κατευθυνθεί προς υποσχόμενες περιοχές του χώρου αναζήτησης. Καθώς ο πληθυσμός έχει αρχίσει να συγκλίνει μπορεί επίσης να βοηθήσει στην αποφυγή της παγίδευσης του πληθυσμού σε περιοχές τοπικών ελαχίστων.

4.4 Αποτελέσματα της μεθόδου

Η απόδοση της προτεινόμενης μεθόδου που ονομάζεται modified FROFI with Plurality of Priority Lists (mFROFI-PPL), εξετάστηκε με την πραγματοποίηση τριών σειρών υπολογιστικών πειραμάτων.

Στο πρώτο υπολογιστικό πείραμα, εξετάζεται η επίδραση που έχει η χρήση πολλαπλών Λιστών Προτεραιότητας στην απόδοση του αλγορίθμου. Η μελέτη γίνεται σε συστήματα που αποτελούνται από 10, 20, 40, 60, 80 και 100 μονάδες [14]. Τα αποτελέσματα της μεθόδου mFROFI-PPL, συγκρίνονται με τις δύο εξής παραλλαγές της:

- Στην πρώτη χρησιμοποιείται ο $mFROFI$ μαζί με τη Λίστα Προτεραιότητας βάσει του μέσου κόστους των μονάδων στο $Pmax$.

- Στην δεύτερη χρησιμοποιείται στον $mFROFI$ η Λίστα Προτεραιότητας βάσει του μέσου κόστους στο $Pmean = (Pmax + Pmin)/2$.

Η ανάλυση των αποτελεσμάτων αναδεικνύει τα εξής:

- Το σημείο λειτουργίας των μονάδων που επιλέγεται για τη κατασκευή της Λίστας Προτεραιότητας επιδρά σημαντικά στα τελικά αποτελέσματα της μεθόδου. Για διαφορετικά σημεία, αλλάζει τόσο η βέλτιστη λύση που βρίσκεται από τον αλγόριθμο όσο και η διασπορά της κατανομής των λύσεων.

- Η χρήση πολλαπλών Λιστών Προτεραιότητας, βελτιώνει σημαντικά τόσο τις καλύτερες λύσεις που βρίσκει ο αλγόριθμος όσο και τη διασπορά τους ειδικά για τα συστήματα μεγαλύτερου αριθμού μονάδων.

Στο δεύτερο υπολογιστικό πείραμα πραγματοποιείται εξέταση της επίδρασης του Ελιτιστικού Τελεστή Μετάλλαξης στα αποτελέσματα της μεθόδου. Για την ακρίβεια τα αποτελέσματα του **mFROFI-PPL** συγκρίνονται με εκείνα στα οποία ο αλγόριθμος δεν περιλαμβάνει τον Ελιτιστικό Τελεστή Μετάλλαξης. Η μελέτη της απόδοσης του αλγορίθμου πραγματοποιήθηκε στα συστήματα που εξετάστηκαν στο πρώτο υπολογιστικό πείραμα. Η ανάλυση των αποτελεσμάτων αναδεικνύει τα εξής:

- Η χρήση του Ελιτιστικού Τελεστή Μετάλλαξης βελτιώνει τις καλύτερες λύσεις που επιτυγχάνονται από τον αλγόριθμο σε όλα τα εξεταζόμενα συστήματα.

- Όσον αφορά τη διασπορά των λύσεων για τα συστήματα των 40, 60, 80 και 100 μονάδων, είναι μεγαλύτερη όταν χρησιμοποιείται ο Ελιτιστικός Τελεστής Μετάλλαξης. Παρόλα αυτά στην περίπτωση που ο τελευταίος δεν χρησιμοποιείται, ο αλγόριθμος φαίνεται να συγκλίνει πρόωρα σε τοπικά ακρότατα με αποτέλεσμα οι λύσεις που παρέχονται να εμφανίζουν μικρή διασπορά.

- Εξετάζοντας τη μέση σύγκλιση του αλγορίθμου για τα εξεταζόμενα συστήματα, αναδεικνύεται ότι η χρήση του Τελεστή Μετάλλαξης επιταχύνει την εύρεση λύσεων χαμηλότερου κόστους ενώ παράλληλα βοηθάει τον πληθυσμό λύσεων να αποφύγει την παγίδευση σε τοπικά βέλτιστα.

Στην τρίτη σειρά υπολογιστικών πειραμάτων ο mFROFI-PPL εφαρμόζεται σε μία πληθώρα συστημάτων της βιβλιογραφίας και η απόδοσή του συγκρίνεται με εκείνη σύγχρονων μεθόδων που εφαρμόστηκαν στα ίδια συστήματα. Οι μέθοδοι αυτές είναι αιτιοκρατικές, στοχαστικές ή υβριδικές. Στις τελευταίες συνδυάζονται αλγόριθμοι από τις κατηγορίες των αιτιοκρατικών και στοχαστικών μεθόδων. Η ανάλυση των αποτελεσμάτων δίνει τα εξής:

Όσον αφορά το σύστημα των 10 έως 100 μονάδων χωρίς του περιορισμούς ανάληψης/απόρριψης φορτίου:

- Σε σχέση με τους προηγούμενους αλγορίθμους της βιβλιογραφίας που βασίζονται στον αλγόριθμο της Διαφορικής Εξέλιξης η προτεινόμενη μέθοδο κατάφερε να παράγει λύσεις χαμηλότερου κόστους στα συστήματα των 10, 20, 40, 60, 80 και 100 μονάδων. Επίσης σε όλα τα συστήματα η μέση και η μέγιστη τιμή κόστους της κατανομής των λύσεων που παράγονται από τον αλγόριθμο είναι καλύτερη από εκείνη των προηγούμενων αλγορίθμων.

- Στο σύστημα των 10 μονάδων η προτεινόμενη μέθοδος επιτυγχάνει την καλύτερη λύση. Παράλληλα παράγει κατανομή λύσεων με καλύτερο μέσο και μεγαλύτερο κόστος σε σχέση με όλες τις υπόλοιπες μεθόδους.

- Στα συστήματα 20, 40, 80 και 100 μονάδων παράγει κατανομές λύσεων με χαμηλότερο μέσο και μεγαλύτερο κόστος, παρουσιάζοντας συστηματικά πολύ ανταγωνιστική απόδοση.

- Σχεδόν σε όλα τα εξεταζόμενα συστήματα ο προτεινόμενος αλγόριθμος παρήγαγε καλύτερες λύσεις σε σχέση με προηγούμενους αλγορίθμους που βασίζονται σε στοχαστικές μεθόδους αλλά και σε σχέση με υβριδικούς αλγορίθμους που παράγονται από συνδυασμό στοχαστικών μεθόδων.

- Ο υπολογιστικός χρόνος που απαιτείται για την εκτέλεση του αλγορίθμου σε σχέση με τις προηγούμενες μεθόδους που χρησιμοποιήθηκε η Διαφορική Εξέλιξη είναι χαμηλότερος

Οπότε όσον αφορά το σύστημα 10-100 μονάδων η απόδοση του αλγορίθμου κρίνεται ιδιαιτέρως ικανοποιητική.

Όσον αφορά το σύστημα των 10-100 μονάδων λαμβάνοντας υπόψη τους περιορισμούς ανάληψης/απόρριψης φορτίου η ανάλυση των αποτελεσμάτων δείχνει τα εξής:

- Ο αλγόριθμος για τα συστήματα 10, 20 και 40 μονάδων επιτυγχάνει να παράγει λύσεις χαμηλότερου κόστους σε σχέση με τις αντίστοιχες των μεθόδων της βιβλιογραφίας. Παράλληλα στα ίδια συστήματα το μέσο και το μέγιστο κόστος της κατανομής των λύσεων που παράγονται από τον **mFROFI-PPL** είναι επίσης καλύτερα, επιδεικνύοντας συστηματικότητα όσον αφορά την ποιότητα των λύσεων που επιτυγχάνει.

- Στα συστήματα των 60, 80 και 100 μονάδων ο προτεινόμενος αλγόρθμος κατατάσσεται δεύτερος βάσει της καλύτερης λύσης που παρέχει.

- Σε σχέση με τους προηγούμενους στοχαστικούς και υβριδικούς αλγορίθμους που εφαρμόστηκαν στα εξεταζόμενα συστήματα ο προτεινόμενος αλγόριθμος παράγει καλύτερες λύσεις για τα συστήματα με 10, 20, 40, 80 και 100 μονάδες.

Οπότε όσον αφορά το σύστημα 10-100 μονάδων με τους περιορισμούς ανάληψης και απόρριψης φορτίου ο αλγόριθμος λειτούργησε ανταγωνιστικά.

Η απόδοση του αλγορίθμου εξετάστηκε και στο σύστημα 26 μονάδων της IEEE [15]. Στο συγκεκριμένο σύστημα ο αλγόριθμος κατάφερε να επιτύχει καλύτερη λύση σε σχέση με τους προηγούμενους αλγορίθμους της βιβλιογραφίας κατά 0.21% (1291\$). Επίσης, παρείχε κατανομές λύσεων με χαμηλότερο μέσο κόστος. Παράλληλα ο χρόνος εκτέλεσης του αλγορίθμου είναι πολύ ανταγωνιστικός σε σχέση με τις μεθόδους της βιβλιογραφίας.

Τέλος η απόδοση του αλγορίθμου εξετάστηκε και σε σύστημα 38 μονάδων (**Tai Power System**) [16]. Και σε αυτό το σύστημα ο αλγόριθμος κατάφερε να επιτύχει καλύτερη λύση σε σχέση με τους προηγούμενους αλγορίθμους της βιβλιογραφίας κατά 0.76% ($1.49M\$$). Επίσης, παρείχε κατανομές λύσεων με χαμηλότερο μέσο κόστος και μεγαλύτερο κόστος σε ανταγωνιστικό χρόνος εκτέλεσης σε σχέση με τις μεθόδους της βιβλιογραφίας.

ΚΕΦΑΛΑΙΟ 5
ΒΕΛΤΙΣΤΟΠΟΙΗΣΗ ΠΡΟΓΡΑΜΜΑΤΙΣΜΟΥ ΠΑΡΑΓΩΓΗΣ ΜΕ ΠΕΡΙΟΡΙΣΜΟΥΣ ΑΞΙΟΠΙΣΤΙΑΣ

Στο συγκεκριμένο κεφάλαιο η μέθοδος που περιγράφηκε στο προηγούμενο κεφάλαιο επεκτείνεται για να επιλύσει μία μορφή του προβλήματος βραχυπρόθεσμου προγραμματισμού κατά την οποία λαμβάνεται υπόψη η αξιοπιστία του συστήματος. Σύμφωνα με ένα κοινά αποδεκτό ορισμό, ως αξιοπιστία ορίζεται η πιθανότητα μία συσκευή ή ένα σύστημα να επιτελέσει επαρκώς την αποστολή του για τη σχεδιαζόμενη χρονική περίοδο και τις επικρατούσες συνθήκες [17]. Ο ορισμός αυτός μπορεί να χρησιμοποιηθεί και στα συστήματα παραγωγής ηλεκτρικής ενέργειας.

Στο συγκεκριμένο κεφάλαιο λαμβάνεται υπόψη η αξιοπιστία των μονάδων παραγωγής καθώς και η αβεβαιότητα στην πρόβλεψη του φορτίου στο μοντέλο βραχυπρόθεσμου προγραμματισμού, με τον υπολογισμό των εξής δεικτών αξιοπιστίας:

1. Της πιθανότητας απώλειας φορτίου (Loss of Load Probability - LOLP), η οποία εκφράζει την πιθανότητα (%) το σύστημα να μην μπορέσει να εξυπηρετήσει το ζητούμενο φορτίο την εξεταζόμενη χρονική περίοδο.

2. Της αναμενόμενης μη εξυπηρετούμενης ενέργειας (Expected Energy Not Served - EENS), η οποία εκφράζει το αναμενόμενο ποσό ενέργειας (MWh) που δεν θα εξυπηρετηθεί από το σύστημα λόγω της απώλειας φορτίου.

Για κάθε ένα από τους παραπάνω δείκτες τίθεται ένα άνω όριο ανάλογα με το επιθυμητό επίπεδο αξιοπιστίας του συστήματος, και αυτοί οι περιορισμοί εντάσσονται στο μοντέλο του προβλήματος.

Στον κλασική μορφή του προβλήματος βέλτιστου βραχυπρόθεσμου προγραμματισμού, οι απαιτήσεις του συστήματος για στρεφόμενη εφεδρεία καθορίζονται βάσει εμπειρικών κριτηρίων, παραδείγματος χάριν τίθενται ίσες με την μέγιστη ισχύ της μεγαλύτερης μονάδας του συστήματος. Τέτοια κριτήρια όμως δεν λαμβάνουν υπόψη την αξιοπιστία των μονάδων παραγωγής ούτε αβεβαιότητες στην πρόβλεψη του φορτίου. Αντίθετα, με την εισαγωγή των δεικτών αξιοπιστίας στο μοντέλο του προβλήματος βραχυπρόθεσμου προγραμματισμού, οι απαιτήσεις του συστήματος για στρεφόμενη εφεδρεία μπορούν να υπολογιστούν μέσω της διαδικασίας βελτιστοποίησης, λαμβάνοντας υπόψη την αξιοπιστία των μονάδων παραγωγής καθώς και τις αβεβαιότητες στην πρόβλεψη του φορτίου.

Στο κεφάλαιο αυτό η μέθοδος του προηγούμενου κεφαλαίου επεκτείνεται για να επιλύσει το πρόβλημα βραχυπρόθεσμου προγραμματισμού όταν σε αυτό περιλαμβάνονται οι περιορισμοί αξιοπιστίας. Πιο συγκεκριμένα δύο νέοι μηχανισμοί επιδιόρθωσης των προαναφερθέντων περιορισμών προτείνονται και ενσωματώνονται στη μέθοδο του προηγούμενου κεφαλαίου. Επίσης, μηχανισμοί που εξετάστηκαν και στο προηγούμενο κεφάλαιο, προσαρμόζονται για να λάβουν υπόψη τους περιορισμούς αξιοπιστίας του συστήματος.

5.1 Μαθηματική διατύπωση του προβλήματος

Η μαθηματική διατύπωση του προβλήματος είναι παρεμφερής με εκείνη του κλασικού μοντέλου βραχυπρόθεσμου προγραμματισμού που παρουσιάστηκε στο προηγούμενο κεφάλαιο με τη μόνη διαφορά να είναι η αντικατάσταση των περιορισμών στρεφόμενης εφεδρείας από τους περιορισμούς αξιοπιστίας του συστήματος. Άρα η αντικειμενική συνάρτηση περιλαμβάνει την ελαχιστοποίηση του συνολικού κόστους λειτουργίας του συστήματος (Εξίσωση 4.1). Η ελαχιστοποίηση υπόκειται στους περιορισμούς της ωριαίας ζήτησης του συστήματος (Εξίσωση 4.2, ελαχίστου χρόνου λειτουργία/κράτησης μίας μονάδας (Ανισότητες 4.5 και 4.6), ανάληψης/απόρριψης φορτίου (Ανισότητα 4.7 και 4.8) και των ορίων της ενεργού παραγωγής των θερμικών μονάδων (Ανισότητα 4.4). Οι περιορισμοί αξιοπιστίας του συστήματος ορίζονται ως εξής:

$$LOLP^t \leq LOLP^{max}, \quad t \in [1, T] \tag{5.1}$$

$$EENS_{tot} \leq EENS^{max} \tag{5.2}$$

όπου τα μέγιστα επιτρεπόμενα όρια των τιμών των δεικτών αξιοπιστίας καθορίζονται από το διαχειριστή του συστήματος ανάλογα με το επιθυμητό επίπεδο αξιοπιστίας. Μετά το τέλος της βελτιστοποίησης, το ποσό στρεφόμενης εφεδρείας του συστήματος υπολογίζεται ως εξής:

$$SR^t = \sum_{i=1}^{NTG} ST_i^t \cdot Pmax_i - P_d^t, \quad t \in [1, T] \tag{5.3}$$

5.2 Υπολογισμός των δεικτών αξιοπιστίας

Για τον υπολογισμό των δεικτών αξιοπιστίας του συστήματος απαιτείται η κατασκευή του πίνακα πιθανότητας απώλειας φορτίου (Capacity Outage Probability Table - COPT) για κάθε ώρα της εξεταζόμενης περιόδου βάσει των μονάδων που είναι προγραμματισμένες να λειτουργήσουν. Κάθε γραμμή του COPT περιλαμβάνει ένα διαφορετικό επίπεδο απώλειας ισχύος, την ισχύ που παραμένει σε λειτουργία, καθώς και την πιθανότητα εμφάνισης του. Τα βήματα για τον υπολογισμό των τιμών των δεικτών αξιοπιστίας είναι τα εξής:

- Υπολογίζεται η πιθανότητας βλάβης μίας θερμικής μονάδας σε μια χρονική περίοδο στο μέλλον, που ονομάζεται και μη διαθεσιμότητα της μονάδας (Outage Replacement Rate - ORR). Για τον υπολογισμό αυτού του μεγέθους θεωρείται ότι κάθε θερμική μονάδα μπορεί να περιγραφεί από ένα μοντέλο δύο καταστάσεων σύμφωνα με το οποίο η μονάδα είτε είναι διαθέσιμη για παραγωγή είτε βρίσκεται σε βλάβη.

- Δημιουργείται ο COPT. Για τη δημιουργία του χρησιμοποιείται ο επαναληπτικός αλγόριθμος που περιγράφεται στη βιβλιογραφική παραπομπή [17].

- Έπειτα υπολογίζονται οι τιμές των δεικτών **LOLP** και **EENS**, μέσω της συνέλιξης (convolution) του **COPT** και της καμπύλης φορτίου του συστήματος.

Ακολουθώντας τη συνήθη πρακτική, η αβεβαιότητα της πρόβλεψης φορτίου σε κάθε ώρα, μοντελοποιείται με χρήση της κανονικής κατανομής με μέση τιμή την αναμενόμενη τιμή του φορτίου κάθε ώρας, και τυπική απόκλιση ίση με ένα ποσοστό της αναμενόμενης τιμής του φορτίου. Η κατανομή αυτή χωρίζεται σε επτά διακριτά διαστήματα $(0, \pm\sigma, \pm 2\cdot\sigma, \pm 3\sigma)$. Κάθε διάστημα αντιστοιχεί στην πιθανότητα το φορτίο να είναι ίσο με την ενδιάμεση τιμή του διαστήματος. Έτσι για κάθε διάστημα υπολογίζονται ξεχωριστά οι τιμές των δεικτών αξιοπιστίας με χρήση της αντίστοιχης τιμής του φορτίου. Οι τελικές τιμές των δεικτών αξιοπιστίας υπολογίζονται ως το σταθμισμένο άθροισμα των τιμών των δεικτών για κάθε διάστημα επί την πιθανότητα του αντίστοιχου διαστήματος.

5.3 Η προτεινόμενη μέθοδος

Η προτεινόμενη μέθοδος βασίζεται στον αλγόριθμο **FROFI**, τη βηματική συνάρτηση για τον καθορισμό των καταστάσεων λειτουργίας, τη μέθοδο δημιουργίας πληθώρας Λιστών Προτεραιότητας και τον Ελιτιστικό Τελεστή Μετάλλαξης. Για τη διαχείριση των περιορισμών του προβλήματος χρησιμοποιούνται μηχανισμοί επιδιόρθωσης κατάλληλα διαμορφωμένοι ώστε να επιδιορθώνουν τυχόν παραβιάσεις των περιορισμών αξιοπιστίας.

Σε κάθε δοκιμαστικό άτομο εφαρμόζονται οι μηχανισμοί επιδιόρθωσης ως εξής:

1. Ελέγχεται αν για κάθε ώρα η ισχύ σε λειτουργία επαρκεί για να καλύψει τη ζήτηση. Αν σε κάποια ώρα αυτό δεν ισχύει πραγματοποιείται ένταξη των μονάδων, ξεκινώντας από την οικονομικότερη στην PL_n^g, έως ότου η συνολική ισχύ σε λειτουργία επαρκεί για να ικανοποιήσει τη ζήτηση.

2. Έπειτα για κάθε μονάδα ελέγχονται οι περιορισμοί ελάχιστου χρόνου λειτουργίας/κράτησης των θερμικών μονάδων και επιδιορθώνονται βάσει του μηχανισμού που περιγράφηκε στο

προηγούμενο κεφάλαιο.

3. Υπολογίζονται οι τιμές των δεικτών αξιοπιστίας. Σε περίπτωση που υπάρχει περίσσεια ποσότητα στρεφόμενης εφεδρείας σε κάποια ώρα, τότε εφαρμόζεται μηχανισμός που θέτει μονάδες εκτός λειτουργίας, ξεκινώντας από την ακριβότερη προς τη φθηνότερη βάσει της PL_n^g, έως ότου η περίσσεια στρεφόμενη εφεδρεία μειωθεί στο ελάχιστο. Η ικανοποίηση των περιορισμών αξιοπιστίας καθώς και ελάχιστου χρόνου λειτουργίας/κράτησης των θερμικών μονάδων ελέγχονται προτού η μονάδα τεθεί εκτός λειτουργίας.

4. Ελέγχεται αν για τις μονάδες που βρίσκονται εντός λειτουργίας παραβιάζονται οι περιορισμοί ανάληψης/απόριψης φορτίου. Σε περίπτωση παραβίασής τους η ενεργός παραγωγή των μονάδων τίθεται στα όρια του επιτρεπόμενου εύρους παραγωγής που καθορίζεται βάσει της ενεργού ισχύος της προηγούμενης ώρας και της ικανότητας ανάληψης και απόρριψης φορτίου της μονάδας.

5. Εφαρμόζεται μηχανισμός για την επιδιόρθωση της παραβίασης του περιορισμού του δείκτη EENS. Πιο συγκεκριμένα, ο αλγόριθμος εντοπίζει την ώρα με τη μεγαλύτερη ωριαία τιμή του δείκτη EENS και θέτει σε λειτουργία την κλειστή μονάδα με την υψηλότερη θέση στην PL_n^g, επιδιορθώνοντας τυχόν παραβιάσεις των περιορισμών ελαχίστου χρόνου λειτουργίας και κράτησης. Η διαδικασία επαναλαμβάνεται μέχρις ότου επιδιορθωθεί ο περιορισμός.

6. Εφαρμόζεται μηχανισμός για την επιδιόρθωση της παραβίασης των περιορισμών του δείκτη LOLP. Πιο συγκεκριμένα, ο αλγόριθμος εντοπίζει τις ώρες στις οποίες υπάρχει παραβίαση του περιορισμού και θέτει σε λειτουργία κλειστές μονάδες, ξεκινώντας από εκείνη με την υψηλότερη θέση στην PL_n^g, επιδιορθώνοντας τυχόν παραβίαση των περιορισμών ελαχίστου χρόνου λειτουργίας και κράτησης έως ότου επιδιορθωθεί ο περιορισμός.

7. Τέλος, επιδιορθώνεται ο περιορισμός του ισοζυγίου ισχύος βάσει του μηχανισμού που περιγράφηκε στο προηγούμενο κεφάλαιο.

5.4 Αποτελέσματα της μεθόδου

Μία σειρά από υπολογιστικά πειράματα πραγματοποιούνται για να διαπιστωθεί η αποτελεσματικότητα της προτεινόμενης μεθόδου. Σε κάθε ένα από αυτά, οι δύο παρακάτω συνδυασμοί ανώτατων ορίων των δεικτών εξετάζονται για να εκτιμηθεί η επίδραση αυτών των τιμών στο αποτελέσματα της μεθόδου.

- Συνδυασμός 1: $EENS^{max} = 0.01\%$ της συνολικής αναμενόμενης ζήτησης και $LOLP^{max} = 1\%$.
- Συνδυασμός 2: $EENS^{max} = 0.05\%$ της συνολικής αναμενόμενης ζήτησης $LOLP^{max} = 1.5\%$.

Στην πρώτη μελέτη περίπτωσης εξετάζεται η επίδραση της τιμής της μη διαθεσιμότητας των μονάδων στα αποτελέσματα της μεθόδου. Πιο συγκεκριμένα, αυξάνοντας την τιμή του OPP μελετάται η επίδρασή του στα αποτελέσματα της μεθόδου. Το σύστημα που μελετάται είναι το **IEEE-RTS** με 26 μονάδες [18]. Η ανάλυση των αποτελεσμάτων δείχνει τα εξής:

- Στην συγκεκριμένη περίπτωση η χρήση της πληθώρας Λιστών Προτεραιότητας δεν δημιουργεί διαφορά στα αποτελέσματα της μεθόδου. Μετά από ανάλυση των χαρακτηριστικών των μονάδων του συστήματος διαπιστώθηκε ότι η πιθανότητα να δημιουργηθεί διαφορετική Λίστα Προτεραιότητας, από εκείνη που δημιουργείται με βάσει το μέγιστο σημείο λειτουργίας, είναι πολύ μικρή (0.6%) και αυτό έχει ως αποτέλεσμα πρακτικά στη μεγάλη πλειοψηφία των ατόμων να ανατίθεται μία λίστα προτεραιότητας.
- Ο Ελιτιστικός Τελεστής Μετάλλαξης επίσης δεν επιφέρει σημαντική διαφορά στα αποτελέσματα. Η χρήση των μηχανισμών επιδιόρθωσης καταλήγει πάντα σε εφικτά άτομα και κατευθύνει γρήγορα τον πληθυσμό προς αποτελεσματικές λύσεις. Αυτό έχει ως αποτέλεσμα η επίδραση του Ελιτιστικού Τελεστή Μετάλλαξης να μην είναι τόσο έντονη.

- Η προτεινόμενη μέθοδος παράγει καλύτερες λύσεις σε σχέση με τη μέθοδο της βιβλιογραφίας που αντιμετώπισε το ίδιο πρόβλημα. Αυτό γίνεται για όλες σχεδόν τις εξεταζόμενες περιπτώσεις.

- Τα αποτελέσματα επιβεβαιώνουν ότι όσο αυξάνεται η τιμή της μη διαθεσιμότητας των μονάδων τόσο αυξάνεται το κόστος λειτουργίας του συστήματος. Αυτό συμβαίνει γιατί η αύξηση της μη διαθεσιμότητας των μονάδων απαιτεί μεγαλύτερο ποσό στρεφόμενης εφεδρείας ανά ώρα για να επιτευχθεί το επιθυμητό επίπεδο αξιοπιστίας του συστήματος. Αυτό έχει ως αποτέλεσμα περισσότερες μονάδες να μην λειτουργούν αποτελεσματικά και άρα να αυξάνεται το κόστος του συστήματος.

- Μετά από εξέταση των καλύτερων λύσεων του αλγορίθμου διαπιστώθηκε ότι πληρούν τους περιορισμούς αξιοπιστίας. Αυτό υποδεικνύει τη σωστή λειτουργία των μηχανισμών επιδιόρθωσης.

Στην δεύτερη μελέτη περίπτωσης εκτιμάται η επίδραση της αβεβαιότητας στην πρόβλεψη του φορτίου στα αποτελέσματα της μεθόδου. Αξίζει να σημειωθεί ότι μιας και η χρήση πληθώρας Λιστών Προτεραιότητας και του Ελιτιστικού Τελεστή Μετάλλαξης δεν προκάλεσαν σημαντικές διαφορές στη απόδοση του αλγορίθμου στην προηγούμενη σειρά πειραμάτων, δεν χρησιμοποιούνται στον εξεταζόμενο αλγόριθμο στα υπόλοιπα υπολογιστικά πειράματα. Στη συγκεκριμένη μελέτη περίπτωσης, μεταβάλλοντας την τιμή της τυπικής απόκλισης της κανονικής κατανομής που χρησιμοποιείται για να εκφράσει την αβεβαιότητα της πρόβλεψης φορτίου μελετάται η επίδρασή του στα αποτελέσματα της μεθόδου. Το σύστημα που εξετάζεται είναι το IEEE-RTS με 26 μονάδες [18]. Η ανάλυση των αποτελεσμάτων αναδεικνύει τα εξής:

- Η προτεινόμενη μέθοδο παρέχει λύσεις χαμηλότερου κόστους πιο συστηματικά στη πλειοψηφία των εξεταζόμενων περιπτώσεων σε σχέση με τη μέθοδο της βιβλιογραφίας που επιλύει το ίδιο πρόβλημα.

- Επιβεβαιώνεται από τα αποτελέσματα της μεθόδου στους δύο εξεταζόμενους συνδυασμούς, ότι μία αύξηση της τιμής της αβεβαιότητας του φορτίου προκαλεί αύξηση του κόστους λειτουργίας του συστήματος. Αυτό συμβαίνει γιατί καθώς αυξάνεται η τιμή της αβεβαιότητας του φορτίου απαιτείται μεγαλύτερη στρεφόμενη εφεδρεία για να παρέχει το επιθυμητό επίπεδο αξιοπιστίας.

- Εξετάζοντας τα συστήματα παραγωγής επιβεβαιώθηκε ότι καθώς αυξάνεται η τιμή της αβεβαιότητας του φορτίου, πιο ακριβές μονάδες τίθενται σε λειτουργία ώστε να εξασφαλιστεί η απαιτούμενη ποσότητα εφεδρείας, με αποτέλεσμα να αυξάνεται το κόστος λειτουργίας τους συστήματος.

- Οι μηχανισμοί που προτάθηκαν για την επιδιόρθωση των περιορισμών αξιοπιστίας λειτούργησαν και σε αυτή την περίπτωση καθώς μετά από μελέτη των προγραμμάτων καλύτερου κόστους σε κάθε εξεταζόμενη περίπτωση φαίνεται ότι πληρούν τους περιορισμούς αξιοπιστίας.

Στην τρίτη μελέτη περίπτωσης η προτεινόμενη μέθοδος εφαρμόζεται σε συστήματα μεγαλύτερου αριθμού μονάδων. Για την ακρίβεια το σύστημα 26 μονάδων αντιγράφεται 2 και 3 φορές, για να δημιουργηθούν συστήματα 52 και 78 μονάδων αντίστοιχα. Η ανάλυση των αποτελεσμάτων αναδεικνύει ότι η μέθοδος μπορεί αποδοτικά να εφαρμοστεί και σε συστήματα μεγαλύτερου αριθμού μονάδων.

ΚΕΦΑΛΑΙΟ 6

ΒΕΛΤΙΣΤΟΠΟΙΗΣΗ ΠΡΟΓΡΑΜΜΑΤΙΣΜΟΥ ΠΑΡΑΓΩΓΗΣ ΜΕ ΟΙΚΟΝΟΜΙΚΑ ΚΑΙ ΠΕΡΙΒΑΛΛΟΝΤΙΚΑ ΚΡΙΤΗΡΙΑ ΣΕ ΥΔΡΟΘΕΡΜΙΚΑ ΣΥΣΤΗΜΑΤΑ ΜΕ ΕΝΕΡΓΕΙΑ ΑΠΟ ΑΙΟΛΙΚΑ ΠΑΡΚΑ

Τα τελευταία χρόνια η αιολική ενέργεια αποτελεί σημαντικό μέρος των συστημάτων παραγωγής ηλεκτρικής ενέργειας, σε μια προσπάθεια να αντικατασταθούν οι τεχνολογίες παραγωγής που χρησιμοποιούν ορυκτά καύσιμα. Η μη προβλεψιμότητα όμως της αιολικής ενέργειας, μπορεί να επηρεάσει το βραχυπρόθεσμο προγραμματισμό των μονάδων του συστήματος. Οι διαχειριστές των συστημάτων ενέργειας προσπαθούν να αντιμετωπίσουν την αβεβαιότητα στην αιολική ενέργεια με τον καθορισμό κατάλληλης στρεφόμενης εφεδρείας του συστήματος. Συνήθως θέτουν την ποσότητα της απαραίτητης στρεφόμενης εφεδρείας με βάση ορισμένα εμπειρικά κριτήρια, τα οποία όμως δεν μπορούν να λάβουν υπόψη την αβεβαιότητα της αιολικής ενέργειας. Αυτό μπορεί να οδηγήσει είτε σε υποεκτίμηση είτε σε υπερεκτίμηση της στρεφόμενης εφεδρείας, που μπορεί να προκαλέσει αύξηση του κόστους παραγωγής και των εκπεμπόμενων ρύπων του συστήματος ή ακόμα να προκαλέσει αποκοπή φορτίου (load shedding), ή περικοπή μέρους της παραγόμενης ενέργειας (energy curtailment). Στο κεφάλαιο αυτό προτείνεται μία μέθοδο, η οποία μπορεί να συμβάλλει στην εκτίμηση της στρεφόμενης εφεδρείας σε συστήματα παραγωγής όπου υπάρχει αιολική ενέργεια, λαμβάνοντας υπόψη την αβεβαιότητα της παραγόμενης ενέργειας από τα αιολικά πάρκα όσο και την αξιοπιστία το συστήματος παραγωγής. Ως συνέπεια ένα τέτοιο μοντέλο μπορεί να συμβάλλει στην καλύτερη εκτίμηση των ποσοτήτων στρεφόμενης εφεδρείας για την ασφαλή λειτουργία του συστήματος.

Στο συγκεκριμένο κεφάλαιο αναπτύσσεται μία μέθοδος βασιζόμενη στον αλγόριθμο της Διαφορικής Εξέλιξης για τη βελτιστοποίηση του προβλήματος βραχυπρόθεσμου προγραμματισμού με κριτήρια την ελαχιστοποίηση του κόστους λειτουργίας καθώς και των παραγόμενων ρύπων από τις μονάδες. Στο σύστημα παραγωγής περιλαμβάνονται υδροηλεκτρικοί σταθμοί καθώς και ενέργεια από αιολικά πάρκα. Στο μοντέλο λαμβάνεται υπόψη η αξιοπιστία του συστήματος και πιο συγκεκριμένα η μη διαθεσιμότητα των μονάδων καθώς και αβεβαιότητες στην πρόβλεψη του φορτίου και της παραγόμενης ισχύος από τον άνεμο, ώστε να εκτιμηθεί η ποσότητα στρεφόμενης εφεδρείας του συστήματος. Το προτεινόμενο μοντέλο επιτρέπει την αξιολόγηση της επίδρασης των προαναφερθέντων αβεβαιοτήτων στο κόστος και τους εκπεμπόμενους ρύπους του συστήματος. Για τη βελτιστοποίηση του μοντέλου, αναπτύσσεται υβριδικός αλγόριθμος, που συνδυάζει τη Διαφόρικη Εξέλιξη μαζί με μία τεχνική τοπικής βελτιστοποίησης.

6.1 Μαθηματική διατύπωση του προβλήματος

Στο μοντέλο λαμβάνονται υπόψη θερμικές μονάδες, υδροηλεκτρικοί σταθμοί παραγωγής καθώς και ενέργεια παραγόμενη από αιολικά πάρκα. Οι δύο αντικειμενικές συναρτήσης του προβλήματος αφορούν την ελαχιστοποίηση του συνολικού κόστους λειτουργίας του συστήματος (Εξίσωση 6.1) καθώς και την ελαχιστοποίηση των συνολικών εκπομπών ρύπων από την ηλεκτροπαραγωγή (Εξίσωση 6.2):

$$f_1 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} [FC_i(P_i^t) \cdot ST_i^t + SUC_i \cdot ST_i^t \cdot (1 - ST_i^{t-1}) + SDC_i \cdot (1 - ST_i^t) \cdot ST_i^{t-1}] \quad (6.1)$$

$$f_2 = \sum_{t=1}^{T} \sum_{i=1}^{NTG} ST_i^t \cdot PE_i(P_i^t) \quad (6.2)$$

Αξίζει να σημειωθεί ότι οι υδροηλεκτρικοί σταθμοί παρουσιάζουν αμελητέο λειτουργικό κόστος και ρύπους επειδή η λειτουργία τους δε στηρίζεται σε ορυκτά καύσιμα. Για αυτό και οι αντικειμενικές συναρτήσεις του προβλήματος αναφέρονται στο λειτουργικό κόστος και τους εκπεμπόμενους ρύπους των θερμικών μονάδων παραγωγής.

Η ελαχιστοποίηση υπόκειται σε περιορισμούς που διαχωρίζονται σε τρεις κατηγορίες. Η πρώτη περιλαμβάνει τους περιορισμούς των θερμικών μονάδων, που αφορούν τον ελαχίστο χρόνο λειτουργίας/κράτησης μίας μονάδας (Ανισότητες 4.5 και 4.6), ανάληψης/απόρριψης φορτίου (Ανισότητα 4.7 και 4.8) και των ορίων της ενεργού παραγωγής τους (Ανισότητα 4.4).

Η δεύτερη περιλαμβάνει τους περιορισμούς στη λειτουργία των υδροηλεκτρικών σταθμών, οι οποίοι αφορούν τα όρια του ρυθμού εκροής ύδατος των σταθμών (Ανισότητα 6.3), τα όρια της ποσότητας αποθηκευμένου ύδατος των ταμιευτήρων (Ανισότητα 6.4), την αρχική και τελική κατάσταση των ταμιευτήρων (Εξισώσεις 6.5 και 6.6), και τους περιορισμούς στη συνέχεια της ροής ύδατος (Εξισώση 6.7):

$$Qmin_j \le Q_j^t \le Qmax_j,\ j \in [1, NHP],\ t \in [1, T] \tag{6.3}$$

$$Vmin_j \le V_j^t \le Vmax_j,\ j \in [1, NHP],\ t \in [1, T] \tag{6.4}$$

$$V_j^0 = V_j^{init} \tag{6.5}$$

$$V_j^T = V_j^{final} \tag{6.6}$$

$$V_j^t = V_j^{t-1} - Q_j^t - SP_j^t + IN_j^t + \sum_{l=1}^{UHP} (Q_l^{t-\tau_{lj}} + SP_l^{t-\tau_{lj}}),\ j \in [1, NHP],\ t \in [1, T] \tag{6.7}$$

Η τρίτη κατηγορία περιλαμβάνει τους περιορισμούς του συστήματος που αφορούν την κάλυψη της ωριαίας ζήτησης από τις τεχνολογίες του συστήματος (Εξίσωση 6.8), καθώς και τους περιορισμούς αξιοπιστίας (Ανισότητες 6.9 και 6.10):

$$\sum_{i=1}^{NTG} ST_i^t \cdot P_i^t + \sum_{j=1}^{NHP} Ph_j^t + Pw^t = P_d^t,\ t \in [1, T] \tag{6.8}$$

$$LOLP^t \leq LOLP^{max}, \quad t \in [1, T] \tag{6.9}$$

$$EENS_{tot} \leq EENS^{max} \tag{6.10}$$

6.2 Υπολογισμός των δεικτών αξιοπιστίας

Για τον υπολογισμό των δεικτών αξιοπιστίας χρησιμοποιείται παρεμφερή διαδικασία με αυτή που περιγράφηκε στο προηγούμενο κεφάλαιο. Γενικά οι υδροηλεκτρικές μονάδες θεωρούνται μονάδες αυξημένης αξιοπιστίας και έτσι η πιθανότητα να υποστούν βλάβη θεωρείται πρακτικά αμελητέα σε σχέση με την αντίστοιχη των θερμικών μονάδων. Για αυτό το λόγο βλάβες των υδροηλεκτρικών σταθμών δεν λαμβάνονται υπόψη στο προτεινόμενο μοντέλο. Αντίθετα, για τη μη διαθεσιμότητα των θερμικών μονάδων χρησιμοποιείται το μοντέλο δύο καταστάσεων και η αβεβαιότητα στην πρόβλεψη του φορτίου μοντελοποιείται με τη χρήση της κανονικής κατανομής όπως περιγράφηκε στο προηγούμενο κεφάλαιο. Η μοντελοποίηση της αβεβαιότητας στην πρόβλεψη της παραγόμενης ενέργειας από τα αιολικά πάρκα γίνεται επίσης με χρήση κανονικής κατανομής.

Έπειτα υπολογίζεται η αβεβαιότητα στην καθαρή ζήτηση ενέργειας (που είναι η συνολική ζήτηση μείον την παραγωγή από τα αιολικά για κάθε ώρα της εξεταζόμενης περιόδου). Αρχικά υπολογίζεται η αναμενόμενη καθαρή ζήτηση ενέργειας για κάθε ώρα της εξεταζόμενης περιόδου. Η αβεβαιότητα στην καθαρή ζήτηση ενέργειας μοντελοποιείται με χρήση κανονικής κατανομής στην οποία η μέση τιμή είναι η αναμενόμενη καθαρή ζήτηση ενώ η τυπική απόκλιση προκύπτει λαμβάνοντας υπόψη τις τυπικές αποκλίσεις του αναμενόμενου φορτίου και την τυπική απόκλιση της παραγόμενης ενέργειας από τα αιολικά πάρκα. Η κανονική κατανομή διακριτοποιείται σε εφτά τμήματα καθένα από τα οποία αντιπροσωπεύει την πιθανότητα η καθαρή ζήτηση να είναι ίση με τη μέση τιμή του τμήματος. Από αυτό το φορτίο αφαιρείται η συνολική παραγωγή από τα υδροηλεκτρικά εργοστάσια και έτσι έχουμε την κανονική κατανομή που εκφράζει το φορτίο που θα καλυφθεί από τις θερμικές μονάδες. Για τον υπολογισμό των δεικτών αξιοπιστίας, γίνεται συνέλιξη της προαναφερθείσας κατανομής με τον **COPT** όπως περιγράφηκε στο προηγούμενο κεφάλαιο.

6.3 Παραλλαγή της Διαφορικής Εξέλιξης που χρησιμοποιήθηκε

Για την επίλυση του προβλήματος δημιουργήθηκε ένας αλγόριθμος βασιζόμενος στον αλγόριθμο Διαφορικής Εξέλιξης, στον οποίο ο τελεστής επιλογής έχει αντικατασταθεί από τη διαδικασία ταξινόμησης και κατάταξης των λύσεων του **NSGA-II** [9].

6.4 Η προτεινόμενη μέθοδος

Η τελική λύση του προβλήματος θα είναι το πρόγραμμα παραγωγής που θα περιλαμβάνει την κατάσταση λειτουργίας και την ενεργό ισχύ των θερμικών μονάδων καθώς και τον ρυθμό εκροής ύδατος των υδροηλεκτρικών σταθμών για κάθε ώρα της εξεταζόμενης περιόδου. Για αυτό κάθε άτομο του πληθυσμού $\mathbf{x}$ αποτελείται από $(NTG + NHP) \cdot T$ πραγματικές μεταβλητές ως εξής:

$$\mathbf{x} = \{\mathbf{p}, \mathbf{Q}\} \tag{6.11}$$

όπου

$$\mathbf{p} = [p_1^1, p_1^2, ..., p_i^t, ..., p_{NTG}^T] \tag{6.12}$$

και

$$\mathbf{Q} = [Q_1^1, Q_1^2, ..., Q_j^t, ..., Q_{NHP}^T] \tag{6.13}$$

Βάσει του $\mathbf{p}$, το διάνυσμα $\mathbf{ST}$ με τις καταστάσεις λειτουργίας των θερμικών μονάδων παράγεται χρησιμοποιώντας τη βηματική συνάρτηση που περιγράφηκε στο Κεφάλαιο 4.

Σημειώνεται ότι στον αλγόριθμο εντάσσεται και ο τελεστής μετάλλαξης Window Mutation [14]. Σε αυτόν τον τελεστή επιλέγεται τυχαία μία θερμική μονάδα και με ίση πιθανότητα είτε τίθεται εκτός λειτουργίας είτε εντάσσεται στο σύστημα για όλες τις ώρες ενός τυχαία επιλεγμένου χρονικού διαστήματος εντός του ορίζοντα προγραμματισμού. Αυτός ο τελεστής χρησιμοποιείται με ίση πιθανότητα μαζί με τον τελεστή $DE/rand/1$ στο τμήμα $\mathbf{p_n^g}$ του $\mathbf{x_n^g}$. Αντίθετα, ο $DE/rand/1$ εφαρμόζεται πάντα στο τμήμα $\mathbf{Q_n^g}$.

Σε κάθε δοκιμαστικό διάνυσμα που δημιουργείται από εφαρμογή των τελεστών μετάλλαξης και διασταύρωσης ακολουθείται η διαδικασία που περιγράφεται παρακάτω.

Αρχικά σε κάθε δοκιμαστικό διάνυσμα ανατίθεται μία Λίστα Ένταξης των μονάδων. Αξίζει να σημειωθεί ότι η μέθοδο για την κατασκευή πληθώρας Λιστών Προτεραιότητας αντικαθίσταται σε αυτόν τον αλγόριθμο. Ο βασικός λόγος για αυτό είναι ότι η μέθοδο της πληθώρας Λιστών Προτεραιότητας δεν επιτρέπει να δοθεί προτεραιότητα σε μονάδες που μπορεί να είναι λιγότερο οικονομικά αποδοτικές (ή πιο ρυπογόνες). Παρόλα αυτά τέτοιες μονάδες μπορεί να παρουσιάζουν αυξημένη ευελιξία που μπορεί να φανεί χρήσιμη σε περιπτώσεις όπου το φορτίο του συστήματος παρουσιάζει σημαντικές αυξομειώσεις, όπως γίνεται σε συστήματα με αυξημένη αιολική ενέργεια. Πιο συγκεκριμένα προτείνεται μία μέθοδο για την κατασκευή πολλαπλών Λιστών Ένταξης των μονάδων με επιλογή των μονάδων βάσει της μεθόδου τουρνουά (Τουρναμεντ Σελεστιον). Σε αυτή, γίνονται διαδοχικά Τουρνουά μεταξύ TS τυχαία επιλεγμένων μονάδων και η μονάδα με την καλύτερη τιμή του μέτρου σύγκρισης, που μπορεί να είναι είτε το μέσο κόστος είτε οι μέσες εκπομπές των μονάδων στο $Pmax$, τοποθετείται σε καλύτερη θέση της Λίστας

Ένταξης CPO_n^g. Αυτή η λίστα χρησιμοποιείται μετά κατά την επιδιόρθωση των περιορισμών των μονάδων.

Έπειτα ακολουθείται η εξής διαδικασία:

1. Επιδιορθώνονται τυχόν παραβιάσεις του περιορισμού τελικής κατάστασης του ταμιευτήρα με μεταβολή του ρυθμού εκροής ύδατος σε τυχαία επιλεγμένες ώρες του ορίζοντα προγραμματισμού.

2. Επιδιορθώνονται τυχόν παραβιάσεις των περιορισμών των ορίων της ποσότητας αποθηκευμένου ύδατος στους ταμιευτήρες. Όταν ο περιορισμός αυτός παραβιάζεται για ένα υδροηλεκτρικό σταθμό σε κάποια ώρα του ορίζοντα προγραμματισμού, τότε μεταβάλλεται ο ρυθμός εκροής ύδατος του σταθμού για ένα αριθμό ωρών πριν και μετά την ώρα παραβίασης έως ότου επιτευχθεί επιδιόρθωση του περιορισμού.

3. Υπολογίζεται η ενέργεια που θα καλυφθεί από τις θερμικές μονάδες του συστήματος, αφαιρώντας από τη συνολική ζήτηση του συστήματος την παραγόμενη ενέργεια από τα υδροηλεκτρικά εργοστάσια καθώς και την παραγόμενη ισχύ από τα αιολικά πάρκα.

4. Ελέγχεται αν για κάθε ώρα η ισχύ σε λειτουργία των θερμικών μονάδων επαρκεί για να καλύψει την υπολειπόμενη ζήτηση. Για τις ώρες που αυτό δεν ισχύει πραγματοποιείται ένταξη των μονάδων, ξεκινώντας από την οικονομικότερη στην CPO_n^g, έως ότου η συνολική ισχύ σε λειτουργία επαρκεί για να ικανοποιήσει την υπολειπόμενη ζήτηση.

5. Έπειτα για κάθε μονάδα ελέγχονται οι περιορισμοί ελάχιστου χρόνου λειτουργίας/κράτησης των θερμικών μονάδων και επιδιορθώνονται βάσει του μηχανισμού που περιγράφηκε στο προηγούμενο κεφάλαιο.

6. Υπολογίζονται οι τιμές των δεικτών αξιοπιστίας. Σε περίπτωση που υπάρχει περίσσεια ποσότητα στρεφόμενης εφεδρείας σε κάποια ώρα, τότε εφαρμόζεται μηχανισμός που θέτει

μονάδες εκτός λειτουργίας, ξεκινώντας από την ακριβότερη προς τη φθηνότερη βάσει της CPO_n^g, έως ότου η περίσσεια στρεφόμενη εφεδρεία μειωθεί στο ελάχιστο.

7. Εφαρμόζεται μηχανισμός για την επιδιόρθωση της παραβίασης του περιορισμού του δείκτη EENS και των περιορισμών του δείκτη LOLP όπως παρουσιάστηκε στο προηγούμενο κεφάλαιο

8. Τέλος, επιδιορθώνονται παραβιάσεις των περιορισμών ανάληψης/απόρριψης φορτίου των θερμικών μονάδων καθώς και ο περιορισμός του ισοζυγίου ισχύος βάσει των μηχανισμών που περιγράφηκαν σε προηγούμενα κεφάλαια.

Μέθοδος τοπικής βελτιστοποίησης   Για να επιταχυνθεί η σύγκλιση του προτεινόμενου αλγορίθμου προς το μέτωπο Pareto αναπτύσσεται μία μέθοδος τοπικής βελτίωσης που συνδυάζεται με τη Διαφορική Εξέλιξη. Στη μέθοδο αυτή συνδυάζονται μία τεχνική στην οποία η σύγκριση των ατόμων γίνεται βάσει του ορισμού της κατά Pareto κυριαρχίας και μία τεχνική στην οποία η σύγκριση των ατόμων γίνεται με χρήση ενός σταθμισμένου γραμμικού αθροίσματος των αντικειμενικών συναρτήσεων. Η προτεινόμενη μέθοδος εφαρμόζεται σε κάθε γενιά του προτεινόμενου ΕΑ ενώ τα άτομα στα οποία θα εφαρμοστεί επιλέγονται από το σετ μη-κυριαρχούμενων λύσεων της κάθε γενιάς. Η μέθοδος τοπικής αναζήτησης που θα εφαρμοστεί σε κάθε λύση εξαρτάται από τη θέση της στο μέτωπο μη-κυριαρχούμενων λύσεων. Στα άτομα που αντιστοιχούν στα άκρα του μετώπου μη-κυριαρχούμενων λύσεων εφαρμόζεται η μέθοδος κατά την οποία η σύγκριση γίνεται βάσει της κατά Pareto κυριαρχίας. Στα υπόλοιπα άτομα εφαρμόζεται η μέθοδος στην οποία χρησιμοποιείται η συνάρτηση σταθμισμένου γραμμικού αθροίσματος.

Η μέθοδο βάσει τη κυριαρχίας κατά Pareto επαναλαμβάνεται p_{PD} φορές για κάθε λύση που αντιστοιχεί στο ακραίο σημείο του μετώπου Pareto. Σε κάθε επανάληψη, η τιμή μίας αντικειμενικής μεταβλητής της τρέχουσας λύσης CS επαναρχικοποιείται εντός του πεδίου ορισμού της, για να σχηματιστεί η καινούργια λύση NS. Η τελευταία επιδιορθώνεται βάσει των μηχανισμών επιδιόρθωσης. Έπειτα, η CS και η NS συγκρίνονται με χρήση της κυριαρχίας κατά

Pareto. Αν η CS κυριαρχεί της NS τότε η τελευταία απορρίπτεται. Σε περίπτωση που η CS και η NS δεν κυριαρχούν η μία της άλλης, η NS τοποθετείται σε ένα εξωτερικό αρχείο H, εφόσον δεν κυριαρχείται από καμία άλλη λύση του H. Όσες λύσεις του H κυριαρχούνται από την NS διαγράφονται από το αρχείο. Αν η NS κυριαρχήσει της CS τότε την αντικαθιστά. Και σε αυτή την περίπτωση όσες λύσεις του H κυριαρχούνται από την NS διαγράφονται. Η χρήση της μεθόδου αυτής στις υποψήφιες λύσεις που αντιστοιχούν στα άκρα του μετώπου μη-κυριαρχούμενων λύσεων αποσκοπεί στο να συμβάλλει στην αύξηση του εύρους του μετώπου μη-κυριαρχούμενων λύσεων.

Η μέθοδος τοπικής βελτιστοποίησης με χρήση σταθμισμένου γραμμικού αθροίσματος εφαρμόζεται στο σετ μη-κυριαρχούμενων λύσεων που δεν αντιστοιχούν στα ακραία σημεία του μετώπου μη-κυριαρχούμενων λύσεων. Ας ονομάσουμε αυτό το σετ λύσεων S. Κατά τη μέθοδο αυτή χρησιμοποιείται η εξής συνάρτηση σταθμισμένου γραμμικού αθροίσματος:

$$y(\mathbf{x}|\lambda) = \lambda_1 \cdot f_1(\mathbf{x}) + \lambda_2 \cdot f_2(\mathbf{x}) \tag{6.14}$$

όπου $\lambda = [\lambda_1, \lambda_2]$, με $\lambda_1, \lambda_2 \geq 0$ και $\lambda_1 + \lambda_2 = 1$. Σε κάθε εφαρμογή της μεθόδου ορίζεται ένα διαφορετικό ζεύγος βαρών, και ως αρχική λύση CS για να εκκινήσει η διαδικασία επιλέγεται η εφικτή λύση του S με την χαμηλότερη τιμή του $y(\mathbf{x}|\lambda)$. Έπειτα από τη λύση CS παράγεται η λύση NS. Αν η τελευταία είναι μη-εφικτή απορρίπτεται. Αλλιώς η NS και CS συγκρίνονται βάσει της τιμής της συνάρτησης σταθμισμένου γραμμικού αθροίσματος, και σε περίπτωση που η NS παρουσιάζει καλύτερη τιμή τότε αντικαθιστά την CS. Η διαδικασία επαναλαμβάνεται p_{WS} φορές.

Ο αριθμός των ατόμων που θα επιλεγούν για εφαρμογή της τοπική αναζήτησης σε κάθε γενιά εξαρτάται από τον αριθμό των ατόμων στο σετ μη κυριαρχούμενων λύσεων $FNS(Ppop^g)$. Στα αρχικά στάδια της βελτιστοποίησης ο πληθυσμός κατευθύνεται προς το μέτωπο Pareto κατά κύριο λόγω από τους τελεστές του ΕΑ καθώς ο αριθμός των μη-κυριαρχούμενων λύσεων είναι σχετικά μικρός. Η μέθοδος τοπικής αναζήτησης εφαρμόζεται πιο συχνά σε επόμενες γενιές, καθώς ο αριθμός μη-κυριαρχούμενων λύσεων αυξάνεται, στην προσπάθεια για τοπική βελτίωση των υπαρχόντων λύσεων. Επίσης ορίζεται και η παράμετρος p_{ls} που είναι το ποσοστό του μετώπου των μη-κυριαρχούμενων λύσεων που θα υποστούν τοπική βελτιστοποίηση. Ο μηχανισμός ελέγχου της τοπικής βελτιστοποίησης εντάσσεται στην προσπάθεια να επιτευχθεί μία ισορροπία μεταξύ της ολικής αναζήτησης και της τοπικής βελτιστοποίησης [19].

6.5 Αποτελέσματα της μεθόδου

Η απόδοση του προτεινόμενου αλγορίθμου (που ονομάζεται **hMOEA**) εκτιμάται μέσω τριών μελετών περίπτωσης. Στις δύο πρώτες μελέτες περίπτωσης εξετάζονται τα εξής 4 συστήματα: Το πρώτο περιλαμβάνει 10 θερμικές μονάδες και 2 υδροηλεκτρικούς σταθμούς, το δεύτερο 20 θερμικές μονάδες και 4 υδροηλεκτρικούς σταθμούς, το τρίτο 40 θερμικές μονάδες και 8 υδροηλεκτρικούς σταθμούς, και το τέταρτο 26 θερμικές μονάδες και 4 υδρο-ηλεκτρικούς σταθμούς. Στο τελευταίο σύστημα οι ταμιευτήρες βρίσκονται σε αλυσωτή διάταξη (in cascade).

Για την αξιολόγηση των λύσεων σε κάθε εξεταζόμενη περίπτωση χρησιμοποιείται ο δείκτης του υπερόγκου (hypervolume).

Στην πρώτη μελέτη περίπτωσης εξετάζεται η επίδραση της διαδικασίας για την κατασκευή πληθώρας Λιστών Ένταξης μέσω της χρήσης επιλογής τουρνουά. Σε αυτήν την περίπτωση το ποσό της στρεφόμενης εφεδρείας του συστήματος είναι προκαθορισμένο. Στην συγκεκριμένη περίπτωση εξετάζονται τα εξής:

- Αρχικά μελετάται η επίδραση του αριθμού των μονάδων που συμμετέχουν στα τουρνουά που πραγματοποιούνται για τη δημιουργία των Λιστών Ένταξης. Μετά από την ανάλυση των αποτελεσμάτων προέκυψε ότι το TS επηρεάζει τα αποτελέσματα του αλγορίθμου. Στα πρώτα τρία συστήματα τα καλύτερα αποτελέσματα προέκυψαν για $TS = 2$ ενώ στο τέταρτο σύστημα προέκυψε ότι η μέθοδος παράγει τα καλύτερα αποτελέσματα όταν $TS = 15$.

Ανάλογα με τα χαρακτηριστικά των μονάδων του συστήματος καθώς και της ζήτησης είναι λογικό το TS να έχει επίδραση στα αποτελέσματα. Μεγαλύτερο TS σημαίνει ότι η τελική Λίστα Ένταξης θα προσομοιάζει την Λίστα προτεραιότητας βάσει του μέσου κόστους ή των μέσων εκπεμπόμενων ρύπων στο $Pmax$. Αντίθετα μικρότερο TS συνεπάγεται ότι πιο ακριβές (ή ρυπογόνες) αλλά ευέλικτες μονάδες μπορεί να τοποθετηθούν σε καλύτερες θέσεις της CPO. Κάτι τέτοιο μπορεί να ωφελήσει τη βελτιστοποίηση σε περιπτώσεις που έχουμε σημαντικές αυξομειώσεις στο ωριαίο φορτίο, καθώς σε τέτοιες περιπτώσεις μπορεί να είναι αποδοτικότερο να ανοίξει μία ακριβή μονάδα για μικρό αριθμό ωρών παρά να ανοίξει μία λιγότερο ακριβή ή λιγότερο ρυπογόνα μονάδα η οποία θα χρειαστεί να παραμείνει ανοιχτή για μεγαλύτερο αριθμό ωρών.

- Έπειτα συγκρίνεται η απόδοση της μεθόδου με τη χρήση επιλογής τουρνουά για τη δημιουργία των Λιστών Ένταξης, με τις μεθόδους της απλής Λίστας Προτεραιότητας στο $Pmax$ και της μεθόδου για τη δημιουργία πληθώρας Λιστών Προτεραιότητας. Μετά από την ανάλυση των αποτελεσμάτων προέκυψε ότι σε όλα τα εξεταζόμενα συστήματα η χρήση της μεθόδου με επιλογή τουρνουά βελτιώνει τα αποτελέσματα που επιτυγχάνει ο αλγόριθμος.

Στην δεύτερη μελέτη περίπτωσης εξετάζεται η επίδραση της μεθόδου τοπικής βελτιστοποίησης καθώς και του τελεστή Window Mutation στα αποτελέσματα του αλγορίθμου. Για αυτό το λόγο τα αποτελέσματα της μεθόδου συγκρίνονται με τα αποτελέσματα του απλού MODE και του MODE όπου χρησιμοποιείται το Window Mutation (MODE+WM). Η ανάλυση των αποτελεσμάτων δείχνει ότι σε κάθε περίπτωση ο hMOEA παράγει συστηματικά καλύτερα μέτωπα μη κυριαρχούμενων λύσεων σε σχέση με τα μέτωπα που παράγονται από τον MODE και τον MODE+WM. Μάλιστα, τα μέτωπα μη-κυριαχούμενων λύσεων του hMOEA προσεγγίζουν συστηματικά τα μέτωπα Pareto των εξεταζόμενων συστημάτων.

Στην τρίτη μελέτη περίπτωσης εξετάζεται η αποτελεσματικότητα της μεθόδου για το πρόβλημα στο οποίο περιλαμβάνονται οι περιορισμοί αξιοπιστίας. Αρχικά μελετάται η επίδραση της μη διαθεσιμότητας των μονάδων στα παραγόμενα μέτωπα μη-κυριαρχούμενων λύσεων της μεθόδου. Μικρότερη μη διαθεσιμότητα των μονάδων οδηγεί σε μέτωπα μη κυριαρχούμενων λύσεων εγγύτερα στη αρχή των αξόνων. Αυτό οφείλεται κατά κύριο λόγω στη χαμηλότερη στρεφόμενη εφεδρεία που προγραμματίζεται σε αυτές τις περιπτώσεις. Έπειτα εξετάζεται η επίδραση της αβεβαιότητας της πρόβλεψης φορτίου στα τελικά αποτελέσματα. Μικρότερη αβεβαιότητα της πρόβλεψης φορτίου οδηγεί σε μέτωπα λύσεων τα οποία είναι εγγύτερα στην αρχή των αξόνων. Ομοίως με προηγουμένως αυτό μπορεί να αιτιολογηθεί από τις μικρότερες απαιτήσεις για στρεφόμενη εφεδρεία σε αυτές τις περιπτώσεις. Τέλος εκτιμάται η επίδραση της αβεβαιότητας του ανέμου στα αποτελέσματα της μεθόδου.

ΚΕΦΑΛΑΙΟ 7
ΕΠΙΛΟΓΟΣ - ΣΥΜΠΕΡΑΣΜΑΤΑ

Στην παρούσα Διδακτορική Διατριβή αναπτύχθηκαν μέθοδοι βασιζόμενες στους Εξελικτικούς Αλγορίθμους για την επίλυση δύο προβλημάτων βελτιστοποίησης που συναντώνται στον κλάδο της διαχείρισης ενεργειακών συστημάτων. Το πρώτο πρόβλημα είναι ο μακροχρόνιος προγραμματισμός επέκτασης του δυναμικού παραγωγής και το δεύτερο είναι ο βραχυπρόθεσμος προγραμματισμός παραγωγής ηλεκτρικής ενέργειας.

Για το πρώτο πρόβλημα αναπτύχθηκε μοντέλο το οποίο προσομοιώνει τη λειτουργία μίας ημι-απελευθερωμένης αγοράς ηλεκτρικής ενέργειας (semi-regulated market). Το μοντέλο βελτιστοποιεί την Καθαρή Παρούσα Αξία του τομέα ηλεκτρικής ενέργειας λαμβάνοντας υπόψη ενεργειακούς στόχους που τίθενται για την προώθηση επενδύσεων σε τεχνολογίες παραγωγής από ΑΠΕ. Παράλληλα προτάθηκε η χρήση του αλγορίθμου ISRES-IPA για τη βελτιστοποίηση του προβλήματος. Η μελέτη περίπτωσης στην οποία εφαρμόστηκε το μοντέλο ήταν ο ελληνικός τομέας παραγωγής ηλεκτρικής ενέργειας με έτος βάσης το 2015. Έπειτα από την εξέταση των αποτελεσμάτων τα βασικά συμπεράσματα που εξάχθηκαν ήταν τα εξής:

1. Ο αλγόριθμος ISRES-IPA μπορεί να παρέχει καλύτερες λύσεις στο πρόβλημα με μεγαλύτερη συστηματικότητα σε σχέση με τον IPA, τον GA και ένα υβριδικό αλγόριθμο IPA-GA. Οπότε, η χρήση του ISRES για ολική αναζήτηση και η τροφοδότηση του IPA με την τελική λύση του ISRES μπορεί να βοηθήσει τον IPA να συγκλίνει σε καλύτερη λύση.

2. Όταν αυξάνεται ο συντελεστής χαλάρωσης το feasibility rate των αλγορίθμων αυξάνεται. Παράλληλα μειώνεται η διασπορά των παραγόμενων λύσεων.

3. Εξετάστηκαν δύο σχέδια δράσης, που θέτουν ενεργειακούς στόχους σε βραχυχρόνιο (2020) και πιο μακροχρόνιο ορίζοντα (2050). Διαπιστώθηκε ότι η ύπαρξη των συγκε-

κριμένων στόχων μεταβάλλει την δομή του τομέα παραγωγής ηλεκτρικής ενέργειας σε σχέση με την περίπτωση κατά την οποία οι στόχοι αυτοί δεν λαμβάνονται υπόψη. Για την ακρίβεια, λόγω της ύπαρξης των στόχων προωθούνται επενδύσεις σε τεχνολογίες όπως είναι τα μικρά υδροηλεκτρικά εργοστάσια και τα συγκεντρωτικά ηλιακά συστήματα, ενώ μειώνεται η παραγωγή που βασίζεται σε ορυκτά καύσιμα όπως ο λιγνίτης. Παράλληλα μετά από σύγκριση με το μοντέλο βάσης στο οποίο δεν λαμβάνονται υπόψη οι ενεργειακοί στόχοι προέκυψε ότι λόγω της αυξημένης εισαγωγής των ΑΠΕ μακροχρόνια μπορεί να υπάρξει μείωση της οριακής τιμής συστήματος και των συνολικών εκπομπών CO_2.

Στην περίπτωση του προβλήματος βραχυπρόθεσμου προγραμματισμού, αρχικά εξετάστηκε η βασική μορφή του προβλήματος. Η συνεισφορά της διατριβής έγκειται στα εξής:

- Την ανάπτυξη εξελικτικού αλγορίθμου βασιζόμενου στη Διαφορική Εξέλιξη για την αποτελεσματική επίλυση του προβλήματος. Ο αλγόριθμος αυτός χρησιμοποιεί πραγματική κωδικοποίηση ενώ μία βηματική συνάρτηση προτείνεται για τον καθορισμό των καταστάσεων λειτουργίας των μονάδων. Έτσι και τα δύο υπο-προβλήματα που αφορούν την κατάσταση λειτουργίας των μονάδων καθώς και την φόρτιση της κάθε μονάδας επιλύονται ταυτόχρονα με τη χρήση ενός αλγορίθμου.

- Προτείνεται μέθοδος για δημιουργία πολλαπλών Λιστών Προτεραιότητας που χρησιμοποιούνται κατά τους μηχανισμούς επιδιόρθωσης των ατόμων του πληθυσμού. Στη σχετική βιβλιογραφία όταν οι αλγόριθμοι χρησιμοποιούν μηχανισμούς επιδιόρθωσης χρησιμοποιείται μοναδική Λίστα Προτεραιότητας. Κατά την επιδιόρθωση των περιορισμών οι μονάδες που θα έχουν προτεραιότητα για ένταξη στο σύστημα καθορίζονται από αυτή τη μοναδική Λίστα. Αυτό μπορεί να οδηγήσει τον αλγόριθμο σε πρόωρη σύγκλιση σε τοπικό ακρότατο, καθώς μειώνει την ποικιλία των εξεταζόμενων προγραμμάτων κατά τη βελτιστοποίηση.

- Προτείνεται ο Ελιτιστικός Τελεστής Μετάλλαξης, ο οποίος εκμεταλλεύεται την πληροφορία από το άτομο με την καλύτερη τιμή της αντικειμενικής για να επιταχύνει τη σύγκλιση του αλγορίθμου, βοηθώντας παράλληλα τη σύγκλιση σε υποσχόμενες περιοχές του χώρου αναζήτησης.

Η μέθοδος εφαρμόστηκε σε πληθώρα συστημάτων τα οποία εξετάζονται στη βιβλιογραφία όταν προτείνονται μέθοδοι για τη βελτιστοποίηση του προβλήματος. Τα βασικά συμπεράσματα που προκύπτουν από την ανάλυση των αποτελεσμάτων είναι τα εξής:

- Η χρήση της μεθόδου για τη δημιουργία πολλαπλών Λιστών Προτεραιότητας ενισχύει σημαντικά την απόδοση του αλγορίθμου σε σχέση με τις μεθόδους που χρησιμοποιούνται στη βιβλιογραφία. Πιο συγκεκριμένα στα εξεταζόμενα συστήματα, οι κατανομές λύσεων που παρέχονται από την προτεινόμενη μέθοδο όταν χρησιμοποιούνται πολλαπλές Λίστες Προτεραιότητας, παρουσιάζουν καλύτερη μέση τιμή και μικρότερη διασπορά, ενώ παράλληλα επιτυγχάνονται λύσεις χαμηλότερου κόστους.

- Η ένταξη του Ελιτιστικού Τελεστή Μετάλλαξης ενισχύει σημαντικά την απόδοση του αλγορίθμου, καθώς επιταχύνει τη σύγκλιση και βοηθάει τον αλγόριθμο να αποφύγει την πρόωρη σύγκλιση σε τοπικά ακρότατα.

- Μετά από σύγκριση της απόδοσης του προτεινόμενου αλγορίθμου με σύγχρονους αλγορίθμους της βιβλιογραφίας, διαπιστώθηκε ότι ο αλγόριθμος παρέχει συστηματικά καλές λύσεις στο εξεταζόμενο πρόβλημα σε πολύ ανταγωνιστικούς χρόνους. Στα συστήματα 26 και 38 μονάδων, μάλιστα βελτιώνει σημαντικά τις καλύτερες λύσεις της σχετικής βιβλιογραφίας.

Έπειτα προτείνεται μέθοδος για την επίλυση του βραχυπρόθεσμου προγραμματισμού, όταν σε αυτόν εντάσσονται περιορισμοί αξιοπιστίας. Στην περίπτωση αυτή, στο μοντέλο του προβλήματος εντάσσονται περιορισμοί άνω ορίου στους δείκτες αξιοπιστίας LOLP και EENS. Έτσι, κατά τη βελτιστοποίηση καθορίζεται η στρεφόμενη εφεδρεία του συστήματος σε κάθε ώρα της περιόδου λαμβάνοντας υπόψη την αξιοπιστία των μονάδων ηλεκτροπαραγωγής καθώς και αβεβαιότητες στην πρόβλεψη του φορτίου. Η συνεισφορά της διατριβής όσον αφορά την επίλυση του συγκεκριμένου προβλήματος έγκειται στα εξής:

- Αναπτύχθηκε μέθοδος βασιζόμενη στη Διαφορική Εξέλιξη για την επίλυση του προβλήματος. Στη σχετική βιβλιογραφία δεν υπάρχει μέθοδος βασιζόμενη στη Διαφορική Εξέλιξη που να επιλύει το συγκεκριμένο πρόβλημα. Επίσης στην προτεινόμενη μέθοδο, η μόνη παράμετρος που πρέπει να ρυθμιστεί είναι το μέγεθος του πληθυσμού που θα χρησιμοποιηθεί από την Διαφορική Εξέλιξη, καθιστώντας την έτσι πιο εύκολη προς χρήση. Η μέθοδος αυτή αποτελεί επέκταση της μεθόδου που αναπτύχθηκε για την επίλυση της κλασικής μορφής του προβλήματος.

- Προτείνεται τρόπος για να μειωθούν οι υπολογισμοί του **COPT** κατά τη διάρκεια της βελτιστοποίησης, μειώνοντας έτσι σημαντικά τον χρόνο εκτέλεσης της μεθόδου. Κατά τη διάρκεια της βελτιστοποίησης εξετάζονται οι συνδυασμοί των μονάδων που είναι προγραμματισμένες να λειτουργήσουν σε κάθε ώρα και υπολογίζεται ο αντίστοιχος **COPT**, ο οποίος αποθηκεύεται σε εξωτερικό αρχείο. Αν κατά τη διάρκεια της βελτιστοποίησης, κάποιος συνδυασμός επαναληφθεί ο αντίστοιχος **COPT** λαμβάνεται από το εξωτερικό αρχείο. Έτσι αποφεύγεται ο υπολογισμός του ίδιου **COPT** περισσότερες της μία φοράς.

- Προτείνεται μία σειρά από μηχανισμούς επιδιόρθωσης των περιορισμών του προβλήματος. Για την ακρίβεια μηχανισμοί που χρησιμοποιήθηκαν στην κλασική μορφή του προβλήματος τροποποιούνται ώστε να μπορούν να εφαρμοστούν σε αυτό το πρόβλημα. Παράλληλα, προτείνονται δύο νέοι μηχανισμοί οι οποίοι επιδιορθώνουν τους περιορισμούς αξιοπιστίας. Στους μηχανισμούς αυτούς λαμβάνεται υπόψη πληροφορία από τη Λίστα Προτεραιότητας των μονάδων συμβάλλοντας στην ταχύτερη εύρεση λύσεων χαμηλότερου κόστους.

Μετά από την ανάλυση των αποτελεσμάτων τα βασικά συμπεράσματα είναι τα εξής:

- Ο προτεινόμενος αλγόριθμος παράγει καλύτερες λύσεις (προγράμματα χαμηλότερου κόστους) σε σχέση με τον προηγούμενο αλγόριθμο της βιβλιογραφίας που εφαρμόστηκε στο ίδιο πρόγραμμα στις περισσότερες από τις εξεταζόμενες περιπτώσεις. Παράλληλα, οι απαιτήσεις του αλγορίθμου σε υπολογιστικό χρόνο είναι χαμηλότερες στην πλειοψηφία των εξεταζόμενων περιπτώσεων.

- Επιβεβαιώνεται ότι η αύξηση της τιμής μη διαθεσιμότητας των μονάδων αυξάνει το κόστος λειτουργίας του συστήματος. Αυτό συμβαίνει γιατί η αύξηση της μη διαθεσιμότητας των μονάδων απαιτεί μεγαλύτερο ποσό στρεφόμενης εφεδρείας ανά ώρα για να επιτευχθεί το επιθυμητό επίπεδο αξιοπιστίας του συστήματος. Αυτό έχει ως αποτέλεσμα περισσότερες μονάδες να μην λειτουργούν αποτελεσματικά και άρα να αυξάνεται το κόστος του συστήματος.

- Επιβεβαιώνεται από τα αποτελέσματα της μεθόδου ότι η αύξηση της τιμής της αβεβαιότητας του φορτίου προκαλεί αύξηση του κόστους λειτουργίας του συστήματος. Αυτό συμβαίνει γιατί καθώς αυξάνεται η τιμή της αβεβαιότητας του φορτίου απαιτείται μεγαλύτερη στρεφόμενη εφεδρεία για να παρέχει το επιθυμητό επίπεδο αξιοπιστίας.

- Η προτεινόμενη μέθοδος μπορεί να εφαρμοστεί για την επίλυση του προβλήματος όταν συστήματα μεγαλύτερου αριθμού μονάδων εξετάζονται. Η μέθοδος εφαρμόστηκε σε συστήματα 52 και 78 μονάδων. Η ανάλυση των αποτελεσμάτων αναδεικνύει ότι η μέθοδος μπορεί αποδοτικά να επιλύσει τα συστήματα σε λογικό υπολογιστικό χρόνο.

Έπειτα προτείνεται μοντέλο για τον βραχυπρόθεσμο προγραμματισμό της παραγωγής ηλεκτρικής ενέργειας σε συστήματα στα οποία υπάρχουν θερμικές μονάδες ηλεκτροπαραγωγής, υδροηλεκτρικοί σταθμοί καθώς και παραγόμενη ενέργεια από αιολικά πάρκα. Το μοντέλο λαμβάνει υπόψη τη μη διαθεσιμότητα των θερμικών μονάδων, καθώς και την αβεβαιότητα στην πρόβλεψη φορτίου και την παραγωγή από αιολικά πάρκα. Αυτό έχει ως αποτέλεσμα, η στρεφόμενη εφεδρεία να υπολογίζεται μέσω της βελτιστοποίησης λαμβάνοντας υπόψη τις προαναφερθείσες αβεβαιότητες. Παράλληλα, το προτεινόμενο μοντέλο είναι πολυκριτηριακό καθώς εκτός από την ελαχιστοποίηση του λειτουργικού κόστους των μονάδων στοχεύει και στην ελαχιστοποίηση των εκπεμπόμενων ρύπων. Η συνεισφορά της διατριβής όσον αφορά την επίλυση του συγκεκριμένου προβλήματος έγκειται στα εξής:

- Το μοντέλο αφορά το πρόβλημα υδροηλεκτρικού προγραμματισμού παραγωγής με πολλαπλά κριτήρια όπου λαμβάνεται υπόψη η ενέργεια από αιολικά πάρκα καθώς και η αξιοπιστία του συστήματος. Στη σχετική βιβλιογραφία τα προτεινόμενα μοντέλα για υδροηλεκτρικό πρόβλημα δεν λαμβάνουν υπόψη την παραγόμενη ενέργεια από αιολικά πάρκα. Επιπρόσθετα, τα μοντέλα που λαμβάνουν υπόψη την αξιοπιστία του συστήματος δεν εξετάζουν συστήματα τα οποία να περιλαμβάνουν υδροηλεκτρικούς σταθμούς.

- Αναπτύσσεται υβριδικός αλγόριθμος βασιζόμενος στην Διαφορική Εξέλιξη με πραγματική κωδικοποίηση για τη βελτιστοποίηση του προβλήματος. Αυτός ο αλγόριθμος πρακτικά αποτελεί επέκταση του αλγορίθμου που εφαρμόστηκε για την επίλυση του προβλήματος βραχυπρόθεσμου προγραμματισμού στο μοντέλο που λαμβάνει υπόψη τους περιορισμούς αξιοπιστίας.

- Αναπτύχθηκε μέθοδος τοπικής βελτιστοποίησης η οποία συνδυάζει δύο τεχνικές τοπικής βελτιστοποίησης. Η πρώτη βασίζεται στη σύγκριση βάσει της κυριαρχίας κατά Pareto και η δεύτερη στην χρήση σταθμισμένου γραμμικού αθροίσματος. Στη σχετική βιβλιογραφία δεν έχει προταθεί μέθοδος που να συνδυάζει αυτές τις δύο τεχνικές. Για τον έλεγχο των ατόμων του πληθυσμού στους οποίους θα εφαρμοστεί η τοπική αναζήτηση αναπτύχθηκε μέθοδος η οποία ελέγχει τον αριθμό ατόμων στον οποίο θα εφαρμοστεί η τοπική βελτίωση βάσει των ατόμων που βρίσκονται στο μέτωπο μη-κυριαρχούμενων λύσεων.

- Προτείνεται μία μέθοδο για την κατασκευή πολλαπλών Λιστών Ένταξης των μονάδων με επιλογή των μονάδων βάσει της μεθόδου τουρνουά (Tournament Selection). Αυτή η μέθοδος επιτρέπει να δοθεί προτεραιότητα σε μονάδες που μπορεί να είναι λιγότερο οικονομικά αποδοτικές (ή πιο ρυπογόνες), αλλά παρουσιάζουν αυξημένη ευελιξία που μπορεί να φανεί χρήσιμη σε περιπτώσεις όπου το φορτίο του συστήματος παρουσιάζει σημαντικές αυξομειώσεις, όπως γίνεται σε συστήματα με αυξημένη αιολική ενέργεια.

Από την ανάλυση των αποτελεσμάτων τα πιο σημαντικά συμπεράσματα που προκύπτουν είναι τα εξής:

- Η απόδοση της μεθόδου με τη χρήση επιλογής τουρνουά για τη δημιουργία των Λιστών Ένταξης είναι καλύτερη σε σχέση με τις μεθόδους της απλής Λίστας Προτεραιότητας στο Pmax και της μεθόδου για τη δημιουργία πληθώρας Λιστών Προτεραιότητας.

- Η ανάλυση των αποτελεσμάτων δείχνει ότι σε κάθε περίπτωση ο υβριδικός αλγόριθμος παράγει συστηματικά καλύτερα μέτωπα μη κυριαρχούμενων λύσεων σε σχέση με τα μέτωπα που παράγονται από τον αλγόριθμο Διαφορικής Εξέλιξης χωρίς την μέθοδο τοπικής βελτιστοποίησης. Μάλιστα, τα μέτωπα μη-κυριαχούμενων λύσεων του hMOEA προσεγγίζουν συστηματικά τα μέτωπα Παρετο των εξεταζόμενων συστημάτων.

- Μελετάται η επίδραση της μη διαθεσιμότητας των μονάδων στα παραγόμενα μέτωπα μη-κυριαρχούμενων λύσεων της μεθόδου. Μικρότερη μη διαθεσιμότητα των μονάδων οδηγεί σε μέτωπα μη κυριαρχούμενων λύσεων εγγύτερα στη αρχή των αξόνων. Αυτό οφείλεται κατά κύριο λόγω στη χαμηλότερη στρεφόμενη εφεδρεία που προγραμματίζεται σε αυτές τις περιπτώσεις.

- Αναλύθηκε η εξέταση της επίδρασης της αβεβαιότητας της πρόβλεψης φορτίου στα τελικά αποτελέσματα. Μικρότερη αβεβαιότητα της πρόβλεψης φορτίου οδηγεί σε μέτωπα μη-κυριαχούμενων λύσεων τα οποία είναι εγγύτερα στην αρχή των αξόνων. Ομοίως με προηγουμένως αυτό μπορεί να αιτιολογηθεί από τις μικρότερες απαιτήσεις για στρεφόμενη εφεδρεία σε αυτές τις περιπτώσεις.

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