National Technical University of Athens

Department of Electrical and Computer Engineering

Division of Communication, Electronic and Information Engineering

PhD THESIS

Optimization and Game Theory Methods for Smart Energy Grids

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Abstract

The global power sector is undergoing a radical transition in the way electricity is produced, distributed and consumed. Firstly, the deregulation of the power sector with the introduction of liberalized electricity markets has drastically changed the decision-making framework in the planning and operational stages of the power systems. Furthermore, the rapidly increasing penetration of unpredictable and variable renewable energy into the generation mix due to environmental concerns has highly complicated the task of constantly balancing production with consumption, and therefore has greatly increased the Transmission System Operator's (TSO) need for *flexibility* in the power system. Moreover, the ever-increasing installation of "behind-the-meter" resources, along with the electrification of industry, transportation, heating and cooling sectors have shifted the focus of system operators towards the low and medium voltage networks. This evolving decentralization of power systems brought by the advent of Distributed Energy Resources (DERs) has introduced new technical and operational challenges for the Distribution System Operators (DSOs) as well. Thus, the role of the DSOs should be evolved from network operators to active system operators, in order to closely collaborate with TSOs and procure the necessary flexibility that will allow them to ensure the smooth operation of their networks. The aforementioned trends necessitate bottom-up investments in distributed energy and flexibility resources, which are able to provide low-cost energy and network services to both the DSOs and TSOs via various marketplaces. To this end, coordination schemes between DSOs and TSOs should be established in order for the seamless participation of DERs in local and system-wide electricity markets to be ensured.

In this context, the business model of an Energy Service Provider (ESP) emerges. ESPs are private-based power system stakeholders and market actors that own portfolios of diverse assets that seek to secure the sustainability of their investments through providing energy and flexibility services to the system operators and the end-users. In this dissertation, we envisage an ESP that operates as a retailer and also invests in a portfolio of diverse distributed energy and flexibility resources. ESP offers energy and ancillary network services to both the TSO and the DSO via its participation in the respective electricity markets and the optimal management of its assets. Towards the financial sustainability of its investments, we propose algorithmic tools that model the decision-making process of the ESP in both investment and operational stages. More specifically, we first propose an ESP-DSO-TSO coordination framework using bilevel modeling, within which network-aware and market-aware investments are determined. Our proposed investment model produces benefits for all the involved parties. Then, we examine the market strategy of an ESP in two distinct use cases, i.e., regulated and deregulated operation of the distribution network. In the second use case particularly, we introduce an innovative energy market architecture, in which a distribution-level flexibility market is introduced, which: (1) provides DSOs with the flexibility they need in order to maintain the secure operation of their networks at minimum cost, and (2) creates new revenue streams for the distributed energy and flexibility units. In both use cases, we have used bilevel programming in order to model the strategic participation of the ESP in various electricity markets. Finally, in order to reduce the ESP's cost of energy required to meet the demand of its costumers/end-users, we propose an innovative pricing mechanism that triggers changes in electricity consumer's behavior promoting energy efficiency.

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1. Chapter 1: Introduction

1.1. Evolution of Power Systems

1.1.1. Global Trends in Modern Smart Electricity Grids

For most of the 20th century, the electricity sector was considered a monopoly. Vertically integrated public utilities were responsible for the supervision, management and control of the three basic components of the electric power industry; generation, transmission and distribution. Utilities generated power in bulk thermal or hydro units connected to high voltage lines, transmitted it to the load centers and finally distributed it to the price-inelastic end-users, who paid a regulated tariff. However, since 1980s, political issues, environmental concerns, the projected growth in global electric demand along with the rapid advancements in Renewable Generation (RG), Energy Storage (ES) and Information and Communication Technologies (ICT) have triggered the ongoing transition to **Smart Grids** [1] through massive changes in the electric power sector:

Liberalization: The electric power industry has been evolving into a deregulated and competitive industry, where market forces drive the electricity price with a view to reducing the energy and network security cost through the introduction of competitive electricity markets. Electricity is treated as a commodity and traded on wholesale deregulated markets, where private companies seek to maximize their payoff. Furthermore, competitive Ancillary Services (AS) markets have been introduced, where System Operators (SOs) buy the needed flexibility from profit-based Balancing Service Providers (BSPs), in order to secure the reliable operation of their networks. Finally, competitive Retail markets have arisen, where the end-users can choose their supplier based on the retail price and the quality of the provided services.

Decarbonization: Environmental goals set by the international community concerning the containment of global warming [2] and the reduction of greenhouse gas emissions [3], have headed towards increasing the penetration of Renewable Energy Sources (RES) into the electricity generation mix. Also, in most countries the major part of new investments in RES takes place in the distribution network ('behind-the-meter' resources), with approximately 179GW of distributed photovoltaic (PV) units having been installed globally from 2017 to 2020 [4].

Decentralization: The high distributed RES penetration and the growing electrification of the industry, transportation, and heating and cooling sectors [5] leads to an increased decentralization of energy resources. Distributed Energy Resources (DERs) can produce or store electrical energy and manage the electricity consumption based on the technology. Distributed renewable energy capacity, ES units and Demand Responsive (DR) load (e.g., EVs, Heat Pumps, etc.) can support decarbonization reducing the system's dependency on fossil fuels, provide valuable services to the Distribution System Operators (DSOs) and the Transmission System Operators (TSOs), and create innovative business models.

Digitalization: In order to boost the decentralization trend and unleash the potential of DERs, the power system evolves into a cyber-physical system. The development of ICT solutions, smart metering and IoT infrastructure will enhance the utilization of the physical network assets, unfold the full potential of distributed energy and flexibility resources and facilitate the collaboration among the power sector stakeholders.

1.1.2. Challenges in the New Era of Power Systems

The aforementioned trends raise new challenges for the System Operators. Most electricity grids are decades old and built for outdated power systems, where power flowed in only one direction (from centralized generators to end-users), demand was unvarying and price-inelastic. The main concerns for system operators were the occurrence of failures in network assets and the provision of sufficient production and transmission capacity to satisfy the peak load. The only option considered to tackle these issues was the costly network reinforcements.

In the Smart Grid era, DSOs and TSOs have to cope with the unpredictable and variable RES generation, which greatly complicates the task of balancing production with demand at all times. Also, the advent of DERs introduces bi-directional power flows, which eventually result in more frequent occurrence of network congestion and voltage limit violations. Furthermore, the SOs have to deal with network contingencies resulting from increasing peak load and the unpredictable demand patterns that the further electrification of demand will bring up. These challenges radically increase the need for flexibility [6]. Using the power system's flexibility instead of costly network investments [7], taking full advantage of the capabilities of the cyber-physical system (digitalization trend), can create the necessary financial motivation towards bottom-up investments in DERs, which can provide the necessary flexibility to both the distribution and the transmission level.

In today's power sector, the TSOs are the main actors that are able to procure flexibility services via AS markets or long-term contracts. Moreover, the interaction between the TSO and the DSO is negligible and the clearing process of the electricity markets does not take into account the distribution network limitations. Consequently, the participation of the DERs in these markets may rise violations of the distribution network constraints and lead in inefficient (economically and technically) market outcomes. The latter dictates: a) a shift of the DSO's role towards a more **active distribution network operator**, and b) the development of **market or non-market coordination schemes between the TSOs and the DSOs** in order to maximize the utilization of the DERs and minimize the networks' operating costs [8]. For example, local Flexibility Markets are a solution concept that can ensure that the DSO will obtain the necessary flexibility to deal with potential network contingencies and on the other hand can create new revenue streams for the DERs. Additionally, TSO-DSO coordination frameworks are necessary so that the TSO can also benefit from the distributed low-cost clean energy and flexibility provided by the DERs.

1.1.3. The ESP Business Model – System Architecture

In the context of liberalized electricity markets and the decarbonized, decentralized and digitalized Smart Grid, the business model of an **Energy Service Provider (ESP)** emerges. In this dissertation, we consider that an ESP operates as a Retailer, i.e. it has customers/end-users whose demand must satisfy, but it also owns a portfolio of diverse distributed energy and flexibility resources (e.g. generating units, energy storage assets, demand responsive loads, etc.), and offers energy and flexibility services to both the TSO and the DSO via its participation in the respective electricity markets and the optimal management of its portfolio (see Figure 1).

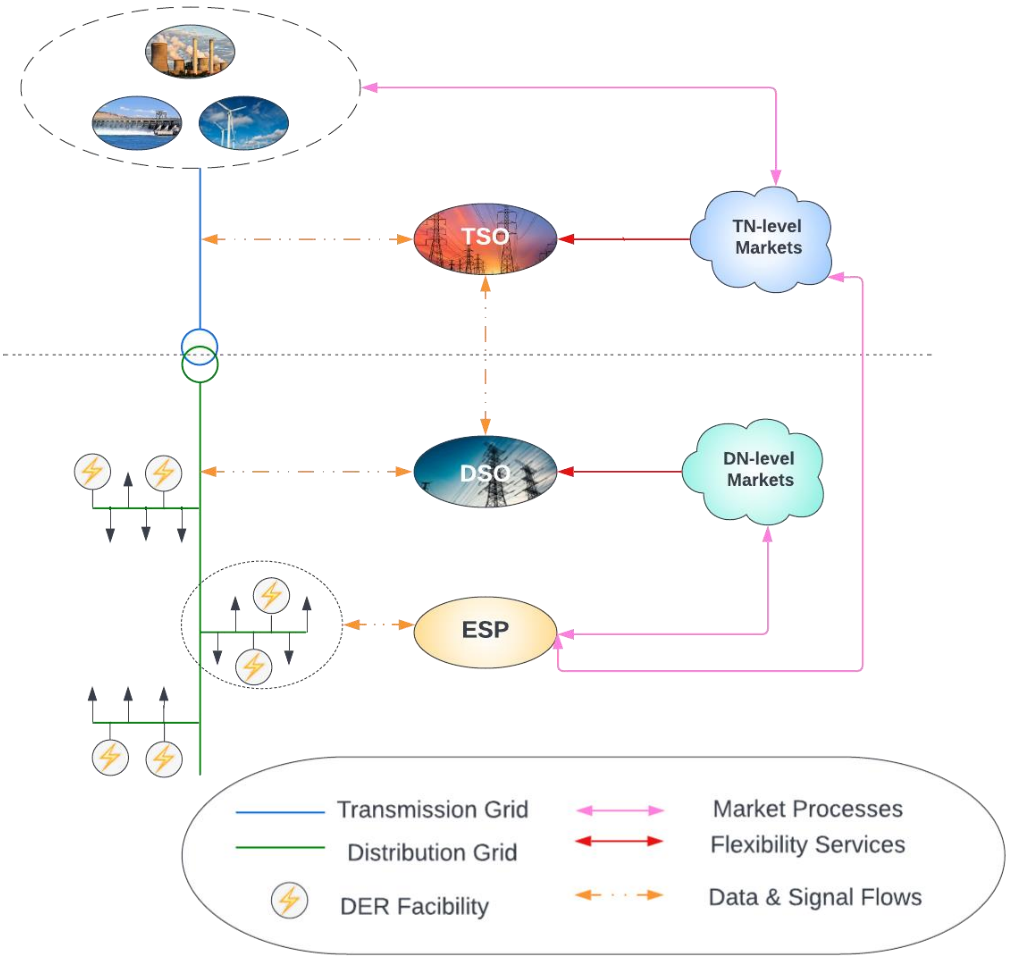

Figure 1: System Architecture

Various power system entities can act as an ESP, e.g., an Energy Community Controller, an Aggregator, an Active Distribution Network Operator, a Balancing Service Provider, etc. We also formulate *TSO-DSO* coordination schemes, which enable the participation of the DERs in distribution-level and transmission-level energy and flexibility markets. Thus, ESPs can: a) trade energy through wholesale electricity markets, b) participate through the aggregation of their flexibility assets in AS markets by offering flexibility services to the system operators (DSOs/TSOs), and c) sell energy to their price-responsive customers (end-users) through liberalized retail markets. In order to be financially sustainable, an ESP has to make optimal decisions in the planning and the operational stage (Figure 2).

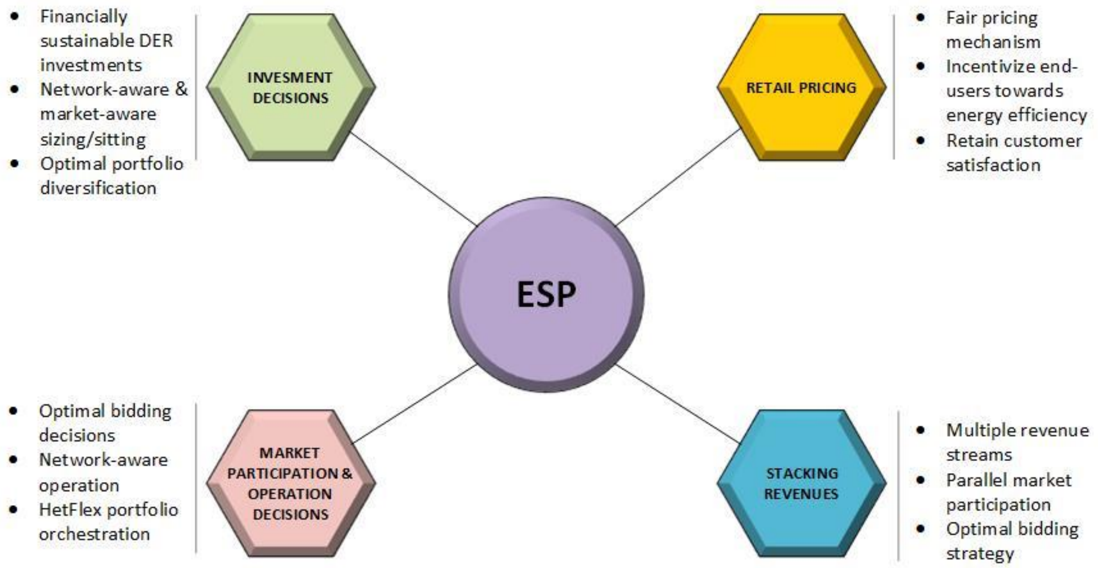

Figure 2: ESP's Decision-Making Framework

1.1.3.1. DERs Investment Decision Making Process

The liberalization of the electricity markets along with the ever-increasing penetration of RES in the generation mix has highly complicated the task of investment decision making. Investors are now exposed to much higher risks, since they have to deal with the uncertainty pertaining to the market competition, demand, renewable generation and fuel prices among others. In order to ensure the sustainability of the investments, first of all, the ESP has to choose the optimal asset allocation, so that a profitable portfolio of various DERs to be built. To this end, the ESP has to take into account the market price signals and the market competition in order to more accurately estimate the potential revenues and ultimately the return on its investments (*market-aware planning decisions*). On top of that, the DER investment decisions need also to take into account the distribution network limitations as is emphasized in [9], in order to be guaranteed that the newly installed DERs will not compromise the reliable and smooth operation of the distribution network. Therefore, the size and the location (sizing/siting) of the DERs have to be carefully selected, in order for the newly installed assets not to be under-utilized for network security reasons and for the ESP to avoid any over- or under-investment contexts (*network-aware planning decisions*).

Numerous research works have dealt with the *network-aware* investment problem of DERs. The relative studies can be divided into two categories based on the ownership of the DERs. Works that fall into the first category (e.g. [10], [11], [12], [13], [14], [15], [16], [17] and [18]) assume that the DERs are owned and operated by the DSO. In this case, the DERs investment decision making process is modeled as a stochastic optimization problem with the objective of determining a set of investment (size, location) and scheduling variables under various operating conditions. The objective function includes a single or multiple objectives, which can incorporate: a) investment costs, b) technical criteria (e.g., minimizing thermal losses, voltage deviation, load curtailments, etc.), or c) economic (market) criteria (profit maximization) in case the DSO acts as a market entity (DisCo). The constraint set includes the distribution network constraints and DERs operating constraints, in order for the network's feasible operation to be ensured. The second strand of research (e.g. [19], [20], [21], [22], [23], [24], [25], [26]) considers that the DERs are owned by private for-profit ESPs. These studies formulate multi-stage or multi-level optimization problems in order to model ESP-DSO coordination frameworks, within which the financial sustainable and distribution network-aware investment decisions are taken. The main difference with our approach is that the existing works do not take into account the TSO's objective to optimally exploit the available distributed low-cost energy and flexibility. To the best of our knowledge, there is no modeling framework for merchant investments in DERs that unlocks the TSO-DSO coordination in order to enhance the utilization of DERs for providing energy and flexibility services in both systems.

1.1.3.2. ESP's Market Participation and DERs' Operation Decision Making Process

Apart from the investment decisions, the ESP has to optimally choose its market participation strategy and DERs' scheduling decisions. The ESP has to orchestrate its portfolio in order to maximize its profitability by optimizing its participation in the liberalized electricity markets. Moreover, as in the investment stage, so in the operating phase of the DERs, the distribution network constraints should be considered (*network-aware bidding strategy and operation*), in order to avoid any societal and monetary costs incurred from a potential network contingency and for the ESP's profitability not to be hampered.

There is a great deal of studies dealing with the bidding and scheduling problem of a Virtual Power Plant (VPP) that acts as an ESP and controls distributed generators, Energy Storage Systems (ESSs), flexible and non-flexible demand. Works in [27], [28], [29], [30] and [31] devise bidding strategies for Virtual Power Plants (VPPs) that own and control various technologies of DERs in different electricity markets. However, these works do not take into account the distribution network limitations. Thus, in case of voltage or congestion issues, corrective actions will be needed, leading in very high monetary or societal costs. Studies [32] and [33] assumed Distribution Companies (DisCos) acting as ESPs and studied their market participation and DER scheduling problem, while ensuring the reliable operation of the distribution network since they take into consideration technical network constraints. All the aforementioned works, [27] - [33], considered *price-taker* ESPs, i.e., ESPs that with their actions cannot affect the market prices. However, the ability of DERs to produce and store energy renders the ESPs *price makers*, i.e., able to affect the market prices by performing temporal arbitrage and changing their roles from producers to consumers and vice versa. In addition, the above research studies considered just one distribution network connected to a single transmission network bus. Hence, there is no bidding model in the literature that considers the coordination of DERs geographically dispersed and connected to different distribution networks.

1.1.3.3. Multiple Markets Participation and Stacked Revenues Optimization

In order to reduce its risks and eventually guarantee the sustainability of its investments, the ESP should have various revenue streams. Depending on the resources in its portfolio, the network services that they can provide and the profit opportunities of each market, the ESP should decide on the energy and flexibility markets that it should participate. Then, bidding strategies have to be devised that will maximize ESP's revenues from its parallel participation in multiple electricity market (*Stacked Revenues*).

Recent literature has dealt with the problem of optimizing a multi-service portfolio of DERs owned by a private entity (ESP). Authors in [34], [35], [36], [37], [38] and [39] considered ESPs controlling energy and flexibility assets connected to a distribution network that provide energy and ancillary services to both the DSO and the TSO. Nevertheless, these works assumed that the distribution grid services are compulsory, or that they are compensated based on a price arbitrarily set by the DSO, without examining how this price is calculated.

1.1.3.4. Retail Pricing Mechanism

In the Smart Grid era, the concept of Demand Side Management (DSM) has been introduced. The rationale behind DSM is to motivate electricity consumers to adjust their consumption so as to reduce the system's energy cost. The ESPs can design smart and effective retail pricing schemes that will trigger behavioral changes to their customers, providing them with attractive monetary incentives. This will result in lower wholesale electricity costs for the ESPs, and at the same time, provide them with additional flexibility that will boost their revenues from the provision of flexibility to the SOs.

In the context of liberalized retail electricity markets, a pricing mechanism has to achieve an attractive trade-off between the following requirements: (i) consumers' welfare, (ii) energy cost and (iii) fairness in cost allocation. The first requirement determines the willingness of the end users to participate in a DSM program. The objective of the DSM mechanisms proposed in studies [40], [41], [42] and [43] was the maximization of users' welfare. The second requirement expresses the capability of a pricing scheme to motivate energy consumers to adopt energy efficient consumption patterns, and ultimately fulfill the objective that the ESP sets. Studies in [44], [45], [46] [47] and [48] devised DSM algorithms in order to minimize the energy costs without sacrificing consumers' comfort. Lastly, the third requirement refers to how fairly the energy cost savings are allocated among the end-users. Works in [49], [50] and [51] opt for enhancing the system's fairness. In [49] the efficiency (cost minimization) is sacrificed in order to achieve higher levels of fairness, while in [50] the trade-off between cost minimization and fairness is studied, however disregarding users' welfare. The trade-off between all the three above-mentioned requirements has not been studied in the literature.

1.2. Modeling ESP's Decision Making

1.2.1. Bilevel Modeling

Bilevel Programming (BP) refers to the area of optimization dealing with problems that have a hierarchical structure [52]. This concept originated from the field of economic Game Theory and was introduced by Heinrich Freiherr von Stackelberg in [53], with Bracken and McGill in [54] introducing the first mathematical model. A bilevel problem involves two decision-making levels: a Leader and one or multiple Followers (see Figure 3).

As depicted in Figure 3, the so-called Leader in the Upper-Level optimizes its objective function subject to a set of constraints, which is in part composed by the optimal decisions of the Follower (Lower-Level). The Leader's decisions influence the feasible set and the objective function of the Lower-Level problem. In turn, the reaction of the Follower has a

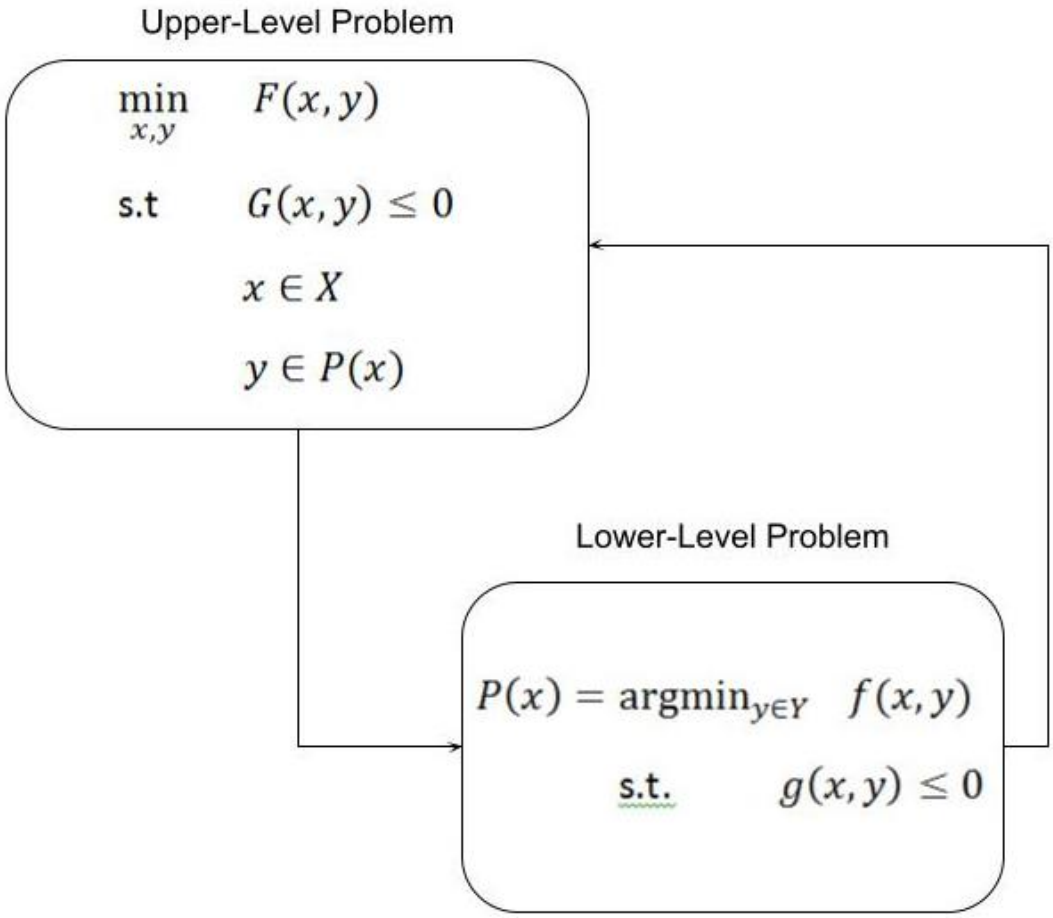

Figure 3: Hierarchical structure of a Bilevel Problem

significant impact on the Leader's feasibility set and its payoff. Ultimately, the bilevel optimization problem is the Leader's optimization problem, mathematically formulated using the graph of the solution set of the Follower's optimization problem.

Bilevel Programming is very important in modeling decision making in various liberalized electricity markets, since it provides models and tools towards understanding the functioning of these markets and identifying decisions for public or private power sector actors. More specifically, BP allows for the:

- Direct manipulation of both primal (physical) and dual (price) variables.
- Capturing the opposing interests of different parties, as they are embodied by different objective functions in the upper- and the lower-level.
- Modeling of closed-loop investment models through the uncoupling of investment and operation decisions.
- Unlocking the coordination between System Operators (DSO and TSO)
- Modeling of the strategic behavior of market participants, whose decisions affect the outcome of other agents.
- Equilibrium analysis of electricity markets with oligopolistic characteristics.

In recent years, BP has been extensively used in the literature to aid decision making in the planning and operational stages of the liberalized power sector. Research studies in [55], [56], [57] and [58] have used BP in order to model network planning decisions on behalf of

System Operators. In the upper-level problem, TSO or DSO optimizes its investments in transmission capacity or energy storage by minimizing the network operation and investment costs, while the lower-level problem represents the electricity market clearing process. Another strand of research considered merchant ESPs that seek to invest in conventional generation ([59], [60], [61], [62]), RES units ([63], [64], [65]) or energy storage capacity ([66], [67], [68], [69]) with the objective of maximizing their market profitability (upper-level problem), while taking into account how their investment decisions affect the results of the market clearing process (lower-level problem). Additionally, numerous works have dealt with the bidding problem of an ESP that strategically participates in one or more electricity markets. These works have devised market strategies for generators ([70], [71] [72], [73], [74], [75], [76], [77], [78]), storage owners ([79], [80], [81], [82], [83], [84]), demand aggregators ([85], [86]) and convergence bidders ([87]) that participate in different energy or ancillary services markets.

In general, bilevel optimization problems are highly non-convex problems. The more common approach to solve them is by converting them into single-level problems. To this end, the lower-level problem is replaced by its (under certain assumptions) necessary and sufficient optimality conditions, the Karush-Kuhn-Tucker (KKT) conditions. In this way, the bilevel problem is converted into a Mathematical Program with Equilibrium Constraints (MPEC), which is Mixed Integer Non-linear Problem (MINLP). Using specific linearization techniques, the MINLP is finally transformed into a Mixed Integer Linear Problem (MILP) that can be solved using off-the-shelf solvers. However, large-scale problems, such as stochastic bilevel problems, can possibly not be solved in a reasonable amount of time. In order for these problems to be efficiently solved in a scalable fashion, algorithms that reduce the complexity of the BP models, like decomposition techniques ([88]), have been introduced.

1.2.2. Game-Theoretical Frameworks for Demand Side Management

Game Theory is considered as a key analytical tool in the design of Demand Side Management programs, enabling ESPs to optimize their pricing strategies that adapt to the state of the grid and the electricity markets. Game Theory is a formal analytical and conceptual framework that studies the strategic interactions among independent rational agents and can be divided into two main branches: a) Cooperative Game Theory and b) Noncooperative Game Theory. In Cooperative Game Theory it is assumed that independent decision makers can cooperate and act together as one entity so as to improve their position in the game. On the contrary, Noncooperative Game Theory can be used to analyze the strategic decision-making processes of a number of independent entities, i.e., players that have partially or totally conflicting interest over the outcome of a decision process that is affected by their actions. Essentially, noncooperative games can be seen as capturing a distributed decision-making process that allows the players to optimize, without any consideration or communication, objective functions coupled in the actions of the involved players. A noncooperative game Γ is defined by:

- A set of *Players*: $\boldsymbol{N}$
- The sets of the *Strategies* of each *Player* i: $(\boldsymbol{S_i})_{i \in \boldsymbol{N}}$
- The sets of the *Payoffs* of the *Players*: $(u_i)_{i \in \boldsymbol{N}}$

In such a game, each *Player* i selects a *Strategy* $s_i \in \boldsymbol{S_i}$ in order to maximize its *Payoff* $u_i(s_i, \boldsymbol{s_{-i}})$, which depends not only on its own choice of s_i, but also on the vector of

Strategies chosen by the other *Players* in $\boldsymbol{N} \backslash \{i\}$, denoted by $\boldsymbol{s}_{-i}$. The objective of Noncooperative Game Theory is to provide methods and algorithms suitable for solving such optimization problems, analyzing their outcomes and eventually finding a Nash Equilibrium. The Nash Equilibrium characterizes a state of the game in which no *Player i* can improve its *Payoff* u_i by changing unilaterally its *Strategy* s_i, given that the *Strategies* of the other *Players* $\boldsymbol{s}_{-i}$ are fixed.

Game Theoretical frameworks have been extensively proposed in the literature ([89]) in order to design price-based DSM programs, where the electricity consumer is envisaged as a rational agent (*Player*) that derives a particular utility (*Payoff*) from her/his electricity consumption pattern (*Strategy*). Hence, the consumer chooses a specific consumption pattern in order to maximize her/his *Payoff*, based on a specific monetary incentive (price) provided by the designer of the DSM program.

1.3. Contributions and Structure of this Thesis

In this thesis, we deal with the decision-making framework of an ESP, whose objective is to ensure the financial sustainability of its investments in distributed energy and flexibility resources. More specifically, we devise algorithmic tools that model the four decision-making processes illustrated in Figure 2.

First of all, in order to fill the research gap discussed in subsection 1.1.3.1, we use bilevel modeling in order to define a coordination scheme between DSO-TSO. Within this context, we propose a DER investment model which: (a) guarantees the return on investments of the ESP, (b) takes into account the impact of the newly installed DERs on the market prices, and (c) ensures the smooth operation of the distribution network. In order to efficiently solve it in a scalable fashion, we propose a nested decomposition algorithm based on the Lagrangian Relaxation and the Bender's Decomposition technique. Chapter 2 discusses the open research issues in this area, presents in detail the proposed bilevel investment model, describes the solution algorithm and evaluates the proposed framework.

In Chapter 3, a bidding strategy of an ESP that owns a portfolio of diverse assets located at various geographical areas is proposed. We assume that the operation of the distribution network is regulated and a Distribution Company (DisCo) has control over the network assets, representing them in the wholesale energy market. In contrast to the relative research works that consider *price-taker* DisCos, we assume that performing spatio-temporal arbitrage DisCo can have impact on the market prices. Therefore, we formulate a bilevel problem in order to calculate the optimal bidding strategy of the DisCo. The bilevel problem is converted into a solvable single-level MILP using the MPEC method. The simulation results demonstrate how a DisCo can significantly reduce its energy costs acting strategically, and how the market dispatch and prices are affected by its actions.

In Chapter 4 we consider a deregulated distribution network environment, where the DSO's only responsibility is the secure operation of its network. We propose a novel energy market architecture, where the ESPs participate autonomously in transmission-level markets. In order to avoid any distribution network contingencies, a Distribution-Level Flexibility Market (DLFM) is introduced, via which the DSO purchases the needed flexibility from the ESPs. The interactions between transmission-level and distribution-level markets are explicitly described. In opposition to the relative literature, the DLFM clearing process explicitly quantifies the need for flexibility per distribution network node and calculates the

Distribution Locational Marginal Prices (DLMPs), which accurately reflect the flexibility costs. In this context, we deal with the bidding and scheduling problem of an ESP owning a portfolio of distributed battery storage units, that provides energy and flexibility services to the System Operators, participating in both transmission-level (Day-Ahead Energy, Reserve and Balancing Market) and distribution-level (DLFM) markets. To this end, we formulate a bilevel model for the bidding and scheduling problem of the ESP. In order to solve our bilevel model in a scalable fashion, we first transform it into a single-level MINLP using the MPEC method, and consequently we apply a novel iterative process.

In Chapter 5 the absence of a retail pricing mechanism that simultaneously considers the three requirements described in 1.1.3.4 is highlighted. We present a novel personalized energy pricing scheme, referred to as Behavioral Real-Time Pricing (B-RTP) assuming strategic end-users. The proposed DSM strategy incentivizes price-responsive end-users towards energy efficient patterns of consumption, by achieving high level of fairness. We also introduce a mechanism that parameterizes the proposed pricing scheme, enabling the ESP to dynamically adjust the degree of incentives. In this way, the ESP can select the more attractive trade-off among energy cost, users' welfare and fairness. Comparing B-RTP with a version of an existing RTP scheme that is widely adopted in the literature, we demonstrate that B-RTP outperforms RTP in terms of energy cost reduction, without sacrificing users' welfare and enhancing fairness.

Finally, Chapter 6 concludes the dissertation. We analyze the most important research findings and discuss about potential directions to further extend our work. Moreover, we consider the various stakeholders for whom our work can provide useful tools.

2. Chapter 2: Financially Sustainable Network-Aware DER Investments

In this Chapter a financially sustainable network-aware and market-aware DER investment decision-making framework is proposed for an ESP (Figure 4). As DER penetration levels and distributed flexibility investments are continuously growing, various power system stakeholders need to coordinate their decisions towards optimal DER siting and sizing. First, ESPs want to secure their long-term profits and avoid economically unsustainable DER investments. Second, DSOs need to ensure the reliable operation of their networks in an economically efficient way. Third, TSOs want to optimally exploit the available "clean" DERs in close collaboration with the downstream DSOs. In this thesis, we propose a novel ESP-DSO-TSO coordination scheme to co-optimize distributed renewable energy and storage planning at the distribution network level, while modeling the coordinated TSO-DSO operations. We formulate a bi-level program, the upper-level of which minimizes the DSO's costs, ensuring a minimum rate of return on ESP's investments, while the lower-level models the transmission network-constrained wholesale market. A nested decomposition technique is used to achieve computational tractability. Simulation results showcase a trade-off analysis between sustainable DER investments and system cost minimization and prove that an ESP-DSO-TSO interaction can benefit all involved actors to a certain extent. Finally, the computational efficiency of the proposed solution algorithm is demonstrated via numerical results.

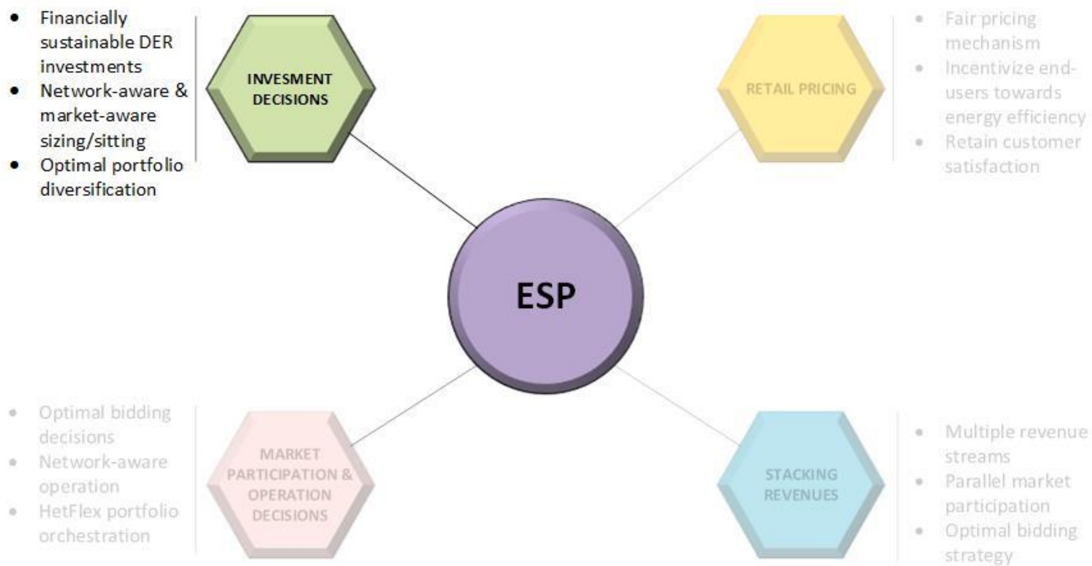

Figure 4: ESP's DER Investments Decision-Making

This Chapter's structure is organized as follows: Section 2.1 is introductory and describes the motivation behind our proposed investment model. Section 2.2 discusses related work and underlines our contributions. Section 2.3 describes the proposed bi-level formulation of the problem. Section 2.4 presents the solution method. Section 2.5 discusses potential model extensions. Section 2.6 provides a detailed evaluation of the proposed solution. Finally, Section 2.7 concludes Chapter 2 and discusses future work.

Nomenclature

	Sets		*Parameters*
$\boldsymbol{B_i}$	Set of nodes at DN $\boldsymbol{i}$, indexed by $\boldsymbol{n,k,j}$	$c^{\uparrow/\downarrow}$	Price offers/bids of DN assets (€/MW)
$\boldsymbol{H}$	Set of timeslots in the scheduling horizon, indexed by t	$c^{es/w/pv}$	Marginal operating cost of ES/Wind/PV units (€/MW)
$\boldsymbol{L_i^D}$	Set of branches at DN i	$c^{g/d}$	Price bids of Generators/Demand Aggregators (€/MW)
$\boldsymbol{L_i^T}$	Set of TN lines	C	Capital costs (€/MW)
$\boldsymbol{N}$	Set of nodes at TN, indexed by i,j	$\tilde{C}$	Annualized capital costs (€/MW)
$\boldsymbol{X^{U/L/MP}}$	Set of optimization variables	$\overline{C^{inv}}$	Investment budget (€)
$\boldsymbol{\Omega}$	Set of representative days, indexed by ω	D	Load of distribution network (MW)
$\boldsymbol{\Omega^i_{d/p}(n)}$	Set of decedent/precedent nodes connected to node n of the DN i	$\overline{f^S}$	Maximum apparent power of DN branches (MVA)
	Superscripts	I/W	PV energy output/Wind intensity factor
$\boldsymbol{e/p}$	Superscript indicating the energy/power component of ES	$\overline{K}$	Maximum capacity that can be installed (MW)
$\boldsymbol{es/w/pv}$	Superscripts indicating the Storage/Wind/PV technology	$\overline{p_\iota}$	TSO-DSO connection point (substation) capacity (MW)
$\boldsymbol{m/g/d}$	Superscripts indicating the TN nodes with DNs/Generators/Demand Aggregators	$\overline{p^{g/d}}$	Maximum power of generation/demand (MW)
$(\cdot)$	Superscript indicating the algorithm's iteration	r/x	Resistance/Reactance of DN branches
	Variables	RU/RD	Ramping up/down capabilities of Generators (MW/h)
$\boldsymbol{dis/ch}$	Scheduled ES discharge/charge power (MW)	T	Last timeslot of the scheduling horizon
$\boldsymbol{f^{p/q}}$	Active/reactive power flow in distribution network (MW/MVAr)	$\overline{T}$	Transmission network line capacity (MW)
$\boldsymbol{g^{w/pv}}$	Power output of wind/PV units (MW)	$\underline{V}/\overline{V}$	Lower/Upper bounds on square voltage magnitude (kV^2)
$\boldsymbol{h}$	Binary variable denoting the direction of power traded between DSO-TSO	y	Transmission line admittance
$\boldsymbol{K}$	Size variables	β	Minimum ES state of charge at the end of the scheduling period
$\boldsymbol{o/b}$	Quantity offer/bid by the DN assets to the electricity market (MW)	γ^{min}	Large negative constant
$\boldsymbol{p^{\uparrow/\downarrow}}$	Power traded (sold/bought) between DSO-TSO (MW)	δ	Parameters converting active power into their reactive power – tan(arccos(power factor))
$\boldsymbol{p^{g/d}}$	Electricity market dispatch of Generators/Demand Aggregators (MW)	ϵ_1/ϵ_2	Convergence tolerance for the inner/outer decomposition procedures

$\boldsymbol{SOE}$	State-of-Energy of ES (MWh)	$\eta^{d/c}$	Discharging/Charging efficiency of ES
$\boldsymbol{V}$	Square voltage magnitude in distribution network (kV^2)	η^{pv}	PV efficiency
$\boldsymbol{w}$	Binary variable denoting the operating mode of ES	$\kappa, \rho, \upsilon, \tau$	Algorithm iteration counters
$\boldsymbol{z}/\boldsymbol{\xi}$	Auxiliary variables in outer decomposition	π_{ω}	Weight of representative day ω
$\boldsymbol{\gamma_{\omega}}/\boldsymbol{\mu}$	Auxiliary variables in inner decomposition	ρ	Energy/Power ratio of ES
$\boldsymbol{\theta}$	Transmission network's voltage phase angle	Φ	Large constant
$\boldsymbol{\lambda}$	Locational Marginal Price (€/MW)	χ	Desired rate of return on DERs investment
$\boldsymbol{\phi}$	Dual variables of the lower-level problem		

2.1. Co-optimization of Distributed Renewable Energy and Storage Investment Decisions in a TSO-DSO Coordination Framework

Regulatory authorities from the world's most developed economies have undertaken clean energy transition initiatives and respective legislative efforts, towards actively incentivizing investments in distributed energy (e.g. photovoltaics, wind turbines, etc.), and flexibility (e.g. battery, storage, etc.) installations at the distribution network (DN) level ([90], [91], [92]). For example, US FERC [90] emphasizes the need for coordinated DER planning via the collaboration of three main actors, namely: the ISO/RTO (i.e., transmission level), the distribution utility, and the DER aggregator. In EU legislation [91], the DSO's main role is unbundled from profit-based ESPs, i.e., distributed energy and flexibility owners. In other words, ESPs are the main responsible market actors for DER investments, while DSOs are mainly responsible for operating the DN in a reliable, secure and economically efficient manner. As a result, ESPs and DSOs should closely collaborate towards DN-aware DER investments, while DSOs should closely collaborate with TSOs in order to facilitate seamless DER market participation. Complementarily, work in [92] also focuses on *investment-friendly* and *system-friendly* renewable energy deployments implying the need for achieving a balance between these two contradictory objectives.

In this thesis, we deal with the problem of co-optimizing distributed renewable energy and storage investments (i.e., optimal sizing and siting of distributed PV, wind and storage assets), while modeling also the operational stage of the distribution and transmission networks. We formulate a bi-level model, in which the payoff of all DN users is optimized, to incentivize DERs profitability and maximum exploitation of distributed energy and flexibility services in both DN and TN levels. The central contribution lies in the modelling of an integral *ESP-DSO-TSO coordination scheme*, which jointly addresses the current real-life business challenges of these three actors. More specifically, the main problem of actual ESPs is not having access to detailed DN topology data, which leads them to inadequate, sub-optimal and/or financially unsustainable DER and flexibility investments. On the other hand, the DSOs cannot provide access to sensitive network topology data to profit-based ESPs and would strongly prefer to have full control of the DN-level investment planning process. However, regulated investments would dis-incentivize merchant DER investments and would be in contradiction with previously mentioned regulatory directives that press the DSOs towards providing the appropriate transparent, non-discriminatory and market-based procedures for procuring novel energy and flexibility services from profit-based ESPs [91]. Finally, today's TSO problem is that it cannot optimally exploit the available DN-level energy and flexibility due to lack of an efficient TSO-DSO coordination framework and because profit-based DER investments are DN-unaware.

2.2. Related Work

Three main research threads can be identified in the related literature. The first thread deals with ESP-TSO coordination schemes for optimal RES and/or storage sizing and siting at the transmission network (TN) level. The work in [65] proposes a Bender's decomposition algorithm to solve a bi-level problem, in which the upper-level problem represents the wind investment and operation decisions of an ESP at TN level, and the lower-level problems describe the wholesale market clearing under different wind and load conditions. Authors in [56], [66], [68], [69] [93], [94] and [95], and propose various bi-level models for optimal storage planning at the TN level together with novel decomposition techniques to deal with the computational complexity. Works [56], [68], [94] and [95], and guarantee the ESP's profits ensuring a desirable Return-on-Investment (RoI) considering the storage asset's market participation with respect to the asset's expected lifetime. In [69] and [95], the risk management problem of the TN-level storage investment is also investigated, trying to achieve an acceptable trade-off between maximum (average) expected profits and minimum guaranteed profits for the ESP's investment portfolio. Authors in [96] co-optimize the ESP's RES and storage planning decisions at TN-level via its participation in day-ahead, intra-day energy and reserve markets. While the studies mentioned in this paragraph model assets connected to the transmission network, in this thesis we focus on investments in DN-level assets. Under this consideration, it is critical to model the DN topology constraints [9] in order to guarantee DN reliability and security and ultimately avoid miscalculations of the DN-level energy and flexibility value [97].

The second related research thread deals with TSO-DSO coordination schemes. The TSO-DSO coordination has been previously studied in the literature. Studies in [98] and [99] analyze the advantages and drawbacks of several TSO-DSO coordination schemes with respect to business interest prioritization of each actor, while works [100] and [101] propose decomposition algorithms for the coordinated economic dispatch of both TN- and DN-level systems that can capture the heterogeneous technical characteristics of both systems. Integrated investment models in a TSO-DSO coordination framework have been proposed in [58], [102] and [103]. Work in [102] proposes an integrated approach for transmission and distribution system expansion planning, where both RES and network assets are planned. In [103], a bi-level model is proposed to coordinate the decisions of Distribution Companies (DisCos) for distribution expansion problem (i.e., upper-level) and TN-level market clearing decisions (i.e., lower-level). Authors in [58] proposed a modeling framework for the coordinated storage investment under a unified TSO-DSO collaboration scheme. However, works in [58], [102] and [103] do not consider the latest regulations (e.g. [91]) dictating the unbundling of profit-based ESPs and non-profit DSOs. In contrast to these works, our study emphasizes the need to quantify the impact of privately-owned DER investment decisions on the Transmission and Distribution (T&D) systems' operating costs by aspiring to find an optimal equilibrium point that satisfies all three involved actors. Also, unlike [58], we consider a co-optimized planning model of both distributed energy and flexibility (i.e., storage) assets.

Finally, the third research thread is related with *ESP-DSO coordination schemes*. The main difference with our approach is that related works [19], [20], [21], [22], [23], [24], [25] and [26] do not take into account the TSO's objective to optimally exploit the available distributed energy and flexibility. Thus, a rather myopic DER planning is realized, that does not consider the impact of the newly installed low-cost energy and flexibility units on the transmission-level market prices. The work in [19] deals with a two-stage stochastic problem, in which initially the DSO minimizes its DN reinforcement costs and in the second stage the ESP's planning and scheduling problem takes place. Study [20] co-optimizes the ESP's and DSO's investment decisions showing that the ESP's flexibility significantly defers costly network upgrades. Authors in [21] achieve an optimal trade-off between the mobile storage profits during normal system operations and their ability to enhance DN resilience in emergency situations. Research work in [22] formulates an optimization problem in a way that includes both the ESP's profits and the DN constraints that guarantee power quality. Studies [23] and [24] propose bi-level models to achieve the collaborative optimization between planning and operation of DN-level storage assets. Furthermore, the bi-level model proposed by [25] considers a local energy market clearing at the lower-level, while the upper-level problem makes the DN-level investment decisions to minimize the DSO's costs by guaranteeing a minimum RoI for the ESP like works [56], [68], [94] and [95], and do. Finally, authors in [26] try to find an optimal equilibrium between three market actors, namely a DisCo that tries to maximize profit from DN assets' investment (i.e. upper-level), a DGENCO that tries to maximize profit from DER investment (i.e. middle-level) and an independent DSO that tries to minimize system's operating costs (i.e. lower-level). Our work is inspired by this trade-off analysis and aims at finding a "win-win-win" equilibrium among the ESP, the DSO and TSO. Once more, the main difference with models in [19], [20], [21], [22], [23], [24], [25] and [26] is that our proposed planning strategy involves the TSO, which is critical towards exploiting low-cost distributed energy and flexibility assets at TN-level.

The contributions of this thesis can be summarized as follows:

1. Instead of modeling investments on behalf of a *vertical utility* actor (e.g. DisCo) as in [58], [102] and [103] we follow the recent regulatory framework updates, which dictate the complete unbundling of market roles for DER investment planning between a profit-based ESP and a system operator. Thus, we conduct a trade-off analysis between sustainable DER investments (i.e., investment-friendly planning) and system cost minimization (i.e., system-friendly planning) by demonstrating that ESP-DSO-TSO interaction can achieve T&D operating costs' reduction and sufficient levels of profitability for the ESP.
2. We *co-optimize* network-aware and market-aware distributed energy (RES) and flexibility (storage) investments in multiple DNs within a TSO-DSO coordination scheme. To the best of our knowledge, this is the first work that models private DER and storage investments by taking into account both the DSO's (i.e., network-aware) and TSO's (i.e., market-aware) objectives.
3. In contrast to [19], [20], [21], [22], [23], [24], [25] and [26], we capture the impact of the newly installed DERs on the transmission-level energy market prices, by formulating a stochastic bi-level investment model. This is particularly relevant in

order for the ESP to avoid over-investment contexts that may take place in local DN areas, as demonstrated in subsection 2.6.4.

4. The bi-level model is efficiently solved in a scalable fashion using a nested decomposition technique. We compare the computational performance of the proposed method to a non-decomposed MILP approach and demonstrate the algorithm's accuracy and scalability.

2.3. System Model & Problem Formulation

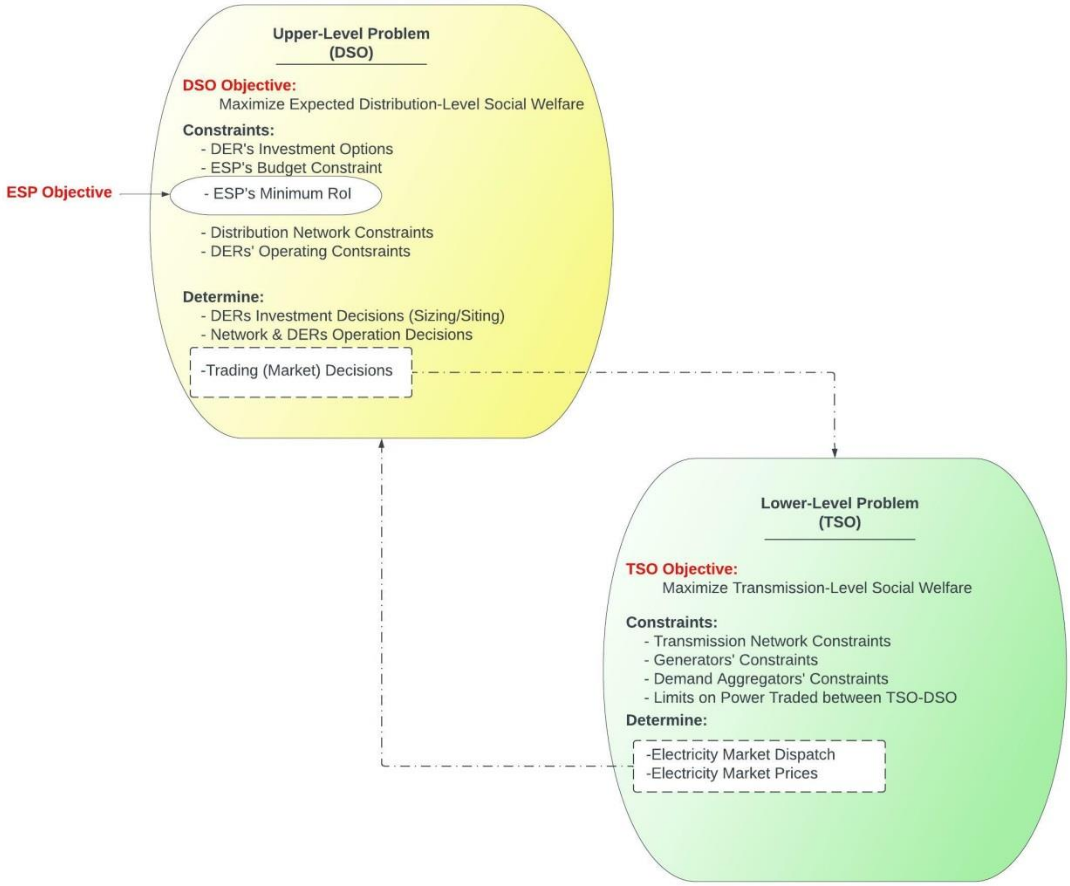

Figure 5: The proposed bi-level approach for private investments in DERs

We model the interaction between a DSO, a TSO and a private ESP that seeks to invest in distributed wind and PV generation units as well as in Energy Storage (ES) units in multiple DNs dispersed in various geographical areas (TN nodes) and make profit by participating in the TN-level electricity market. The DSO decides on the DER investments with respect to its network limitations and ensuring that its decisions are financially sustainable for the ESP. To this end, we propose a stochastic bi-level model in order to formulate the ESP-DSO-TSO coordination, which is depicted in Figure 5. Bilevel modeling allows us to:

- Capture the distinct objectives of all the involved parties,
- Take into account both the DN and TN constraints,
- Decouple the investment and market decisions,
- Explicitly take into account the impact of the investments on the market prices.

The objective of the upper-level problem is to decide the new investments so as to minimize the total expected costs of the DNs' stakeholders (or else maximize expected DN-level *Social Welfare*), i.e., achieving a balance between the ESP's profits from the new investments and the electricity cost of consumers already connected to each DN. The former consists of the ESP's expected revenues stemming from the optimal DA market participation minus the operational costs and investment costs. The objective of the ESP is to guarantee the economic viability of its investments. Therefore, a minimum rate of return on the investments is imposed on the upper-level problem, in order for the profitability of ESP to be preserved. Additionally, the operation of the DERs and the overall distribution grid is modeled in this level. The upper-level problem decides on the distribution network operation and the energy trade with the upstream grid. Note that the relevant optimal operational decisions are contingent on the investment decisions as well as the DN constraints, including power flow and voltage limits. The trading decisions are input parameters for the lower-level problem.

The lower-level problem represents the TN-constrained day-ahead electricity market clearing process, with the TSO's objective being the social welfare maximization. Thus, the objectives of all involved actors (DSO-TSO-ESP) are taken into account. The market clearing results (dispatches and prices) are used in the upper-level problem for the calculation of the expected market revenues of all DN users. In order to model the uncertainty associated with the overall system's load, the DN's demand and the wind/solar production, we produce a plausible number of scenarios by using data of diverse representative historical days. As it is customary in static investment analysis (e.g. [56], [65], [66], [68], [93], [94]), the investment study is performed for a single target year, while the operational decisions are optimized for each representative day individually.

2.3.1. Upper-level Problem: Siting and Sizing of DERs

The upper-level problem minimizes the total expected DN cost (or, equivalently, maximize expected DN *Social Welfare*) over all representative days, i.e., the annualized DER investment cots ($\tilde{C}^{inv}$) and the DN assets' expected operating cost. The latter includes the expected cost of electricity traded with the upstream grid ($\sum_{\omega\in\Omega} C_\omega^{DN}$) and the expected DER operating costs ($\sum_{\omega\in\Omega} C_\omega^{oper}$):

$$\min_{X^U} \sum_{\omega\in\Omega} \left(C_\omega^{DN} + C_\omega^{oper}\right) + \tilde{C}^{inv} \tag{2.a.1}$$

where the annualized investment cost, the cost of electricity traded in the electricity market, and the DERs' operating costs in each representative day (weighted by the relative importance π_ω of the day they represent), are calculated as follows:

$$C_\omega^{DN} = \pi_\omega \cdot \sum_{i\in N^m} \sum_{t\in H} \left(\lambda_{it\omega} \cdot \left(p_{it\omega}^{\downarrow} - p_{it\omega}^{\uparrow}\right)\right) \tag{2.a.2}$$

$$C_\omega^{oper} = \pi_\omega \cdot \sum_{i\in N^m} \left(\sum_{t\in H} \left(\sum_{n\in B_i^{es}} c^{es} \cdot \left(dis_{int\omega} + ch_{int\omega}\right) + \sum_{n\in B_i^{w}} c^{w} \cdot g_{int\omega}^{w} + \sum_{n\in B_i^{pv}} c^{pv} \cdot g_{int\omega}^{pv}\right)\right) \tag{2.a.3}$$

$$\tilde{C}^{inv} = \sum_{i\in N^m} \left(\sum_{n\in B_i^{es}} \left(\tilde{C}^{e} \cdot K_{in}^{e} + \tilde{C}^{p} \cdot K_{in}^{p}\right) + \sum_{n\in B_i^{w}} \tilde{C}^{w} \cdot K_{in}^{w} + \sum_{n\in B_i^{pv}} \tilde{C}^{pv} \cdot K_{in}^{pv}\right) \tag{2.a.4}$$

The set of DNs in which DERs can be installed is denoted by N^m. The overall DN assets' cost from the electricity traded in the day-ahead electricity market in representative day ω is defined in Eq. (2.a.2), where the nodal prices at the transmission buses connected to the root nodes of the DNs ($\lambda_{it\omega}$) and the wholesale market decisions on the power injected from the DSO to the TSO ($p^{\uparrow}_{it\omega}$) and vice versa ($p^{\downarrow}_{it\omega}$) are endogenously obtained from the lower-level problem. The DERs' operating costs in representative day ω are presented in (2.a.3) and the annualized investment cost is computed in (2.a.4), where parameters $\tilde{C}^e, \tilde{C}^p, \tilde{C}^w$ and $\tilde{C}^{pv}$ are the annualized costs in net present value approach [97]:

$$\tilde{C} = C \cdot \frac{\Gamma \cdot (1+\Gamma)^{\Lambda}}{(1+\Gamma)^{\Lambda} - 1}$$

where Γ is the annual discount rate and Λ is the unit's lifetime. In general, not all DN buses are available for installation of DERs, e.g., due to land availability. The sets of DN's buses that are eligible for the installation of wind/PV generation and ES units are B_i^w, B_i^{pv} and B_i^{es} respectively ($B_i^w, B_i^{pv}, B_i^{es} \subseteq B_i, \forall i \in N^m$). The investment decisions ($K_{in}^w, K_{in}^{pv}, K_{in}^e, K_{in}^p$) are constrained by limits on the capacity per technology to be installed, the available investment budget ($\overline{C^{inv}}$) and by the ESP's desired minimum rate on return (χ) on its investments:

$$0 \le K_{in}^w \le \overline{K_{in}^w}, \qquad \forall i \in N^m, n \in B_i^w \tag{2.a.5}$$

$$0 \le K_{in}^{pv} \le \overline{K_{in}^{pv}}, \qquad \forall i \in N^m, n \in B_i^{pv} \tag{2.a.6}$$

$$0 \le K_{in}^e \le \overline{K_{in}^e}, \qquad \forall i \in N^m, n \in B_i^{es} \tag{2.a.7}$$

$$0 \le K_{in}^p \le \overline{K_{in}^p}, \qquad \forall i \in N^m, n \in B_i^{es} \tag{2.a.8}$$

$$\rho \cdot K_{in}^p = K_{in}^e, \qquad \forall i \in N^m, n \in B_i^{es} \tag{2.a.9}$$

$$C^{inv} \le \overline{C^{inv}} \tag{2.a.10}$$

$$\textstyle\sum_{\omega \in \Omega} \left(Pr_\omega^{inv} - C_\omega^{oper} \right) \ge \chi \cdot \tilde{C}^{inv} \tag{2.a.11}$$

Constraints (2.a.5) – (2.a.8) limit the available capacity of wind, PV, ES energy and ES power capacity at each eligible DN area (node) respectively due to several restrictions, such as land availability. Constraint (2.a.9) enforces the Energy-to-Power ratio of the ES units. For the sake of simplicity, the investment variables are considered continuous. Equation (2.a.10) enforces that the total investment cost, which is computed in (2.a.12), cannot exceed the total ESP's investment budget. Constraint (2.a.11) enforces that the ESP's expected annual financial benefit gained from the investment is sufficient to provide a certain desired rate of return χ. Eq. (2.a.13) expresses the ESP's market profit in representative day ω.

$$C^{inv} = \textstyle\sum_{i \in N^m} \left(\sum_{n \in B^{es}} \left(C^e \cdot K_{in}^e + C^p \cdot K_{in}^p \right) + \sum_{n \in B_i^w} C^w \cdot K_{in}^w + \sum_{n \in B_i^{pv}} C^{pv} \cdot K_{in}^{pv} \right) \tag{2.a.12}$$

$$Pr_\omega^{inv} = \pi_\omega \cdot \textstyle\sum_{i \in N^m} \sum_{t \in H} \Big(\lambda_{it\omega} \cdot \Big(\sum_{n \in B_i^w} g_{int\omega}^w + \sum_{n \in B_i^{pv}} g_{int\omega}^{pv} + \sum_{n \in B_i^{es}} (dis_{int\omega} - ch_{int\omega}) \Big) \Big) \tag{2.a.13}$$

Moreover, the DERs' scheduling decisions for each representative day are limited based on the investment decisions and their individual technical characteristics:

$$0 \le g^{w}_{int\omega} \le W_{it\omega} \cdot K^{w}_{in}, \qquad \forall i \in N^m, n \in B^{w}_{i}, t \in H, \omega \in \Omega \tag{2.a.14}$$

$$0 \le g^{pv}_{int\omega} \le \eta^{pv} \cdot I_{it\omega} \cdot K^{w}_{in}, \qquad \forall i \in N^m, n \in B^{pv}_{i}, t \in H, \omega \in \Omega \tag{2.a.15}$$

$$0 \le dis_{int\omega}, ch_{int\omega} \le K^{p}_{in}, \qquad \forall i \in N^m, n \in B^{es}_{i}, t \in H, \omega \in \Omega \tag{2.a.16}$$

$$dis_{int\omega} \le \Phi \cdot w_{int\omega}, \qquad \forall i \in N^m, n \in B^{es}_{i}, t \in H, \omega \in \Omega \tag{2.a.17}$$

$$ch_{int\omega} \le \Phi \cdot (1 - w_{int\omega}), \qquad \forall i \in N^m, n \in B^{es}_{i}, t \in H, \omega \in \Omega \tag{2.a.18}$$

$$w_{int\omega} \in \{0,1\}, \qquad \forall i \in N^m, n \in B^{es}_{i}, t \in H, \omega \in \Omega \tag{2.a.19}$$

$$SOE_{int\omega} = SOE_{in0\omega} - \sum_{\tau=1}^{t} \left(\frac{dis_{in\tau\omega}}{\eta^d} - ch_{in\tau\omega} \cdot \eta^c \right), \quad \forall i \in N^m, n \in B^{es}_{i}, t \in H, \omega \in \Omega \tag{2.a.20}$$

$$0 \le SOE_{int\omega} \le K^{e}_{in}, \qquad \forall i \in N^m, n \in B^{es}_{i}, t \in H, \omega \in \Omega \tag{2.a.21}$$

$$SOE_{inT\omega} \ge \beta \cdot SOE_{in0\omega}, \qquad \forall i \in N^m, n \in B^{es}_{i}, \omega \in \Omega \tag{2.a.22}$$

Constraints (2.a.14) and (2.a.15) limit the wind and solar generation to the wind and solar power availability. Wind power availability is calculated based on a wind intensity factor ($W_{it\omega}$) [65], while the PV maximum output in a representative day is calculated based on the PV energy output factor ($I_{it\omega}$) and the efficiency of the PV panels output (η^{pv}) [104]. Note that in our model, renewable energy spillage is allowed. Constraints (2.a.16) – (2.a.19) impose the bounds on the charge/discharge schedules of the ES units, with binary variable $w_{int\omega}$ indicating the operating mode of the ES units, being equal to 1 in the discharge mode and 0 in the charge mode. Equation (2.a.20) describes the State-of-Energy of the ES units, which is limited in (2.a.21). Also, constraints (2.a.22) declares that the ES units' State-of-Energy at the end of the scheduling horizon must be at least equal to a portion (β) of their initial State-of-Energy at the beginning of the day.

The DN operation is described in Eqs. (2.a.23) – (2.a.28). We use the linearized DistFlow equations [105] to model the DN:

$$\sum_{k \in \Omega^{i}_{d}(n)} f^{p}_{i(nk)t\omega} = \sum_{k \in \Omega^{i}_{p}(n)} f^{p}_{i(jn)t\omega} - D_{int\omega} + g^{w}_{int\omega} + g^{pv}_{int\omega} + dis_{int\omega} - ch_{int\omega},$$
$$\forall i \in N^m, n \in B_i, t \in H, \omega \in \Omega \tag{2.a.23}$$

$$\sum_{k \in \Omega^{i}_{d}(n)} f^{q}_{i(nk)t\omega} = \sum_{k \in \Omega^{i}_{p}(n)} f^{q}_{i(jn)t\omega} - \delta^{d}_{in} \cdot D_{int\omega} + \delta^{w}_{in} \cdot g^{w}_{int\omega} + \delta^{pv}_{in} \cdot g^{pv}_{int\omega},$$
$$\forall i \in N^m, n \in B_i, t \in H, \omega \in \Omega \tag{2.a.24}$$

$$V_{int\omega} = V_{ijt\omega} - 2 \cdot \left(r_{i(jn)} \cdot f^{p}_{i(jn)t\omega} + x_{i(jn)} \cdot f^{q}_{i(jn)t\omega} \right), \quad \forall i \in N^m, n \in B_i, t \in H, \omega \in \Omega \tag{2.a.25}$$

$$\left(f^{p}_{i(nk)t\omega} \right)^2 + \left(f^{q}_{i(nk)t\omega} \right)^2 < \left(\overline{f^{S}_{i(nk)}} \right)^2, \quad \forall i \in N^m, (nk) \in L^{D}_{i}, t \in H, \omega \in \Omega \tag{2.a.26}$$

$$\underline{V_{in}} \leq V_{int\omega} \leq \overline{V_{in}}, \qquad \forall i \in N^m, n \in B_i, t \in H, \omega \in \Omega \qquad (2.a.27)$$

$$\sum_{k\in\Omega_d^i(n_0)} f^p_{i(n_0k)t\omega} = p^{\downarrow}_{it\omega} - p^{\uparrow}_{it\omega}, \qquad \forall i \in N^m, t \in H, \omega \in \Omega \qquad (2.a.28)$$

Equations (2.a.23) – (2.a.25) are the *branch flow equations*, where $f^p_{i(nk)t\omega}$ and $f^q_{i(nk)t\omega}$ denote the active and reactive power flow respectively in branch nk of DN i, connecting nodes $n \in B_i$ and $k \in B_i$ at timeslot t and representative day ω. Constraint (2.a.26) sets the apparent power capacity of the lines ($\overline{f^S_{i(nk)}}$) and constraint (2.a.27) sets the lower and upper bounds of the square voltage magnitude ($\underline{V_{in}}, \overline{V_{in}}$). Constraint (2.a.26) is a quadratic inequality constraint, which is linearized via a polygonal inner approximation as in [106]. Finally, equation (2.a.28) represents the active power balance in the root of the DN (n_0), i.e., the connection point to the transmission grid.

Constraints (2.a.29) – (2.a.31) limit the offered/bid quantity ($o_{it\omega}/b_{it\omega}$) to the wholesale market by the DN assets with respect to the capacity of the substations connecting the transmission and distribution networks. Note that the DN assets' market participation could take place through an aggregating entity, e.g., a load serving entity, a demand-response aggregator, a DisCo, etc. Binary variable $h_{it\omega}$ (2.a.31) ensures that the DNs can either supply or draw power from the main grid for a specific timeslot in each representative day.

$$0 \leq o_{it\omega} \leq h_{it\omega} \cdot \overline{p_i}, \qquad \forall i \in N^m, t \in H, \omega \in \Omega \qquad (2.a.29)$$

$$0 \leq b_{it\omega} \leq (1 - h_{it\omega}) \cdot \overline{p_i}, \qquad \forall i \in N^m, t \in H, \omega \in \Omega \qquad (2.a.30)$$

$$h_{it\omega} \in \{0,1\}, \qquad \forall i \in N^m, t \in H, \omega \in \Omega \qquad (2.a.31)$$

Finally, the set of decision variables of the upper-level problem (X^U) includes the set of investment variables $X^U_S = \{K^e_{in}, K^p_{in}, K^w_{in}, K^{pv}_{in}\}$, and the set of scenario-dependent operation phase variables $X^U_{O,\omega} = \{g^w_{int\omega}, g^{pv}_{int\omega}, o_{it\omega}, b_{it\omega}, h_{it\omega}, dis_{int\omega}, ch_{int\omega}, w_{int\omega}, SOE_{int\omega}, f^p_{i(nk)t\omega}, f^q_{i(nk)t\omega}, V_{int\omega}\}$, i.e. $X^U = \{X^U_S \cup X^U_{O,\omega}, \forall\omega\}$.

2.3.2. Lower-level Problem: Day-ahead Electricity Market Clearing Process

$$\left\{ \min_{X^L_\omega} \sum_{t\in H} \left(\sum_{i\in N^g} c^g_{it} \cdot p^g_{it\omega} - \sum_{i\in N^d} c^d_{it} \cdot p^d_{it\omega} + \sum_{i\in N^m} \left(c^{\uparrow}_{it} \cdot p^{\uparrow}_{it\omega} - c^{\downarrow}_{it} \cdot p^{\downarrow}_{it\omega} \right) \right) \right. \qquad (2.b.1)$$

Subject to

$$-p^g_{it\omega} + p^d_{it\omega} - p^{\uparrow}_{it\omega} + p^{\downarrow}_{it\omega} + \sum_{j\neq i} y_{ij} \cdot (\theta_{it\omega} - \theta_{jt\omega}) = 0; \quad (\lambda_{it\omega}), \quad \forall i \in N, t \in H \quad (2.b.2)$$

$$0 \leq p^g_{it\omega} \leq \overline{P^g_i}; \qquad (\underline{\phi^g_{it\omega}}, \overline{\phi^g_{it\omega}}), \quad \forall i \in N^g, t \in H \qquad (2.b.3)$$

$$RD_i \leq p^g_{it\omega} - p^g_{i(t-1)\omega} \leq RU_i; \qquad (\phi^{grd}_{it\omega}, \phi^{gru}_{it\omega}), \quad \forall i \in N^g, t > 1 \qquad (2.b.4)$$

$$RD_i \leq p^g_{it\omega} - p^g_{i0} \leq RU_i; \qquad (\phi^{grd}_{it\omega}, \phi^{gru}_{it\omega}), \quad \forall i \in N^g, t = 1 \qquad (2.b.5)$$

$$0 \leq p^d_{it\omega} \leq \overline{P^d_{it\omega}}; \qquad (\underline{\phi^d_{it\omega}}, \overline{\phi^d_{it\omega}}), \quad \forall i \in N^d, t \in H \qquad (2.b.6)$$

$$0 \le p_{it\omega}^{\uparrow} \le o_{it\omega}; \qquad (\underline{\phi_{it\omega}^{p\uparrow}}, \overline{\phi_{it\omega}^{p\uparrow}}), \quad \forall i \in N^m, t \in H \quad (2.b.7)$$

$$0 \le p_{it\omega}^{\downarrow} \le b_{it\omega}; \qquad (\underline{\phi_{it\omega}^{p\downarrow}}, \overline{\phi_{it\omega}^{p\downarrow}}), \quad \forall i \in N^m, t \in H \quad (2.b.8)$$

$$-\overline{T_{ij}} \le y_{ij} \cdot (\theta_{it\omega} - \theta_{jt\omega}) \le \overline{T_{ij}}; \qquad (\underline{\phi_{(ij)t\omega}^{l}}, \overline{\phi_{(ij)t\omega}^{l}}), \quad \forall (ij) \in L^T, i < j, t \in H \quad (2.b.9)$$

$$\Big\}, \forall \omega \in \Omega$$

where $X_\omega^L = \{p_{it\omega}^g, p_{it\omega}^d, p_{it\omega}^{\uparrow}, p_{it\omega}^{\downarrow}, \theta_{it\omega}\}$. In the lower-level problem (2.b), the TSO clears the wholesale day-ahead electricity market for each representative day ω, by minimizing the social cost (or else maximizing the TN *Social Welfare*), given the DN assets' supply price offers ($c_{it}^{\uparrow}$) and demand price bids ($c_{it}^{\downarrow}$), price offers from generators (c_{it}^{g}) and price bids from demand aggregators (c_{it}^{d}). The transmission network is modeled using the DC power flow model. Equation (2.b.2) expresses the nodal power balance, while constraints (2.b.3) and (2.b.6) set the active power capacities of conventional generators and demand aggregators respectively. Constraints (2.b.4) - (2.b.5) express the ramping capabilities of the conventional generators and equations (2.b.7) - (2.b.8) limit the power traded between the TN and the DNs. Constraint (2.b.9) binds the active power flow in the transmission lines. The dual variables pertaining to each constraint are specified following a semicolon. Finally, note that the voltage angle of the reference bus is set to zero.

2.4. Solution Method

The formulated stochastic bi-level program can be solved through converting it into a Mathematical Program with Equilibrium Constraints (MPEC) and eventually into a MILP, as in [56], [58], [64] and [67]. We denote the optimal value of this single-level mixed integer linear problem as Ψ_P. The computational complexity of this method increases dramatically with the number of representative days. In order to circumvent intractability, we decompose the bi-level problem in representative days ω. Note that the ESP's minimum profit constraint (2.a.11) and the investment variables ($K_{in}^{w}, K_{in}^{pv}, K_{in}^{e}$ and K_{in}^{p}) prevent the decoupling of the problem per representative day. Thus, we apply a nested decomposition algorithm, which renders the problem computationally tractable. The outer decomposition algorithm deals with the complicating constraint (2.a.11), while the inner decomposition procedure deals with the complicating variables ($K_{in}^{w}, K_{in}^{pv}, K_{in}^{e}$ and K_{in}^{p}).

2.4.1. Outer Decomposition: Relaxing the ESP's Minimum Profit Constraint

Initially, we deal with the complicating constraint (2.a.11) using the Lagrangian Relaxation (LR) technique [107]. We relax constraint (2.a.11) by removing it from the set of constraints inserting a penalty for violations. Let ξ be a non-negative scalar and consider the following problem:

$$\Psi_D(\xi) = \min_{X^U \cup X^L} \sum_{\omega \in \Omega} \left(C_\omega^{DN} + C_\omega^{oper}\right) + \tilde{C}^{inv} + \xi \cdot \left(\sum_{\omega \in \Omega} \left(-Pr_\omega^{inv} + C_\omega^{oper}\right) + \chi \cdot \tilde{C}^{inv} \right) \quad (2.c.1)$$

Subject to

(2.a.5) – (2.a.10), (2.a.14) – (2.a.31), (2.b.1) – (2.b.9) (2.c.2)

where $X^L = \{X_\omega^L, \forall\omega\}$. In other words, partial duality over constraint (2.a.11) has been carried out, with ξ being the corresponding Lagrangian multiplier. The above problem (2.c) is a relaxed version of problem (2.a) - (2.b). We convert the above bi-level problem into a MILP using the MPEC method as explained in APPENDIX A. It can be easily seen that the relaxed problem (2.c) provides a lower bound for the initial (non-relaxed) problem, i.e., $\Psi_D(\xi) \le \Psi_P$, since $\sum_{\omega\in\Omega}\left(-Pr_\omega^{inv} + C_\omega^{oper}\right) + \chi \cdot \tilde{C}^{inv} \le 0$ and $\xi \ge 0$. Function $\Psi_D(\xi)$ is the *dual function* of problem (2.a)-(2.b). Our goal is to find the optimal value of ξ that will result in the best bound $\Psi_D(\xi^*)$ of Ψ_P, solving the optimization problem: $\max_{\xi}\{\Psi_D(\xi) | \xi \in \mathbb{R}^+\}$, which is the *Lagrangian dual* problem of the original problem.

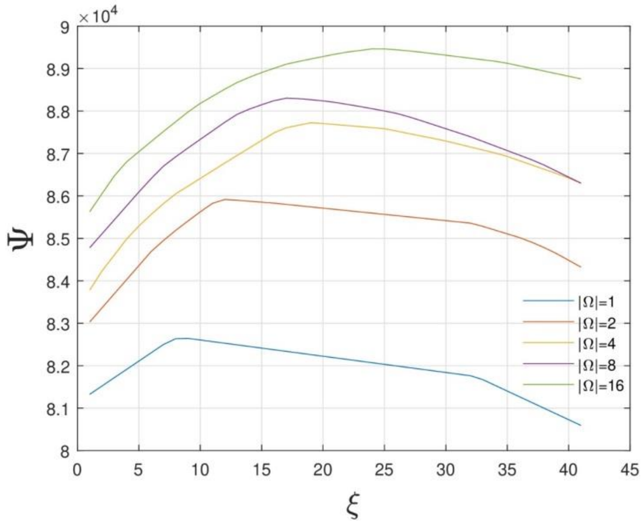

Figure 6: Value of dual function Ψ for different values of ξ and various numbers of representative days $|\Omega|$

Towards this objective, we use the LR decomposition algorithm. This is an iterative procedure, in each iteration of which the relaxed problem (2.c) is converted into a MILP (cf. APPENDIX A) and solved for a specific value of ξ. Given the optimal solution and the respective values of $\sigma = \left(\sum_{\omega\in\Omega}\left(-Pr_\omega^{inv} + C_\omega^{oper}\right) + \chi \cdot \tilde{C}^{inv}\right)$, we update the value of ξ using the Cutting Plane (CP) method [88]. This updating method reconstructs the dual function $\Psi_D(\xi)$, which is a concave piecewise linear function as it is demonstrated in Figure 6, using cutting planes. More specifically, in outer-loop iteration κ, the value of ξ is updated via solving the following linear program:

$$\max_{z,\xi} z \tag{2.d.1}$$

Subject to

$$z \le \Psi_D\left(\xi^{(\rho)}\right) + \sigma^{(\rho)} \cdot \left(\xi - \xi^{(\rho)}\right); \quad \rho = 1, \ldots, \kappa \tag{2.d.2}$$

$$\xi \ge 0 \tag{2.d.3}$$

Constraints (2.d.2) represent hyperplanes in the variable ξ space. Problem (2.d) is a relaxed version of the Lagrangian dual problem, which approaches the actual Lagrangian dual problem as the number of iterations increases. The optimal solution of problem (2.d) provides an upper bound of the optimal objective function value of the Lagrangian dual problem $\Psi_D(\xi^*)$, since the piecewise linear reconstruction of $\Psi_D(\xi)$ overestimates the actual function [88], i.e. $z^{(\kappa)} \geq \Psi_D(\xi^*) \geq \Psi_D(\xi^{(\kappa)})$. The right inequality follows from the fact that the optimal objective function value of the aforementioned Lagrangian dual maximization problem is always greater than or equal to any other feasible solution provided by the solution of problem (2.c). The algorithm terminates when the per unit gap is below a threshold, that is $\frac{z^{(\kappa)}-\Psi_D(\xi^{(\kappa)})}{\Psi_D(\xi^{(\kappa)})} \leq \epsilon_1$.

Under convexity assumptions, the best bound $\Psi_D(\xi^*)$ is equal to the optimal value of Ψ_P (*Strong Duality Theorem*). In general, however, it falls short. The difference between $\Psi_D(\xi^*)$ and Ψ_P is the *duality gap*. In our model, the LR provides a high quality bound on Ψ_P. We confirm this claim by simulation on a test system (see Figure 7). Note that the maximum duality gap (difference between Ψ_P and $\Psi_D(\xi^*)$) is 0.11% (in case $|\Omega| = 1$), while the average per unit gap is 0.03%.

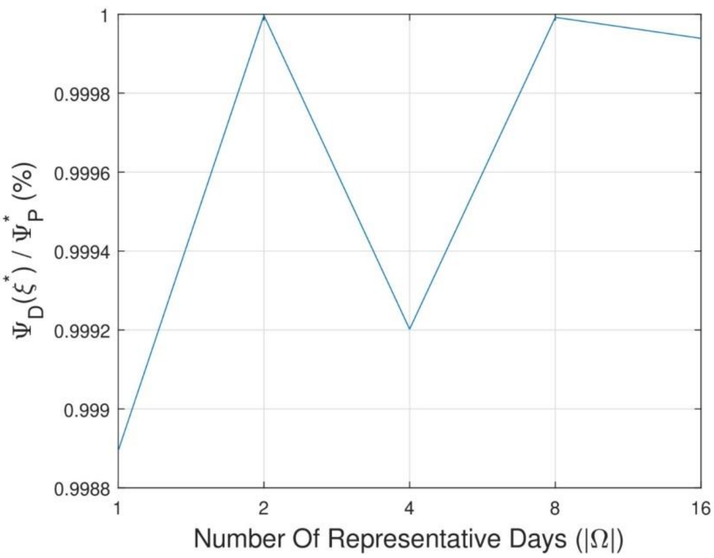

Figure 7: Ratio between optimal values of $\Psi_D(\xi)$ and Ψ_P for different numbers of representative days $|\Omega|$

2.4.2. Inner Decomposition: Bender's Decomposition Technique

We now deal with the investment decision variables, namely $K_{in}^{w}, K_{in}^{pv}, K_{in}^{e}$ and K_{in}^{p} that prevent the solution of the problem (2.c) by blocks (one for each representative day). We apply a Bender's Decomposition (BD) technique that has been proposed in [61]. In general, the BD algorithm does not provide convergence guarantees for non-convex problems. Nevertheless, studies on the optimal investments in the power systems using stochastic bi-level modeling ([61], [65], [66], [68]) have shown that the objective function of the original (non-decomposed) problem convexifies with respect to the investment (complicating) variables as the number of scenarios and their diversity increases. The bi-level problem (2.c) is decomposed into a Master Problem (MP) and a number of subproblems, one per representative day. At first, the linear and continuous MP is solved and provides updated investment decisions. In BD algorithm's iteration v, the MP resulting from decomposing the original problem (2.c) follows:

$$\min_{X^{MP}} \underline{G^{(v)}} = (1 + \xi \cdot \chi) \cdot \tilde{C}^{inv} + \sum_{\omega \in \Omega} \gamma_{\omega}^{(v)}$$

(2.e.1)

Subject to

(2.a.5) – (2.a.10) (2.e.2)

$$\gamma_{\omega}^{(v)} \geq \gamma^{min}, \qquad \forall \omega \in \Omega \tag{2.e.3}$$

$$\gamma_{\omega}^{(v)} \geq \tilde{G}_{\omega}^{(v)} + \sum_{i \in N^m} \left(\sum_{n \in B_i^w} \mu_{in\omega}^{w,(\tau)} \cdot \left(K_{in}^{w,(v)} - K_{in}^{w,(\tau)} \right) + \sum_{n \in B_i^{pv}} \mu_{in\omega}^{pv,(\tau)} \cdot \left(K_{in}^{pv,(v)} - K_{in}^{pv,(\tau)} \right) + \sum_{n \in B_i^{es}} \left(\mu_{in\omega}^{e,(\tau)} \cdot \left(K_{in}^{e,(v)} - K_{in}^{e,(\tau)} \right) + \mu_{in\omega}^{p,(\tau)} \cdot \left(K_{in}^{p,(v)} - K_{in}^{p,(\tau)} \right) \right) \right)$$
$$\forall \omega \in \Omega, \tau = 0, .., v-1 \tag{2.e.4}$$

where $X^{MP} = \{K_{in}^{w,(v)}, K_{in}^{pv,(v)}, K_{in}^{e,(v)}, K_{in}^{p,(v)}, \gamma_{\omega}^{(v)}\}$. In (2.e.1), $\gamma_{\omega}^{(v)}$ is a scalar representing the optimal value of the subproblem in representative day ω, in BD algorithm's iteration v. Constraint (2.e.3) imposes a lower bound on $\gamma_{\omega}^{(v)}$ to accelerate convergence. Constraints (2.e.4) are the Bender's cuts, where $\mu_{in\omega}^{w}, \mu_{in\omega}^{pv}, \mu_{in\omega}^{e}$ and $\mu_{in\omega}^{p}$ are sensitivities obtained from the subproblems' solution. Parameters including superscripts (τ) are obtained from the previous iterations. The solution of the MP updates the values of the DERs' sizes and location. The MP is a relaxed version of the original problem (2.c) and the objective function (2.e.1) approximates from below the objective function of the original problem ($\underline{G^v} \leq \Psi_D(\xi)$). Then, for each representative day ω, a subproblem is formulated:

$$\min_{X_{O,\omega}^U \cup X_{\omega}^L} \tilde{G}_{\omega} = (1+\xi) \cdot C_{\omega}^{oper} + C_{\omega}^{DN} - \xi \cdot Pr_{\omega}^{inv}$$

(2.f.1)

Subject to

(2.a.14) – (2.a.31), (2.b.1) – (2.b.9) (2.f.2)

$$K_{in}^{w} = \tilde{K}_{in}^{w}; \qquad (\mu_{in\omega}^{w}), \qquad \forall i \in N^m, n \in B_i^w \tag{2.f.3}$$

$$K_{in}^{pv} = \tilde{K}_{in}^{pv}; \qquad (\mu_{in\omega}^{pv}), \qquad \forall i \in N^m, n \in B_i^{pv} \tag{2.f.4}$$

$$K_{in}^{e} = \tilde{K}_{in}^{e}; \qquad (\mu_{in\omega}^{e}), \qquad \forall i \in N^m, n \in B_i^{es} \tag{2.f.5}$$

$$K_{in}^{p} = \tilde{K}_{in}^{p}; \qquad (\mu_{in\omega}^{p}), \qquad \forall i \in N^m, n \in B_i^{es} \tag{2.f.6}$$

Note that in the above problem, all variables pertain to each algorithm's iteration v, but for notational clarity, such a superscript is omitted. The objective in the above problem ($\tilde{G}_{\omega}$) is to minimize the operating costs of the DNs assets in representative day ω plus the part of the dualized ESP profit constraint that contains only daily operation variables. Equations (2.f.3) - (2.f.6) fix the wind production, solar production, ES energy rating and ES power rating respectively, to the values computed in the MP. Consequently, the bi-level subproblems (2.f) are converted into MILPs with the MPEC method (SP1), as described in APPENDIX B. Since the solution of the MILPs does not provide accurate dual variables to build the Bender's cuts, we reformulate the subproblems into equivalent linear continuous problems, using the Mathematical Programming with Primal and Dual Constraints (MPPDC) formulation of the bi-level subproblems (SP2), as explained in APPENDIX C. Solving SP2 provides $\tilde{G}_\omega$ and dual variables $\mu_{in\omega}^{w}, \mu_{in\omega}^{pv}, \mu_{in\omega}^{e}$ and $\mu_{in\omega}^{p}$. The value of $\bar{G}^{(v)}$ to be used in the convergence check is:

$$\bar{G}^{(v)} = \sum_{\omega\in\Omega} \tilde{G}_\omega^{(v)} + \sum_{i\in N^m}\left(\sum_{n\in B_i^w} \tilde{C}^w \cdot \widetilde{K}_{in}^{w,(v)} + \sum_{n\in B_i^{pv}} \tilde{C}^{pv} \cdot \widetilde{K}_{in}^{pv,(v)} + \sum_{n\in B_i^{es}}\left(\tilde{C}^e \cdot \widetilde{K}_{in}^{e,(v)} + \tilde{C}^p \cdot \widetilde{K}_{in}^{p,(v)}\right)\right) \quad (2.g.1)$$

Each subproblem is a further restricted version of the original problem (2.c). Hence, its optimal objective function value is an upper bound to the optimal value of the objective function of the original problem ($\bar{G}^{(v)} \geq \Psi_D(\xi)$). The procedure continues until $\left(\bar{G}^{(v)} - \underline{G}^{(v)}\right)/\bar{G}^{(v)} \leq \epsilon_2$. The details of the overall algorithm are described in Table 1.

Table 1: Nested Decomposition Algorithm

1:	$\boldsymbol{\kappa \leftarrow 1}$, $\boldsymbol{\xi^{(\kappa)} := 0}$, $\boldsymbol{\underline{\Psi}^{(\kappa)} := -\infty}$, $\boldsymbol{\overline{\Psi}^{(\kappa)} := +\infty}$
2:	**while** $\left(\left(\overline{\Psi}^{(\kappa)} - \underline{\Psi}^{(\kappa)}\right)/\underline{\Psi}^{(\kappa)}\right) > \epsilon_1$ **do**
3:	$\kappa \leftarrow \kappa + 1$
4:	$v \leftarrow 1, \bar{G}^{(v)} := +\infty, \underline{G}^{(v)} := -\infty$
5:	**while** $(\bar{G}^{(v)} - \underline{G}^{(v)})/\bar{G}^{(v)} > \epsilon_2$ **do**
6:	$v \leftarrow v + 1$
7:	Solve problem (2.e).
8:	Obtain $\widetilde{K}_{in}^{w,(v)}, \widetilde{K}_{in}^{pv,(v)}, \widetilde{K}_{in}^{e,(v)}, \widetilde{K}_{in}^{p,(v)}, \underline{G}^{(v)}$.
9:	**for all** $\omega \in \Omega$ **do**
10:	Convert problem (2.f) into MILP using the MPEC method (i.e., formulate SP1).
11:	Solve SP1.
12:	Obtain optimal set of variables $X_{O,\omega}^{U,(v)}, X_{\omega}^{L,(v)}$.
13:	Convert problem (2.f) into LP using the MPPDC method (i.e., formulate SP2).
14:	Solve SP2.
15:	Obtain $\tilde{G}_\omega^{(v)}, \mu_{in\omega}^{w,(v)}, \mu_{in\omega}^{pv,(v)}, \mu_{in\omega}^{e,(v)}, \mu_{in\omega}^{p,(v)}$.
16:	**end for**
17:	Calculate $\bar{G}^{(v)}$ using (2.g.1).
18:	Add Bender's Cuts to the MP (Problem (2.e)).
19:	**end while**
20:	$\Psi_D\left(\xi^{(\kappa)}\right) := \bar{G}^{(v)}, \underline{\Psi}^{(\kappa)} := \Psi_D\left(\xi^{(\kappa)}\right)$
21:	$\sigma^{(\kappa)} := \sum_{\omega\in\Omega}\left(-Pr_\omega^{inv,(v)} + C_\omega^{oper,(v)}\right) + \chi \cdot \tilde{C}^{inv,(v)}$
22:	Add cutting hyperplanes to problem (2.d).
23:	Solve problem (2.d). Obtain $\xi^{(\kappa)}, z^{(\kappa)}$.
24:	$\overline{\Psi}^{(\kappa)} := z^{(\kappa)}$
25:	**end while**
26:	$\Psi_D(\xi^*) := \overline{\Psi}^{(\kappa)}$

2.5. Remarks and Extensions

In this Section, a few remarks are discussed regarding some directions to extend our investment model. In this Chapter, we have proposed an ESP-DSO-TSO coordination framework in order to decide on the private network-aware and market-aware investments in renewable energy and energy storage units. The proposed model can readily accommodate more DER technologies for the ESP to invest in (e.g., CHP units, microturbines, etc.) without notable technical complications. Furthermore, although we have assumed a single ESP that seeks to invest in new DERs, there might be multiple potential investors in practice. In this case, our model should be slightly modified. Let E be the set of ESPs seeking to invest in DERs. Then constraint (2.a.10) would be modified in order to capture the different budget options of each investor:

$$C_e^{inv} \leq \overline{C_e^{inv}}, \quad \forall e \in E$$

where

$$C_e^{inv} = \sum_{i \in N^m} \left(\sum_{n \in B_i^{es}} \left(C^e \cdot K_{ein}^e + C^p \cdot K_{ein}^p \right) + \sum_{n \in B_i^w} C^w \cdot K_{ein}^w + \sum_{n \in B_i^{pv}} C^{pv} \cdot K_{ein}^{pv} \right)$$

In the above expression, $K_{ein}^w, K_{ein}^{pv}, K_{ein}^e$ and K_{ein}^p denote the capacity of each DER technology that is to be installed by ESP $e \in E$, at node n of DN i. Additionally, since each ESP would anticipate a different minimum rate of return on its investments, constraint (2.a.11) would be modified as follows:

$$\sum_{\omega \in \Omega} \left(Pr_{e\omega}^{inv} - C_{e\omega}^{oper} \right) \geq \chi_e \cdot \tilde{C}_e^{inv}, \quad \forall e \in E$$

where

$$Pr_{e\omega}^{inv} = \pi_\omega \cdot \sum_{i \in N^m} \sum_{t \in H} \left(\lambda_{it\omega} \cdot \left(\sum_{n \in B_i^w} g_{eint\omega}^w + \sum_{n \in B_i^{pv}} g_{eint\omega}^{pv} + \sum_{n \in B_i^{es}} (dis_{eint\omega} - ch_{eint\omega}) \right) \right)$$

$$C_{e\omega}^{oper} = \pi_\omega \cdot \sum_{i \in N^m} \left(\sum_{t \in H} \left(\sum_{n \in B_i^{es}} c^{es} \cdot (dis_{eint\omega} + ch_{eint\omega}) + \sum_{n \in B_i^w} c^w \cdot g_{eint\omega}^w + \sum_{n \in B_i^{pv}} c^{pv} \cdot g_{eint\omega}^{pv} \right) \right)$$

$$\tilde{C}_e^{inv} = \sum_{i \in N^m} \left(\sum_{n \in B_i^{es}} \left(\tilde{C}^e \cdot K_{ein}^e + \tilde{C}^p \cdot K_{ein}^p \right) + \sum_{n \in B_i^w} \tilde{C}^w \cdot K_{ein}^w + \sum_{n \in B_i^{pv}} \tilde{C}^{pv} \cdot K_{ein}^{pv} \right)$$

Finally, regarding the solution algorithm, since there would be $|E|$ complicating constraints (2.a.11), with $|E|$ denoting the cardinality of the set of ESPs E, the only modification would concern the penalty variable ξ, which would be a vector $\xi \in \mathbb{R}^{|E|}$.

2.6. Performance Evaluation

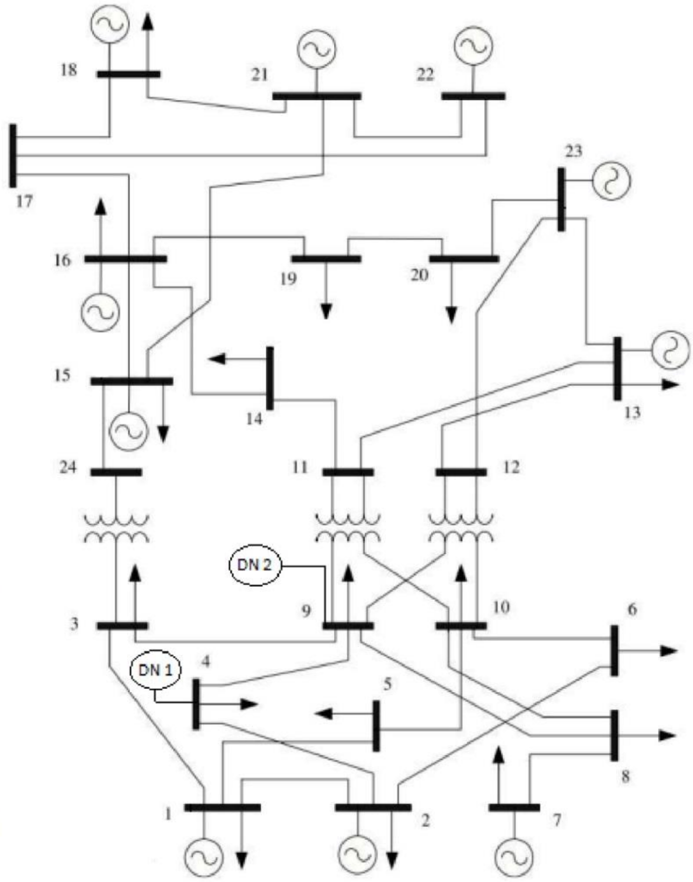

Figure 8: IEEE One-Area Reliability Test System

The proposed methodology is tested on the IEEE One Area Reliability Test System [108], which is illustrated in Figure 8. The generation, load and line data can be found in [109]. We consider that the DER investments can take place on two 33-bus distribution networks (see [110] for network details) with their root nodes being connected to transmission buses 4 and 9. Detailed distribution network data can be found in [109]. Load and renewable energy production profiles are based on realistic annual data from the European Network of Transmission System Operators for Electricity (ENTSO-E) and the Hellenic Distribution Network Operator (HEDNO) respectively [109], which are reduced to eight representative days with 24-time intervals using the k-means clustering algorithm. The wind intensity and PV energy output factors were selected from two different locations (distribution networks) in Greece, while without loss of generality we assumed that the demand follows the same pattern in both the transmission and distribution network. The weighted average of demand, wind intensity and PV energy output scenarios are depicted in Figure 9. The eligible distribution network nodes are presented in Table 2. We assume that the capital costs of DERs are $C^{w} = 1300$€/kW, $C^{pv} = 830$€/kW, $C^{e} = 20$€/kW and $C^{p} = 500$€/kW, with their marginal operating costs being $c^{w} = 3.5$€/MW, $c^{pv} = 2.5$€/MW and $c^{es} = 0.5$€/MW. The lifetimes of DERs are 15 years and the annual discount rate is 5% ($\Lambda = 15, \Gamma = 0.05$). Without loss of generality, we set the maximum capacity of DERs to $\overline{K_{in}^{w}} = 20MW, \overline{K_{in}^{pv}} = 10MW$ and $\overline{K_{in}^{e}} = 20MWh$, for every eligible DN node. The energy-to-power ratio of candidate storage units is set to $\rho = 6h$ and the charging and discharging efficiencies are $\eta^{c} = \eta^{d} = 0.93$. The initial state-of-charge of the storage units is assumed to be 50%, while at the end of the day the state-of-charge should be at least 10% ($\beta = 0.1$). The power factor of the candidate wind and PV generating units is assumed to be 0.95, while the efficiency of the PV panels output is $\eta^{pv} = 0.95$. The maximum power flow on the coupling points between the transmission and distribution systems (substations) is set to $\overline{p_l} = 46MW$. The price bids and offers of the DNs assets are set to $c_{it}^{\downarrow} = 450$€/MW and $c_{it}^{\uparrow} = 0$€/MW in order to ensure they can always be cleared in the day-ahead electricity market. Finally, the total investment budget is set to $\overline{C^{inv}} = 200 \cdot 10^6$€. The algorithm is implemented in MATLAB and the MILP problems are solved using Gurobi 9.0.2. All simulations were performed on a desktop computer with Intel Core i7 4.00GHz and 32GB RAM.

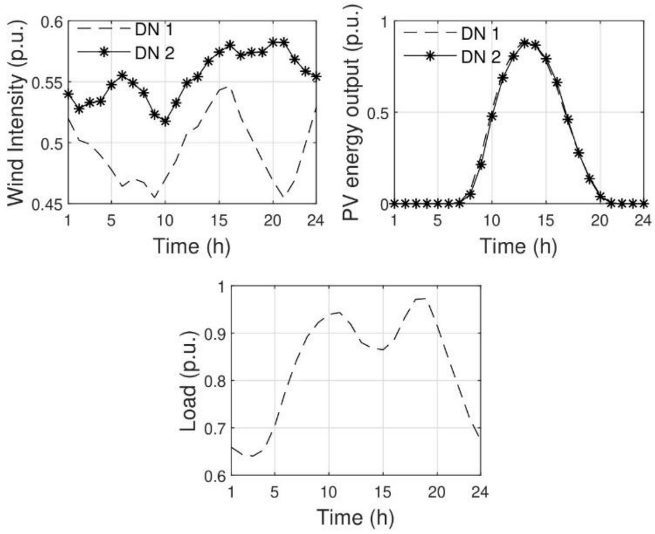

Figure 9: Expected values of load, wind intensity and PV energy output

Table 2: Eligible Nodes for DER Installation

	Eligible DN Nodes	
	DN 1 (TN Bus #4)	**DN 2 (TN Bus #9)**
Wind	11, 16, 18, 19, 21, 23	6, 25, 27, 29, 31, 32
PV	16, 22, 24, 26, 28, 30	1, 2, 7, 17, 20, 25
Storage	5, 8, 16, 21, 22, 28	1, 2, 8, 15, 25, 30

2.6.1. Sizing and Siting Decisions

This subsection describes the DER investment decisions with the rate of return that the ESP anticipates to receive from the investment being $\chi = 1.15$. Figure 10 illustrates the DERs' investment decisions per node of each DN.

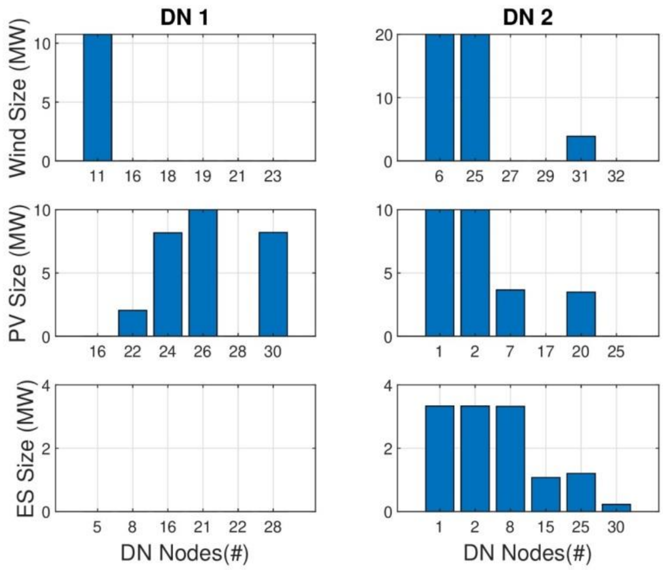

Figure 10: DERs sizing and siting decisions

One can see that higher DER capacity is installed in DN 2 than in DN 1. This is mainly explained by two factors: first DN 2 is located in a location (TN node #9) with much higher wind intensity (cf. Figure 9), and second, the available nodes for wind and PV units' installation in DN 2 allow the ESP to install higher wind and solar capacity without violating the distribution network constraints. In DN 1, only solar (28MW) and wind (10.75MW) production units are installed, with the investment costs and the eligible nodes for solar production making the PV technology more attractive investment for the ESP than the wind production. Wind capacity is installed only at node #11, while PV units are installed at nodes #22, 24, 26 and 30, where either the lines connected to these nodes have enough capacity for the generated power to flow through them, or the local loads are sufficiently high in order for the net load to flow through the adjacent lines without causing over- or under-voltage issues. In DN 2, the wind intensity and the candidate DN nodes for wind capacity installation makes the wind capacity the most profitable investment in this area. Thus, a total of 44MW of wind capacity is installed together with 27MW of solar capacity and 75MWh/12.5MW ES units. Again, for reasons of high adjacent lines capacities and local loads, 20MW of wind turbines are installed at nodes #6 and 25, and 4MW at node #31. Moreover, two PV units of 10MW each are installed very close to the DN root (nodes #1 and 2), and two PV units of 3.5MW each at nodes #7 and 20. In order for high wind and solar production at DN 2 to be efficiently exploited and the DN assets' payoff to be maximized, storage capacity is chosen to be installed at all eligible nodes. In more detail, the maximum possible ES capacity is installed at nodes #1 and 2 to support the PV units installed at these nodes, and 7.2MWh/1.2MW ES units are installed at node #25 where 20MW of wind capacity is also installed. Also, 20MWh/3.3MW, 6.40MWh/1.06MW and 1.35MWh/0.23MW of storage capacity are installed at nodes #8, 15 and 30 to support the smooth operation of the DN and the profitability of the DN users. The DER investment decisions, which cost $124.9\cdot 10^6$€, benefit all the involved actors. The ESP achieves the anticipated rate of return on its investments (15%), while the electricity cost for DN users declines compared to the case without DER investments. The total annual DN users' electricity cost is $19.81\cdot 10^6$€ without DERs, which is reduced by 5.45% with the newly installed DERs. Finally, the TSO benefits from the DER investments, since expensive TN-level electricity production is replaced in the generation mix by low-cost renewable energy units. More specifically, the TN generation cost ($428.07 \cdot 10^6$€ without DERs investments) declines by 4.29%.

2.6.2. Impact of the ESP's Minimum Profit Constraint

As stated above (cf. Section 2.2), in contrast to [58], [102] and [103] we consider private investments in DERs. In this subsection, we examine the impact that the choice of the rate of return (χ) has on the DER investments. To this end, we consider three different values of χ (1.15, 1.20 and 1.25) along with the case where the ESP's profit constraint (Eq. (2.a.11)) is not included in our model (i.e., regulated investments). In Figure 11, the sizes of the DER investments are compared for the different choices of χ, while in Table 3 the ESP investment costs and the T&D operating cost savings are presented.

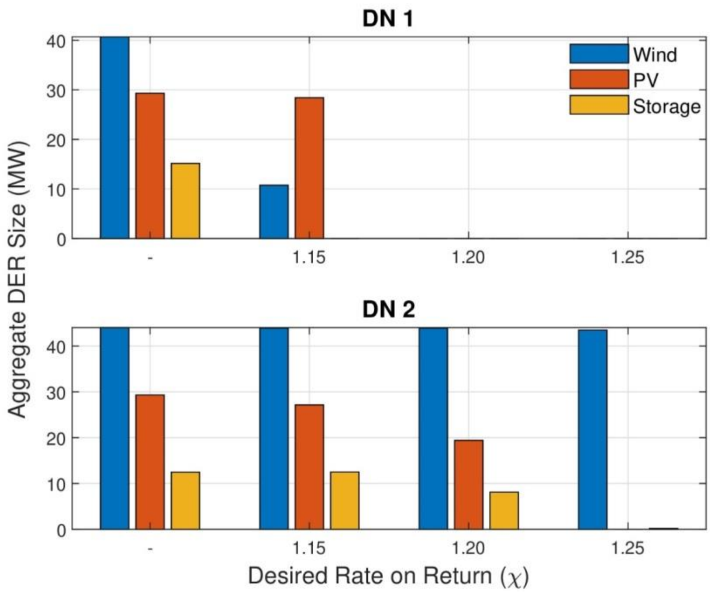

Figure 11: DERs investments for various values of χ

Without constraint (2.a.11), the ESP installs a total of 84MW wind capacity, 58 MW solar production and 165MWh/27.5MW ES capacity, which are almost evenly distributed between the two DNs, with the ESP yielding a 11% rate of return, the electricity cost of the DN consumers declining by 6.79% comparing to the case where no DERs are installed, and the transmission-level generation cost dropping by 5.87% (Table 3). Incorporating constraint (2.a.11) and as the value of χ rises, our investment model, in order for the ESP to achieve the anticipated rate of return, decides lower DER capacity, which leads in lower generation cost reduction and hence higher nodal LMPs. As a result, the energy cost reduction for the DN consumers declines and the DERs' profit increase. This is evident in Table 3. Increasing χ even more ($\chi = 1.20$ and $\chi = 1.25$), it is in the interest of the ESP to install DERs only in DN 2 and not in DN 1, due to the increased wind intensity in this area and network characteristics as previously explained (see subsection 2.6.1). Thus, for all values of χ under study the ESP installs 44MW of wind turbines in DN 2. In case $\chi = 1.20$, it also installs 20MW of solar capacity, which (in order to be profitable and network feasible) is followed by investments in energy storage, as far as the latter are financially justified (48MWh/8MW). When $\chi = 1.25$, the only option is wind technology so as to maximize the DN assets' payoff ensuring the ESP's desired rate of return on the investments.

Table 3: Investment Cost, Operating Cost Savings of the T&D Systems, for Various Values of χ

χ	-	1.15	1.20	1.25
Investment Cost (10^6€)	175.89	124.90	78.20	56.65
DN Users Cost Savings (%)	6.79	5.45	5.12	4.24
TN Generation Cost Savings (%)	5.87	4.29	2.83	2.15

2.6.3. Effect of Co-optimizing RES and Storage Investments

In this subsection we consider three investment scenarios:

- Scenario 1: Only investments in storage units.
- Scenario 2: Only investments in renewable energy.
- Scenario 3: The ESP co-optimizes renewable energy and storage investments.

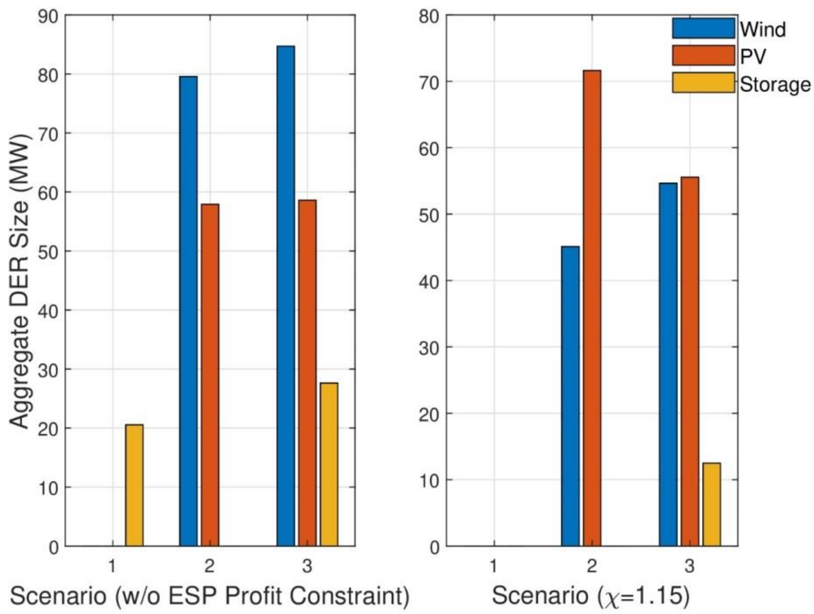

Figure 12: DERs investments in different investment scenarios

In Figure 12, the DER sizes are compared for the different investment scenarios in case of not including the ESP profit constraint (Eq. (2.a.11)) and in case of $\chi = 1.15$. In the left bar graph, where Eq. (2.a.11) is not included, we can see that in Scenario 3, the ESP, being entitled to invest in storage units, installs 6% higher wind capacity and 1.2% higher PV capacity comparing to Scenario 2. This results in 12% higher annual profits for the ESP than Scenario 2, slightly lower electricity cost for the local load and lower overall generation costs (see Table 4). Also, the installed storage capacity in Scenario 3 exceeds storage investments in Scenario 1 by 25%, since this enables larger RES capacity installation and ultimately higher aggregate DN users market gain. In Table 4, one can see that investing solely in storage assets, not taking into consideration the ESP's return on investments, which is the case in [58], the optimal investment decisions achieve a 4.42% energy cost reduction for end users. However, the ESP does not cover its capital costs losing 0.4 million euros annually.

In case of $\chi = 1.15$ (right bar graph), in Scenario 1 the ESP does not invest in energy storage at all, since the storage capital costs, the market prices, the eligible nodes for storage investments and the distribution network limitations do not enable the ESP to make adequate market profits so as to reach the desired rate of return on its investments. As it is also evident in subsection 2.6.2, incorporating the ESP's profit constraint, investments in storage increasingly decline with increasing χ. Comparing investment scenarios 2 and 3 when $\chi = 1.15$, we can see in Figure 12 that co-optimizing RES and storage investments, the ESP achieves 15% profit by installing 5.5% less renewable energy capacity comparing to the case in which the ESP installs only renewable energy capacity. The ESP in Scenario 3 achieves 6% higher annual net profits comparing to Scenario 2, while co-optimizing RES and ES investments, the generation cost reduction and the DN consumers energy cost reduction is slightly larger than in the case where only RES units are considered.

Table 4: Investment Cost, Operating Cost Savings of the T&D Systems, and ESP Market Profits in Different Investment Scenarios

χ	-			1.15		
Scenario	**1**	**2**	**3**	**1**	**2**	**3**
Investment Cost (10^6€)	12.74	151.48	175.89	0	118.10	124.90
DN Users Cost Savings (%)	4.42	6.66	6.79	0	5.40	5.45
TN Generation Cost Savings (%)	0.31	5.13	5.87	0	4.07	4.29
ESP Annualized Clear Profits (10^6€)	-0.40	2.06	2.31	0	2.07	2.19

2.6.4. Bi-level vs. Single-level Modeling

This subsection compares our bi-level model to a single-level investment model setting $\chi = 1.25$. In the latter case, only problem (2.a) is solved with market prices being input parameters based on price forecasts. The price forecasts are produced solving problem (2.b) for each representative day considering no DER investments. Hence, as in the investment models in [19], [20], [21], [22], [23], [24], [25] and [26], the impact of the DER investments on energy market price is not taken into consideration, resulting in over-investments that hamper the ESP's return on investment.

More specifically, solving the single-level model, 85MW of wind capacity, 7.5MW of PV capacity and a total of 7MWh/1.16MW storage capacity are installed. These investments, with a total investment cost of $118 \cdot 10^6$€ are calculated based on the assumed market prices and seemingly achieve the desired rate of return on DER investments. However, the installed DERs lead in market price changes, which eventually produce lower market profits for the ESP than the ones that had been calculated solving the single-level model. The T&D operating cost reduction is higher in case of the single-level model (see Table 5), since larger DER capacities achieve lower LMPs at the TSO-DSO coupling points, but on the other hand the resulting rate of return is insufficient for the ESP.

Table 5: Investment Cost, Operating Cost Savings of the T&D Systems, and Rate of Return on ESP Investments in Single-level and Bi-level Investment Models

	Single-Level Model	**Bi-Level Model**
Investment Cost (10^6€)	118.36	56.64
DN Users Cost Savings (%)	6.33	4.24
TN Generation Cost Savings (%)	4.10	2.15
Rate of Return (%)	13	25

2.6.5. Computational Efficiency

We test the computational efficiency of our proposed nested decomposition algorithm using the IEEE 118-bus system [111] and the IEEE 33-Node Distribution Test System. Towards this goal, we compare our algorithm to the non-decomposed MILP (which results from converting the bi-level problem (2.a)-(2.b) through an MPEC problem as in [56], [58] and [64]) for various numbers of representative days ($|\Omega|$) in terms of solution time.

As we can see in Table 6, for a single DN, in case $|\Omega| = 4$, the non-decomposed MILP (ND-MILP) achieves the optimal solution much faster than our proposed solution method, which reaches a sub-optimal solution by 0.42%. However, the computational burden increases with the number of representative days $|\Omega|$. Thus, the execution time for the non-decomposed MILP upsurges for $|\Omega| = 8$, while for $|\Omega| = 16$ and $|\Omega| = 24$, the non-decomposed MILP cannot find a feasible integer solution within the predefined time limit (48h or 172,800 sec). On the other hand, our proposed nested decomposition algorithm reaches the optimal solution in 4 or 5 outer decomposition iterations. The average number of inner decomposition iterations reduces with $|\Omega|$, since as also stated in subsection 2.4.2 the objective function of the problem convexifies with respect to the investment variables as $|\Omega|$ increases. Since the functioning of outer and inner decomposition procedures improves with

$|\Omega|$ (as explained in Section 2.4), the optimality loss also declines with increasing number of representative days. Conclusively, our proposed algorithm reaches an optimal solution within a finite number of iterations, without sacrificing optimality, significantly reducing the computational burden that results in intractability issues for the non-decomposed MILP.

Table 6: Computational Performance for a single DN

Solution Method	$\|\Omega\|$	κ	v	Exec. Time (sec)	Opt. Result	Opt. Loss (%)
ND-MILP	4	-	-	637	73517	-
	8	-	-	10079	76242	-
	16	-	-	172800	-	-
	24	-	-	172800	-	-
Proposed Method	4	4	55	11594	73826	0.42
	8	5	38	15143	76287	0.06
	16	5	33	28375	74020	-
	24	5	29	43814	75605	-

Furthermore, we have tested the computational performance of our algorithm in case more than one DNs are candidate for DER installation ($N^m > 1$). For this purpose, we considered three 33-bus distribution networks connected to different buses of the IEEE 118-bus transmission system. The results are shown in Table 7, where the well-functioning of our algorithm as $|\Omega|$ increases is evident. For 16 and 24 representative days, the ND-MILP was terminated at 48h. In the first case, the ND-MILP could not reach the optimal solution (producing a sub-optimal solution), while for $|\Omega| = 24$ it could not find a feasible solution. Finally, it can be seen in Table 7 that the solution time of our proposed method could be further improved by solving the subproblems in parallel.

Table 7: Computational Performance for multiple DNs

Solution Method	$\|\Omega\|$	κ	v	Exec. Time (sec)	Par. Exec. Time (sec)	Opt. Result	Opt. Loss (%)
ND-MILP	4	-	-	651	-	120116	-
	8	-	-	61021	-	121157	-
	16	-	-	172800	-	123712	1.27
	24	-	-	172800	-	-	-
Proposed Method	4	3	75	17221	6716	121488	1.14
	8	4	46	41124	11677	121747	0.48
	16	3	37	55588	13250	122160	-
	24	3	29	71734	19400	123631	-

2.7. Conclusions and Future Work

In this Chapter, we model the DER investment problem of a private ESP, which installs distributed renewable energy and energy storage units in multiple DNs within a TSO-DSO coordination scheme. The rate of return on the DER investment is ensured. A stochastic bi-level investment model is formulated, which is efficiently solved using a nested decomposition algorithm based on the concepts of Bender's decomposition and Lagrangian relaxation. Our algorithm calculates the DER sizing and sitting decisions in a finite number of iterations without sacrificing optimality. The proposed framework can be used by a regulator or policy making entity to efficiently coordinate the business interests of ESP, DSO and TSO to facilitate a quicker renewable energy transition. As a future work, we plan to study the coordination of private DER investments and distribution network expansion in the proposed ESP-DSO-TSO coordination framework, capturing the objectives of all involved parties. Also, our study can be extended taking into account more revenue streams for the DERs (e.g., ancillary services provision to both the TSO and the DSO) and including non-convex characteristics of conventional generators in the electricity market clearing process.

3. Chapter 3: Market Participation and Operation Decisions

In this Chapter, we turn our attention to the network-aware bidding and operation decision-making problem of an ESP that owns a portfolio of diverse DERs (RES, Energy Storage Systems, and Demand Side Management) and participates in the Day-Ahead Energy Market (Figure 13).

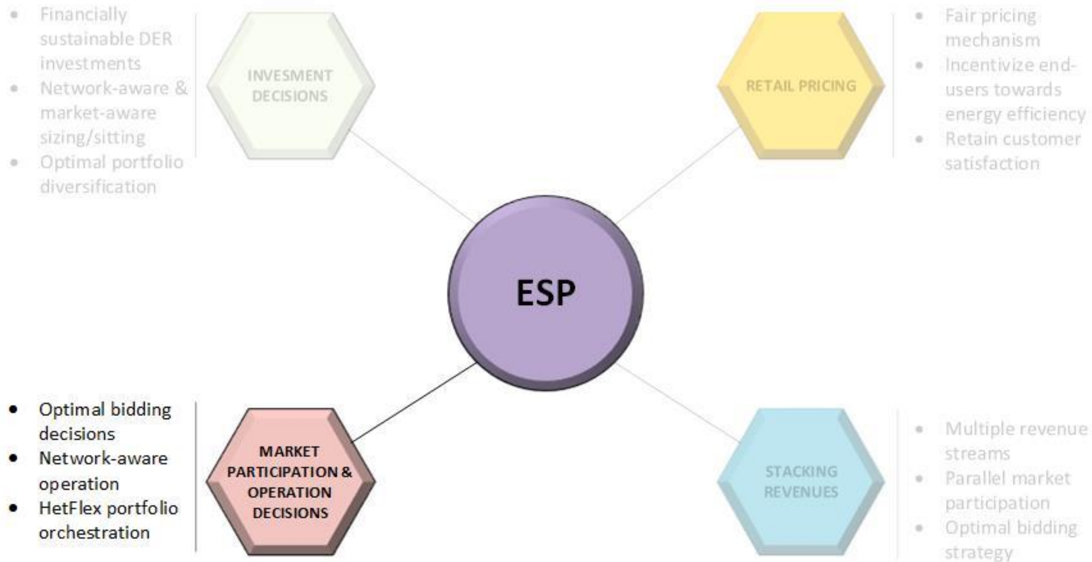

Figure 13: ESP's Market Participation and Operation Decision-Making

We assume a regulated operation of the distribution network, where a DisCo acts as an ESP that directly controls the assets considering the distribution network's constraints and represents them in the market. We propose an algorithm that optimally schedules DERs in order to devise a bidding strategy for a strategic ESP. We use bilevel modeling in order to formulate the profit maximization problem of the ESP. The bilevel problem is finally transformed into a tractable MILP. We show that: (i) ESP's profits can be considerably increased, by on average 20% compared to the price taker solution, (ii) the impact of DERs' siting and sizing can be accurately quantified, (iii) even if the ESP accounts for a small portion of market's supply or demand capacity, significant profit benefits can be obtained, and (iv the network-aware feature leads not only to higher profits, but also to the avoidance of vital distribution network constraints' violation.

The Chapter's structure is as follows: Section 3.1 presents the requirements for a financially sustainable operation of the DERs and highlights the contributions of this thesis. Section 3.2 discusses related work. Section 3.3 formulates ESP's bidding and scheduling problem. Section 3.4 presents and analyzes the solution method in detail. Section 3.5 provides a detailed evaluation of the proposed solution, enhanced with useful comparisons. Finally, Section 3.6 concludes Chapter 3 and discusses future work.

3.1. Strategic and Network-Aware Bidding Policy for Electric Utilities through the Optimal Orchestration of a Virtual and Heterogeneous Flexibility Assets' Portfolio

High penetration of RES in the generation mix delivers clean and low-cost energy and can lead to autonomous societies. On the other hand, in such a dynamic environment, the current electricity grid architectures are facing severe efficiency and stability issues. This triggers the utilization of distributed energy and flexibility resources able to adapt consumption to production and guarantee the efficiency and stability of Smart Grids.

These Heterogeneous Flexibility (HetFlex) assets (e.g. Energy Storage Systems, RES, DSM schemes) can be categorized according to: (i) their type of operation, (ii) the impact that their size and network location have on the Smart Grid planning process, (iii) the impact that their scheduling decisions have on optimally responding to dynamically changing network and market states, (iv) other business logic issues, which are related to ESP's business strategy (e.g., risk hedging, Return on Investment – RoI models, strategic business plans, etc.). Hence, the optimal orchestration of HetFlex assets placed in a given geographical area and belonging to a specific ESP's portfolio is a prerequisite for ESP's financial sustainability.

As analyzed in Chapter 1, traditional electric utilities are being transformed into ESPs that: (a) trade energy in the wholesale market, (b) sell energy through retail markets, and (c) further ensure their financial sustainability through the aggregation of HetFlex assets and providing services to the System Operators. There are five key elements that ESPs have to take into account in the operational stage.

The first is the large-scale use of ESSs, which have expanded rapidly during recent years and are expected to increase at a higher rate in the future [112]. Consequently, ESPs have to optimally schedule the ESS' operation according to the energy markets' state in order to secure their profitability. The second relates to the aggregation of distributed flexible load resources and their scheduling (DSM) towards the ESP's optimal participation in the energy market(s). Thus, ESPs have to design integrated schedulers and enable in this way the deep interaction between ESS and DSM towards competitive design of business models. The third fundamental challenge is to derive models and algorithms that provide optimal orchestration of the HetFlex assets, while respecting the operational limits of a physical distribution network. In particular, high RES penetration increases the challenges related to the congestion and voltage control of the distribution grid. Thus, network-aware scheduling models for an ESP are of high importance. The fourth critical issue for an ESP relates to the management of RES units. An ESP must be able to optimize the use of its HetFlex assets so as to optimize energy utilization from its own renewable generators. This would render the ESP more independent and more competitive. Finally, the fifth key element regards the optimal participation of the ESP in the liberalized energy markets. In this perspective, the ESP's decision process can be formulated through complementarity modeling [113] and more specifically as a bilevel problem in which the upper-level problem represents the maximization of ESP's profits and the lower-level one represents the market clearing process. Thus, an MPEC is generated that is ultimately transformed into a MILP. This model constitutes the ESP a price maker that, in contrast to a price taker ESP, is able to anticipate the electricity market's reaction to its bidding decisions and affect the market prices.

In a nutshell, the major contribution of the current thesis is a holistic and sophisticated ESP's business model that simultaneously:

- Offers strategic ESPs the capability to optimally bid in an imperfect Day-Ahead Energy Market taking into account the outer environment in terms of the decisions of electricity market competitors. It is shown that even if an ESP represents only a small portion of market's total generation or consumption capacity, it can gain significantly more profit by acting strategically.

- Allows the adjustment and the respect of operational limits of a physical distribution network, ensuring that they will not be violated at any time. In this way, the ESP plans a distribution network-aware bidding strategy that saves it from high societal and monetary costs.
- Orchestrates a virtual HetFlex portfolio that comprises distributed renewable production, DSM and ESS units. The coordinated planning and scheduling of HetFlex assets results in higher RES utilization and cost-effective network operation

To the best of our knowledge, this is the first work to model the decision-making process of a strategic ESP that takes into account the aforementioned five key elements and demonstrates this in detail through accurate comparisons.

3.2. Related Work

A number of works that have appeared in the literature use bi-level programming and complementarity modeling to model decision making of strategic players in liberalized energy markets. Works in [61], [72], [73], [74], [76], [114], [115] and deal with the strategic operation of a Generator Company (GenCo) in electricity pool markets. More specifically, authors in [73] formulate a bi-level model, in which a GenCo maximizes its profit in the upper-level, while in the lower-level a Market Operator (MO) clears the market by solving an Optimal Power Flow (OPF) problem. In [76], the profit maximization problem of a GenCo is formulated as an MPEC, which in [74] is transformed into a MILP through binary expansion. The binary expansion approach was presented in [72], which also modeled the uncertainty in rival GenCos' bids and system's load. In [114], a non-interior point algorithm is used in order to find the equilibrium in a Stackelberg Game between a GenCo and a MO, thus clearing the market on top of an AC power system model. The authors in [115] modeled a bi-level problem to study the strategic behavior of GenCos under two different pricing mechanisms in electricity markets, namely uniform and price-as-bid pricing. Finally, Kazempour and Conejo [61] formulated an MPEC in order to study the problem of a GenCo's strategic investment. The authors used Benders Decomposition technique in order to tackle scalability issues. Furthermore, [66], [79], [80], [81], [82], [83] and [116] examine the strategic participation of a merchant ESS owner in an energy market. The authors in [79] formulate the profit maximization problem of a strategic ESS owner participating in wholesale day-ahead market as a Mathematical Program with Primal and Dual Constraints (MPPDC). The study in [80] considers a price maker merchant ESS owner aiming to maximize its profits through the coordination of the operation of geographically dispersed ESSs. The authors in [83] propose a look-ahead technique to optimize ESS's operator bidding strategy in the wholesale DA energy market considering also the operation in the following day. The work in [82] studies the impact on the profits of a price maker ESS owner when ramp-up/down limits of generating units are considered in the market-clearing process. The optimal sizing of a price maker energy storage facility is studied in [66]. A stochastic bi-level problem is formulated and a Benders' decomposition technique is implemented to make the model tractable. In addition, the same authors in [81] formulated an MPEC in order to study the parallel participation of an ESS owner in both energy and reserve markets. In [116], the authors studied the problem of the optimal investment of a strategic ESS owner, taking into account the transmission capacity expansion plans of the TSO. For the case of strategic load serving entities (LSEs), [85] formulated an MPEC in order to investigate the strategic bidding of an LSE in day-ahead markets, while [86] expanded the previous study to co-optimize LSE's bidding strategy in both energy and reserve markets. Our work differs from the previous research works by considered a progressive electric utility as a strategic market player. More specifically, in this thesis we use complementarity modeling to model the decision of an ESP, which controls a Virtual Power Plant (VPP) with multiple HetFlex assets, while it must simultaneously satisfy the distribution network constraints.

There is a great deal of studies dealing with the scheduling and bidding problem of a *price taker* ESP that is in control of a VPP. A VPP comprises distributed generators, ESSs, flexible and inflexible loads. The work in [27] studied the problem of optimal bidding in day-ahead and real-time market of an EV aggregator, while [28] dealt with the bidding problem of a Microgrid aggregator in day-ahead market. The aggregator's objective is the profit maximization without sacrificing users' thermal comfort. The problem studied in [29] is the Real-Time scheduling of a Microgrid composed of an RG, an ESS and an aggregated load, in order to minimize its electricity costs. The authors in [117] used robust optimization for the bidding problem of a VPP (in both day-ahead and real-time market) in order to tackle the challenges arising from uncertainties pertaining to: market prices, load variation and renewable production. For the same problem, [30] and [31] formulated hybrid stochastic/robust optimization models. Works in [32] and [33] studied the optimal scheduling and market participation problem of a VPP in day-ahead and real-time market, while ensuring the reliable operation of distribution network incorporating into their models technical network constraints. The aforementioned works, [27]- [33], considered price taker ESPs in contrast with our work which studies the optimal bidding and scheduling problem of a **price maker** ESP controlling a VPP with multiple HetFlex assets.

3.3. System Model & Problem Formulation

We consider a transmission grid, which is characterized by a set of buses V^G and a set of transmission lines $L \subseteq V^G \times V^G$. The transmission line between buses *i* and *j* is denoted by ij, $(i,j) \in L$. An ESP acts as an orchestrator/aggregator of HetFlex assets over multiple geographically dispersed Distribution Networks (DNs). These DNs are connected to a set of buses of the transmission grid, denoted by $V^M \subseteq V^G$. For notational simplicity, a DN connected in bus *i* of the transmission grid is also indexed with *i*. RGs, ESSs, flexible (shiftable) and inflexible loads are located in each DN $i \in V^M$ turning it into a *VPP*, which can supply/draw power to/from the rest of the grid. More specifically, the DN connected to bus $i \in V^M$ is characterized by a set of nodes (DN buses) V_i, a set of edges (DN branches) $B_i \subseteq V_i \times V_i$, a set of ESSs S_i, a set of renewable generators R_i, a set of shiftable loads F_i and a set of inflexible loads I_i. Throughout this Chapter we refer to the edges of the transmission grid as lines and to those of a distribution network as branches, which are denoted by nk, $(n,k) \in B_i$, $i \in V^M$. The ESP is responsible for controlling the ESSs and the deferrable loads in order to strategically participate in the wholesale day-ahead market and maximize its profits. In addition, the ESP has to ensure the reliable operation of DNs. The goal of our work is to calculate the ESP's optimal bidding strategy in day-ahead market and the optimal schedule of the HetFlex assets, while simultaneously taking into account the distribution network constraints.

3.3.1. Energy Storage Systems

As mentioned earlier, the ESP manages the ESSs' charging/discharging schedules. At each DN $i \in V^M$ and timeslot $t \in H$, each ESS *s* (physical or virtual through the aggregation of several distributed battery systems) has to be charged or discharged. Charging (or discharging) power $r_{i,s,t}^{ch}$ (or $r_{i,s,t}^{dis}$) is limited by the ESS' maximum charging (or discharging) rate $r_{i,s}^{ch,max}$ (or $r_{i,s}^{dis,max}$, respectively). Thus:

$$0 \le r_{i,s,t}^{ch} \le \left(1 - x_{i,s,t}\right) \cdot r_{i,s}^{ch,max} \qquad \forall i \in V^M, s \in S_i, t \in H \tag{3.1}$$

$$0 \le r_{i,s,t}^{dis} \le x_{i,s,t} \cdot r_{i,s}^{dis,max} \qquad \forall i \in V^M, s \in S_i, t \in H \tag{3.2}$$

In (3.1) and (3.2), $x_{i,s,t}$ is a binary variable indicating the operating status (charging or discharging) of each DN's ESS at *t*. Thus, $x_{i,s,t} = 1$ when ESS *s* located in DN *i* is discharged at *t*, and $x_{i,s,t} = 0$ when it is charged. We denote by *H* = {1, 2…, *T*} the scheduling horizon considered. Additionally, the State of Charge $SOC_{i,s,t}$ of each ESS in DN *i* at any time interval *t* cannot exceed a lower bound $SOC_{i,s}^{min}$ and an upper bound $SOC_{i,s}^{max}$:

$$SOC_{i,s,t} = SOC_{i,s,0} - \sum_{\tau=1}^{t}(\eta_{i,s}^{d} \cdot r_{i,s,\tau}^{dis} - \eta_{i,s}^{c} \cdot r_{i,s,\tau}^{ch}) \qquad \forall i \in V^M, s \in S_i, t \in H, \tag{3.3}$$

$$SOC_{i,s}^{min} \le SOC_{i,s,t} \le SOC_{i,s}^{max} \qquad \forall i \in V^M, s \in S_i, t \in H. \tag{3.4}$$

In (3.3) and (3.4), the constants $\eta_{i,s}^{d}$ and $\eta_{i,s}^{c}$ denote the discharge and charge efficiency factors, respectively. In addition, we specify the final SoC of each ESS in order to take into account next day's operation:

$$SOC_{i,s,T} = w_{i,s} \cdot SOC_{i,s,0} \qquad \forall i \in V^M, s \in S_i\,. \tag{3.5}$$

In (3.5), $w_{i,s} \ge 0$ is a design parameter (it is equal to 1 for a neutral ESS schedule).

3.3.2. Shiftable Loads

Shiftable Loads is the second type of HetFlex assets in the hands of the ESP. Each shiftable load $d \in F_i, i \in V^M$, must fulfill a specific task within the scheduling horizon, meaning that a certain amount of energy $E_{i,d}^{fl}$ must be consumed by load *d* in that period. Every shiftable load has a desired time schedule $[\alpha_{i,d}, \beta_{i,d}] \subseteq H$, within which the operation must take place. Outside this desired time interval, the power consumption of the shiftable loads is zero, while inside, it has an upper limit on its consumption rate ($p_{i,d}^{fl,max}$). Thus, the operating constraints of the shiftable load *d* in *i* are:

$$\begin{cases} 0 \le p_{i,d,t}^{fl} \le p_{i,d}^{fl,max}, & \text{if } t \in [\alpha_{i,d}, \beta_{i,d}] \\ p_{i,d,t}^{fl} = 0, & \text{otherwise} \end{cases} \qquad \forall i \in V^M, d \in F_i, t \in H \tag{3.6}$$

$$\sum_{t=\alpha_{i,d}}^{\beta_{i,d}} p_{i,d,t}^{fl} = E_{i,d}^{fl} \qquad \forall i \in V^M, d \in F_i. \tag{3.7}$$

3.3.3. Distribution Network

The decisions made by the ESP must satisfy the DN's power flow constraints. In order to model the distribution network, we use the widely used by the literature ([32], [33], [105], [118], [119], [120], [121]) linearized DistFlow equations, introduced in [105]. The use of linearized DistFlow equations is justified by the fact that the power losses (nonlinear terms) are in practice much smaller than the branch power flows, i.e., $p_{i,nk,t}$ and $q_{i,nk,t}$ ([105]). Additionally, authors in [120] verified this assumption, by demonstrating that the linear equations lead to an insignificant difference in the results comparing to the nonlinear equations. The linearized DistFlow equations are presented below:

$$\sum_{k\in\Omega_d^i(n)} p_{i,nk,t} = \sum_{j\in\Omega_p^i(n)} p_{i,jn,t} - p_{i,n,t}^{fl} - p_{i,n,t}^{infl} + p_{i,n,t}^{rg} + r_{i,n,t}^{dis} - r_{i,n,t}^{ch}$$

$$\forall i \in V^M, n \in V_i, t \in H \tag{3.8}$$

$$\sum_{k\in\Omega_d^i(n)} q_{i,nk,t} = \sum_{j\in\Omega_p^i(n)} q_{i,jn,t} - \delta_{i,n}^{fl} \cdot p_{i,n,t}^{fl} - \delta_{i,n}^{infl} \cdot p_{i,n,t}^{infl} + \delta_{i,n}^{rg} \cdot p_{i,n,t}^{rg}$$

$$\forall i \in V^M, n \in V_i, t \in H \tag{3.9}$$

$$U_{i,n,t} = U_{i,j,t} - 2 \cdot \left(r_{i,jn} \cdot p_{i,jn,t} + x_{i,jn} \cdot q_{i,jn,t}\right)$$

$$\forall i \in V^M, n \in V_i, j \in \Omega_p^i(n), t \in H \tag{3.10}$$

$$U_{i,n}^{min} \le U_{i,n,t} \le U_{i,n}^{max} \qquad \forall i \in V^M, n \in V_i, t \in H \tag{3.11}$$

$$p_{i,nk}^{min} \le p_{i,nk,t} \le p_{i,nk}^{max} \qquad \forall i \in V^M, (n,k) \in B_i, t \in H \tag{3.12}$$

$$q_{i,nk}^{min} \le q_{i,nk,t} \le q_{i,nk}^{max} \qquad \forall i \in V^M, (n,k) \in B_i, t \in H \tag{3.13}$$

Equations (3.8) - (3.10) are the *branch flow equations.* Thus, $p_{i,nk,t}$ and $q_{i,nk,t}$ denote the active and reactive power flowing in the branch nk connecting nodes $n \in V_i$ and $k \in V_i$. Furthermore, $p_{i,n,t}^{fl}$, $p_{i,n,t}^{infl}$ and $p_{i,n,t}^{rg}$ are the active powers of: flexible loads, inflexible loads and RG in node $n \in V_i$ at timeslot *t,* respectively. In addition, $\delta_{i,n}^{fl}$, $\delta_{i,n}^{infl}$ and $\delta_{i,n}^{rg}$ convert the active power of the shiftable loads, inflexible loads and RGs at node $n \in V_i$ into their reactive power ($\delta = \tan(cos^{-1}(power\,factor))$. Furthermore $U_{i,n,t}$ is the square of the voltage magnitude, while $r_{i,jn}$ and $x_{i,jn}$ are the resistance and the reactance, respectively, of branch *jn* in DN *i*. Equation (3.11) imposes the lower ($U_{i,n}^{min}$) and the upper ($U_{i,n}^{max}$) limit on the square voltage amplitude of node *n* in DN *i*. Finally, (3.12) and (3.13) constraint up ($p_{i,nk}^{max}$, $q_{i,nk}^{max}$) and down ($p_{i,nk}^{min}$, $q_{i,nk}^{min}$) the active and reactive power flows of branch *nk* in DN *i,* respectively. The sets $\Omega_d^i(n)$ and $\Omega_p^i(n)$ represent the decedent and precedent nodes, respectively, connected to node *n* in any radial DN.

The root of each radial DN ($n = 0$), connected to the transmission grid, is the substation. In substations (where the power is sold/purchased to/from the market), the active and reactive power balance must hold:

$$\sum_{0k} p_{i,0k,t} = -p_{i,t}^M \qquad \forall i \in V^M, t \in H \tag{3.14}$$

$$\sum_{0k} q_{i,0k,t} = -Q_{i,t} \qquad \forall i \in V^M, t \in H \tag{3.15}$$

In (3.14), $p_{i,t}^M$ denotes the power that DN *i* supplies to the grid at timeslot *t*. A negative value of $p_{i,t}^M$ indicates that DN *i* draws power from the grid. In (3.15) $Q_{i,t}$ denotes the reactive power that *i* exchanges with the grid at timeslot *t*.

3.3.4. Quantity Offers/Bids

In this Chapter, we assume a nodal wholesale electricity market, in which ESP has to optimally choose for each DN *i* and time instants $t \in H$ its energy offer/bids $(o_{i,t}, b_{i,t})$. The latter are limited by each DN's total power net capacity (parameters $o_{i,t}^{max}$ and $b_{i,t}^{max}$):

$$0 \leq o_{i,t} \leq h_{i,t} \cdot o_{i,t}^{max} \qquad \forall i \in V^M, t \in H \tag{3.16}$$

$$0 \leq b_{i,t} \leq (1 - h_{i,t}) \cdot b_{i,t}^{max} \qquad \forall i \in V^M, t \in H \tag{3.17}$$

In (3.16) and (3.17), $h_{i,t} = 1$ if DN i sells power in wholesale market at t and $h_{i,t} = 0$ if it buys power.

$$o_{i,t}^{max} = \sum_{n \in R_i} p_{i,n,t}^{rg} + \sum_{n \in S_i} r_{i,n}^{dis,max} - \sum_{n \in I_i} p_{i,n,t}^{infl} \qquad \forall i \in V^M, t \in H \tag{3.18}$$

$$b_{i,t}^{max} = -\sum_{n \in R_i} p_{i,n,t}^{rg} + \sum_{n \in S_i} r_{i,n}^{ch,max} + \sum_{n \in F_i} p_{i,n}^{fl,max} + \sum_{n \in I_i} p_{i,n,t}^{infl} \qquad \forall i \in V^M, t \in H \tag{3.19}$$

Equations (3.18) and (3.19) express the maximum quantity offer $(o_{i,t}^{max})$ and bid $(b_{i,t}^{max})$ that DN *i* can submit at time *t*, respectively. In (3.18) - (3.19) recall that R_i, S_i, I_i and F_i denote the sets of nodes in which RG, ESS, inflexible load and flexible loads are located in DN i, respectively.

Quantity offers/bids are also limited by the active power capacity of the coupling point between the DN *i* and the transmission grid:

$$o_{i,t}, b_{i,t} \leq \sum_{0k} p_{i,0k}^{max} \quad . \tag{3.20}$$

Finally, the ESP decides on the price bid that DN *i* submits to the day-ahead market in timeslot *t*, which is denoted by $c_{i,t}^{M}$.

3.3.5. ESP's Profit Maximization Problem

In order for the ESP to schedule its HetFlex assets in a network-aware and cost-effective manner, its profit maximization problem is defined as:

$$\max_{X_U} \sum_{t \in H} \sum_{i \in V^M} \lambda_{i,t} \cdot p_{i,t}^{M}$$

Subject to (3.1) - (3.20)

(3.21)

In more detail, the objective of ESP is the maximization of its profits that result from its participation in the nodal electricity pool market. When a DN located at bus $i \in V^M$ supplies power to the grid at time *t*, it sells this power in the pool market at price $\lambda_{i,t}$, which is the nodal price at bus *i*. In contrast, when a DN *i* draws power from the grid, it buys that power from the pool market at price $\lambda_{i,t}$. The set of decision variables of ESP's problem (3.21) is $X_U = \{r_{i,s,t}^{dis}, r_{i,s,t}^{ch}, x_{i,s,t}, SOC_{i,s,t}, p_{i,d,t}^{fl}, p_{i,nk,t}, q_{i,nk,t}, U_{i,n,t}, Q_{i,t}, o_{i,t}, b_{i,t}, h_{i,t}, c_{i,t}^{M} \mid (i,s,t) \in V^M \times S_i \times H, (i,d,t) \in V^M \times S_i \times H, (i,(n,k),t) \in V^M \times B_i \times H, (i,n,t) \in V^M \times V_i \times H, (i,t) \in V^M \times H\}$. Hence, the ESP, given the production of the RGs and the inflexible loads that must run at any cost, decides on the quantity and price bids to the wholesale market, along with the optimal schedule of the ESSs and the flexible loads located at the DNs, in order to maximize its profits, while satisfying the DN constraints.

3.3.6. Market Clearing Process

As analyzed earlier, a nodal transmission-constrained electricity pool market is considered. Apart from the ESP, generators and demand aggregators participate in this market. We adopt the 'Central dispatch' model (Article 2, Paragraph 18 in [122]) for the market clearing process, in which the generators are obliged to declare their operating constraints (including ramping constraints). The set of transmission grid buses in which generators are located is denoted by $G \subseteq V^G$ and the set of buses that demand loads are located is denoted by $D \subseteq V^G$. In optimization problem (3.21), dispatches and LMPs are calculated by the MO, which clears the electricity market. MO maximizes the Social Welfare by taking into account: i) the transmission grid constraints, ii) the participants' quantity offers/bids, iii) generators' ramping constraints and iv) price bids. In other words, the MO decides on the energy dispatch schedules of the market participants (generators, demand aggregators and ESP) by solving a DC-OPF problem:

$$\min_{X_L} \sum_{t\in H}\left(\sum_{i\in G}\left(c_{i,t}^{g} \cdot g_{i,t}\right) - \sum_{i\in D}\left(c_{i,t}^{d} \cdot d_{i,t}\right) + \sum_{i\in V^M}\left(c_{i,t}^{M} \cdot p_{i,t}^{M}\right)\right) \tag{3.22}$$

Subject to

$$-g_{i,t} + d_{i,t} - p_{i,t}^{M} + \sum_{j\neq \iota} y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t}\right) = 0 \ ; (\lambda_{i,t}) \ \ \forall i \in V^G, \forall (i,j) \in L, t \in H \tag{3.23}$$

$$g_i^{min} \le g_{i,t} \le g_i^{max} \quad ; \quad (\varphi_{i,t}^{gmin}, \varphi_{i,t}^{gmax}) \quad \forall i \in G, t \in H \tag{3.24}$$

$$-RD_i \le g_{i,t} - g_{i,t-1} \le RU_i \ ; \quad (\varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}) \quad \forall i \in G, t{>}1 \tag{3.25}$$

$$-RD_i \le g_{i,t} - g_{i,0} \le RU_i \quad ; \quad (\varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}) \quad \forall i \in G, t{=}1 \tag{3.26}$$

$$d_{i,t}^{min} \le d_{i,t} \le d_{i,t}^{max} \quad ; \quad (\varphi_{i,t}^{dmin}, \varphi_{i,t}^{dmax}) \quad \forall i \in D, t \in H \tag{3.27}$$

$$-b_{i,t} \le p_{i,t}^{M} \le o_{i,t} \quad ; \quad (\varphi_{i,t}^{mmin}, \varphi_{i,t}^{mmax}) \quad \forall i \in V^M, t \in H \tag{3.28}$$

$$-T_{ij}^{max} \le y_{ij} * (\theta_{i,t} - \theta_{j,t}) \le T_{ij}^{max}; \quad (\varphi_{ij,t}^{lmin}, \varphi_{ij,t}^{lmax}) \quad \forall (i,j) \in L, i < j, t \in H \tag{3.29}$$

In other words, the objective of the MO is to minimize the social cost (objective function of problem (3.22)), i.e., the cost of energy production minus the willingness of demand aggregators to pay for that energy. We consider that the system's demand is elastic and each demand aggregator can submit a price/quantity bid indicating how much it is willing to pay for a certain level of consumption. The decision variables of optimization problem (3.22) are: i) the power supply $g_{i,t}$ of each generator $i \in G$, ii) the power consumption $d_{i,t}$ of each demand aggregator $i \in D$, iii) the power supply/consumption $p_{i,t}^{M}$ of each DN $i \in V^M$ and iv) the voltage phase angles $\theta_{i,t}$ at all buses $i \in V^G$ at every timeslot t ($X_L = \{g_{i,t} | (i,t) \in G \times H, d_{i,t} | (i,t) \in D \times H, p_{i,t}^{M} | (i,t) \in V^M \times H, \theta_{i,t} | (i,t) \in V^G \times H\}$). The price bids of generators and demand aggregators at timeslot t are denoted by $c_{i,t}^{g}$ and $c_{i,t}^{d}$, respectively. Equation (3.23) expresses the power balance at each bus i of the power grid. The dual variables of these constraints provide the LMPs. In (3.23), y_{ij} is the admittance of transmission line ij, $(i,j) \in L$. Equation (3.24) concerns the generators' minimum and maximum capacity. Furthermore, equations (3.25) and (3.26) express the constraints on the ramp up and down limits, denoted by RU_i and RD_i, respectively. Equation (3.27) refers to demand loads' upper ($d_{i,t}^{max}$) and lower bounds ($d_{i,t}^{min}$) while equation (3.29) constraints power flow to the transmission lines' *ij* capacity limits (T_{ij}^{max}). Additionally, constraint (3.28) enforces MO's decision concerning the power that is traded with the DNs to be not higher than the submitted offers/bids. The dual variables pertaining to each constraint of DC-OPF are specified at each constraint (Eqs. (3.23) - (3.29)) following a semicolon. Finally, it is highlighted that the voltage phase angle of the reference bus is zero throughout the whole scheduling period ($\theta_{ref,t} = 0$).

3.4. Solution Method

ESP does not simply act as a price taker, but is able to anticipate the electricity market's reaction to its decisions (quantity/price bids). In order to model this process, a Stackelberg Game is formulated in which the ESP is the *Leader* and the electricity market is the *Follower*. The problem is solved from the ESP's point of view that acts strategically. Hence, an Optimization Problem constrained by an Optimization Problem (OPcOP) is formulated, in which the Upper-level Problem (Problem (3.21)) is constrained by the Lower-level Problem (Problem (3.22)):

$$\max \sum_{t\in H} \sum_{i\in V^G} \lambda_{i,t} \cdot p_{i,t}^M$$

$$\text{Subject to } \begin{pmatrix} \text{Constraints } (3.1)\text{–}(3.20) \\ \text{Optimization Problem } (3.22) \end{pmatrix}$$

In the above bi-level optimization problem, the constraining lower-level problem (3.22) is a Linear Program and therefore, Slater's condition holds [123]. Thus, DC-OPF problem's Karush-Kuhn-Tucker conditions are necessary and sufficient optimality conditions (satisfy convexity and constraint qualification). Thus, solving the following nonlinear system of equations is equivalent to solving Problem (3.22):

$$-g_{i,t} + d_{i,t} - p_{i,t}^M + \sum_{j\neq \iota} y_{ij} \cdot (\theta_{i,t} - \theta_{j,t}) = 0 \qquad \forall i \in V^G, (i,j) \in L, t \in H \qquad (3.23)$$

$$c_{i,t}^g - \lambda_{i,t} - \varphi_i^{gmin,t} + \varphi_i^{gmax,t} - \varphi_i^{grd,t} + \varphi_i^{grd,t+1} + \varphi_i^{gru,t} - \varphi_i^{gru,t+1} = 0$$

$$\forall i \in G, t < T \qquad (3.30)$$

$$c_{i,t}^g - \lambda_{i,t} - \varphi_i^{gmin,t} + \varphi_i^{gmax,t} - \varphi_i^{grd,t} + \varphi_i^{gru,t} = 0 \qquad \forall i \in G, t = T \qquad (3.31)$$

$$-c_{i,t}^d + \lambda_{i,t} - \varphi_{i,t}^{dmin} + \varphi_{i,t}^{dmax} = 0 \qquad \forall i \in D, t \in H \qquad (3.32)$$

$$c_{i,t}^M - \lambda_{i,t} - \varphi_{i,t}^{mmin} + \varphi_{i,t}^{mmax} = 0 \qquad \forall i \in V^M, t \in H \qquad (3.33)$$

$$\sum_{j\neq i,(i,j)\in L} y_{ij} \cdot (\lambda_{i,t} - \lambda_{j,t}) - \sum_{j>i} y_{ij} \cdot (\varphi_{ij,t}^{lmin} - \varphi_{ij,t}^{lmax}) + \sum_{j<i} y_{ji} \cdot (\varphi_{ji,t}^{lmin} - \varphi_{ji,t}^{lmax}) = 0$$

$$\forall i \in V^G, t \in H \qquad (3.34)$$

$$0 \leq \varphi_{i,t}^{gmin} \perp g_{i,t} - g_i^{min} \geq 0 \qquad \forall i \in G, t \in H \qquad (3.35)$$

$$0 \leq \varphi_{i,t}^{gmax} \perp -g_{i,t} + g_i^{max} \geq 0 \qquad \forall i \in G, t \in H \qquad (3.36)$$

$$0 \leq \varphi_{i,t}^{grd} \perp g_{i,t} - g_{i,t-1} + RD_i \geq 0 \qquad \forall i \in G, t \in H \qquad (3.37)$$

$$0 \le \varphi_{i,t}^{gru} \perp -g_{i,t} + g_{i,t-1} + RU_i \ge 0 \qquad \forall i \in G, t \in H \qquad (3.38)$$

$$0 \le \varphi_{i,t}^{dmin} \perp d_{i,t} - d_{i,t}^{min} \ge 0 \qquad \forall i \in D, t \in H \qquad (3.39)$$

$$0 \le \varphi_{i,t}^{dmax} \perp -d_{i,t} + d_{i,t}^{max} \ge 0 \qquad \forall i \in D, t \in H \qquad (3.40)$$

$$0 \le \varphi_{i,t}^{mmin} \perp p_{i,t}^{M} + b_{i,t} \ge 0 \qquad \forall i \in V^M, t \in H \qquad (3.41)$$

$$0 \le \varphi_{i,t}^{mmax} \perp -p_{i,t}^{M} + o_{i,t} \ge 0 \qquad \forall i \in V^M, t \in H \qquad (3.42)$$

$$0 \le \varphi_{ij,t}^{lmin} \perp y_{ij} \cdot (\theta_{i,t} - \theta_{j,t}) + T_{ij}^{max} \ge 0 \qquad \forall (i,j) \in L, i < j, t \in H \qquad (3.43)$$

$$0 \le \varphi_{ij,t}^{lmax} \perp -y_{ij} \cdot (\theta_{i,t} - \theta_{j,t}) + T_{ij}^{max} \ge 0 \qquad \forall (i,j) \in L, i < j, t \in H \qquad (3.44)$$

Equations (3.23), (3.30) – (3.44) are the KKT conditions of Problem (3.22). Equation (3.23) represents the equality constraint of DC-OPF problem, while in Eqs (3.30) - (3.34) the partial derivatives of its Lagrangian function with respect to its primal variables are set to zero. Equations (3.35) – (3.44) express the complementarity conditions. We use the perpendicular symbol (⊥) to indicate complementarity, i.e., $0 \le x \perp y \ge 0 \equiv \begin{cases} x \ge 0, y \ge 0 \\ x \cdot y = 0 \end{cases}$.

Replacing the constraining optimization problem (3.22) with its KKT conditions in our OPcOP results in the following MPEC problem:

$$\min_{X_U \cup X_L \cup \Xi_L} -\sum_{t \in H} \sum_{i \in V^M} \lambda_{i,t} \cdot p_{i,t}^{M}$$

Subject to Eqs. (3.1) – (3.20), (3.23), (3.30) – (3.44)

(3.45)

Problem (3.45) is a single-level mixed integer non-linear optimization problem. The nonlinearities are due to complementarity conditions (3.35) – (3.44) and its objective function. The optimization variables of problem (3.45) are: i) the set of the primal variables of upper-level problem (denoted by vector X_U) which has been defined in subsection 3.3.5, ii) the set of the primal variables of the constraining lower-level problem (denoted by vector X_L) which has been defined in subsection 3.3.6 and iii) set of the dual variables (denoted by vector Ξ_L) of the lower-level problem, where $\Xi_L = \{\lambda_{i,t}, \varphi_{i,t}^{gmin}, \varphi_{i,t}^{gmax}, \varphi_{i,t}^{grd}, \varphi_{i,t}^{gru}, \varphi_{i,t}^{dmin}, \varphi_{i,t}^{dmax}, \varphi_{i,t}^{mmin}, \varphi_{i,t}^{mmax}, \varphi_{ij,t}^{lmin}, \varphi_{ij,t}^{lmax} \mid (i,t) \in V^M \times H, ((i,j),t) \in L \times H\}$. In order to tackle the nonlinearities that come from complementarity conditions we use the Fortuny-Amat & McCarl linearization technique [124]. Complementarity constraints of the type $0 \le x \perp y \ge 0$ can be replaced by the following set of linear constraints below.

$$0 \le x \le M \cdot u$$

$$0 \le y \le M \cdot (1 - u)$$

Constant *M* is large enough and *u* is an auxiliary binary variable. In our model, care is exercised to select a proper constant *M* to avoid numerical ill-conditioning. Therefore, Eqs. (3.35) – (3.44) are replaced by the following set of linear constraints:

$$0 \leq g_{i,t} - g_i^{min} \leq M \cdot u_{i,t}^{gmin} \qquad \forall i \in G, t \in H \tag{3.46}$$

$$0 \leq \varphi_{i,t}^{gmin} \leq M \cdot (1 - u_{i,t}^{gmin}) \qquad \forall i \in G, t \in H \tag{3.47}$$

$$0 \leq -g_{i,t} + g_i^{max} \leq M \cdot u_{i,t}^{gmax} \qquad \forall i \in G, t \in H \tag{3.48}$$

$$0 \leq \varphi_{i,t}^{gmax} \leq M \cdot (1 - u_{i,t}^{gmax}) \qquad \forall i \in G, t \in H \tag{3.49}$$

$$0 \leq g_{i,t} - g_{i,t-1} + RD_i \leq M \cdot u_{i,t}^{grd} \qquad \forall i \in G, t \in H \tag{3.50}$$

$$0 \leq \varphi_{i,t}^{grd} \leq M \cdot (1 - u_{i,t}^{grd}) \qquad \forall i \in G, t \in H \tag{3.51}$$

$$0 \leq -g_{i,t} + g_{i,t-1} + RU_i \leq M \cdot u_{i,t}^{gru} \qquad \forall i \in G, t \in H \tag{3.52}$$

$$0 \leq \varphi_{i,t}^{gru} \leq M \cdot (1 - u_{i,t}^{gru}) \qquad \forall i \in G, t \in H \tag{3.53}$$

$$0 \leq d_{i,t} - d_{i,t}^{min} \leq M \cdot u_{i,t}^{dmin} \qquad \forall i \in D, t \in H \tag{3.54}$$

$$0 \leq \varphi_{i,t}^{dmin} \leq M \cdot (1 - u_{i,t}^{dmin}) \qquad \forall i \in D, t \in H \tag{3.55}$$

$$0 \leq -d_{i,t} + d_{i,t}^{max} \leq M \cdot u_{i,t}^{dmax} \qquad \forall i \in D, t \in H \tag{3.56}$$

$$0 \leq \varphi_{i,t}^{dmax} \leq M \cdot (1 - u_{i,t}^{dmax}) \qquad \forall i \in D, t \in H \tag{3.57}$$

$$0 \leq p_{i,t}^M + b_{i,t} \leq M \cdot u_{i,t}^{mmin} \qquad \forall i \in V^M, t \in H \tag{3.58}$$

$$0 \leq \varphi_{i,t}^{mmin} \leq M \cdot (1 - u_{i,t}^{mmin}) \qquad \forall i \in V^M, t \in H \tag{3.59}$$

$$0 \leq -p_{i,t}^M + o_{i,t} \leq M \cdot u_{i,t}^{mmax} \qquad \forall i \in V^M, t \in H \tag{3.60}$$

$$0 \leq \varphi_{i,t}^{mmax} \leq M \cdot (1 - u_{i,t}^{mmax}) \qquad \forall i \in V^M, t \in H \tag{3.61}$$

$$0 \leq B_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t}\right) + T_{ij}^{max} \leq M \cdot u_{ij,t}^{lmin} \qquad \forall (i,j) \in L, i < j, t \in H \tag{3.62}$$

$$0 \leq \varphi_{ij,t}^{lmin} \leq M \cdot (1 - u_{ij,t}^{lmin}) \qquad \forall (i,j) \in L, i < j, t \in H \tag{3.63}$$

$$0 \leq -y_{ij} \cdot \left(\theta_{i,t} - \theta_{j,t}\right) + T_{ij}^{max} \leq M \cdot u_{ij,t}^{lmax} \qquad \forall (i,j) \in L, i < j, t \in H \tag{3.64}$$

$$0 \leq \varphi_{ij,t}^{lmax} \leq M \cdot (1 - u_{ij,t}^{lmax}) \qquad \forall (i,j) \in L, i < j, t \in H \tag{3.65}$$

As far as the objective function nonlinearities are concerned, we use an ad hoc linearization technique. First, we multiply Eq. (3.33) by $p_{i,t}^M$:

$$c_{i,t}^M \cdot p_{i,t}^M - \lambda_{i,t} \cdot p_{i,t}^M - \varphi_{i,t}^{mmin} \cdot p_{i,t}^M + \varphi_{i,t}^{mmax} \cdot p_{i,t}^M = 0 \qquad \forall i \in V^M, t \in H \tag{3.66}$$

In (3.66), the terms are re-arranged as follows:

$$-\lambda_{i,t} \cdot p_{i,t}^M = -c_{i,t}^M \cdot p_{i,t}^M + \varphi_{i,t}^{mmin} \cdot p_{i,t}^M - \varphi_{i,t}^{mmax} \cdot p_{i,t}^M \qquad \forall i \in V^M, t \in H \tag{3.67}$$

In addition, from complementarity conditions (3.41) and (3.42), we have

$\varphi_{i,t}^{mmin} \cdot p_{i,t}^M = -\varphi_{i,t}^{mmin} \cdot b_{i,t}$ and $\varphi_{i,t}^{mmax} \cdot p_{i,t}^M = \varphi_{i,t}^{mmax} \cdot o_{i,t}$.

Hence, the objective function of MPEC problem (3.45) is replaced by the expression

$$-\sum_{t\in H}\sum_{i\in V^M}\left(c_{i,t}^M \cdot p_{i,t}^M\right) - \sum_{t\in H}\sum_{i\in V^M}\left(\varphi_{i,t}^{mmin} \cdot b_{i,t}\right) - \sum_{t\in H}\sum_{i\in V^M}\left(\varphi_{i,t}^{mmax} \cdot o_{i,t}\right).$$

Now, we make use of the Strong Duality Theorem for Problem (3.22), according to which the value of the primal objective function at the global optimal point is equal to the value of the dual objective function:

$$\sum_{t\in H}\left(\sum_{i\in G}\left(c_{i,t}^g \cdot g_{i,t}\right) - \sum_{i\in D}\left(c_{i,t}^d \cdot d_{i,t}\right) + \sum_{i\in V^M}\left(c_{i,t}^M \cdot p_{i,t}^M\right)\right) =$$

$$-\left\{-\sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmin} \cdot g_i^{min}\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmax} \cdot g_i^{max}\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{grd} \cdot RD_i\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gru} \cdot RU_i\right) - \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmin} \cdot d_{i,t}^{min}\right) + \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmax} \cdot d_{i,t}^{max}\right) + \sum_{i\in V^M}\sum_{t\in H}\left(\varphi_{i,t}^{mmin} \cdot b_{i,t}\right) + \sum_{i\in V^M}\sum_{t\in H}\left(\varphi_{i,t}^{mmax} \cdot o_{i,t}\right) + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmin}\right) + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmax}\right)\right\} \tag{3.68}$$

By re-arranging the terms in Eq. (3.68), we obtain:

$$-\sum_{t\in H}\sum_{i\in V^M}\left(c_{i,t}^M \cdot p_{i,t}^M\right) - \sum_{t\in H}\sum_{i\in V^M}\left(\varphi_{i,t}^{mmin} \cdot b_{i,t}\right) - \sum_{t\in H}\sum_{i\in V^M}\left(\varphi_{i,t}^{mmax} \cdot o_{i,t}\right) = \sum_{t\in H}\sum_{i\in G}\left(c_{i,t}^g \cdot g_{i,t}\right) - \sum_{t\in H}\sum_{i\in D}\left(c_{i,t}^d \cdot d_{i,t}\right) - \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmin} \cdot g_i^{min}\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmax} \cdot g_i^{max}\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{grd} \cdot RD_i\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gru} \cdot RU_i\right) - \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmin} \cdot d_{i,t}^{min}\right) + \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmax} \cdot d_{i,t}^{max}\right) + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmin}\right) + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmax}\right) \tag{3.69}$$

Problem (3.45) is finally formulated as:

$$\begin{aligned}\min_{X_U\cup X_L\cup \Xi_L\cup \Xi_B} &\sum_{t\in H}\sum_{i\in G}\left(c_{i,t}^g \cdot g_{i,t}\right) - \sum_{t\in H}\sum_{i\in D}\left(c_{i,t}^d \cdot d_{i,t}\right) - \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmin} \cdot g_i^{min}\right)\\ &+ \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gmax} \cdot g_i^{max}\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{grd} \cdot RD_i\right) + \sum_{i\in G}\sum_{t\in H}\left(\varphi_{i,t}^{gru} \cdot RU_i\right)\\ &- \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmin} \cdot d_{i,t}^{min}\right) + \sum_{i\in D}\sum_{t\in H}\left(\varphi_{i,t}^{dmax} \cdot d_{i,t}^{max}\right)\\ &+ \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmin}\right) + \sum_{i<j,(i,j)\in L}\sum_{t\in H}\left(T_{ij}^{max} \cdot \varphi_{ij,t}^{lmax}\right)\end{aligned}$$

Subject to Eqs. (3.1) – (3.20), (3.23), (3.30) – (3.34), (3.46) – (3.65)

(3.70)

We observe that the objective function of problem (3.70) is a sum of linear terms. Therefore, we have reformulated the initial OPcOP into a tractable Mixed Integer Linear Problem (MILP), which can be solved using a commercial MILP solver. The control variables of problem (3.70) are those of (3.45), with the addition of the set of auxiliary binary variables u of Eqs. (3.46) – (3.65), $\Xi_B = \{u_{i,t}^{gmin}, u_{i,t}^{gmax}, u_{i,t}^{gru}, u_{i,t}^{grd}, u_{i,t}^{dmin}, u_{i,t}^{dmax}, u_{i,t}^{mmin}, u_{i,t}^{mmax}, u_{ij,t}^{lmin}, u_{ij,t}^{lmax} | (i,t) \in V^M \times H,\ (ij,t) \in L \times H\}$.

3.5. Performance Evaluation

In order to demonstrate the performance of the proposed methodology, we consider two case studies: 1) a 6-bus illustrative example, in which ESP controls a single DN and 2) the IEEE one-area reliability test system, in which ESP practices spatiotemporal arbitrage controlling multiple DNs distributed among the transmission grid. In both cases, we consider a 15-node radial distribution network [125] as shown in Figure 14. The line parameters are shown in Table A of Appendix D. The base power and voltage are 30 MVA and 11kV, respectively. A time horizon of T=24h is considered. Finally, the large constant M is chosen to be 2000 throughout the simulations.

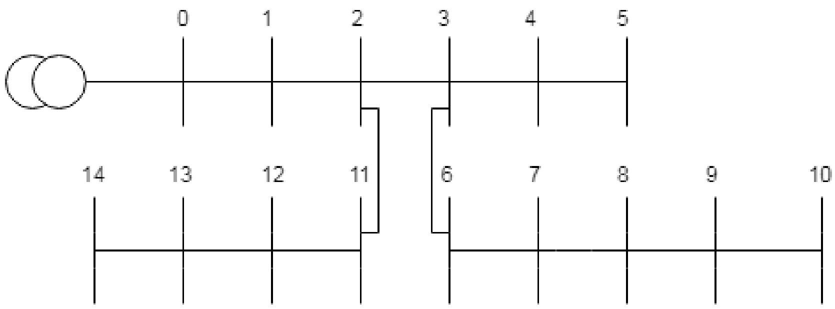

Figure 14: A 15-Node Radial Distribution Network

3.5.1. Case Study A: A 6-Bus Illustrative Example

This case study is considered in order for the numerical results to be tracked. In Figure 15, a 6-bus test system [82] is presented, which is used to analyze the ESP's strategic bidding and scheduling of HetFlex assets. Transmission lines, conventional generators and load data are taken from [82] and are presented in Appendix D (Tables B, C and D). Bus 1 is considered to be the reference bus.

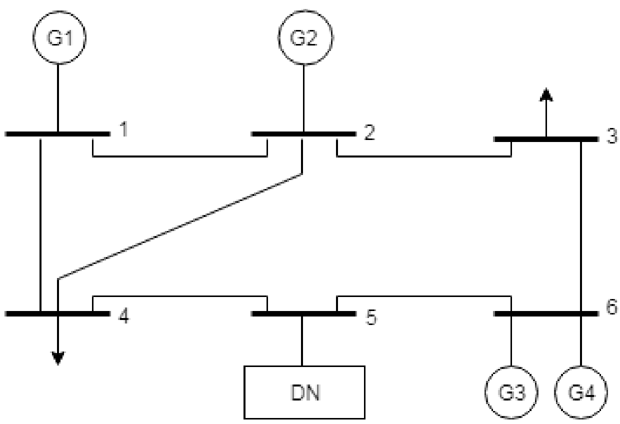

Figure 15: A 6-Bus Test System

A DN (namely, the one given in Figure 14) is located at bus 5. We assume that three solar PVs are located at nodes 2, 5 and 13 of DN and 3 wind turbines at nodes 8, 10 and 11. Renewable production data are derived from [126] and the power factors of every RG is set to 0.95. Additionally, inflexible loads are located at nodes 1, 2, 3, 4, 6, 7, 10, 11 and 12 and their consumption curves are based on load data from [125]. Figure 16 presents the total renewable energy production ($\sum_{n \in R_5} p_{5,n,t}^{rg}$) and inflexible load consumption curves ($\sum_{n \in I_5} p_{5,n,t}^{infl}$) as a function of time.

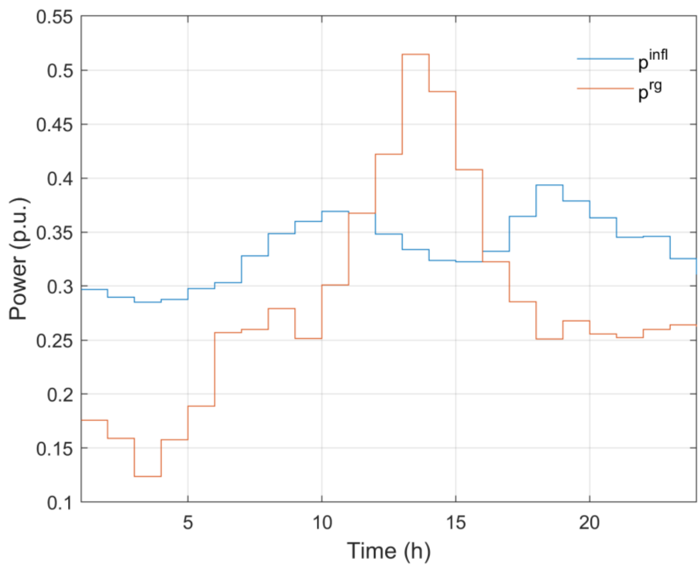

Figure 16: Renewable energy production and inflexible load consumption daily curves

Furthermore, we assume that 4 ESSs of energy capacity 0.1667pu are located at nodes 5, 8, 10 and 13 of the DN. Their charge/discharge rate is 0.0833pu, their initial SoC is 0.0833pu and we set parameters $\boldsymbol{w_{5,s}} = \mathbf{1}$, $\forall \boldsymbol{s} \in \boldsymbol{S_5}$ (cf. Appendix D, Table E). Also, without loss of generality, we assume lossless ESSs ($\boldsymbol{\eta^{d}_{5,s}}$, $\boldsymbol{\eta^{c}_{5,s}}$=1). Finally, we consider 6 shiftable loads located at nodes 4, 9, 10, 11, 13 and 14, which can consume from time $\boldsymbol{\alpha_{5,d}} = \mathbf{8}$h to time $\boldsymbol{\beta_{5,d}}$= 18h, $\forall \boldsymbol{d} \in \boldsymbol{F_5}$. Their total energy consumption and their maximum power consumption per timeslot is 0.02667pu, while their power factor is 0.9 (cf. Appendix D, Table F). In order to demonstrate the advantages of the proposed system, three cases are presented:

Case 1: ESP controlling a DN with renewable production, energy storage and flexible loads participates in day-ahead market as a price taker, considering DN physical constraints

Case 2: ESP acts as a price maker but without considering the DN constraints (Eqs. (3.8) – (3.15))

Case 3: ESP acts as a price maker considering DN constraints and implementing the proposed methodology.

Case 1: In this case, ESP is a non-strategic player in a perfect competition market. Thus, in order to calculate market equilibrium, a single-level optimization problem is solved (DC-OPF), in which MO maximizes social welfare. ESP makes a profit of 747.50€ from its participation in Day-Ahead electricity market as a price taker. Schedules of ESSs and shiftable loads are presented below (Figure 17 and Table 8).

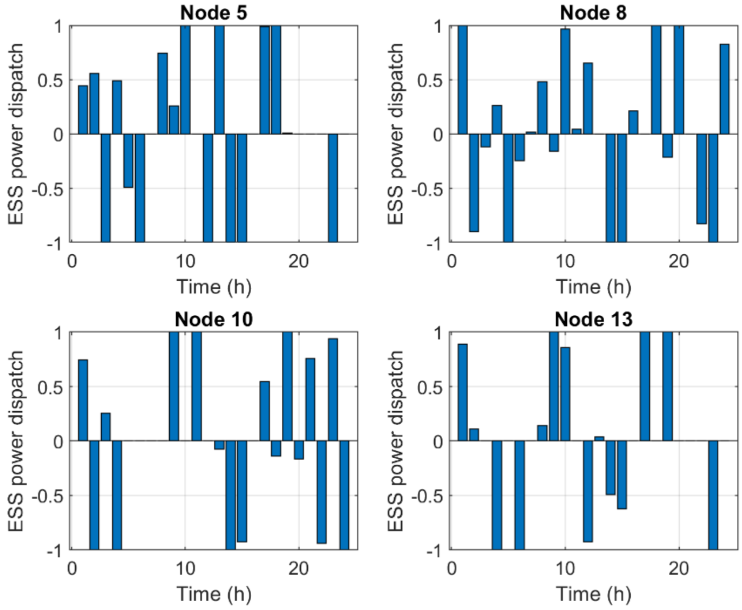

Figure 17: ESSs power dispatch schedules in Case 1 as a percentage of their maximum charge/discharge rates – Negative values indicate charging mode

Table 8: Power dispatch schedule of shiftable loads in Case 1 as a percentage of their total energy consumption

Node \ t	8	9	10	11	12	13	14	15	16	17	18
4	0	0	0	0.384	0	0.616	0	0	0	0	0
9	0	0	0	0	0	1.000	0	0	0	0	0
10	0	0	0	0	0	1.000	0	0	0	0	0
11	0	0	0	0	0	1.000	0	0	0	0	0
13	0	0	0	0	0	1.000	0	0	0	0	0
14	0	0	0	0	0	1.000	0	0	0	0	0

Market results regarding LMPs at bus 5 and DN dispatch are presented in Figure 18 (for more details on market results of case study A see Appendix D, Table G). We can conclude from Figure 17 and Table 8, that ESSs and shiftable loads are utilized to maximize social welfare, i.e., maximizing total utility of load demand with the minimum production cost, while satisfying operational constraints. For instance, at time interval t=1, ESSs provide enough power, not only to satisfy DN's net load, but also to supply power to the grid in order for the System's Marginal Cost (SMC) to decline (SMC = 20€/MWh). If DN did not supply power to the grid, generators G1, G2 and G3 would satisfy the total demand load of the system, resulting in an SMC of 50€/MWh (i.e., price bid of G3). Furthermore, at time interval t=6, the ESSs in Nodes 5, 8 and 13 are charged in order for the DN to draw more power than is needed to satisfy its net load. This occurs because of the ramp down rates of generators G1 and G2, which cannot lower their production fast enough to match the total demand in that interval. The distribution network's power drawing creates more demand in order to absorb the excess production and prevent negative LMPs' occurrence. Another example of the utilization of DN's controllable assets towards social welfare maximization is the ESSs operation in timeslot t=17. In that time interval, the ESSs in nodes 5, 10 and 13 are discharged. Thus, DN supplies power to the grid reducing the generation cost by curtailing production power from G4 and decreasing the consumption curtailment (due to congestion in transmission line 4) of load in node 4. Flexible loads in this situation are mainly used to avoid voltage limit violations. Therefore, most of flexible load is chosen to operate in *t*=13 (only the 38.4% of shiftable load at node 4 consumes at a different timeslot, i.e., *t*=11), in which DN supplies power to the grid that mainly comes from the DN's net production (renewable production minus inflexible load).

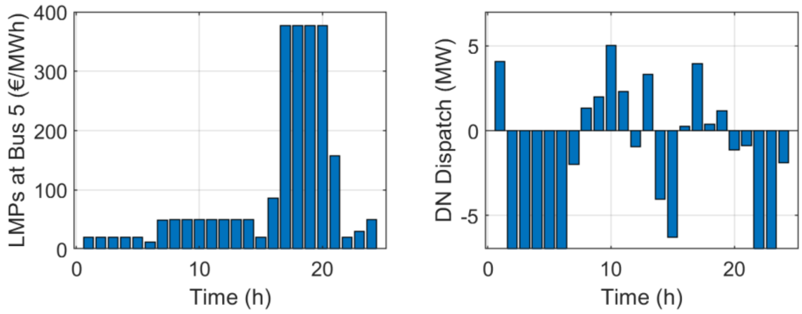

Figure 18: Market Results - LMPs at Bus 5 and Power Dispatch of DN in Case 1

Case 2: In this case, ESP strategically bids in day-ahead electricity market, but does not take into account distribution network constraints. Thus, ESP solves an MPEC problem in which Equations (3.8) – (3.15) are not included in the set of constraints of the upper-level problem. ESP schedules ESSs and shiftable loads with the objective to supply more power to the grid in times when LMPs are higher and draw power when LMPs are lower. In this way, voltage issues arise in areas that lie in the distribution grid's edges, at which RGs (nodes 10, 11 and 13) and loads (nodes 10, 11, 12, 13 and 14) are located. More specifically, voltage limit violations occur at node 10 during intervals *t*=11, 17 and 24, at node 11 during *t*=13, at node 12 during *t*=12, 13 and at nodes 13 and 14 during *t*=10, 11, 12 and 13. Moreover, active power flow limits are violated at several branches and timeslots. In order to maximize its profits from the participation in day-ahead market, ESP decides to fully utilize DN's net production to supply power to the grid in times when LMPs are rising. This, however, results in power flows in the distribution network higher than the branches' capacity allows (see Appendix D, Tables H and I for more details).

This case yields an apparent profit of 1700.3€ for the ESP. However, due to voltage and congestion issues, the ESP will have to perform corrective actions in real time market, with either very high monetary or societal (renewable energy curtailment/reduction in consumption of inflexible loads) costs. Thus, Case 2 ultimately leads to more expensive or, even worse, *technically infeasible schedules* of ESSs and shiftable loads.

Case 3: In this case, ESP implements the proposed methodology. Market outcomes in this case are presented in Figure 19 (cf. Appendix D, Table J), while ESSs' and shiftable loads' schedules are presented in Figure 20 and Table 9, respectively. ESP earns 897.33€, **which outperforms price taker solution (Case 1) by 20%**.

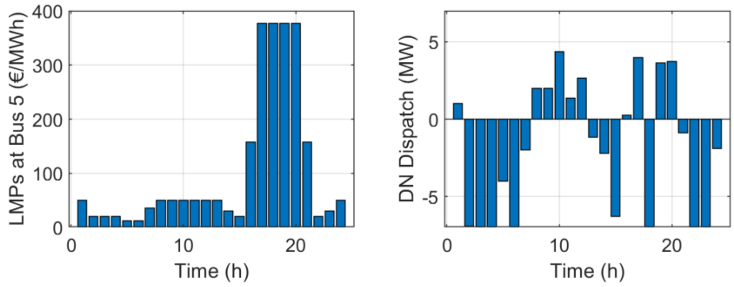

Figure 19: Market Results – LMPs at Bus 5 and Power Dispatch of DN in Case 3

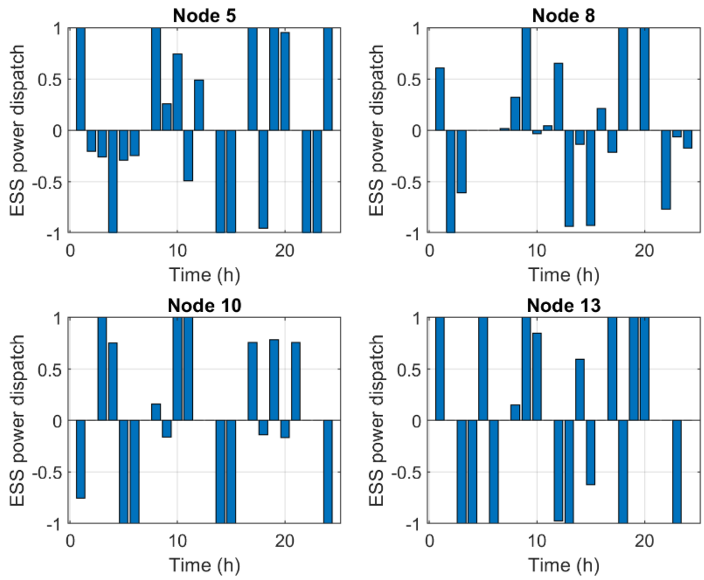

Figure 20: The ESSs power schedules (Case 3) as a percentage of their charge/discharge rates – Negative values indicate charging mode

Table 9: Power dispatch schedule of shiftable loads in Case 3 as a percentage (%) of their total energy capacity

Node \ t	8	9	10	11	12	13	14	15	16	17	18
4	0	0	0	0	0	0	1.000	0	0	0	0
9	0	0	0	0	0	0	1.000	0	0	0	0
10	0	0	0	0	0	0	1.000	0	0	0	0
11	0	0	0	0	0	1.000	0	0	0	0	0
13	0	0	0	0	0	1.000	0	0	0	0	0
14	0	0	0	0.036	0	0.157	0.807	0	0	0	0

Studying Figure 18 and Figure 19, we note that, comparing to Case 1, the proposed methodology results in different LMPs at bus 5 in timeslots 1, 5, 7, 14 and 16. In particular, at *t*=1 ESP supplies 1MW at 50 €/MWh, discharging ESSs at nodes 5, 8 and 13. The total demand load is covered from G1, G2 and the DN, making DN the marginal supplier. At *t*=5, ESP purchases 4 MW at 12€/MWh, which is the lowest price bid that it can submit (cheapest generator's offer) in order to buy the necessary power amount to satisfy DN's inflexible loads and charge ESSs at nodes 5 and 10. Then, at *t*=7, ESP buys 2MW making a price bid at

36 €/MWh. LMP at bus 5 is determined by the cost of generating an extra MW by G3 (50 €/MWh) minus the value of dual variable concerning generator's G3 lower bounds ($\varphi_{6,t}^{gmin} = 14$ €/MWh). If ESP demanded more than 2MW, then G3 would be the marginal generator with $\varphi_{6,t}^{gmin}$ being 0 (according to complementarity condition (3.35)). In that case, LMP at bus 5 would be higher (50 €/MWh). Later, at *t*=14, ESP takes advantage of the generator's G3 ramp up limitation, and it purchases 2.22 MW at 30€/MWh in order to: a) complete the task of shiftable loads at nodes 4, 9, 10 and 14, and b) charge ESSs at nodes 5, 8 and 10. ESP's price bid sets LMP at bus 5 at 30€/MWh, since the cost of generating an extra 1 MW is 50€ (price bid of G3) minus 20€, which is the value of dual variable concerning ramp up constraint of G3 at t=15 (in case G3 generates 24.22MW at *t*=14, ramp up constraint of G3 will not be binding). At *t*=16, ESP takes advantage of the congested line 4 to make more profit by offering 0.25MW at 157.2368 €/MWh. ESS at node 10 supplies power 0.53 MW in order for ESP to satisfy DN's net demand (0.28MW) and sell 0.25MW in the market.

In general, we see that DN does not simply inject power to the grid at timeslots in which LMPs are higher due to congestion (i.e., $t \in [16, 21]$) or at timeslots during which its renewable production surpasses its load demand (i.e.„ $t \in [12, 15]$). This is due to distribution network physical constraints (voltage and power flow limits). For example, in *t*=13 we have the higher net production (5.4128 MW). At that time, ESP decides to run its shiftable loads at nodes 11, 13 and 14 in order to prevent nodal voltage amplitude rising above its upper limit (i.e., 1.05pu). In contrast, at *t*=14 and t=15 the excess production (4.6847 and 2.5669 MW, respectively) is used to charge ESSs and run shiftable loads. This happens in order to: a) keep voltage amplitude within the safe operation area (i.e., 0.95 – 1.05pu), and b) ensure that ESSs will be fully charged in order for the DN to sell power in the market at *t*=16 and *t*=17, when the price will be much higher.

3.5.1.1. Impact of HetFlex Assets' Siting

RGs' Location*:* In addition to the simulation setup used previously, we investigate one more scenario of DN setup: we consider the same RGs as before but located at different nodes of the DN. More specifically, wind turbines are located at nodes 3, 6 and 7, while solar PVs at nodes 2, 5 and 14. With this setup, if the ESP acts as price taker (Case 1), it enjoys a profit of 1162.7€. On the other hand, if the ESP acts as a price maker (Case 3) it earns 1413.1€, which is 21.54% higher than in Case 1. Higher profits are justified by the fact that in cases with high renewable production deep in the radial distribution network, ESSs are not fully utilized to maximize profits from energy temporal arbitrage, but they are partially operated to prevent network constraint violation. Hence, the siting of RGs can have a significant impact on ESP's profits.

ESSs' Location*:* In order to study the impact of ESSs' location on ESP's profits, we assume that 4 ESSs (with the same technical characteristics with those that we used before) are located at nodes 2, 8, 9 and 14. ESP's profits are 1140.6€ in Case 1 and 1393.1€ in Case 3 (i.e., 22.13% higher if ESP implements the proposed methodology, and 55.25% higher than the former DN setup). Furthermore, if we locate ESSs at nodes 4, 5, 6 and 10 then there will be no control on power injections from RGs in nodes 11 and 13 resulting in nodal voltage rising higher than 1.05pu, in which case problem (3.70) becomes infeasible. Thus, given the locations of RGs, ESSs, siting must be exercised carefully towards: a) the feasible operation of the DN, and b) the maximum possible profit from temporal arbitrage.

Shiftable Loads' Location*:* The relocation of shiftable loads from nodes 4, 9 and 10 to nodes 2, 5 and 12, respectively, will lead to profits of 766.44€ for a price taker ESP and 918.31€ for a price maker (i.e., 19.81% increase). We see that by relocating the shiftable loads, ESP increases its income by only 2.3%. However, if loads at nodes 11, 13 and 14 are moved and relocated elsewhere, then the problem becomes infeasible due to the upper bounds on the nodal voltage magnitude.

3.5.1.2. Impact of HetFlex Assets' Sizing

We now study the impact of the aggregate size of renewable generation, storage capacity and flexible loads on the results obtained. Initially, we consider a DN with the same storage capacity as in the former DN setup (4 ESS units at nodes 5, 8, 10 and 13), with a varying number of RG units and flexible loads (Figure 21). Figure 21 depicts the ESP's financial balance (positive when ESP earns money from its participation in Day-Ahead Market (DAM) and negative when it experiences a trade deficit) in various cases regarding the number of RG units and shiftable loads. First, we observe, as expected, that the ESP's financial balance from the wholesale market participation increases with the number of RG units. Moreover, the proposed methodology (blue bars) always yields more profit for the ESP than the price-taker solution (red bars) by a percentage varying from 2.59% (2 RG units and 6 shiftable loads) up to 94.10% (4 RG units and 6 flexible loads). Particularly, in some cases (4 RG units with 4 or 6 shiftable loads), Case 3 yields a positive balance, while Case 1 results in negative balance for the ESP. In case that 6 RG units and 2 shiftable loads are located in the DN, then the problem is infeasible due to voltage violation for this specific ESS allocation.

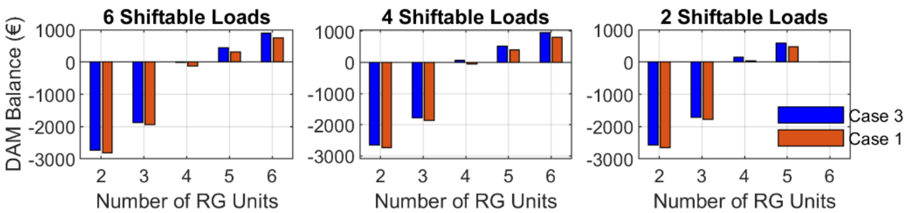

Figure 21: ESP's financial balance in Day-Ahead Market for different numbers of RG units and shiftable loads for a given number of ESS units

In addition, we consider another scenario where RES generation remains untouched (3 solar PVs at nodes 2, 5, 13 and 3 wind turbines at nodes 8, 10 and 11), while the number of ESS changes from 2 to 6 and shiftable loads can be 2, 4 or 6 (each one of both ESS units and shiftable loads have the same characteristic as in the former setup). As shown in Figure 22, increasing the number of ESS units results in larger profit for ESP in both Case 1 and 3. However, a price maker ESP earns more profit than a price taker ESP by 2.57-20.04%. In case of 2 shiftable loads, nodal voltage violation occurs and the problem becomes infeasible.

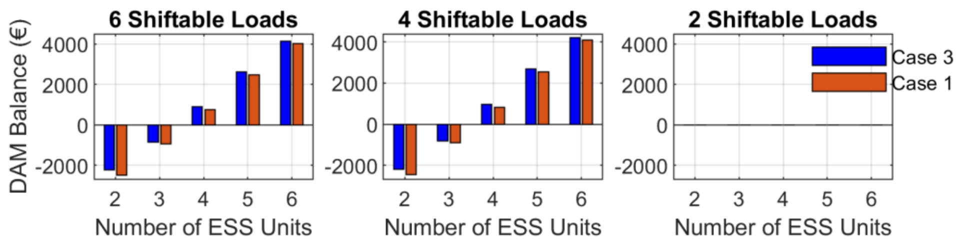

Figure 22: ESP's financial balance in Day-Ahead Market for different numbers of ESS units and shiftable loads for a given number of RG units

Finally, we study how the size of RES and storage capacity affects the financial balance of the ESP when 6 flexible loads are located in the DN. In Figure 23, we see ESP's profits increase with the number of RG units. In case of 2 RG units, 6 ESS units are needed for Case 3 to yield a positive financial balance (in this case price taker solution still results in negative balance for ESP).

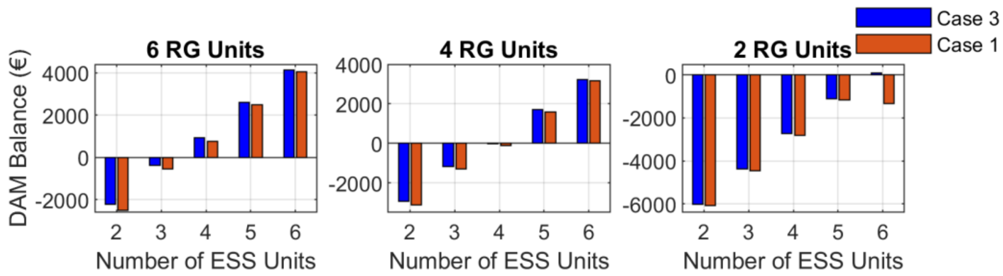

Figure 23: ESP's financial balance in Day-Ahead Market for different numbers of ESS units RG units for a given number of shiftable loads

3.5.2. Case Study B: The IEEE One-Area Reliability Test System

In this case study, we study an ESP coordinating geographically dispersed DNs in order to maximize its profits through employing spatio-temporal arbitrage. For this purpose, the IEEE One-Area Reliability Test System [127] is used, which is presented in Figure 24. Transmission lines, conventional generators and load data are taken from [128], while price bids of generators from [82] (cf. Appendix D, Tables K, L, and M). The price bids of demand aggregators are the same as in Case Study A. Bus 13 is considered to be the system's slack bus.

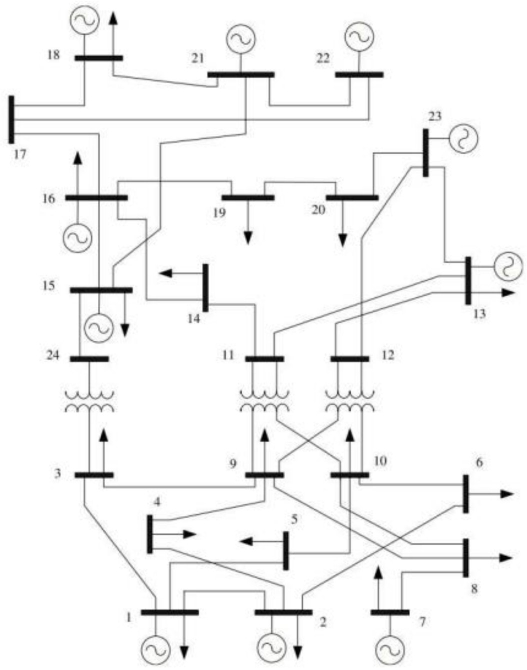

Figure 24: The IEEE One-Area Reliability Test System

Initially, it is assumed that ESP controls the HetFlex assets of 3 different DNs (namely DN1, DN2 and DN3), which are located at buses 14, 15 and 23. The technical characteristics of the DN branches are the same as in the previous case study (Appendix D, Table A), while DNs' assets data are presented in Appendix D, Tables N, O and Figure A. The resulting LMPs at buses 14, 15 and 23 and the dispatches of DNs and are presented in Figure 25 and Figure 26 below.

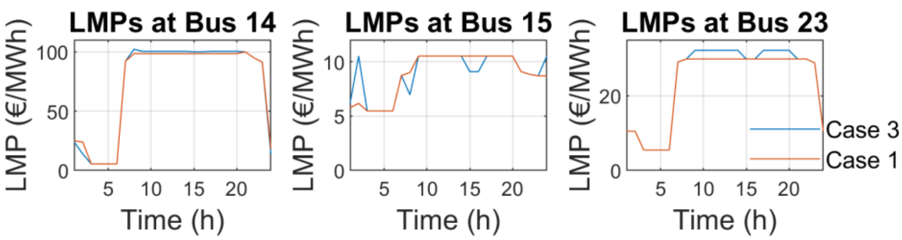

Figure 25: LMPs at Buses 14, 15 and 23

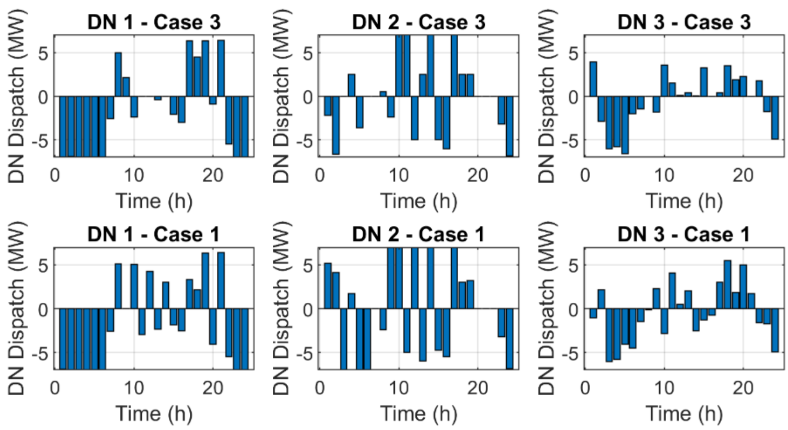

Figure 26: Power dispatch schedules of DN1, DN2 and DN3 in Cases 1 and 3

Figure 25 and Figure 26 present the impact of the strategic bidding and HetFlex assets' scheduling of the ESP on LMPs and DNs' dispatch respectively. Strategic participation in day-ahead market decreases LMP at buses and timeslots in which DNs absorb power from the grid (e.g., Bus 15 at t=8, 15, 16). On the other hand, ESP increases its profits through strategic price bidding at buses and timeslots that DNs supply power to the grid (e.g., Bus 23 at t =17, 18, 19, 20). Additionally, in Figure 26, we can notice ESP exercising spatio-temporal arbitrage. For example, at t=1, DNs 1 and 2 buy power, while DN 3 sells power at day-ahead market. At t=4, DNs 1 and 3 draw power, while DN 2 supplies power to the grid. ESP also exercises arbitrage at timeslots 9, 10, 12, 13, 15, 20 and 22. ESP makes 456.64€ in Case 1 and 589.81€ in Case 3. Thus, ESP gains 29.16% more profit than Case 1 through the proposed methodology. Therefore, we conclude that, even if ESP possesses a very small portion of market's total generation (in each timeslot each DN can supply/draw to/from the grid 7MW of power, resulting in ESP possessing <1% of the total market generation and demand capacity) or consumption capacity, it can achieve significantly more profit if it acts as a price maker rather than a price taker.

3.6. Conclusions and Future Work

In this Chapter, we considered an ESP that controls a virtual and heterogeneous flexibility assets' portfolio (i.e., set of VPPs) throughout the transmission grid, and participates in an imperfect wholesale electricity market. The portfolio consists of HetFlex assets, namely: demand loads that must be satisfied by all means, distributed RES generation, energy storage capacity and shiftable loads. Complementarity modeling is proposed to derive both the optimal schedule of HetFlex assets and strategic market decisions for ESP. In the proposed model, the distribution network constraints are taken into account in order for the ESP's quantity and price market bids to be reliable. Thus, an MPEC is formulated, which is transformed into an equivalent MILP. We have shown that the proposed methodology results in significantly larger profit for the ESP, even if it possesses a small portion of market's production or consumption capacity. Moreover, we discuss the impact on the results of RGs, flexible loads and ESSs location and size. Finally, we show that if distribution network constraints are not considered, this results in infeasible and costly schedules. As our model is rather deterministic, we plan to perform in the future on the impact of uncertainties in various model parameters (e.g., RES production, generators' and demand aggregators' bids). Also, we will work on the bidding problem of an ESP, which participates in both energy and reserve markets. Finally, our work can be extended in order to study the case in which there are more than one strategic ESPs competing in an electricity market.

4. Chapter 4: Stacked Revenues Optimization

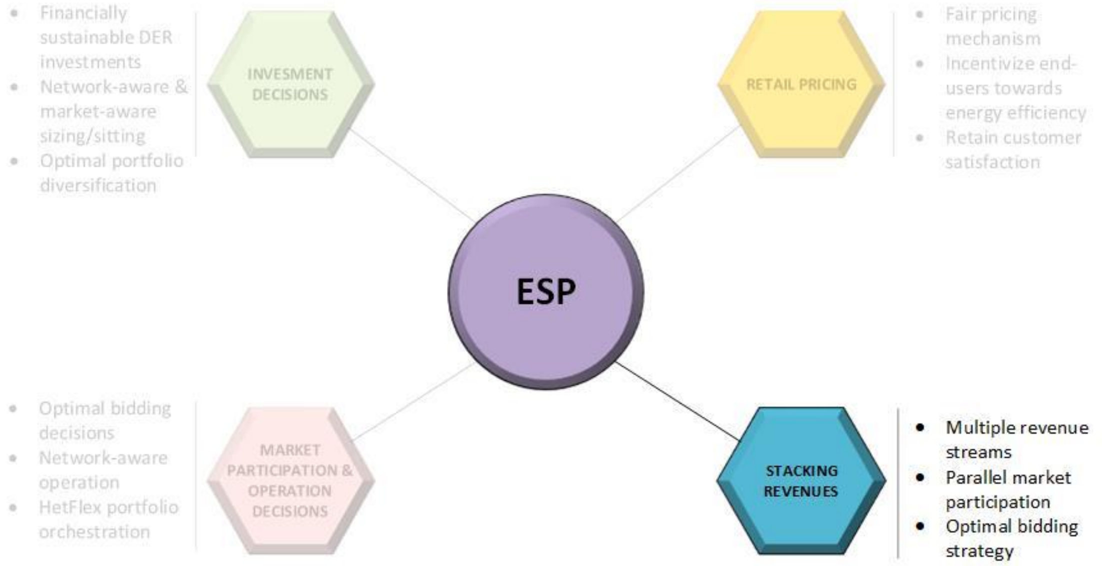

Figure 27: ESP's Stacking Revenues Decision-Making

In this Chapter, the ESP’s problem of stacking revenues is studied (Figure 27). As stated in Chapter 1, DERs can provide the necessary flexibility to: (a) maintain a stable frequency and a secure energy supply in an overall system perspective, and (b) maintain bus voltages and secure transfer capacities in their local networks. In this context, ESPs facilitate the management of the transmission and the distribution network, while at the same time they increase their profitability by stacking revenues. This thesis proposes a bilevel model for an ESP owning distributed Battery Storage Units and participating in: (i) wholesale energy, reserve and balancing markets, and (ii) a novel distribution-level Flexibility Market. The case study results demonstrate that the developed model achieves super-additive gains. Finally, a sensitivity analysis is conducted to study the impact of several externalities on the ESP’s decisions.

This Chapter's structure is organized as follows: Section 4.1 is introductory and analyzes the power system’s need for flexibility and cooperation between System Operators. Section 4.2 discusses the research gaps and states the contribution points of this thesis. Section 4.3 describes the proposed market architecture and the bilevel structure of the problem under discussion. Section 4.4 presents the solution method. Section 4.5 provides a detailed evaluation of the proposed solution. Finally, Section 4.6 concludes the Chapter and discusses future work.

Nomenclature

Sets

$\boldsymbol{X^{UL/RM/FM}}$	Sets of optimization variables of the upper- and lower-level problems
$\boldsymbol{H}$	Set of timeslots in the scheduling horizon
$\boldsymbol{S}$	Set of BSUs
$\boldsymbol{G}$	Set of generators participating in the reserve market
$\boldsymbol{N}$	Set of nodes of the distribution network
$\boldsymbol{B}$	Set of branches of the distribution network
$\boldsymbol{F_r}$	Set of competing ESPs
$\boldsymbol{\Omega_d(n)}$ $/\boldsymbol{\Omega_p(n)}$	Set of decedent/precedent nodes connected to node n of the distribution network
$\boldsymbol{\Omega}$	Set of scenarios concerning the balancing market prices

Subscripts and Superscripts

$\boldsymbol{t}$	Subscript indicating the timeslot
$\boldsymbol{i}$	Subscript indicating the resources
$\boldsymbol{n, j, k}$	Subscript indicating the nodes
$\boldsymbol{nk}$	Subscript indicating the network lines connecting nodes n and k
$\boldsymbol{\omega}$	Subscript indicating the balancing market price scenarios
s	Superscript for the BSUs
g	Superscript for the generators in the reserve market
r	Superscript for the competitors in the flexibility market
P/Q	Superscript for the active/reactive power in the distribution network
up/dn	Superscript for the upward/downward services
e/b	Superscript for the energy/balancing market

Variables

$\widehat{[\cdot]}$	Indicates quantity offers
$\underline{[\cdot]}/\overline{[\cdot]}$	Indicates minimum/maximum bounds
dis/ch	Scheduled BSU's discharge/charge power sold/bought in the wholesale energy market
r	Reserve capacity commitment
p/q	Flexibility market active/reactive power dispatch
p^{BSU} $/q^{BSU}$	BSUs' overall active/reactive power schedule
h	Binary variable indicating the operating mode of BSUs
E	State of energy of BSUs
c	Price bid of the ESP
f	Power flow in the distribution network
U	Square voltage magnitude
λ	Market prices
ϕ, ψ	Dual variables of the reserve and flexibility markets clearing processes

Parameters

T	Last timeslot of the scheduling horizon
$\bar{S}$	Apparent power rating of converter of BSU
η^c/η^d	Charge/Discharge efficiency
$\tilde{c}$	Price bids of the competitors
R	System's reserve capacity requirements
d/g	Scheduled demand/generation in the distribution network
δ^d/δ^g	Parameters converting active power into their reactive power – tan(arccos(power factor))

v	Iteration counter of the proposed algorithm	r/x	Resistance/Reactance of branches
		ξ_{ω}	Probability of scenario ω
		ϵ	Convergence tolerance of the proposed algorithm

4.1. Stacked Revenues Maximization of Distributed Battery Storage Units via Emerging Flexibility Markets

The ongoing decarbonization and decentralization of the electric power landscape delivers clean, sustainable and low-cost energy as well as autonomous societies [129]. On the other hand, the rapid proliferation of distributed, variable and unpredictable generation can result in various challenges for the network operators, such as line and transformer congestion, voltage limit violations, and eventually dramatically increase the demand for flexibility [130]. Using the power system's flexibility instead of costly network investments can create financial opportunities for the end users facilitating the integration of RES. Thus, DERs can provide the necessary flexibility services at both the distribution and the transmission level, as long as an economically efficient market environment is designed to motivate the investments in such technologies [131].

In today's power sector, the procurement of flexibility is characterized by a monopsony, since the TSO is the main buyer of such services. In addition, the interaction between the TSO and the DSOs is insufficient and the clearing process of the wholesale energy markets does not take into account the distribution grid operation. Consequently, the participation of distributed generators (DGs) and other DERs in such markets can lead to violations of the physical constraints that the Distribution Network (DN) imposes and, consequently, inefficient (technically and economically) market results. The latter dictates the need for a shift of the DSO's role towards a more active network operator, which will be able to purchase flexibility services from the local DERs.

The aforementioned issues can be addressed by the development of Distribution-Level Flexibility Markets (DLFMs). In a DLFM, ESPs declare their flexibility capacity and cost to a neutral Flexibility Market Operator (FMO), which in turn clears the DLFM by minimizing the cost of acquiring the flexibility needed to ensure the participation of the DERs in the wholesale markets without jeopardizing the operation of the distribution grid.

In this market environment, an ESP owning Battery Storage Units (BSUs) can increase its profitability and consequently the return on its investments by providing energy and ancillary services at both the transmission and the distribution level. BSUs with smart AC/DC converters can provide valuable grid services to the TSOs and DSOs [132], such as peak shaving, energy (wholesale energy and regulation) and power (frequency containment) balancing, alleviation of grid contingencies (voltage and congestion issues), black-start services, etc. In this chapter we consider an ESP that owns a set of distributed BSUs and provides services to both the system-wide grid (TSO) and the local distribution network (DSO).

4.2. Related Work

There is a great deal of studies that have dealt with the problem of optimizing the multi-service portfolio of merchant-owned BSUs. Works in [133] and [134] studied the optimal bidding of a BSU in the day-ahead and real-time energy-only markets, while [135] and [136] dealt with energy storage devices participating in energy and frequency regulation markets. Authors in [137] and [138] studied the problem of optimal bidding and operating strategies for a storage owner participating in the energy and performance-based regulation markets. Similarly, [139] and [140] considered storage units participating in the day-ahead energy and reserve, as well as the real-time energy and regulation markets. While the aforementioned works considered storage units that cannot affect the market prices and acting only as price takers, works in [68] and [81] used bilevel programming to model the revenue maximization problem of a merchant storage owner acting as a price maker in transmission-level energy and reserve markets. All these works differ from our study as they optimize the participation of storage units in only transmission-level energy and ancillary services' markets.

Another strand of research considered distributed BSUs that provide services to both the transmission and distribution systems. Authors in [34] consider a storage owner simultaneously participating in three markets: energy, TSO ancillary services and DSO (congestion) market. The authors proposed a portfolio theory-based approach to decide the optimal storage capacity allocated to each market in order to maximize the benefits at minimum risk. The DSO services' remuneration is based on the congestion cost savings and is calculated based on a congestion cost index. Work in [35] formulated a Mixed-Integer Linear Program (MILP) to model the profit maximization problem of a storage that provides system–wide (energy arbitrage and system balancing) and local network services (peak demand shaving to alleviate the distribution network congestion). The DSO services' remuneration is assumed to be equal to the opportunity cost of a storage plant associated with the DSO's services, i.e., its revenue increase from the energy and balancing markets when no storage capacity is allocated to provide the DSO services. Work in [36] maximized the aggregated profits of an energy storage providing energy, reserve and frequency regulation services to the transmission system and congestion management to the distribution grid. The distribution grid services are considered compulsory and are not remunerated. A model predictive control approach was employed in [37] to dynamically allocate storage power and energy capacities to either a local or a grid service with the objective of maximizing the profit of an energy storage aggregator. The energy storage profits result from energy price arbitrage and primary frequency control minus the costs of load curtailment reduction and transformer overheating. In [38], a generic formulation of the scheduling problem of a multi-service energy storage owner was designed. Based on this generic framework, the authors decide on the portion of energy and power to be allocated for dispatching the operation of a medium-voltage feeder and providing primary frequency control services. Moreover, the authors in [39] proposed a joint optimization framework for energy storage units to reduce energy bills of commercial consumers (peak shaving) and seek profit through the provision of frequency regulation services. Unlike these works, we consider a distribution-level marketplace, which determines the magnitude of the local grid services and their compensation through solving an Optimal Power Flow (OPF) problem.

Lastly, the bilevel interdependencies between two markets result in bilinear terms in the objective function which cannot be solved using the standard linearization techniques (big-M [124] and exact linearization methods [113]). Works in [81] and [87] use the binary expansion method [72] to deal with this source of non-linearity. However, this approach increases complexity by adding new binary variables. In contrast to [81] and [87], in this thesis we adopt a novel iterative approach that avoids the extra computational burden of the binary expansion method.

In light of the recent smart grid architectural progress in the development of distribution-level flexibility markets [141], this work co-optimizes the transmission and distribution grid services provided by an ESP owning distributed BSUs as in [34] - [39], using bilevel programming as in [68] and [81]. By considering market scales, we assume that the ESP is acting as a price maker in the Reserve Market (RM) and the DLFM, while it cannot affect the market prices in the wholesale energy and balancing markets. Thus, the contribution of this thesis lies in the following:

- It proposes a novel energy market architecture, in which a DLFM is introduced in the timeframe between the day-ahead energy and the balancing markets. An innovative DLFM clearing process is proposed, which enables the DSO to buy the needed flexibility to tackle the possible contingencies resulting from the wholesale energy market dispatch decision, calculating the optimal flexibility dispatch and compensation.
- A new bidding strategy is proposed for an ESP that stacks revenues based on four products: 1) wholesale energy arbitrage, 2) reserve capacity and 3) balancing energy for the TSO and 4) local constraint support for the DSO. Bilevel modeling is used to model the strategic participation of a BSUs' owner in both the TSO and DSO markets.
- A novel iterative process is proposed to deal with non-linearities due to the ESP's participation in two interdependent markets.

To the best of our knowledge, this is the first work that uses bilevel programming to model the decision process of a strategic ESP owning distributed BSUs and providing services both system-wide and to the local network operator.

4.3. System Model & Problem Formulation

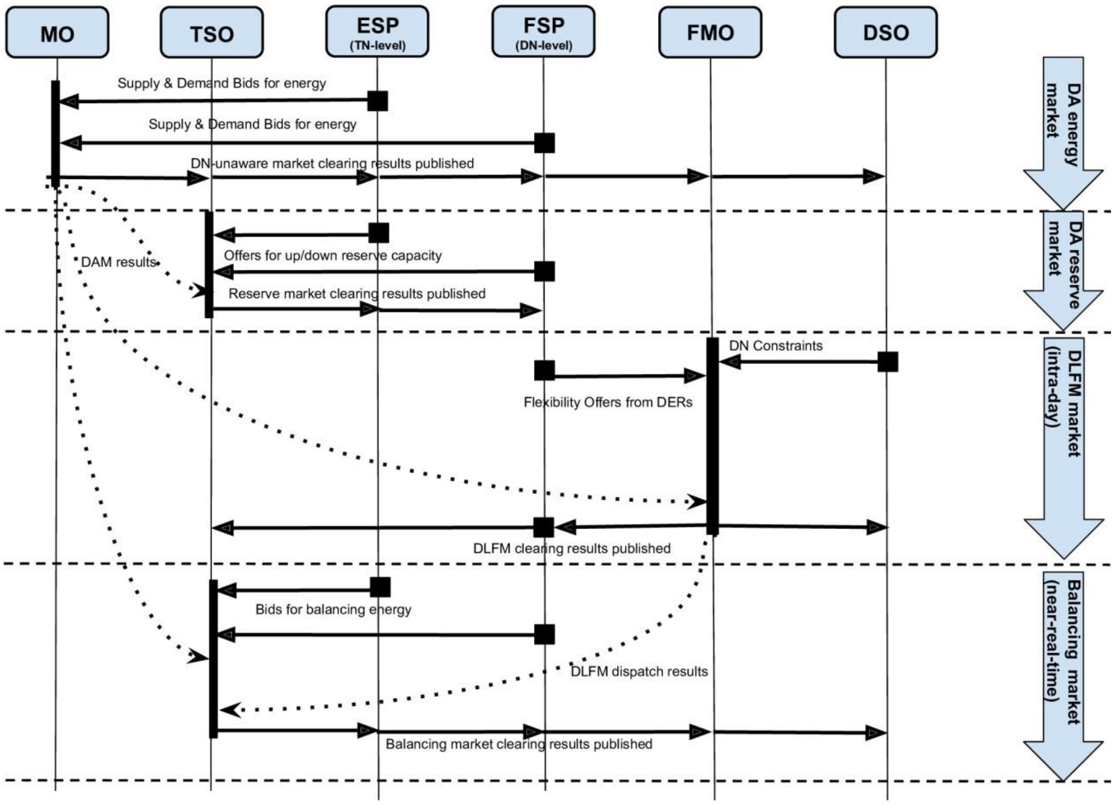

Figure 28: Proposed Reactive Distribution-Level Flexibility Market (R-DLFM) architecture

This thesis presents a market architecture in which a DLFM follows in an optimal way the decisions made by the DN-unaware day-ahead energy and reserve markets (intra-day timeframe), without changing the existing TSO wholesale market structure being thus compatible with the existing regulatory framework (Figure 28). This Reactive DLFM (R-DLFM) architecture enables: a) the DERs to participate in the TSO wholesale markets without jeopardizing the smooth operation of their underlying network, and b) the DSO to buy the needed flexibility to remove contingencies resulting from the wholesale energy market dispatch process.

In a first step, as shown in Figure 28, the Market Operator (MO) runs the Transmission Network (TN)-level day-ahead energy market after the TN-level Energy Service Providers (ESPs), such as generating companies, demand aggregators, retailers, etc., and the DN-level ESPs having submitted their energy offers/bids. Subsequently, the TSO operates the day-ahead reserve market given the MO's dispatch schedules (DAM dispatch) and the reserve capacity offers from the RM participants. This practice is common in most European markets (e.g. Nord Pool, EPEX, OMEL, GME, MIBEL), where the energy and reserve markets are sequentially cleared ([142], [143]). The role of the RM is to provide to the TSO the required upward/downward reserve capacity to keep its system balanced in the real-time (balancing) stage.

In the third step, the distribution-level ESPs submit their flexibility offers (active and reactive up/down flexibility) to the FMO, which in turn clears the local DLFM, taking into consideration the DAM results, the particularities and the constraints of the DN (provided by the DSO), thus performing the DN-aware market clearing. The role of the DLFM is to ensure that the DN operates within its safety limits, i.e., to remove local congestion, local balancing and voltage control issues that might occur due to the DN-unaware DAM clearing process. Thus, the FMO clears the DLFM by running an OPF problem, which takes as input: i) the MO's decisions pertaining to the local DERs that participate in the DAM, ii) the active/reactive up/down flexibility offers submitted by the ESPs and iii) the DN constraints provided by the DSO. In case the TN-level DAM has not produced dispatches that violate the DN constraints, the DLFM results in zero flexibility procurement and, of course, zero DLFM prices. Otherwise, the DLFM produces non-zero active/reactive and upward/downward flexibility dispatches and the corresponding flexibility prices per DN node at which the ESPs will be paid for their services. Therefore, the DLFM clearing process will re-adjust the DAM position of the DERs located in the specific DN. Thus, these DERs will have to balance their portfolio in the TSO's balancing market (sell/buy power), in order to respect their commitment to the MO (DAM dispatches). For more details regarding the market architecture, we kindly refer an interested reader to [144], [145].

In the context of the proposed R-DLFM architecture, we propose a bidding strategy of a profit-seeking ESP that owns a set of BSUs located at various nodes of a radial DN and participates in the TN-level energy, reserve and balancing markets, as well as in the DLFM. We assume that the ESP cannot affect the DAM and BM prices (acts as a price taker), while its total BSUs' capacity is able to influence the RM and the DLFM prices. The objective of the ESP is to maximize its stacked revenues by optimizing its bidding strategy in the four aforementioned markets. The ESP submits: 1) self-scheduling bids in the DAM and BM, 2) price-quantity pairs for upward and downward reserve capacity in the RM, and 3) price-quantity pairs for four products in the DLFM, i.e., i) upward active power (MW - €/MW), ii) downward active power (MW - €/MW), iii) upward reactive power (MVAr - €/MVAr), and iv) downward reactive power (MVAr - €/MVAr). Uncertainties pertaining to market competition and local grid consumption/production power are not considered. We perform a deterministic analysis, allowing us to focus on studying the interactions between the individual markets, and how the ESP can manage its BSU portfolio to increase its profitability by participating in the four markets in a co-optimized manner. A stochastic optimization technique can be transparently implemented in the proposed model to tackle the aforementioned uncertainties. In this case, however, an extensive computational burden would be added, so mathematical approaches such as decomposition techniques or robust optimization could offer interesting studies and promising solutions.

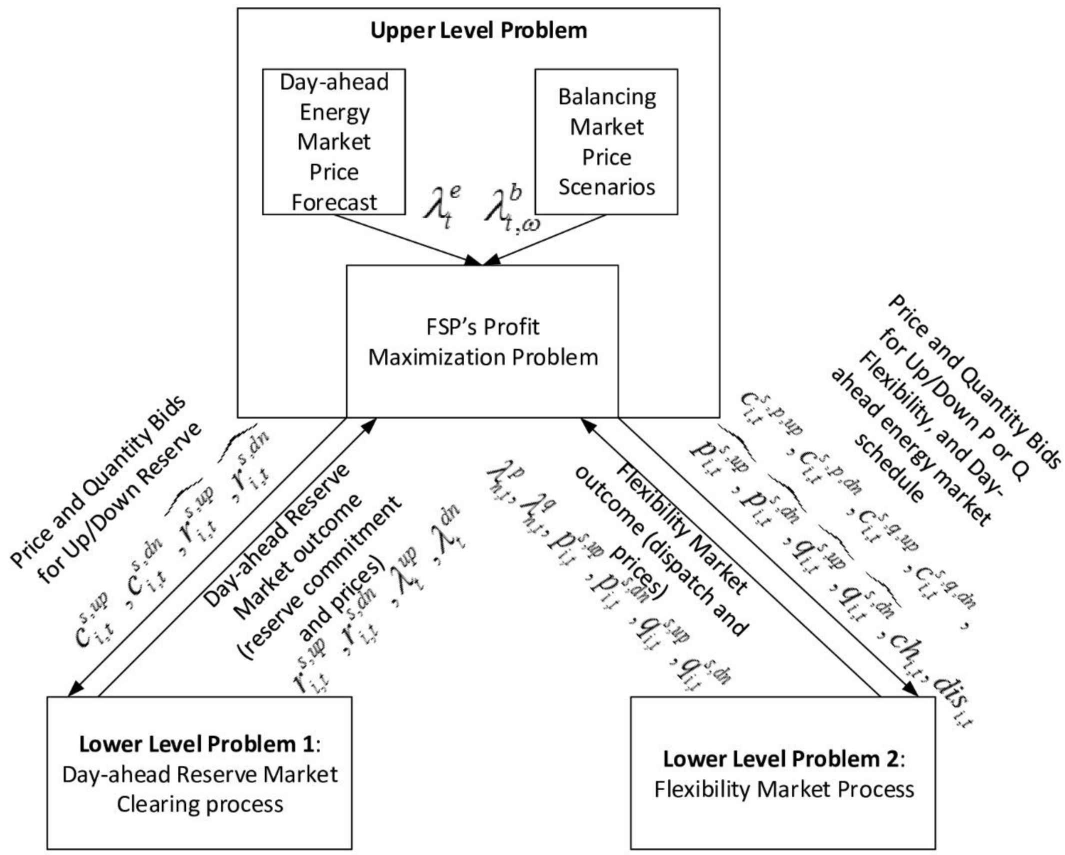

Figure 29: The proposed bilevel model

A bilevel model (Figure 29) is proposed to formulate the ESP's problem of determining the optimal bidding strategy and the charging/discharging schedule of the BSUs. In the upper-level the ESP decides on the BSUs' operating schedule and its bidding strategy, while taking as input the day-ahead energy prices and balancing market forecast prices and anticipating the impact of its decisions on the reserve and flexibility markets. The ESP's decisions include the energy traded in the day-ahead energy market, the price and quantity bids to the RM and DLFM and the power bought/sold in the BM. In the lower-level, for given ESP's decisions, the TSO and the FMO clear the RM and the DLFM, respectively. In the RM and the DLFM clearing processes the bids of the other market participants are treated as parameters. Also, the decisions of the DAM concerning the distribution-level demand and production are also treated as input parameters in the DLFM clearing process.

4.3.1. Upper-level Problem: Profit Maximization

The upper-level problem maximizes the ESP's profits in various markets by selecting the optimal bidding/offering schedule and is formulated below.

$$\min_{X^{UL}} \sum_{t\in H}\left(\sum_{i\in S}\left(\lambda_t^e\cdot\left(ch_{i,t}-dis_{i,t}\right)-\lambda_t^{up}\cdot r_{i,t}^{s,up}-\lambda_t^{dn}\cdot r_{i,t}^{s,dn}-\lambda_{i,t}^{P}\cdot\left(p_{i,t}^{s,up}-p_{i,t}^{s,dn}\right)-\lambda_{i,t}^{Q}\cdot\left(q_{i,t}^{s,up}-q_{i,t}^{s,dn}\right)-\sum_{\omega\in\Omega}\xi_\omega\cdot\lambda_{i,t}^{b}\cdot\left(p_{i,t}^{s,up}-p_{i,t}^{s,dn}\right)\right)\right)$$

(4.a.1)

Subject to

$$0 \leq dis_{i,t} \leq h_{i,t} \cdot \overline{S_i}, \qquad \forall i \in S, t \in H \qquad (4.a.2)$$

$$0 \leq ch_{i,t} \leq (1 - h_{i,t}) \cdot \overline{S_i}, \qquad \forall i \in S, t \in H \qquad (4.a.3)$$

$$h_{i,t} \in \{0,1\}, \qquad \forall i \in S, t \in H \qquad (4.a.4)$$

$$0 \leq \widehat{r_{i,t}^{s,up}} \leq \overline{S_i} + (ch_{i,t} - dis_{i,t}), \qquad \forall i \in S, t \in H \qquad (4.a.5)$$

$$0 \leq \widehat{r_{i,t}^{s,dn}} \leq \overline{S_i} - (ch_{i,t} - dis_{i,t}), \qquad \forall i \in S, t \in H \qquad (4.a.6)$$

$$0 \leq \widehat{p_{i,t}^{s,up}} \leq \overline{S_i} + \left(ch_{i,t} - dis_{i,t} - \widehat{r_{i,t}^{s,up}}\right), \qquad \forall i \in S, t \in H \qquad (4.a.7)$$

$$0 \leq \widehat{p_{i,t}^{s,dn}} \leq \overline{S_i} + \left(dis_{i,t} - ch_{i,t} - \widehat{r_{i,t}^{s,dn}}\right), \qquad \forall i \in S, t \in H \qquad (4.a.8)$$

$$E_{i,t} = E_{i,t-1} - \frac{dis_{i,t} + p_{i,t}^{s,up}}{\eta_i^d} + \eta_i^c \cdot (ch_{i,t} + p_{i,t}^{s,dn}), \qquad \forall i \in S, t \in H \qquad (4.a.9)$$

$$E_{i,t} + \widehat{r_{i,t}^{s,dn}} \cdot \eta_i^c \leq \overline{E_i}, \qquad \forall i \in S, t \in H \qquad (4.a.10)$$

$$E_{i,t} - \frac{\widehat{r_{i,t}^{s,up}}}{\eta_i^d} \geq \underline{E_i}, \qquad \forall i \in S, t \in H \qquad (4.a.11)$$

$$E_{i,T} \geq E_{i,0}, \qquad \forall i \in S \qquad (4.a.12)$$

$$p_{i,t}^{BSU} = dis_{i,t} - ch_{i,t} + p_{i,t}^{s,up} - p_{i,t}^{s,dn}, \qquad \forall i \in S, t \in H \qquad (4.a.13)$$

$$q_{i,t}^{BSU} = q_{i,t}^{s,up} - q_{i,t}^{s,dn}, \qquad \forall i \in S, t \in H \qquad (4.a.14)$$

$$\left(p_{i,t}^{BSU}\right)^2 + \left(q_{i,t}^{BSU}\right)^2 \leq (\overline{S_i})^2, \qquad \forall i \in S, t \in H \qquad (4.a.15)$$

$$0 \leq \widehat{q_{i,t}^{s,up}}, \widehat{q_{i,t}^{s,dn}} \leq \overline{S_i}, \qquad \forall i \in S, t \in H \qquad (4.a.16)$$

$$c_{i,t}^{s,P,up}, c_{i,t}^{s,P,dn}, c_{i,t}^{s,Q,up}, c_{i,t}^{s,Q,dn} \geq 0, \qquad \forall i \in S, t \in H \qquad (4.a.17)$$

Objective function of the upper-level problem (4.a.1) maximizes the ESP's overall profits. The first line is associated with the DAM and RM profits of the ESP. Energy price is taken as an input (λ_t^e), while the upward/downward RM prices ($\lambda_t^{up}, \lambda_t^{dn}$) and the reserved quantities ($r_{i,t}^{s,up}, r_{i,t}^{s,dn}$) are obtained endogenously from the Lower-Level Problem 1 (cf. subsection 4.3.2). The second line in (4.a.1) is associated with the DLFM profit due to the provision of active and reactive power flexibility (hereinafter referred to as P-flexibility and Q-flexibility) to the DSO. The DLFM nodal active and reactive locational marginal prices (hereinafter referred to as PLMPs and QLMPs respectively) and the upward/downward P-flexibility and Q-flexibility dispatches are calculated endogenously in the clearing process of the DLFM (cf. subsection 4.3.3). Finally, since we consider that the DLFM follows the wholesale energy market, the active power DLFM dispatch concerning the ESP's BSUs will urge the ESP to readjust its energy market position by trading power in the Balancing Market. Thus, the last line in (4.a.1) represents the ESP's cost/profit from buying/selling in the BM the additional discharged/charged power (equal to the downward/upward P-flexibility provided in the

DLFM by the BSUs). We assume that energy is traded in the BM at a single price ($\lambda_{t,\omega}^{b}$) as in [71]. In contrast to the wholesale energy market prices (λ_t^e) which can be predicted with high accuracy [146], the BM prices are highly volatile and thus considered stochastic in this thesis. We tackle this uncertainty via a finite number of scenarios. Note that we consider a *risk-neutral* ESP that maximizes its expected profits. In order to explicitly address risk management and control the trade-off between profits and risk, one could use the Conditional Value at Risk (CVaR) in the objective function as a risk measure, see e.g., [84].

Constraints (4.a.2) and (4.a.3) state that the battery discharged/charged power is constrained by the battery converter's apparent power rating ($\overline{S_\iota}$). Binary variable $h_{i,t}$ indicates the operating mode of the BSUs, equal to 1 in the discharge mode and 0 in the charge mode (4.a.4). Constraint (4.a.5) states that the upward reserve capacity provision is constrained by the scheduled discharge/charge power traded in the energy market and the AC/DC converter's apparent power rating. The downward reserve capacity provision is constrained by the power traded in the energy market and the BSUs' power rating (4.a.6).

Additionally, the (upward/downward) flexibility provision to the DSO is constrained by the BSUs' apparent power rating and the energy and reserve schedules ((4.a.7), (4.a.8)). The dynamic equation of BSUs' state of charge is presented in Eq. (4.a.9), while constraints (4.a.10) and (4.a.11) define the BSUs' capability of upward/downward reserve capacity provisioning. Constraint (4.a.12) defines that at the end of the scheduling horizon, the BSUs' state of charge should be at least equal to their initial value. Each BSU is also controlled to inject/absorb reactive power. The overall active/reactive power schedules of the BSUs are presented in Eqs. (4.a.13) and (4.a.14), and should be calculated such that the apparent power at each timeslot does not exceed the apparent power rating (4.a.15). Finally, the Q-flexibility quantity bids of the BSUs are constrained in (4.a.16), while nonnegativity on the flexibility market price bids is imposed in constraint (4.a.17). The set of optimization variables of the problem (4.a.1) - (4.a.17) is $X^{UL} = \{\, dis_{i,t}, ch_{i,t}, \widehat{r_{\iota,t}^{s,up}}, \widehat{r_{\iota,t}^{s,dn}}, \widehat{p_{\iota,t}^{s,up}}, \widehat{p_{\iota,t}^{s,dn}},$

$\widehat{q_{\iota,t}^{s,up}}, \widehat{q_{\iota,t}^{s,dn}}, h_{i,t}, E_{i,t}, c_{i,t}^{s,up}, c_{i,t}^{s,dn}, c_{i,t}^{s,P,up}, c_{i,t}^{s,P,dn}, c_{i,t}^{s,Q,up}, c_{i,t}^{s,Q,dn}\}$.

Constraint (4.a.15) is linearized via a polygonal inner approximation, which we derived, described by the following set of linear constraints:

$$A_{i,m} \cdot p_{i,t}^{BSU} + B_{i,m} \cdot q_{i,t}^{BSU} \le \cos\left[\frac{\pi}{L}\right] \cdot \overline{S_\iota}, \quad \forall i \in S, t \in H, m \in [1, L] \tag{4.a.18}$$

where L is the number of the sides of the polygon and

$$A_{i,m} = \cos\left[\frac{(-1+2\cdot m)\cdot\pi}{L}\right], B_{i,m} = \sin\left[\frac{(-1+2\cdot m)\cdot\pi}{L}\right]$$

The case with $L = 12$ is illustrated in Figure 30.

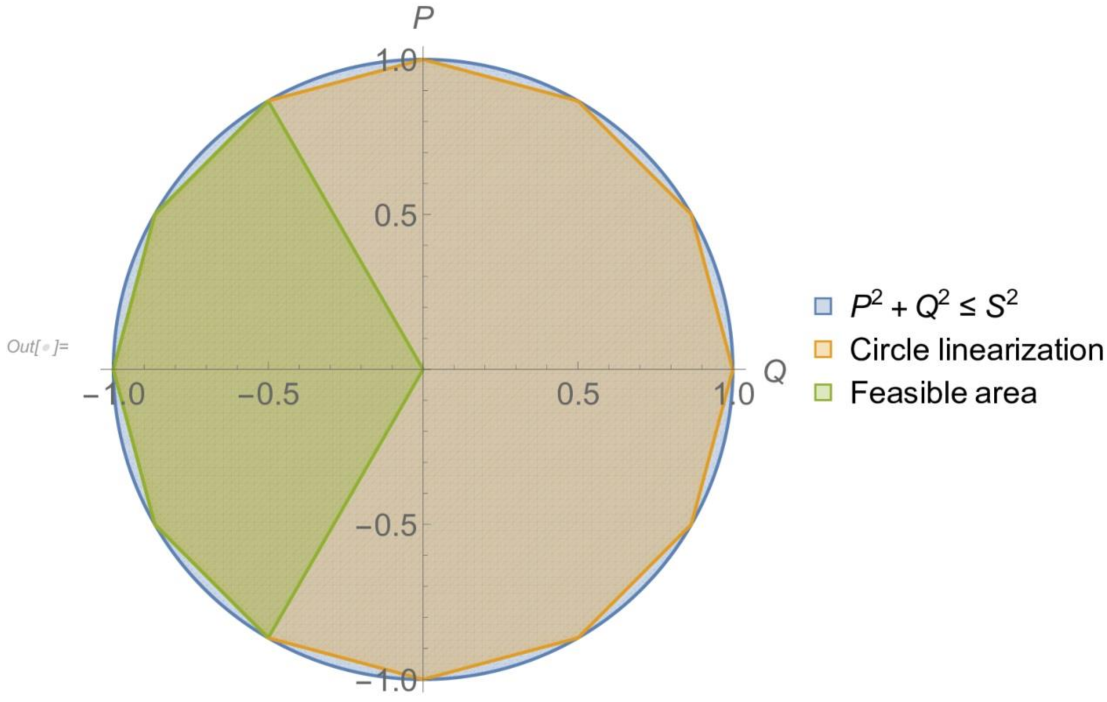

Figure 30: Piecewise linear approximation of a circular region with a regular polygon of 12 sides.

4.3.2. Lower-level Problem 1: Clearing of the Reserve Market

The Lower-Level Problem 1 represents the clearing process of the reserve market, which we assume is cleared independently from the energy market. The reserve market clearing process is formulated below.

$$\min_{X^{RM}} \sum_{t\in H} \left(\sum_{i\in G} \left(\tilde{c}_{i,t}^{g,up} \cdot r_{i,t}^{g,up} + \tilde{c}_{i,t}^{g,dn} \cdot r_{i,t}^{g,dn} \right) + \sum_{i\in S} \left(c_{i,t}^{s,up} \cdot r_{i,t}^{s,up} + c_{i,t}^{s,dn} \cdot r_{i,t}^{s,dn} \right) \right) \tag{4.b.1}$$

Subject to

$$\textstyle\sum_{i\in G} r_{i,t}^{g,up} + \sum_{i\in S} r_{i,t}^{s,up} \geq R_t^{up}; \qquad (\lambda_t^{up}) \qquad \forall t \in H \tag{4.b.2}$$

$$\textstyle\sum_{i\in G} r_{i,t}^{g,dn} + \sum_{i\in S} r_{i,t}^{s,dn} \geq R_t^{dn}; \qquad (\lambda_t^{dn}) \qquad \forall t \in H \tag{4.b.3}$$

$$0 \leq r_{i,t}^{g,up} \leq \widehat{r_{i,t}^{g,up}}; \qquad (\phi_{i,t}^{gupmin}, \phi_{i,t}^{gupmax}) \qquad \forall i \in G, t \in H \tag{4.b.4}$$

$$0 \leq r_{i,t}^{g,dn} \leq \widehat{r_{i,t}^{g,dn}}; \qquad (\phi_{i,t}^{gdnmin}, \phi_{i,t}^{gdnmax}) \qquad \forall i \in G, t \in H \tag{4.b.5}$$

$$0 \leq r_{i,t}^{s,up} \leq \widehat{r_{i,t}^{s,up}}; \qquad (\phi_{i,t}^{supmin}, \phi_{i,t}^{supmax}) \qquad \forall i \in S, t \in H \tag{4.b.6}$$

$$0 \leq r_{i,t}^{s,dn} \leq \widehat{r_{i,t}^{s,dn}}; \qquad (\phi_{i,t}^{sdnmin}, \phi_{i,t}^{sdnmax}) \qquad \forall i \in S, t \in H \tag{4.b.7}$$

Objective function (4.b.1) minimizes the reserve capacity procurement cost based on the market participants' reserve prices and capacity offers. The upward/downward reserve requirements are enforced in constraints (4.b.2) and (4.b.3), respectively. The dual variables of constraints (4.b.2) and (4.b.3) set the reserve up and down prices. The up and down reserve provision of the generators and the BSUs are limited in (4.b.4)-(4.b.7), based on their respecting offers. In this thesis, we assume that the rest of the RM participants form a competitive fringe and thus their price and quantity offers are treated as input parameters to our model. The dual variables pertaining to each constraint of the Lower-Level Problem 1 are specified at each constraint (4.b.2) - (4.b.7) following a semicolon. The set of the primal variables of Lower-Level Problem 1 is $X^{RM} = \{r_{i,t}^{g,up}, r_{i,t}^{g,dn}, r_{i,t}^{s,up}, r_{i,t}^{s,dn}\}$.

4.3.3. Lower-level Problem 2: Clearing of the Flexibility Market

The proposed DLFM is a network-constrained auction-based market that is cleared solving Lower-Level Problem 2. The ESPs, either operating their own flexibility assets or acting as flexibility aggregators, submit aggregated flexibility bids, i.e. how much they can deviate from their DAM position, ($\widehat{\boldsymbol{P^s}} \coloneqq \{\widehat{p_{i,t}^{s,up}}, \widehat{p_{i,t}^{s,dn}}, \widehat{q_{i,t}^{s,up}}, \widehat{q_{i,t}^{s,dn}}; \forall i \in S, t \in H\}, \widehat{\boldsymbol{P^r}} \coloneqq \{\widehat{p_{i,t}^{r,up}}, \widehat{p_{i,t}^{r,dn}}, \widehat{q_{i,t}^{r,up}}, \widehat{q_{i,t}^{r,dn}}; \forall i \in F_r, t \in H\}$) and cost ($\boldsymbol{C^s} \coloneqq \{c_{i,t}^{s,P,up}, c_{i,t}^{s,P,dn}, c_{i,t}^{s,Q,up}, c_{i,t}^{s,Q,dn};$

$\forall i \in S, t \in H\}, \widetilde{\boldsymbol{C^r}} \coloneqq \{\widetilde{c_{i,t}^{r,P,up}}, \widetilde{c_{i,t}^{r,P,dn}}, \widetilde{c_{i,t}^{r,Q,up}}, \widetilde{c_{i,t}^{r,Q,dn}}; \forall i \in F_r, t \in H\}$) to the FMO. The FMO's objective is to ensure the necessary active and reactive flexibility at a minimum cost in order to address the possible contingencies (congestion and voltage issues). In other words, in case the DAM results violate the DN constraints, then the FMO will calculate the least-cost required flexibility dispatch, and the selected DERs will have to re-adjust their DAM position based on the DLFM results, in order for the DSO to secure a secure operation of its DN. The DLFM clearing process is formulated below.

$$\min_{X^{FM}} \boldsymbol{C^s}^{\mathrm{T}} \cdot \boldsymbol{P^s} + \widetilde{\boldsymbol{C^r}}^{\mathrm{T}} \cdot \boldsymbol{P^r} \tag{4.c.1}$$

Subject to

$$0 \le \boldsymbol{P}^s \le \widehat{\boldsymbol{P^s}}; \qquad (\underline{\boldsymbol{\psi}^s}, \overline{\boldsymbol{\psi}^s}) \tag{4.c.2}$$

$$0 \le \boldsymbol{P}^r \le \widehat{\boldsymbol{P^r}}; \qquad (\underline{\boldsymbol{\psi}^r}, \overline{\boldsymbol{\psi}^r}) \tag{4.c.3}$$

$$\sum_{k \in \Omega_d(n)} f_{nk,t}^P = \sum_{k \in \Omega_p(n)} f_{jn,t}^P - d_{n,t} + g_{n,t} - ch_{n,t} + dis_{n,t} + p_{n,t}^{s,up} + p_{n,t}^{r,up} - p_{n,t}^{s,dn} - p_{n,t}^{r,dn}; \qquad (\lambda_{n,t}^P) \qquad \forall n \in N, t \in H \tag{4.c.4}$$

$$\sum_{k \in \Omega_d(n)} f_{nk,t}^Q = \sum_{k \in \Omega_p(n)} f_{jn,t}^Q - \delta_{n,t}^d \cdot d_{n,t} + \delta_{n,t}^g \cdot g_{n,t} + q_{n,t}^{s,up} + q_{n,t}^{r,up} - q_{n,t}^{s,dn} - q_{n,t}^{r,dn}; \qquad (\lambda_{n,t}^Q) \qquad \forall n \in N, t \in H \tag{4.c.5}$$

$$U_{n,t} = U_{j,t} - 2 \cdot \left(r_{jn} \cdot f_{jn,t}^P + x_{jn} \cdot f_{jn,t}^Q\right); \qquad \left(\lambda_{n,t}^v\right) \qquad \forall n \in N, j \in \Omega_p(n), t \in H \tag{4.c.6}$$

$$\underline{V_n} \le U_{n,t} \le \overline{V_n}; \qquad \left(\underline{\psi_{n,t}^v}, \overline{\psi_{n,t}^v}\right) \quad \forall n \in N, t \in H \tag{4.c.7}$$

$$\underline{f_{nk}^P} \le f_{nk,t}^P \le \overline{f_{nk}^P}; \qquad \left(\underline{\psi_{nk,t}^{pf}}, \overline{\psi_{nk,t}^{pf}}\right) \quad \forall (n,k) \in B, t \in H \tag{4.c.8}$$

$$\underline{f_{nk}^Q} \le f_{nk,t}^Q \le \overline{f_{nk}^Q}; \qquad \left(\underline{\psi_{nk,t}^{qf}}, \overline{\psi_{nk,t}^{qf}}\right) \quad \forall (n,k) \in B, t \in H \tag{4.c.9}$$

Objective function of the Lower-Level Problem 2 (4.c.1) minimizes the flexibility procurement cost. Constraints (4.c.2) and (4.c.3) bound the DLFM dispatch of the ESP ($\boldsymbol{P^s} \coloneqq \{p_{i,t}^{s,up}, p_{i,t}^{s,dn}, q_{i,t}^{s,up}, q_{i,t}^{s,dn}; \forall i \in S, t \in H\}$) and its competitors ($\boldsymbol{P^s} \coloneqq \{p_{i,t}^{r,up}, p_{i,t}^{r,dn}, q_{i,t}^{r,up}, q_{i,t}^{r,dn}; \forall i \in F_r, t \in H\}$) based on their flexibility supply offers. As in the RM, the competing ESPs' bids are treated as parameters; we assume that they form a competitive fringe (price takers). In order to model the DN, we use the linearized DistFlow model (4.c.4)-(4.c.9) first introduced in [105]. Equations (4.c.4)-(4.c.6) are the *branch flow* equations. In (4.c.4) and (4.c.5) the local production ($g_{n,t}$) and demand ($d_{n,t}$) are decided in the DAM, which precedes the DLFM clearing process, and thus are treated as parameters. The lower/upper limits of the square voltage magnitude ($U_{n,t}$), active power flows ($f_{nk,t}^{P}$) and reactive power flows ($f_{nk,t}^{Q}$) are presented in constraints (4.c.7)-(4.c.9). Potential DERs' DAM positions (i.e., parameters $d_{n,t}, g_{n,t}, ch_{n,t}, dis_{n,t}$) that require power flows violating constraints (4.c.7) - (4.c.9) will dictate the demand for flexibility. The dual variables pertaining to each constraint of the Lower-Level Problem 2 are specified at each constraint (4.c.2)-(4.c.9) following a semicolon. The PLMPs and QLMPs, at which the ESPs will be compensated for their P/Q-flexibility services, arise from the dual variables of constraints (4.c.4) and (4.c.5). These prices, taking into account the type (over/under-voltage issue or thermal line congestion), the magnitude and the location of the contingency, optimally reflect the demand for P-flexibility (PLMPs) or Q-flexibility (QLMPs). Furthermore, dual variables $\lambda_{n,t}^{P}$, $\lambda_{n,t}^{Q}$ are free variables; positive DLFM prices indicate the need for supplying power to the grid, while negative DLFM prices imply the need for absorbing power by the ESPs. As long as the DAM dispatch does not violate any constraints of the DN, then naturally $\boldsymbol{P^s}, \boldsymbol{P^r} = \boldsymbol{0}$ and $\lambda_{n,t}^{P}, \lambda_{n,t}^{Q} = 0, \forall n \in N, t \in H$. Finally, our proposed DLFM as an LP-based market satisfies the economic properties of efficiency, cost recovery and revenue adequacy [147].

4.4. Solution Method

The formulated non-linear bilevel problem can be recast into a Mathematical Program with Equilibrium Constraints (MPEC). To this end, we replace problems (4.b) and (4.c) with their respective Karush-Kuhn-Tucker (KKT) conditions. Note that these problems are continuous and linear, and therefore their KKT conditions are necessary and sufficient optimality conditions [123]. The resulting single-level problem contains non-linear complementarity slackness conditions, which can be linearized using the Big-M approach, as in Chapter 3. In addition, in order to tackle the non-linearities in the objective function (4.a.1), we use the Strong Duality Theorem and the optimality conditions of the two lower-level problems and some algebraic operations (see Chapter 3). The resulting objective function of our single-level problem is:

$$\sum_{t\in H}\Big(\sum_{i\in S}\big(\lambda_t^e \cdot (ch_{i,t} - dis_{i,t})\big) + \sum_{i\in G}\big(\tilde{c}_{i,t}^{g,up} \cdot r_{i,t}^{g,up} + \tilde{c}_{i,t}^{g,dn} \cdot r_{i,t}^{g,dn}\big) - R_t^{up} \cdot \lambda_t^{up} - R_t^{dn} \cdot \lambda_t^{dn} + \sum_{i\in G}\Big(\phi_{i,t}^{gupmax} \cdot \widehat{r_{i,t}^{g,up}} + \phi_{i,t}^{gdnmax} \cdot \widehat{r_{i,t}^{g,dn}}\Big) + \widetilde{\boldsymbol{C^r}}^{\mathrm{T}} \cdot \boldsymbol{P^r} + \widehat{\boldsymbol{P^r}} \cdot \overline{\boldsymbol{\psi^r}} - \sum_{n\in N}\Big(\underline{V_n} \cdot \underline{\psi_{n,t}^{v}} - \overline{V_n} \cdot \overline{\psi_{n,t}^{v}}\Big) - \sum_{(\boldsymbol{n},\boldsymbol{k})\in \boldsymbol{B}}\Big(\underline{f_{nk}^{P}} \cdot \underline{\psi_{nk,t}^{pf}} - \overline{f_{nk}^{P}} \cdot \overline{\psi_{nk,t}^{pf}} + \underline{f_{nk}^{Q}} \cdot \underline{\psi_{nk,t}^{qf}} - \overline{f_{nk}^{Q}} \cdot \overline{\psi_{nk,t}^{qf}}\Big) + \sum_{n\in N}\big(g_{n,t} \cdot \lambda_{n,t}^{P} - d_{n,t} \cdot \lambda_{n,t}^{P} + dis_{n,t} \cdot \lambda_{n,t}^{P} - ch_{n,t} \cdot \lambda_{n,t}^{P} + \delta_{n,t}^{g} \cdot g_{n,t} \cdot \lambda_{n,t}^{Q} - \delta_{n,t}^{d} \cdot d_{n,t} \cdot \lambda_{n,t}^{Q}\big) + \sum_{n\in \Omega_d(n_0)} \lambda_{n,t}^{v} - \sum_{\omega\in\Omega}\sum_{i\in S} \xi_\omega \cdot \lambda_{t,\omega}^{b} \cdot (p_{i,t}^{s,up} - p_{i,t}^{s,dn})\Big) \quad (4.d.1)$$

The above expression still contains bilinear terms ($dis_{n,t} \cdot \lambda^{P}_{n,t}$ and$ch_{n,t} \cdot \lambda^{P}_{n,t}$). This non-linearity comes from the interdependency between the DAM and the DLFM, and more specifically from constraints (4.c.4) and (4.c.5) that link decision variables from the two markets. Authors in [81] and [87] use the binary expansion technique in order to tackle the non-linearities originated from the interdependencies between two markets. In this Chapter, we use an iterative process to deal with these non-linearities, which achieves much higher computational efficiency as will be discussed in 4.5.4. The steps of this procedure are:

1. Replace nonlinear terms $dis_{n,t} \cdot \lambda^{P}_{n,t}$ and$ch_{n,t} \cdot \lambda^{P}_{n,t}$ with linear terms $dis_{n,t} \cdot \overline{\lambda^{P}_{n,t}}$ and $ch_{n,t} \cdot \overline{\lambda^{P}_{n,t}}$, where $\overline{\lambda^{P}_{n,t}}$ is a constant. This constitutes our model linear and the resulting optimization problem is a MILP.
2. Initialize the iteration counter $v = 1$ and set $\overline{\lambda^{P,v}_{n,t}} = 0$.
3. Solve the MILP and calculate the optimal values $\overline{\lambda^{P,v}_{n,t}}^{*}$ and the optimal objective function value ϕ^{v}. Set $\overline{\lambda^{P,v}_{n,t}} = \overline{\lambda^{P,v}_{n,t}}^{*}$ and update iteration counter $v = v + 1$ and
4. If $\phi^{v} - \phi^{v-1} \leq \epsilon$, with ϵ being a small real number, then stop the process. Otherwise, go to 3.

4.5. Performance Evaluation

This section studies the performance of our proposed model using a modified IEEE 33-Bus test distribution system. The algorithm is implemented in MATLAB and in each iteration the MILP problem is solved using Gurobi 9.0.2. All simulations were performed on a personal computer with Intel Core i7 4.00GHz and 32 GB RAM.

4.5.1. Input Data

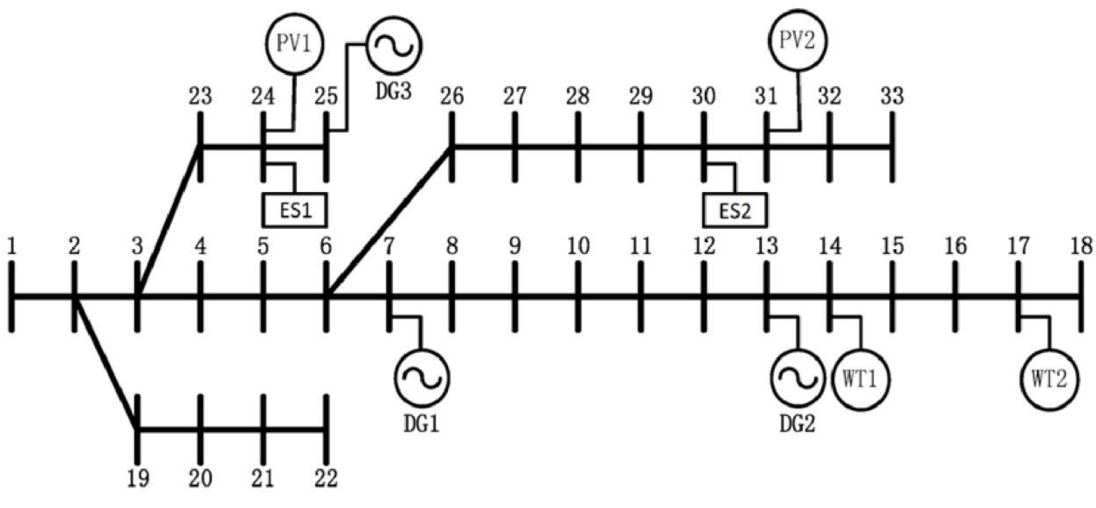

Figure 31: IEEE 33-node distribution system

The single-line diagram of the IEEE 33-Bus test system [105] is illustrated in Figure 31. The total installed DG nominal capacity is 39 MW and the total base load is 18.575 MW and 11.5 MVAr. Detailed network, load and generation data of this modified system can be found in [148]. We considered two 2.5 MW x 1.6h BSUs, located at buses 24 and 30 in the distribution network (see Figure 31). Their discharging/charging efficiencies are set to $\eta_i^d = \eta_i^c = 0.93$, while the initial state of energy of the BSUs is assumed to be 87.5%. Thirteen competing ESPs are assumed to provide flexibility services to the DSO through their participation in the DLFM. These ESPs control assets that are located at buses 13, 14, 16, 17, 18, 22, 24, 25, 29, 30, 31, 32 and 33 and their active and reactive power bidding prices are set to 15 €/MWh and 3 €/MVAr, similar to [149]. Data from Mavir, the Hungarian TSO [150], and the HUPX, the Hungarian Power Exchange [151], were used for the Day-Ahead Energy, Reserve and Balancing Markets with Monday, April 1 2019 as a reference date. Regarding the Reserve Market, data from the Frequency Containment Reserve market clearing process were used. Balancing Market price scenarios were formed from historical data for all Mondays of 2019 of the Mavir's Balancing Energy Market. Since the Mavir's data contains 15-minute separate up and down regulating prices, for our purposes they were transformed into hour basis and single price form using weighted average with a quantity as a weight. On the other hand, scenario weights were assigned using least distance scenario reduction technique [152] (probability of a scenario is added to the first next closest scenario, while the original scenario is removed) until only 12 scenarios remained. An interested reader can find a complete set of input data in [148]. Finally, a daily (24-h) time horizon is considered.

4.5.2. Case Study Results

To evaluate the proposed model, we examine and compare the following four cases:

1. *Case 1*: The ESP provides (energy and regulation) services to only the TSO through its participation in the DAM and RM.
2. *Case 2*: The ESP delivers flexibility services to the DSO through its participation in the DLFM. For its upward/downward P-flexibility provided to the DSO, the ESP will be paid/pay at the BM price.
3. *Case 3*: The ESP participates in all 4 markets (DAM, RM, DLFM, and BM) in a sequential manner. More specifically, the ESP initially optimizes its BSUs portfolio in order to maximize its profits from a certain market, without taking into consideration the markets that follow.
4. *Case 4*: The ESP participates in all 4 markets taking full advantage of the proposed model.

Table 10: The ESP's Scheduling and Bidding Decisions, and Market Prices in Case 1

Hour	dis_t/ch_t (MW)	$r_t^{s,up}, r_t^{s,dn}$ (MW)	$c_t^{s,up}, c_t^{s,dn}$ (€/MW)	λ_t^e (€/MW)	$\lambda_t^{up}, \lambda_t^{dn}$ (€/MW)
1	2.86	2.15, 4.38	12.73, 12.73	36.09	12.73, 12.73
2	-	3.65, 4.38	12.73, 12.73	34.69	12.73, 12.73
3	-	3.65, 4.38	12.73, 12.73	35.08	12.73, 12.73
4	-0.27	3.89, 4.10	12.73, 12.73	34.57	12.73, 12.73
5	-1.28	5, 2.82	12.73, 12.73	34.75	12.73, 12.73
6	-	5, 2.82	12.73, 12.73	39.9	12.73, 12.73
7	-	5, 2.82	12.73, 12.73	49.8	12.73, 12.73

8	1.55	3.45, 4.61	12.73, 12.73	57.75	12.73, 12.73
9	0.33	3.12, 5	12.73, 12.73	58.6	12.73, 12.73
10	-	3.12, 5	12.73, 12.73	52.2	12.73, 12.73
11	-	3.12, 5	12.73, 12.73	48.81	12.73, 12.73
12	-	3.12, 5	12.73, 12.73	45.66	12.73, 12.73
13	-	3.12, 5	12.73, 12.73	45.46	12.73, 12.73
14	-	3.12, 5	12.73, 12.73	42.57	12.73, 12.73
15	-	3.12, 5	12.73, 12.73	41.92	12.73, 12.73
16	-	3.12, 5	12.73, 12.73	41.39	12.73, 12.73
17	-2.18	5, 2.82	12.73, 12.73	42.05	12.73, 12.73
18	-	5, 2.82	12.73, 12.73	46.02	12.73, 12.73
19	-	5, 2.82	12.73, 12.73	47.07	12.73, 12.73
20	1.88	3.12, 5	12.73, 12.73	62.41	12.73, 12.73
21	-	3.12, 5	12.73, 12.73	64.3	12.73, 12.73
22	-0.96	3.95, 4.04	12.73, 12.73	48.12	12.73, 12.73
23	-0.10	4.03, 3.94	12.73, 12.73	42.5	12.73, 12.73
24	-2.86	6.51, 1.08	12.09, 12.73	37.5	12.09, 12.73

*A negative/positive value corresponds to the BSUs' charging/discharging mode

**$dis_t = \sum_{i \in S} dis_{i,t} \,.\, ch_t = \sum_{i \in S} ch_{i,t} \,, r_t^{s,up} = \sum_{i \in S} r_{i,t}^{s,up} \,, r_t^{s,dn} = \sum_{i \in S} r_{i,t}^{s,dn}$

In Case 1, the ESP makes profits from providing energy and frequency regulation services to the TSO through its participation in the day-ahead energy and the reserve market, respectively. Table 10 illustrates the scheduling and bidding decisions of the ESP, along with the DAM and RM prices. In this case, the ESP's main target is to guarantee that the BSUs will have the maximum capacity available to offer in the RM, since this market brings the highest profits. Hence, the ESP trades energy in the DAM mainly to gain more profit opportunities but also to pre-charge energy for the RM. For example, the ESP sells total power of 2.86 MW in $t = 1$, when the energy price is higher as compared to the following hours. Also, this enables the ESP to offer higher downward regulation reserve capacity. The ESP seldom performs energy arbitrage between the low-cost hours (e.g., $t = 4$ and $t = 5$) and high-cost hours (e.g., $t = 8$ and $t = 9$). In discharge hours, the ESP offers higher downward reserve capacity, while the BSUs' charging process enables it to offer higher upward reserve capacity. However, in most hours the ESP keeps its BSUs idle. The ESP's main objective is to offer high combined reserve capacity at all times (note that the upward and downward reserve prices are equal with the exception of $t = 24$), while in parallel take advantage of the most significant energy price fluctuations over time in the DAM. As shown in Figure 32, the ESP gains 26.25€ from its participation in the DAM, and 2417.9€ from providing ancillary services to the TSO, resulting in a total profit of 2444.2€.

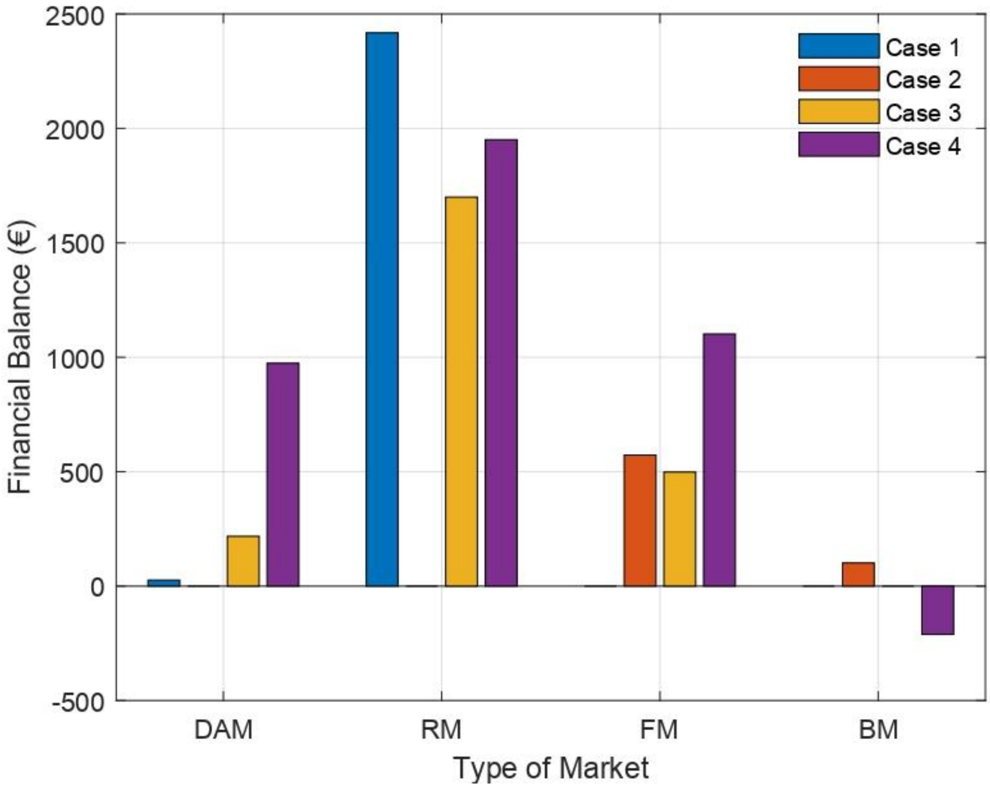

Figure 32: Financial balance per market for all four case studies

In Case 2, the ESP provides flexibility (upward or downward, P- or Q-flexibility services) to the DSO. For the BSUs' active power activations decided in the DLFM, the ESP will also have to pay/be paid in the BM. The purpose of the existence and operation of a DLFM is to ensure a direct participation of the DERs in the wholesale (TSO) markets without putting at risk the distribution network operation. The energy market produces a dispatch that violates several distribution network constraints at multiple hours. The FMO runs the DLFM in order for the DSO to purchase flexibility services to stabilize its network. The DLFM clearing process results are presented in Table 11. In this specific case study, taking into consideration the production of the DGs and the local demand decided in the DAM, the distribution network faces mostly the over-voltage and under-voltage issues, and thus, the DSO mostly requires Q-flexibility services. Hence, we see in Table 11 that the BSU at node 24 draws reactive power during most of the day, when the negative QLMPs indicate the need for absorbing reactive power, while the BSU at node 30 offers reactive power in all hours (positive QLMPs). The ESP chooses only a few hours during the day to offer upward or downward P-flexibility services and using only the BSU at node 24. More specifically, the BSU at node 24 draws active power at hours $t = 11$ and $t = 15$, when the absolute value of the negative PLMP is high and, in parallel, the BM expected price is relatively low. On the other hand, the ESP chooses to discharge power at hours $t = 7$, $t = 8$ and $t = 22$ with zero PLMP, since the BM prices are high enough. Overall, the ESP gains a total of 674.04€ (571.81€ from the DLFM and 102.23€ from the BM).

Table 11: The DLFM Clearing Results in Case 2

Hour	$p_{1,t}^{s,up}/p_{1,t}^{s,dn}$ (MW)	$p_{2,t}^{s,up}/p_{2,t}^{s,dn}$ (MW)	$q_{1,t}^{s,up}/q_{1,t}^{s,dn}$ (MVAr)	$q_{2,t}^{s,up}/q_{2,t}^{s,dn}$ (MVAr)	$\lambda_{24,t}^{P}, \lambda_{30,t}^{P}$ (€/MW)	$\lambda_{24,t}^{Q}, \lambda_{30,t}^{Q}$ (€/MVAr)	$\sum_{\omega\in\Omega} \xi_{\omega} \cdot \lambda_{t,\omega}^{b}$
1	0	0	-2.81	1.70	-10.27, 2.98	-6.97, 3	18.59
2	0	0	-2.31	1.57	-10.27, 2.98	-6.97, 3	21.96
3	0	0	-2.50	1.37	-10.27, 2.98	-6.97, 3	24.10
4	0	0	-2.50	1.19	-10.27, 2.98	-6.97, 3	25.52
5	0	0	-2.50	1.28	-10.27, 2.98	-6.97, 3	28.33
6	0	0	-1.93	1.96	-10.27, 2.98	-6.97, 3	33.14
7	0.70	0	-2.21	0.39	0, 11.43	-0.05, 8.47	61.73
8	0.69	0	-2.22	1.33	0, 12.46	-0.25, 8.87	25.98
9	0	0	-2.40	1.98	-9.59, 13.74	-6.88, 10.34	21.63
10	0	0	-2.50	1.47	-9.59, 13.74	-6.88, 10.34	38.24
11	-1.63	0	-1.83	0.89	-9.54, 15	-6.87, 11.24	12.76
12	0	0	-1.91	2.5	-15, 3.55	-10.61, 3	29.81
13	0	0	-2.5	2.5	-15, 3.01	-10.40, 3	39.82
14	0	0	-2.34	2.5	-15, 3.01	-10.40, 3	41.31
15	-0.52	0	-2.29	2.5	-9.94, 3.44	-6.93, 3	18.71
16	0	0	-2.5	2.5	-9.97, 3.41	-6.93, 3	41.56
17	0	0	-2.5	1.12	-9.59, 13.74	-6.88, 10.34	36.79
18	0	0	-0.91	2.45	-9.64, 12.02	-6.89, 9.12	24.53
19	0	0	1.65	2.19	1.83, 15	0.93, 10.54	21.85
20	0	0	2.28	2.5	1.52, 12.55	0.78, 8.83	32.62
21	0	0	0.88	2.5	1.51, 12.53	0.77, 8.82	36.68
22	1.87	0	-1.52	2.5	0.26, 12.04	0, 8.69	83.26
23	-0.73	0	-2.2	1.75	0, 8.55	0, 6.41	54.68
24	-0.89	0	0	2.5	-10.27, 2.98	-6.97, 3	50.47

*A negative/positive value corresponds to downward/upward flexibility services

In Case 3, the ESP initially decides on its energy trading in the DAM ignoring the next steps (participation in RM, DLFM and BM). Then, given the BSUs' power schedule, the ESP offers reserve capacity in the RM without considering its strategy in the subsequent markets. Finally, the ESP offers its remaining power capacity to the DSO in DLFM, disregarding the forecast BM prices, at which the ESP eventually will pay/be paid its DLFM active power dispatch. Table 12 illustrates the final BSUs' active/reactive power schedules and reserve capacity commitments. At first, the ESP performs energy arbitrage to maximize its profit from the DAM and results in 217.67€. This, however, hampers the BSUs' ability to offer regulation services through the RM. Comparing the RM prices in Table 10 and Table 12, we see that not co-optimizing the bidding strategies for energy and reserve leads to a reduction in the upward reserve prices during hours $t = 4$ and $t = 16$ and in the downward reserve prices during hours $t = 9$ and $t = 21$ by 5%. The lowered prices, along with the diminished available capacity to offer to the RM, reduce to a RM profit for the ESP of 1699.7€, which is 30% lower than the profit that the ESP gains in the RM in Case 1. On the other hand, the ESP's previous scheduling and bidding decisions leave the BSUs with neither the upward nor the downward active power capacity to offer to the DSO. Thus, the BSUs provide only Q-flexibility in the DLFM, which is constrained by the maximum apparent power of the converter (Constraint 4.a.15). Studying the DLFM QLMPs in Cases 2 and 3 (Table 11 and Table 12), we notice that the ESP, through its bidding policy, manages to increase by absolute value the DLFM prices at nodes 24 and 30 in most hours. However, the inability to provide P-flexibility services leaves the ESP earning 498€, which is 13% lower than the ESP's profits from DLFM in Case 2. Ultimately, the *myopic* behavior of the ESP, which participates in each market disregarding the profit opportunities that follow, results in its total profit of 2415.7€, which is 1.17% lower than in Case 1, even if the ESP participates in all four markets.

Table 12: The BSUs' Power and Reserve Schedules in Case 3

Hour	dis_t/ch_t (MW)	$r_t^{s,up}, r_t^{s,dn}$ (MW)	$p_{1,t}^{s,up}, p_{1,t}^{s,dn}$ (MW)	$p_{2,t}^{s,up}, p_{2,t}^{s,dn}$ (MW)	$q_{1,t}^{s,up}, q_{1,t}^{s,dn}$ (MVAr)	$q_{2,t}^{s,up}, q_{2,t}^{s,dn}$ (MVAr)	$\lambda_t^{up}, \lambda_t^{dn}$ (€/MW)	$\lambda_{24,t}^{P}, \lambda_{30,t}^{P}$ (€/MW)	$\lambda_{24,t}^{Q}, \lambda_{30,t}^{Q}$ (€/MVAr)
1	0	5, 1.08	0	0	-1.99	2.06	12.73, 12.73	-10.27, 2.98	-6.97, 3
2	0	5, 1.08	0	0	-2.11	1.93	12.73, 12.73	-10.27, 2.98	-6.97, 3
3	0	5, 1.08	0	0	-2.37	1.71	12.73, 12.73	-10.27, 2.98	-6.97, 3
4	-1.08	6.08, 0	0	0	-1.77	2.28	12.09, 12.73	-10.27, 2.98	-6.97, 3
5	0	5, 0	0	0	-2.49	1.63	12.73, 12.73	-10.27, 2.98	-6.97, 3
6	0	5, 0	0	0	-1.74	2.32	12.73, 12.73	-10.27, 2.98	-6.97, 3

7	0	5, 0	0	0	-0.98	2.50	12.73, 12.73	-10.27, 2.98	-6.97, 3
8	2.44	2.56, 2.82	0	0	-1.99	1.99	12.73, 12.73	-10.01, 3.36	-6.94, 3
9	5	0, 8.6	0	0	0	0	12.73, 12.09	-9.92, 3.25	-6.93, 3
10	0	0, 5	0	0	-2.5	1.81	12.73, 12.73	-9.54, 15	-6.87, 11.24
11	0	0, 5	0	0	-2.5	1.14	12.73, 12.73	-9.17, 15	-6.82, 10.85
12	0	0, 5	0	0	-1.75	2.5	12.73, 12.73	-15, 3.54	-10.62, 3
13	0	0, 5	0	0	-2.4	2.5	12.73, 12.73	-15, 3.54	-10.62, 3
14	0	0, 5	0	0	-2.12	2.5	12.73, 12.73	-15, 3.54	-10.62, 3
15	-3.60	3.12, 1.40	0	0	-1.69	1.69	12.73, 12.73	-9.26, 15	-6.83, 10.94
16	-5	7.44, 0	0	0	0	0	12.09, 12.73	-9.54, 15	-6.87, 11.24
17	0	5, 0	0	0	-2.5	1.50	12.73, 12.73	-9.54, 15	-6.87, 11.24
18	0	5, 0	0	0	-0.72	2.37	12.73, 12.73	-9.17, 15	-6.82, 10.85
19	0	5, 0	0	0	1.88	2.50	12.73, 12.73	1.83, 15	0.93, 10.54
20	2.44	2.56, 2.82	0	0	0.61	1.99	12.73, 12.73	1.55, 12.57	0.79, 8.83
21	5	0, 8.6	0	0	0	0	12.73, 12.09	-9.65, 12	-6.89, 9.11
22	0	0, 5	0	0	1.40	2.5	12.73, 12.73	1.02, 12.07	0.52, 8.67
23	-2.53	2.19, 2.47	0	0	1.98	1.98	12.73, 12.73	0.61, 15	0.31, 11
24	-5	6.51, 0	0	0	0	0	12.73,	0.61, 15	0.31, 11

							12.73		

*A negative/positive value corresponds to the BSUs' charging/discharging mode or downward/upward flexibility services

** $dis_t = \sum_{i \in S} dis_{i,t} \,.\, ch_t = \sum_{i \in S} ch_{i,t} \,, r_t^{s,up} = \sum_{i \in S} r_{i,t}^{s,up} \;, r_t^{s,dn} = \sum_{i \in S} r_{i,t}^{s,dn}$

Implementation of our proposed bidding strategy, which co-optimizes the stacked revenues of the ESP coming from all four markets under study (Case 4), produces the results presented in Table 13.

Table 13: The BSUs' Power and Reserve Schedules in Case 4

Hour	$dis_{1,t}$ / $ch_{1,t}, dis_{2,t}$/ $ch_{2,t}$ **(MW)**	$r^{s,up}_{1,t}, r^{s,up}_{2,t}$ **(MW)**	$r^{s,dn}_{1,t}, r^{s,dn}_{2,t}$ **(MW)**	$p^{s,up}_{1,t}$ $/p^{s,dn}_{1,t}$ **(MW)**	$p^{s,up}_{2,t}$ $/p^{s,dn}_{2,t}$ **(MW)**	$q^{s,up}_{1,t}$ $/q^{s,dn}_{1,t}$ **(MVAr)**	$q^{s,up}_{2,t}$ $/q^{s,dn}_{2,t}$ **(MVAr)**	$\lambda^{up}_t, \lambda^{dn}_t$ **(€/MW)**	$\lambda^P_{24,t}, \lambda^P_{30,t}$ **(€/MW)**	$\lambda^Q_{24,t}, \lambda^Q_{30,t}$ **(€/MVAr)**
1	2.5, 2.5	0, 0	1.61, 2.5	-1.81	-0.93	-2.22	1.82	12.73, 12.73	-10.36, 0	-6.99, 0.86
2	2.5, 0	0, 1.56	2.11, 2.5	-2.4	0	-2.46	1.57	12.73, 12.73	-10.27, 2.98	-6.97, 3
3	2.5, 0	0, 1.56	2.22, 2.5	-2.78	0	-2.16	1.38	12.73, 12.73	-10.27, 2.98	-6.97, 3
4	2.5, -0.46	0, 1.96	2.25, 2.04	-2.75	0	-2.40	1.84	12.73, 12.73	-10.27, 2.98	-6.97, 3
5	0.85, -0.67	1.65, 2.54	2.39, 1.37	-0.96	0	-2.45	2.22	12.73, 12.73	-10.27, 2.98	-6.97, 3
6	0.7, -0.29	1.80, 2.79	2.22, 1.07	-0.98	0	-1.49	2.38	12.73, 12.73	-10.27, 2.98	-6.97, 3
7	1.77, 0	0.03, 1.27	4.27, 2.5	0	1.23	-1.77	1.03	12.73, 12.09	-10.27, 2.98	-6.97, 3
8	2.5, 0	0, 1.56	2.14, 2.5	-2.86	0	-0.66	1.47	12.73, 12.73	-9.68, 11.99	-6.89, 9.12
9	2.5, 0	0, 1.56	1.51, 2.5	-3.49	0	-0.95	2.02	12.73, 12.73	-9.59, 13.74	-6.88, 10.34
10	2.5, -0.21	0, 1.74	2.71, 2.29	-2.29	0	-2.41	1.76	12.73, 12.73	-9.59, 13.74	-6.88, 10.34
11	2.5, -0.88	0, 2.5	0, 1.41	-5	0	0	2.14	12.73, 12.73	-9.26, 15	-6.83, 10.94
12	2.5, 0.71	0, 1.79	2.77, 2.23	-2.23	0	-2.39	2.21	12.73,	-15, 3.14	-10.50, 3

								12.73		
13	2.5, 0.16	0, 1.63	2.52, 2.41	-2.48	0	-2.49	2.43	12.73, 12.73	-15, 3.01	-10.40, 3
14	1.94, 0	0.56, 1.63	2.59, 2.41	-1.85	0	-2.46	2.5	12.73, 12.73	-15, 3.01	-10.40, 3
15	2.5, 0	0, 1.63	0.73, 2.41	-4.27	0	-1.77	2.5	12.73, 12.73	-9.94, 3.44	-6.93, 3
16	0.86, 0	1.64, 1.56	2.41, 2.5	-0.86	0.07	-2.5	2.47	12.73, 12.73	-9.97, 3.41	-6.93, 3
17	0.60, -0.80	1.90, 2.25	2.11, 1.7	-1	0	-2.34	2.17	12.73, 12.73	-9.54, 15	-6.87, 11.24
18	2.5, -0.14	0, 2.37	1.86, 1.56	-3.14	0	0	2.16	12.73, 12.73	-9.54, 15	-6.87, 11.24
19	-0.45, -0.16	2.5, 2.5	1.41, 1.41	0	0	2.31	2.43	12.73, 12.73	1.83, 15	0.93, 10.54
20	0, 0	2.5, 2.5	1.41, 1.41	0	0	2.28	2.5	12.73, 12.73	1.52, 12.55	0.78, 8.83
21	-0.34, -0.39	2.8, 2.84	1.07, 1.02	0	0	2.36	2.34	12.09, 12.73	1.30, 15	0.66, 10.75
22	-2.5, -2.5	0.61, 1.73	0, 0	4.35	3.27	-1.58	1.69	12.73, 12.73	0.26, 12.04	0, 8.69
23	-2.3, -2.5	2.6, 2.34	0.2, 0	0	1.55	0.48	2.11	12.73, 12.73	0.60, 15	0.31, 11
24	-0.76, -2.5	3.26, 3.26	0.54, 0	0	1.24	-0.07	1.98	12.09, 12.73	-10.03, 11.02	-6.94, 8.76

*A negative/positive value corresponds to the BSUs' charging/discharging mode or downward/upward flexibility services

In this Case, the ESP attempts to take advantage of all business opportunities. Figure 32 indicates that in Case 4 the ESP achieves DAM profits far higher (974.09€) than in Cases 1 or 3. Note that the DAM dispatch ($dis_{i,t}, ch_{i,t}$) does not determine the BSUs' state-of-charge alone, but it is only one of the two components of the final charging/discharging schedule (the other one is the DLFM active power dispatch, see Eqs (4.a.9), (4.a.13)). Thus, the ESP can perform arbitrage between the DAM and the DLFM (discharge in DAM and charge in DLFM and vice versa), in contrast with Cases 1, 2 and 3 where the ESP does not have this opportunity. Therefore, the ESP chooses to trade energy in the DAM much more frequently than in the previous Cases. The ESP's decision on the charging/discharging DAM schedule of the two BSUs does not consider only the DAM prices but also the profit opportunities in the

RM, the nodal DLFM prices (and therefore the location of each BSU in the distribution network) and the expected BM prices. More specifically, the ESP, expecting the PLMPs at node 24 to be negative (DSO's signal that it needs downward P-flexibility in this area) during most of the day (t = 1-18, 24), uses the BSU at this node at maximum discharge power (2.5 MW) in hours t = 1-4, 8-13, 15 and 18. In this way, the ESP creates profit opportunities in the RM by maximizing its available downward reserve capacity (defined at the right-hand side of constraint 4.a.6). However, in order for the ESP to be able to sell energy and downward regulation in the DAM and the RM respectively, the ESP has to provide downward P-flexibility to the DSO, even if it means that the ESP will have to pay for it, since the expected BM prices are higher in absolute value than the DSO's reward per unit ($\lambda_{i,t}^{P}$). Hence, the ESP commits the maximum downward reserve capacity to the RM that the state-of-charge constraints of the BSU allow (constraint 4.a.10) and the rest of the available downward power capacity is sold in the DLFM (see Figure 33, Figure 34).

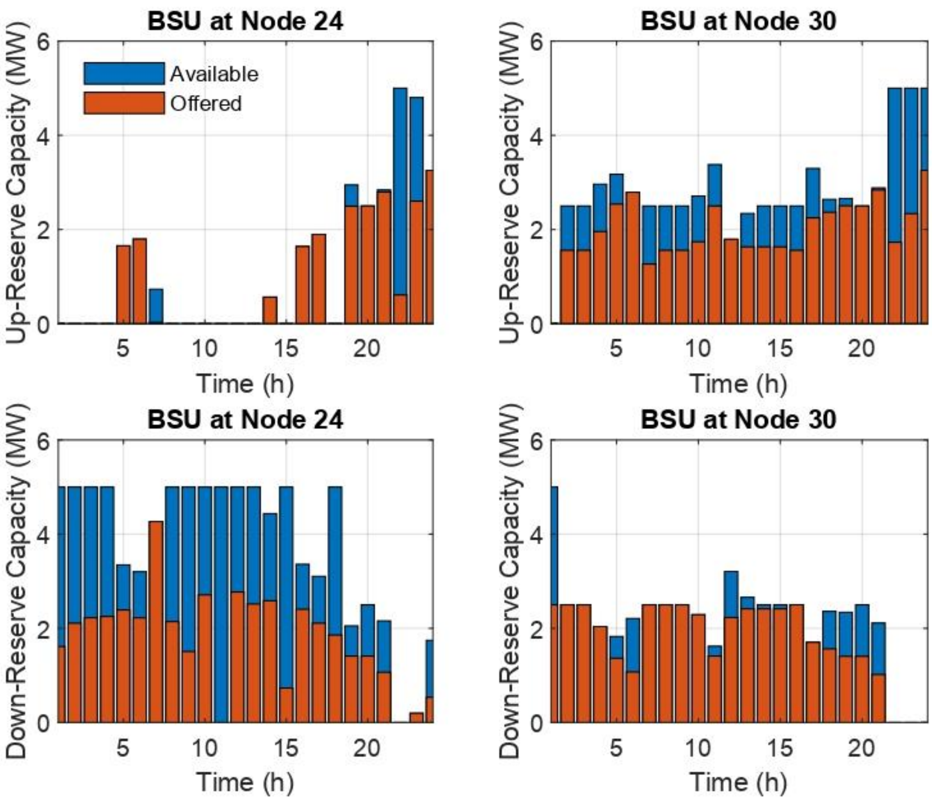

Figure 33: BSUs' available and offered to the RM reserve capacity

In hours 5-7, 14, 16 and 17 the BSU at node 24 is decided to discharge power, but not at its full capacity. This produces available upward reserve capacity (defined at the right-hand side of constraint 4.a.5) and enables the ESP to also provide upward reserve capacity in the RM. This capacity is entirely sold in the RM, except in hour when state-of-charge constraints do not allow it (see Figure 33). In hours 20-23 the PLMPs are positive, indicating that the DSO requires upward P-flexibility. However, constraint 4.a.12 dictates the BSU at node 24 to charge power in order to restore the state-of-charge at the end of the day. Nevertheless, in hour 22 the BM price is expected to reach its peak (83.26€), and thus the ESP provides the DSO with 4.35 MW of upward P-flexibility, even if the DLFM price is quite low at this time.

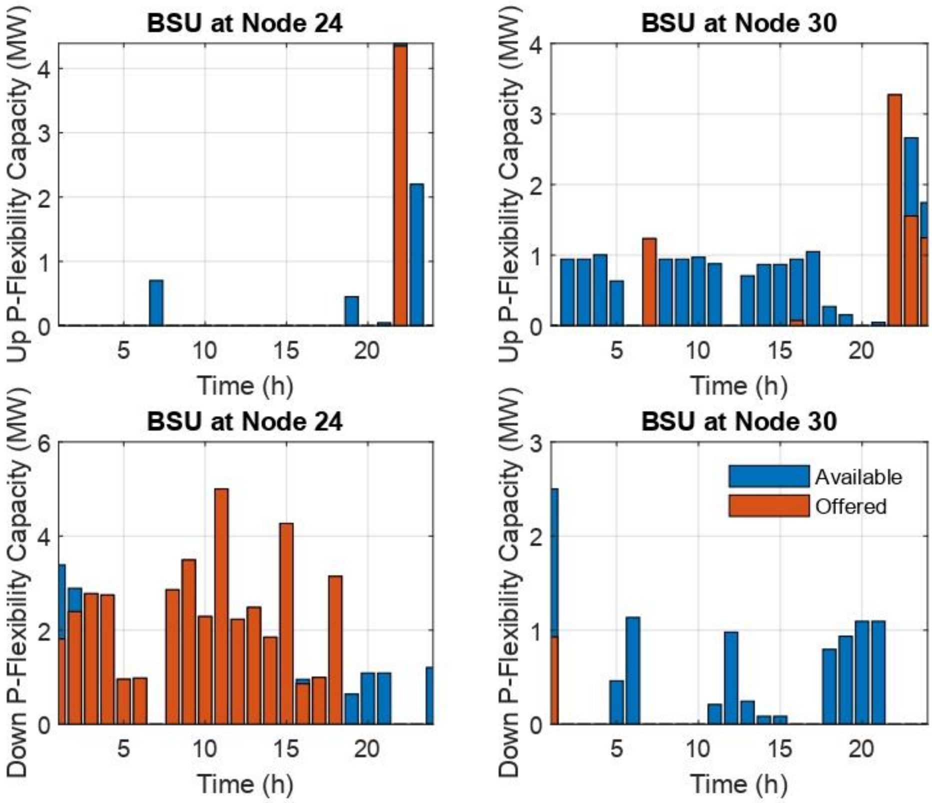

Figure 34: BSUs' available and offered to the DLFM active power capacity

At node 30, i.e., the location of the second ESP's BSU, the DSO requires only upward P- and Q-flexibility services throughout the day (except for the first hour, when $\lambda_{30,1}^{P} = 0$). In order for a BSU to be able to provide upward P-flexibility services, it should buy power in DAM. Thus, the main criterion for the ESP to decide whether the BSU will sell active power in the DLFM is the comparison between the energy price (at which the ESP will have to pay the charging power) and the sum of the PLMP at node 30 and the expected BM price (at which the ESP will be paid for the upward P-flexibility service). Therefore, the BSU at node 30 provides upward P-flexibility services to the DSO in hours 7, 16, 22, 23 and 24, when this is financially advantageous (see Figure 35). During the rest of the day, we see in Table 13 that the BSU chooses to trade power in the DAM, with the objective to have the highest possible available upward and downward reserve capacity. Hence, as shown in Figure 33, the BSU offers upward reserve capacity throughout the day and downward reserve capacity from the beginning of the day until hour 21. In the last 3 hours the high profit opportunities in DLFM and BM leads the ESP to leave no space for downward reserve capability.

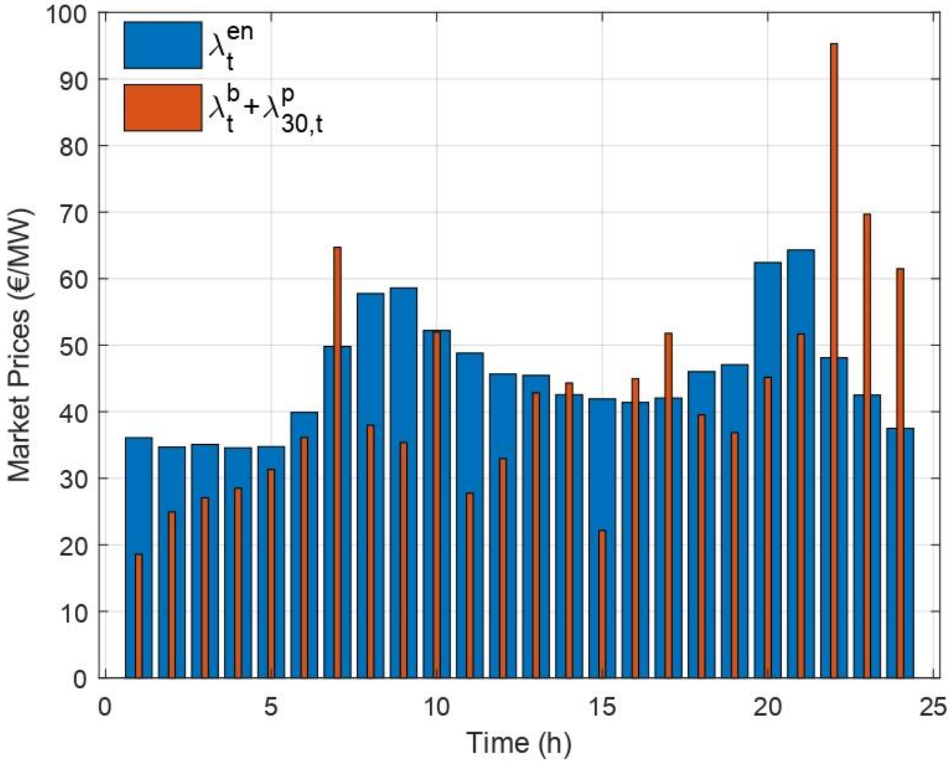

Figure 35: Comparison between the DAM prices and the sum of the BM and the active power DLFM prices

Finally, throughout the day, the ESP makes profit by also providing voltage support services to the DSO, by absorbing (in hours when the QLMP is negative, $\lambda_{i,t}^{Q} <= 0$) or supplying (in hours when the QLMP is positive, $\lambda_{i,t}^{Q} > 0$) reactive power to the grid. The capability of the BSUs to trade reactive power depends on their active power schedule and the apparent power rating of the converters (constraint 4.a.15). For example, in hours 12, 13 and 14, when the absolute values of the QLMPs at node 24 are the highest throughout the day, the aggregate active power schedule of the BSU located at this node is close to zero. Therefore, the BSU can absorb reactive power at a rate very close to the maximum and increase its profits. On the contrary, in hour 11 the aggregate active power dispatch of the same BSU leaves no room for reactive power services, since it reaches the maximum apparent power potential of the BSU. At node 30, the BSU supplies reactive power the local grid at all times, as the positive QLMPs dictate.

Overall, Figure 32 indicates that the RM profits in Case 4 are lower than in Case 1, but higher than in Case 3. In Case 1 the ESP, co-optimizing the energy and reserve services to the TSO, tries to maximize its storage capacity that is available to be offered to the TSO for regulation purposes, using the energy market. In Case 4 though, the ESP chooses not to offer its entire available capacity in the RM, since the DLFM and the BM, which chronologically follow, provide additional revenue streams. Even so, being much more active in the DAM comparing to Case 3, the ESP has higher reserve potential in Case 4 and thus derives 14.7% higher RM revenues (1950.6€). The ESP's decisions bring it profits of 1101.7€ from the DLFM, which surpass by far the ESP's profits from the local grid services in Cases 2 and 3 (higher by 92.67% and 121.22%, respectively). However, the BSUs' P-flexibility services provision to the DSO, which modify the agreed energy schedule in the DAM, lead the ESP to pay in the BM 210.94€, in contrast with the Case 2, in which the ESP earns 102.23€ and Case 3, in which the ESP does not participate in the BM. In Table 14, the aggregate ESP's profits in all four

Cases are presented. Our proposed strategy achieves a total gain of 3815.5€, which is super-linear, i.e., the revenues from jointly optimizing the BSUs' services to both the TSO and the DSO is larger than the sum of performing the individual applications (Case 1 and Case 2). In fact, the ESP earns 22.36% higher revenues in Case 4, than in Cases 1 and 2 combined. Moreover, our model (Case 4) accomplishes 57.95% higher revenues than the 'myopic' strategy of Case 3.

Table 14: Total Profits of ESP

	Case 1	**Case 2**	**Case 3**	**Case 4**
ESP's Profits (€)	2444.2	674.04	2415.7	3815.5

4.5.3. Sensitivity Analysis

This subsection studies sensitivity of the proposed decision-making procedure and the profitability of the ESP to some externalities, such as the location of the BSUs and the competing ESPs' offers.

4.5.3.1. Impact of the Location of BSUs

In this subsection, we demonstrate how the locations of the BSUs (i.e., the nodes in the DN) affect the profitability of the ESP. For this purpose, we consider three potential scenarios for the BSUs locations, namely: i) nodes 2 and 3, ii) nodes 25 and 32 and iii) nodes 24 and 30 (cf. 4.5.2). The ESP's individual market revenues for each location scenario are illustrated in Figure 36. In the first scenario, the BSUs are located close to the root of the distribution grid, where the demand for flexibility, and correspondingly the DLFM prices, are low. In this case, the ESP exploits the DSO's request for downward P-flexibility, so as to perform market arbitrage and sell energy in the DAM. Thus, we observe that the DAM profits in this scenario are higher than in any other market. The second highest source of revenues for the ESP is the RM, while in the DLFM the ESP is paid only for its Q-flexibility services at a quite low price. In the BM, the ESP pays for its downward P-flexibility services. In the second scenario, the BSUs are placed at nodes 25 and 32, where the DSO's need for flexibility is rather high, rendering the DLFM much more profitable for the ESP than in other two scenarios. The BSU at node 25, since the DG3 production (see Figure 31) mainly requires the provision of downward P-flexibility, is eligible to sell energy in the DAM during most of the day. On the other hand, the under-voltage issues at node 32 force the DSO to demand upward Q- and P-flexibility services, which leads this BSU to strategically lose money in the DAM in order to offer remunerative flexibility services to the DSO. Overall, the total revenues for the ESP are higher for location 2 (4120€), followed by location 3 (3815.5€) and location 1 (3358.2€) profits.

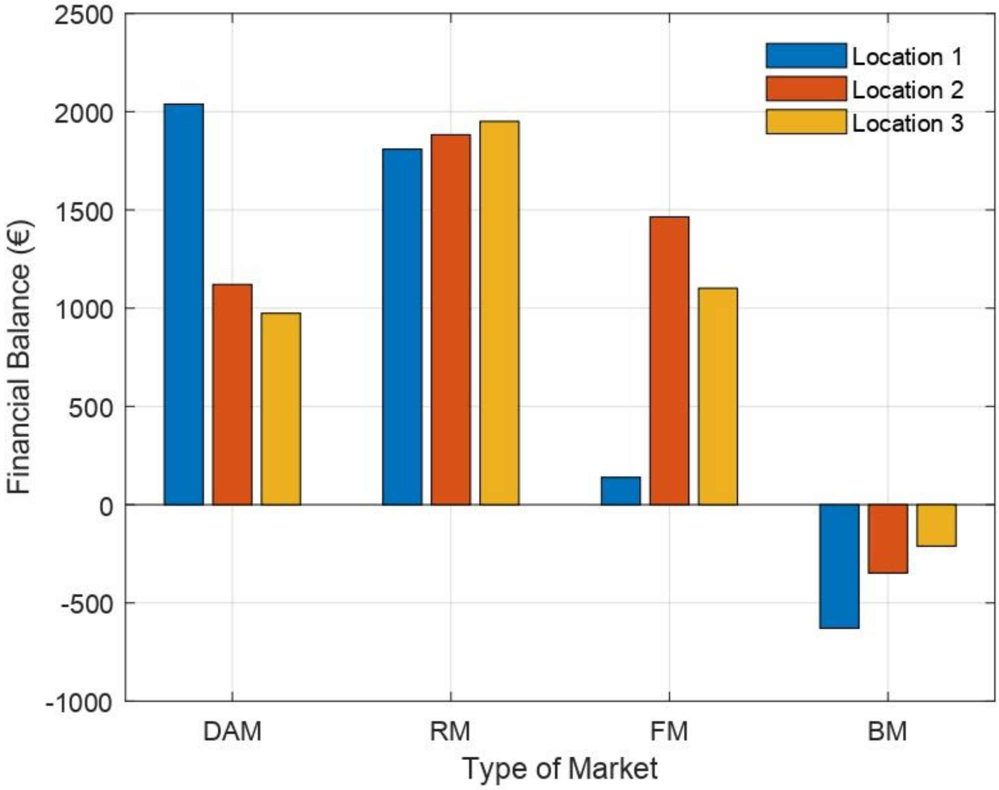

Figure 36: Breakdown of the ESP's market revenues for each BSU location

4.5.3.2. Impact of Competing ESPs' Price Offers

In subsection 4.5.2 we assumed that price offers of the competing ESPs are 15 €/MW for P-flexibility and 3 €/MVAr for Q-flexibility services, as in [149]. Now we study the effect the magnitude of these offers has on the results that our bidding strategy produces. To this end, we examine three scenarios of the price offers presented in Table 15. The DLFM prices in each scenario are illustrated in Figure 37, while the individual market ESP's revenues for each scenario are presented in Figure 38. The DLFM profits increase when increasing the competing ESP's offers since the DLFM prices rise. On the other hand, while the DAM profits in Scenario 2 are higher than in Scenario 1, they plummet in Scenario 3. This is explained by the fact that in Scenario 3 the high DLFM prices prompt the ESP to provide upward P-flexibility services to the DSO at node 30. To do that, the BSU at this node has to charge higher amounts of power in the DAM and ultimately downscale the DAM revenues. Additionally, in Scenario 3 the ESP, in contrast with Scenarios 1 and 2, makes a small profit in the BM, since the increase of the DLFM prices (and their comparison to the DAM prices) makes it profitable for the ESP to provide upward P-flexibility services, which are compensated in both the DLFM and the BM. Conclusively, the ESP in Scenarios 2 and 3 gains 30.67% and 66.57% higher profits than in Scenario 1 (i.e., 4985.8€ and 6355.5€ as compared to 3815.5€).

Table 15: Scenarios of Competing ESPs' Price Offers

	$c_{i,t}^{s,P,up}/c_{i,t}^{s,P,dn}$ (€/MW)	$c_{i,t}^{s,Q,up}/c_{i,t}^{s,Q,dn}$ (€/MVAr)
Scenario 1	15	3
Scenario 2	30	6
Scenario 3	45	9

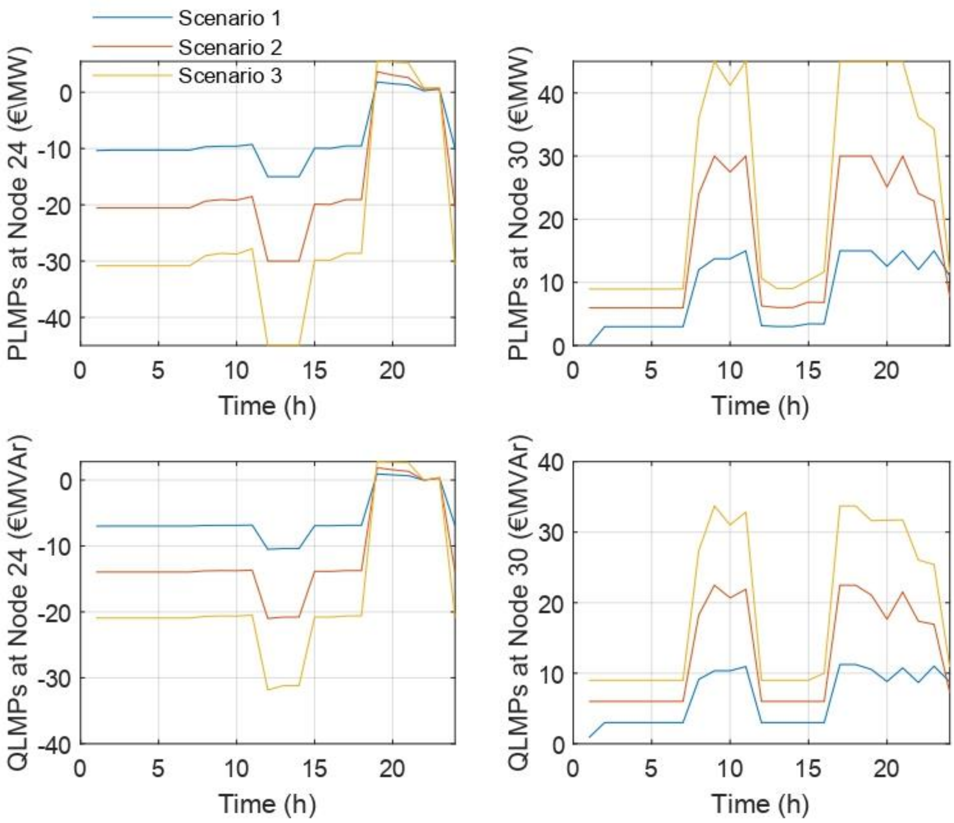

Figure 37: DLFM prices at nodes 24 and 30 under various scenarios of competing ESPs' price offers

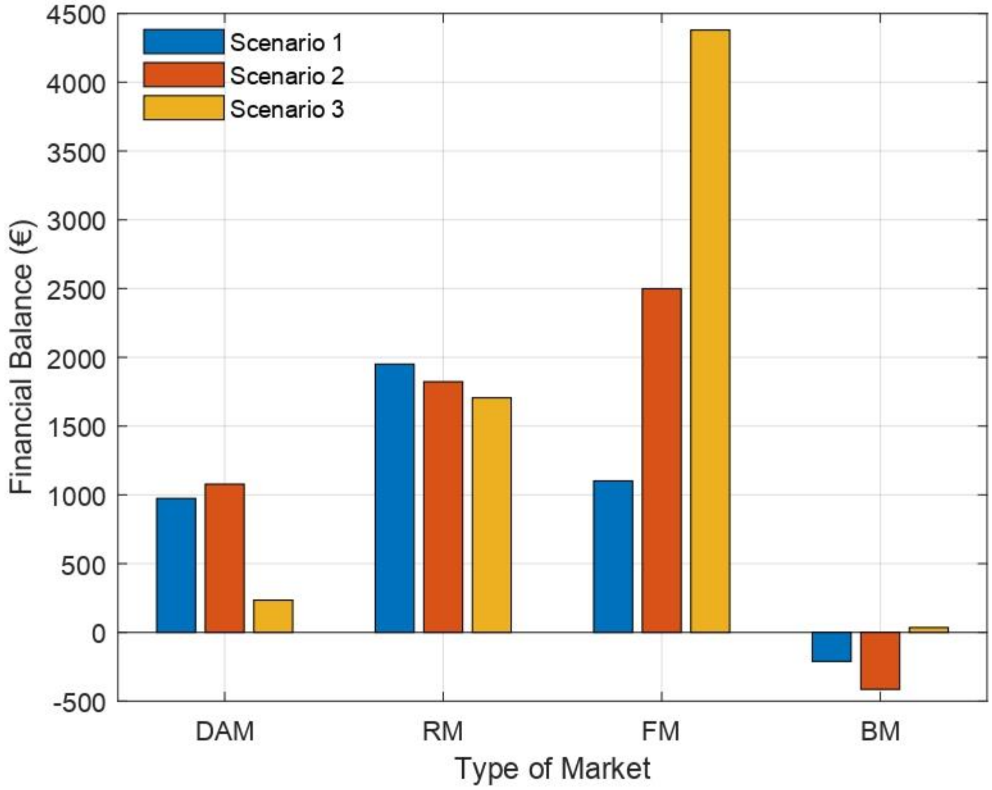

Figure 38: ESP's individual market revenues in each price offer scenario

4.5.4. Computational Efficiency

We evaluate the computational performance of our proposed iterative procedure using 3 case studies: a) the 15-bus radial distribution network from [125], b) the IEEE 33-bus radial distribution system, and c) the 69-bus radial distribution system. The number of iterations and the solution times are presented in Table 16. Our algorithm terminates in 3 or 4 iterations, with each iteration requiring on average 96.3, 452.5 and 958.8 seconds, respectively, in each case study.

The binary expansion method is used as a benchmark to evaluate our solution method. In the binary expansion case, the remaining bilinear terms in (4.d.1) are linearized using binary approximations of variables $dis_{n,t}$ and $ch_{n,t}$, combined with additional linear constraints. In the 15-bus distribution network case study, the solver was manually stopped at 10,000 sec, achieving a sub-optimal solution (5% less profits than the proposed method), while the solver is terminated at 20,000 sec in the 33-bus network case study resulting in 6% less profits than our method. Finally, in the 69-bus distribution network the binary expansion method was terminated at 40,000 sec, resulting in 12% less profit than our proposed procedure.

Table 16: Computational Speed Comparison

	Proposed Solution Method			Binary Expansion Method		
	15-Bus	33-Bus	69-Bus	15-Bus	33-Bus	69-Bus
Iterations	3	4	4	-	-	-
Time (sec)	289	1810	3834	10000*	20000*	40000*
Profits (€)	4081.6	3815.5	2452.5	3889.8	3602.9	2159.3

* The solver reached a predefined time limit

4.6. Conclusions and Future Work

In this Chapter, we considered a novel market architecture that introduces a distribution level flexibility market operating in the intra-day timeframe, between the day-ahead energy and the near-real-time balancing markets. In this context, we formulated a bilevel model for an ESP owning distributed BSUs to optimally calculate its market strategy. The bilevel problem is recast into an MPEC through a KKT-based method. An exact linearization approach, the Big-M method and an iterative process are implemented to tackle nonlinearities. Performance evaluation results demonstrate that our model achieves super-additive gains: the ESP obtains significantly higher profits through the joint optimization of both the TSO and the DSO services than the sum of the individual profits from devoting the BSUs to one of the two applications. Finally, a sensitivity analysis was conducted to showcase the impact of some externalities on the results. The proposed model can be of use to flexibility providers in the modern electricity market structure that accommodated distribution-level flexibility market. Such market is expected in the democratized and DG-rich power systems. Furthermore, our work can provide useful insights to policy makers, regulators and market operators regarding the operation of the DLFM and the TSO-DSO interaction. As a future work, we find it worthwhile to take into account uncertainties in renewable generation, load and market competition, and study the impact of the associated risks on the ESP's profitability. Also, our future research will be focused on the balancing stage, including the activation of reserves.

5. Chapter 5: Retail Pricing Scheme

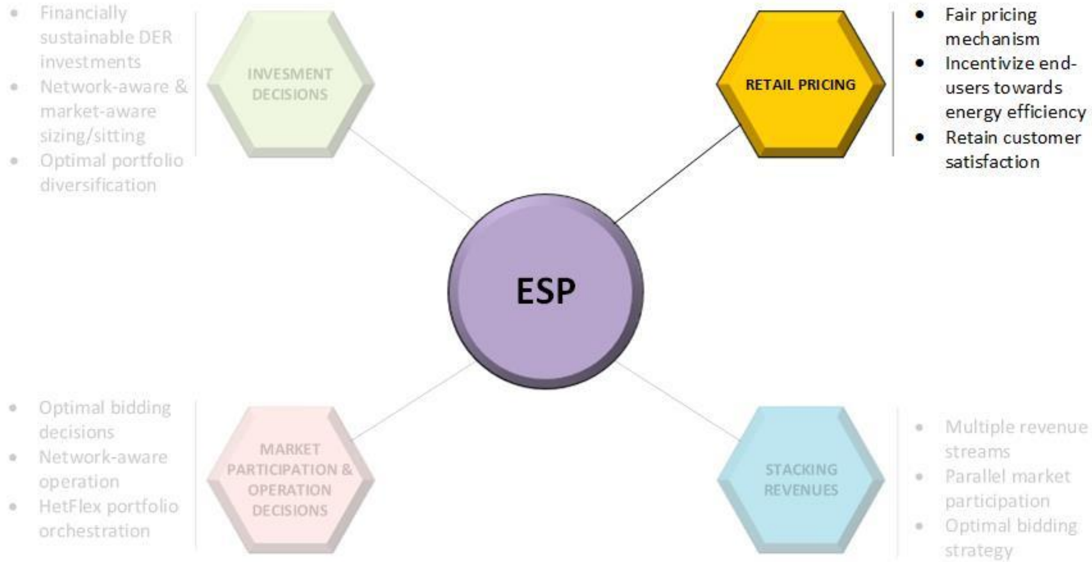

Figure 39: ESP's Retail Pricing Scheme Choice

In this Chapter, we examine a novel pricing mechanism that can be applied by the ESP to its customers/end-users in order to reduce its energy costs (Figure 39). An ESP can considerably lower the cost of energy they purchase from the wholesale market and create new revenues streams, while offering consumers lower electricity bills and digital services via online software platforms. Price-based DSM techniques can trigger the desired behavioral changes and generate novel services and business models for the ESP's participation in flexibility markets. The energy pricing schemes proposed so far, do not strongly motivate consumers to modify their electricity consumption habits, as they are unfair and thus unable to effectively trigger behavioral changes and offer flexibility services. Based on this observation, we develop a Behavioral Real Time Pricing (B-RTP) scheme, which offers an easily adjustable level of financial incentives to consumers, by fairly rewarding the desirable behavioral electricity consumption changes. Performance evaluation results demonstrate that the proposed billing scheme affects the consumers' behavior much more efficiently than the traditional Real Time Pricing (RTP) mechanism, outperforming the latter in all widely adopted metrics. Our billing mechanism is able to simultaneously: i)significantly reduce energy cost compared with Real Time Pricing (10%-30%), ii) slightly increase consumers' welfare (2%-4%) and iii)ensure the fair allocation of financial benefits among the consumers. All these result in significantly increased competitiveness of our billing mechanism in the flexibility markets.

The remaining of this Chapter is organized as follows: Section 5.1 is introductory and presents the requirements that a price-based DSM strategy has to fulfill. In Section 5.2, we discuss the related work and we highlight the contributions of this thesis. In Section 5.3, we describe the proposed system model. In Section 5.4, we propose our innovative B-RTP scheme. In Section 5.5, we evaluate our proposed billing mechanism through extensive simulations, using the RTP scheme as a benchmark. Finally, in Section 5.6 we conclude and discuss future work.

5.1. A Novel Behavioral Real Time Pricing Scheme for the Active Energy Consumers' Participation in Emerging Flexibility Markets

The aging infrastructure of the traditional electricity grid, the projected growth in global electric power demand [153], [154], the increasing environmental concerns and the circumstances in global economy [155] have triggered an increasing interest in energy efficiency [156]. Moreover, the ongoing power system decarbonization results in high levels of uncertainty and variability in the energy production rate. DSM is recognized as a promising tool able to improve energy efficiency and network stability. DSM techniques are deployed in order to incentivize electricity consumers to modify their Energy Consumption Curves (ECCs) in a more energy-efficient way, aiming to achieve a continuous and steady balance between production and consumption. Furthermore, the liberalization of electricity markets boost the importance of the trade-off between the quality of services (QoS) that an ESP offers and its profitability margins with respect to the new revenue streams that it can create. Therefore, the development of advanced DSM strategies, able to efficiently deliver more competitive energy services, is of a great importance.

Electricity consumers that participate in DSM programs take actions that can be classified into two categories: (i) *load shedding*, by either adopting energy efficiency policies or following a more conservative consumption pattern, and (ii) *load shifting*, by operating flexible appliances in off-peak hours. Both of the aforementioned strategies elevate the level of discomfort for the consumers. Therefore, for most consumers, financial incentives are crucial to the design of effective DSM programs.

Intelligent energy pricing schemes are automated DSM strategies, which try to incentivize electricity consumers towards a consumption pattern that provides an attractive trade-off between their desired ECC and the one that is cost-efficient for the power system [157]. As analyzed in Section 5.2, recent research has focused on the development of pricing schemes with the objective to efficiently schedule flexible loads. Historically, the energy pricing models started with flat electricity tariffs. Under this scheme, consumers are charged with an identical and time invariant price per energy unit and are not really motivated to consume electricity in an efficient way. This leads to over-investments by the DSOs and/or TSOs in order to meet the load demand and ensure grid stability [158]. The pricing scheme of Inclining Block Rates (IBR) was a first attempt to interact with the electricity consumers' behavior. In the IBR scheme, the price per unit increases with the total energy that the user consumes, creating a barrier that prevents the over-use of energy and consequently a power shortage and/or network failures. The next step was the Time-Of-Use (ToU) pricing method, which motivates consumers to shift loads into low pricing hours; however, a priori set prices do not reflect the real-time needs of the grid. Hence, it may result in congestion issues during the low-price hours. Real – Time Pricing (RTP) schemes ([40], [50], [159], [160], [161]) have been proposed as a way to directly connect the actual energy production, transmission and distribution costs with the retail energy price. However, RTP schemes still suffer from the 'tragedy of the commons' phenomenon [162], in which a consumer that changes her ECC (behavioral change in energy consumption) generates a benefit for the entire system. In the average case, only a small portion of this benefit is returned to her, while the major part of it is shared among all the consumers. In this regard, RTP schemes are not fair and do not efficiently incentivize behavioral changes. This issue is a major motivator for the design of our proposed Behavioral RTP (B-RTP) scheme towards efficiently engaging end users in DSM programs.

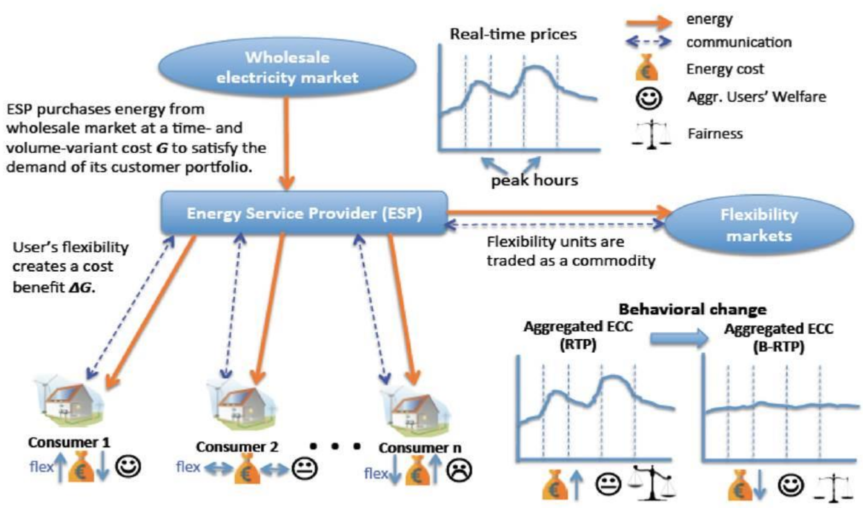

Figure 40: Proposed architecture and business model for the energy flexibility units trading

In Figure 40, the role and use of the proposed B-RTP scheme for facilitating the trading of DSM units in flexibility markets is illustratively explained. In the assumed business model, the ESP purchases energy from the wholesale electricity market at a time- and volume-variant cost G in order to satisfy the demand of its customer portfolio (energy consumers). The aggregated users' flexibility (behavioral changes) can create a cost reduction ΔG. Subsequently, ESP can trade its ability to control the demand (e.g. reduce energy cost) as a commodity in various types of transmission- or distribution-level flexibility markets. This cost reduction ΔG can be fully returned back as a reimbursement/discount to the end-users or a fraction of ΔG can also be used to increase ESP's profits. In this chapter, we assume the former case.

The objective of the proposed B-RTP scheme is the reduction of the energy system's cost without deteriorating the users' quality of experience (or else, aggregated users' welfare). Moreover, B-RTP has to fairly allocate the cost reduction benefits among the users that create them, which is very important for the success of the proposed pricing scheme. According to the extensive performance evaluation results presented in Section 5.5 for the proposed personalized energy billing mechanism, B-RTP achieves an energy system's cost decrease between 10% and 30%, depending on the cost of energy in the wholesale market and the various users' flexibility levels. For the majority of the simulation scenarios, the users' quality of experience is not affected at all. Actually, in some cases, it is enhanced by a factor of 2-4%. Of course, in extreme simulation scenarios, in which flexibility need is crucial for the network's operation, the quality of experience may be slightly deteriorated (but again remain within acceptable levels) at the expense of much better financial benefits returned back to the end users. Finally, B-RTP achieves a fair allocation of the financial benefits to all end users according to the degree of each one's participation in the total energy system's cost decrease. What's more interesting is that ESP can dynamically configure the trade-off between the afore-mentioned Key Performance Indicators (KPIs) in order to achieve its optimal participation in the flexibility markets (cf. parameter 'γ').

5.2. Related Work

In the context of liberalized electricity markets and progressive ESP business models in the smart grid sector, a pricing scheme has to fulfill specific requirements (by achieving an attractive trade-off) such as: i) the consumer's satisfaction (or else user's welfare), ii) the stability/efficiency of the power grid (or else energy system's cost), and iii) fairness (or else ensure that each user receives a financial reward, which is exactly proportional to her contribution in the energy system's cost decrease).

The first requirement is widely known as user's welfare and is determined as the satisfaction (level of comfort) of a user at a given time instance as described by her ECC, minus the bill she has to pay for it. The users' welfare achieved by a DSM program determines the willingness of a user to participate in the DSM program. In other words, it demonstrates which program leads to more competitive services in an open energy market. In [40], [41], [42] and [43] users' welfare is considered as the system's objective. In [40], a distributed algorithm is proposed, where users shed their consumption attempting to maximize their welfare as a response to price signals from the ESP. In [41] and [43], game-theoretic approaches are used, in which users shift or shed their loads with the objective to maximize their own welfare, while the ESP sets the real-time energy prices based on users' decisions. Authors in [42] consider users that can operate both shiftable and curtailable loads with the same objective; however, prices are set a priori and the interaction between the ESP and the end users is not considered. Our work's novelty is that we examine user's welfare together with the decrease of energy system's cost and fairness KPI.

The second requirement expresses the capability of a pricing model to incentivize energy consumers to adopt ECCs that minimize the production and distribution cost of the energy that they consume. In our case, this cost is the one that the ESP pays to the wholesale market in order to purchase the required energy to satisfy the aggregated ECC (i.e. demand) of its users. Therefore, this requirement is denoted as behavioral efficiency and it reflects which pricing model is able to fulfill the objectives that energy producers, DSOs, TSOs and BRPs set. In [44], [45], [46], [47] and [48] behavioral efficiency is evaluated in terms of reduction of the total energy cost. In [45], an online Electric Vehicle (EV) charging scheduling algorithm is proposed that minimizes total energy cost, while in [46] an optimization-based algorithm is proposed for the operation of different classes of devices with the objective to minimize the energy cost without sacrificing users' comfort. Researchers in [47] consider both energy cost and users' welfare as their system's objective, while Soliman et al in [48] present a game-theoretic approach to analyze the interaction between end users and the ESP in the presence of storage devices. The objective of the model is the minimization of energy cost. In [163], users schedule their consumption in order to reduce the system's Peak-To-Average Ratio (PAR), which is linked to system's energy cost. On the other hand, users' comfort is not taken into consideration. Again, our proposal goes one step further by considering all three above-mentioned KPIs at the same time.

The third requirement is fairness. It refers to how fairly the system's energy savings, which result from the behavioral changes of the participating users, are allocated among them. Baharlouei et al [50] propose a pricing model based on the principle that the users' bills should be analogous with their contribution to the system's energy cost reduction. Finally, the design of a pricing scheme should take into consideration the profitability of the ESP, if the business model facilitates this option [159], [164]. However, these fairness-related works admit that they sacrifice energy system's cost savings in order to achieve their objective, which is a problem that our proposed scheme addresses, too.

In the majority of the aforementioned works, the sole objective is social welfare maximization, which is defined as the users' comfort minus the system's cost (or user welfare plus the ESP's profits). In these pricing schemes, social welfare maximization generally comes with budget revenue (profit) for the ESP, which is not the case of the business model assumed in this thesis. This thesis considers cases, in which ESPs sell energy with (close to) zero profit to retail markets, such as: i) liberalized markets with perfect competition [165] as analyzed in [166], ii) energy cooperatives [167] or islanded energy sharing communities [168], where energy prosumers share their energy in order to ensure the energy autonomy of the community, and iii) ESPs that participate in a flexibility market [169] and provide profitable flexibility services to DSOs, TSOs and BRPs. Furthermore, in contrast with the majority of related work, we consider that users are not just price takers; however, they act as price anticipators. That is, they can have an impact on their energy bills exploiting their flexible appliances.

Studies that propose DSM algorithms with active user participation use a user model in order to evaluate their algorithms' performance. Many works ([40], [159], [170], [171], [172], [173], [174], [175], [176]) exploit the assumed user model in order to design model-specific pricing schemes leveraging analytic solutions. However, the electricity consumer model is still unclear for the research community because there are no public large-scale data from field trials. A comprehensive critique of this approach is presented in [177], [178]. In this thesis, we propose a discriminative pricing scheme based on each user's behavior, which preserves efficiency in terms of social welfare, while at the same time achieves a budget-balanced system (or profits close to zero), fairness and reduced system cost. The proposed algorithm, however, is not tuned to any specific user model. Rather, it performs equally well for any user model that fulfills some mild assumptions. These attributes make the proposed B-RTP an advantageous scheme for all above-mentioned business cases. Finally, it fits very well the latter case, where an ESP participates in a flexibility market, as it is able to motivate its users (customers) to adjust their ECCs according to the needs of the market while keeping them well-satisfied. To the best of our knowledge, there is no existing work to have dealt with this type of emerging business model considering at the same time the three above-mentioned KPIs. Conclusively, the contribution points of this Chapter can be summarized as follows:

- A novel non-profitable energy pricing scheme, referred to as Behavioral Real-Time Pricing, which exploits as incentives its high levels of fairness to remarkably reduce the aggregated energy cost, while simultaneously slightly increasing user's welfare. B-RTP quantifies the system cost reduction achieved by each end user's load shifts and curtailments and rewards her accordingly.
- A mechanism that parameterizes the proposed scheme, enabling it to dynamically adjust the degree of incentives. Thus, it indirectly controls the aggregated energy cost. This gives ESP the opportunity to dynamically select the best trade-off among the aforementioned three requirements according to its dynamically changing business needs.
- A holistic comparison between the proposed B-RTP and a non-profit version of an existing RTP scheme that is widely adopted in the literature. We demonstrate that B-

RTP scheme achieves a more attractive trade-off among the aforementioned requirements by reducing the system's cost, while preserving social welfare efficiency and enhancing fairness.

5.3. System Model & Problem Formulation

We consider a smart community, which consists of a set of electricity users (denoted as $\boldsymbol{N}$) and an ESP. An electricity consumer can be a single smart home or a group of smart homes acting as a single unit. Each user $i \in \boldsymbol{N}$ is equipped with advanced Smart Meters that monitor her appliances' ECCs and an Energy Management System (EMS) that schedules her energy consumption over the scheduling horizon, according to the preferences that she sets. We do not consider price-taking consumers as in [42]; on the contrary, users interact with the ESP in order to reach an agreement on the energy consumption schedules and energy prices. A communication network lies on top of the electric grid, enabling the message exchange between the users and a Price Controller (PC) installed at ESP's premise. The PC receives each user's *i* aggregate consumption and sends back to the users' EMSs their energy bills. As we later analyze, our proposed architecture includes limited information disclosure from the energy consumers and thus preserves their privacy by following the same data exchange model as in [179].

In order for an ESP to evaluate each end user's behavioral change, 2 use cases are considered: i) Users' "base" ECC is a priori known (before the behavioral changes that B-RTP will incentivize) and ii) Users' "base" ECC is unknown. By "base", we mean the natural/voluntary (unforced) consumption behavior of a user, in the absence of incentivized time varying penalties or rewards. B-RTP applies to the first use case. Examples of this use case are:

- Working environments in which operations that include power consumption are scheduled and invariant from one day to another.
- Direct contract between ESPs and a large industrial client with standard ECCs.
- Aggregated consumption patterns of groups of users (which are accurate enough because of statistical multiplexing).

The monetary gains from the total energy cost reduction ΔG may be fully given as discounts to the end users, or other market stakeholders (e.g., ESPs) may acquire a certain fraction as their profit. In addition, stakeholders that participate in flexibility markets ([171]) obtain additional revenues from these markets for their ability to control energy consumption/cost. In this thesis, we consider the demanding subcase of a highly competitive environment (as in [166]), where discounts are fully given to end users and revenues from flexibility markets are close to zero; the relaxation of this assumption is left as future work.

Next, we present the user model and the energy generation cost model. Both models are widely adopted in the literature. Their purpose is only to facilitate the evaluation of the proposed B-RTP scheme through the comparison between B-RTP and RTP. Note that they do not constitute a novelty aspect, but rather emphasize that the proposed B-RTP is utility-agnostic and thus can be applicable in any type of user and cost modeling. Finally, without harm of generality, we consider a discrete-time model with a finite horizon that models the scheduling period $\boldsymbol{H}$. Each period is divided into T timeslots of equal duration.

5.3.1. Demand Side Model

Each user $i \in \boldsymbol{N}$ owns a set $\boldsymbol{D_i}$ of household devices, and each device $d \in \boldsymbol{D}_i$ consumes energy $x_{i,d}^t$ at time $t \in \boldsymbol{H}$. The total amount of energy that all devices in $\boldsymbol{D_i}$ consume at time t is denoted as x_i^t. According to the literature ([42], [159], [180]) a user's devices can be categorized into three categories with respect to their load flexibility: *curtailable*, *shiftable* or *non-adjustable*.

5.3.1.1. Curtailable Loads

This category of loads includes appliances such as: heating, ventilation, and air conditioning (HVAC) system, building lights with adjustable volume, etc. We denote by $\boldsymbol{D}_{c,i} \subseteq \boldsymbol{D}_i$ the set of curtailable appliances of user *i*. For each device $d \in \boldsymbol{D}_{c,i}$, each user $i \in \boldsymbol{N}$ a priori declares a desired consumption schedule $\widetilde{x_{i,d}} = \left\{\widetilde{x_{i,d}^t}, t \in \boldsymbol{H}, d \in \boldsymbol{D}_{c,i}\right\}$ according to her preferences, and a minimum consumption level $\underline{x_{i,d}^t}$, $t \in \boldsymbol{H}, d \in \boldsymbol{D}_{c,i}$ (see Eq. (5.1)). User's satisfaction in every time slot t depends on the amount of energy that a curtailable device actually consumes, denoted as $x_{i,d}^t$, and on how close it is to the desired consumption $\widetilde{x_{i,d}^t}$. Therefore, user *i* attains a utility $U_{i,d}^t(x_{i,d}^t)$ in time interval t when her device *d* consumes $x_{i,d}^t$, which varies according to her lifestyle and preferences.

$$\underline{x_{i,d}^t} \leq x_{i,d}^t \leq \widetilde{x_{i,d}^t} \tag{5.1}$$

In order to have a benchmark for the evaluation of B-RTP, we use the concept of utility function, drawn from the fields of Microeconomics [181], which models the end users' preferences regarding the operation of a device. In the case of curtailable devices, it is reasonable to assume that the users' utility function is increasing (the more a user consumes, the more utility she perceives) and concave (the more a user consumes, the less the incremental added utility is). This approach is also in line with the vast majority of the literature (e.g. [40], [170], [182], [183]) where a quadratic form is usually considered for the utility function, expressed as:

$$U_i^t(x_i^t, \omega_i^t) = \begin{cases} \omega_{i,d}^t \cdot x_i^t - \frac{a}{2} \cdot (x_i^t)^2, & if \;\; 0 < x_i^t < \frac{\omega_{i,d}^t}{a} \\ \frac{(\omega_{i,d}^t)^2}{2 \cdot a} & , \; if \;\; x_i^t > \frac{\omega_{i,d}^t}{a} \end{cases} \tag{5.2}$$

In Eq. (5.2), a and ω_i^t are predetermined parameters, with ω_i^t denoting the responsiveness of user *i* to financial incentives (*flexibility*) at time interval *t* in terms of reduction of her energy consumption, while parameter a expresses how the rate of change of user's utility changes as consumption changes. Another utility function that is used by the literature ([43], [184]), exploits $\widetilde{x_i^t}$ in order to calculate the utility that user attains:

$$U_i^t(x_i^t) = \begin{cases} -\left(x_i^t - \widetilde{x_i^t}\right)^2, & if \; 0 \leq x_i^t \leq \widetilde{x_i^t} \\ 0, & if \; x_i^t > \widetilde{x_i^t} \end{cases} \tag{5.3}$$

In order to combine the advantages of the two aforementioned functions, we use a utility function, which is mathematically expressed as:

$$U_{i,d}^{t}\left(x_{i,d}^{t}\right) = \begin{cases} U_{\max,i,d}^{t} - \omega_{i,d}^{t} \cdot \left(x_{i,d}^{t} - \widetilde{x_{i,d}^{t}}\right)^{2}, & if\ 0 \leq x_{i,d}^{t} \leq \widetilde{x_{i,d}^{t}} \\ U_{\max,i,d}^{t}\ , & if\ x_{i,d}^{t} > \widetilde{x_{i,d}^{t}} \end{cases} \tag{5.4}$$

$U_{\max,i,d}^{t}$ denotes the maximum user satisfaction concerning appliance d, i.e., the one achieved when she consumes her desired load. The proposed utility function of Eq. (5.4) is a composition of the two aforementioned functions and is able to: i) capture the heterogeneity in the flexibility among participating users, just as Eq. (5.2) does through ($\omega_{i,d}^{t}$) and ii) explicitly correlate maximum user's satisfaction with her desired consumption $\widetilde{x_{i,d}^{t}}$, as utility function of Eq. (5.3) is also able to do. In Eq. (5.4), $\omega_{i,d}^{t}$ is once again a predetermined parameter that captures the flexibility of user *i* concerning appliance d in time slot *t*. More specifically, the lower the value of parameter $\omega_{i,d}^{t}$, the more tolerant user will be towards a particular change in her desired energy schedule of device *d*. Figure 41 depicts user's *i* utility at time slot *t* as a function of $x_{i,d}^{t}$ for a given $U_{\max,i,d}^{t}$ and different values of $\omega_{i,d}^{t}$.

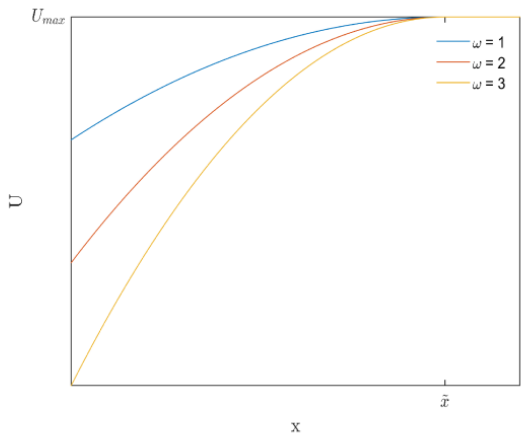

Figure 41: User's *i* utility in timeslot *t* as a function of her energy consumption for various flexibility levels

5.3.1.2. Shiftable Loads

This category of loads includes appliances that can shift their consumption according to user's preferences. Appliances such as: EVs, the dishwasher, the washing machine and the clothes dryer can be considered available for consumption shift. We denote by $\boldsymbol{D}_{s,i}$ the set of shiftable appliances of user *i*. For this type of appliances, energy consumer sets a desired operating schedule $\widetilde{x_{i,d}^{t}}, t \in \widetilde{\boldsymbol{H}_s}$, where $\widetilde{\boldsymbol{H}_s} = [\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}]$ is a time interval where $\widetilde{t_{i,d}^{a}}$ is the timeslot at which it is desirable for the device to start and $\widetilde{t_{i,d}^{b}}$, is the timeslot at which *d* normally finishes its task if it starts operation at $\widetilde{t_{i,d}^{a}}$. Additionally, user *i* sets a deadline $t_{i,d}^{l}$, which is the latest time by which the task of device *d* should be completed. Thus, regardless of the shifts that will take place, the total energy consumption of user's *i* device $d \in \boldsymbol{D}_{s,i}$ must reach a certain energy threshold $E_{i,d}$ by $t_{i,d}^{l}$, that is,

$$0 \leq x_{i,d}^{t} \leq E_{i,d}\ , \quad \forall t \in \left[\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}\right] \tag{5.5}$$

$$\sum_{t=\widetilde{t_{i,d}^{a}}}^{t_{i,d}^{l}} x_{i,d}^{t} = E_{i,d}, \qquad \forall i \in \boldsymbol{N}, d \in \boldsymbol{D_{s,i}} \tag{5.6}$$

Therefore, regarding user's *i* shiftable loads, we can define a feasible scheduling set X_i that is,

$$X_i = \{x_i | \sum_{t=\widetilde{t_{i,d}^{a}}}^{t_{i,d}^{l}} x_{i,d}^{t} = E_{i,d}, \ \ \forall d \in \boldsymbol{D_{s,i}},$$

$$0 \leq x_{i,d}^{t} \leq E_{i,d}\ , \qquad \forall t \in \left[\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}\right],$$

$$x_{i,d}^{t} = 0, \quad \forall t \in H \setminus \left[\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}\right] \} \tag{5.7}$$

We assume that each user is fully satisfied when the operation of her device $d \in \boldsymbol{D}_{s,i}$ does not deviate from her desired energy schedule $\widetilde{\boldsymbol{x_{i,d}}} = \left\{\widetilde{x_{i,d}^{t}}, t \in \widetilde{\boldsymbol{H_s}}\right\}$, where $\widetilde{\boldsymbol{H_s}}$ =[$\widetilde{t_{i,d}^{a}}$, $\widetilde{t_{i,d}^{b}}$] $\subseteq$ $\boldsymbol{H_s}$ and $\boldsymbol{H_s} = [\widetilde{t_{i,d}^{a}}, t_{i,d}^{l}] \subseteq \boldsymbol{H}$. The degree (monetary value) of each user's *i* dissatisfaction for every unit of energy that a shiftable device d consumes in any other time slot ($t \in \boldsymbol{H_s} \setminus \widetilde{\boldsymbol{H_s}}$) depends on user's individual lifestyle and preferences. In the literature, this particular behavior of users is modeled by a disutility function ([41], [159], [182], [185], [186], [187], [188]). In this thesis, we assume that user's dissatisfaction increases as her shiftable devices consume more energy at later hours in $\boldsymbol{H_s}$**,** which intuitively means that her waiting time increases. Thus, we exploit the utility function used in [182], where user's *i* dissatisfaction for her/his device d is given by:

$$DU_{i,d} = \sum_{t \in \boldsymbol{H_s}} \frac{(\delta_{i,d})^{t-\widetilde{t_{i,d}^{b}}} \cdot x_{i,d}^{t}}{E_{i,d}}. \tag{5.8}$$

In Eq. (5.8), $\delta_{i,d} \geq 1$ is an adjustable control parameter. The higher the value of $\delta_{i,d}$ the higher the dissatisfaction of user *i* for a given change in her desired energy schedule of device *d* will be. In other words, the lower the value of parameter $\delta_{i,d}$, the more responsive user *i* will be to price incentives. As we did in the case of curtailable loads, we once again note that this utility function (Eq. 5.8) is used only for evaluation purposes and the proposed B-RTP is transparent to any utility function that fulfills the following properties:

i. Non-decreasing functions. Users' satisfaction increases with power consumption level until the latter reaches a certain threshold ($\tilde{x}$):

$$\frac{\partial U}{\partial x} \geq 0 \tag{5.9}$$

ii. The marginal utility (Eq. (5.10)) that users perceive is a non-increasing function:

$$V(x) \equiv \frac{\partial U}{\partial x} \tag{5.10}$$

$$\frac{\partial V}{\partial x} \leq 0 \tag{5.11}$$

In any other case, convex optimization may not be applicable to solve the user's problem, but rather some other heuristic algorithm (e.g., simulated annealing) may be required, which is out of the scope of this thesis.

5.3.1.3. Non-adjustable Loads

Each user *i* a priori declares which of her devices fall into this category. These loads have predetermined consumption schedules and are not controllable by the EMS. We denote by $\boldsymbol{D}_{f,i}$ the set of the devices that user *i* categorize as non-adjustable. Examples of this category of appliances are: refrigerator, freezer, TV, etc. For non-adjustable loads, we should have:

$$x_{i,d}^{t} = \widetilde{x_{i,d}^{t}} \ , \forall i \in \boldsymbol{N}, t \in \boldsymbol{H}, d \in \boldsymbol{D}_{f,i}. \tag{5.12}$$

5.3.2. Energy Cost Model

In the literature [29], [40], [50], [159], [161], [164], [170], [189], in order for the pricing models to be evaluated, an increasing convex function *G(x)* is often adopted to (approximately) model the cost of energy that comes from conventional generation. Piece-wise linear functions and quadratic functions are two examples of cost functions. In this thesis, we use a quadratic energy cost function, the mathematical expression of which is given by:

$$G^{t} = G\left(\sum_{i=1}^{N} x_{i}^{t}\right) = c \cdot \left(\sum_{i=1}^{N} x_{i}^{t}\right)^{2} + b \cdot \left(\sum_{i=1}^{N} x_{i}^{t}\right) + a, \tag{5.13}$$

where $c > 0$, $b, a \geq 0$ are predetermined parameters that depend on the energy generators characteristics. This cost function models either the cost of the ESP to purchase the necessary energy units from the wholesale electricity market, or the actual cost of the ESP to produce energy by operating its own generation units.

5.4. Proposed System

We consider electricity consumers (users) that participate in a DSM program (which is modeled as a game). We suppose users are price anticipators, i.e., they are aware of the billing mechanism and they consider the impact of their actions on their electricity bills. Their objective is to maximize their payoff. User's *i* payoff is defined as her individual welfare, which equals to the total utility attained, when her schedulable appliances consume a certain amount of energy (as analyzed in the previous section) minus her energy bill B_i given by Eq. (5.14). Thus, each user's EMS calculates her energy consumption schedule by solving problem (5.15), and then informs ESP about the updated consumption schedule x_i. ESP, in turn, sets the energy prices so as to achieve an attractive trade-off among the three requirements that have been described in Section 5.2. Its primary goal is to motivate consumers to change their ECCs through a *fair* billing scheme in order to reduce the *total energy cost* without sacrificing efficiency in terms of *social welfare.* Social Welfare (*SW*) is defined as the aggregate users' comfort minus the total energy cost (Eq. (5.16)). Users and ESP repeat the aforementioned steps until the process converges to the Nash Equilibrium (NE).

$$W_i = \sum_{d=1}^{D_{c,i}} \sum_{t=1}^{T} U_{i,d}^{t}\left(x_{i,d}^{t}\right) - \sum_{d=1}^{D_{s,i}} \left(DU_{i,d}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right)\right) - B_i \tag{5.14}$$

$$x_i = \operatorname{argmax} \mathrm{W}_i \tag{5.15}$$

Subject to (5.1), (5.7), (5.12)

$$SW = \sum_{i=1}^{N} \left(\sum_{d=1}^{D_{c,i}} \sum_{t=1}^{T} U_{i,d}^{t}\left(x_{i,d}^{t}\right) - \sum_{d=1}^{D_{s,i}} DU_{i,d}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right)\right) - \sum_{t=1}^{H} G^{t} \tag{5.16}$$

In what follows, we start by presenting the RTP scheme and follow with the description of our proposed B-RTP scheme. The RTP scheme will be used in Section 5.5 as a benchmark, in order to evaluate the performance of B-RTP.

5.4.1. State-of-the-art Real-Time Pricing (RTP) Scheme

In the initial phase of the RTP ([159], [161]) algorithm, ESP collects the desired schedule $\widetilde{x_i}$ of each user *i* from their EMSs, and calculates their nominal energy bills $\widetilde{B}_{i,RTP}, \forall i \in \boldsymbol{N}$. In order to do so, ESP exploits Eq. (5.17) to calculate the price (average cost) per unit of energy at each time interval *t* as

$$\rho^t = \frac{G(\sum_{i=1}^{N} x_i^t)}{\sum_{i=1}^{N} x_i^t} \quad . \tag{5.17}$$

ESP, through the communication infrastructure, informs its customers about the energy bills, calculated by

$$B_{i,RTP} = \sum_{t=1}^{N} \rho^t \cdot x_i^t \tag{5.18}$$

Eq. (5.17) corresponds to a non-profit version of RTP ([159], [161]). In [159], it is proven that social welfare is maximized when ρ^t is set to the marginal cost of energy, (i.e. $dG(\sum_{i=1}^{N} x_i^t)/d(\sum_{i=1}^{N} x_i^t)$). However, in this case, social welfare maximization comes with budget revenue, which violates the budget-balance property of the assumed business model (cf. Section 5.2). Thus, in order to evaluate B-RTP, we exploit a non-profit RTP version according to Eq. (5.17). The algorithm of RTP scheme is summarized in Table 17, where *k* is an index for the algorithm's iterations.

Table 17: Algorithm for the Calculation of the Energy Bills and the Energy Consumption Schedules in RTP

Initialization: $\boldsymbol{k = 1, x_i^k = \widetilde{x_i^k}, B_{i,RTP}^k = \widetilde{B}_{i,RTP}}$
Repeat
$k \rightarrow k+1$
For each user $i \in \boldsymbol{N}$
Receive $B_{i,RTP}^k$ from ESP
Repeat
Update x_i^k
$B_{i,RTP}^k$ is updated through (5.17), (5.18)
Calculate W_i^k using (5.14)
Until Reach solution of (5.15) subject to (5.1), (5.7) and (5.12)
End for
Calculate $divergence = max\left|x_i^{t,k+1} - x_i^{t,k}\right| \qquad \forall i \in \boldsymbol{N}, t \in \boldsymbol{H}$
Until $divergence < desired\ accuracy$
End

5.4.2. Proposed Behavioral Real-Time Pricing (B-RTP) Scheme

B-RTP model is a hybrid billing mechanism that is able to take full advantage of users' flexibility. This is achieved through a personalized billing policy, which rewards consumers' behavioral change (i.e., ECC adjustment) in a fair manner. In more detail, consumers receive a discount in their energy bill, which is equal or proportional to their contribution to the total energy cost reduction. Users that do not change their ECCs do not receive similar treatment and may even be penalized in cases of emergency situations, in which a significant energy cost reduction is demanded (e.g., network congestion, lack of energy in islanded mode, etc.). In these cases, as our evaluation results will show, ESPs using B-RTP are able to participate in various types of flexibility markets ([169], [190]) without sacrificing user's welfare and fairness.

As in RTP algorithm, in the initialization phase of B-RTP users set their desired consumption schedules $\widetilde{x_i}$ (desired ECC). Based on those, ESP calculates $\widetilde{B}_{i,RTP}$, $\forall i \in \boldsymbol{N}$, using Eqs. (5.17) - (5.18), and communicates them to the users. Each user, in turn, having knowledge of the method of her energy bill's calculation, keeps updating her ECC until she reaches the solution of (5.15). This process is repeated until its convergence to the final (actual) ECCs and energy bills. As it is obvious from the above, the valuation of an ECC for a specific user *i* (e.g., the evaluation of RTP price from Eq. (5.17)) is not a standalone process. The bill of each user *i* depends on the ECCs of the other users in set *N*, as Eq. (5.18) depicts for RTP. RTP scheme, as well as other DSM algorithms (e.g. [50], [159], [170]), considers that users determine their ECCs sequentially and subsequently, ESP determines the valuation of the ECCs until the convergence of this iterative process. In more detail, in each and every iteration of the aforementioned process, a user *i* is implicitly but adequately informed (through the billing system) about the decisions (ECCs) of the users that acted before her and exploits this information to update x_i^t.

In the case of B-RTP, as far as the shiftable loads are concerned, this sequential process creates an advantage for the users who act first over those who act later. For example, two equally flexible users with identical ECCs would be similarly responsive to a specific financial incentive given by the ESP. However, if the one that acts first shifts a load from a peak-hour to a low-cost time interval, the second user will not be able to do the same, as that would lead to a reverse peak. Thus, the first user will get a discounted energy bill, while the second user will not. Consequently, users' order of action plays a major role in the final energy schedules and energy bills. To overcome this problem, we exploit and enhance [191], in which users act in parallel and therefore they decide their actions without knowing what the others do in each iteration of the aforementioned process. Thus, in every iteration k of B-RTP, all users, based on the same information on billing mechanism, calculate their energy schedule by solving (5.15) simultaneously. This approach, may temporarily create reverse peaks, since every user, in order to achieve a larger total cost reduction and receive a larger discount in her energy bill, shifts her shiftable loads to low–cost hours. In order to overcome this problem, in each iteration k, we impose a restriction in the changes that users are allowed to make in their energy schedules. In more detail, the updates are done so that shifts are done in an incremental way, satisfying,

$$\left|x_i^{t,k} - x_i^{t,k-1}\right| < \theta^k \cdot x_i^{t,k-1}, \tag{5.19}$$

where $\theta^K < 1$ is a parameter that sets the upper bound of the volume of shift that a user can make in a certain step k of B-RTP. If there is a reduction in total energy cost after users' decisions (i.e. no peak shifting), θ^{k+1} will remain the same as in iteration k. Otherwise, if the reduction of the total cost of the system is negligible, i.e. $G^{k+1} > G^k * (1 - \varepsilon)$ for some small $\varepsilon > 0$, B-RTP will continue in the next step with a smaller $\theta^{k+1} = \theta^k \cdot \zeta$, where $0 < \zeta < 1$ in order to approach the equilibrium more accurately. The iterations continue until θ gets sufficiently small ($\theta < \theta_{min}$) (i.e., users are allowed to change a negligible fraction of their energy schedules).

At step k of B-RTP, each user i alters her desired/initial energy schedule $\widetilde{x_i}$ into x_i^k, according to her flexibility and the B-RTP's billing. This leads to a total energy cost reduction

$$\Delta C^k = \sum_{t=1}^{T}\left(G\left(\sum_{i=1}^{N}\widetilde{x_i^t}\right) - G\left(\sum_{\substack{j=1\\ j\neq i}}^{N}\left(x_j^{t,k-1}\right) + x_i^{t,k}\right)\right) \tag{5.20}$$

Through B-RTP, ESP rewards each user i for her contribution to total energy cost reduction, by an energy bill discount

$$\Delta B_i^k = \frac{\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1\\ j\neq i}}^{N}\left(x_j^{t,k-1}\right)+\widetilde{x_i^t}\right) - G\left(\sum_{\substack{j=1\\ j\neq i}}^{N}\left(x_j^{t,k-1,}\right)+x_i^{t,k}\right)\right)}{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1\\ j\neq i}}^{N}\left(x_j^{t,k-1}\right)+\widetilde{x_i^t}\right) - G\left(\sum_{\substack{j=1\\ j\neq i}}^{N}\left(x_j^{t,k-1}\right)+x_i^{t,k}\right)\right)\right)} \cdot \Delta C^k \tag{5.21}$$

In Eq. (5.21), the numerator represents the energy cost reduction that user's i behavioral change generated in step k of B-RTP. Note that each user acts knowing only what the rest of the users have done in the previous iteration *k-1* of B-RTP and having no knowledge of their actions in the current iteration. The denominator equals to the summation of every user's corresponding contribution and thus we have $\sum_{i=1}^{N}\Delta B_i^k = \Delta C^k$. Therefore, the energy bill discount that each user receives is a fraction of the total energy cost reduction, and equal to her contribution.

In order to combine the volume-aware pricing that RTP proposes and the incentives that B-RTP offers, we designed a hybrid billing mechanism which, in every iteration k, calculates the $B_{i,B-RTP}^k$ of each user i according to

$$B_{i,B-RTP}^k = \tilde{B}_{i,RTP} - \gamma \cdot \Delta B_i^k - (1-\gamma)\cdot\left(\tilde{B}_{i,RTP} - B_{i,RTP}^k\right) \tag{5.22}$$

Here, $B_{i,RTP}^k$ denotes the energy bill of user i in step k of the algorithm in case that ESP applies the RTP model (according to Table 17). By studying Eq. (5.22), we observe that for γ = 0, B-RTP is reduced to the RTP model, while for $\gamma = 1$, the total cost reduction that is derived from the behavioral change of a user is converted into an equivalent reduction in her energy bill. In case $0 < \gamma < 1$, a fraction γ of the cost reduction derived from the behavioral change of a user is converted into discount in her bill and the remaining fraction 1-γ is allocated to all participating users according to RTP. In case that $\gamma > 1$, B-RTP actually penalizes the set of users who are more reluctant to deviate from their desired energy schedule, in order to further favor the flexible users.

By replacing Eqs. (5.18) and (5.21) into Eq. (5.22) for ΔB_i^k and $B_{i,RTP}^k$, respectively, one can easily prove that $\sum_{i=1}^{N} B_{i,B-RTP}^k = G\left(\sum_{i=1}^{N} x_i^{t,k}\right)$, which means that our scheme is budget-balanced and does not generate surplus or deficit of money. B-RTP is summarized in Table 18. As proved in [191], the convergence time of the algorithm of B-RTP is approximately the same for different number of consumers. Moreover, the impact of the number of flexible appliances per user on convergence time is negligible. Finally, the convergence of the following algorithm is shown in [191].

Table 18: Algorithm for the Calculation of Energy Bills and the Energy Consumption Schedules in B-RTP

1	Initialization: $\boldsymbol{k = 0, x_i^k = \tilde{x}_i, B_{i,B-RTP}^k = \widetilde{B_{i,RTP}}}, \forall \boldsymbol{i} \in \boldsymbol{N}, \boldsymbol{\theta = \theta^0, \theta_{min}, \varepsilon, \zeta}$
2	**While** $\theta^k > \theta_{min}$ do
3	Calculate G^k
4	$k \rightarrow k + 1$
5	**For** each user $i \in \boldsymbol{N}$
6	Receive B_i^k
7	**Repeat**
8	Update x_i^k
9	$B_{i,B-RTP}^k$ is updated through (17), (18), (21) and (22)
10	Calculate W_i^k using (14)
11	**Until** reach solution of (15) subject to (1), (7), (12), (19)
12	**End for**
13	Calculate G^{k+1}
14	**If** $G^{k+1} > G^k * (1 - \varepsilon)$
15	$\theta^{k+1} = \theta^k * \zeta$
16	**Else**
17	$\theta^{k+1} = \theta^k$
18	**End**

5.5. Performance Evaluation

In this section, we evaluate our proposed B-RTP scheme using the state-of-the-art RTP scheme as a benchmark. We consider a system consisting of *N* = 10 energy consumers, each of whom operates two curtailable and four shiftable devices. The selection of the 6 categories of devices was done in order to include in the evaluation all possible types of loads. More specifically, each energy consumer may conserve energy through the curtailment of the operation of an A/C and a lighting system, and additionally shift the operation of an oven, a washing machine, a spin dryer and the charging of an EV. Moreover, every user characterizes some of her appliances as non-adjustable loads. In more detail:

- **Lights**: We assume that each household is illuminated by 14 bulbs, which can be LED (8W), CFL (14W) or incandescent bulbs (60W), and that users want the lights on from 18:00 until 24:00. Thus, user's *i* total desired lighting energy consumption is randomly selected over the interval [0.672 – 5.040 kWh]. We assume that in every time slot, equal energy amounts are consumed.
- **A/C**: Each user operates an A/C system from 14:00 until 22:00. Single A/C units come in different sizes and use from 500 to 1500 watts. User's *i* total desired A/C energy consumption is randomly selected over the interval [4.0-12.0 kWh]. As we did with the lights, we assume that equal energy amounts are consumed in every time slot
- **Oven**: We consider that users classify the oven as a shiftable device. Ovens use 1000 to 5000 watts and are assumed to require at most one hour to complete their task. Therefore, user's *i* total desired oven's energy consumption is randomly selected over the interval [1.0 – 5.0 kWh]. Users' desired oven plug-in times vary from 17:00 to 19:00.
- **Washing Machine**: It falls into the category of shiftable appliances. Washing machines use 400 to 1300 watts and finish their task in less than an hour. User's *i*

total desired washing machine energy consumption is randomly selected over the interval [0.4-1.3 kWh]. Users' desired plug-in times vary from 09:00 to 12:00.

- **Spin Dryer**: It is also accounted as a shiftable device. The energy use of a spin dryer varies between 1800 and 5000 watts and it takes less than an hour for it to finish its task. User's *i* total desired energy consumption is randomly selected over the interval [0.4-1.3 kWh]. Users' desired plug-in times vary from 13:00 to 18:00.
- **EV**: The battery capacity is randomly chosen over the interval [5.5-6 kWh] and the maximum charging rate is 2 kW. Thus, the minimum time that an EV demands in order to be charged is 3 hours. We assume that users desire their EV to start charging somewhere between 00:00 and 05:00 or 18:00 and 21:00, and to finish ideally in 3 hours.
- **Non-adjustable loads**: We assume that users categorize as nonadjustable loads devices, such as the refrigerator, the TV, the freezer, the Wi-Fi Router, etc., which are meant to be ON whenever requested. Thus, users' aggregate energy consumption of critical loads is randomly chosen from [3.6-11.4 kWh] at each timeslot.

Table 19: Electricity Consumption of Households' Appliances

Appliance	Power (kW)	Type of device	$\widetilde{t_{i,d}^{a}}$	Duration (h)	$\widetilde{t_{i,d}^{b}}$	Energy (kwh)
-	-	Non-adjustable	00:00	24	24:00	[3.6-11.4]
Lighting	[0.008-0.060]	Curtailable	18:00	6	24:00	[1.2-5.0]
A/C	[0.5-1.5]	Curtailable	14:00	8	22:00	[4.0-12.0]
Oven	[1.0-5.0]	Shiftable	[17:00-19:00]	1	[17:00-19:00]	[1.0-5.0]
Washing Machine	[0.4-1.3]	Shiftable	[10:00-13:00]	1	[10:00-13:00]	[0.4-1.3]
Spin Dryer	[1.8-5.0]	Shiftable	[14:00-19:00]	1	[14:00-19:00]	[1.8-5.0]
EV	[0.0-2.0]	Shiftable	[00:00-05:00,18:00-21:00]	3	[03:00-08:00,21:00-24:00]	[5.5-6.0]

The above datasets are derived from [192], [193], [194] and are summarized in Table 19. The aggregate desired ECC is presented in Figure 42. The scheduling horizon consists of T = 24 time slots of hourly duration. For the step size, we set $\theta^0 = 0.95$, $\zeta = 0.50$, $\varepsilon = 0.001$ and $\theta_{min} = 0.01$ throughout the simulations. Regarding the parameters of energy cost function in Eq. (5.13), b and a are usually set to 0, while the value of parameter c varies from 10^{-4} to 0.05 in [29], [40], [50], [164] and [170]. In this thesis, parameters b and a are also set 0, while c is chosen to be 0.01, 0.02 or 0.03, which is the usual case in the aforementioned works also. Moreover, in [182] parameter δ of Eq. (5.8) is set to 1 implying perfectly flexible energy consumers. In this thesis, in order to evaluate B-RTP in scenarios of various flexibility classes of end users δ varies from 1 to 1.5. For the same reason, we choose ω of Eq. (5.4) to vary from 0.1 to 6.

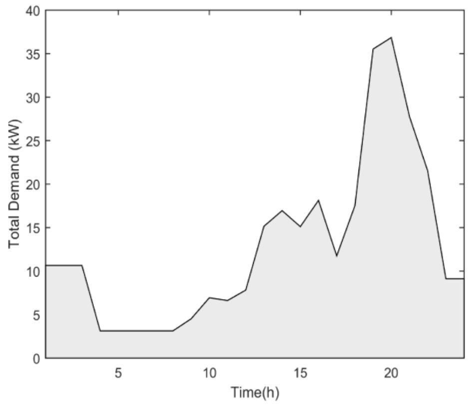

Figure 42: Aggregate daily users' Energy Consumption Curve (ECC)

In order to demonstrate the performance of the B-RTP model for different classes of energy consumers – ESP customers, we consider three use cases:

a) Low Flexibility: Energy consumers are reluctant to change their energy consumption habits. Parameter $\delta_{i,d}$ for each user $i \in \boldsymbol{N}$ and $d \in \boldsymbol{D_{s,i}}$ is randomly selected over [1.20-1.50], while parameter ω_i is randomly chosen over [3, 6]. Finally, in this use case, we consider users that set relatively strict deadlines, i.e., they allow their EMSs to schedule their shiftable loads not more than one to two hours after $\widetilde{t_{i,d}^{b}}$.
b) Medium Flexibility: Energy consumers are more price-sensitive than in the 'Low Flexibility' use case. Parameter $\delta_{i,d}$ is randomly selected over [1.10, 1.20] $\forall\, i \in \boldsymbol{N}, d \in \boldsymbol{D_{s,i}}$. Parameter ω_i is randomly chosen over [1.0, 3.0]. Users set their deadlines two to four hours after their $\widetilde{t_{i,d}^{b}}$.
c) High Flexibility: In this use case, energy consumers are most willing to participate in DSM programs, even for a relatively small repayment. Parameter $\delta_{i,d}$ is randomly selected over [1.00, 1.10] $\forall\, i \in \boldsymbol{N}, d \in \boldsymbol{D_{s,i}}$. Parameter ω_i is randomly chosen over [0.1, 0.5]. Users set their deadlines two to six hours after their $\widetilde{t_{i,d}^{b}}$.

Without loss of generality, in all of the above cases, parameter U_{max} in the utility function for curtailable loads is set to 0. Moreover, $\underline{x_{i,d}^{t}}$ is set to 0 $\forall i \in \boldsymbol{N}, d \in \boldsymbol{D_{c,i}}$. In order to assess the performance of B-RTP algorithm, the following Key Performance Indicators (KPIs) are used:

- Energy Cost (*G)*, as defined in Eq. (5.13), which is the cost of ESP to acquire the electricity needed to fulfill the requirements of its customers. This is an index of how energy-efficient a pricing scheme is, that is, how successful it is in incentivizing customers to adopt energy-efficient habits.
- Aggregate Users' Welfare (*AUW)* is a KPI that expresses the competitiveness of an ESP that adopts a billing strategy in an open electricity market:

$$AUW = \sum_{i=1}^{N}\left(\sum_{d=1}^{D_{c,i}}\sum_{t=1}^{T} U_{i,d}^{t}\left(x_{i,d}^{t}\right) - \sum_{d=1}^{D_{s,i}}\sum_{t=1}^{T} DU_{i,d}^{t}\left(\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}, x_{i,d}^{t}\right) - B_{i,RTP}\right) \quad (5.23)$$

- Fairness (F_i) is a KPI that indicates the fraction of user's *i* contribution to system cost reduction that she will be rewarded in terms of energy bill discount:

$$F_i = \frac{D_i^R}{D_i^A}, \forall i \in \boldsymbol{N}, \tag{5.24}$$

where,

$$D_i^R = \frac{\widetilde{B_{i,RTP}} - B_i}{\sum_{i=1}^{N}(\widetilde{B_{i,RTP}} - B_i)}, \forall i \in \boldsymbol{N} \tag{5.25}$$

represents the discount that user *i* receives in her energy bill as a portion of the total discount in all users' bills, and

$$D_i^A = \frac{\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1\\ j\neq 1}}^{N} x_i^t + \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^t\right)\right)}{\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(G\left(\sum_{\substack{j=1\\ j\neq 1}}^{N} x_i^t + \widetilde{x_i^t}\right) - G\left(\sum_{i=1}^{N} x_i^t\right)\right)\right)} \tag{5.26}$$

represents the discount achieved by user *i*, i.e., her contribution to system cost reduction, as a fraction of the summation of all users' corresponding contributions. This is calculated employing the concept of Shapley value from cooperative Game Theory [49]. In this regard, user's impact in the reduction of system cost is measured through the comparison of the total energy cost in: 1) the case in which user *i* performs the alterations in her ECC, 2) the case in which user *i* follows her desired ECC. Values of F_i close to 1 indicate a fairer correlation between the behavioral change of user *i* and the reward that she gets for it.

The adaptability of the Hybrid B-RTP(γ) scheme gives ESP the opportunity to select its own strategy with respect to users' reward, by adjusting properly the value of γ. According to the price elasticity of its customers and the DR services it has to provide to the various smart grid market stakeholders, ESP will select a certain value of γ in order to achieve an attractive trade-off among the above KPIs.

5.5.1. Low Flexibility Use Case

In the Low Flexibility case, ESP needs to provide its customers with more generous financial incentives in order to motivate them towards more energy-efficient ECCs, as they are not so price-sensitive. Figure 43 depicts the ratio between the energy cost G (across the whole time horizon) with hybrid B-RTP and the energy cost G with RTP as a function of γ. The graphs in Figure 43, represent the cases of energy with low generation cots (c = 0.01), medium-cost energy (c = 0.02) and high-cost energy (c = 0.03). We notice that even in the low flexibility use case, B-RTP is able to bring a cost reduction of 10% in comparison with RTP (for γ=2), in case of low- and medium-cost energy (c=0.01, c=0.02) and 13% in case of high-cost energy (c = 0.03). As cost of energy rises, it is reasonable for G to further decline, since the energy bills are higher and thus customers are more willing to exploit their schedulable loads.

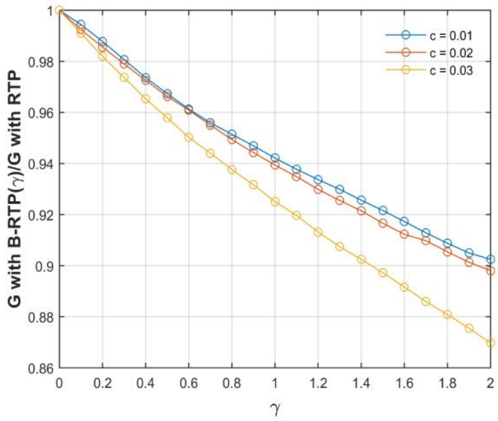

Figure 43: Ratio between *G* with B-RTP(*γ>0*) and *G* with RTP (γ=0) as a function of *γ* in Low Flexibility use case

These results are expected for $\gamma = 2$, which could correspond to a case, for example, of an imminent congestion event in a certain area. As it is inferred from Eq. (5.22), values of γ greater than 1 imply that ESP over-rewards the more flexible users for their DSM actions, while it imposes a monetary penalty to the less flexible ones. Figure 44 presents the ratio between *AUW* with B-RTP and *AUW* with RTP scheme as a function of γ. According to it, the aforementioned energy cost reduction does not come with any significant users' welfare decrease even in the low flexibility use case. In fact, ESP could select γ to be up to 1.8 and *AUW* would not be lower than that under RTP scheme. This is explained firstly by the fact that a load shift or a load cut, which are the reasons of the decrease of a users' comfort, are higher compensated by the ESP, when $\gamma > 1$. Moreover, even the more flexible users in this inelastic set of energy consumers manage a relatively small cost reduction ΔC. Thus, the penalties in the energy bills of the less energy efficient users are too small compared to their RTP bills to justify a large decrease in *AUW*. In other words, given that ESP's customers are a set of inelastic users, increasing γ diminishes *AUW* by a slow rate. Hence, B-RTP (comparing to RTP), manages to reduce energy costs by 9-12%, depending on conventional energy generation cost level (c), without sacrificing at all the aggregate users' welfare. ESP could continue increasing γ in order to further motivate users to shift or shed their loads and therefore achieve even higher energy cost reduction. However, this would be done at the expense of users' welfare. Finally, we note in Figure 44 that *AUW* reaches its peak for $\gamma = 0.8$ independently of the value of c. Apparently, in case of high-cost energy ($c = 0.03$), the gap between *AUW* under B-RTP and *AUW* under RTP is larger, since the financial motivation for the users is larger. This leads them to more energy efficient actions (load shifts and cuts) and hence lower energy bills and finally higher AUW. In other words, the bill discounts are greater than their marginal utility, which they sacrifice to get them.

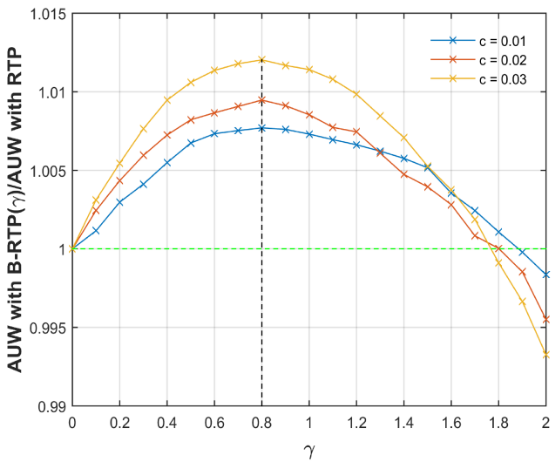

Figure 44: Ratio between AUW with B-RTP(γ>0) and AUW with RTP(γ=0) as a function of γ in Low Flexibility Case

In order to examine the impact of γ on users' welfare in more detail, we depict in Figure 45 the ratio between users' welfare in case of $\gamma \in [0\,, 0.8\,, 1, 1.5]$ and in case of RTP for every user $i \in \boldsymbol{N}$ and *c* = 0.02. Ten users are sorted based on their flexibility, with *i*=1 denoting the more flexible user and *i*=10 the less flexible one[1]. Studying Figure 45, we observe that, as we expected, W_i of the less price inelastic users *i* increases with γ. On the other hand, RTP is in the best interest of price inelastic users, since not being willing to change their energy consumption patterns, it provides them with financial benefits that others created. As in Figure 44, in Table 20 we establish the preference of users for B-RTP(γ=0,8) on average. Also, we note that in B-RTP(γ=1,5), even if price inelastic users are penalized in order for the flexible users to receive a generous bonus for their behavioral change, users' welfare is marginally higher on average than in RTP in this low flexibility use case.

[1] Flexibility is a function of parameters ω and δ, used in Eqs. (5.4) and (5.8), respectively, and also $\widetilde{t_{i,d}^{a}}, \widetilde{t_{i,d}^{b}}, t_{i,d}^{l}$ (i.e., users' desired ECC). Thus, sorting users based on their flexibility is not a straightforward task and has been done approximately. This is why there is not continuity in the variation of users' welfare for a certain value of γ. This is also observed in corresponding graphs for the other use cases.

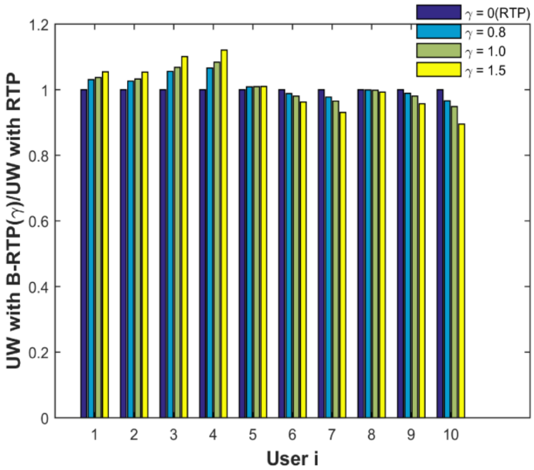

Figure 45: Ratio between users' welfare for various values of *γ* and users' welfare for *γ*=0 (RTP) in Low Flexibility use case

Table 20: Ratio Between Average Users' Welfare for Different Values of *γ* and Average Users' Welfare for *γ*=0 (RTP) in Low Flexibility Use Case

γ	0 (RTP)	0.8	1.0	1.5
$\overline{UW}(B-RTP(\gamma)) / \overline{UW}(RTP)$	1	1.0094	1.0085	1.0039

Figure 46 depicts the Cumulative Distribution Function (CDF) of F_i for a different value of γ. Cost parameter *c* is set to 0.02. As analyzed above, F_i is an index of how fairly the energy cost reduction is allocated to users. The fairest way of distributing energy savings among the users is represented by $F_i = 1$. Figure 46 shows that B-RTP (*γ*=1) is the fairest billing mechanism. This was expected as it incentivizes users towards an energy-efficient behavior so that they receive a generous discount in their bills. Under RTP (*γ* = 0), inflexible users benefit from the others' actions and thus are not motivated to change their energy consumption behavior, while demand responsive customers see their actions not being sufficiently compensated. This discourages users to deviate from their desired ECC. For gradually increasing *γ* the distribution of users around $F_i = 1$ gets narrower (i.e., fairer billing) and for *γ*=0.8 (which maximizes *AUW*), it is much closer to $F_i = 1$. For values of *γ* greater than 1, the distribution of users around $F_i = 1$ starts getting wider again as we can see in case of γ = 1.5. Still, the mean value of F_i (Table 21) is closer to 1 than RTP, meaning that B-RTP(γ=1.5) is a fairer billing scheme than RTP on average. If ESP chooses to impose the fairest possible pricing scheme, B-RTP will manage a cost reduction of 6-7.5% comparing to RTP and a slightly higher *AUW*.

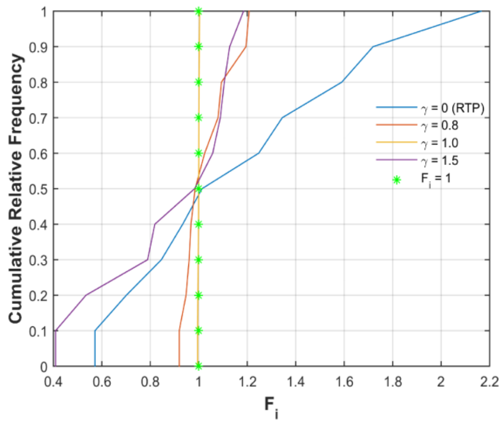

Figure 46: CDF of F_i among participating users under B-RTP for various values of γ in Low Flexibility use case

Table 21: Mean Values of F_i for Different Values of γ in Low Flexibility Use Case

γ	0 (RTP)	0,8	1	1,5
$\overline{F}$	1.2131	1.0379	1	0.9097

5.5.2. Medium Flexibility Use Case

In the medium flexibility use case, the concept of Figure 47, Figure 48, Figure 49, Figure 50 is similar to that of Figure 43, Figure 44, Figure 45, Figure 46, respectively, of the previous low flexibility use case. In this use case, several of the ESP clients represent energy consumers with DR capability. They are more price-sensitive than in the former case but still not eager to change their energy behavior without a significant financial reimbursement. Thus, in Figure 47, we observe that B-RTP achieves a larger energy cost reduction comparing to RTP scheme. Similarly to the low flexibility use case, as γ increases the cost reduction declines in almost linear fashion. However, for $\gamma > 1.3$, this happens at the expense of *AUW* (Figure 48), which declines as the less flexible users are penalized so that the more flexible ones achieve a quite generous bonus. In this use case, users seem to be less tolerant to the increase of γ above 1. This is because users, being more price elastic comparing to the low flexibility use case, create a larger cost reduction, which translates into stricter penalties for the less DR-active users. Nevertheless, in case of *c* = 0.02, B-RTP reduces energy cost by up to 16% compared to RTP without sacrificing AUW ($\gamma = 1{,}3$). In case of higher or lower cost of energy, this cost reduction is larger (21%) or smaller (11%) respectively. Here, we observe a larger gap between the 3 plots of Figure 47 when we compare them with those of Figure 43, since users are more price-responsive and higher energy costs lead them to even more load shifts and cuts in order for them to benefit from B-RTP.

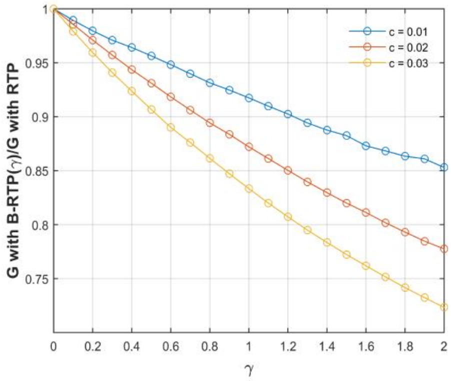

Figure 47: Ratio between *G* with B-RTP(γ>0) and *G* with RTP (γ=0) as a function of *γ* in Medium Flexibility use case

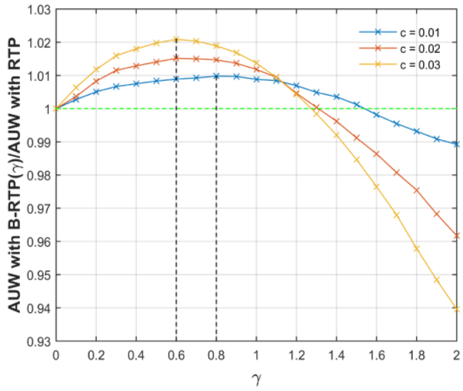

Figure 48: Ratio between *AUW* with B-RTP(γ>0) and G with RTP (γ=0) as a function of γ in Medium Flexibility use case

In Figure 49 and Table 22, we can see that, as in the low flexibility use case, increasing *γ* benefits the more price elastic users, who take advantage of the billing mechanism and receive a high discount in their energy bills. On the other hand, the rest of the users experience a steeper downfall in their Welfare as *γ* increases compared to the previous use case. This can be interpreted, not only by the higher penalties these users have to pay, but also by the fact that they are not totally price inelastic energy consumers as in the low flexibility use case.

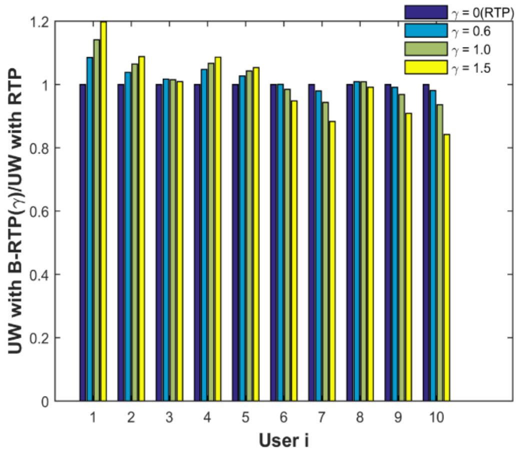

Figure 49: Ratio between users' welfare for various values of γ and users' welfare for γ = 0 (RTP) in Medium Flexibility use case

Table 22: Ratio between Average Users' Welfare for Different Values of *γ* and Average Users' Welfare for *γ*=0 (RTP) in Medium Flexibility Use Case

γ	0 (RTP)	0,6	1,0	1,5
$\overline{UW}(\mathbf{B-RTP}(\gamma)) / \overline{UW}(RTP)$	1	1.0149	1.0117	0.9911

As in the low flexibility use case, we see in Figure 50 and Table 23 that B-RTP (γ=1) is the fairest billing mechanism, while RTP is the least fair among B-RTP schemes with parameter $0 \leq \gamma \leq 1$. Even B-RTP (γ=1.5) compensates in a fairer way more users than RTP does. So, ESP can choose *γ*=1 to efficiently incentivize its customers to alter their ECCs and achieve a cost reduction of 6.5, 12.5 or 17% over RTP, depending on energy generation cost parameter *c*. Alternatively, ESP could choose *γ*=0.6 to maximize *AUW* in cases of medium-cost and high-cost energy and achieve a 7.5 and 11% larger cost reduction than RTP, respectively, in a fairer manner. In case of low-cost energy (*c* = 0.01), ESP in order to maximize *AUW* should select *γ* = 0.8 which results in a 5% cost reduction over RTP.

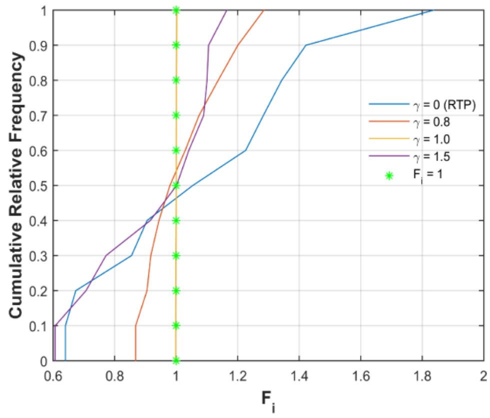

Figure 50: CDF of F_i among participating users under B-RTP for various values of γ in Medium Flexibility use case

Table 23: Mean Values of F_i for Different Values of γ in Medium Flexibility Use Case

γ	0 (RTP)	0,6	1	1,5
$\overline{F}$	1.1239	1.0341	1	0.9504

5.5.3. High Flexibility Use Case

In this subsection, we examine the case when ESP's customers are a set of highly price-sensitive users, who are eager to exploit their schedulable loads in order to gain discounts in their energy bills. In this high flexibility use case, Figure 51, Figure 52, Figure 53, Figure 54 are once again similar to their corresponding Figure 43, Figure 44, Figure 45, Figure 46 of the low flexibility use case. Thus, Figure 51 illustrates a downturn in energy cost comparing to RTP scheme. However, increasing *γ* diminishes *AUW* in much steeper fashion in comparison to the two former use cases (Figure 52). This is because B-RTP (γ>1) will penalize users who are much more willing to provide flexibility services in order for them to get financially rewarded and not users who are price-inelastic. This result is very interesting from the ESP's business perspective in case it participates in various types of flexibility markets, where DSM units can be sold in really competitive prices (e.g., to solve an imminent congestion problem). In the latter case, users would be more tolerant to a fine imposed to their energy bills. This is illustrated in Figure 53 and Table 24 (*c* = 0.02), in which it is clear that the welfare of less flexible users decreases for *γ*=1.5. Conclusively, B-RTP reduces energy cost by 16 % over RTP when *c* = 0.01, by 24% when *c* = 0.02 and even by 27% when *c* = 0.03, while simultaneously managing to keep *AUW* above that of RTP. In case of B-RTP(γ=0,5) which maximizes *AUW* for *c* = 0.02 or *c* = 0.03, the energy cost reduction reaches 14% and 17%, respectively. In case of low-cost energy (*c* = 0.01) *AUW* is maximized for *γ* = 0.6 and the equivalent cost reduction is 10.5% in comparison with RTP.

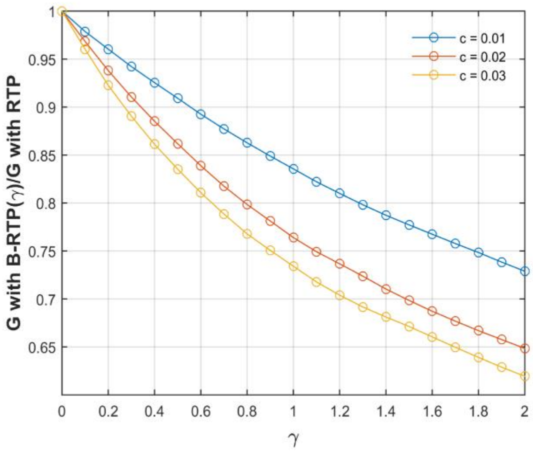

Figure 51: Ratio between *G* with B-RTP(*γ*>0) and *G* with RTP (*γ*=0) as a function of γ in High Flexibility use case

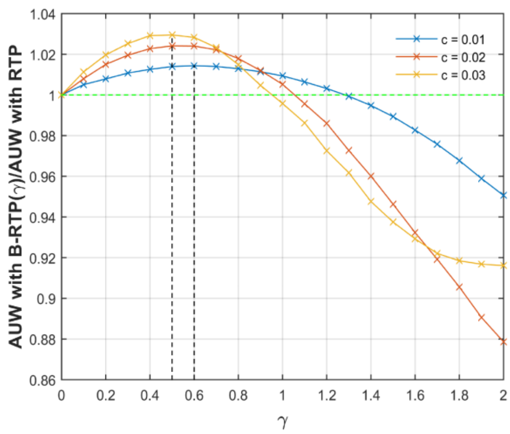

Figure 52: Ratio between *AUW* with B-RTP(*γ*>0) and *AUW* with RTP (*γ*=0) as a function of γ in High Flexibility use case

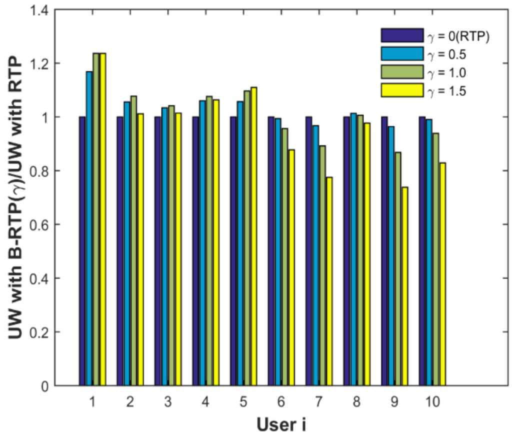

Figure 53: Ratio between users' welfare for various values of γ and users' welfare for γ=0 (RTP) in High Flexibility use case

Table 24: Ratio Between Average Users' Welfare for Different Values of *γ* and Average Users' Welfare for *γ*=0 (RTP) in High Flexibility Use Case

γ	0 (RTP)	0,5	1,0	1,5
$\overline{UW}(\mathbf{B-RTP}(\boldsymbol{\gamma}))\big/\overline{UW}(RTP)$	1	1.0236	1.0052	0.9432

In the CDF of F_i (Figure 54), we re-establish that B-RTP(γ=1) is the fairest billing mechanism, while RTP the least fair one. By gradually increasing γ and as it approaches 1, the distribution of users gets narrower (fairer pricing), until γ surpasses 1 and the users' distribution starts widening again. We also notice that even B-RTP with γ=1.5 allocates the energy cost reduction to the users in a fairer way than RTP (Table 25). In more detail, B-RTP with γ=1.5 overcharges some users for their energy consumption, although it charges users more fairly and thus it is a stronger motivator towards energy-efficient ECCs than RTP. This policy would bring a large cost reduction (e.g., 30% for c = 0.02) although it would decrease *AUW* (e.g., 6% for c = 0.02). This policy could be selected in the case of emergency situations (e.g., congestion issues in a specific network location, governmental policies to cope with energy poverty issues, etc.), when energy cost is requested to severely decrease at any cost.

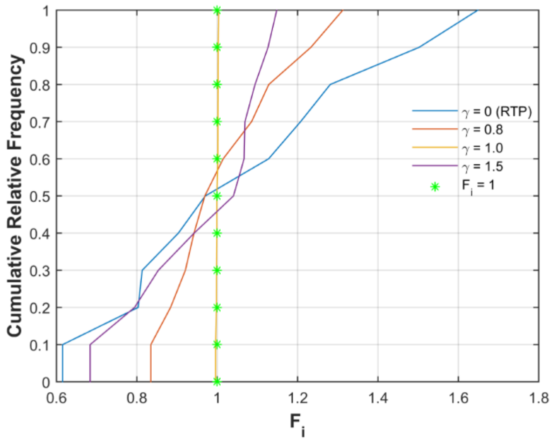

Figure 54: CDF of F_i among participating users under B-RTP for various values of γ In High Flexibility use case

Table 25: Mean Values of F_i for Different Values of γ in High Flexibility Use Case

γ	0 (RTP)	0.5	1	1.5
$\overline{F}$	1.0873	1.0325	1	0.9819

In the 3 use cases examined above, we demonstrated that B-RTP offers a much more attractive trade-off between widely accepted KPIs than the RTP scheme for all levels of energy generation cost and all levels of the end users' elasticity. Based on these results, we consider B-RTP a very useful tool in the hands of an ESP, which can exploit it in order to participate in several types of flexibility markets (i.e., balancing, congestion management, voltage control, frequency control, N-1 adequacy) with efficient DSM services, while being fair towards its customers and without sacrificing the level of eligibility of its services in an open and competitive retail market. In emergency circumstances, where the stability of the system is at risk and the energy cost is about to increase dramatically (e.g., congestion market), an ESP making use of B-RTP, can carry through the task with a relatively smooth reduction of users' welfare.

5.6. Conclusions and Future Work

In this Chapter, we focused on modern energy pricing models and argued that they do not fairly reward demand responsive users, who are more willing than others to adopt energy-efficient habits. Thus, existing pricing models are not designed to trigger behavioral changes as they do not provide energy consumers with attractive incentives in the form of fair compensation. Motivated by this observation, we developed a hybrid billing mechanism, namely Behavioral Real Time Pricing. B-RTP disposes an adjustable level of rewarding users by offering them financial incentives to modify their ECCs. B-RTP can be a valuable tool in the hands of an ESP in order for the latter to employ innovative business models and respective revenue streams mainly by selling DSM units in various types of flexibility markets. It aims at motivating its customers to exploit their shiftable and curtailable devices in order to reduce the cost of conventional energy usage. Our evaluation uses a non-profit version of RTP as a benchmark and we show that B-RTP manages to prompt energy behavioral changes of users much more efficiently than RTP does. In this thesis we assume that the desired ECC is a priori known. In our future work, we will advance the model of B-RTP in order to take into account use cases, where the desired ECC is unknown. Finally, we plan to study the impact of the B-RTP in: islanded microgrids, energy communities and innovative business models for ESPs towards the latter's' participation in the emerging flexibility markets.

6. Chapter 6: Conclusions, Lessons Learnt and Future Work

In this dissertation, we dealt with the efficient integration of distributed energy and flexibility resources in the modern power system. We considered a market entity, namely Energy Service Provider, which invests in a portfolio of DERs and provides valuable energy and ancillary services to both the local network operator (DSO) and the entire system (TSO), by participating in various electricity markets. Various power system entities can act as an ESP, e.g., an Energy Community Controller, an Aggregator, an Active Distribution Network Operator, a Balancing Service Provider, etc. We presented market and non-market schemes, within which private bottom-up investments in DERs can be profitable and sustainable.

More specifically, we have modeled the DER investment problem of the ESP, which installs distributed renewable energy and energy storage units at the distribution network within a DSO-TSO coordination scheme, as a stochastic bilevel problem. The financial sustainability of the investments is ensured imposing a minimum desired rate of return on the investments. The bilevel model is efficiently solved using a nested decomposition algorithm. Our simulations demonstrated that our proposed investment model can benefit all three involved actors. Furthermore, the co-optimization of energy and flexibility resources can attain higher gains for both the ESP and the System Operators. Finally, the ESP's choice on the minimum desired return on investments, can significantly affect the installed capacities and eventually the payoffs of the System Operators.

Additionally, we have dealt with the problem of DERs' participation in the various electricity markets within two separate use cases:

a) The operation of the distribution network is regulated and a DisCo has control over the network assets, representing them in the energy market as an Aggregator.
b) The operation of the distribution network is deregulated, with the ESPs participating autonomously in transmission-level markets, while the DSO ensures the smooth operation of its network by purchasing the necessary flexibility via a distribution-level flexibility marketplace.

In use case (a), we have considered a strategic DisCo/ESP and we proposed a bilevel model in order for the DisCo to: 1) derive the optimal bidding strategy, and 2) orchestrate its flexibility assets in order to minimize its energy costs. Comparing our bilevel bidding model to a single-level one (used to model a price-taker DisCo/ESP), we demonstrated that the DisCo/ESP can significantly reduce its costs acting strategically, even if it possesses a small portion of market's production or consumption capacity. In addition, a sensitivity analysis was conducted to showcase the impact of the assets' size and location on the DisCo's energy costs. On the other hand, in use case (b), we proposed a novel energy market architecture that introduces a distribution-level flexibility market. In this context, we formulated a bilevel model for an ESP owning a portfolio of BSUs connected to the distribution network, in order to optimally calculate its market strategy. We have proved via simulations that our model achieves super-additive gains: the ESP obtains significantly higher profits through the joint optimization of both the TSO and DSO services than the sum of the individual profits from devoting the BSUs to one of the two applications.

Lastly, we designed a personalized energy pricing mechanism for the end-users, which rewards the flexible consumers when they adopt an energy-efficient behavior. Modern pricing schemes do not fairly reward price-responsive consumers. Thus, existing pricing schemes are not designed to trigger behavioral changes as they do not provide energy consumers with attractive incentives in the form of fair compensation. Motivated by this observation, we developed a billing mechanism, namely Behavioral Real Time Pricing, which disposes an adjustable level of rewarding consumers by offering them financial incentives to modify their consumption habits. Comparing our B-RTP mechanism to the widely used in the literature Real Time Pricing scheme, we have showed that B-RTP achieves much higher energy cost reduction, without deteriorating consumers' welfare. This is achieved, since B-RTP is much 'fairer' than RTP in terms of rewarding the flexibility offered by the end-users.

Our research can be used by: (i) regulators or policy making entities to efficiently coordinate the business interests of ESP, DSO and TSO to facilitate a quicker renewable energy transition, (ii) system operators, market operators and regulators in order to acquire valuable insights regarding the setup and operation of distribution-level flexibility markets and the TSO-DSO interaction, (iii) ESPs in the modern electricity market structure so as to stack revenues, by providing various energy and flexibility services, and ensure the sustainability of their investments, and (iv) market operators to perform market analysis and tackle market power abuse phenomena.

Future research can use this study as an input in: (a) more complex investment models, which would for example consider more revenue streams for the DERs, integrate more sophisticated distribution network or DER models and non-convex characteristics in the electricity market clearing process, (b) the coordination of DER investments and network expansion planning, (c) market participation strategies that take into account different market rules and the uncertainty in the operation of the network and market along with the respective risks, (d) bidding and scheduling models that take into consideration the real-time system operation, (e) algorithms that explore the market equilibrium when more than one ESPs act strategically.

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Appendix

A. Transforming bi-level problem (2.c) into a MILP

Lower-level problem (2.b) is an LP and therefore, Slater's condition holds. Thus, Karush-Kuhn-Tucker (KKT) conditions are necessary and sufficient optimality conditions (satisfy convexity and constraint qualification). The KKT conditions of problem (2.b) are presented below:

$$-p_{it\omega}^{g} + p_{it\omega}^{d} - p_{it\omega}^{\uparrow} + p_{it\omega}^{\downarrow} + \textstyle\sum_{j\neq i} y_{ij} \cdot \left(\theta_{it\omega} - \theta_{jt\omega}\right) = 0, \quad \forall i \in N, t \in H \tag{h.1}$$

$$c_{it\omega}^{g} - \lambda_{it\omega} - \underline{\phi_{it\omega}^{g}} + \overline{\phi_{it\omega}^{g}} - \phi_{it\omega}^{grd} + \phi_{i(t+1)\omega}^{grd} + \phi_{it\omega}^{gru} - \phi_{i(t+1)\omega}^{gru} = 0, \quad \forall i \in N^{g}, t < T \tag{h.2}$$

$$c_{it\omega}^{g} - \lambda_{it\omega} - \underline{\phi_{it\omega}^{g}} + \overline{\phi_{it\omega}^{g}} = 0, \quad \forall i \in N^{g}, t = T \tag{h.3}$$

$$-c_{it\omega}^{d} + \lambda_{it\omega} - \underline{\phi_{it\omega}^{d}} + \overline{\phi_{it\omega}^{d}} = 0, \quad \forall i \in N^{d}, t \in H \tag{h.4}$$

$$c_{it\omega}^{\uparrow} - \lambda_{it\omega} - \underline{\phi_{it\omega}^{p\uparrow}} + \overline{\phi_{it\omega}^{p\uparrow}} = 0, \quad \forall i \in N^{m}, t \in H \tag{h.5}$$

$$-c_{it\omega}^{\downarrow} + \lambda_{it\omega} - \underline{\phi_{it\omega}^{p\downarrow}} + \overline{\phi_{it\omega}^{p\downarrow}} = 0, \quad \forall i \in N^{m}, t \in H \tag{h.6}$$

$$\sum_{j\neq i,(i,j)\in L^{T}} y_{ij} \cdot \left(\lambda_{it\omega} - \lambda_{jt\omega}\right) - \sum_{j>i} y_{ji} \cdot \left(\underline{\phi_{(ij)t\omega}^{l}} - \overline{\phi_{(ij)t\omega}^{l}}\right) + \sum_{j<i} y_{ji} \cdot \left(\underline{\phi_{(ij)t\omega}^{l}} - \overline{\phi_{(ij)t\omega}^{l}}\right) = 0, \quad \forall\, i \in N, t \in H \tag{h.7}$$

$$0 \leq \underline{\phi_{it\omega}^{g}} \perp p_{it\omega}^{g} \geq 0, \quad \forall i \in N^{g}, t \in H \tag{h.8}$$

$$0 \leq \overline{\phi_{it\omega}^{g}} \perp -p_{it\omega}^{g} + \overline{P_{i}^{g}} \geq 0, \quad \forall i \in N^{g}, t \in H \tag{h.9}$$

$$0 \leq \phi_{it\omega}^{grd} \perp p_{it\omega}^{g} - p_{i(t-1)\omega}^{g} + RD_{i} \geq 0, \quad \forall i \in N^{g}, t \in H \tag{h.10}$$

$$0 \leq \phi_{it\omega}^{gru} \perp -p_{it\omega}^{g} + p_{i(t-1)\omega}^{g} + RU_{i} \geq 0, \quad \forall i \in N^{g}, t \in H \tag{h.11}$$

$$0 \leq \underline{\phi_{it\omega}^{d}} \perp p_{it\omega}^{d} \geq 0, \quad \forall i \in N^{d}, t \in H \tag{h.12}$$

$$0 \leq \overline{\phi_{it\omega}^{d}} \perp -p_{it\omega}^{d} + \overline{P_{it\omega}^{d}} \geq 0, \quad \forall i \in N^{d}, t \in H \tag{h.13}$$

$$0 \leq \underline{\phi_{it\omega}^{p\uparrow}} \perp p_{it\omega}^{\uparrow} \geq 0, \quad \forall i \in N^{m}, t \in H \tag{h.14}$$

$$0 \leq \overline{\phi_{it\omega}^{p\uparrow}} \perp -p_{it\omega}^{\uparrow} + o_{it\omega} \geq 0, \quad \forall i \in N^{m}, t \in H \tag{h.15}$$

$$0 \leq \underline{\phi_{it\omega}^{p\downarrow}} \perp p_{it\omega}^{\downarrow} \geq 0, \quad \forall i \in N^{m}, t \in H \tag{h.16}$$

$$0 \leq \overline{\phi_{it\omega}^{p\downarrow}} \perp -p_{it\omega}^{\downarrow} + b_{it\omega} \geq 0, \quad \forall i \in N^{m}, t \in H \tag{h.17}$$

$$0 \leq \underline{\phi^{l}_{(ij)t\omega}} \perp y_{ij} \cdot (\theta_{it\omega} - \theta_{jt\omega}) + \overline{T_{ij}} \geq 0, \quad \forall (i,j) \in L, t \in H \tag{h.18}$$

$$0 \leq \overline{\phi^{l}_{(ij)t\omega}} \perp -y_{ij} \cdot (\theta_{it\omega} - \theta_{jt\omega}) + \overline{T_{ij}} \geq 0, \quad \forall (i,j) \in L, t \in H \tag{h.19}$$

Equation (h.1) is the equality constraint of the Lower-Level problem, while Eqs. (h.2) – (h.7) are the stationarity conditions. Finally, (h.8) – (h.19) are the complementarity slackness conditions. We use the perpendicular symbol (⊥) to indicate complementarity. Replacing the constraining problem (2.b) with its KKT conditions results in the following MPEC problem:

$$\min_{X_S^U \cup X_{O,\omega}^U \cup X_\omega^L, \forall \omega} \sum_{\omega \in \Omega} \left(C_\omega^{DN} + C_\omega^{oper} \right) + \tilde{C}^{inv} + \xi \cdot \left(\sum_{\omega \in \Omega} \left(-\mathrm{Pr}_\omega^{inv} + C_\omega^{oper} \right) + \chi \cdot \tilde{C}^{inv} \right) \tag{i.1}$$

Subject to

(2.a.5) - (2.a.10), (2.a.14) – (2.a.31), (h.1) – (h.19) (i.2)

Problem (i) is a single-level MINLP. The nonlinearities due to the complementarity conditions are linearized using the Big-M approach [124]. In order to tackle the nonlinearities in the objective function concerning expression in (2.a.2), we first multiply Eqs. (h.5) and (h.6) by $p^{\uparrow}_{it\omega}$ and $p^{\downarrow}_{it\omega}$ respectively:

$$c^{\uparrow}_{it\omega} \cdot p^{\uparrow}_{it\omega} - \lambda_{it\omega} \cdot p^{\uparrow}_{it\omega} - \underline{\phi^{p\uparrow}_{it\omega}} \cdot p^{\uparrow}_{it\omega} + \overline{\phi^{p\uparrow}_{it\omega}} \cdot p^{\uparrow}_{it\omega} = 0, \quad \forall i \in N^m, t \in H$$

$$-c^{\downarrow}_{it\omega} \cdot p^{\downarrow}_{it\omega} + \lambda_{it\omega} \cdot p^{\downarrow}_{it\omega} - \underline{\phi^{p\downarrow}_{it\omega}} \cdot p^{\downarrow}_{it\omega} + \overline{\phi^{p\downarrow}_{it\omega}} \cdot p^{\downarrow}_{it\omega} = 0, \quad \forall i \in N^m, t \in H$$

Then, using the complementarity conditions (h.14) – (h.17) and re-arranging terms, we have:

$$\sum_{i \in N^m} \sum_{t \in H} \left(\lambda_{it\omega} \cdot \left(p^{\uparrow}_{it\omega} - p^{\downarrow}_{it\omega} \right) \right) = \sum_{i \in N^m} \sum_{t \in H} \left(c^{\uparrow}_{it\omega} \cdot p^{\uparrow}_{it\omega} - c^{\downarrow}_{it\omega} \cdot p^{\downarrow}_{it\omega} + \overline{\phi^{p\uparrow}_{it\omega}} \cdot o_{it\omega} + \overline{\phi^{p\downarrow}_{it\omega}} \cdot b_{it\omega} \right)$$

Now, we make use of the Strong Duality Theorem for problem (2.b), which states:

$$\sum_{t \in H} \left(\sum_{i \in N^g} c^{g}_{it} \cdot p^{g}_{it\omega} - \sum_{i \in N^g} c^{d}_{it} \cdot p^{d}_{it\omega} + \sum_{i \in N^m} \left(c^{\uparrow}_{it\omega} \cdot p^{\uparrow}_{it\omega} - c^{\downarrow}_{it\omega} \cdot p^{\downarrow}_{it\omega} \right) \right) = -\sum_{t \in H} \left(\sum_{i \in N^g} \left(\overline{\phi^{g}_{it\omega}} \cdot \overline{P^{g}_{i}} + \phi^{grd}_{it\omega} \cdot RD_i + \phi^{gru}_{it\omega} \cdot RU_i \right) + \sum_{i \in N^d} \left(\overline{\phi^{d}_{it\omega}} \cdot \overline{P^{d}_{it\omega}} \right) + \sum_{i \in N^m} \left(\overline{\phi^{p\uparrow}_{it\omega}} \cdot o_{it\omega} + \overline{\phi^{p\downarrow}_{it\omega}} \cdot b_{it\omega} \right) + \sum_{i<j,(i,j) \in L} \left(\overline{T_{ij}} \cdot \underline{\phi^{l}_{(ij)t\omega}} + \overline{T_{ij}} \cdot \overline{\phi^{l}_{(ij)t\omega}} \right) \right)$$

Re-arranging the terms in the above expression, we obtain:

$$\sum_{t \in H} \left(\sum_{i \in N^m} \left(c^{\uparrow}_{it\omega} \cdot p^{\uparrow}_{it\omega} - c^{\downarrow}_{it\omega} \cdot p^{\downarrow}_{it\omega} + \overline{\phi^{p\uparrow}_{it\omega}} \cdot o_{it\omega} + \overline{\phi^{p\downarrow}_{it\omega}} \cdot b_{it\omega} \right) \right) = -\sum_{t \in H} \left(\sum_{i \in N^g} \left(c^{g}_{it} \cdot p^{g}_{it\omega} + \overline{\phi^{g}_{it\omega}} \cdot \overline{P^{g}_{i}} + \phi^{grd}_{it\omega} \cdot RD_i + \phi^{gru}_{it\omega} \cdot RU_i \right) + \sum_{i \in N^d} \left(-c^{d}_{it} \cdot p^{d}_{it\omega} + \overline{\phi^{d}_{it\omega}} \cdot \overline{P^{d}_{it\omega}} \right) + \sum_{i<j,(i,j) \in L} \left(\overline{T_{ij}} \cdot \underline{\phi^{l}_{(ij)t\omega}} + \overline{T_{ij}} \cdot \overline{\phi^{l}_{(ij)t\omega}} \right) \right)$$

Hence, nonlinear expression (2.a.2) is replaced by its linear equivalent expression:

$$Pr_{\omega}^{DN} = -\pi_{\omega} \cdot \sum_{t \in H} \Big(\sum_{i \in N^g} \Big(c_{it}^{g} \cdot p_{it\omega}^{g} + \overline{\phi_{it\omega}^{g}} \cdot \overline{P_{i}^{g}} + \phi_{it\omega}^{grd} \cdot RD_i + \phi_{it\omega}^{gru} \cdot RU_i \Big) + \sum_{i \in N^d} \Big(-c_{it}^{d} \cdot p_{it\omega}^{d} + \overline{\phi_{it\omega}^{d}} \cdot \overline{P_{it\omega}^{d}} \Big) + \sum_{i<j,(i,j) \in L} \Big(\overline{T_{ij}} \cdot \underline{\phi_{(ij)t\omega}^{l}} + \overline{T_{ij}} \cdot \overline{\phi_{(ij)t\omega}^{l}} \Big) \Big)$$

Finally, in order to linearize the expression in (2.a.13), since we have considered a lossless DN model, we use the active power balance equations of the DN (i.e. (2.a.23) and (2.a.28)):

$$\pi_{\omega} \cdot \sum_{i \in N^m} \sum_{t \in H} \Big(\lambda_{it\omega} \cdot \Big(\sum_{n \in B_i^w} g_{int\omega}^{w} \sum_{n \in B_i^{pv}} g_{int\omega}^{pv} + \sum_{n \in B_i^{es}} (dis_{int\omega} - ch_{int\omega}) \Big) \Big) = \pi_{\omega} \cdot \sum_{i \in N^m} \sum_{t \in H} \Big(\lambda_{it\omega} \cdot \Big(\big(p_{it\omega}^{\uparrow} - p_{it\omega}^{\downarrow}\big) + \sum_{n \in B_i} D_{nt\omega} \Big) \Big)$$

Then, the remaining nonlinear term $\lambda_{it\omega} \cdot (p_{it\omega}^{\uparrow} - p_{it\omega}^{\downarrow})$ is linearized as previously mentioned. Thus, we have transformed the bi-level problem (2.c) into a MILP.

B. Formulation of SP1

We transform the bi-level problem (2.f) into a MILP using the MPEC method. We replace the lower-level problem (2.b) with its KKT conditions. Hence, problem (2.f) can be recast into the following MINLP problem:

$$\min_{X_{O,\omega}^{U} \cup X_{\omega}^{L}} \tilde{G}_{\omega} = (1+\xi) \cdot C_{\omega}^{oper} + C_{\omega}^{DN} - \xi \cdot Pr_{\omega}^{inv} \tag{j.1}$$

Subject to

(2.a.14) - (2.a.31), (h.1) – (h.19), (2.f.3) – (2.f.6) (j.2)

The above MINLP is transformed into a MILP as explained in APPENDIX A, which can be solved using off-the-shelf solvers. The optimal values $h_{it\omega}^{*}, x_{int\omega}^{*}, \overline{\phi_{it\omega}^{p\uparrow *}}, \underline{\phi_{it\omega}^{p\uparrow *}}, \overline{\phi_{it\omega}^{p\downarrow *}}, \underline{\phi_{it\omega}^{p\downarrow *}}$ provided by the solution of problem (j) will be used in the formulation of SP2 (cf. APPENDIX C).

C. Formulation of SP2

Now, we transform the bi-level problem (2.f) into an LP using the MPPDC method. We replace the lower-level problem (2.b) with its primal constraints, its dual constraints and the Strong Duality Theorem expression. Also, we relax the integrality conditions (2.a.19) and (2.a.31), and we fix the values of $h_{it\omega}$ and $x_{int\omega}$ to their optimal values calculated in SP1. Furthermore, bilinear terms in the Strong Duality Theorem expression are linearized replacing dual variables $\overline{\phi_{it\omega}^{p\uparrow}}, \overline{\phi_{it\omega}^{p\downarrow}}$ with their respective optimal values calculated solving SP1 (i.e., $\overline{\phi_{it\omega}^{p\uparrow *}}, \overline{\phi_{it\omega}^{p\downarrow *}}$). Therefore, problem (2.f) is converted into the following NLP:

$$\min_{X_{O,\omega}^{U} \cup X_{\omega}^{L}} \tilde{G}_{\omega} = (1+\xi) \cdot C_{\omega}^{oper} + C_{\omega}^{DN} - \xi \cdot Pr_{\omega}^{inv} \tag{k.1}$$

Subject to

(2.a.14) – (2.a.18), (2.a.20) – (2.a.30) (k.2)

(2.b.2) – (2.b.9) (k.3)

$$\underline{\phi^{g}_{it\omega}}, \overline{\phi^{g}_{it\omega}}, \phi^{grd}_{it\omega}, \phi^{gru}_{it\omega}, \underline{\phi^{d}_{it\omega}}, \overline{\phi^{d}_{it\omega}}, \underline{\phi^{p\uparrow}_{it\omega}}, \overline{\phi^{p\uparrow}_{it\omega}}, \underline{\phi^{p\downarrow}_{it\omega}}, \overline{\phi^{p\downarrow}_{it\omega}}, \underline{\phi^{l}_{(ij)t\omega}}, \overline{\phi^{l}_{(ij)t\omega}} \geq 0 \quad (k.4)$$

(h.2) – (h.7) (k.5)

$$\sum_{t\in H}\left(\sum_{i\in N^g} c^g_{it}\cdot p^g_{it\omega} - \sum_{i\in N^g} c^d_{it}\cdot p^d_{it\omega} + \sum_{i\in N^m}\left(c^{\uparrow}_{it\omega}\cdot p^{\uparrow}_{it\omega} - c^{\downarrow}_{it\omega}\cdot p^{\downarrow}_{it\omega}\right)\right) =$$
$$-\sum_{t\in H}\left(\sum_{i\in N^g}\left(\overline{\phi^{g}_{it\omega}}\cdot \overline{P^g_i} + \phi^{grd}_{it\omega}\cdot RD_i + \phi^{gru}_{it\omega}\cdot RU_i\right) + \sum_{i\in N^d}\left(\overline{\phi^{d}_{it\omega}}\cdot \overline{P^d_{it\omega}}\right) + \right.$$
$$\left.\sum_{i\in N^m}\left(\overline{\phi^{p\uparrow *}_{it\omega}}\cdot o_{it\omega} + \overline{\phi^{p\downarrow *}_{it\omega}}\cdot b_{it\omega}\right) + \sum_{i<j,(i,j)\in L}\left(\overline{T_{ij}}\cdot \underline{\phi^{l}_{(ij)t\omega}} + \overline{T_{ij}}\cdot \overline{\phi^{l}_{(ij)t\omega}}\right)\right) \quad (k.6)$$

(2.f.3) – (2.f.6) (k.7)

$$h_{it\omega} = h^{*}_{it\omega} \quad (k.8)$$

$$x_{it\omega} = x^{*}_{int\omega} \quad (k.9)$$

$$\underline{\phi^{p\uparrow}_{it\omega}} = \underline{\phi^{p\uparrow *}_{it\omega}} \quad (k.10)$$

$$\overline{\phi^{p\uparrow}_{it\omega}} = \overline{\phi^{p\uparrow *}_{it\omega}} \quad (k.11)$$

$$\underline{\phi^{p\downarrow}_{it\omega}} = \underline{\phi^{p\downarrow *}_{it\omega}} \quad (k.12)$$

$$\overline{\phi^{p\downarrow}_{it\omega}} = \overline{\phi^{p\downarrow *}_{it\omega}} \quad (k.13)$$

The above problem (k) is a continuous non-linear optimization problem. Non-linearities in the objective function (k.1) are linearized as explained in APPENDIX B and eventually problem (2.f) is converted into an LP.

D. Input Data and Results from Chapter 3

Table A: Technical characteristics of DN in Case Study A

Branch (#)	From Node (#)	To Node (#)	r (pu)	x (pu)	p^{max} (pu)	p^{min} (pu)	q^{max} (pu)	q^{min} (pu)	U^{max} (pu)	U^{min} (pu)
1	0	1	0.00315	0.075207	0.233	-0.233	0.233	-0.233	1,05	0,95
2	1	2	0,00033	0.001849	0.233	-0.233	0.233	-0.233	1,05	0,95
3	2	3	0,00667	0.030808	0.233	-0.233	0.233	-0.233	1,05	0,95
4	3	4	0,00579	0.014949	0.233	-0.233	0.233	-0.233	1,05	0,95
5	4	5	0,01414	0.036549	0.233	-0.233	0.233	-0.233	1,05	0,95
6	3	6	0,00800	0.036961	0.233	-0.233	0.233	-0.233	1,05	0,95
7	6	7	0,00900	0.041575	0.233	-0.233	0.233	-0.233	1,05	0,95
8	7	8	0,00700	0.032346	0.233	-0.233	0.233	-0.233	1,05	0,95
9	8	9	0,00367	0.016940	0.233	-0.233	0.233	-0.233	1,05	0,95
10	9	10	0,00900	0.041575	0.233	-0.233	0.233	-0.233	1,05	0,95
11	2	11	0,02750	0.127043	0.233	-0.233	0.233	-0.233	1,05	0,95
12	11	12	0,03150	0.081405	0.233	-0.233	0.233	-0.233	1,05	0,95

13	12	13	0,03965	0.102984	0.233	-0.233	0.233	-0.233	1,05	0,95
14	13	14	0,01061	0.004153	0.233	-0.233	0.233	-0.233	1,05	0,95

Table B. Technical characteristics of the 6-Bus Illustrative Example (Case Study A)

Line (#)	From Bus (#)	To Bus (#)	Reactance (pu)	y_{ij} (pu)	T_{ij}^{max} (MW)
1	1	2	0,17	5,882352941	150
2	1	4	0,258	3,875968992	150
3	2	3	0,037	27,02702703	150
4	2	4	0,197	5,076142132	33
5	3	6	0,018	55,55555556	150
6	4	5	0,037	27,02702703	150
7	5	6	0,14	7,142857143	150

Table C. Generating units' data in Case Study A

Gen. Unit	Bus (#)	g_i^{max} (MW)	g_i^{min} (MW)	RU_i (MW/h)	RD_i (MW/h)	$g_{i,0}$ (MW)	c_i^g (€/MWh)
G1	1	100	0	5	5	100	12
G2	2	75	0	8	8	75	20
G3	6	50	0	10	10	0	50
G4	6	50	0	20	20	0	100

Table D. Demand loads' data in Case Study A

t (h)	$d_{i,t}^{max}$ (MW)		$d_{i,t}^{min}$ (MW)		$c_{i,t}^{d}$(€/MWh)	
	Load in bus $i = 3$	Load in bus $i = 4$	Load in bus $i = 3$	Load in bus $i = 4$	Load in bus $i = 3$	Load in bus $i = 4$
1	88	88	0	0	450	450
2	82.5	82.5	0	0	450	450
3	79	79	0	0	450	450
4	77	77	0	0	450	450
5	77.5	77.5	0	0	450	450
6	79.5	79.5	0	0	450	450
7	86.5	86.5	0	0	450	450
8	88.5	88.5	0	0	450	450
9	88.5	88.5	0	0	450	450
10	90.5	90.5	0	0	450	450
11	94	94	0	0	450	450
12	95	95	0	0	450	450
13	97.5	97.5	0	0	450	450
14	98	98	0	0	450	450
15	98.5	98.5	0	0	450	450
16	109	109	0	0	450	450
17	124.5	124.5	0	0	450	450
18	126	126	0	0	450	450
19	122	122	0	0	450	450
20	118.5	118.5	0	0	450	450
21	110	110	0	0	450	450

22	99.5	99.5	0	0	450	450
23	98	98	0	0	450	450
24	97.5	97.5	0	0	450	450

Table E. Data of ESSs in Case Study A

Node (#)	SOC^{max} (pu)	SOC^{min} (pu)	$r^{dis,max}$ (pu)	$r^{ch,max}$ (pu)	SOC_0 (pu)	η^d	η^c	w
5	0.166667	0	0.0833	0.0833	0.0833	1	1	1
8	0.166667	0	0.0833	0.0833	0.0833	1	1	1
10	0.166667	0	0.0833	0.0833	0.0833	1	1	1
13	0.166667	0	0.0833	0.0833	0.0833	1	1	1

Table F. Data of shiftable loads in Case Study A

Node (#)	$p^{fl,max}$ (pu)	E^{fl} (pu)	α	β	PF
4	0.026667	0.026667	8	18	0.9
9	0.026667	0.026667	8	18	0.9
10	0.026667	0.026667	8	18	0.9
11	0.026667	0.026667	8	18	0.9
13	0.026667	0.026667	8	18	0.9
14	0.026667	0.026667	8	18	0.9

Table G. Market results in Case 1 (power dispatch schedules and LMPs at bus 5) – Case Study A

t (h)	$d_{i,t}$ (MW)		$g_{i,t}$ (MW)				$p^M_{i,t}$ (MW)	$\lambda_{i,t}$ (€/MWh)
	i=3	*i=4*	*G1*	*G2*	*G3*	*G4*	*i=5*	*i=5*
1	88	88	100	71.94	0	0	4.06	20
2	82.5	82.5	100	72	0	0	-7	20
3	79	79	100	65	0	0	-7	20
4	77	77	100	61	0	0	-7	20
5	77.5	77.5	100	62	0	0	-7	20
6	79.5	79.5	99	67	0	0	-7	12
7	86.5	86.5	100	75	0	0	-2	48.9778
8	88.5	88.5	100	75	0.67	0	1.33	50
9	88.8	88.5	100	75	0	0	2	50
10	90.5	90.5	100	75	0.98	0	5.02	50
11	94	94	100	75	10.70	0	2.30	50
12	95	95	100	75	15.95	0	-0.95	50
13	97.5	97.5	100	75	16.67	0	3.33	50
14	98	98	100	75	25.05	0	-4.05	50
15	98.5	98.5	100	70.09	33.22	0	-6.30	20
16	109	109	100	74.54	43.22	0	0.25	86.3277
17	124.5	116.00	100	66.54	50	20	3.97	376.8362
18	126	115.81	100	58.54	50	32.89	0.38	376.8362
19	122	117.82	100	52.74	50	35.91	1.17	376.8362
20	118.5	113.16	100	60.74	50	22.05	-1.14	376.8362
21	110	110	100	68.74	48	4.15	-0.89	157.2368
22	99.5	99.5	100	68	38	0	-7	20
23	98	98	100	75	28	0	-7	30

24	97.5	97.5	100	75	21.89	0	-1.89	50

Table H. Satisfaction (✓) or violation (✗) of nodal voltage limits in DN for each time instant in Case 2 – Case Study A

Node / t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
8	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
9	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗
11	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✗	✗
12	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗
13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗
14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
15	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓
18	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
21	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
22	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
23	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
24	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓

Table I. Satisfaction (✓) or violation (✗) of active power flow limits for each branch of DN for each time instant in Case 2 – Case Study A

Branch / t	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
8	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
9	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓
10	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
11	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓
12	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓
13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
15	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
17	✗	✗	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓
18	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓
19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
21	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
22	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
23	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
24	✓	✓	✓	✓	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓

Table J. Market results in Case 3 (power dispatch schedules and LMPs at bus 5) – Case Study A

t (h)	$d_{i,t}$ (MW)		$g_{i,t}$ (MW)				$p^M_{i,t}$ (MW)	$c^M_{i,t}$ (€/MWh)	$\lambda_{i,t}$ (€/MWh)
	i=3	*i=4*	*G1*	*G2*	*G3*	*G4*	*i=5*	*i=5*	*i=5*
1	88	88	100	75	0	0	1	50	50
2	82.5	82.5	100	71.94	0	0	-6.94	20	20
3	79	79	100	65	0	0	-7	20	20
4	77	77	100	61	0	0	-7	20	20
5	77.5	77.5	100	59	0	0	-4	12	12
6	79.5	79.5	99	67	0	0	-7	12	12
7	86.5	86.5	100	75	0	0	-2	36	36
8	88.5	88.5	100	75	0	0	2	50	50
9	88.8	88.5	100	75	0	0	2	50	50
10	90.5	90.5	100	75	1.65	0	4.35	50	50
11	94	94	100	75	11.65	0	1.35	50	50
12	95	95	100	75	12.35	0	2.65	50	50
13	97.5	97.5	100	75	21.15	0	-1.15	50	50
14	98	98	100	75	23.22	0	-2.22	30	30
15	98.5	98.5	100	70.09	33.22	0	-6.30	20	20
16	109	109	100	74.54	43.22	0	0.25	157.2368	157.2368
17	124.5	116.02	100	66.54	50	20	3.99	376.8362	376.8362
18	126	109.97	100	58.54	50	34.43	-7	376.8362	376.8362
19	122	119.78	100	52.74	50	35.39	3.64	376.8362	376.8362
20	118.5	117.02	100	60.74	50	21.03	3.74	376.8362	376.8362
21	110	110	100	68.74	48	4.15	-0.89	157.2368	157.2368
22	99.5	99.5	100	68	38	0	-7	20	20
23	98	98	100	75	28	0	-7	30	30
24	97.5	97.5	100	75	21.89	0	-1.89	50	50

Table K. Technical characteristics of the IEEE One-Area Reliability Test System (Case Study B)

Line (#)	From Bus (#)	To Bus (#)	Reactance (pu)	y_{ij} (pu)	Max Line Flow (MW)
1	1	2	0,0146	68,49315068	175
2	1	3	0,2253	4,438526409	175
3	1	5	0,0907	11,02535832	350
4	2	4	0,1356	7,374631268	175
5	2	6	0,205	4,87804878	175
6	3	9	0,1271	7,867820614	175
7	3	24	0,084	11,9047619	400
8	4	9	0,111	9,009009009	175
9	5	10	0,094	10,63829787	350
10	6	10	0,0642	15,57632399	175
11	7	8	0,0652	15,33742331	350
12	8	9	0,1762	5,675368899	175
13	8	10	0,1762	5,675368899	175
14	9	11	0,084	11,9047619	400
15	9	12	0,084	11,9047619	400
16	10	11	0,084	11,9047619	400
17	10	12	0,084	11,9047619	400
18	11	13	0,0488	20,49180328	500
19	11	14	0,0426	23,4741784	500
20	12	13	0,0488	20,49180328	500
21	12	23	0,0985	10,15228426	500
22	13	23	0,0884	11,31221719	200
23	14	16	0,0594	16,83501684	250
24	15	16	0,0172	58,13953488	500
25	15	21	0,0249	40,16064257	400
26	15	24	0,0529	18,90359168	500
27	16	17	0,0263	38,02281369	500
28	16	19	0,0234	42,73504274	500
29	17	18	0,0143	69,93006993	500
30	17	22	0,1069	9,35453695	500
31	18	21	0,0132	75,75757576	1000
32	19	20	0,0203	49,26108374	1000
33	20	23	0,0112	89,28571429	1000
34	21	22	0,0692	14,45086705	500

Table L. Generating units' data in Case Study B

Gen. Unit	Bus (#)	g_i^{max} (MW)	g_i^{min} (MW)	RU_i (MW/h)	RD_i (MW/h)	$g_{i,0}$ (MW)	c_i^g (€/MWh)
G1	1	152	30,4	120	120	76	48,32
G2	2	152	30,4	120	120	76	48,32
G3	7	350	75	350	350	0	57,7
G4	13	591	206,85	240	240	0	78,93
G5	15	60	12	60	60	0	60,11

G6	15	155	54,25	155	155	0	10,52
G7	16	155	54,25	155	155	124	10,52
G8	18	400	100	280	280	240	5,47
G9	21	400	100	280	280	240	5,47
G10	22	300	300	300	300	240	1
G11	23	310	108,5	180	180	248	10,52
G12	23	350	140	240	240	280	29,89

Table M. Demand loads' data in Case Study B

t(h)	$d_{i,t}^{max}$ (MW)																
	i=1	**i=2**	**i=3**	**i=4**	**i=5**	**i=6**	**i=7**	**i=8**	**i=9**	**i=10**	**i=13**	**i=14**	**i=15**	**i=16**	**i=18**	**i=19**	**i=20**
1	67	60	112	46	44	85	78	107	108	121	165	121	197	62	208	114	80
2	63	57	105	43	42	80	73	100	102	114	155	114	185	58	195	107	75
3	60	54	100	41	40	76	70	95	97	108	148	108	177	56	186	102	72
4	59	53	99	41	39	75	69	94	95	106	145	106	174	55	183	100	70
5	59	53	99	41	39	75	69	94	95	106	145	106	174	55	183	100	70
6	60	54	100	41	40	76	70	95	97	108	148	108	177	56	186	102	72
7	75	67	124	51	49	94	86	118	120	133	182	133	218	69	229	126	88
8	87	78	144	59	57	109	100	137	139	155	212	155	253	80	267	146	103
9	96	86	159	65	63	121	111	151	154	171	234	171	279	88	295	161	113
10	97	87	160	66	64	122	112	153	155	173	237	173	282	89	298	163	115
11	97	87	160	66	64	122	112	153	155	173	237	173	282	89	298	163	115
12	96	86	159	65	63	121	111	151	154	171	234	171	279	88	295	161	113
13	96	86	159	65	63	121	111	151	154	171	234	171	279	88	295	161	113
14	96	86	159	65	63	121	111	151	154	171	234	171	279	88	295	161	113
15	94	84	155	64	62	118	108	148	150	168	229	168	274	86	288	158	111
16	94	84	155	64	62	118	108	148	150	168	229	168	274	86	288	158	111
17	100	89	165	68	66	126	115	157	160	178	244	178	291	92	307	168	118
18	101	90	167	69	66	127	117	159	162	180	246	180	294	93	310	170	119
19	101	90	167	69	66	127	117	159	162	180	246	180	294	93	310	170	119
20	97	87	160	66	64	122	112	153	155	173	237	173	282	89	298	163	115
21	92	82	152	63	60	116	106	145	147	164	224	164	268	84	282	154	109
22	84	75	139	57	55	106	97	132	134	150	205	150	244	77	257	141	99
23	74	66	122	50	48	93	85	116	118	132	180	132	215	68	226	124	87
24	63	57	105	43	42	80	73	100	102	114	155	114	185	58	195	107	75

Table N. Data of DNs' Shiftable loads in Case Study B

DN 1					
Node (#)	$p^{fl,max}$ **(pu)**	E^{fl} **(pu)**	**α**	**β**	**PF**
3	0.026667	0.026667	8	18	0.9
6	0.026667	0.026667	8	18	0.9
14	0.026667	0.026667	8	18	0.9
DN 2					
Node (#)	$p^{fl,max}$ **(pu)**	E^{fl} **(pu)**	**α**	**β**	**PF**

4	0.026667	0.026667	8	18	0.9
9	0.026667	0.026667	8	18	0.9
10	0.026667	0.026667	8	18	0.9
11	0.026667	0.026667	8	18	0.9
13	0.026667	0.026667	8	18	0.9
14	0.026667	0.026667	8	18	0.9
DN 3					
Node (#)	$p^{fl,max}$ **(pu)**	E^{fl} **(pu)**	α	β	**PF**
8	0.026667	0.026667	8	18	0.9
9	0.026667	0.026667	8	18	0.9
10	0.026667	0.026667	8	18	0.9

Table O. Data of DNs' ESSs in Case Study B

DN 1								
Node (#)	SOC^{max} **(pu)**	SOC^{min} **(pu)**	$r^{dis,max}$ **(pu)**	$r^{ch,max}$ **(pu)**	SOC_0 **(pu)**	η^d	η^c	**w**
3	0.166667	0	0.0833	0.0833	0.0833	1	1	1
12	0.166667	0	0.0833	0.0833	0.0833	1	1	1
DN 2								
Node (#)	SOC^{max} **(pu)**	SOC^{min} **(pu)**	$r^{dis,max}$ **(pu)**	$r^{ch,max}$ **(pu)**	SOC_0 **(pu)**	η^d	η^c	**w**
5	0.33333	0	0.1667	0.1667	0.1667	1	1	1
8	0.166667	0	0.0833	0.0833	0.0833	1	1	1
10	0.166667	0	0.0833	0.0833	0.0833	1	1	1
13	0.33333	0	0.1667	0.1667	0.1667	1	1	1
DN 3								
Node (#)	SOC^{max} **(pu)**	SOC^{min} **(pu)**	$r^{dis,max}$ **(pu)**	$r^{ch,max}$ **(pu)**	SOC_0 **(pu)**	η^d	η^c	**w**
2	0.166667	0	0.0833	0.0833	0.0833	1	1	1
5	0.166667	0	0.0833	0.0833	0.0833	1	1	1
10	0.166667	0	0.0833	0.0833	0.0833	1	1	1
13	0.166667	0	0.0833	0.0833	0.0833	1	1	1

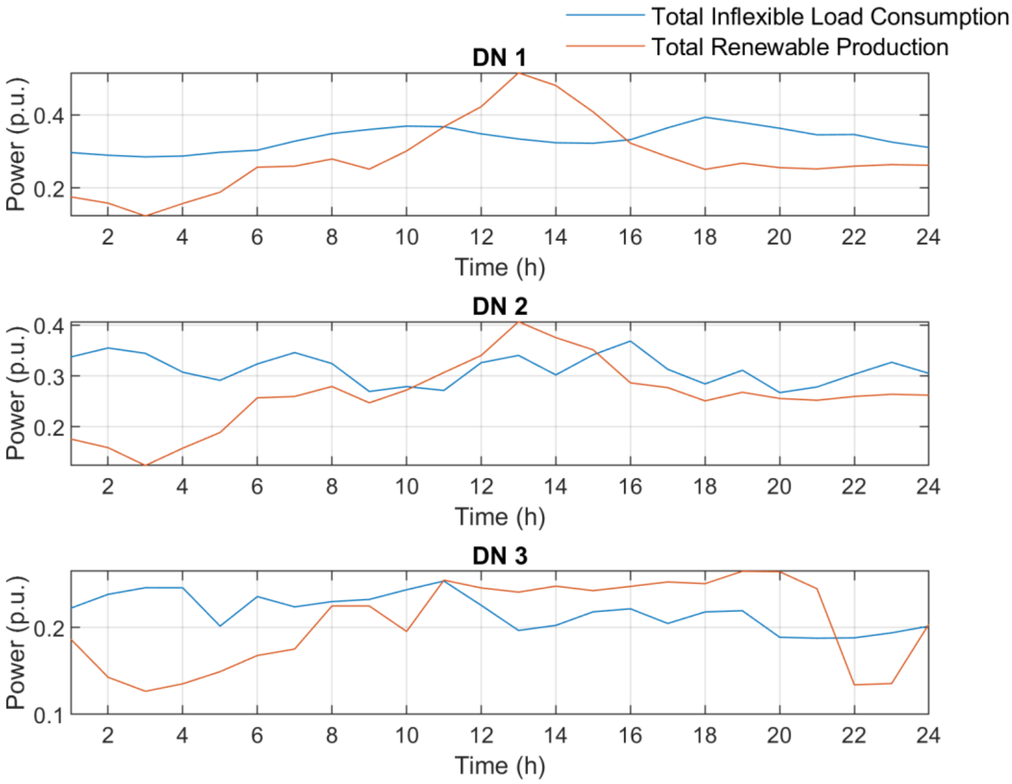


Figure A: Renewable energy production and inflexible load consumption daily curves of DNs in Case Study B

Summary in Greek language

Η Εξέλιξη των Συστημάτων Ηλεκτρικής Ενέργειας

Οι Κυρίαρχες Τάσεις στα Σύγχρονα Έξυπνα Ηλεκτρικά Δίκτυα

Κατά το μεγαλύτερο μέρος του 20^{ου} αιώνα, ο τομέας της ηλεκτρικής ενέργειας θεωρούνταν φυσικό μονοπώλιο. Αποκλειστικές υπεύθυνες για τη διαχείριση και τον έλεγχο της παραγωγής, της μεταφοράς και της διανομής ηλεκτρικής ισχύος ήταν καθετοποιημένες επιχειρήσεις κοινής ωφέλειας. Αυτές οι κρατικά ρυθμιζόμενες επιχειρήσεις παρήγαγαν ισχύ σε θερμικές ή υδροηλεκτρικές μονάδες συνδεδεμένες στο δίκτυο υψηλής τάσης (ΥΤ), μέσω του οποίου τη μετέφεραν στους υποσταθμούς ΥΤ/ΜΤ και ΥΤ/ΧΤ, και τελικά τη διένειμαν στους, ανελαστικούς ως προς την τιμή, τελικούς καταναλωτές. Οι τελευταίοι πλήρωναν για την παρεχόμενη ενέργεια με βάση μία κρατικά ρυθμισμένη τιμή. Ωστόσο, από την δεκαετία του 1980, συγκεκριμένες πολιτικές αποφάσεις, μαζί με τις ολοένα αυξανόμενες περιβαλλοντικές ανησυχίες, την προβλεπόμενη αύξηση της παγκόσμιας ζήτησης σε ηλεκτρική ενέργειας και τις ραγδαίες τεχνολογικές εξελίξεις στις Ανανεώσιμες Πηγές Ενέργειας (ΑΠΕ), στα Συστήματα Αποθήκευσης Ενέργειας (ΣΑΕ), αλλά και στις Τεχνολογίες Πληροφοριών και Επικοινωνιών (Information and Communication Technologies - ICT), έχουν πυροδοτήσει τη μετάβαση προς τα Έξυπνα Δίκτυα (Smart Grids) [1] μέσω μιας σειράς από εκτενείς αλλαγές στον τομέα της ηλεκτρικής ενέργειας:

<u>Απελευθέρωση των Αγορών:</u> Ο τομέας της ηλεκτρικής ισχύος έχει εξελιχθεί σε μία απορυθμισμένη και ανταγωνιστική βιομηχανία, όπου οι δυνάμεις της αγοράς πλέον καθορίζουν την τιμή της ηλεκτρικής ενέργειας. Σκοπός αυτής της μετάβασης υπήρξε η μείωση του κόστους της ενέργειας και της διασφάλισης της ομαλής λειτουργίας των δικτύων. Η ηλεκτρική ενέργειας πλέον αντιμετωπίζεται ως προϊόν και αγοραπωλείται σε απορυθμισμένες χονδρικές αγορές, όπου ιδιωτικές εταιρίες επιδιώκουν να μεγιστοποιήσουν την κερδοφορία τους. Επιπλέον, ανταγωνιστικές αγορές Επικουρικών Υπηρεσιών (ΕΥ – Ancillary Services - AS) έχουν δημιουργηθεί, όπου οι διαχειριστές των συστημάτων αγοράζουν τις απαιτούμενες υπηρεσίες ευελιξίας (Flexibility Services) από Πάροχους Υπηρεσιών Εξισορρόπησης (Balancing Service Providers), προκειμένου να εξασφαλίσουν την αξιόπιστη λειτουργία των δικτύων τους. Τέλος, οι τελικοί καταναλωτές πλέον μπορούν ελεύθερα να επιλέξουν τον πάροχό τους στην λιανική αγορά, με βάση την τιμή και την ποιότητα των παρεχόμενων υπηρεσιών.

<u>Απανθρακοποίηση:</u> Οι περιβαλλοντικοί στόχοι που έχουν τεθεί από τη διεθνή κοινότητα σχετικά με τον περιορισμό της υπερθέρμανσης του πλανήτη [2] και τη μείωση των εκπομπών αερίων του θερμοκηπίου [3], έχουν οδηγήσει στην επιταχυνόμενη αύξηση της διείσδυσης των ΑΠΕ στο ενεργειακό μείγμα ηλεκτροπαραγωγής. Επίσης, στις περισσότερες χώρες, το μεγαλύτερο μέρος των νέων επενδύσεων σε ΑΠΕ αφορά μονάδες συνδεδεμένες στο δίκτυο διανομής («behind-the-meter»). Για παράδειγμα, περίπου 179 GW κατανεμημένων φωτοβολταϊκών πάρκων (PV) να έχουν εγκατασταθεί παγκοσμίως από το 2017 έως το 2020 [4].

<u>Αποκεντροποίηση:</u> Το μεγάλο ποσοστό διείσδυσης κατανεμημένων μονάδων ΑΠΕ, αλλά και ο εξηλεκτρισμός των τομέων της βιομηχανίας, των μεταφορών και της θέρμανσης/ψύξης [5] οδηγεί στην αποκεντροποίηση των Συστημάτων Ηλεκτρικής Ενέργειας

(ΣΗΕ). Οι Κατανεμημένοι Ενεργειακοί Πόροι (ΚΕΠ – Distributed Energy Resources – DERs) έχουν τη δυνατότητα να παράγουν ή να αποθηκεύουν ηλεκτρική ενέργεια, αλλά και να διαχειρίζονται την κατανάλωσή της ανάλογα με την εκάστοτε τεχνολογία. Οι κατανεμημένες μονάδες ΑΠΕ, ΣΑΕ και τεχνολογίες Απόκρισης της Ζήτησης (Demand Response – DR) μπορούν να υποστηρίξουν την απανθρακοποίηση των ΣΗΕ, μειώνοντας την εξάρτησή τους από τα ορυκτά καύσιμα. Ακόμα, μπορούν να παρέχουν πολύτιμες υπηρεσίες στους Διαχειριστές των Δικτύων Διανομής (Distribution System Operators - DSOs) και στους Διαχειριστές των Δικτύων Μεταφοράς (Transmission System Operators – TSOs) δημιουργώντας καινοτόμα επιχειρηματικά μοντέλα.

Ψηφιοποίηση: Με στόχο την επιτάχυνση της αποκεντροποίησης και την πλήρη αξιοποίηση των οφελών που προσφέρουν οι DERs, τα ΣΗΕ εξελίσσονται σε κυβερνο-φυσικά (cyber-physical) συστήματα. Η ανάπτυξη ICT λύσεων, η εγκατάσταση έξυπνων μετρητών (smart meters) και ο σχεδιασμός Internet-of-Things (IoT) υποδομών θα οδηγήσουν στη βέλτιστη χρήση των επιμέρους στοιχείων των δικτύων, θα απελευθερώσουν τις δυνατότητες των κατανεμημένων μονάδων ενέργειας και ευελιξίας και θα διευκολύνουν τη συνεργασία μεταξύ των εμπλεκόμενων φορέων στον τομέα της ηλεκτρικής ισχύος.

Οι Προκλήσεις των Συστημάτων Ηλεκτρικής Ενέργειας της Νέας Εποχής

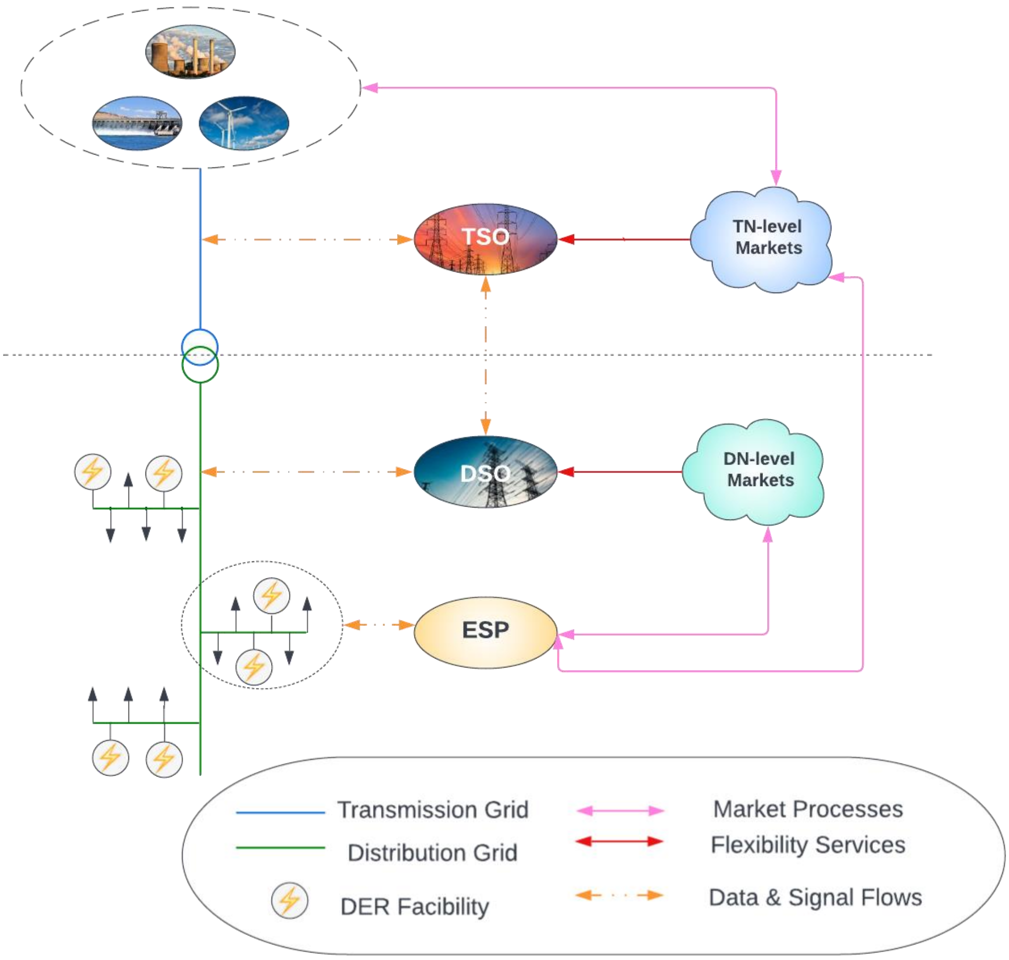
Οι προαναφερθείσες αλλαγές θέτουν νέες προκλήσεις για τους διαχειριστές των ΣΗΕ. Τα περισσότερα δίκτυα ηλεκτρικής ενέργειας κατασκευάστηκαν πριν από δεκαετίες για συστήματα όπου η ισχύς έρεε προς μία μόνο κατεύθυνση (από τις κεντρικές παραγωγικές μονάδες προς τους τελικούς καταναλωτές), ενώ η ζήτηση ήταν αμετάβλητη και ανελαστική ως προς τις τιμές. Οι κύριες ανησυχίες για τους διαχειριστές των συστημάτων ήταν τα ενδεχόμενα σφαλμάτων στη λειτουργία ορισμένων στοιχείων του δικτύου και η εξασφάλιση επαρκούς ικανότητας παραγωγής και μεταφοράς για την ικανοποίηση του φορτίου αιχμής. Η μόνη επιλογή για την αντιμετώπιση αυτών των ζητημάτων ήταν οι κοστοβόρες επενδύσεις σε ενίσχυση του δικτύου.

Στην εποχή των Έξυπνων Δικτύων, οι διαχειριστές των συστημάτων μεταφοράς και διανομής (TSO/DSO) έχουν επιπλέον να αντιμετωπίσουν την απρόβλεπτη και συνεχώς μεταβλητή παραγωγή από μονάδες ΑΠΕ, η οποία περιπλέκει το έργο της συνεχούς εξισορρόπησης της παραγωγής με τη ζήτηση. Επίσης, καθώς ο αριθμός και το συνολικό μέγεθος των μονάδων που συνδέονται στο δίκτυο διανομής (DERs) συνεχώς αυξάνονται, φαινόμενα συμφόρησης του δικτύου και απόκλισης της τάσης από τα όρια ασφαλείας γίνονται όλο και συχνότερα. Επιπλέον, οι διαχειριστές των ΣΗΕ θα πρέπει να αντιμετωπίσουν και την αυξανόμενη αιχμή του φορτίου, αλλά και τα απρόβλεπτα μοτίβα κατανάλωσης, τα οποία προκύπτουν από τον εξηλεκτρισμό της συνολικής ενεργειακής ζήτησης. Οι προκλήσεις αυτές αυξάνουν ραγδαία την ανάγκη για ευελιξία (flexibility) [6]. Η αξιοποίηση της υπάρχουσας ευελιξίας του συστήματος έναντι των δαπανηρών επενδύσεων για την ενίσχυση του δικτύου [7], αξιοποιώντας πλήρως τις δυνατότητες που προσφέρουν τα κυβερνο-φυσικά πλέον ΣΗΕ, μπορεί να δημιουργήσει τα απαραίτητα κίνητρα για «από τα κάτω προς τα πάνω» («bottom-up») επενδύσεις σε κατανεμημένες μονάδες ενέργειας και ευελιξίας, οι οποίες έχουν την δυνατότητα να καλύψουν ένα σημαντικό μέρος των αναγκών σε ευελιξία, τόσο στο επίπεδο του δικτύου διανομής όσο και σε αυτό του συστήματος μεταφοράς.

Μέχρι και σήμερα, οι κύριοι αγοραστές υπηρεσιών ευελιξίας, μέσω των αγορών Επικουρικών Υπηρεσιών ή μέσω διμερών μακροχρόνιων συμβάσεων, είναι οι TSOs με τους DSOs να μην έχουν αυτή τη δυνατότητα. Επιπλέον, η αλληλεπίδραση μεταξύ TSOs και DSOs είναι σχεδόν ανύπαρκτη, με τη διαδικασία εκκαθάρισης των αγορών ηλεκτρικής ενέργειας να μη λαμβάνει τους τεχνικούς περιορισμούς των δικτύων διανομής. Συνεπώς, η συμμετοχή κατανεμημένων μονάδων ενέργειας και ευελιξίας στις αγορές αυτές δύναται να θέσει σε κίνδυνο την εύρωστη λειτουργία των δικτύων μέσης και χαμηλής τάσης, οδηγώντας σε οικονομικά και τεχνικά μη αποδοτικά αποτελέσματα των αγορών. Αυτό υπαγορεύει: α) τη μετατόπιση του ρόλου του DSO προς έναν πιο **ενεργό διαχειριστή δικτύου διανομής** (**active distribution network operator**), και β) την ανάπτυξη **πλαισίων συνεργασίας μεταξύ TSOs-DSOs** (**TSO-DSO coordination schemes**) με στόχο τη μέγιστη αξιοποίηση των κατανεμημένων μονάδων και την ελαχιστοποίηση των λειτουργικών κοστών των δικτύων [8]. Για παράδειγμα, οι Αγορές Ευελιξίας (Flexibility Markets) σε τοπικό επίπεδο (δίκτυο διανομής) μπορούν αφενός να διασφαλίσουν ότι οι DSOs θα εξασφαλίσουν την απαραίτητη ευελιξία για την αντιμετώπιση πιθανών σφαλμάτων στα δίκτυά τους, και αφετέρου να δημιουργήσουν νέες ροές εισόδων για τους επενδυτές σε κατανεμημένες μονάδες ενέργειας και ευελιξίας. Επιπροσθέτων, ο σχεδιασμός πλαισίων συνεργασίας TSO-DSO είναι απαραίτητος, ώστε και ο TSO να μπορεί να επωφεληθεί από τη χαμηλού κόστους «πράσινη» ενέργεια και ευελιξία που παρέχεται από τους κατανεμημένους πόρους.

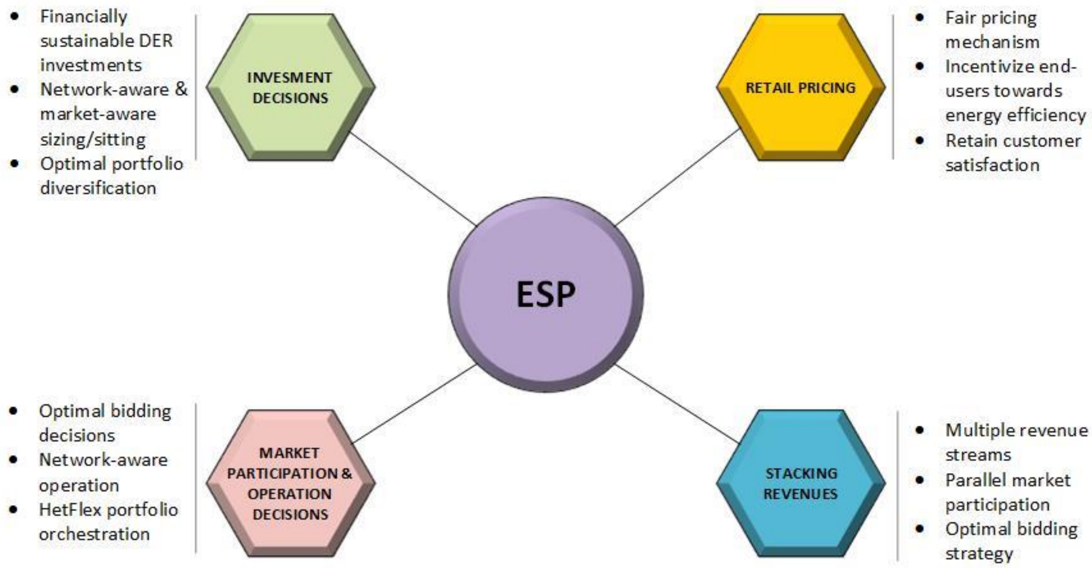
Το Επιχειρηματικό Μοντέλο ενός Παρόχου Ενεργειακών Υπηρεσιών

Στο πλαίσιο των απελευθερωμένων αγορών ηλεκτρικής ενέργειας και του απανθρακοποιημένου, αποκεντρωμένου και ψηφιοποιημένου Ευφυούς Δικτύου, αναδύεται το επιχειρηματικό μοντέλο ενός Παρόχου Ενεργειακών Υπηρεσιών (ΠΕΥ – Energy Service Provider – ESP). Στην παρούσα διατριβή θεωρούμε ότι ένας ΠΕΥ λειτουργεί αφενός ως Πάροχος Ηλεκτρικής Ενέργειας (Retailer), έχει δηλαδή πελάτες/τελικούς καταναλωτές των οποίων πρέπει να ικανοποιήσει τη ζήτηση, και αφετέρου κατέχει ένα χαρτοφυλάκιο κατανεμημένων μονάδων διαφόρων τεχνολογιών (π.χ. μονάδες παραγωγής, αποθήκευσης, απόκρισης της ζήτησης, κλπ.). Ο ΠΕΥ προσφέρει υπηρεσίες ενέργειας και ευελιξίας τόσο στον TSO όσο και στον DSO μέσω της συμμετοχής του στις αντίστοιχες αγορές ηλεκτρικής ενέργειας και της βέλτιστης διαχείρισης του χαρτοφυλακίου του (βλ. Εικόνα 1).



Εικόνα 1: Αρχιτεκτονική Συστήματος

Τον ρόλο του ESP μπορούν να τον αναλάβουν διάφορες οντότητες, όπως Φορείς Σωρευτικής Εκπροσώπησης (ΦοΣΕ – Aggregators), Πάροχοι Υπηρεσιών Εξισορρόπησης (ΠΥΕ – Balancing Service Providers – BSPs), Διαχειριστές Ενεργητικών Δικτύων Διανομής (Active Distribution Network Operators), Εκπρόσωποι Ενεργειακών Κοινοτήτων (Energy Community Controllers), κλπ. Επίσης, σχεδιάζουμε σχήματα συνεργασίας μεταξύ TSO-DSO, τα οποία επιτρέπουν την απρόσκοπτη συμμετοχή των κατανεμημένων μονάδων στις αγορές ενέργειας και ευελιξίας, τόσο στο επίπεδο του συστήματος διανομής όσο και σε αυτό του συστήματος μεταφοράς. Επομένως, οι ESPs μπορούν: α) να αγοραπωλούν ενέργεια μέσω των χονδρικών αγορών ηλεκτρικής ενέργειας (wholesale markets), β) να συμμετέχουν μέσω της συσσώρευσης των μονάδων ευελιξίας σε αγορές Επικουρικών Υπηρεσιών προσφέροντας υπηρεσίες ευελιξίας στους διαχειριστές των δικτύων, και γ) να πωλούν ενέργεια στους πελάτες τους (καταναλωτές) μέσω των απελευθερωμένων αγορών λιανικής (retail markets). Για να διασφαλίσει την οικονομική βιωσιμότητά του, ένας ESP θα πρέπει να λάβει βέλτιστες αποφάσεις, τόσο στο επενδυτικό στάδιο, όσο και στην επιχειρησιακή φάση (βλ. Εικόνα 2).



Εικόνα 2: Πλαίσιο Λήψης Αποφάσεων του ΠΕΥ

Η Διαδικασία Λήψης Επενδυτικών Αποφάσεων σε Κατανεμημένους Ενεργειακούς Πόρους

Η απελευθέρωση των αγορών ηλεκτρικής ενέργειας μαζί με τη διαρκώς αυξανόμενη διείσδυση των ΑΠΕ στο μείγμα ηλεκτροπαραγωγής έχει περιπλέξει ιδιαίτερα τη λήψη των επενδυτικών αποφάσεων. Οι επενδυτές είναι πλέον εκτεθειμένοι σε πολύ υψηλότερους κινδύνους, καθώς έχουν να αντιμετωπίσουν την αβεβαιότητα που σχετίζεται μεταξύ άλλων με τον ανταγωνισμό της αγοράς, τη ζήτηση, την παραγωγή από τις μονάδες ΑΠΕ και τις τιμές των καυσίμων. Προκειμένου να διασφαλιστεί η βιωσιμότητα των επενδύσεων, πρώτα από όλα, ο ΠΕΥ θα πρέπει να επιλέξει το βέλτιστο επενδυτικό μείγμα το οποίο θα δημιουργήσει ένα κερδοφόρο χαρτοφυλάκιο από διάφορες τεχνολογίες DERs. Για τον σκοπό αυτό, ο ΠΕΥ πρέπει να λάβει υπόψιν του τις τιμές και τον ανταγωνισμό των αγορών προκειμένου να εκτιμήσει με μεγαλύτερη ακρίβεια τα πιθανά κέρδη και εν τέλει την απόδοση των επενδύσεών του (market-aware planning decisions). Επιπλέον, οι επενδύσεις σε DERs θα πρέπει να γίνονται λαμβάνοντας υπόψιν τους τεχνικούς περιορισμούς του δικτύου διανομής, όπως τονίζεται στο [9], ώστε να διασφαλιστεί ότι οι καινούριες μονάδες δεν θα θέσουν σε κίνδυνο την αξιόπιστη και ομαλή λειτουργία του δικτύου διανομής. Ως εκ τούτου, η διαστασιολόγηση (sizing) και η χωροθέτηση (siting) των μονάδων πρέπει να επιλεγούν με τέτοιο τρόπο ώστε να είναι δυνατή η πλήρης αξιοποίηση του δυναμικού τους και να αποφευχθεί η υπερεκτίμηση/υποεκτίμηση της απόδοσης της επένδυσης (network-aware planning decisions).

Πολλές ερευνητικές μελέτες έχουν ασχοληθεί με επενδύσεις σε DERs λαμβάνοντας υπόψιν τους περιορισμούς του δικτύου διανομής. Οι σχετικές μελέτες μπορούν να χωριστούν σε 2 κατηγορίες με βάση το ποια οντότητα πραγματοποιεί τις επενδύσεις. Οι μελέτες που εμπίπτουν στην πρώτη κατηγορία (π.χ. [10], [11], [12], [13], [14], [15], [16], [17] και [18]) υποθέτουν ότι οι κατανεμημένες μονάδες ανήκουν και ελέγχονται από τον DSO. Σε αυτή την περίπτωση, η διαδικασία λήψης των επενδυτικών αποφάσεων μοντελοποιείται ως ένα πρόβλημα στοχαστικής βελτιστοποίησης με στόχο τον προσδιορισμό της διαστασιολόγησης των νέων μονάδων, την χωροθέτησή τους (επενδυτική φάση) και του χρονοπρογραμματισμού τους (λειτουργική φάση) κάτω από διαφορετικές συνθήκες λειτουργίας. Η αντικειμενική συνάρτηση σε αυτά τα προβλήματα βελτιστοποίησης περιλαμβάνει ένα ή παραπάνω κριτήρια, όπως: α) το κόστος της επένδυσης, β) τεχνικά κριτήρια (π.χ. ελαχιστοποίηση θερμικών απωλειών, απόκλισης τάσης, περικοπών φορτίων, κλπ.) ή γ) κριτήρια σχετικά με τις αγορές (ελαχιστοποίηση κόστους προμήθειας της ενέργειας από τη χονδρική αγορά) σε περίπτωση που ο DSO ενεργεί ως οντότητα της αγοράς. Το σύνολο των περιορισμών περιλαμβάνει τους τεχνικούς περιορισμούς του δικτύου διανομής και τους λειτουργικούς περιορισμούς των μονάδων ΚΕΠ, προκειμένου να διασφαλιστεί η ομαλή λειτουργία του δικτύου. Η δεύτερη κατηγορία περιλαμβάνει ερευνητικές μελέτες (π.χ. [19], [20], [21], [22], [23], [24], [25], [26]) οι οποίες υποθέτουν ότι οι επενδύσεις σε DERs πραγματοποιούνται από ιδιώτες ESPs. Οι μελέτες αυτές μοντελοποιούν προβλήματα βελτιστοποίησης πολλαπλών σταδίων (multi-stage) ή πολλαπλών επιπέδων (multi-level) με στόχο να προτείνουν πλαίσια συνεργασίας μεταξύ ESP-DSO, εντός των οποίων λαμβάνονται οικονομικά βιώσιμες επενδυτικές αποφάσεις λαμβάνοντας υπόψιν τους περιορισμούς των δικτύων διανομής. Η κύρια διαφορά με την προσέγγιση που υιοθετείται στην παρούσα διατριβή, είναι ότι οι μελέτες αυτές δεν λαμβάνουν υπόψιν την πρόθεση του TSO να αξιοποιήσει τη διαθέσιμη χαμηλού κόστους ενέργεια και ευελιξία που παρέχεται από τις κατανεμημένες μονάδες. Εξ όσων γνωρίζουμε, δεν έχει μοντελοποιηθεί στη βιβλιογραφία σχήμα ιδιωτικών επενδύσεων σε DERs, μέσα σε ένα πλαίσιο συνεργασίας DSO-TSO ώστε να διασφαλίζεται η απρόσκοπτη παροχή υπηρεσιών ενέργειας και ευελιξίας και στα δύο συστήματα (διανομής και μεταφοράς).

Συμμετοχή των Παρόχων Ενεργειακών Υπηρεσιών στις Αγορές και η Διαδικασία Λήψης Αποφάσεων στο Επιχειρησιακό Στάδιο

Εκτός των επενδυτικών αποφάσεων, ο ESP θα πρέπει να επιλέξει τη βέλτιστη στρατηγική συμμετοχής στις αγορές και παράλληλα, τον χρονοπρογραμματισμό των κατανεμημένων μονάδων ενέργειας και ευελιξίας. Ο ESP πρέπει να διαχειριστεί το χαρτοφυλάκιό του με τέτοιο τρόπο ώστε να μεγιστοποιήσει την κερδοφορία, του βελτιστοποιώντας τη συμμετοχή του στις απελευθερωμένες αγορές ηλεκτρικής ενέργειας. Ακόμα, όπως και στη φάση των επενδυτικών αποφάσεων, έτσι και στη φάση λειτουργίας των μονάδων, θα πρέπει να ληφθούν υπόψιν οι περιορισμοί του δικτύου διανομής (network-aware bidding strategy and operation), ώστε να αποφευχθεί το όποιο κόστος (οικονομικό ή κοινωνικό) που προκύπτει από το ενδεχόμενο εμφάνισης σφαλμάτων στο δίκτυο.

Στο παρελθόν, πολλές ερευνητικές μελέτες έχουν ασχοληθεί με το πρόβλημα απόφασης ενός ESP σχετικά με την κατάθεση προσφορών στις αγορές και την διαχείριση του χαρτοφυλακίου του, το οποίο περιέχει κατανεμημένη παραγωγή, ΣΑΕ, ευέλικτα και μη ευέλικτα φορτία. Μελέτες όπως οι [27], [28], [29], [30] και [31] προτείνουν στρατηγικές συμμετοχής σε διάφορες ηλεκτρικής ενέργειας για ESPs, οι οποίοι διαχειρίζονται χαρτοφυλάκια που περιλαμβάνουν DERs διαφόρων τεχνολογιών. Ωστόσο, οι μελέτες αυτές δεν λαμβάνουν υπόψιν τους περιορισμούς ασφαλείας των δικτύων διανομής. Έτσι, σε περιπτώσεις προβλημάτων τάσης ή συμφόρησης, θα χρειαστούν διορθωτικές ενέργειες, οι οποίες ωστόσο θα οδηγήσουν σε υψηλό χρηματικό ή κοινωνικό κόστος. Οι μελέτες [32] και [33] υπέθεσαν ότι Εταιρίες Διανομής (Distribution Companies - DisCos) ενεργούν ως ESPs και ασχολήθηκαν με τη συμμετοχή τους στις αγορές και το πρόβλημα χρονοπρογραμματισμού των μονάδων, διασφαλίζοντας παράλληλα και την αξιόπιστη λειτουργία του δικτύου διανομής, με το λαμβάνουν υπόψιν τους τεχνικούς περιορισμούς του δικτύου. Όλες οι προαναφερθείσες εργασίες, [27] – [33], θεώρησαν ότι οι αποφάσεις των ESPs δεν μπορούν να επηρεάσουν τις τιμές των αγορών. Η παραδοχή αυτή ονομάζεται ευρέως «price-taking» και λέμε ότι οι ESPs έχουν θεωρηθεί ως «price-takers». Ωστόσο, η ικανότητα των DERs να παράγουν και να αποθηκεύουν ενέργεια καθιστά τους ESPs ως «price-makers». Είναι ικανοί δηλαδή να επιδρούν στις τιμές των αγορών, εφαρμόζοντας εξισορροπητική κερδοσκοπία («αρμπιτράζ»), εναλλάσσοντας τους ρόλους τους κατά διαστήματα από παραγωγοί σε καταναλωτές και αντίστροφα. Επιπλέον, οι παραπάνω ερευνητικές μελέτες εξέτασαν επενδύσεις περιορισμένες σε ένα μόνο υποδίκτυο διανομής. Κατά συνέπεια, δεν υπάρχει μελέτη στη βιβλιογραφία μοντέλο συμμετοχής στις αγορές ηλεκτρικής ενέργειας ενός ESP που να ελέγχει και να συντονίζει κατανεμημένες μονάδες γεωγραφικά διασκορπισμένες σε διαφορετικά υποδίκτυα διανομής.

Παράλληλη Συμμετοχή των Παρόχων Ενεργειακών Υπηρεσιών σε Πολλαπλές Αγορές

Για να μειώσει τα επενδυτικά του ρίσκα και για να διασφαλίσει τη βιωσιμότητα των επενδύσεών του, ο ESP θα πρέπει να επιδιώξει να έχει διάφορες ροές εισόδων. Ανάλογα με τη σύνθεση του χαρτοφυλακίου του, τις υπηρεσίες που μπορεί να παρέχει στους διαχειριστές των δικτύων και τις ευκαιρίες κέρδους της εκάστοτε αγοράς, ο ESP θα πρέπει να αποφασίσει για τις αγορές (ενέργειας και ευελιξίας) που θα συμμετέχει. Στη συνέχεια, θα πρέπει να σχεδιάσει στρατηγικές συμμετοχής στις αγορές αυτές, οι οποίες θα μεγιστοποιήσουν τα έσοδά του από την παράλληλη συμμετοχή του σε παραπάνω από μία αγορές ηλεκτρικής ενέργειας (*Stacked Revenues*).

Η πρόσφατη βιβλιογραφία έχει ασχοληθεί με το πρόβλημα της μεγιστοποίησης της κερδοφορίας ενός ιδιώτη ESP που προσφέρει πολλαπλές υπηρεσίες στους διαχειριστές των δικτύων. Οι μελέτες [34], [35], [36], [37], [38] και [39] θεώρησαν ESPs με μονάδες ενέργειας και ευελιξίας συνδεδεμένες σε δίκτυα ΜΤ και ΧΤ, οι οποίοι παρέχουν ισχύ και επικουρικές υπηρεσίες τόσο στον TSO όσο και στον DSO. Ωστόσο, οι εργασίες αυτές υποθέτουν πως οι παρεχόμενες υπηρεσίες των ESPs προς τους DSOs είναι είτε υποχρεωτικές ή αποζημιώνονται βάσει μιας αυθαίρετα καθορισμένης από τους DSOs τιμής, χωρίς να εξετάζεται ο τρόπος υπολογισμού της.

Μηχανισμοί Λιανικής Τιμολόγησης

Στην εποχή των Έξυπνων Δικτύων, ένα πολύ σημαντικό εργαλείο στα χέρια των διαχειριστών των δικτύων για την διασφάλιση της ομαλής λειτουργίας των ΣΗΕ είναι η Διαχείριση της Ζήτησης (Demand Side Management – DSM). Το σκεπτικό πίσω από το Demand Side Management είναι η κινητροδότηση των τελικών χρηστών ώστε να υιοθετήσουν ενεργειακά αποδοτικές συνήθειες κατανάλωσης της ηλεκτρικής ενέργειας. Οι ESPs μπορούν να σχεδιάσουν έξυπνες και αποτελεσματικές πολιτικές τιμολόγησης που θα προκαλέσουν αλλαγές στην συμπεριφορά των πελατών τους (καταναλωτές), παρέχοντάς τους ελκυστικά οικονομικά κίνητρα. Αυτό θα οδηγήσει σε χαμηλότερα κόστη αγοράς της ενέργειας για τον ESP και, ταυτόχρονα, θα τους παρέχει επιπρόσθετη ευελιξία που θα αυξήσει τα έσοδά τους από την παροχή επικουρικών υπηρεσιών στους TSOs/DSOs.

Στο πλαίσιο των απελευθερωμένων λιανικών αγορών ηλεκτρισμού, ένας μηχανισμός τιμολόγησης πρέπει να επιτυγχάνει έναν αποδοτικό συμβιβασμό μεταξύ των ακόλουθων επιθυμητών ιδιοτήτων: (1) Ευημερία των καταναλωτών, (2) ενεργειακό κόστος, και (3) 'δίκαιη' κατανομή του κόστους ενέργειας. Η πρώτη ιδιότητα καθορίζει την προθυμία των τελικών χρηστών να συμμετάσχουν σε ένα DSM πρόγραμμα. Ο στόχος των DSM προγραμμάτων που προτείνονται στις μελέτες [40], [41], [42] και [43] είναι η μεγιστοποίηση της ευημερίας των συμμετεχόντων στο πρόγραμμα. Η δεύτερη ιδιότητα εκφράζει την ικανότητα του μηχανισμού να κινητροδοτεί τους καταναλωτές να υιοθετήσουν ενεργειακά αποδοτικά μοτίβα κατανάλωσης και τελικά να εκπληρώσουν τον στόχο που θέτει ο ESP (μείωση ενεργειακού κόστους). Οι ερευνητικές εργασίες [44], [45], [46], [47] και [48] επινόησαν DSM αλγόριθμους προκειμένου να ελαχιστοποιήσουν το ενεργειακό κόστος. Τέλος, η τρίτη ιδιότητα αναφέρεται στο πόσο δίκαια κατανέμεται η εξοικονόμηση τους κόστους ενέργειας μεταξύ των τελικών χρηστών. Οι μελέτες [49], [50] και [51] επιλέγουν τη βελτίωση της 'Δικαιοσύνης' του DSM προγράμματος. Η αποδοτικότητα (ελαχιστοποίηση κόστους) στη μελέτη [49] θυσιάζεται για να επιτευχθούν υψηλότερα επίπεδα 'Δικαιοσύνης', ενώ στη [50] μελετάται η αντιστάθμιση μεταξύ ελαχιστοποίησης κόστους και 'Δικαιοσύνης', αγνοώντας ωστόσο την ευημερία των χρηστών. Ο συμβιβασμός μεταξύ των τριών προαναφερθέντων ιδιοτήτων δεν έχει μελετηθεί στη βιβλιογραφία.

Μοντελοποίηση της Λήψης Αποφάσεων ενός ESP

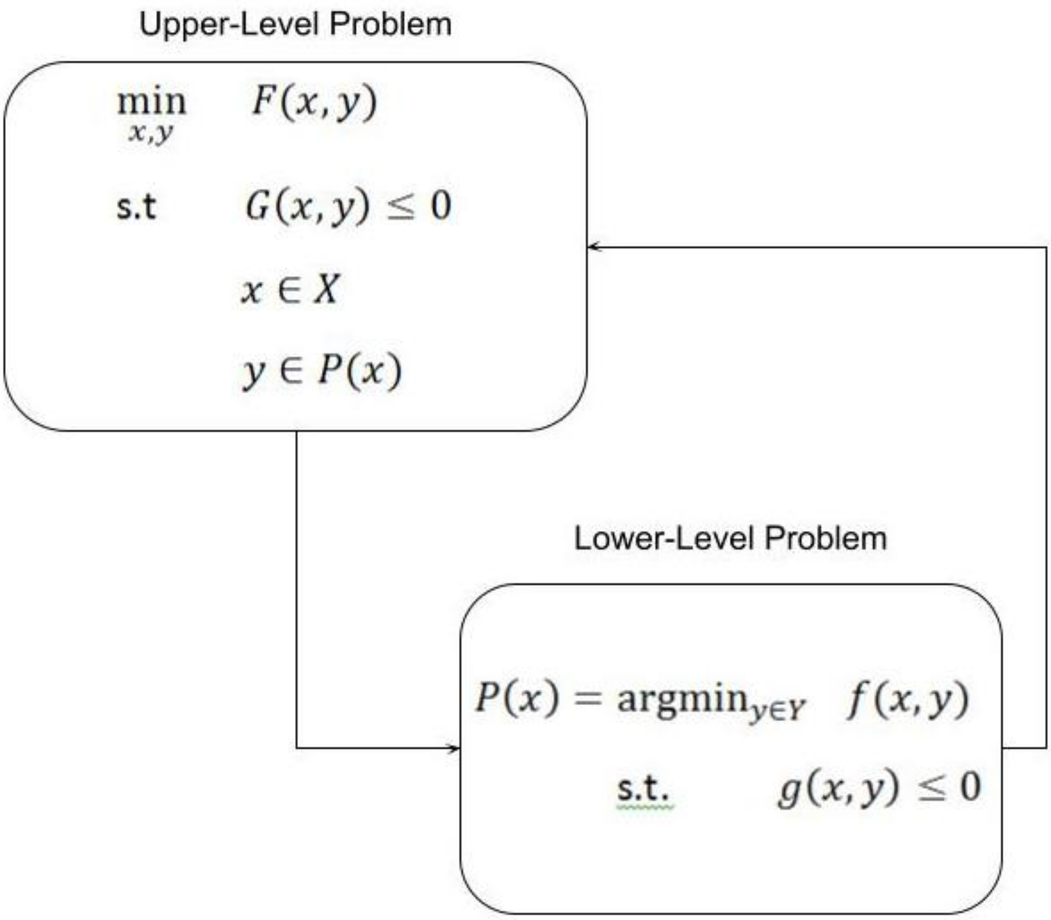
Μοντελοποίηση Διεπίπεδου Προγραμματισμού

Ο Διεπίπεδος Προγραμματισμός (ΔΠ – Bilevel Programming – BP) αναφέρεται στον κλάδο της Μαθηματικής Βελτιστοποίησης που ασχολείται με προβλήματα με ιεραρχική δομή [52]. Η έννοια του Διεπίπεδου Προγραμματισμού προέρχεται από το πεδίο της Θεωρίας Παιγνίων και συστήθηκε από τον Heinrich Freiherr von Stackelberg [53], με τους Bracken και McGill να παρουσιάζουν την πρώτη μαθηματική μοντελοποίηση [54]. Ένα πρόβλημα ΔΠ περιλαμβάνει δύο επίπεδα λήψης αποφάσεων: έναν Ηγέτη (*Leader*) και έναν ή περισσότερους Ακόλουθους (*Followers*) (βλ. Εικόνα 3).

Όπως απεικονίζεται στην Εικόνα 3, ο Ηγέτης στο Πάνω-Επίπεδο (Upper-Level) βελτιστοποιεί την αντικειμενική του συνάρτηση, λαμβάνοντας υπόψιν ένα σύνολο περιορισμών, το οποίο εν μέρει αποτελείται από τις βέλτιστες αποφάσεις του Ακόλουθου στο Κάτω-Επίπεδο (Lower-Level). Οι αποφάσεις του Ηγέτη επηρεάζουν την εφικτή περιοχή (feasible region) και την αντικειμενική συνάρτηση του προβλήματος βελτιστοποίησης του Κάτω-Επιπέδου. Έπειτα, η αντίδραση του Ακόλουθου (βέλτιστη λύση του προβλήματος στο Κάτω-Επίπεδο) έχει σημαντικό αντίκτυπο στη βέλτιστη απόφαση του Ηγέτη. Εν τέλει, ένα πρόβλημα ΔΠ είναι το πρόβλημα βελτιστοποίησης του Ηγέτη, διατυπωμένο χρησιμοποιώντας τον γράφο του συνόλου των λύσεων του προβλήματος βελτιστοποίησης του Ακόλουθου.

Ο Διεπίπεδος Προγραμματισμός είναι πολύ σημαντικός στη μοντελοποίηση λήψης αποφάσεων στις απελευθερωμένες αγορές ηλεκτρικής ενέργειας, καθώς παρέχει μοντέλα και εργαλεία για την κατανόηση της λειτουργίας αυτών των αγορών και τη λήψη αποφάσεων εκ μέρους διαφόρων δημόσιων ή ιδιωτικών οντοτήτων. Πιο συγκεκριμένα, ο ΔΠ μας επιτρέπει:

- Να χειριζόμαστε άμεσα πρωτεύουσες (primal) και δυικές (dual) μεταβλητές.
- Να αποτυπώνουμε αντίρροπα συμφέροντα διαφορετικών οντοτήτων, καθώς αυτά αντικατοπτρίζονται στις αντικειμενικές συναρτήσεις στο Πάνω- και στο Κάτω-Επίπεδο.
- Να μοντελοποιούμε επενδυτικά μοντέλα κλειστού βρόχου (closed-loop) μέσω της αποσύνδεσης των αποφάσεων σχετικά με το επενδυτικό από το επιχειρησιακό στάδιο.
- Να σχεδιάζουμε πλαίσια συνεργασίας μεταξύ των διαχειριστών των συστημάτων (DSO-TSO).
- Να μοντελοποιούμε την στρατηγική συμπεριφορά συμμετεχόντων στις αγορές, των οποίων οι αποφάσεις επηρεάζουν τα αποτελέσματα των αγορών (price-makers).
- Να διεξάγουμε ανάλυση ισορροπίας (equilibrium analysis) των αγορών ηλεκτρικής ενέργειας με ολιγοπωλιακά χαρακτηριστικά.



Εικόνα 3: Η ιεραρχική δομή ενός προβλήματος ΔΠ

Τα τελευταία χρόνια, η ΔΠ έχει χρησιμοποιηθεί εκτενώς στη βιβλιογραφία για την μοντελοποίηση διαδικασιών λήψης απόφασης τόσο στο επενδυτικό όσο και στο επιχειρησιακό στάδιο του απορυθμισμένου τομέα της ηλεκτρικής ισχύος. Μελέτες όπως οι [55], [56], [57] και [58] χρησιμοποίησαν μοντέλα ΔΠ για αποφάσεις σχετικά με τον σχεδιασμό των ΣΗΕ από τους διαχειριστές των δικτύων. Στο πρόβλημα βελτιστοποίησης του Πάνω-Επιπέδου, ο TSO υπολογίζει τις βέλτιστες επενδύσεις σε χωρητικότητα των γραμμών ή σε ΣΑΕ ελαχιστοποιώντας τα κόστη επένδυσης και λειτουργίας του δικτύου, με το πρόβλημα στο Κάτω-Επίπεδο να αντιστοιχεί στη διαδικασία εκκαθάρισης της χονδρικής αγοράς ενέργειας. Μία άλλη κατηγορία μελετών εξέτασε ιδιώτες ESPs που επιδιώκουν να επενδύσουν σε συμβατική παραγωγή ([59], [60], [61], [62]), μονάδες ΑΠΕ ([63], [64], [65]) και μονάδες ΣΑΕ ([[66], [67], [68], [69]]) με στόχο τη μεγιστοποίηση της απόδοσης της επένδυσής τους (Πάνω-Επίπεδο), λαμβάνοντας παράλληλα υπόψιν τον τρόπο με τον οποίο οι επενδυτικές τους αποφάσεις επηρεάζουν τα αποτελέσματα της διαδικασίας εκκαθάρισης της αγοράς ενέργειας (Κάτω-Επίπεδο). Επιπλέον, πολλοί ερευνητές έχουν ασχοληθεί με τον σχεδιασμό της στρατηγικής συμμετοχής ενός ESP σε μία ή περισσότερες αγορές ηλεκτρικής ενέργειας. Οι ερευνητές αυτοί έχουν προτείνει στρατηγικές συμμετοχής σε αγορές για παραγωγούς ([70], [71], [72], [73], [74], [75], [76], [77], [78]), ιδιοκτήτες ΣΑΕ ([79], [80], [81], [82], [83], [84]), παρόχους ηλεκτρικής ενέργειας ([85], [86]) και εικονικούς πλειοδότες (virtual/convergence bidders) ([87]) που συμμετέχουν στην αγορά ενέργειας ή και σε αγορές επικουρικών υπηρεσιών.

Γενικά, τα προβλήματα βελτιστοποίησης ΔΠ είναι εξαιρετικά μη κυρτά (non-convex) προβλήματα. Η συνηθέστερη προσέγγιση επίλυσής τους είναι η μετατροπή τους σε προβλήματα ενός επιπέδου. Για τον σκοπό αυτόν, το πρόβλημα βελτιστοποίησης του Κάτω-Επιπέδου αντικαθίσταται από τις (υπό ορισμένες παραδοχές) αναγκαίες και ικανές συνθήκες ύπαρξης βέλτιστων σημείων, τις συνθήκες Karush-Kuhn-Tucker (KKT). Με τον τρόπο αυτόν, ένα πρόβλημα ΔΠ μετατρέπεται σε Μαθηματικό Πρόβλημα με Περιορισμούς Ισορροπίας (Mathematical Program with Equilibrium Constraints – MPEC), το οποίο είναι ένα πρόβλημα Μικτού Μη Γραμμικού Ακέραιου Προγραμματισμού (Mixed Integer Non Linear Programming – MINLP). Στη συνέχεια, χρησιμοποιώντας συγκεκριμένες τεχνικές γραμμικοποίησης, το MINLP πρόβλημα μετατρέπεται τελικά σε ένα πρόβλημα Μικτού Γραμμικού Ακέραιου Προγραμματισμού (Mixed Integer Linear Programming – MILP), το οποίο μπορεί να επιλυθεί χρησιμοποιώντας ήδη υπάρχοντες αλγορίθμους. Ωστόσο, με τη μέθοδο αυτή, μεγάλης κλίμακας στοχαστικά προβλήματα ΔΠ ενδεχομένως να μην μπορούν να λυθούν μέσα σε ένα αποδεκτό χρονικό διάστημα. Προκειμένου να μειωθεί η ταχύτητα επίλυσης των προβλημάτων αυτών και να ενισχυθεί η δυνατότητα κλιμάκωσής τους (scalability), έχουν προταθεί αλγόριθμοι που μειώνουν την πολυπλοκότητα των μοντέλων ΔΠ, όπως οι τεχνικές αποσύνθεσης ([88]).

Διαχείριση της Ζήτησης και Θεωρία Παιγνίων

Η Θεωρία Παιγνίων θεωρείται ένα βασικό εργαλείο ανάλυσης στον σχεδιασμό DSM προγραμμάτων, επιτρέποντας στους ESPs να βελτιστοποιούν και να προσαρμόζουν τις πολιτικές τιμολόγησης στην κατάσταση των δικτύων και των αγορών ηλεκτρικής ενέργειας. Η Θεωρία Παιγνίων είναι ένα αναλυτικό και εννοιολογικό πλαίσιο που μελετά τις στρατηγικές αλληλεπιδράσεις μεταξύ ορθολογικών πρακτόρων (agents) και μπορεί να χωριστεί σε δύο κύριους κλάδους: α) Συνεργατική Θεωρία Παιγνίων και β) Μη Συνεργατική Θεωρία Παιγνίων. Η Συνεργατική Θεωρία Παιγνίων υποθέτει ότι οι πράκτορες μπορούν να συνεργαστούν και να δράσουν από κοινού ως μία οντότητα, ώστε να αυξήσουν τα οφέλη τους. Αντίθετα, η Μη Συνεργατική Θεωρία Παιγνίων μπορεί να χρησιμοποιηθεί για να αναλυθούν οι διαδικασίες λήψης στρατηγικών αποφάσεων ανεξάρτητων πρακτόρων, οι οποίοι έχουν εν μέρει ή πλήρως αντικρουόμενα συμφέροντα όσον αφορά το αποτέλεσμα του Παιγνίου που επηρεάζεται από τις αποφάσεις τους. Ουσιαστικά, τα Μη Συνεργατικά Παίγνια αποτυπώνουν μία κατανεμημένη διαδικασία λήψης αποφάσεων που επιτρέπει στον κάθε πράκτορα, χωρίς καμία επικοινωνία με τους υπόλοιπους, να μεγιστοποιεί τα προσωπικά του οφέλη, τα οποία εξαρτώνται και από τις ενέργειες των υπολοίπων πρακτόρων. Ένα Μη Συνεργατικό Παίγνιο ορίζεται από:

- Το σύνολο των *Παικτών*: $\boldsymbol{N}$
- Τα σύνολα των *Στρατηγικών* κάθε *Παίκτη* i: $(\boldsymbol{S_i})_{i\in\boldsymbol{N}}$
- Τα σύνολα των *Ωφελειών* των *Παικτών*: $(u_i)_{i\in\boldsymbol{N}}$

Σε ένα τέτοιο Μη Συνεργατικό Παίγνιο, κάθε *Παίκτης* i επιλέγει μία *Στρατηγική* $s_i \in \boldsymbol{S_i}$ με στόχο να μεγιστοποιήσει των *Ωφέλειά* του $u_i(s_i, \boldsymbol{s_{-i}})$, η οποία δεν εξαρτάται μόνο από την δική του επιλογή s_i, αλλά και από το σύνολο των *Στρατηγικών* που επιλέγουν οι υπόλοιποι *Παίκτες* $\boldsymbol{N}\backslash\{i\}$, το οποίο συμβολίζεται ως $\boldsymbol{s}_{-i}$. Ο στόχος της Μυ Συνεργατικής Θεωρίας Παιγνίων είναι να παρέχει μεθόδους και αλγορίθμους κατάλληλους για την επίλυση τέτοιων προβλημάτων βελτιστοποίησης, την ανάλυση των αποτελεσμάτων τους και στην τελική την εύρεση της Ισορροπίας Nash (Nash Equilibrium). Η Ισορροπία Nash χαρακτηρίζει μία κατάσταση του Παιγνίου κατά την οποία κανένας *Παίκτης* i δεν μπορεί να βελτιώσει την *Ωφέλειά* του u_i αλλάζοντας μονομερώς την *Στρατηγική* του s_i, δεδομένου ότι οι *Στρατηγικές* των υπολοίπων *Παικτών* $\boldsymbol{s_{-i}}$ είναι σταθερές.

Μη Συνεργατικά Παίγνια έχουν προταθεί εκτενώς στη βιβλιογραφία ([89]) προκειμένου να σχεδιαστούν προγράμματα DSM βάσει τιμής, όπου ο καταναλωτής θεωρείται ως ένας ορθολογικός *Παίκτης* που αποκομίζει *Ωφέλεια* από τον τρόπο που καταναλώνει την ηλεκτρική ενέργεια (*Στρατηγική*). Ως εκ τούτου, ο καταναλωτής επιλέγει ένα συγκεκριμένο μοτίβο κατανάλωσης προκειμένου να μεγιστοποιήσει την *Ωφέλειά* του, με βάση ένα συγκεκριμένο οικονομικό κίνητρο (τιμή) που παρέχεται από τον σχεδιαστή του προγράμματος DSM.

Συνεισφορά και Δομή της Διατριβής

Στη διατριβή αυτή, ασχολούμαστε με το πλαίσιο λήψης αποφάσεων ενός ESP, στόχος του οποίου είναι να διασφαλίσει την οικονομική βιωσιμότητα των επενδύσεών του σε κατανεμημένους πόρους ενέργειας και ευελιξίας. Πιο συγκεκριμένα, προτείνουμε αλγοριθμικά εργαλεία που μοντελοποιούν τις τέσσερις διαδικασίες λήψης αποφάσεων που απεικονίζονται στην Εικόνα 2.

Αρχικά, για να καλύψουμε το κενό στη σχετική βιβλιογραφία που συζητήθηκε παραπάνω, χρησιμοποιούμε μοντέλα ΔΠ προκειμένου να ορίσουμε ένα σχήμα συντονισμού μεταξύ DSO-TSO. Σε αυτό το πλαίσιο, προτείνουμε ένα επενδυτικό μοντέλο σε DERs, το οποίο: (α) εγγυάται την απόδοση των επενδύσεων του ESP, (β) λαμβάνει υπόψιν τον αντίκτυπο των καινούριων μονάδων στις τιμές της αγοράς και (γ) διασφαλίζει την ομαλή λειτουργία του δικτύου διανομής. Για να λύσουμε το πρόβλημα αυτό αποτελεσματικά και με δυνατότητα κλιμάκωσης, προτείνουμε έναν αλγόριθμο Εμφωλευμένης Αποσύνθεσης (Nested Decomposition) που βασίζεται στις τεχνικές Lagrangian Relaxation και Bender’s Decomposition. Στο Κεφάλαιο 2 περιγράφονται τα ανοιχτά ερευνητικά ζητήματα στο συγκεκριμένο ερευνητικό πεδίο, παρουσιάζεται αναλυτικά το προτεινόμενο μοντέλο ΔΠ, περιγράφεται ο αλγόριθμος επίλυσης και αξιολογείται το συνιστώμενο επενδυτικό πλαίσιο.

Στο Κεφάλαιο 3 της διατριβής μελετάται η στρατηγική συμμετοχή στην χονδρική αγορά ενέργειας ενός ESP που διαθέτει ένα χαρτοφυλάκιο από διαφορετικής τεχνολογίας κατανεμημένες μονάδες ενέργειας και ευελιξίας εγκατεστημένες σε διάφορες γεωγραφικές περιοχές. Στο Κεφάλαιο αυτό, υποθέτουμε μια καθετοποιημένη οργάνωση του δικτύου διανομής, με μία Εταιρία Διανομής (DisCo) να έχει τον άμεσο έλεγχο των μονάδων, εκπροσωπώντας τις στη χονδρική αγορά ενέργειας. Σε αντίθεση με τις πρόσφατες σχετικές ερευνητικές μελέτες που υποθέτουν ότι οι DisCos λειτουργούν ως “price-takers”, στην διατριβή αυτή θεωρούμε ότι η εφαρμογή εξισορροπητικής κερδοσκοπίας μπορεί να έχει αντίκτυπο στις τιμές της αγοράς. Συνεπώς, διαμορφώνουμε ένα πρόβλημα βελτιστοποίησης ΔΠ προκειμένου να υπολογίζουμε τη βέλτιστη στρατηγική συμμετοχής στην αγορά για μία “price-maker” DisCo που λειτουργεί ως ESP. Το πρόβλημα ΔΠ μετατρέπεται σε ένα πρόβλημα MILP χρησιμοποιώντας την MPEC μέθοδο που περιγράφτηκε προηγουμένως. Τα αποτελέσματα των προσομοιώσεων καταδεικνύουν ότι μία DisCo μπορεί να μειώσει σημαντικά το ενεργειακό κόστος λειτουργίας του δικτύου διανομής συμμετέχοντας στρατηγικά στην αγορά και πώς τα αποτελέσματα της αγοράς επηρεάζονται από τις ενέργειές της.

Στο 4^{ο} Κεφάλαιο της διατριβής θεωρούμε απορυθμισμένη λειτουργία του δικτύου διανομής, με τον ρόλο του DSO να περιορίζεται στην εξασφάλιση της εύρυθμης λειτουργίας του δικτύου. Προτείνουμε μία καινοτόμα αρχιτεκτονική αγορών ενέργειας, με την εισαγωγή μίας Αγοράς Ευελιξίας στο επίπεδο του Δικτύου Διανομής (Distribution-Level Flexibility Market), μέσω της οποίας ο DSO εξασφαλίζει την απαραίτητη ευελιξία για την αποφυγή προβλημάτων συμφόρησης και τάσης. Οι αλληλεπιδράσεις μεταξύ των αγορών στα επίπεδα της μεταφοράς και της διανομής περιγράφονται ρητά. Σε αντίθεση με την σχετική βιβλιογραφία, η διαδικασία εκκαθάρισης της αγοράς DLFM ποσοτικοποιεί ρητά την ανάγκη για ευελιξία ανά κόμβου του δικτύου διανομής και υπολογίζει τις βέλτιστες οριακές κομβικές τιμές στη διανομή (Distribution Locational Marginal Prices – DLMPs), οι οποίες αντικατοπτρίζουν με ακρίβεια το κόστος της ευελιξίας. Σε αυτό το περιβάλλον, ένας ESP που έχει στη διάθεσή του ένα χαρτοφυλάκιο από κατανεμημένες μονάδες ΣΑΕ, προσφέρει υπηρεσίες ενέργειας και ευελιξίας τόσο στον DSO όσο και στον TSO, μέσω της συμμετοχής του στις αντίστοιχες αγορές. Μοντελοποιείται η διαδικασία λήψης απόφασης του ESP όσον αφορά τη βέλτιστη παράλληλη συμμετοχή του στις αγορές αυτές. Για τον σκοπό αυτό, προτείνεται ένα μοντέλο ΔΠ για το πρόβλημα της βέλτιστης συμμετοχής του ESP στις αγορές και του αντίστοιχου χρονοπρογραμματισμού των μονάδων ΣΑΕ. Για να λύσουμε το μοντέλο αυτό αποδοτικά και με δυνατότητα κλιμάκωσης, το μετασχηματίζουμε πρώτα σε ένα MINLP πρόβλημα χρησιμοποιώντας την MPEC μέθοδο και εν συνεχεία εφαρμόζουμε μια καινοτόμα επαναληπτική διαδικασία.

Στο 5^{ο} Κεφάλαιο της διατριβής επισημαίνεται η απουσία από την βιβλιογραφία ενός μηχανισμού λιανικής τιμολόγησης της ενέργειας που να λαμβάνει ταυτόχρονα υπόψιν τις τρεις ιδιότητες που περιγράφονται παραπάνω. Παρουσιάζουμε έναν καινοτόμο μηχανισμό εξατομικευμένης τιμολόγησης της ενέργειας, που τον ονομάζουμε Behavioral Real Time Pricing (B-RTP) υποθέτοντας στρατηγικούς (“price-maker”) τελικούς χρήστες. Το προτεινόμενο «δίκαιο» πρόγραμμα DSM κινητροδοτεί τους συμμετέχοντες να υιοθετήσουν ενεργειακά αποδοτικά πρότυπα κατανάλωσης. Εισάγουμε επίσης έναν μηχανισμό παραμετροποίησης της προτεινόμενης πολιτικής τιμολόγησης, ο οποίος επιτρέπει στον ESP να προσαρμόζει δυναμικά το ύψος της κινητροδότησης. Με τον τρόπο αυτόν, ο ESP μπορεί να επιλέξει τον πιο ελκυστικό συμβιβασμό μεταξύ του ενεργειακού κόστους, της ευημερίας των συμμετεχόντων και της «Δικαιοσύνης» του μηχανισμού. Συγκρίνοντας τον προτεινόμενο μηχανισμό (B-RTP) με μία έκδοση του ευρέως χρησιμοποιημένου από την βιβλιογραφία RTP μηχανισμού, αποδεικνύουμε ότι ο B-RTP μηχανισμός υπερέχει του RTP όντας πιο «δίκαιος» και μειώνοντας το ενεργειακό κόστος, χωρίς να θυσιάζεται η ευημερία των τελικών χρηστών.

Στο 6^{ο} και τελευταίο Κεφάλαιο συνοψίζονται οι συνεισφορές της διατριβής, αναλύονται τα πιο σημαντικά ερευνητικά ευρήματα και προτείνονται πιθανές κατευθύνσεις για περαιτέρω επέκταση της έρευνάς μας. Τέλος, αναλύουμε τη χρησιμότητα της παρούσας έρευνας για διάφορους ενδιαφερόμενους.

Γλωσσάριο αντιστοιχίας τεχνικών όρων

Ancillary Services	Επικουρικές Υπηρεσίες
Balancing Market	Αγορά Εξισορρόπησης
Bi-level Programming	Διεπίπεδος Προγραμματισμός
Constraints	Περιορισμοί
Day-Ahead Energy Market	Προημερήσια Αγορά Ενέργειας
Decomposition	Αποσύνθεση
Distributed Energy Resources	Κατανεμημένοι Ενεργειακοί Πόροι
Distribution Company	Εταιρία Διανομής
Demand Side Management	Διαχείριση Ζήτησης
Distribution System Operator	Διαχειριστής Συστήματος Διανομής
Energy Service Provider	Πάροχος Ενεργειακών Υπηρεσιών
Flexibility Market	Αγορά Ευελιξίας
Mixed Integer Linear Programming	Μικτός Ακέραιος Γραμμικός Προγραμματισμός
Mathematical Program with Equilibrium Constraints	Μαθηματικό Πρόβλημα με Περιορισμούς Ισορροπίας
Objective Function	Αντικειμενική Συνάρτηση
Price-Maker	Διαμορφωτής τιμών
Price-Taker	Δέκτης τιμών
Renewable Energy Sources	Ανανεώσιμες Πηγές Ενέργειας
Reserve Market	Αγορά Εφεδρειών
Scalability	Δυνατότητα κλιμάκωσης
Smart Grid	Έξυπνο Δίκτυο
Transmission System Operator	Διαχειριστής Συστήματος Μεταφοράς