NATIONAL TECHNICAL UNIVERSITY OF ATHENS

SCHOOL OF CHEMICAL ENGINEERING

Department of Process Analysis and Plant Design

Laboratory of Industrial & Energy Economics

MULTI-OBJECTIVE OPTIMIZATION OF DISTRIBUTED ENERGY SYSTEMS WITH FOCUS ON ROBUST SOLUTIONS

Marios Karmellos

A thesis submitted for the degree of
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Athens, 2019

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Doctoral Thesis

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To my parents,

Ioakim & Chrystalla

for all their support

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Marios Karmellos

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Executive Summary

Primary energy consumption has increased exponentially in the last decades due to global economic growth. Energy is necessary for all aspects of modern life and is used in many sectors, such as electricity, heating and cooling generation, transportation and industry. However, energy consumption comes at a cost. Conventional energy systems rely on fossil fuels which have high carbon dioxide (CO_2) emissions. As a result, the environment is affected due to the contribution of CO_2 emissions to the greenhouse effect and by extension to climate change. Providing clean energy and tackling climate change are two of the most important challenges our planet faces. In the last years, the international community took measures to reduce CO_2 emissions, such as the Kyoto protocol and more recently the Paris Agreement. European Union (EU) is implementing an ambitious set of policies in the fields of energy efficiency, promotion of renewable energy sources (RES) and reduction of CO_2. Greece has also released an ambitious national energy plan recently based on European energy policies.

Moreover, in the last decades global population has increased dramatically, which leads to increased consumption of resources, including energy. Additionally, it has been calculated that about 52% of the global population live in cities, with the number expected to rise in the following decades. Urban areas account to a large share of energy demand, which leads to several challenges in order to satisfy it. In this context, urban energy systems are expected to play a significant role. The future urban energy systems need to be redesigned and offer sustainable solutions.

A solution towards this goal is the development of Distributed Energy Systems (DES). DES have many advantages, with the most significant one being the local energy generation which minimizes energy losses. DES can offer better integration between conventional energy systems and renewables and can satisfy the energy demand at a single building, a complex of buildings or even up to a whole city with a varied degree of decentralization. A DES can be designed to satisfy local energy needs in electricity, heating, and cooling. Also, they can lead to a reduction of total annual cost (TAC) and CO_2 emissions. In the last years, several models have been proposed for the design of DES, based on mathematical programming. Those models applied either single- or multi- objective optimization problems with the most common objective functions being the minimization of TAC (which includes capital, operational and maintenance costs) and CO_2 emissions.

Designing a DES is a complex problem in which many aspects need to be considered. This thesis aims to provide a methodology for the optimal design of DES using multi-objective mixed-integer linear programming (MILP), with TAC and CO_2 emissions as the objective functions. The candidate technologies are: (a) cogeneration units, (b) heat pumps, (c) absorption chillers, (d) boilers, (e) solar thermal collectors, (f) solar photovoltaics, (g) wind turbines, (h) thermal energy storage, (i) electric energy storage, (j) district heating network (DHN) and (k) microgrid. The results offer as outputs the selected technologies and their respective sizes at each building, the layout of the DHN (if formed), the operational profile of the installed technologies, and the electricity exchange through the microgrid (if selected) and the national grid. Additionally, in literature all the developed methods can be broadly separated into two categories, namely: (a) "Method A" in which a simultaneous selection and sizing of candidate technologies and (b) "Method B" in which the sizes of the candidate technologies are predefined.

This thesis presents some innovative aspects in the field of optimal design of DES. Particularly, two approaches for the modelling of technologies are developed, expanding previous relevant work in literature. In addition, mathematical models for all available candidate technologies are presented. Those approaches are compared as they offer different solutions, and their advantages and disadvantages are assessed. Moreover, this thesis examines the robustness of solutions and it combines multi-objective mathematical programming with several techniques for optimization under uncertainty.

To examine the benefits of DES and to compare these two methods, a case study was carried out for a neighbourhood of six buildings in an area in Attica and three scenarios are depicted, with Scenario 1 being business-as-usual, Scenario 2 – Renewables and Scenario 3 – Green. The results show that between these three scenarios, Scenario 3 offers the most attractive solutions. In addition, the comparison between "Method A" and "Method B" shows that "Method A" offers better results at each solution, specifically between 3% and 11% for TAC, which was expected due to the higher degrees of freedom it has. Regarding carbon emissions both methods show similar results. Moreover, several differences exist between each solution at each method regarding system's structure, operational profiles of technologies, formation of DHN and electricity exchange with microgrid and national grid. A recommended strategy for designing a DES it is suggested to apply "Method A" at first to get a first approximation of the capacities of technologies, and afterwards, when the capacity bounds become constrained (which means less combinations and therefore lower computational complexity) apply "Method B" which will offer more accurate results.

Furthermore, this thesis aims to examine the optimal design of DES under uncertainty. Changes in the values of several parameters can affect the optimal design of a DES, and the scope of this thesis is to provide a decision-maker (DM) with robust solutions. In this thesis uncertainty is assumed to exist in energy prices (electricity and natural gas), interest rate, energy loads (electricity, heating, and cooling), solar radiation, and wind speed. To examine uncertainty and identify robust solutions four techniques are used, which are in the fields of robust optimization (RO) and stochastic optimization (SO), namely: (a) objective-wise worst case, (b) minimax regret criterion (MMR), (c) minimax expected regret (MER) and (d) Monte Carlo simulations. Those techniques are applied to “Method A” either as multi-objective optimization problem (objective-wise method) or as single-objective optimization problems (MMR, MER and Monte Carlo simulations). For the transformation of the multi-objective deterministic problem to a single-objective one it is assumed that the TAC is the objective function and carbon emissions becoming a constraint with an upper bound of 100,000 kg/year.

For the application of MMR and MER it is assumed that uncertainty exists only in economic parameters (interest rate and energy prices) and five scenarios are depicted, namely Scenario R1 to Scenario R5, where parameters take a high and low value respectively. Regarding the application of MER, it is assumed that each Scenario R1 to R5 has a specific probability to occur, which leads to less conservative results. As for the application of objective-wise worst case and Monte Carlo simulations, two scenarios are depicted for each method, Scenarios OW1 and OW2 and Scenarios MC1 and MC2, respectively. Scenarios OW1 and MC1 assume that uncertainty exists in economic parameters, while Scenarios OW2 and MC2 assume uncertainty in all parameters. Each method generates different solutions, with the worst results occurring at objective-wise worst-case method as it considers the worst value of the uncertain parameters. MMR and MER show solutions with small values of regret, indicating that uncertainty in economic parameters does not affect results significantly. Finally, at the application of Monte Carlo simulations each parameter is assigned a specific probability distribution and the results show the range of TAC values at each scenario. It is noted that for each method the results of system’s configuration and operation profile of technologies are different.

Overall, these techniques provide solutions that are notably different of the results of the deterministic approach and can be characterized as robust, highlighting the importance of considering uncertainty for the design process. This thesis concludes that considering uncertainty in designing a DES is necessary as the optimal solutions change significantly, which is very important for the optimal design of the system, its financial viability and

operational stability. Finally, it is noted that the developed methodologies are generic and can be easily adopted and applied according to the preferences of a DM.

Εκτεταμένη Περίληψη

Η κατανάλωση πρωτογενούς ενέργειας έχει αυξηθεί εκθετικά τις τελευταίες δεκαετίες εξαιτίας της παγκόσμιας οικονομικής ανάπτυξης. Η ενέργεια είναι απαραίτητη σε όλα τα πεδία της σύγχρονης ζωής και χρησιμοποιείται σε πολλούς τομείς, όπως την παραγωγή ηλεκτρισμού, θερμότητας και ψύξης, στις μεταφορές, στη βιομηχανία και σε πολλούς άλλους τομείς. Όμως η κατανάλωση ενέργειας έρχεται μαζί με συγκεκριμένο κόστος καθώς τα συμβατικά ενεργειακά συστήματα βασίζονται σε ορυκτά καύσιμα και παράγουν υψηλές εκπομπές διοξειδίου του άνθρακα (CO_2). Αυτό έχει ως αποτέλεσμα να επηρεάζεται το περιβάλλον, καθώς οι εκπομπές CO_2 συμβάλλουν στο φαινόμενο του θερμοκηπίου και κατ' επέκταση στην κλιματική αλλαγή. Η παροχή καθαρής ενέργειας και η αντιμετώπιση της κλιματικής αλλαγής είναι δύο από τις μεγαλύτερες προκλήσεις που αντιμετωπίζει ο πλανήτης. Τα τελευταία έτη η διεθνής κοινότητα έχει λάβει μέτρα για τη μείωση των εκπομπών CO_2, όπως το Πρωτόκολλο του Κιότο και η Συμφωνία του Παρισίου. Η Ευρωπαϊκή Ένωση (ΕΕ) εφαρμόζει ένα φιλόδοξο πλαίσιο πολιτικών στα πεδία της εξοικονόμησης ενέργειας, της προώθησης των ανανεώσιμων πηγών ενέργειας (ΑΠΕ) και της μείωσης των εκπομπών CO_2. Επιπλέον η Ελλάδα έχει θέσει ένα φιλόδοξο ενεργειακό σχέδιο βασισμένο στις ευρωπαϊκή ενεργειακή πολιτική.

Επίσης, στις τελευταίες δεκαετίες ο παγκόσμιος πληθυσμός έχει αυξηθεί δραματικά, οδηγώντας σε αυξημένη κατανάλωση πόρων, συμπεριλαμβανομένης και της ενέργειας. Επιπλέον, υπολογίζεται ότι το 52% του παγκόσμιου πληθυσμού ζει σε πόλεις, με αυτό το νούμερο να αναμένεται να αυξηθεί στις επόμενες δεκαετίες. Οι αστικές περιοχές κατέχουν ένα μεγάλο ποσοστό της ενεργειακής ζήτησης, με αποτέλεσμα η κάλυψη των φορτίων να αποτελεί πρόκληση. Σε αυτό το πλαίσιο, τα αστικά ενεργειακά συστήματα αναμένεται να διαδραματίσουν σημαντικό ρόλο. Είναι ανάγκη τα μελλοντικά αστικά ενεργειακά συστήματα να επανασχεδιαστούν και να προσφέρουν βιώσιμες λύσεις.

Μια λύση για την κάλυψη αυτού το στόχου είναι η ανάπτυξη των συστημάτων διεσπαρμένης παραγωγής ενέργειας (ΣΔΠΕ). Τα ΣΔΠΕ έχουν πολλά πλεονεκτήματα με το σημαντικότερο να είναι η παραγωγή ενέργειας σε τοπικό επίπεδο, ελαχιστοποιώντας έτσι τις απώλειες. Τα ΣΔΠΕ μπορούν να προσφέρουν καλύτερη ενσωμάτωση μεταξύ των συμβατικών ενεργειακών συστημάτων και των ΑΠΕ, και μπορούν να καλύψουν τις ενεργειακές ανάγκες είτε πρόκειται για ένα κτήριο, ένα σύμπλεγμα κτηρίων ή ακόμη και μια πόλη, με το βαθμό αποκέντρωσης να διαφέρει. Ένα ΣΔΠΕ μπορεί να σχεδιαστεί για να καλύπτει τις ενεργειακές ανάγκες σε ηλεκτρισμό, θερμότητα και ψύξη. Επίσης, τα συστήματα αυτά μπορούν να προσφέρουν λύσεις με χαμηλό ετήσιο κόστος και χαμηλές εκπομπές CO_2. Τα τελευταία χρόνια στη βιβλιογραφία έχουν αναπτυχθεί αρκετά μοντέλα για το σχεδιασμό ΣΔΠΕ βασισμένα στη χρήση μαθηματικού προγραμματισμού. Αυτά τα μοντέλα εφαρμόζονται είτε σε προβλήματα μονο-κριτηριακού ή πολυ-κριτηριακού μαθηματικού προγραμματισμού, με την ελαχιστοποίηση του συνολικού ετήσιου κόστος (που περιλαμβάνει το κόστος κεφαλαίου, λειτουργίας και συντήρησης) και τις εκπομπές CO_2 να είναι οι πιο συχνές αντικειμενικές συναρτήσεις.

Ο σχεδιασμός ενός ΣΔΠΕ είναι ένα περίπλοκο πρόβλημα στο οποίο πολλές πτυχές πρέπει να λαμβάνονται υπόψη. Αυτή η διατριβή έχει σκοπό να παρουσιάσει μια μεθοδολογία για τον βέλτιστο σχεδιασμό ΣΠΔΕ χρησιμοποιώντας πολυ-κριτηριακό μικτό-ακέραιο γραμμικό προγραμματισμό (ΜΑΓΠ) με αντικειμενικές συναρτήσεις το συνολικό ετήσιο κόστος και τις εκπομπές CO_2. Οι υποψήφιες τεχνολογίες είναι: (α) μονάδες συμπαραγωγής ηλεκτρισμού και θερμότητας, (β) αντλίες θερμότητας, (γ) μονάδες ψύξεις με απορρόφηση, (δ) λέβητες, (ε) ηλιακοί συλλέκτες, (στ) φωτοβολταϊκά, (ζ) ανεμογεννήτριες, (η) μονάδες αποθήκευσης θερμότητας, (θ) μονάδες αποθήκευσης ηλεκτρισμού, (ι) δίκτυο διανομής θερμότητας και (κ) μικροδίκτυο. Τα αποτελέσματα δίνουν ως λύσεις τις τεχνολογίες που επιλέγονται να εγκατασταθούν σε κάθε κτήριο και την αντίστοιχη ισχύ τους, τη διάταξη του δικτύου διανομής θερμότητας (αν σχηματιστεί), το επιχειρησιακό προφίλ των τεχνολογιών, και την ανταλλαγή ηλεκτρισμού διαμέσου του μικροδικτύου καθώς και μεταξύ των κτηρίων και του εθνικού δικτύου ηλεκτρισμού. Επιπλέον, οι αντίστοιχες μελέτες που υπάρχουν στη βιβλιογραφία διαχωρίζονται σε δύο γενικές κατηγορίες, (α) στη «Μέθοδο Α» όπου γίνεται ταυτόχρονη επιλογή και διαστασιολόγηση των υποψήφιων τεχνολογιών, και (β) στη «Μέθοδο Β» όπου οι διαστάσεις των τεχνολογιών είναι προκαθορισμένες.

Αυτή η διατριβή παρουσιάζει αρκετά καινοτομικά στοιχεία αναφορικά με τον βέλτιστο σχεδιασμό ΣΔΠΕ. Συγκεκριμένα, παρουσιάζονται δύο προσεγγίσεις για την μοντελοποίηση τεχνολογιών, επεκτείνοντας την σχετική βιβλιογραφία. Επιπλέον, παρουσιάζονται μαθηματικά μοντέλα για όλες οι διαθέσιμες τεχνολογίες. Αυτές οι προσεγγίσεις συγκρίνονται καθώς προσφέρουν διαφορετικές λύσεις, και εξετάζονται πλεονεκτήματα και μειονεκτήματα που έχουν. Επιπλέον, η διατριβή εξετάζει την ευρωστία των λύσεων και συνδυάζει πολύ-κριτηριακό μαθηματικό προγραμμαατισμό με τεχνικές για βελτιστοποίηση υπό συνθήκες αβεβαιότητας.

Για την αξιολόγηση των πλεονεκτημάτων που έχουν τα ΣΔΠΕ καθώς και για τη σύγκριση μεταξύ των δύο αυτών μεθοδολογιών έχει εφαρμοστεί μια μελέτη περίπτωσης σε μια γειτονιά αποτελούμενη από έξι κτήρια σε μια περιοχή της Αττικής, και έχουν αναπτυχθεί τρία σενάρια, το Σενάριο 1 – business-as-usual, το Σενάριο 2 – ΑΠΕ και το Σενάριο 3 – Πράσινο. Τα αποτελέσματα δείχνουν ότι μεταξύ των τριών αυτών σεναρίων το Σενάριο 3 προσφέρει τις καλύτερες λύσεις. Επιπλέον, αναφορικά με τη σύγκριση της «Μεθόδου Α» και «Μεθόδου Β», τα αποτελέσματα δείχνουν ότι η «Μέθοδος Α» δίνει καλύτερες λύσεις για το συνολικό ετήσιο κόστος, που κυμαίνονται μεταξύ 3% και 11%, κάτι το οποίο αναμενόταν λόγω των περισσότερων βαθμών ελευθερίας. Σε ότι αφορά τις εκπομπές CO_2 οι δύο μέθοδοι δίνουν παρόμοια αποτελέσματα. Επίσης, παρατηρούνται διαφορές μεταξύ κάθε λύσης σε κάθε μέθοδο αναφορικά με τη διαμόρφωση του συστήματος, το επιχειρησιακό προφίλ των τεχνολογιών, τη διάταξη του δικτύου μεταφοράς θερμότητας και την ανταλλαγή ηλεκτρισμού μεταξύ μικροδικτύου και μεταξύ εθνικού δικτύου. Μια προτεινόμενη στρατηγική ενεργειακού σχεδιασμού συστημάτων ΣΔΠΕ θα ήταν να χρησιμοποιείται η Μέθοδος Α για μια πρώτη προσέγγιση των διαστασιολογικών χαρακτηριστικών των μονάδων και στη συνέχεια αφού περιοριστεί το διαστασιολογικό εύρος (άρα και οι εξεταζόμενοι συνδυασμοί και η δυσκολία επίλυσης), να χρησιμοποιείται η μέθοδος Β για μεγαλύτερη ακρίβεια.

Πέρα απ’ αυτά, η διατριβή έχει ως σκοπό τον βέλτιστο σχεδιασμό ΣΔΠΕ υπό συνθήκες αβεβαιότητας. Οι αλλαγές στις τιμές των παραμέτρων σχεδιασμού μπορούν να επηρεάσουν τον βέλτιστο σχεδιασμό και αυτή η διατριβή σκοπεύει να προσφέρει στον αποφασίζων εύρωστες λύσεις. Στο πλαίσιο της διατριβής υποτίθεται ότι οι παράμετροι που είναι υπό αβεβαιότητα είναι οι τιμές ενέργειας (ηλεκτρισμού και φυσικού αερίου), το επιτόκιο αναγωγής, τα ενεργειακά φορτία, η ηλιακή ακτινοβολία και η ταχύτητα του ανέμου. Για την αντιμετώπιση της αβεβαιότητας και τον εντοπισμό των εύρωστων λύσεων χρησιμοποιούνται τέσσερις τεχνικές που ανήκουν στο πεδίο της «εύρωστης βελτιστοποίησης» ή της «στοχαστικής βελτιστοποίησης»: (α) objective-wise worst case, (β) minimax regret criterion (MMR), (γ) minimax expected regret (MER) και (δ) ανάλυση Monte Carlo. Αυτές οι τεχνικές εφαρμόζονται στην «Μέθοδο Α», είτε ως πολύ-κριτηριακό πρόβλημα είτε ως μονο-κριτηριακό πρόβλημα βελτιστοποίησης. Για τον μετασχηματισμό του πολύ-κριτηριακού προβλήματος σε μονο-κριτηριακό θεωρείται ως αντικειμενική συνάρτηση η ελαχιστοποίηση του συνολικού ετήσιου κόστους, με τις εκπομπές CO_2 να μετατρέπονται σε περιορισμό με ανώτατο όριο τις 100,000 kg/έτος.

Για την εφαρμογή του MMR και του MER γίνεται η παραδοχή ότι αβεβαιότητα υπάρχει μόνο στις παραμέτρους οικονομικής φύσεως (επιτόκιο αναγωγής και τιμές ενέργειας) και αναπτύσσονται πέντε σενάρια, Σενάριο R1 – Σενάριο R5, όπου οι παράμετροι παίρνουν μια υψηλή ή χαμηλή τιμή αντίστοιχα. Ειδικότερα για την εφαρμογή της μεθόδου MER γίνεται η παραδοχή ότι για κάθε Σενάριο R1 – Σενάριο R5 υπάρχει μια συγκεκριμένη πιθανότητα να συμβεί, οδηγώντας σε λιγότερο συντηρητικά αποτελέσματα. Όσον αφορά την εφαρμογή της μεθόδου objective-wise και για την ανάλυση Monte Carlo, εξετάζονται δύο σενάριο για κάθε μέθοδο, το Σενάριο OW1 και OW2, καθώς και το Σενάριο MC1 και Σενάριο MC2, αντίστοιχα.

Τα Σενάρια OW1 και MC1 αναφέρονται σε αβεβαιότητα μόνο στις οικονομικές παραμέτρους, ενώ τα Σενάρια OW2 και MC2 αναφέρονται σε αβεβαιότητα σε όλες τις παραμέτρους. Η κάθε μέθοδος δίνει διαφορετικές λύσεις, με τις πιο απαισιόδοξες να προκύπτουν από την μέθοδο objective-wise καθώς λαμβάνει υπόψη τις χειρότερες τιμές των αντίστοιχων παραμέτρων. Οι μέθοδοι MMR και MER δίνουν λύσεις με μικρό «κόστος» υποδεικνύοντας ότι η θεώρηση αβεβαιότητας μόνο στις οικονομικές παραμέτρους δεν επηρεάζει σημαντικά τα αποτελέσματα. Τέλος, στην ανάλυση Monte Carlo κάθε παράμετρος θεωρείται ότι ακολουθεί μια συγκεκριμένη κατανομή πιθανότητας και τα αποτελέσματα δίνουν το εύρος που μπορεί να πάρει το συνολικό ετήσιο κόστος. Σημειώνεται ότι για κάθε μέθοδο οι λύσεις αναφορικά με τη διάταξη του συστήματος και το επιχειρησιακό προφίλ των τεχνολογιών διαφέρουν.

Συνολικά, αυτές οι τεχνικές προσφέρουν λύσεις πολύ διαφορετικές σε σχέση με την ντετερμινιστική προσέγγιση του προβλήματος, οι οποίες μπορούν να χαρακτηριστούν ως εύρωστες, υπογραμμίζοντας τη σημασία της θεώρησης της αβεβαιότητας κατά τη διαδικασία σχεδιασμού. Η διατριβή καταλήγει ότι η αντιμετώπιση της αβεβαιότητας κατά τον σχεδιασμό ενός ΣΔΠΕ είναι πολύ σημαντική καθώς οι λύσεις αλλάζουν σημαντικά, και αυτό έχει ιδιαίτερη σημασία για τον βέλτιστο σχεδιασμό του συστήματος, την οικονομική του βιωσιμότητα καθώς και την επιχειρησιακή του σταθερότητα. Εν τέλει, σημειώνεται ότι οι μεθοδολογίες που έχουν αναπτυχθεί είναι γενικές και μπορούν εύκολα να προσαρμοστούν και να εφαρμοστούν σύμφωνα με τις προτιμήσεις του αποφασίζων.

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Nomenclature

Sets

- i, the set of buildings of the DES;
- d , number of the typical days a year is divided;
- p , number of the periods a typical day d is subdivided;
- *swt*, set of wind turbines.

Parameters regarding the buildings, the time horizon, and the climate:

- $l_{i,j}$, the matrix representing the distance between building i and building j [m];
- n_d , the number of days a typical d day represents in year;
- δ_p , the duration of time periods p in hours;
- α_i , the available surface in building i for the installation of solar photovoltaics and/or collectors [m^2];
- $d^{el}_{i,d,p}$, $\mathrm{d}^{h}_{i,d,p}$, $\mathrm{d}^{c}_{i,d,p}$, are respectively the electric, heating, and cooling energy loads of building *i* at period *p* of day *d* [kW];
- $r^{DHW}_{i,d,p}$, the ratio of demand for DHW over the total heating load of building *i* at period *p* of day *d*;
- $i^{sol}_{d,p}$, the solar irradiance at period *p* of day *d* [kW/m^2]
- $v^{w}_{d,p}$, wind speed at period *p* of day *d* [m/s]

Parameters regarding technologies (size, cost, efficiency) and DHN:

- a_n , capital recovery factor for technologies
- n , lifetime of technologies [years]
- s^{wt}_{swt} , size of wind turbine technologies in set swt ;
- $w_{swt,d,p}$, electricity generation of a wind turbine of swt set at period p of day d [kW];
- ub^{CHP} , lb^{CHP} , upper and lower bound for the size of CHP [kW]
- ub^{HP} , lb^{HP} , upper and lower bound for the size of heat pumps [kW]
- ub^{CH} , lb^{CH} , upper and lower bound for the size of absorption chillers [kW]

- ub^{B}, lb^{B}, upper and lower bound for the size of boilers [kW]
- ub^{PV}, upper bound for the size of photovoltaics [kW]
- ub^{TS}, the maximum thermal energy that can be stored in heat storage technology [kWh]
- ub^{ES}, the maximum electrical energy that can be stored in heat storage technology [kWh]
- c_{swt}^{wt}, the capital cost of wind turbines of swt set [€/kW]
- c_{fix}^{chp}, fixed capital cost of CHP [€]
- c_{lin}^{chp}, linear capital cost of CHP [€/kW]
- c^{HP}, capital cost of heat pumps [€/kW]
- c^{CH}, capital cost of absorption chillers [€/kW]
- c^{B}, capital cost of boilers [€/kW_{th}]
- c^{PV}, capital cost of solar photovoltaics [€/kW]
- c^{ST}, capital cost of solar thermal collectors [€/m^2]
- c^{ES}, capital cost of electricity storage technology [€/kWh]
- c^{TS}, capital cost of thermal storage technology [€/kWh]
- c^{MG}, capital cost of microgrid controller [€]
- c^{P}, capital cost of pipes [€/m]
- μ_{swt}^{WT}, maintenance cost of wind turbines of swt set [€/kWh]
- μ^{CHP}, maintenance cost of CHP technologies [€/kWh]
- μ^{HP}, maintenance cost of heat pumps [€/kWh]
- μ^{CH}, maintenance cost of absorption chillers [€/kWh]
- μ^{B}, maintenance cost of boilers [€/kW_{th}]
- μ^{pv}, maintenance cost of solar photovoltaics [€/kW]
- μ^{st}, maintenance cost of solar thermal collectors [€/m^2]
- μ^{TS}, maintenance cost of thermal storage technology [€/kWh]

- k^{CHP}, part load factor for the operation of CHP
- η^{CHP_el}, the electrical efficiency of CHP [%]
- η^{CHP_th}, the electrical efficiency of CHP [%]
- η^{B}, efficiency of boiler [%]
- η^{CH}, efficiency of absorption chiller [%]
- COP_{th}^{hp}, COP_{c}^{hp}, coefficient of performance of heat pumps for heating and cooling
- η^{pv}, efficiency of solar pv [%]
- η^{st}, efficiency of solar thermal collectors [%]
- $\eta^{es,in}$, $\eta^{es,out}$, charging and discharging efficiency of electric storage [%]
- pv^{cof}, power density of solar pv [kW/m^2]
- β^{p}, heat losses through pipes [1/m]
- d_i^{WT}, a parameter indicating the availability of installing a wind turbine at building *i*
- etl, electricity transmission losses [%]

Other parameters:

- r, discount rate [%]
- f^{grid}, carbon emission factor of the national grid [kg CO_2/kWh]
- f^{ng}, carbon emission factor of natural gas [kg CO_2/kWh]
- c^{ng}, cost of natural gas [€/kWh]
- $c_{d,p}^{el\_buy}$, cost of buying electricity at period *p* of day *d* [€/kWh]
- $c_{d,p}^{CHP\_sell}$, cost of selling electricity from CHP at period *p* of day *d* [€/kWh]
- $c_{d,p}^{PV\_sell}$, cost of selling electricity from PV at period *p* of day *d* [€/kWh]
- $c_{d,p}^{WT\_sell}$, cost of selling electricity from wind turbines at period *p* of day *d* [€/kWh]

Positive decision variables:

- C^{T}, total annual cost (€)
- C^{C}, capital cost (€)

- C^{O} , operational cost (€)
- C^{M} , maintenance cost (€)
- $CARBON^{T}$, total carbon emissions (kg/year)
- $CARBON^{F}$, fuel-based carbon emissions (kg/year)
- $CARBON^{E}$, electricity-based carbon emissions (kg/year)
- S_i^{CHP} , size of CHP unit at building *i* [kW]
- S_i^{HP} , size of heat pump unit at building *i* [kW]
- $S_i^{HP\_h\_aux}$, an auxiliary variable for the linearization of heat pumps operation
- S_i^{CH} , size of absorption chiller unit at building *i* [kW]
- S_i^{B} , size of boiler unit at building *i* [kW]
- S_i^{PV} , size of photovoltaics at building *i* [kW]
- A_i^{PV} , area of photovoltaics at building *i* [m^2]
- A_i^{ST} , size of solar thermal collectors at building *i* [m^2]
- Q_i^{ES} , rated electricity storage at building *i* [kWh]
- Q_i^{TS} , rated thermal storage at building *i* [kWh]
- $Z_{i,d,p}^{CHP}$, primary energy consumption of CHP at building *i* at period *p* of day *d* [kW]
- $Z_{i,d,p}^{B}$, primary energy consumption of boilers at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{el\_grid}$, electricity bought from grid at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{CHP}$, total electricity generation of CHP at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{CHP\_build}$, electricity generation of CHP for use at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{CHP\_sell}$, electricity generation of CHP sold to grid from building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{CHP\_mg}$, electricity generation of CHP sent to microgrid from building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{CHP}$, total heating energy generation of CHP at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{CHP\_build}$, heating energy generation of CHP used at building *i* at period *p* of day *d* [kW]

- $Q_{i,d,p}^{CHP\_net}$, heating energy generation of CHP sent to DHN from building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{HP\_h}$, total heating energy generation of heat pump unit at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{HP\_h\_build}$, heating energy generation of heat pump used at at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{HP\_h\_net}$, heating energy generation of heat pump sent to DHN from building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{HP\_c}$, cooling energy generation of heat pump unit at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{HP}$, electricity used by heat pump unit at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{CH\_c}$, cooling energy generation of absorption chiller at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{CH\_abs}$, thermal energy absorbed from absorption chiller at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{B}$, total heating energy generation of boiler at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{B\_build}$, heating energy generation of boiler used at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{B\_net}$, heating energy generation of boiler sent to DHN from building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{PV}$, total electricity generation from photovoltaics at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{PV\_build}$, electricity generation from photovoltaics used at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{PV\_sell}$, electricity generation from photovoltaics sold to grid from building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{PV\_mg}$, electricity generation from photovoltaics sent to microgrid from building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{WT}$, total electricity generation from wind turbine at building *i* at period *p* of day *d* [kW]

- $E_{i,d,p}^{WT\_build}$, electricity generation from wind turbine used at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{WT\_sell}$, electricity generation from wind turbine sold to grid from building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{WT\_mg}$, electricity generation from wind turbine sent to microgrid from building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{MG}$, electricity received from microgrid at building *i* at period *p* of day *d* [kW]
- $E_{i,d,p}^{sell}$, total electricity sold to grid from building *i* at period *p* of day *d* [kW]
- Q_i^{ES}, rated electricity storage at building *i* [kWh]
- Q_i^{TS}, rated thermal storage at building *i* [kWh]
- $E_{i,d,p}^{ES}$, electricity stored at building *i* at period *p* of day *d* [kWh]
- $E_{i,d,p}^{TS}$, thermal energy stored at building *i* at period *p* of day *d* [kWh]
- $E_{i,d,p}^{ES\_in}$, $E_{i,d,p}^{ES\_out}$, electricity charged and discharged from storage at building *i* at period *p* of day *d* [kW]
- $Q_{i,d,p}^{TS\_in}$, $Q_{i,d,p}^{TS\_out}$, thermal energy charged and discharged to storage at building *i* at period *p* of day *d* [kW]

Binary variables:

- Y_i^{CHP}, if CHP is installed at building *i*
- Y_i^{WT}, if wind turbine is installed at building *i*
- $Y_{i,j}^{HN\_SUP}$, $Y_{i,j}^{HN\_RET}$ if a supply (and a return pipe) is installed between building *i* and building *j*
- Y^{MG}, if microgrid is installed
- Y_i^{HP}, if a heat pump is installed at building *i*
- Y_i^{B}, if a boiler is installed at building *i*
- Y_i^{CH}, if an absorption chiller is installed at building *i*
- X_i^{CHP}, if CHP operates at building *i* at period *p* of day *d*

- $X_{i,d}^{HP\_h}$, if heat pump at building *i* operates in heating mode at day *d*
- $X_{i,d,p}^{HP\_h}$, if heat pump at building *i* operates in heating mode at period *p* of day *d*
- $X_{i,d}^{HP\_c}$, if heat pump at building *i* operates in cooling mode at day *d*
- $X_{i,d,p}^{HP\_c}$, if heat pump at building *i* operates in cooling mode at period *p* of day *d*
- $X_{i,d,p}^{el\_sell}$, if electricity is sold to grid from building *i* at period *p* of day *d*

Abbreviations

AUGMECON	Augmented ε-constraint method
CCHP	Combined cooling, heating and power
CHP	Combined heat and power
CO_2	Carbon dioxide
DER	Distributed energy resources
DES	Distributed energy systems
DHN	District heating network
DHW	Domestic hot water
DM	Decision maker
EES	Electric energy storage
EU	European Union
GHG	Greenhouse gas emissions
HP	Heat pump
LP	Linear programming
LV	Low voltage
MCDA	Multi-criteria decision analysis]
MER	Minimax expected regret
MILP	Mixed-Integer linear programming
MMR	Minimax regret
OR	Operations research
PV	Photovoltaics
RES	Renewable Energy Sources
RO	Robust optimization
SO	Stochastic optimization
TAC	Total annual cost
TES	Thermal energy storage

Chapter 1: Introduction

This chapter provides the introduction for the doctoral thesis with the background and context regarding the applications of Distributed Energy Systems. The scope and the novelty of the thesis are described analytically. Also, the structure of the doctoral thesis is described.

1.1 Background and context

Energy consumption has been necessary to human development since ancient times. Energy is consumed in various forms, mainly thermal and electrical energy to perform everyday activities such as turning on the lights, watching TV or provide heating/cooling during winter or summer. Energy has various forms and types, the two main categories being primary and secondary energy. Primary energy refers to energy taken directly from the environment (natural resources), while secondary energy is converted using technology, into fuel or electricity, as illustrated in Fig. 1.1. This classification is important in order to understand the concepts of energy consumption and energy balance. Primary energy is separated into three main groups, namely: (a) non-renewable energy, such as crude oil, coal, natural gas, (b) renewables, such as solar energy, wind, biomass, hydropower, geothermal and ocean energy and (c) waste. Natural gas, petroleum and coal account to approximately 85% of the global primary energy consumption of fossil fuels [1].

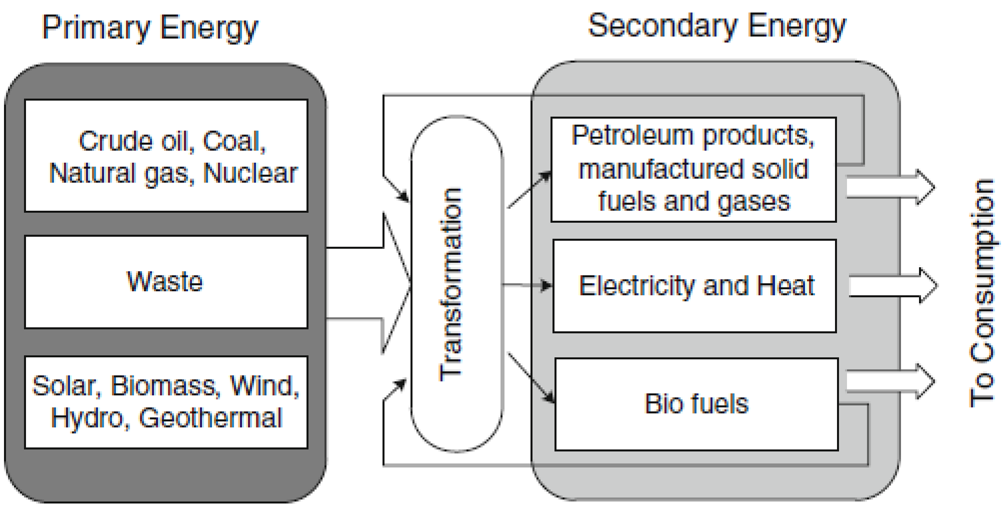


Fig. 1.1. Conversion of primary energy to secondary energy (source: [1]*)*

In the last 120 years the rapid expansion of technology has led to an exponential increase in the exploitation of natural resources. Fig. 1.2 shows the exponential growth of primary energy consumption in the world since 1900. It can be seen for the last 60 years oil and natural gas are the dominant fuels. Energy is highly interconnected with economy and development of countries [2]. Variations in energy prices and increasing cost of energy affects all economic sectors. This is more evident in highly developed industrial countries. Also, the increase of population in the last decades, and the corresponding growth of GDP increased energy demand, and subsequently energy consumption, significantly [3].

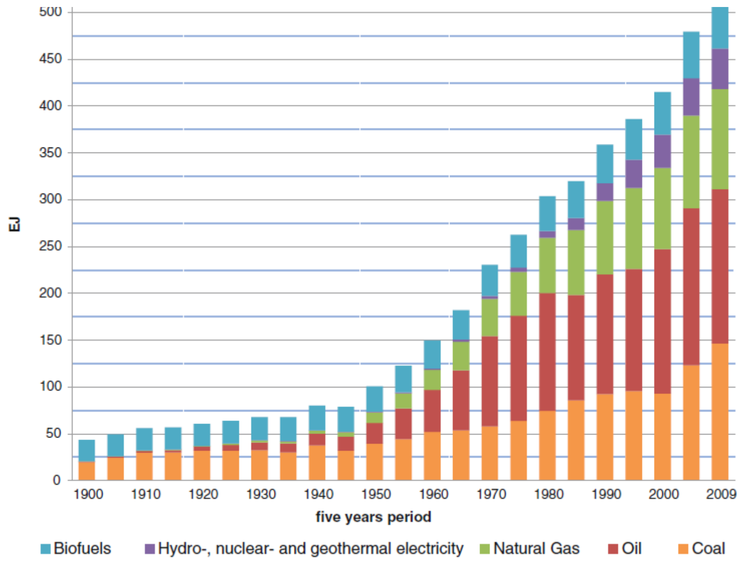


Fig. 1.2. Primary energy consumption in the world (source: [2]*)*

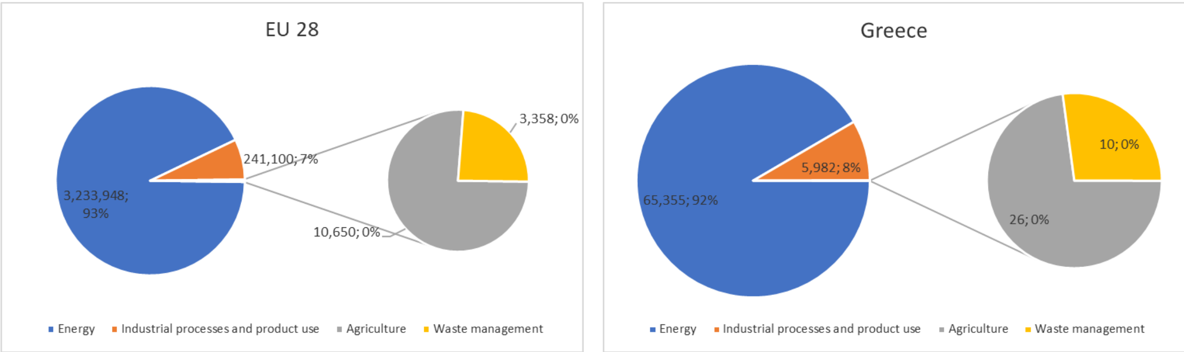
However, consumption of primary energy and specifically fossil fuels has consequences. Energy generation (electricity, heating, cooling, transportation) has significant impacts to the environment, in terms of pollution and associated greenhouse gas (GHG) emissions. Over the last decades concerns regarding energy related environmental impact have been increased to a global issue, due to the increases in human population, resources consumption and industrial activity.

Coal and oil are responsible for increase of anthropogenic GHG, mainly carbon dioxide (CO_2) emissions. The accumulation of greenhouse gases in the atmosphere reabsorbs solar radiation emanating from earth and causes temperature increase. This phenomenon is known as *greenhouse effect* or *global warming*. Greenhouse effect contributes to the climate change which is one of the major challenges our planet faces. The international community in 1992 signed the Kyoto agreement which aimed to reduce carbon emissions based on 1990 levels for the period 2008 – 2012. More recently, the Paris Agreement for climate change was signed in 2016, reflecting the will of international community to take further measures. Governments agreed to keep the increase of global average temperature well below 2 ^{o}C above pre-industrial levels, aiming to limit the increase to 1.5 ^{o}C [4].

Carbon emissions come from many sources, such as industry, agriculture, mining, transportation, and energy generation. European Union (EU) is implementing policies towards a cleaner future energy system, through promotion of energy efficiency measures and renewable energy sources (RES). Specifically, Directive 2009/28/EC introduced the European 2020 energy & climate package with three main targets [5]: (a) a 20% reduction in greenhouse gas emissions from 1990 levels; (b) a 20% energy generation from RES and (c) a 20% improvement in energy efficiency. Recently, EU took a further step, updating these targets in its new “Energy Strategy and Energy Union”, specifically the “Clean energy for all Europeans” package, adopted in 2019, setting a target of at least 32% energy generation from renewables and at least 32.5% energy efficiency target for 2030, with the possibility of an upward revision in 2023. These measures are expected to lead into a further reduction of CO_2 emissions by some 45%, compared to 1990 values [6–8]. Regarding energy planning for Greece, the Ministry of Environment & Energy carried out a National Energy and Climate plan setting ambitious targets for the country. Specifically, the goal is to achieve at least a 30% contribution of RES to gross final energy consumption at 2030, aiming at least a 55% share in final electricity consumption, a 30% share for heating and cooling and 14% for transport. The target for energy efficiency is at least 32.5% by 2030 [9].

Furthermore, EU in its Strategic Energy Technology Plan describes the ongoing research achievements and opportunities in energy systems and technologies, such as photovoltaics, solar thermal electricity, offshore wind energy, ocean energy and geothermal energy. Also, EU aims to transform the central energy system into a decentralized one by converting citizens as active players, in the context of smart cities. EU research is focused on smart grids and integrated energy systems, and to the promotion of energy efficiency [10].

In Fig. 1.3 carbon emissions by source are presented in EU and Greece respectively. It is clear that the major source of carbon emissions is the energy sector by more than 90% in EU and Greece, respectively. The breakdown of the emissions from the energy sector is presented in Fig. 1.4, where energy industries is the dominant sub-sector, especially in Greece. The driving factors for carbon emissions from the energy sector, and specifically for electricity generation in European countries have been studied in [11] showing how the economic activity drives carbon emissions to increase, and improvements in energy efficiency contribute to the reduction of carbon emissions.



(a) (b)

Fig. 1.3. Carbon emissions by source in (a) EU – 28 and (b) Greece for the year 2016 (source: [12]*)*

(a) (b)

Fig. 1.4. Carbon emissions from energy sector in (a) EU – 28 and (b) Greece for the year 2016 (source: [12]*)*

Buildings are responsible for some 40% of final energy consumption in EU. Fig. 1.5 shows the energy consumption by end-use in residential and commercial buildings. Therefore, the need to redesign energy systems for buildings is a very important task. However, this is also a challenging task for which decision makers (DM) need to take into consideration many aspects. The optimal selection of energy technologies or of energy efficiency measures is not a trivial task as the required investment cost and the reduction of carbon emissions are conflicting objectives. A DM needs to make the optimal choice amongst a set of available choices [13].

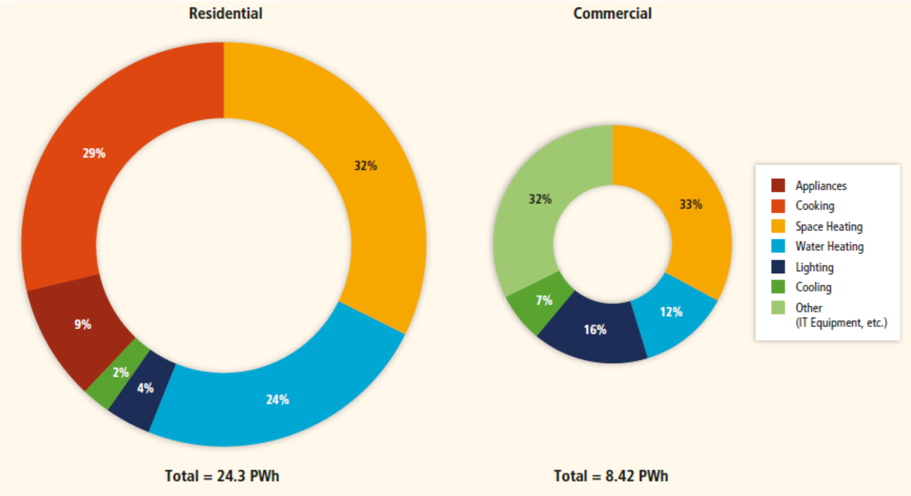


Fig. 1.5. World building final energy consumption by end-use in 2010 (source: [14]*)*

Urban areas have an important role to play towards a cleaner energy future as they have a high concentration of people and economic activities. Some 52% of the global population lives in urban areas, which is expected to rise up to 66% (estimated at 6.3 billion people) by 2050. Urban areas dominate global energy demand, hence the design of sustainable urban energy systems that could help improving energy security along with human health and economic growth is a very important task [15].

The essential role played by energy is often neglected in daily life, as is the complexity of of the infrastructure that provides the energy services we use. For instance, when the lights are turned on there is a whole process taking place, from the extraction and transportation of raw resources (e.g. gas), generation of electricity and delivery to our homes. Economists define energy consumption a 'derived demand' [16].

In order to understand and model the mechanics of technologies used to supply energy in cities physical laws can be applied. However, as no single 'physical' model exists there are three different, yet complementary views, of how an urban energy system can be viewed: (a) Thermodynamic systems, (b) Metabolic systems, and (c) Complex systems. Nevertheless, to be able to find the potential improvement in energy efficiency of urban energy systems requires a mix of technical knowledge of cities as thermodynamic, metabolic or complex systems and an understanding of the broad social and economic factors. Therefore, the task of finding a definition of urban energy systems which takes into account all these aspects is challenging. In [16] an urban energy system is defined as *"the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area*".

In the last years, beyond energy policies implemented at a national (and/or European) level, cities take their own measures to tackle the increase of greenhouse gas emissions. Several organizations, such as Energy cities, Fedarene, ICLEI, Climate Alliance, the Covenant of Mayors, the C40 Climate Leadership Group, Eurocities, and the OECD, aim to the reduction of greenhouse emissions at a city level. Reports show that 70% of global emissions account to cities. By also considering that 70% of world's population is expected to live in cities by 2050 it can be deduced that cities have a major impact and a significant role to play in the effort against climate change. Hence, the optimal usage of resources, such as energy (and water, which is connected to energy) with aim towards low carbon is of vital importance [17].

A shift needs to be made towards sustainable development, commonly defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [18]. A new interdisciplinary branch of engineering has emerged, called sustainable energy engineering aiming to design, develop and promote sustainable energy-generation systems. To achieve sustainable development there is a need for sustainable energy strategies and policies, such as by imposing efficiency standards, supporting energy sector innovation, promotion of energy efficiency and financing large energy projects. Sustainability is a general term, including energy and resources sustainability, economic sustainability, environmental sustainability, and social sustainability. To achieve that, green energy is essential for three main reasons: (a) lower environmental impact compared to other energy sources, (b) renewables cannot be depleted and (c) system decentralization is favoured, increasing system's flexibility and leading to economic benefits. Green energy technologies are crucial towards sustainability, as they are environmentally friendly, they enhance energy security and reduce pollution.

In this context, *Distributed Energy Systems (DES)* could play a major role towards the sustainable future urban energy system and could be used as the foundation of future urban and semi-urban energy systems design. DES could be designed either for a single building up to a whole city, therefore organizing complex buildings into organized energy communities. This solution can take advantage of the local energy resources (renewables), provide operational flexibility, and can satisfy the energy needs of end-users (buildings) in electricity, heating and cooling. Promotion of renewables and/or of other energy efficient and environmentally friendly technologies can help reducing overall costs and mainly provide a cleaner alternative with less CO_2 emissions compared to the conventional energy supply system. A sketch of a DES is illustrated in Fig. 1.6. DES are expected to offer multiple environmental and economic benefits, most notable being [18,19]:

- The diversity of loads at buildings of various sectors could offer lower peak demand and better load factors if aggregated;
- Economics of scale in generation, along with better efficiencies and emission profiles;
- Lower operating and maintenance costs;
- General design and more effective operation;
- District Heating (DH) provides heating from cleaner and economical technologies;
- Increased feasibility of thermal energy storage which offers better energy management;
- Increased fuel flexibility and energy security;
- Infrastructure upgrades that provides social benefits such as the creation of new jobs.

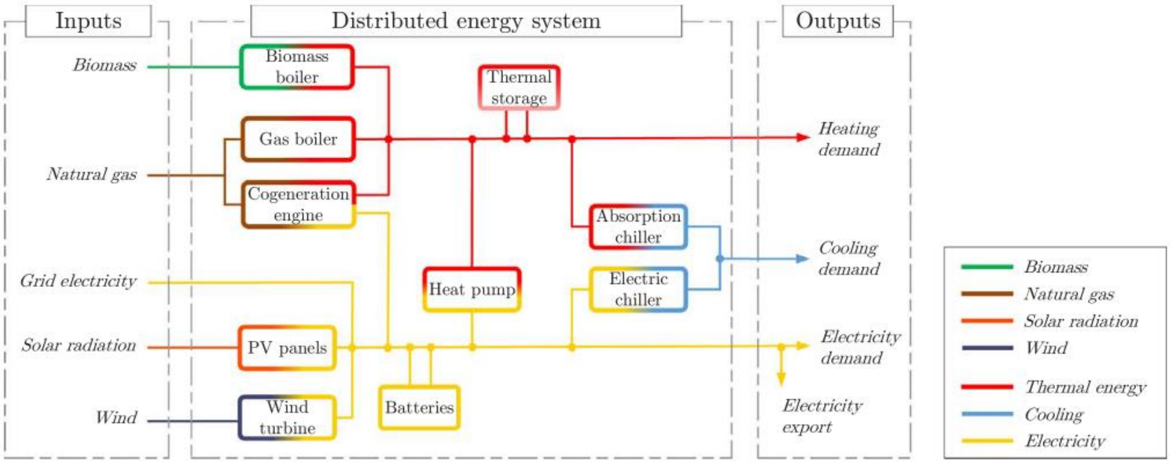


Fig. 1.6. A sketch of a DES configuration (source: [20]*).*

Conventional technologies that are mainly used are cogeneration units (combined heat and power – CHP), boilers, heat pumps and chillers. Renewables are mainly solar photovoltaics, solar thermal collectors, and wind turbines. Also, the degree in which a DES can be decentralized varies. For instance, a CHP could be centrally installed and provide electricity and heating to a district, or several smaller units could be installed at buildings (decentralized). Hence, the selection of technologies, their respective size and the building at which would be installed needs to be decided. Designing a DES is far from a trivial task. As the number of buildings increases and the number of available technologies and resources becomes wider, designing a DES can become a very complex and challenging task.

Mathematical programming techniques can be used to design DES. An optimal design can be achieved using several criteria, such as minimizing cost, or minimizing carbon emissions, or maximizing energy efficiency. Applying a combination of those criteria leads to *multi-objective* mathematical programming, which provides a set of efficient or Pareto optimal solutions. Mathematical programming (or optimization as more commonly known) and multi-criteria decision analysis (MCDA), have been used extensively in related literature, e.g. for energy planning problems, assessment of energy projects, optimal sizing of technologies. Examples of such applications can be found in [21–24]. The most common objectives in the design of DES is the minimization of total annual cost and carbon emissions.

The knowledge of the values of certain parameters is necessary in order to design an energy system. Those parameters are the available technologies and their respective technical characteristics and costs, energy demand of buildings (heating, cooling, and electricity), climate data (solar irradiation, wind speed), and the carbon emission factors. The importance of uncertainty and how it affects the implementation of policies and the associated scenarios in energy planning, considering applications of multi-criteria analysis is highlighted in [25]. Therefore, it is suggested that a DM needs to consider all these parameters and data in order to make a decision, which leads to the question of which the best solution is and according to which criterion.

1.1 Scope and Contribution

The purpose of this thesis is to present a methodology for the design of DES using multi-objective mathematical programming. The objective functions are the total annual cost (TAC), which includes capital, operational and maintenance costs, and the total annual CO_2 emissions. In literature several optimization models have been developed for the design of DES. Those models are based on two design methods, namely: (a) “Method A” in which a simultaneous optimization of the size of the candidate technologies is applied, and (b) “Method B” in which technologies are selected amongst a set with predefined respective sizes. Therefore, there is a need to examine those two methods and perform an assessment of their respecting advantages and disadvantages. The developed methods are expanded versions of previous works in literature, and also three scenarios are constructed with different technology configurations in order to examine the associated benefits of DES. The contribution of the thesis is to expand previous methodologies in the field, by developing new methods consisting of more technologies and with a more detailed approach in the operational aspects of the system, in a multi-objective optimization approach. Also, the thesis contributes in comparing two basic design approaches and provides useful outputs for a DM in order to identify the best solutions.

The DES is comprised of the following technologies: (a) cogeneration units, (b) heat pumps, (c) absorption chillers, (d) boilers, (e) solar thermal collectors, (f) solar photovoltaics, (g) wind turbines, (h) thermal energy storage, (i) electric energy storage, (j) district heating network (DHN) and (k) microgrid. Therefore, a decision-making tool is provided with the following outputs:

- The technologies and their respective sizes that will be installed at each building;
- The layout of the DHN;
- The operational profile of the installed technologies;
- The electricity exchange between the microgrid and the national grid

Moreover, designing a DES is a long-term energy planning problem, based on the values of several parameters that might affect the optimal solution. These parameters are often characterized by a degree of uncertainty. Uncertainty in designing DES lies in many parameters, such as energy prices (electricity and natural gas), interest rates, climate data (e.g. solar irradiance, wind speed), energy demand etc. Hence, the optimal design of DES which tackles these uncertainties and offers robust solutions for the decision makers is a major challenge.

Therefore, this thesis also examines the optimal design of DES under uncertainty, aiming towards robust solutions, using:

a) Objective-wise worst case;
b) Robust optimization, specifically minimax regret criterion (MMR) and minimax expected regret (MER);
c) Stochastic programming, specifically using Monte Carlo analysis for scenarios generation.

The examination of uncertainty in designing a DES is a relatively new approach. The application and comparison of several techniques is another contribution of this thesis in the field. Specifically, several scenarios are developed aiming to examine how uncertainty affects results and provide the DM with robust solutions. Also, the application of MER in the field of DES is a novelty of this thesis.

Specifically, the contribution of this thesis in the field is:

- The modelling of the DES combining elements from previous studies to incorporate all candidate technologies and capabilities;

- A presentation of two approaches regarding the modelling of technologies' sizing and a comparison between them;
- A combination of the two approaches as a new strategy for designing a DES;
- A case study applied in a Greek area and conditions;
- The combined use of the multi-objective approach with a robustness analysis for energy problems (not only for DES);
- The modelling of the minmax regret approach in energy planning problems when scenarios regarding the uncertain parameters are anticipated;
- The modelling of the minimax expected regret scenario when scenarios regarding the uncertain parameters are anticipated with respective probabilities;
- A Monte Carlo simulation approach for DES problems.

1.2 Thesis Structure

This thesis is structured as follows:

- Chapter 1: This is the present chapter, which provides an introduction and outlines the motivation, concept and the scope of the thesis;
- Chapter 2: Introduces the concept of urban energy systems and a brief description of the technologies used in this thesis for designing a DES;
- Chapter 3: Presents aspects of mathematical programming, such as linear programming, mixed-integer linear programming and multi-objective optimization. Also, a description of methods for optimization under uncertainty is carried out.
- Chapter 4: Provides a detailed presentation of the methods developed for the optimal design of DES. Two methods have been developed for the deterministic scenario and four methods have been described for optimal design under uncertainty.
- Chapter 5: Presents a test case application for examining the developed methods. An area in Attica, Greece, is selected and the data for the case study are described analytically.
- Chapter 6: Provides the results of the deterministic test case application for both developed methods. A comparison between the two methods is carried out.
- Chapter 7: Provides the results for the test case application of optimal design of DES under uncertainty, examining four different techniques, either in robust optimization or stochastic optimization, and comparing the results in order to identify robust solutions.
- Chapter 8: This is the final chapter concluding the thesis. The results and the key findings are summarized. Furthermore, the prospects for future work in the field are presented.

Chapter 2: Urban energy and technologies

In this chapter the technologies used for energy generation in urban areas are described. Energy systems in buildings supply heating, domestic hot water (DHW), cooling and electricity to satisfy the respective demand. There are many technologies available that can be installed in residential and commercial buildings, each with specific characteristics (technical efficiency, cost etc.). The technical characteristics and modelling of technologies used in the mathematical model of this thesis to supply heating, cooling, and electricity are presented. Specifically, boilers, heat pumps, absorption chillers, cogeneration technologies, solar photovoltaics, solar thermal collectors, and wind turbines are presented. Also, a brief description of microgrids and district heating networks and their associated benefits is presented.

2.1 Boilers

A boiler generally is any device used to produce hot water. Boilers represent one of the most common technologies installed at buildings, used mainly to provide DHW and heating. Heat is transferred with radiators or via radiant floor. There are two main types of boilers, namely: (a) the conventional and (b) the condensing boilers. The efficiency of a boiler is defined as the energy output over the energy input. Condensing boilers have increased efficiency over the conventional ones, due to the utilization of water latent heat (the lower flue gas temperature at exit causes the vapour to condense, hence exploiting its latent heat) [26,27].

The efficiency of boilers varies between 79% - 99% and their typical size is between 10 – 33 kW_{th} [26]. Efficiency depends on the type of boiler, the input fuel (natural gas, oil, biomass), the rate of fuel flow, the inlet and outlet water temperatures and the heating load that needs to be satisfied.

2.2 Air Conditioners - Heat pumps

Air conditioners have been in use in buildings for many years as a cooling generation technology. Heat pumps follow the same operating principles, but they are available in many types and are able to work reversibly to provide heating and cooling. Heat pumps are the only heat recovery system able to lift the temperature of the waste heat at a useful level (a process which seems to contradict the 2nd law of Thermodynamics).

To allow the transfer of heat from a lower to a higher temperature an amount of work (energy) is required. Most heat pumps rely on a vapor-compression cycle with four basic components, namely: (a) an evaporator, (b) a compressor, (c) a condenser and (d) an expansion valve. A typical configuration of a heat pump system is presented in Fig. 2.1. A working fluid absorbs heat in the evaporator from the heat source which causes it to evaporate, then goes through the compressor where is compressed to a higher pressure and temperature. At stage three, in the condenser the hot vapour releases heat and in the final stage it expands to the evaporator pressure and temperature, hence returning to its original stage. A reversed operation of the condenser and evaporator allows the heat pump to work in cooling mode [28].

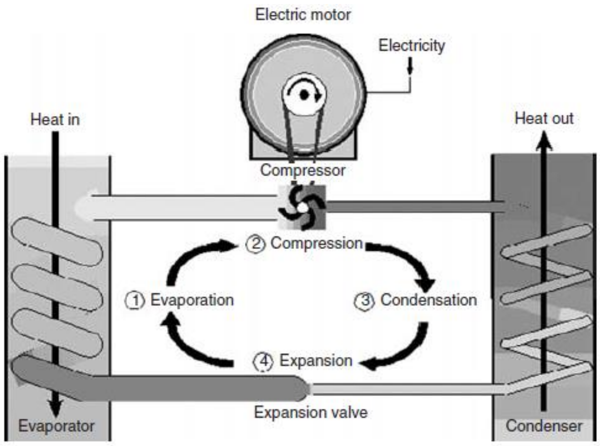


Fig. 2.1. A closed cycle electricity driven vapour-compression heat pump (source: [28]*)*

Heat sources for the operation of heat pumps include air, water, soil and geothermal, and solar energy. Air source heat pumps are the most common. Furthermore, heat pumps can be classified into six main types:

- water to water;
- water to air;
- air to air;
- air to water;
- ground to water;
- ground to air.

The efficiency of heat pumps is measured through a coefficient of performance (COP), defined as the ratio of energy out over work (energy input):

$$COP = \frac{Q}{W} \tag{2.1}$$

2.3 Absorption Chillers

Absorption chillers are based on the principle of heat absorption by liquids or salts of the vapor of a working fluid. The most common working pairs used in absorption chillers are: (a) water as working fluid and lithium bromide (LiBr) as refrigerant, and (b) water as working fluid and ammonia (NH_3) as refrigerant. A configuration of an absorption chiller is presented in Fig. 2.2.

The operation of an absorption chiller is similar to the vapor-compression heat pump. The working fluid is compressed thermally in a solution circuit, consisting of an absorber, a solution pump, a generator and an expansion valve. The low-pressure vapor from the evaporator is absorbed by the absorbent in a process that generates heat. Then, the solution enters the generator after being pumped to high pressure. In the generator the working fluid is heated using an external heat source, reaching a high temperature and converted into a vapour. Then, a condenser is used in which the working fluid is condensed, while the absorbent is through an expansion valve goes back to the absorber. Heat is supplied at the evaporator and given off at a medium temperature in the condenser and the absorber. The solution pump might require a small amount of electricity to operate [28]. Absorption chillers usually have an actual COP less than 1 and they perform best when the heat supply is at high temperatures [29].

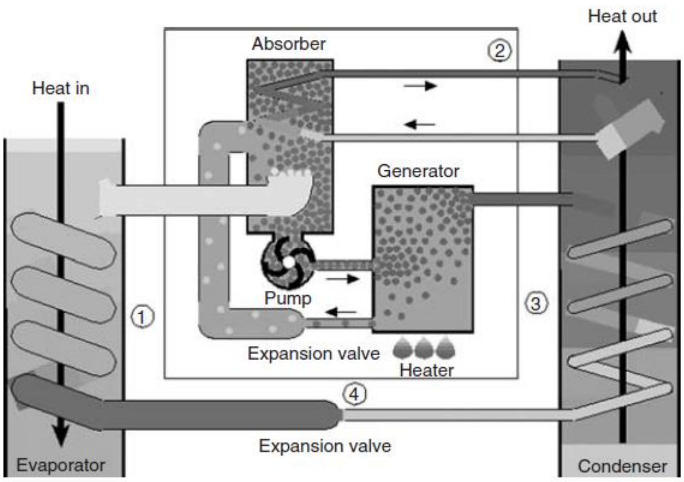


Fig. 2.2. An absorption chiller (source: [28]*)*

2.4 Cogeneration Technologies

Cogeneration technologies, most commonly known as combined heat and power (CHP), refers to the simultaneous generation of electricity and heat. Basically, CHP units take advantage of the wasted heat from power generation. Cogeneration offers increased efficiency by minimizing heat losses and allowing supply of heat to various applications and facilities. In Europe cogeneration has been used by many countries for industrial, commercial and residential applications. CHP technologies offer several benefits, mainly high efficiency, low emissions and high reliability [18] [30].

In Fig. 2.3 the energy balances between the conventional (separate) generation of power and heat and cogeneration is presented, showing the increased efficiency of a CHP system.

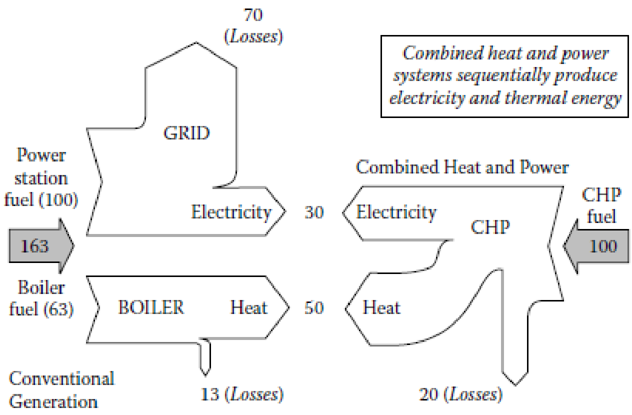


Fig. 2.3. A comparison between conventional and cogeneration (source: [31]*)*

The overall thermal efficiency of a CHP system is the sum of the fuel conversion to electricity plus the fuel conversion to useful thermal energy, and it typically ranges between 65% - 90%:

$$n_{tot} = \frac{E + Q_H}{Q_F} \tag{2.2}$$

In recent years cogeneration technologies have been further developed and moved from industrial to residential applications (micro-cogeneration, mCHP) based on a distributed energy systems approach as shown in Fig. 2.4. Typically, cogeneration technologies consist of four basic components, a prime mover, a power generator, a heat recovery system and a control system. Technologies used for mCHP are based on the following prime movers [32]:

- Steam turbines;
- Gas turbines;
- Reciprocating engines;
- Stirling engines;
- Fuel cells.

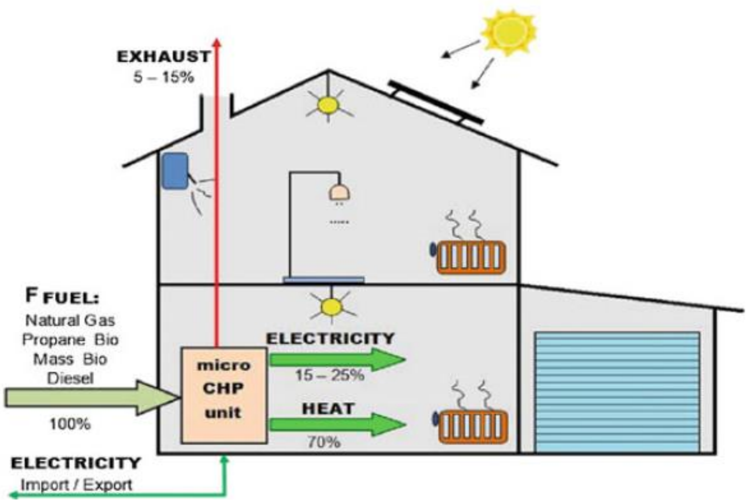


Fig. 2.4. Micro-cogeneration in a residence (source: [32]*)*

Another application of cogeneration is the utilization of generated heat to produce cooling energy, in a concept called combined cooling, heating and power (CCHP), also known as *polygeneration* or *trigeneration, as shown in* Fig. 2.5. A classic trigeneration system is the coupling of CHP with an absorption chiller. Trigeneration makes cogeneration more economically attractive, as the generated heat can also be used in the summer when cooling is required. Application of cogeneration systems has been studied thoroughly by several researchers, particularly combined with mathematical programming (e.g. [33–39]).

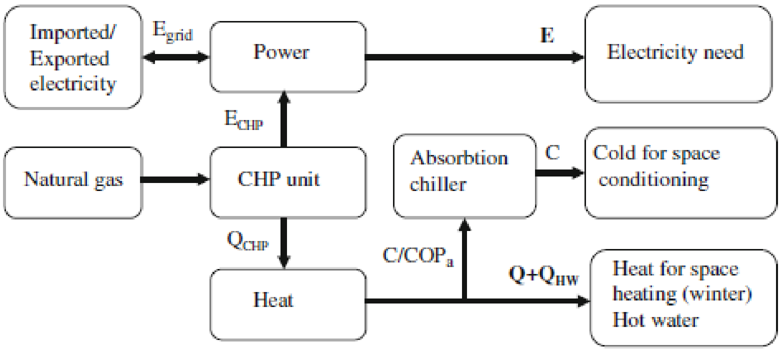


Fig. 2.5. A representation of a trigeneration system (source: [32]*)*

2.5 Solar Energy

Solar energy can be used in various applications in energy systems, either for thermal applications (heating and/or cooling) or for electricity generation. Applications of solar energy take advantage of solar irradiance, which is dependent on the location. The higher the solar irradiance the higher the potential is. The solar irradiation for Europe is presented in Fig. 2.6 and it can be seen that southern countries (such as Greece) have a lot of potential to use solar energy.

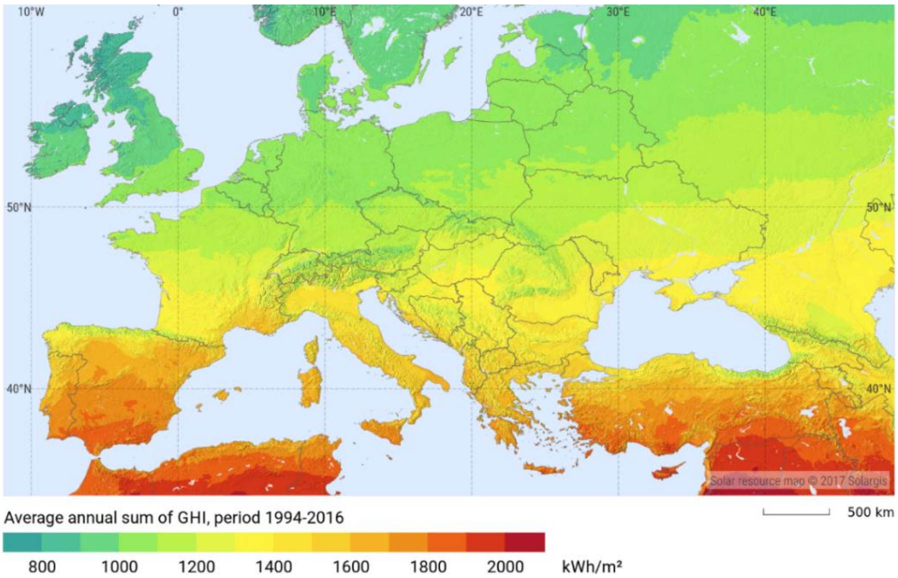


Fig. 2.6. Global Horizontal Irradiation in Europe (source: [40]*)*

2.5.1 Solar water-heating systems

Solar collectors can absorb solar radiation and can be installed to heat water, which can be then used for heating and/or DHW supply. Basically, a conventional solar water-heating system comprises of two units, namely the collector and the storage unit. Typically, a combination of flat-plate collectors (FPCs) is used. There are two modes to transfer water to an insulated storage tank, namely: (a) the thermosiphon/natural model in which hot water is transferred by natural convection and (b) forced-circulation mode, in which a pump is used to circulate water. A schematic of a natural and forced-circulation system is shown in Fig. 2.7 [41].

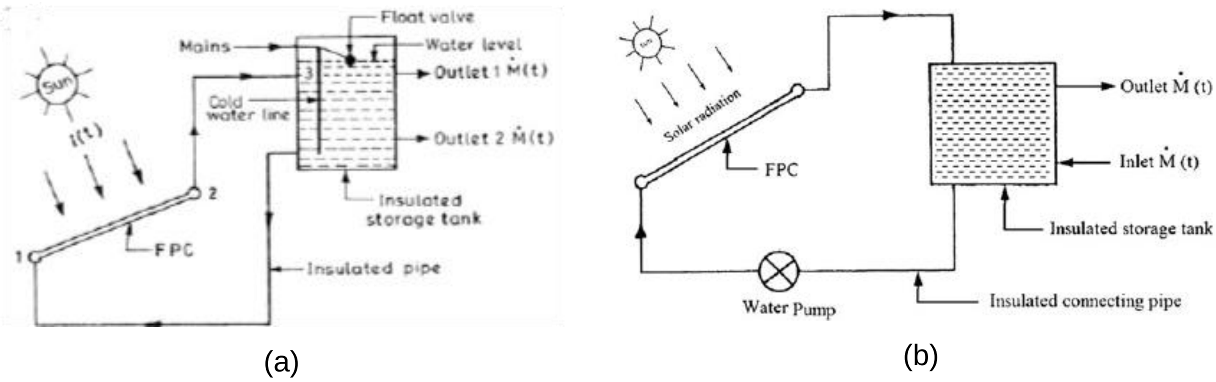


Fig. 2.7. A schematic diagram of: (a) A thermosiphon solar water heating system and (b) a forced-circulation single-loop water heating system [41]

The performance of a solar water heating system depends on the solar radiation absorbed by the collector, the temperature difference between ambient temperature and the mean plate temperature and the efficiency of the collector. The collector efficiency is the ratio of the energy provided by the collector to the solar radiation on the collector over a period. Efficiency of the solar collector drops when the mean plate temperature gets high and ambient temperature and solar radiation get low. The variations of efficiency for different collectors is shown in Fig. 2.8 [42].

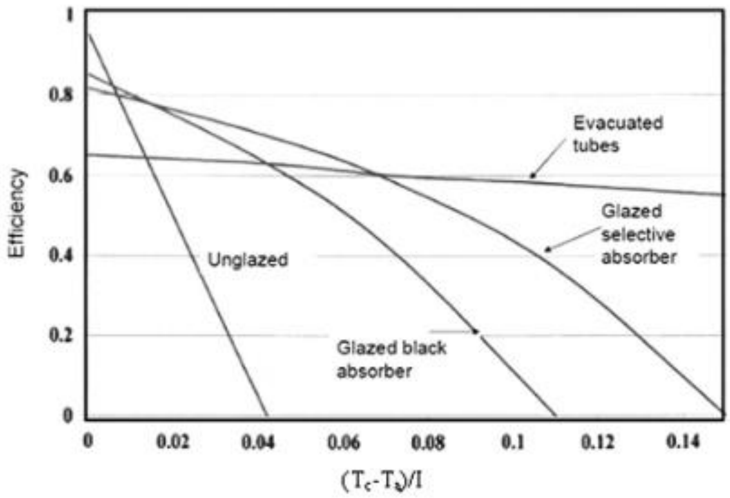


Fig. 2.8. Variations of efficiency for various solar collectors (source: [42]*)*

2.5.2 Photovoltaics

Solar energy can be used to produce electricity using photovoltaics, a technology that utilizes *photovoltaic effect*. When a photovoltaic material absorbs solar radiation of given wavelengths the energy of electrons increases allowing them to jump over to the next conduction band and move freely, thus generating direct current electricity [43]. Several materials are used for solar cells, such as silicon (monocrystalline silicon, polycrystalline silicon, and ribbon silicon), cadmium telluride, copper-indium selenide, single crystal, light-absorbing dyes, organic/polymer, and nanocrystals [41]. The improvement of efficiency for various types of PV cells over the years is shown in Fig. 2.9. The efficiency of a PV cell is defined as the ratio of the maximum electricity output to the incident radiation. Typically, it is defined for standard conditions of cell temperature 25ºC and irradiance of 1000 W/m^2.

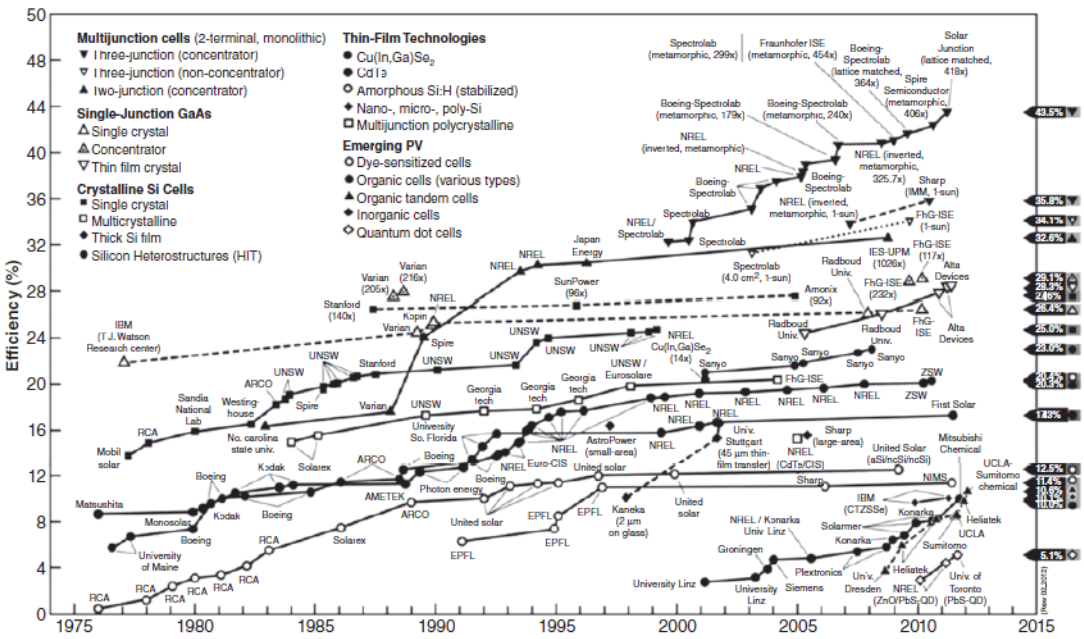


Fig. 2.9. Maximum efficiency of laboratory research PV cells of various types as reported by NREL (source: [44]*)*

Photovoltaic cells (PV) can be either connected in series or in parallel to form a module and generate electricity. A group of pv modules is called a panel and number of interconnected panels is called a solar PV array. Typically, a PV system includes the following parts [41]:

- a charge controller to regulate the DC voltage and protect the batteries from overcharging (if are installed) and against overvoltage;
- a PV battery used for electricity storage and supply energy when there is not enough production (e.g. night);
- an inverter used for the conversion of the DC current into AC current.

PVs can be connected either as direct coupled systems, stand-alone applications, grid-connected or hybrid connected systems. Moreover, they can be used for various types of applications, such as: remote site electrification, communications, remote monitoring, water pumping, charging vehicles batters and as building-integrated photovoltaics (installed in the façade or roof of a building) [43].

2.6 Wind Energy

Wind energy is a RES which gained rapid development in recent years. To convert wind energy to electricity wind turbines are used, which are classified into two main categories, namely: (a) horizontal-axis wind turbines (HAWTs) and (b) vertical-axis wind turbines (VAWTs). Typically, a wind turbine consists of a tower, rotor blades, an inverter, wind generator magnets and charge controllers. Wind turbines offer several benefits, such as low-cost and environmentally friendly energy supply, however there are some disadvantages too such as high noise and intermittency. The power generation of a wind turbine depends on the wind speed, with each turbine having a respective power curve. A typical power curve is shown in Fig. 2.10. The Weibull distribution is used for wind resource analysis, characterized by a shape parameter and a mean wind speed parameter.

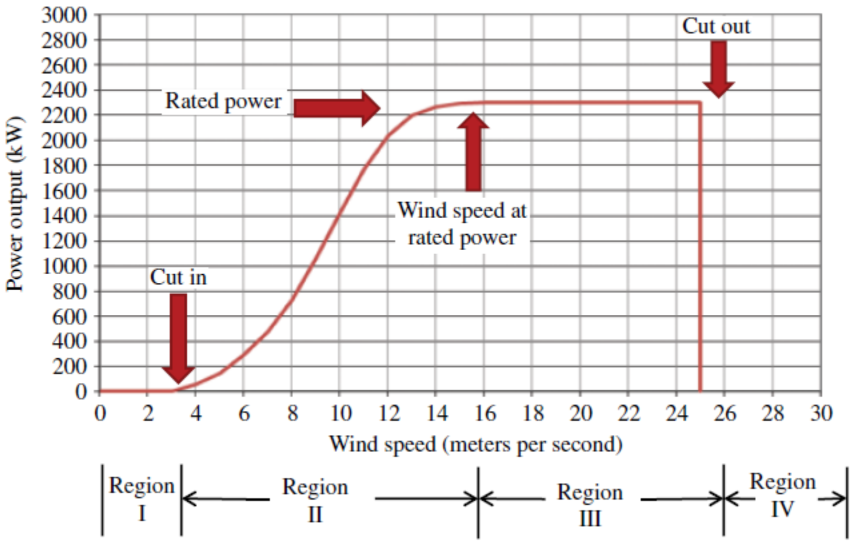


Fig. 2.10. Power curve of a wind turbine (source: [45]*)*

The output of a wind turbine is typically based on the following set of equations:

$$P(v) = \begin{cases} 0, & v<v_{ci} \\ P_f(v), & v_{ci} < v < v_r \\ P_r, & v_r < v < v_{co} \\ 0, & v>v_{co} \end{cases} \quad (2.3)$$

where, v wind velocity, v_{ci}, v_r, v_{co}, cut-in, rated and cut-out velocities, P_r is the rated power (in kW), and $P_f(v)$ is the power fitted to power curve data provided by the manufacturer (typically a polynomial function).

Large wind turbines have a range of sizes up to 5 MW, a figure which is increasing annually. There are also small-scale wind turbines with sizes less than 100 kW. Small wind turbines can be configured as stand-alone systems and provide electricity to houses or remote areas. In terms of designing wind turbines for built environments though several challenges arise. In urban environment wind turbines can be installed at the roof of a building, at the sides of a building or integrated in between buildings. The earth's characteristics and the roughness of the area are important factors to consider [46]. Reviews performed for the assessment of wind turbines in the urban environment conclude that more research is necessary in order to assess factors such as turbulence, wind profiles and issues of aerodynamics [47,48]. Nevertheless, micro wind turbines can be economically viable (if wind speed is greater than 6 m/s), and also cover the demand of a house or also export surplus electricity to the grid [49].

2.7 Energy Storage

As the name suggests, energy storage is a concept of storing useful energy for use at a later period. In the context of urban energy systems two categories of energy storage are significant, namely: (a) thermal energy storage (TES) and (b) electric energy storage (EES).

2.7.1 Thermal energy storage

TES is used for applications such as space heating, hot water, cooling and air-conditioning. Two main mechanisms exist for storing thermal energy, one based on using sensible heat and the other based on using latent heat. In sensible heat applications energy is stored by causing the temperature of a material to rise (absorbing heat) or reduced (releasing heat). Heat is transferred to another material, or the environment via heat transfer mechanisms of convection, conduction or radiation. Common systems include rocks, ground and water. In latent heat applications, energy is stored by causing changes in the state or phase of materials (e.g. organic materials).

Sensible TES need a storage medium, a container, and input/output devices. Important parameters for the selection of storage materials is the cost, thermal capacity and the rate at which heat can be stored or released. In latent heat TES systems heat change is usually higher compared to sensible heat change. Typically, latent heat systems consist of a heat storage substance that is able to change phase in the respective temperature range, a containment and a heat-exchange surface.

There are many factors to consider on selecting a specific type of TES system, such as the storage period, operational profile, and economic viability. In general, TES offers several advantages, such as increase generation capacity, better operation of cogeneration plants, shifting of energy purchases to low-cost periods and increased system reliability [50]. Regarding the combination of cogeneration and TES studies showed several benefits in terms of energy savings and cost reduction, depending on the type of building [51,52].

2.7.2 Electric Energy Storage

Electric energy systems have remerged along with the increase usage of renewables, in order to capture wasted energy for later use. EES can offer several benefits, such as time shifting (storing at off-peak periods and discharge at peak time), power quality (frequency control) and emergency supply. Electricity can be stored in various forms such as potential energy, compressed air, electrochemical energy (batteries), kinetic energy, magnetic fields (inductors) and electric fields (capacitors). EES systems are classified mainly using two criteria: (a) power rating and (b) rated energy capacity [53]. In Fig. 2.11 the classification of various EES systems is presented.

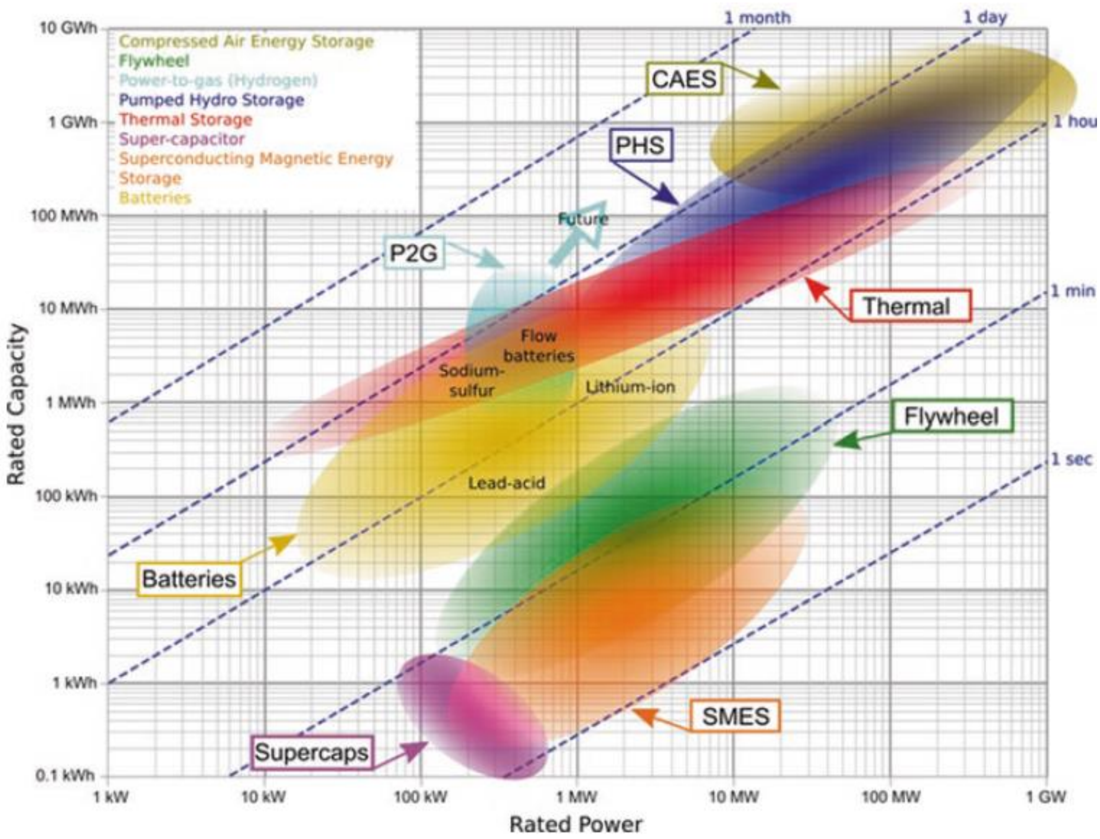


Fig. 2.11. Classification of EES systems (source: [53]*).*

The most established EES technology is electrochemical batteries, specifically lithium-ion technology batteries are the most common for stationary storage, outperforming their inferior lead-acid counterparts. They have an efficiency range between 80 to 85% and a life of 5000 cycles. Batteries can offer power quality in terms of voltage stability and frequency control and also are suitable for energy management. In the last years installation of batteries has expanded. Also, in recent years high temperature sodium-sulphur batteries have also been installed [53].

EES are installed in buildings, despite the high cost, due to the benefits they can offer such as energy security and better energy management. Also, they are expected to play a very important role in the future smart grids [54–57].

2.8 Microgrids

The deployment of distributed generation has been growing significantly during the last years. Typically, DG technologies are connected to distribution networks based on the concept of passive consumer loads and one direction power flows, from the substation to the consumers. Microgrids are a relatively new concept, developed to better facilitate the integration of distributed generation. Examples of microgrids concept are depicted in Fig. 2.12. Their organization relies on the control capabilities of the increasing penetration of distributed generators, such as microturbines, photovoltaics, coupled with energy storage devices. A microgrid is defined as [58]:

"*Microgrids comprise LV (low voltage) distribution systems with distributed energy resources (DER) (microturbines, fuel cells, PV, etc.) together with storage devices (flywheels, energy capacitors and batteries) and flexible loads. Such systems can be operated in a non-autonomous way, if interconnected to the grid, or in an autonomous way, if disconnected from the main grid. The operation of microsources in the network can provide distinct benefits to the overall system performance, if managed and coordinated efficiently".*

From this definition three conclusions can be derived:

a. A microgrid is an integration platform for microgeneration, storage units and controllable loads, at a local distribution grid. This means a focus is given on local supply to nearby loads, and that a microgrid operates at a LV level.
b. A microgrid can operate either in on-grid or off-grid, also known as islanded mode.
c. A microgrid differs from a passive grid penetrated by microsources in terms of management and coordination of resources. A microgrid operator provides load control and needs to follow specific economic, technical and environmental targets. Also, microgrid has the advantage of dealing with conflicts of interests of various stakeholders in order to provide the optimal operation decision.

In literature, several models of the development of microgrids exist in different concepts, e.g. [59–62].

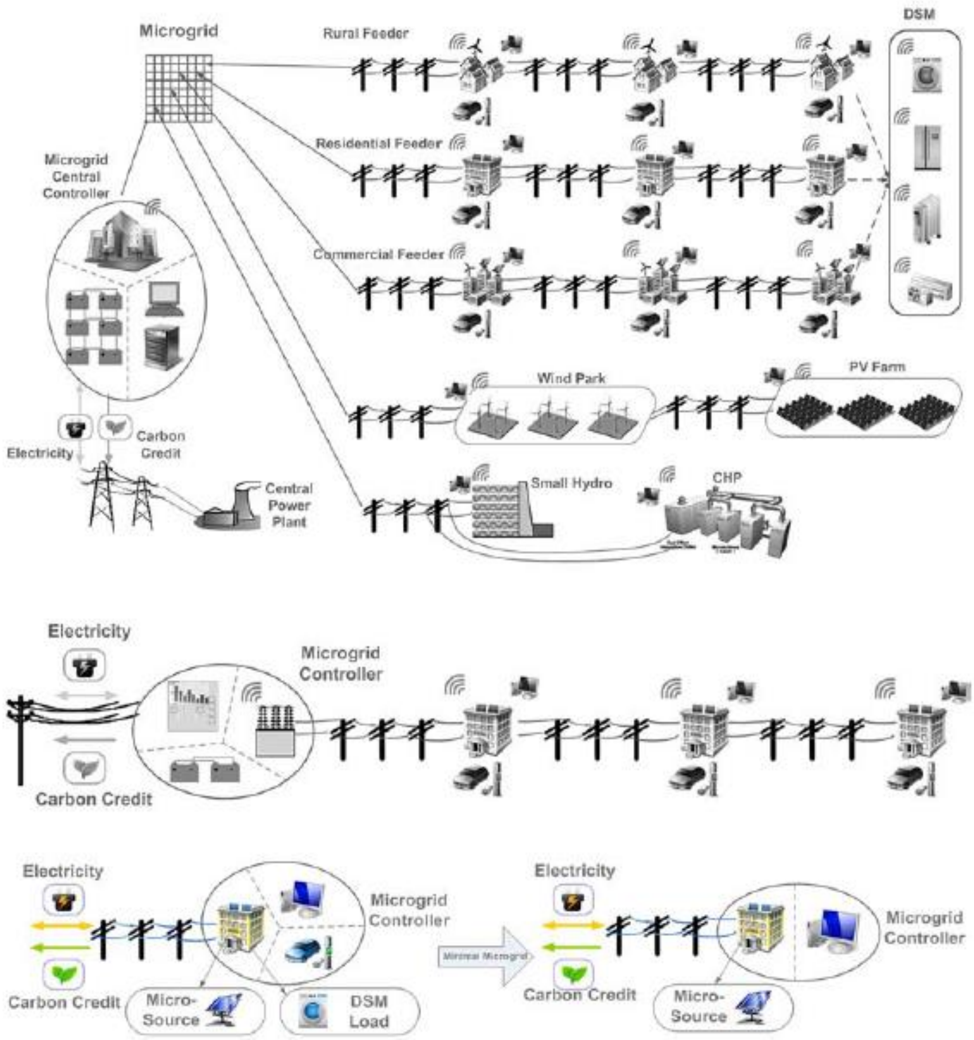


Fig. 2.12. Examples of microgrid: (a) as a LV grid; (b) as a LV feeder; (c) as a LV house (source: [58]*)*

2.9 District heating networks

Conventional heating systems rely on local supply of fuels (e.g. natural gas) to individual energy technologies (e.g. boilers) to convert primary energy into thermal energy and satisfy local energy demand. DHNs are networks that can transfer heat, either between buildings, or from large scale plants (e.g. cogeneration plants) that produce waste heat, to residential, commercial or industrial consumers. Those systems can be designed to transfer either heat or cold (District heating or District cooling networks). In the EU, there is an increasing number of local authorities to integrate cogeneration plants with DHN, which also fits the European long-term energy strategy. The benefits of these systems can be both economical (economy of scale) and environmental (reduction of carbon emissions associated to energy generation) [18].

However, there are some barriers associated with the development of DHNs, such as the high initial cost to develop the necessary infrastructure. Therefore, energy policies and regulation for the development of decentralized networks need to be implemented [63].

In Fig. 2.13 a district energy system is illustrated. Part (a) shows the general layout of a district energy system with a central heat/cold production, the distribution network, the location and equipment of end-users. Part (b) shows the layout of a district heating system. A CHP, boiler, or combinations of technologies can be used to produce heat, using available primary energy sources. Depending on system's design heat can be transferred as hot water or steam. When heat reaches the end-users, heat exchangers can be used to satisfy heat demands, either in space heating, hot water or for industrial processes. Part (c) shows a general district cooling system. At the central site primary thermal energy is converted into cold thermal energy (e.g. by using an absorption chiller). A cold thermal energy storage system can also be used. Regarding costs, the most expensive part is the piping network consisting of pipes made from a combination of field-insulated and pre-insulated pipes, which are embedded in a concrete tunnel or buried in the ground (or a combination). Capital cost of pipes is estimated to be between 50% and 75% of the total cost [18].

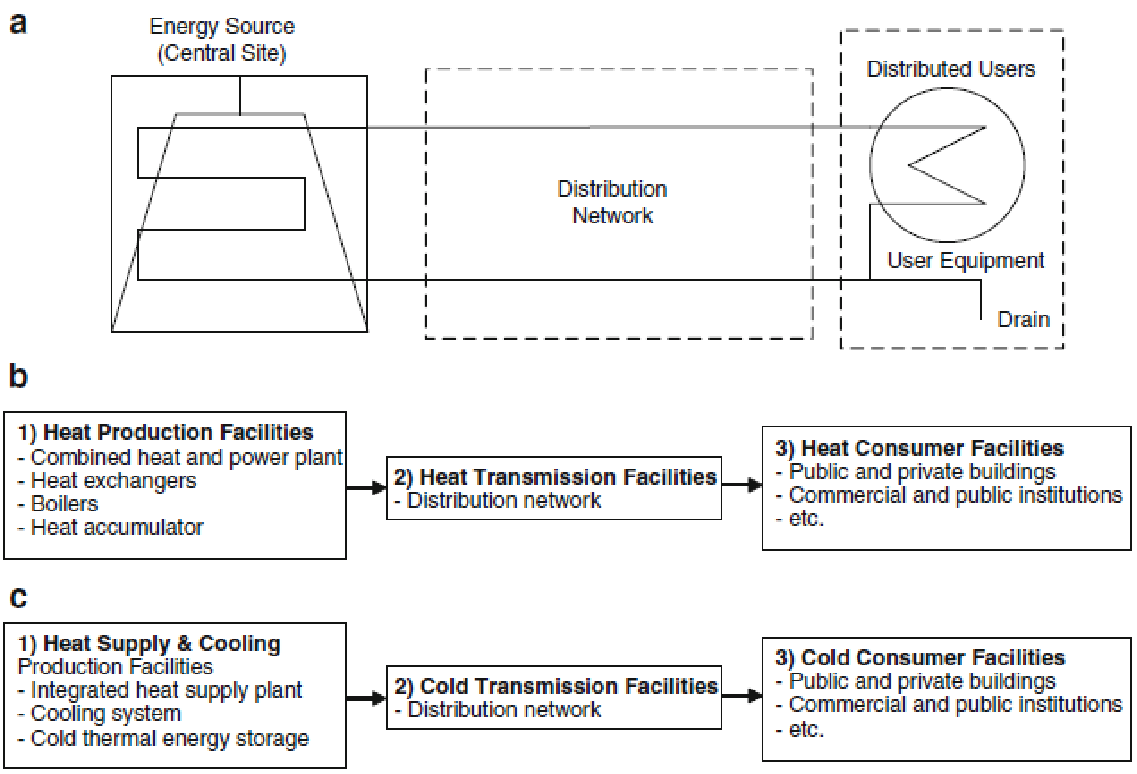


Fig. 2.13. A district energy system: (a) A general layout, (b) flowchart for district heating and (c) flowchart for district cooling applications (source: [18]*)*

Chapter 3: Mathematical programming

In this chapter some key aspects of mathematical programming are presented. Specifically, the basic characteristics of linear programming, mixed-integer linear programming, multi-objective programming and techniques of optimization under uncertainty are presented. Also, the ε-constraint method (and its expansions) which is used to solve multi-objective optimization problems is described.

Regarding uncertainty, four techniques are introduced, which are used in this thesis to provide robust solutions, namely objective-wise uncertainty, robust optimization (MMR and MER), and stochastic optimization (Monte Carlo simulations).

3.1 A brief introduction to mathematical programming

Mathematical programming is considered to be a subtopic of *Operations Research*. Operations Research (OR) is a scientific method of decision making. The aim is to make the optimal choice under a specific set of constraints. Roots of OR have been generally attributed to World War II, when a scientific method was needed to allocate scarce resources to various operations, although some work in the field was done earlier. In literature there are a number of textbooks dedicated to operations research and modelling in mathematical programming, such as [64–66]. This chapter briefly describes some common mathematical programming techniques which are used in this thesis.

The most common categories of MP problems are:

- Linear programming;
- Integer programming;
- Nonlinear programming;
- Mixed-Integer linear programming;
- Dynamic programming;
- Multi-objective programming.

In order to develop any OR model four major concerns apply, namely:

a. *Feasibility* (can this be done?)
b. *Optimality* (is this the best choice?)
c. *Sensitivity* (what happens if input parameters change?)
d. *Implementability* (can this solution actually be applied?).

3.2 Linear Programming

Linear programming (LP) is a tool developed in OR, perhaps the most important one as it is highly used and has major scientific impacts. In LP all mathematical functions of the mathematical model developed to define the problem are linear. The most famous method to solve LP problems is Simplex method, developed by Dantzig. Generally, an LP problem has the following form:

$$\begin{gathered} \min \ f(\vec{x}) \\ s.t. \\ \vec{g}(\vec{x}) \leq 0 \\ \vec{h}(\vec{x}) = 0 \end{gathered} \tag{3.1}$$

where:

- $f(\vec{x})$ represents the objective function
- $\vec{x} \in \mathbb{R}^n$ represents the vector of decision variables
- $\vec{g}(\vec{x}) \in \mathbb{R}^m$ and $\vec{h}(\vec{x}) \in \mathbb{R}^p$ represent *m* inequality and *p* equality constraints that define the search space.

LP has a variety of applications such as production planning, diet problems, allocation problems, employee scheduling, dynamic production, blending problems, transportation and assignment problems. Three fundamental assumptions apply to LP problems:

a. Deterministic property;
b. Divisibility;
c. Linearity.

Deterministic property implies that all parameters are known with certainty. Divisibility allows decision variables to have any value, including real numbers and non-integers. Finally, linearity means that all expressions (objective function and constraints) are linear.

3.3 Mixed-Integer Linear Programming

Mixed-Integer linear programming (MILP) is an extension of LP in which some but not all variables are integer. A MILP problem has the general form:

$$\begin{gathered} \min\ f(\vec{x}) \\ s.t. \\ \vec{g}(\vec{x}) \leq 0 \\ \vec{h}(\vec{x}) = 0 \\ x_j \in \mathbb{Z}\ \forall\ j \in J \end{gathered} \tag{3.2}$$

where, x_j represents the integer decision variables. A special case is when x_j are binary variables $\{0,1\}$.

MILP problems are useful in cases where a selection needs to be made, such as selecting machines, buildings, investments, land use, etc..

3.4 Multi-objective programming

Multi-objective programming problems refer to the case where there are more than one objective functions. In this context, the term of optimality as defined in the single objective cases does no longer apply. A DM needs to decide which of the two (or more) criteria is more important, based on a trade-off between them. Details about multi-objective optimization techniques and its applications can be found in [67–73]. A general multi-objective optimization problem can be written as [72]:

$$\begin{gathered} \min \ \vec{f}(\vec{x}) \\ s.t. \\ \vec{g}(\vec{x}) \leq 0 \\ \vec{h}(\vec{x}) = 0 \end{gathered} \tag{3.3}$$

where, $\vec{x} \in \mathbb{R}^n$, $\vec{f}(\vec{x}) \in \mathbb{R}^k$, $\vec{g}(\vec{x}) \in \mathbb{R}^m$, $\vec{h}(\vec{x}) \in \mathbb{R}^p$.

In multi-objective optimization problems there are many solutions, therefore relationships between solutions are defined as in [72]:

- A vector $\vec{x}_1$ dominates a vector $\vec{x}_2$ if: $\vec{x}_1$ is at least as good as $\vec{x}_2$ for all the objectives, and $\vec{x}_1$ is strictly better than $\vec{x}_2$ for at least one objective.
- A vector $\vec{x} \in \mathbb{R}^n$ is locally optimal in the Pareto sense if there exists a real $\delta > 0$ such that there is no vector $\vec{x}'$ which dominates the vector $\vec{x}$ with $\vec{x}' \in \mathbb{R}^n \cap B(\vec{x}, \delta)$ where $B(\vec{x}, \delta)$ represents a bowl of centre $\vec{x}$ and of radius δ.
- A vector $\vec{x} \in \mathbb{R}^n$ is globally optimal in the Pareto sense (or optimal in the Pareto sense) if there does not exist any vector $\vec{x}'$ such that $\vec{x}'$ dominates the vector $\vec{x}$.

Several methods exist to solve multi-objective optimization problems, such as scalar, interactive, fuzzy or using metaheuristics (e.g. genetic algorithms). A popular method is the ε-constraint method, which is used for the optimal design of DES in this thesis.

3.4.1 The ε-constraint method

In the classic ε-constraint method a multi-objective optimization problem is transformed into a single-objective problem using the following approach [72]:

- choose an objective function to be optimized with high priority;
- choose a vector of initial constraints;

- transform the problem by conserving the objective function to be optimized and transforming all other objective functions into inequality constraints.

To present the problem using ε-constraint method a constraint vector $\varepsilon_i, i \in \{2,...,k\}, \varepsilon_i > 0$ is chosen. Then, the problem defined in eq. (3.3) is transformed:

$$
\begin{gathered}
\min\ f_1(\vec{x}) \\
s.t. \\
f_2(\vec{x}) \leq \varepsilon_2 \\
\vdots \\
f_k(\vec{x}) \leq \varepsilon_k \\
\vec{g}(\vec{x}) \leq 0 \\
\vec{h}(\vec{x}) = 0
\end{gathered}
\tag{3.4}
$$

Mavrotas in [74] proposed an improvement to the classic ε-constraint method, called augmented ε-constraint (AUGMECON), which can effectively be implemented in multi-objective mathematical programming problems. AUGMECON has the advantages of being more efficient and can avoid weak Pareto optimal solutions. An improved version of AUGMECON, called AUGMECON2 was presented by Mavrotas and Florios in [75]. AUGMECON2 is found to be more efficient in multi-objective integer programming problems and can produce the exact Pareto set. An illustration of AUGMECON2 method is presented in Fig. 3.1.

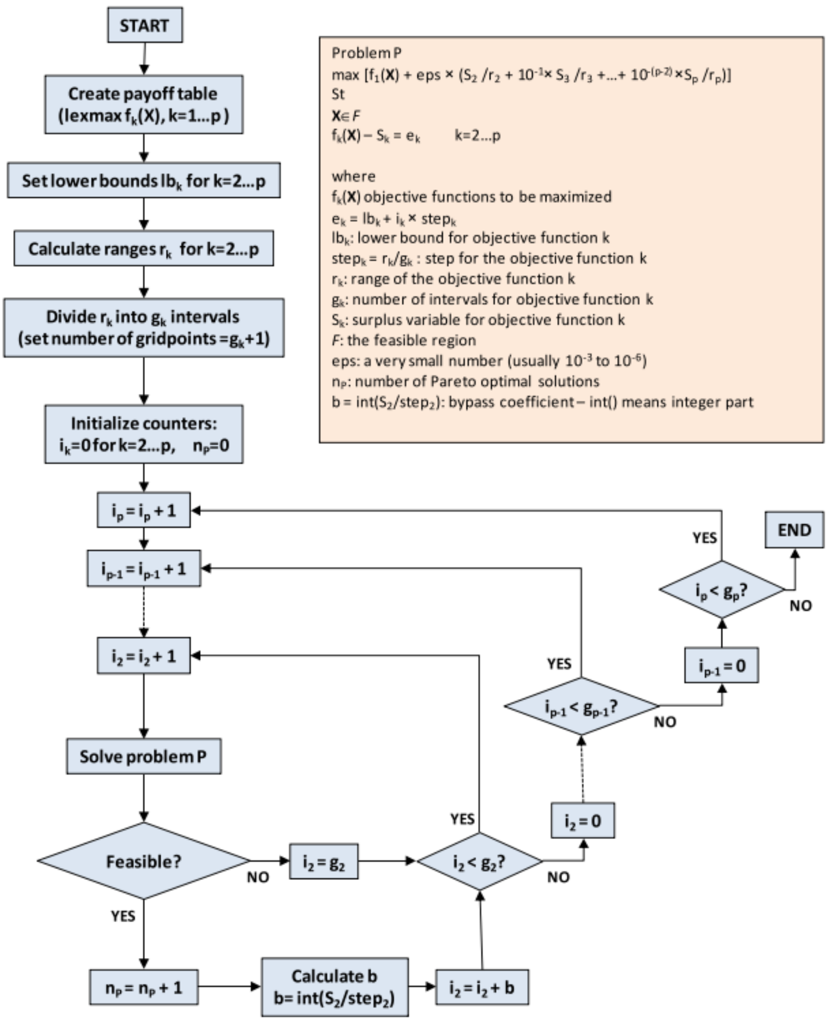


Fig. 3.1. A flowchart of the AUGMECON2 method. (source: [75]*)*

Using AUGMECON2 a multi-objective mathematical programming problem can be redefined as follows:

$$
\begin{gathered}
\min \left[f_1(\vec{x}) + eps \times \left(\frac{s_2}{r_2} + 10^{-1} \times \frac{s_3}{r_3} + \cdots + 10^{-(k-2)} \times \frac{s_k}{r_k} \right) \right] \\
s.t. \\
f_2(\vec{x}) - s_2 = \varepsilon_2 \\
f_3(\vec{x}) - s_3 = \varepsilon_3 \\
\vdots \\
f_k(\vec{x}) - s_k = \varepsilon_k \\
\vec{g}(\vec{x}) \leq 0 \\
\vec{h}(\vec{x}) = 0
\end{gathered}
\qquad (3.5)
$$

where:

- $r_i, i \in 2,...,k$ represent the ranges of objective functions

- $s_i, i \in \ 2,...,k \ \ , s_i \in R^+$ represent the surplus variables of the respective constraints
- $eps \in \left[10^{-6}, 10^{-3}\right]$.

In Fig. 3.2 a graphical representation of ε-constraint method is presented.

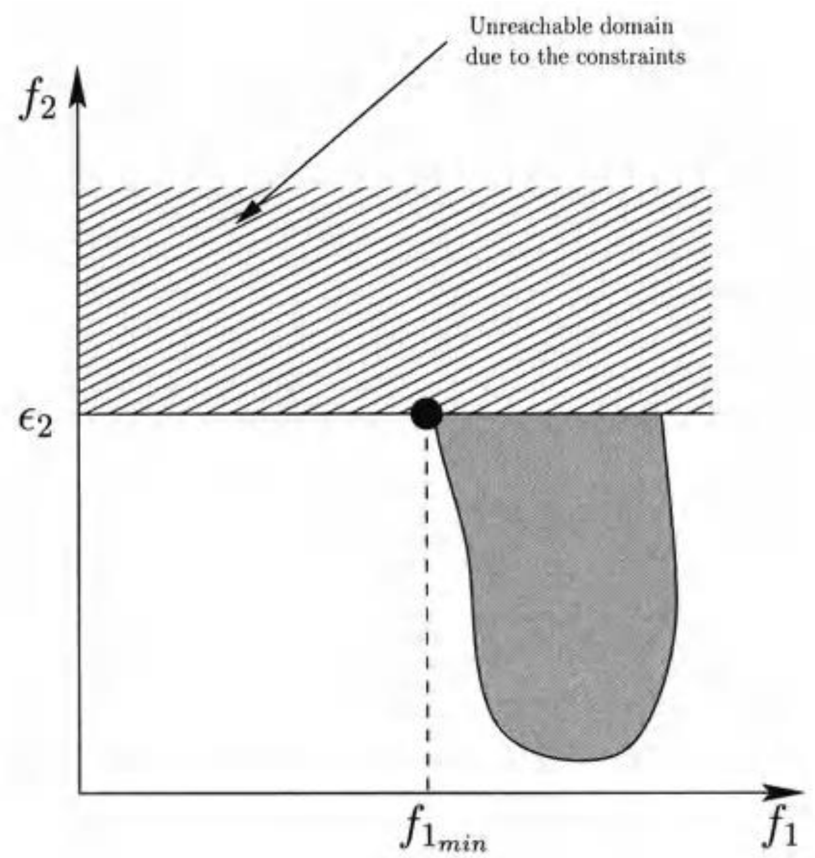


Fig. 3.2. The ε-constraint method (source: [72]*)*

3.5 Optimization under uncertainty

As stated in Section 3.2 a basic assumption used in LP, and generally used in mathematical programming is deterministic property, i.e. knowing the values of parameters with certainty. However, in the real world that is usually not the case. For instance, in energy planning problems parameters such as fuel prices (gas, oil, electricity) are not certain as their value varies in time. Therefore, dealing with uncertainty is an important task, especially in long-term planning problems. Generally, there are three main approaches to deal with uncertainty, namely: (a) *Sensitivity analysis*, (b) *Robust Optimization (RO)* and (c) *Stochastic Optimization (SO)*. Technically, sensitivity analysis is a method used to identify the sensitive parameters rather than provide robust solutions. RO and SO aim to provide robust solutions, even though they are used in different text, and are explained briefly in this section.

3.5.1 Objective-wise uncertainty

Optimization under uncertainty for multi-objective optimization is an area with ongoing research. Ehgrott et al. in [76] provide several methods for minimax robustness for multi-objective optimization problems. One such method is *objective-wise worst case* in which the supremum of the robust counterpart of an uncertain multi-objective optimization problem is not considered a multi-objective maximization problem, rather is interpreted as a point instead of a set. Therefore, is reformulated into a new problem, defined as the objective-wise worst case:

$$\begin{aligned}
&OWC_{P(u)} \ \min f_u^{OWC}(x) \\
&s.t.\ x \in X \\
&\text{where} \\
&f_u^{OWC}(x) \equiv \begin{pmatrix} \sup_{\xi \in u} f_1(x,\xi) \\ \sup_{\xi \in u} f_2(x,\xi) \\ \vdots \\ \sup_{\xi \in u} f_k(x,\xi) \end{pmatrix}
\end{aligned} \tag{3.6}$$

This approach has the advantage of being much easier than solving a multi-objective optimization problem $\max \ f(x,\xi) : \xi \in U$ as it results to solve a deterministic multi-objective problem, which then can be solved using any appropriate method.

3.5.2 Robust Optimization

RO is a relatively new approach in optimization with a growing interest, aiming to provide solutions which are robust and independent of any value of the uncertain parameters. In literature, there are several methods used in RO, such as *minimax regret criterion* and *robust counterpart* with a variety of applications [77–83]. In the context of this thesis when the concept RO is used it refers to the concept of robustness as defined by Kouvelis and Yu in [77] calculated specifically by the *MMR* criterion. Regret is defined as the difference between the result of a decision (cost) and the result of the decision a DM would have made had all the parameters were known in advance (robust deviation decision). Also, regret can be defined as the ratio of these values, which is called relative robust decision. The MMR criterion has the characteristic of providing risk-averse solutions.

Practically, to calculate the MMR criterion the DM uses scenarios based on the possible values the respective parameters can take. For the calculations in this thesis the relative MMR criterion is used which is calculated by eq. (3.7):

$$\begin{gathered} z_{MMR} = \min\ [y] \\ \text{s.t.} \\ f^s \leq (1+y)\cdot z^s, s \in S \\ A^s x \leq b^s \\ x \geq 0 \end{gathered} \tag{3.7}$$

where, z^s is the optimal value of the *s-th* scenario and f^s is the value of the corresponding objective function.

Moreover, another criterion used is the minimax expected regret (MER), which is based on the MMR but with the difference of applying probabilities at each scenario (a_s). This could be useful in case the DM can have a proper estimation of the probability of a scenario because it can lead to less conservative solutions. In this thesis MER is defined similarly to [84], based on the definition of MMR by [77]. Therefore, MER is calculated by eq. (3.8):

$$\begin{gathered} z_{MER} = \min\ [\sum_s a_s R_s] \\ \text{s.t.} \\ f^s \leq (1+R_s)\cdot z^s, s \in S \\ A^s x \leq b^s \\ \sum_s a_s = 1 \\ x \geq 0 \end{gathered} \tag{3.8}$$

3.5.3 Stochastic Optimization

When uncertain parameters are considered in SO, rather than being assigned a specific value for each scenario that might occur, it is assumed that they follow a probability distribution. To solve SO problems Monte Carlo simulation can be used, which is an iterative method using random generated numbers based on the respective distribution of each uncertain parameter [85]. In Fig. 3.3 the combination of mathematical programming and Monte Carlo simulation is shown for three common probability distributions, namely uniform, normal, and triangular.

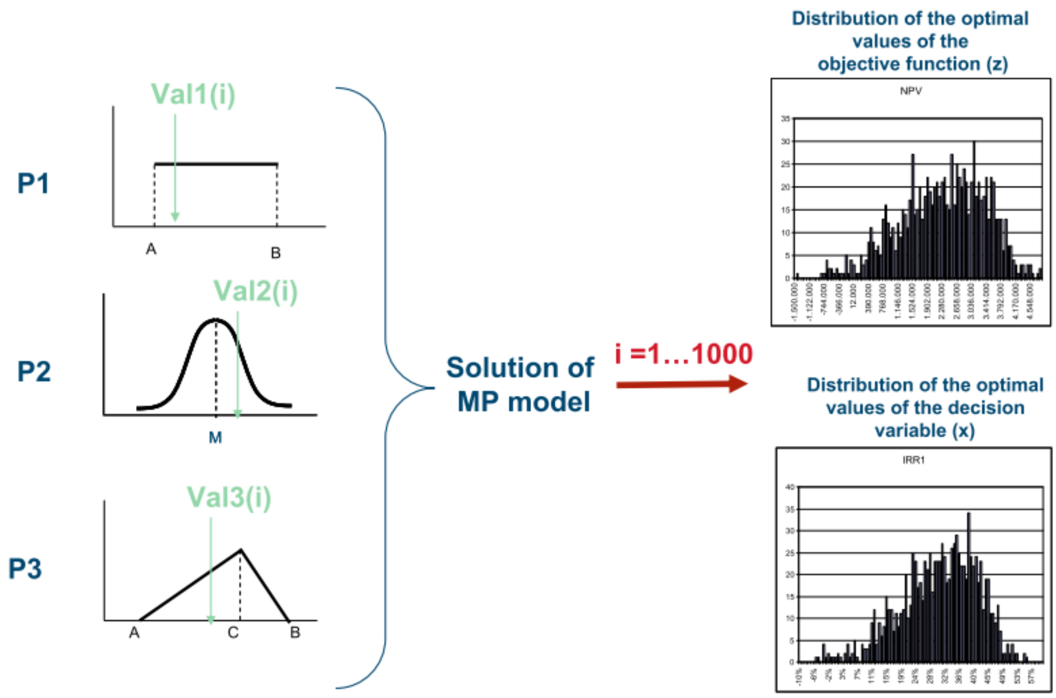


Fig. 3.3. Monte Carlo simulation and mathematical programming (source: [86]*)*

Chapter 4: Optimal design of DES

In this Chapter the methods for the optimal design of DES are presented. The first subsection consists of a detailed literature review of the research in the field and applications of mathematical programming regarding DES. The context and the significance of DES are outline and the novelty of the work in this thesis is introduced.

The two methodologies for the deterministic application of multi-objective mathematical programming for the optimal design and operation of a DES are described analytically. Also, the application of the optimization techniques aiming to robust solutions and the respective scenarios of each method are described.

4.1 Literature Review

Mathematical programming has been used extensively in problems related to energy planning, energy policy or carbon emissions reduction. Regarding the optimal design of DES several approaches have been made by researchers. DES have been designed either in single buildings or for multiple buildings, in the context of a neighbourhood, a complex of buildings or a small town, using both single-objective and multi-objective optimization. Designing DES has been often characterized as a complex task due to the large number of decision variables of the problem, which are separated into three main categories, namely: (a) *Synthesis* (type of technology to be used), (b) *Design* (size of the technologies) and (c) *Operation* (operational profiles of technologies). Due to the interaction of these variables the complexity of integrating them into a single optimization problem increases. A recent study by Goderbauer et al. proved that and showed how designing a DES is a complex problem which is NP-hard [87].

Ren and Gao in [88] developed a MILP model for the optimal integration and operation of DES. The objective function was the minimization the overall cost. A case study was performed for a campus in Japan based on a superstructure approach with several candidate technologies such as gas engine, gas turbine, micro turbine, fuel cell, photovoltaics and thermal energy storage, under four scenarios with different configurations. Also, they performed a sensitivity analysis for energy demand, energy prices and carbon tax. In [89] Ren et al. developed a multi-objective optimization model for the design of DES with minimization of total energy cost and carbon emissions as conflicting objective functions, solved using Chebyshev criterion.

In [90] Buoro et al. developed a MILP optimization model for the energy supply of two buildings, a standard house and an automated home using technologies such as small CHPs, heat pumps, boilers, heat storages, solar thermal and photovoltaics. The results showed high energy savings in both buildings. In [91] Buoro et al. presented a multi-objective MILP model for the optimal design of a DES in an industrial area with economic and environmental objectives, based on a superstructure with small CHPs, a solar plant, thermal storage and a DHN. The problem was solved using the weighted sum method. Another article by Buoro et al. for application of DES in an industrial area is presented in [92]. The scope of the paper was to identify the optimal energy supply system and the optimal operational strategy based on technologies such as a solar thermal plant, CHP, boilers, compression chiller and thermal storage. A MILP model was formulated in which the objective function was the minimization of cost.

Liu et al. in [93] developed a model for the optimal design of energy systems in commercial buildings using multi-objective MILP with economic and environmental criteria applied to a supermarket. The available energy technologies where wind turbine, solar photovoltaics, natural gas and biomass boiler, small and large natural gas CHP, small and large natural gas CHP, and fuel cell CHP. The problem was solved using eps-constraint method and the results showed the potential of the proposed framework. In [94] Liu et al. present a DES engineering framework in residential applications, including the design and operation of microgrid technology. Their results highlighted the need for operational strategies, especially for the microgrid. A mathematical programming framework for the operational planning of a network of micro CHP and also an alternative microgrid structure was developed by Kopanos et al. in [59]. The results showed that the microgeneration networks have advantages over conventional designs.

The design of DES at a neighbourhood level was also studied by Mehleri et al. in [95]. Their framework was based on a MILP super-structure model for the optimal configuration of technologies at a neighbourhood in Athens, using a model of three typical days of a year (winter, mid-day and summer) and six typical periods. Candidate technologies were micro-CHP units, photovoltaics, and boilers. Buildings could also form a DHN to exchange heat. The objective function was the minimization of total annual costs, including a carbon tax to include the environmental cost. Moreover, a case study for 10 buildings was carried out were alternative scenarios were compared, such as centralised CHP unit, no heat exchange and conventional scenario (no distributed technology or network). The results showed the reduction of cost when DES are implemented compared to the conventional scenario. Furthermore, in [96] the same authors expanded their work and presented a MILP model for the optimal design and operation of DES, including a microgrid, with the same objective function. Candidate technologies were solar photovoltaics, CHP, boilers, DHN and a heat storage tank. Three scenarios were examined, first being the conventional scenario, the second with microgrid and the distributed technologies and the third also included the photovoltaics. Also, a sensitivity analysis was performed to evaluate uncertainty in electricity and gas prices. The results of the work showed the economic and environmental benefits of the DES.

Di Somma et al. in [97] presented a model for the optimal design of DES using multi-objective optimization with total energy costs and exergy efficiency as objective functions. Candidate technologies are biomass boiler, solar thermal, CCHP, a reversible heat pump and thermal energy storage. The model was formulated as a MILP multi-objective optimization and solved using the weighted sum method. Their results showed the variation of operation of the DES at each weight combination and demonstrated the overall reduction of energy costs and improved exergy efficiency compared to conventional technologies. A multi-objective optimization model for DES using economic environmental impact (carbon emissions) as objective functions was presented in [98]. The results showed the reduction of both costs and carbon emissions in various configurations. The same authors presented a multi-objective MILP mode for a DES including renewables with objective functions the total annual cost and the exergetic efficiency. Also, in this paper the optimal size of technologies is calculated, and the variation of efficiencies and costs with sizes is examined.

Weber and Shah in [99] developed a method for the optimization of DES for an eco-town in the United Kingdom. A MILP tool was presented which calculates the optimal configuration of technologies with objective of minimizing total annual cost. Decision variables are the type, size and location of technologies in the district, their operational strategies and the layout of the DHN. Candidate technologies were categorised as centralized (wind turbine, large heat pump, CHP) and distributed (photovoltaics, solar thermal collectors, individual heat pump, individual chiller, and boiler). Different scenarios under various constraints were examined and the results showed the economic benefits of the DES and the importance of renewables into the energy mixture. DES have been also studied extensively in [100–104] using multi-objective optimization based on the master and slave decomposition approach. In [100] system's energy efficiency, total annual cost and carbon emissions were used as objective functions for the master optimization using multi-objective mixed-integer non-linear programming (MOMINLP) and then in slave optimization the energy integration was solved with objective functions the operating and emission costs, subject to energy balances and heat constraints (MILP). The model was applied to a case study at a large-scale model (a city similar to Geneva) considering different scenarios between centralised or decentralised technologies.

In [105] Omu et al. presented a MILP model for the design of DIS using a single-objective function for minimizing total annual costs, based on a superstructure of conversion technologies, including natural gas and biomass boiler, gas turbine and reciprocating engine CHP, air source and ground source heat pump, wind turbine, photovoltaics and solar thermal collectors. Buildings can exchange heating and electricity between them. Their model was applied to a case study of six buildings located in the south of England and tested various scenarios, depending on the degree of decentralization and the conflict of electrified heating and combined heat and power. The impact of subsidies was also examined. The results showed that DES have the potential of reducing carbon emissions significantly, while their economic benefit depends on the considered scenario. A similar approach was provided by Bracco et al. by the presentation of their tool, called DESOD (Distributed Energy System

Optimal Design) [106]. Candidate technologies are boilers, reversible heat pumps, absorption chillers, cogeneration technologies, photovoltaics, solar thermal collectors, electric storage, and thermal storage. Buildings can be connected via a DHN to exchange heating, but cooling is provided locally. Also, a microgrid is designed connecting all buildings through a single connection point to the national grid. Moreover, the authors performed a examined the impact of the dimensions on a MILP model by performing a computational analysis of different model sizes. The analysis shows that subdividing into a small number of time intervals leads to a simpler model which results to lower computational times without affecting the value of objective function significantly.

A structural and operational optimization model of DES, emphasizing in DHN was presented by Haikarainen et al. in [107]. Objective function is the minimization of total cost, consisting of investment and operational costs. The model is flexible and can be adapted for various scenarios and has been tested in a case study for an urban area in Finland. The same authors in [108] presented a decomposition MILP model which solves two-dimensional DES design problems. In this work the size of the initial problem was reduced by clustering network nodes into sectors, and then an iterative approach is used to increase them. The model was solved using different approaches, either by minimizing costs or carbon emissions.

Morvaj et al. in [109] developed a multi-objective MILP model for optimizing urban energy systems performing simultaneous system sizing. Total annual costs and carbon emissions were the objective functions and the problem was solved using ε-constraint method. The candidate technologies considered were CHP units, gas boiler, photovoltaics, solar thermal collectors, and thermal storage. Buildings could form a DHN and exchange electricity with national grid. The model was examined via seven scenarios, which showed that carbon emissions and cost are conflicting objectives, and also that the integration of DES could provide reduction to cost and carbon emissions. In [110] Morvaj et al. presented models for designing urban systems while taking into consideration grid constraints. They presented a framework to analyse the impacts of integration of DES into distribution grid, in terms of power flows and voltage stability. This is an important aspect of designing a DES, as some solutions in conventional models might not be feasible from grid perspective. In a more extensive model the impact of electric vehicles into distribution grid, along with DES, was also examined [111].

Another model of designing DES is presented in [112] by Yang et al., in which a superstructure-based MILP model was provided, coupled with heating, cooling and power distribution networks using the total annual cost as objective function. Five different scenarios were examined, and a sensitivity analysis was performed on unit capital costs and energy subsidies. In [113] same authors developed a MILP model that provides simultaneous optimization of locations, type and capacity of equipment, structure of networks and operational strategies.

Opportunities from the development of DES have been examined in [114] and the benefits regarding electricity reduction and profits were shown. The impact of DES on the energy system, specifically regarding different DHN connections has been studied by Dominković et al. in [115]. They developed a linear model with hourly intervals and applied it on a case study in a Danish municipality. The objective function was the minimization of annual socio-economic cost and the results showed the benefits in terms of energy demand, emissions, and costs. The economic and environmental impact of DES coupled with district energy networks (electricity, heating and cooling) has been studied by Li et al. in [116]. A multi-objective MILP framework with two objective functions, the cost-saving ratio, and the CO_2 emission reduction ratio was presented.

In addition, the impact of uncertainty in DES has been studied by several authors, most notably in recent years and is an area of significant concern. An early work in the field was the energy planning of a hotel in Greece by Mavrotas et al. [117], in which a linear programming model was developed examining the uncertainty in fuel costs, which they modelled by incorporating fuzzy parameters. Mavrotas et al. in [118] developed a model for the energy planning of a hospital in Greece while taking into account uncertainties in energy demand. They used cost and the degree of demand satisfaction as objective functions. Also, a minimax regret analysis was carried out to identify the final solution. Another application of a DES in a hospital was presented by Mavrotas et al. in [86]. A MILP model was developed with minimization of annual costs as objective function. Also, three scenarios were examined to examine the effects the size of the model has on solutions, showing that despite some variations in the sizes of technology the model size does not affect the value of objective function significantly. Furthermore, a Monte Carlo simulation was carried out to examine uncertainty in economic parameters (natural gas price, electricity price, discount rate) using various probability distributions (uniform, normal, or triangular).

Zhou et al. in [119] developed a two-stage stochastic model for designing DES using genetic algorithms for the first stage and Monte Carlo simulation for the second stage. Their model was based on a superstructure approach, using MILP and with total annual cost as the objective function. Energy demand, solar energy availability and wind energy availability were chosen as uncertain parameters. For energy demand a normal distribution was assumed within a range of ±20% of the average values. Solar energy availability was assumed to follow a normal distribution for each respective period, but a methodology which predicts hourly global solar radiation was applied at first. Finally, regarding wind energy availability authors used a three-parameter generalized extreme value distribution, based on the probability density function of Weibull distribution. The results of the case study showed that the stochastic and deterministic model have small differences. Similar work has been carried out by Yang et al. in [120] where they designed a DES for a hospital in China. The results showed that uncertainties in renewable energy potential and energy prices have little effect on the solutions, while uncertainties in energy demand have the most significant impact.

In [121] Akbari et al. presented a framework for robust optimization of DES, taking into account two groups of uncertain parameters, namely demand and financial parameters. The problem was structured on a MILP model, using total costs as objective function and solved by implementing the robust counterpart approach. The model was applied on a case study for a hospital using scenarios for different levels of conservatism and the results showed the significant increase in the capacity of technologies. Furthermore, Akbari et al. in [122] presented a method for robust optimization of DES in a neighbourhood. The objective function was the minimization of total annual costs. Authors reformulated the MILP problem into its robust counterpart and considered only uncertainties in demands. The results of the case study showed that the capacity of technologies and the structure of the DHN are highly sensitive to the level of conservatism considered by the DM.

Another interesting study in optimization of DES under uncertainty has been carried out by Majewski et al. in [123], where a two-stage robustness trade-off approach (*TRusT)* was developed to calculate the trade-off between costs of deterministic scenario and a worst-case scenario. In [124] same authors developed a model providing robust solutions using multi-objective optimization based on a MILP model. The objective-wise worst case method described in [76] was used, with objective functions the minimization of TAC and global warming impact (GWI). Natural gas prices, electricity prices (buying and selling), GWI of electricity from the grid, and energy demands were considered the uncertain parameters.

More recently, Mavromatidis et al. in [125] presented an analysis to identify uncertain parameters regarding the design of DES resulting in a total of 27 parameters in energy prices, emission factors, investment costs, technical characteristics, energy demand and solar radiation. Subsequently, they performed a sensitivity analysis to measure the influence of each parameter which showed that energy prices and demand have the most impact. In [126] a two-stage stochastic programming approach was carried out for the design of a DES in a Swiss urban neighbourhood. Energy prices, demand, and solar radiation were considered as the uncertain parameters. Authors used Monte Carlo simulation to generate multiple scenarios using total cost as the objective function and considering multiple strategies for CO_2 emissions reduction. The same authors in [127] carried out a comparison of different decision-making criteria. They used two-stage stochastic programming for the design of a DES and considered decision criteria such as expectation value, minimin, minimax, Hwrwicz criterion, value-at-risk, condition value-at-risk and minimax regret. Each criterion resulted into different configuration and specifically, the minimax regret was considered the “best” choice, due to its ability to offer risk-averse solutions. In [20] Mavromatidis et al. presented a detailed review of techniques used to deal with uncertainty in DES. The most significant uncertain parameters were identified and categorized, and also the approaches used for uncertainty characterisation were presented. It was shown that uncertainty is a complex and multi-faced subject and also the impact of parameters at the input of a DES, the DES components or energy demand was discussed.

The optimal management of micro-scale energy hubs was studied by Roldán-Blay et al. in [128] by presenting an iterative algorithm along with a simulation tool that calculates energy flows by minimizing energy cost, depending on available resources, prices and demand. Di Somma et al. in [129] presented a stochastic model for optimal operation scheduling of a DES, based on multi-objective optimization using a stochastic economic objective function and a stochastic environmental objective function. Solar energy availability, electricity price and energy demand were assumed to be uncertain and modelled by using roulette wheel mechanism and Monte Carlo simulation.

Yokoyama et al. in [130] presented a robust optimization method using MMR for the design of DES, considering the hierarchical relationship amongst design and operation variables, and energy demand. Also, a method for an efficient evaluation of an upper bound for the value of MMR was presented. In [131] Yokoyama et al. developed a MILP model for the robust optimal design of DES under uncertainty in energy demands.

Finally, interesting papers regarding uncertainty can be found for a variety of subjects, such as CHP generation and planning [132,133], energy planning [134–137], and renewables [138–142].

4.2 Description of DES and Methodology

The several optimization models that exist in literature regarding the design of DES, either as single- or multi- objective, are separated into two main approaches, one being the method which simultaneously optimizes the size of the technologies ("Method A") and the second being the method where system components are selected amongst a set of available technologies with predefined sizes ("Method B"). Therefore, these two approaches are presented in order to assess their advantages and disadvantages.

The considered DES comprises of different technologies which could be installed at each building and satisfy end-users energy demands in heating (including domestic hot water (DHW), cooling or electricity. Candidate energy technologies can be both conventional and renewables, namely: CHP units, boilers, heat pumps, absorption chillers, solar photovoltaics, solar collectors, wind turbines, and electric and thermal storage technologies. The concept of the DES is illustrated in Fig. 4.1. This model is based on the principle that buildings are allowed to exchange only heat, therefore an optimal DHN configuration is also an output. That means the optimal interconnections and optimal heat transfer periods will be calculated. Buildings form a decentralized network where heat could either be consumed or produced, and it is assumed that any building could be connected with any other one. In terms of electricity, buildings are allowed to exchange electricity with the grid (buying or selling) or there is the availability to form a microgrid and exchange electricity [96,106]. Cooling demand is satisfied locally at each building with no cooling network design.

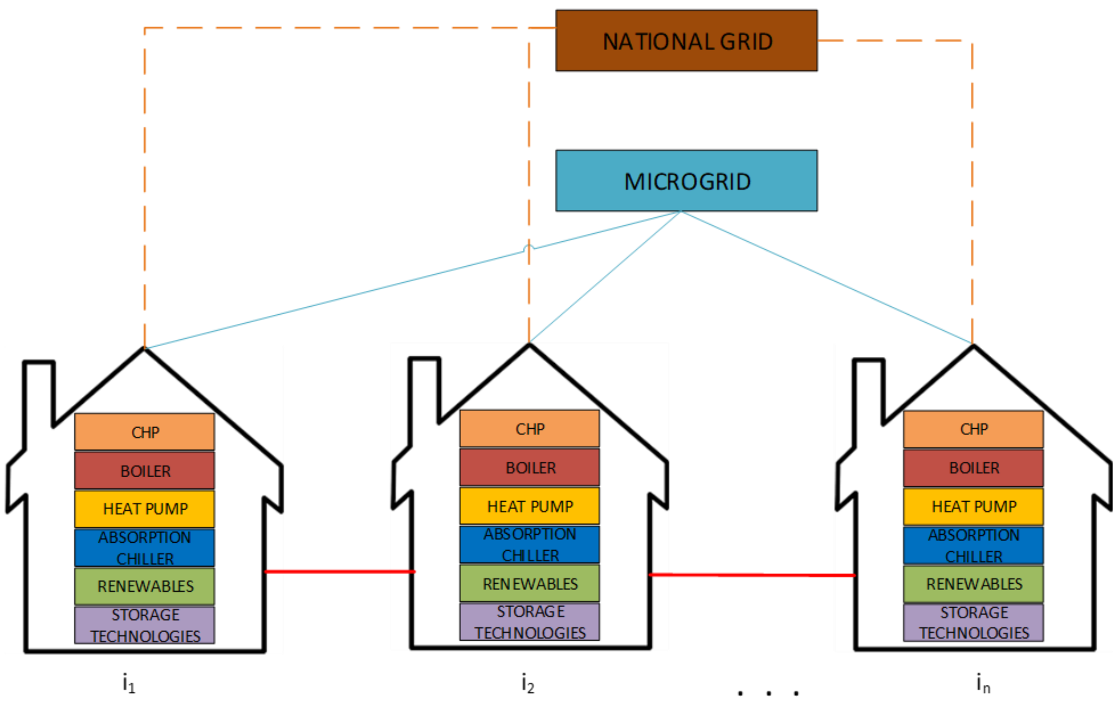


Fig. 4.1. A sketch of the DES

The time horizon for the calculations is set to be a typical year, which can be divided into representative days. Furthermore, the time horizon is further subdivided into typical periods of each day. The model is generic, and the decision maker could set these parameters according to his/her preferences.

Both methods are based on a multi-objective MILP framework solved using the ε – constraint method, which is suitable due its ability to generate non-extreme solutions and providing an efficient trade-off between conflicting objectives [75]. In ε – constraint method a multi-objective problem is reformulated into a single objective one with the TAC being the objective function and carbon emissions converted into a constraint.

4.3 Optimal design of DES using multi-objective optimization - "Method A"

In "Method A" the optimal configuration of the DES and the respective capacities of the technologies are the outputs of the model. The DM can select the available energy conversion technologies and provide their respective economic and technical characteristics, as well as their lower and upper capacity bounds in order to determine the optimal size and operational profiles simultaneously.

4.3.1 Objective functions

TAC comprises of the total capital cost for all technologies, the total operational and the total maintenance cost respectively, as shown in eq. (4.1). Total carbon emissions comprise of the emissions generated from fuel-based and from electricity-based technologies respectively, as shown in eq. (4.2).

$$f_1(x): C^T = C^C + C^O + C^M \tag{4.1}$$

$$f_2(x): \ CARBON^T = CARBON^F + CARBON^E \tag{4.2}$$

For calculating TAC, the capital cost of the DES refers to the annualized capital cost for each technology, the cost of laying pipes for the interconnections in DHN design and the cost for the microgrid, as described in eq. (4.3).

$$C^C = \sum_i \begin{bmatrix} a_n^{CHP} \cdot (c_{fix}^{CHP} \cdot Y_i^{CHP} + c_{lin}^{CHP} \cdot S_i^{CHP}) + a_n^{HP} \cdot c^{HP} \cdot S_i^{HP} + a_n^{CH} \cdot c^{CH} \cdot S_i^{CH} \\ +a_n^{PV} \cdot c^{PV} \cdot S_i^{PV} + a_n^{ST} \cdot c^{ST} \cdot A_i^{ST} + a_n^{B} \cdot c^{B} \cdot S_i^{B} + a_n^{ES} \cdot c^{ES} \cdot Q_i^{ES} \\ +a_n^{TS} \cdot c^{TS} \cdot Q_i^{TS} + a_n^{WT} \cdot \left(\sum_{swt} c_{swt}^{WT} \cdot S_{swt}^{WT} \cdot Y_{i,swt}^{WT} \right) + a_n^{MG} \cdot c^{MG} \cdot Y^{MG} \\ +a_n^{P} \cdot c^{p} \cdot l_{i,j} \cdot (Y_{i,j}^{HN\_SUP} + Y_{i,j}^{HN\_RET}) \end{bmatrix} \quad (4.3)$$

where, a^{tech} is the capital recovery factor calculated by eq. (4.4), which takes into account the lifespan of the equipment n and the discount rate r:

$$a_n = \frac{r(1+r)^n}{(1+r)^n - 1} \quad (4.4)$$

The operational cost is given by eq. (4.5) and consists of the cost of natural gas for the operation of fuel-based technologies (CHP and boilers), and the cost of buying and selling electricity to the grid:

$$C^O = \sum_i \sum_d \sum_p \delta_p \cdot n_d \begin{bmatrix} c^{ng} (Z_{i,d,p}^{CHP} + Z_{i,d,p}^{B}) + c_{d,p}^{el\_buy} \cdot E_{i,d,p}^{el\_grid} \\ -(c^{PV\_sell} \cdot E_{i,d,p}^{PV\_sell} + c^{WT\_sell} \cdot E_{i,d,p}^{WT\_sell} + c^{CHP\_sell} \cdot E_{i,d,p}^{CHP\_sell}) \end{bmatrix} \quad (4.5)$$

Finally, the maintenance cost of the technologies of the DES is calculated by eq. (4.6) as follows:

$$C^M = \sum_i \sum_d \sum_p \delta_p \cdot N_d \cdot \begin{bmatrix} \mu^{CHP} \cdot E_{i,d,p}^{CHP} + \mu^{HP} \cdot E_{i,d,p}^{HP} + \mu^{CH} \cdot Q_{i,d,p}^{CH} \\ +\mu^{B} \cdot Q_{i,d,p}^{B} + \left(\sum_{swt} \mu_{swt}^{WT} \cdot E_{i,d,p}^{WT} \cdot Y_{i,swt}^{WT} \right) + \mu^{TS} \cdot E_{i,d,p}^{TS} \end{bmatrix} + \sum_i \left(\mu^{PV} \cdot S_i^{PV} + \mu^{ST} \cdot A_i^{ST} \right) \quad (4.6)$$

For calculating the second objective function, carbon emissions are calculated by eq. (4.7) and eq. (4.8), for the fuel-based and electricity-based emissions respectively:

$$CARBON^F = \sum_i \sum_d \sum_p \left[\delta_p \cdot n_d \cdot (Z_{i,d,p}^{CHP} + Z_{i,d,p}^{B}) \cdot f^{ng} \right] \quad (4.7)$$

$$CARBON^E = \sum_i \sum_d \sum_p \delta_p \cdot n_d \cdot E_{i,d,p}^{el\_grid} \cdot f^{grid} \quad (4.8)$$

4.3.2 Constraints

Constraints of the model are divided into different categories, such as design and operational constraints for each technology and energy balances (electricity, heating, and cooling).

4.3.2.1 CHP installation and operation

At first a set of constraints regarding CHP is defined to ensure that a unit operates between its lower and upper capacity bound, if installed. Also, the power output of the unit will be lower or equal to its size:

$$S_i^{CHP} \le Y_i^{CHP} \cdot ub^{CHP} \quad \forall i \tag{4.9}$$

$$S_i^{CHP} \ge Y_i^{CHP} \cdot lb^{CHP} \quad \forall i \tag{4.10}$$

$$E_{i,d,p}^{CHP} \le S_i^{CHP} \quad \forall i,d,p \tag{4.11}$$

Moreover, if installed a CHP needs to operate above a minimum part load for technical reasons. The efficiency of the CHP is considered to be roughly constant above this point, which consists a valid assumption in order to keep the model linear [109]:

$$E_{i,d,p}^{CHP} \le C \cdot X_{i,d,p}^{CHP} \quad \forall i,d,p \tag{4.12}$$

$$S_i^{CHP} \cdot k^{CHP} \le E_{i,d,p}^{CHP} + C \cdot (1 - X_{i,d,p}^{CHP}) \quad \forall i,d,p \tag{4.13}$$

where, C a sufficiently large number.

Regarding the electricity output of the CHP, it is assumed that if a CHP unit is installed and operational the generated electricity would be available for local consumption (building), exported to the grid (sale) or exchanged through the microgrid (if it exists):

$$E_{i,d,p}^{CHP} = E_{i,d,p}^{CHP\_build} + E_{i,d,p}^{CHP\_sell} + E_{i,d,p}^{CHP\_mg} \quad \forall i,d,p \tag{4.14}$$

Also, a CHP unit generates heat when is operational, which could be used to satisfy building's heat demand or exported to the DHN:

$$Q_{i,d,p}^{CHP} = E_{i,d,p}^{CHP} \cdot \frac{n^{CHP\_th}}{n^{CHP\_el}} \quad \forall i,d,p \tag{4.15}$$

$$Q_{i,d,p}^{CHP} = Q_{i,d,p}^{CHP\_build} + Q_{i,d,p}^{CHP\_net} \quad \forall i,d,p \tag{4.16}$$

Finally, the fuel consumption of CHP is calculated by eq. (4.17):

$$Z_{i,d,p}^{CHP} = \frac{E_{i,d,p}^{CHP}}{n^{CHP\_el}} \quad \forall i,d,p \tag{4.17}$$

4.3.2.2 Heat Pumps installation and operation

Heat pumps can be used to produce either heating or cooling. As described earlier many models of heat pumps are available using different primary energy sources (e.g. air/air, air/water, water/water etc). In this model heat pumps are reversible air/water heat pumps. The reason for selecting this type of heat pumps is that air/water heat pumps can generate water which could be later sent to the network, or stored, in contrast with the air/air heat pumps that are typically used to satisfy only local needs. However, a heat pump can operate only in heating or cooling mode at a specific representative day and that is ensured by the set of constraints given by eqs. (4.18) – (4.20):

$$X_{i,d}^{HP\_h} + X_{i,d}^{HP\_c} \le Y_i^{HP} \quad \forall i,d \tag{4.18}$$

$$\sum_p X_{i,d,p}^{HP\_h} \le |p| \cdot X_{i,d}^{HP\_h} \quad \forall i,d \tag{4.19}$$

$$\sum_p X_{i,d,p}^{HP\_c} \le |p| \cdot X_{i,d}^{HP\_c} \quad \forall i,d \tag{4.20}$$

Despite the heat pump operating in heating or cooling mode, the generated energy needs to be lower than its capacity. However, due to its dual mode of operation this would result in non-linear equations. To avoid this, auxiliary variables are introduced based on the concept of linearizing the product of a continuous variable (size) and a binary variable (mode of operation) to maintain the linearity of the model. Therefore, for the heating mode of operation the set of equations (4.21) - (4.24) is used. A similar set of equations exists for the cooling mode linearization.

$$S_{i,d,p}^{HP\_h\_aux} \le ub^{HP} \cdot X_{i,d,p}^{HP\_h} \quad \forall i,d,p \tag{4.21}$$

$$S_{i,d,p}^{HP\_h\_aux} \le S_{i,d,p}^{HP} \quad \forall i,d,p \tag{4.22}$$

$$S_{i,d,p}^{HP\_h\_aux} \ge S_{i,d,p}^{HP} - ub^{HP} \cdot (1 - X_{i,d,p}^{HP\_h}) \quad \forall i,d,p \tag{4.23}$$

$$S_{i,d,p}^{HP\_h\_aux} \ge 0 \quad \forall i,d,p \tag{4.24}$$

The size of the heat pump if installed needs to be larger or equal to the generated energy and between an upper and a lower bound, according to equations (4.25) - (4.28):

$$S_{i,d,p}^{HP\_h\_aux} \ge Q_{i,d,p}^{HP\_h} \quad \forall i,d,p \tag{4.25}$$

$$S_i^{HP\_c\_aux} \ge Q_{i,d,p}^{HP\_c} \quad \forall i,d,p \tag{4.26}$$

$$S_i^{HP} \geq Y_i^{HP} \cdot lb^{HP} \ \ \forall i \tag{4.27}$$

$$S_i^{HP} \leq Y_i^{HP} \cdot ub^{HP} \ \ \forall i \tag{4.28}$$

The electricity absorbed for heat pumps operation is equal to:

$$E_{i,d,p}^{HP} = \frac{Q_{i,d,p}^{HP\_h}}{COP_{th}^{HP}} + \frac{Q_{i,d,p}^{HP\_c}}{COP_{c}^{HP}} \ \ \forall i,d,p \tag{4.29}$$

Finally, the heat generated from heat pump, if and when is operating in heating mode, is either used in building or sent to the DHN according to eq. (4.30):

$$Q_{i,d,p}^{HP\_h} = Q_{i,d,p}^{HP\_h\_build} + Q_{i,d,p}^{HP\_h\_net} \ \ \forall i,d,p \tag{4.30}$$

4.3.2.3 Absorption Chiller

Constraints regarding the installation and operation of absorption chillers are similar to the ones describing heat pumps:

$$Q_{i,d,p}^{CH\_abs} = \frac{Q_{i,d,p}^{CH\_c}}{n^{CH}} \ \ \forall i,d,p \tag{4.31}$$

$$S_i^{CH} \geq Q_{i,d,p}^{CH\_c} \ \ \forall i,d,p \tag{4.32}$$

$$S_i^{CH} \geq Y_i^{CH} \cdot lb^{CH} \ \ \forall i \tag{4.33}$$

$$S_i^{CH} \leq Y_i^{CH} \cdot ub^{CH} \ \ \forall i \tag{4.34}$$

Furthermore, eq. (4.35) refers to a constraint regarding system’s layout which states that at most one heat pump or absorption chiller unit can be installed at each building:

$$Y_i^{HP} + Y_i^{CH} \leq 1 \ \forall i \tag{4.35}$$

4.3.2.4 Boilers

Equations referring to the operation of a boiler are similar to those regarding chillers with the difference being that boilers require a fuel source (e.g. natural gas or oil). Also, heating generated from boilers could be directed to the building or distributed to the DHN:

$$Z_{i,d,p}^{B} = \frac{Q_{i,d,p}^{B}}{n^{B}} \ \ \forall i,d,p \tag{4.36}$$

$$S_i^B \geq Q_{i,d,p}^B \quad \forall i,d,p \tag{4.37}$$

$$Q_{i,d,p}^B = Q_{i,d,p}^{B\_build} + Q_{i,d,p}^{B\_net} \quad \forall i,d,p \tag{4.38}$$

$$S_i^B \geq Y_i^B \cdot lb^B \quad \forall i \tag{4.39}$$

$$S_i^B \leq Y_i^B \cdot ub^B \quad \forall i \tag{4.40}$$

4.3.2.5 Solar technologies

Solar photovoltaics and solar thermal collectors are the solar technologies used in buildings to exploit solar energy to produce electricity or hot water, respectively. The constraints describing the size and operation of photovoltaics are given by equations (4.41) - (4.44). Moreover, eq. (4.45) states that the generated electricity from photovoltaics could be used at the building, sold to the grid, or exported to the local microgrid.

$$S_i^{PV} \leq ub^{PV} \quad \forall i \tag{4.41}$$

$$S_i^{PV} \geq E_{i,d,p}^{PV} \quad \forall i,d,p \tag{4.42}$$

$$A_i^{PV} = S_i^{PV} / pv^{cof} \quad \forall i \tag{4.43}$$

$$E_{i,d,p}^{PV} \leq \eta^{PV} \cdot \mathrm{I}_{d,p} \cdot A_i^{PV} \quad \forall i,d,p \tag{4.44}$$

$$E_{i,d,p}^{PV} = E_{i,d,p}^{PV\_build} + E_{i,d,p}^{PV\_sell} + E_{i,d,p}^{PV\_mg} \quad \forall i,d,p \tag{4.45}$$

Solar thermal collectors generate heat to satisfy local DHW demand, which is expressed as a ratio of the total heat demand at building *i*:

$$Q_{i,d,p}^{ST} \leq \eta^{ST} \cdot i_{d,p}^{sol} \cdot A_i^{ST} \quad \forall i,d,p \tag{4.46}$$

$$Q_{i,d,p}^{ST} \leq r_{i,d,p}^{DHW} \cdot d_{i,d,p}^{h} \quad \forall i,d,p \tag{4.47}$$

Also, for the solar technologies, the area used by photovoltaics or solar collectors cannot exceed the available roof area in each building as described in eq. (4.48):

$$A_i^{PV} + A_i^{ST} \leq a_i \quad \forall i \tag{4.48}$$

4.3.2.6 Wind Turbines

To provide a more accurate and realistic approach the models of wind turbines considered as candidates to be installed, and their respective technical characteristics, are assumed to be predefined. Therefore, their respective power curves are constructed. The electricity generation from each wind turbine is calculated based on the wind speed (which is calculated from the available climate data) and provided in the form of a table, for each respective day and period.

Also, a parameter d_i^{WT} is introduced to indicate if a building *i* is available for the installation of a wind turbine ($d_i^{WT}=1$) or not ($d_i^{WT}=0$). That provides a more realistic representation at a neighbourhood level as the installation of a wind turbine is a more complex task and the availability of a location to host one needs to be examined. The generated electricity from the wind turbines can be used locally at the building, sold to the grid, or exported to the local microgrid. Moreover, at most one wind turbine from the available set can be installed at each building, if that building is suitable to host one, as described in eq. (4.49). Therefore, the equations concerning the installation and operation of the wind turbines are:

$$\sum_{swt} Y_{i,swt}^{WT} \leq d_i^{WT} \quad \forall i \tag{4.49}$$

$$E_{i,d,p}^{WT} = Y_{i,swt}^{WT} \cdot wt_{swt,d,p}^{elec} \quad \forall i,d,p \tag{4.50}$$

$$E_{i,d,p}^{WT} = E_{i,d,p}^{WT\_build} + E_{i,d,p}^{WT\_sell} + E_{i,d,p}^{WT\_mg} \quad \forall i,d,p \tag{4.51}$$

4.3.2.7 Storage technologies

Regarding storage technologies equations (4.52) and (4.53) state that the rated energy of the respective technologies does not exceed its maximum value. Moreover, equations (4.54) and (4.55) determine that the stored energy at the respective time period is lower than the rated capacity. Furthermore, equations (4.56) and (4.57) describe the operation of the storage technologies, indicating that for each technology the total energy stored at the end of a period is equal to the energy stored at the previous time-step, plus the energy charged into storage minus the energy discharged. Finally, it is assumed that the energy stored at the first period *p* of day *d* is equal to the energy stored at the last period *p* of day *d*, to apply more realistic conditions as described by equations (4.58) and (4.59), respectively.

$$Q_i^{ES} \leq ub^{ES} \quad \forall i \tag{4.52}$$

$$Q_i^{TS} \leq ub^{TS} \quad \forall i \tag{4.53}$$

$$E_{i,d,p}^{ES} \leq Q_i^{ES} \quad \forall i,d,p \tag{4.54}$$

$$E_{i,d,p}^{TS} \leq Q_i^{TS} \quad \forall i,d,p \tag{4.55}$$

$$E_{i,d,p}^{ES} = E_{i,d,p-1}^{ES} + \Delta_p \cdot \left(\eta_{in}^{ES} \cdot E_{i,d,p}^{ES\_in} - \frac{1}{\eta_{out}^{ES}} \cdot E_{i,d,p}^{ES\_out} \right) \ \forall i,d,p \tag{4.56}$$

$$E_{i,d,p}^{TS} = E_{i,d,p-1}^{TS} + \delta_p \cdot \left(Q_{i,d,p}^{TS\_in} - Q_{i,d,p}^{TS\_out} \right) \ \forall i,d,p \tag{4.57}$$

$$E_{i,d,p_1}^{ES} = E_{i,d,p_6}^{ES} \ \forall i,d \tag{4.58}$$

$$E_{i,d,p_1}^{TS} = E_{i,d,p_6}^{TS} \ \forall i,d \tag{4.59}$$

4.3.2.8 DHN

For the design of the DHN a first set of constraints refers to its layout to assure a realistic approach. Regarding the connections between buildings, an assumption is made that at most one pipeline can be installed between building *i* and building *j*, and that a connection cannot exist between a building and itself as described in eq. (4.60) and eq. (4.61). Also, eq. (4.62) states that only one heat source is allowed for each node, which means the network takes the form of a “forest” in order to avoid the production of cycles and to provide a more simplified, yet realistic approach. Moreover, to eliminate the creation of loops in the produced network eq. (4.63) is introduced, which is motivated by the Travelling Salesman Problem [95]. Finally, a heating return network needs to be installed which is assumed to follow the same structure as the supply heating network, as given by eq. (4.64).

$$Y_{i,j}^{HN\_SUP} + Y_{j,i}^{HN\_SUP} \le 1 \ \forall i,j \tag{4.60}$$

$$Y_{i,i}^{HN\_SUP} = 0 \ \forall i,j \tag{4.61}$$

$$\sum_i Y_{i,j}^{HN\_SUP} \le 1 \ \forall j \tag{4.62}$$

$$O_j \ge O_i + 1 - |i| \cdot (1 - Y_{i,j}^{HN\_SUP}) \ \forall i, j \ne i \tag{4.63}$$

$$Y_{i,j}^{HN\_SUP} = Y_{i,j}^{HN\_RE} \ \forall i,j \tag{4.64}$$

In this type of decentralized network design it is assumed that each building can act both as prosumer and consumer [109]. Therefore, a building can receive thermal energy from other buildings to satisfy its demand, store it in a heat storage unit if one exists, serve as a node and send the respective amount of energy to other buildings, or export thermal energy to the network. Moreover, in this methodology it is assumed that the technologies which can distribute thermal energy to the DHN are the CHP, the boiler, and the heat pump. The operation of the DHN is described by the following equations (4.65) - (4.67):

$$Q_{i,j,d,p}^{DHN} \leq M \cdot Y_{i,j,d,p}^{HP\_SUP} \quad \forall i,j,d,p \tag{4.65}$$

$$\sum_j Q_{i,j,d,p}^{DHN} \geq Q_{i,d,p}^{CHP\_net} + Q_{i,d,p}^{B\_net} + Q_{i,d,p}^{HP\_net} \quad \forall i,d,p \tag{4.66}$$

$$\sum_j Q_{i,j,d,p}^{DHN} \leq Q_{i,d,p}^{CHP\_net} + Q_{i,d,p}^{B\_net} + Q_{i,d,p}^{HP\_net} + \sum_j \left(1-\beta^p \cdot l_{i,j}\right) \cdot Q_{i,j,d,p}^{DHN} \quad \forall i,d,p \tag{4.67}$$

where M, is an appropriate large number calculated as the maximum amount of heat that technologies exporting heat to the network can produce.

4.3.2.9 Electricity transfer and microgrid

Electricity generated from technologies installed at building *i* can be used to satisfy local demand, exported to the microgrid or sold to the grid. Also, in the case of mismatch between local electricity production and electricity from the microgrid then electricity can be bought from the national grid to satisfy the demand. Eq. (4.68) defines the existence of a microgrid, where *N* is a sufficiently large number which can be calculated as the maximum amount of electricity that could be generated throughout the year. Eq. (4.69) defines the electricity transfer within the microgrid in order to maintain power balance. Electricity exchange with the national grid is described by equations (4.70) - (4.72). Moreover, in order to promote generation from RES equations (4.71) and (4.72) are used to prevent buying and selling electricity at the same period *p* of day *d,* where *Z* is a sufficiently large number which can be estimated as the maximum amount of electricity that can be generated at a period *p*.

$$\sum_i \sum_d \sum_p \left[E_{i,d,p}^{WT\_mg} + E_{i,d,p}^{PV\_mg} + E_{i,d,p}^{CHP\_mg} \right] \leq N \cdot Y^{MG} \tag{4.68}$$

$$(1-etl) \cdot \sum_i \left[E_{i,d,p}^{WT\_mg} + E_{i,d,p}^{PV\_mg} + E_{i,d,p}^{CHP\_mg} \right] = \sum_i E_{i,d,p}^{MG} \quad \forall d,p \tag{4.69}$$

$$E_{i,d,p}^{sell} = E_{i,d,p}^{WT\_sell} + E_{i,d,p}^{PV\_sell} + E_{i,d,p}^{CHP\_sell} \quad \forall i,d,p \tag{4.70}$$

$$E_{i,d,p}^{sell} \leq Z \cdot X_{i,d,p}^{el\_sell} \quad \forall i,d,p \tag{4.71}$$

$$E_{i,d,p}^{buy} \leq Z \cdot \left(1 - X_{i,d,p}^{el\_sell}\right) \quad \forall i,d,p \tag{4.72}$$

4.3.2.10 Energy balances

Perhaps the most important part of DES design, is the definition of energy balances for electricity, heating and cooling, which are calculated for each building *i*, at every period *p* of a day *d*. Electricity balance is given by eq. (4.73), where on the left-hand side is the sum of the electricity provided from the available technologies for local consumption, electricity discharged from the storage unit, plus the electricity that is purchased from the national grid and the electricity supplied to building *i* from the microgrid. The right-hand side consists of the sum of the electricity demand at building *i*, plus the electricity absorbed by heat pump and electricity charged to the storage unit.

$$\begin{aligned} & E_{i,d,p}^{CHP\_build} + E_{i,d,p}^{PV\_build} + E_{i,d,p}^{WT\_build} + E_{i,d,p}^{ES\_out} + E_{i,d,p}^{MG} + E_{i,d,p}^{buy} \\ & = d_{i,d,p}^{el} + E_{i,d,p}^{HP} + E_{i,d,p}^{ES\_in} \;\; \forall i, d, p \end{aligned} \tag{4.73}$$

Heating balance is calculated by eq. (4.74), where the left-hand side comprises of the thermal energy generated from the installed technologies, plus the amount of energy arriving from the DHN, and the right hand side consists of the heating demand at building *i*, plus the thermal energy absorbed by the chiller, the storage or supplied to the DHN.

$$\begin{aligned} & Q_{i,d,p}^{CHP} + Q_{i,d,p}^{HP\_h} + Q_{i,d,p}^{B} + Q_{i,d,p}^{ST} + Q_{i,d,p}^{TS\_out} + \sum_{j} \left(1 - \beta^{p} \cdot L_{i,j}\right) \cdot Q_{i,j,d,p}^{DHN} \\ & = d_{i,d,p}^{h} + Q_{i,d,p}^{CH\_abs} + Q_{i,d,p}^{TS\_in} + \sum_{j} Q_{i,j,d,p}^{DHN} \;\; \forall i, d, p \end{aligned} \tag{4.74}$$

Finally, the cooling energy balance is given by eq. (4.75), in which the cooling energy produced from the heat pump and the absorption chiller must satisfy the demand at building *i*:

$$Q_{i,d,p}^{HP\_c} + Q_{i,d,p}^{CH\_c} = d_{i,d,p}^{c} \;\; \forall i, d, p \tag{4.75}$$

4.4 Optimal design of DES using multi-objective optimization - “Method B”

The next method for the optimal design of DES is “Method B”, which is similar to “Method A” with the main difference being that the capacities of the CHP, the heat pumps, the absorption chillers, and the boilers are predefined into respective sets. At first, the sets of the technologies are defined as follows:

- Let *sco* represent the set of cogeneration technologies;
- Let *shp* represent the set of heat pumps;
- Let *sch* represent the set of absorption chillers;
- Let *sb* represent the set of boilers.

The modelling is similar, and the constraints are defined analogously to subsection 4.3.2. However, constraints regarding system layout, CHP, heat pumps, chillers, boilers, electricity transfer and energy balances need to be redefined to follow the new structure.

4.4.1 Objective functions

The concept of the model is the same as "Method A" and the objective functions are the same and defined by equations (4.1) and (4.2). However, due to structural differences with the introduction of sets with predefined capacities of technologies, equations (4.3) and (4.5) - (4.7) change as follows:

$$C^C = \sum_i \left[\begin{array}{l} a_n^{CHP} \cdot \sum_{sco} \left((c_{sco}^{CHP\_fix} + c_{sco}^{CHP\_lin} \cdot s_{i,sco}^{CHP}) \cdot Y_{i,sco}^{CHP} \right) + a_n^{HP} \cdot \sum_{shp} c_{shp}^{HP} \cdot S_{i,shp}^{HP} \cdot Y_{i,shp}^{HP} + \\ a_n^{CH} \cdot \sum_{sch} c_{sch}^{CH} \cdot s_{i,sch}^{CH} \cdot Y_{i,sch}^{CH} + a_n^{PV} \cdot c^{PV} \cdot S_i^{PV} + a_n^{ST} \cdot c^{ST} \cdot A_i^{ST} + \\ a_n^{B} \cdot \sum_{sb} c_{sb}^{B} \cdot s_{i,sb}^{B} \cdot Y_{i,sb}^{B} + a_n^{ES} \cdot c^{ES} \cdot Q_i^{ES} + a_n^{TS} \cdot c^{TS} \cdot Q_i^{TS} + \\ a_n^{WT} \cdot \left(\sum_{swt} c_{swt}^{WT} \cdot S_{swt}^{WT} \cdot Y_{i,swt}^{WT} \right) + a_n^{MG} \cdot c^{MG} \cdot Y^{MG} + \\ a_n^{P} \cdot c^{p} \cdot l_{i,j} \cdot \left(Y_{i,j}^{HN\_SUP} + Y_{i,j}^{HN\_RET} \right) \end{array} \right] \tag{4.76}$$

$$C^O = \sum_i \sum_d \sum_p \Delta_p \cdot N_d \cdot \left[\begin{array}{l} c^{ng} \cdot \left(\sum_{sco} Z_{i,sco,d,p}^{CHP} + \sum_{sb} Z_{i,sb,d,p}^{B} \right) + c_{d,p}^{el\_buy} \cdot E_{i,d,p}^{el\_grid} \\ - \left(\begin{array}{l} c^{PV\_sell} \cdot E_{i,d,p}^{PV\_sell} + c^{WT\_sell} \cdot E_{i,d,p}^{WT\_sell} + \\ c^{CHP\_sell} \cdot \sum_{sco} E_{i,sco,d,p}^{CHP\_sell} \end{array} \right) \end{array} \right] \tag{4.77}$$

$$C^M = \sum_i \sum_d \sum_p \delta_p \cdot n_d \cdot \left[\begin{array}{l} \sum_{sco} \mu_{sco}^{CHP} \cdot E_{i,sco,d,p}^{CHP} + \sum_{shp} \mu_{shp}^{HP} \cdot E_{i,shp,d,p}^{HP} + \sum_{sch} \mu_{sch}^{CH} \cdot Q_{i,sch,d,p}^{CH} \\ + \sum_{sb} \mu_{sb}^{B} \cdot Q_{i,sb,d,p}^{B} + \left(\sum_{swt} \mu_{swt}^{WT} \cdot E_{i,d,p}^{WT} \cdot Y_{i,swt}^{WT} \right) + \mu^{TS} \cdot E_{i,d,p}^{TS} \end{array} \right] \tag{4.78}$$
$$+ \sum_i \left(\mu^{PV} \cdot S_i^{PV} + \mu^{ST} \cdot A_i^{ST} \right)$$

$$CARBON^F = \sum_i \sum_d \sum_p \left[\delta_p \cdot n_d \cdot \left(\sum_{sco} Z_{i,sco,d,p}^{CHP} + \sum_{sb} Z_{i,sb,d,p}^{B} \right) \cdot f^{ng} \right] \tag{4.79}$$

4.4.2 Constraints

4.4.2.1 CHP installation and operation

CHP modelling follows the same principles as described in subsection 4.3.2.1:

$$X_i^{CHP} \le Y_i^{CHP} \quad \forall i \tag{4.80}$$

$$E_{i,sco,d,p}^{CHP} = E_{i,sco,d,p}^{CHP\_build} + E_{i,sco,d,p}^{CHP\_sell} + E_{i,sco,d,p}^{CHP\_mg} \quad \forall i, sco, d, p \tag{4.81}$$

$$E_{i,sco,d,p}^{CHP} = Q_{i,sco,d,p}^{CHP} \cdot \frac{n_{sco}^{CHP\_el}}{n_{sco}^{CHP\_th}} \;\; \forall i, sco, d, p \tag{4.82}$$

$$Q_{i,sco,d,p}^{CHP} = Q_{i,sco,d,p}^{CHP\_build} + Q_{i,sco,d,p}^{CHP\_net} \;\; \forall i, sco, d, p \tag{4.83}$$

$$Z_{i,sco,d,p}^{CHP} = \frac{E_{i,sco,d,p}^{CHP}}{n_{sco}^{CHP\_el}} \;\; \forall i, sco, d, p \tag{4.84}$$

$$P_{i,sco}^{CHP} \cdot k_{sco}^{CHP} \cdot X_{i,sco,d,p}^{CHP} \le E_{i,sco,d,p}^{CHP} \le P_{i,sco}^{CHP} \cdot X_{i,sco,d,p}^{CHP} \;\; \forall i, sco, d, p \tag{4.85}$$

Also, eq. (4.86) states that only one CHP from the set *sco* can be installed at each building *i*:

$$\sum_{sco} Y_{i,sco}^{CHP} \le 1 \; \forall i \tag{4.86}$$

4.4.2.2 Heat pumps

In this Method the modelling of heat pumps is simpler compared to Method ‘’A’’. In this case there are no non-linear terms and all equations can be expressed through MILP modelling without applying any linearization techniques. Equations (4.87) - (4.93) define the installation and operation of heat pumps:

$$X_{i,shp,d}^{HP\_h} + X_{i,shp,d}^{HP\_c} \le Y_{i,shp}^{HP} \;\; \forall i, shp, d \tag{4.87}$$

$$\sum_{p} X_{i,shp,d,p}^{HP\_h} \le |p| \cdot X_{i,shp,d}^{HP\_h} \;\; \forall i, shp, d \tag{4.88}$$

$$\sum_{p} X_{i,shp,d,p}^{HP\_c} \le |p| \cdot X_{i,shp,d}^{HP\_c} \;\; \forall i, d \tag{4.89}$$

$$E_{i,shp,d,p}^{HP\_h} = \frac{Q_{i,shp,d,p}^{HP\_h}}{COP_{th}^{HP}} + \frac{Q_{i,shp,d,p}^{HP\_c}}{COP_{c}^{HP}} \;\; \forall i, shp, d, p \tag{4.90}$$

$$Q_{i,shp,d,p}^{HP\_h} \le X_{i,shp,d,p}^{HP\_h} \cdot P_{i,shp}^{HP} \;\; \forall i, shp, d, p \tag{4.91}$$

$$Q_{i,shp,d,p}^{HP\_c} \le X_{i,shp,d,p}^{HP\_c} \cdot P_{i,shp}^{HP} \;\; \forall i, shp, d, p \tag{4.92}$$

$$Q_{i,shp,d,p}^{HP\_h} = Q_{i,shp,d,p}^{HP\_h\_build} + Q_{i,shp,d,p}^{HP\_h\_net} \;\; \forall i, shp, d, p \tag{4.93}$$

4.4.2.3 Absorption chillers

Regarding the installation and operation of absorption chillers the following constraints apply:

$$Q_{i,sch,d,p}^{CH\_abs} = \frac{Q_{i,sch,d,p}^{CH\_c}}{n_{sch}^{CH}} \;\; \forall i, sch, d, p \tag{4.94}$$

$$X_{i,sch,d,p}^{CH} \leq Y_{i,sch,d,p}^{CH} \;\; \forall i, sch, d, p \tag{4.95}$$

$$Q_{i,sch,d,p}^{CH\_c} \leq P_{i,sch,d,p}^{CH} \cdot X_{i,sch,d,p}^{CH} \;\; \forall i, sch, d, p \tag{4.96}$$

Also, similarly to "Method A", only one heat pump or absorption chiller can be installed at each building *i*:

$$\sum_{shp} Y_{i,shp}^{HP} + \sum_{sch} Y_{i,sch}^{CHIL} \leq 1 \;\forall i \tag{4.97}$$

4.4.2.4 Boilers

Equations representing boiler installation and operation are:

$$Z_{i,sb,d,p}^{B} = \frac{Q_{i,sb,d,p}^{B}}{n_{sb}^{B}} \;\; \forall i, sb, d, p \tag{4.98}$$

$$X_{i,sb,d,p}^{B} \leq Y_{i,sb,d,p}^{B} \;\; \forall i, sb, d, p \tag{4.99}$$

$$Q_{i,sb,d,p}^{B} \leq X_{i,sb,d,p}^{B} \cdot P_{i,sb,d,p}^{B} \;\; \forall i, sb, d, p \tag{4.100}$$

$$Q_{i,sb,d,p}^{B} = Q_{i,sb,d,p}^{B\_build} + Q_{i,sb,d,p}^{B\_net} \;\; \forall i, sb, d, p \tag{4.101}$$

Also, only one boiler can be selected from the available set, similarly to CHP, heat pumps and absorption chillers:

$$\sum_{sb} Y_{i,sb}^{B} \leq 1 \;\forall i \tag{4.102}$$

4.4.2.5 Solar Technologies

Constraints described in sub-section 4.3.2.5 apply.

4.4.2.6 Wind Turbines

Constraints described in sub-section 4.3.2.6 apply.

4.4.2.7 Storage Technologies

Constraints described in sub-section 4.3.2.7 apply.

4.4.2.8 DHN

Constraints defining DHN are the same as those described in sub-section 4.3.2.8, except constraints (4.66) and (4.67), which are defined as:

$$\sum_j Q_{i,j,d,p}^{DHN} \geq \sum_{sgc} Q_{i,sgc,d,p}^{CHP\_net} + \sum_{sb} Q_{i,sb,d,p}^{B\_net} + \sum_{shp} Q_{i,shp,d,p}^{HP\_net} \quad \forall i,d,p \tag{4.103}$$

$$\begin{aligned} \sum_j Q_{i,j,d,p}^{DHN} \leq \sum_{sgc} Q_{i,sgc,d,p}^{CHP\_net} + \sum_{sb} Q_{i,sb,d,p}^{B\_net} + \sum_{shp} Q_{i,shp,d,p}^{HP\_net} + \\ \sum_j \left(1-\beta^p \cdot l_{i,j}\right) \cdot Q_{i,j,d,p}^{DHN} \quad \forall i,d,p \end{aligned} \tag{4.104}$$

4.4.2.9 Electricity transfer

For electricity transfer only equations (4.68) - (4.70) are redefined as:

$$\sum_i \sum_d \sum_p \left[E_{i,d,p}^{WT\_mg} + E_{i,d,p}^{PV\_mg} + \sum_{sco} E_{i,sco,d,p}^{CHP\_mg} \right] \leq N \cdot Y^{MG} \tag{4.105}$$

$$(1-etl) \cdot \sum_i \left[E_{i,d,p}^{WT\_mg} + E_{i,d,p}^{PV\_mg} + \sum_{sco} E_{i,d,p}^{CHP\_mg} \right] = \sum_i E_{i,d,p}^{MG} \quad \forall d,p \tag{4.106}$$

$$E_{i,d,p}^{sell} = E_{i,d,p}^{WT\_sell} + E_{i,d,p}^{PV\_sell} + E_{i,sco,d,p}^{CHP\_sell} \quad \forall i,sco,d,p \tag{4.107}$$

It is noted that equations (4.71) and (4.72) still apply.

4.4.2.10 Energy balances

Energy balances for electricity, heating and cooling are given by equations (4.108) - (4.110), respectively, in the same concept as subsection 4.3.2.10:

$$\begin{aligned} &\sum_{sco} E_{i,sco,d,p}^{CHP\_build} + E_{i,d,p}^{PV\_build} + E_{i,d,p}^{WT\_build} + E_{i,d,p}^{ES\_out} + E_{i,d,p}^{MG} + E_{i,d,p}^{buy} \\ &= d_{i,d,p}^{el} + \sum_{shp} E_{i,d,p}^{HP} + E_{i,d,p}^{ES\_in} \quad \forall i,d,p \end{aligned} \tag{4.108}$$

$$\begin{aligned} &\sum_{sco} Q_{i,sco,d,p}^{CHP} + \sum_{shp} Q_{i,shp,d,p}^{HP\_h} + \sum_{sb} Q_{i,sb,d,p}^{B} + Q_{i,d,p}^{ST} + Q_{i,d,p}^{TS\_out} + \sum_j \left(1-\beta^p \cdot l_{i,j}\right) \cdot Q_{i,j,d,p}^{DHN} \\ &= d_{i,d,p}^{h} + \sum_{sch} Q_{i,sch,d,p}^{CH\_abs} + Q_{i,d,p}^{TS\_in} + \sum_j Q_{i,j,d,p}^{DHN} \quad \forall i,d,p \end{aligned} \tag{4.109}$$

$$\sum_{shp} Q_{i,shp,d,p}^{HP\_c} + \sum_{sch} Q_{i,sch,d,p}^{CH\_c} = d_{i,d,p}^{c} \quad \forall i,d,p \tag{4.110}$$

4.5 Optimal design of DES under uncertainty

Methods used in mathematical programming to deal with uncertainty in parameters have been described in subsection 3.5. Regarding optimal design of DES under uncertainty, despite the method applied to calculate robust solutions the most typical uncertain parameters are energy prices (electricity and natural gas), interest rate, energy loads and climate data (solar irradiance and wind speed) [86,119,120,125]. These values are assumed to be uncertain for the purposes of this thesis. The uncertainty regarding these parameters can affect the results significantly, either in terms of operational costs (e.g. high energy prices) or in terms of possible system's failure (e.g. higher demand than the existing capacity of technologies). Hence, the optimal results can be different in terms of synthesis, design, and operation. It is noted that optimal design of DES under uncertainty is based on the modelling of "Method A" described in subsection 4.3.

4.5.1 Objective-wise uncertainty

For the method of objective-wise uncertainty two scenarios are constructed:

- Scenario OW1: Uncertainty only in financial parameters (energy prices and interest rate).
- Scenario OW2: Uncertainty in all parameters (energy prices, interest rate, solar irradiance, wind speed, and energy demand).

4.5.2 Minimax regret criterion (MMR)

The second method used to provide robust solutions is the MMR, described in subsection 3.5.2, which is applied to a single-objective problem where minimizing TAC is the objective function, and carbon emissions applied as a constraint with a respective upper bound set by the DM. At first, the multi-objective problem is solved, and the Pareto front is depicted. Then the DM chooses an upper bound for carbon emissions based on his/her preferences.

The concept of the application of MMR is that uncertainty lies only in the financial parameters, i.e. in the energy prices and interest rate which can have high values or low values. It is assumed that energy prices increase or decrease simultaneously; therefore, five scenarios are constructed as follows:

- Scenario R1: This is the deterministic BAU scenario;
- Scenario R2: High energy prices and high discount rate;

- Scenario R3: High energy prices and low discount rate;
- Scenario R4: Low energy prices and high discount rate;
- Scenario R5: Low energy prices and low discount rate.

4.5.3 Minimax expected regret criterion (MER)

The application of MER in optimization of DES under uncertainty is introduced in this work (to the best of author’s knowledge). MER has been defined in subsection 3.5.2 and it is noted that in this case the same scenarios as those defined in the MMR method apply.

4.5.4 Stochastic programming (Monte Carlo Simulation)

As aforementioned Monte Carlo simulation is an iterative method, in which a value of each uncertain parameter is drawn from the respective distribution at each iteration. Monte Carlo simulation, is also applied to the single objective optimization problem of minimizing TAC, as defined in Section 4.5.2. Also, two scenarios are depicted for this method as well:

- Scenario MC1: Uncertainty only in financial parameters (energy prices and interest rate).
- Scenario MC2: Uncertainty in all parameters (energy prices, interest rate, solar irradiance, wind speed, and energy demand).

Chapter 5: Case study for application of a DES

This Chapter shows the application of the methodologies proposed for DES with the respective candidate technologies considered in a case study. The developed methods are applied at a complex of six buildings, located in Attica region, Greece. At first, the application of DES is examined using multi-objective optimization, based on the models of “Method A” and “Method B”, as described in subsections 4.3 and 4.4, respectively by developing three Scenarios. Then, the methods for the optimal design of DES under uncertainty described in subsection 4.5 are applied in order to examine the impact of uncertainties and provide robust solutions to the DM, by developing several scenarios for each method.

5.1 Input Data

In Table 5.1 the distances between buildings are depicted. Regarding time horizon, it is assumed that a year is divided into three typical days each one representing a season, winter (day 1, November – February), mid-season (day 2, March – May, October) and summer (day 3, June – September). Buildings i1 - i4 refer to typical residential dwellings, building i5 is a small commercial building and building i6 is a small school. Moreover, a typical day is divided to six typical periods (h7-h9, h9-h12, h12-h13, h13-h18, h18-h22, h22-h7). It is noted that the model is generic, hence a DM could change it in order to use a more detailed representation of a typical year. However, this would increase the complexity of the problem and would require higher computational intensity to solve it. Nevertheless, the results would not change significantly and this level of analysis is considered adequate [106].

Table 5.1. Distances between buildings (m)

	i1	**i2**	**i3**	**i4**	**i5**	**i6**
i1	0	30	40	50	70	40
i2	30	0	30	20	40	80
i3	40	30	0	50	70	80
i4	50	20	50	0	20	80
i5	70	40	70	20	0	20
i6	40	80	80	80	20	0

The energy loads for the buildings for the three respective days are depicted in Fig. 5.1 - Fig. 5.3. The energy loads for the buildings (electricity, heating, and cooling) were based on values existing in literature (e.g. [95]) or were calculated approximately depending on the energy load pattern of each respective building (according to its type and size). It is noted that a detailed calculation of the energy demand is out of the scope of this thesis.

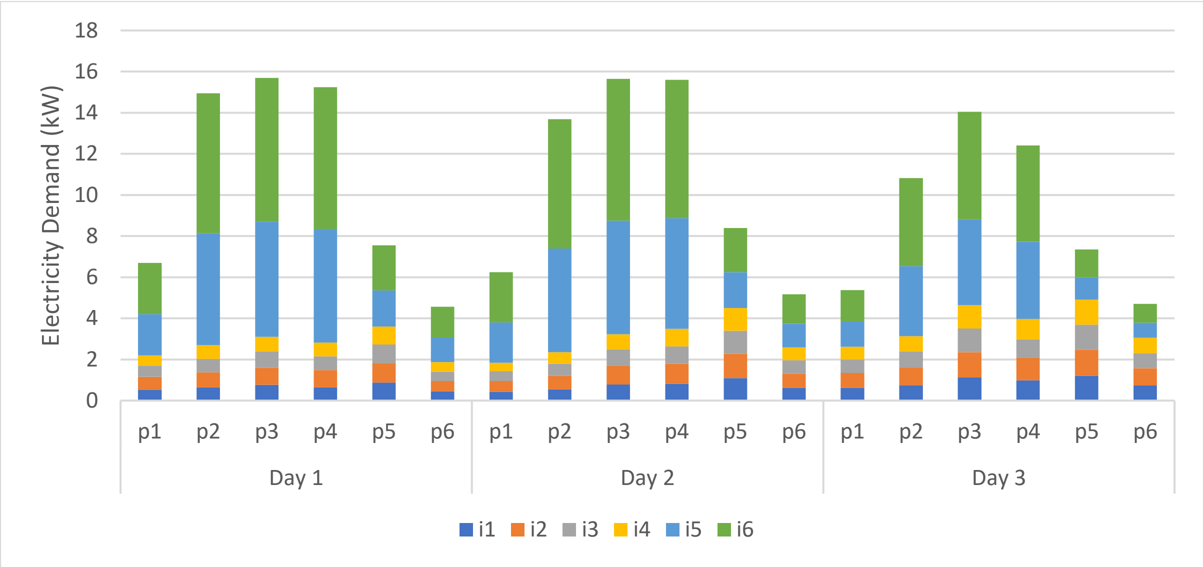


Fig. 5.1: Electricity demand of district buildings for the three typical days (Day1: Winter, Day 2: Mid-season, Day 3: summer)

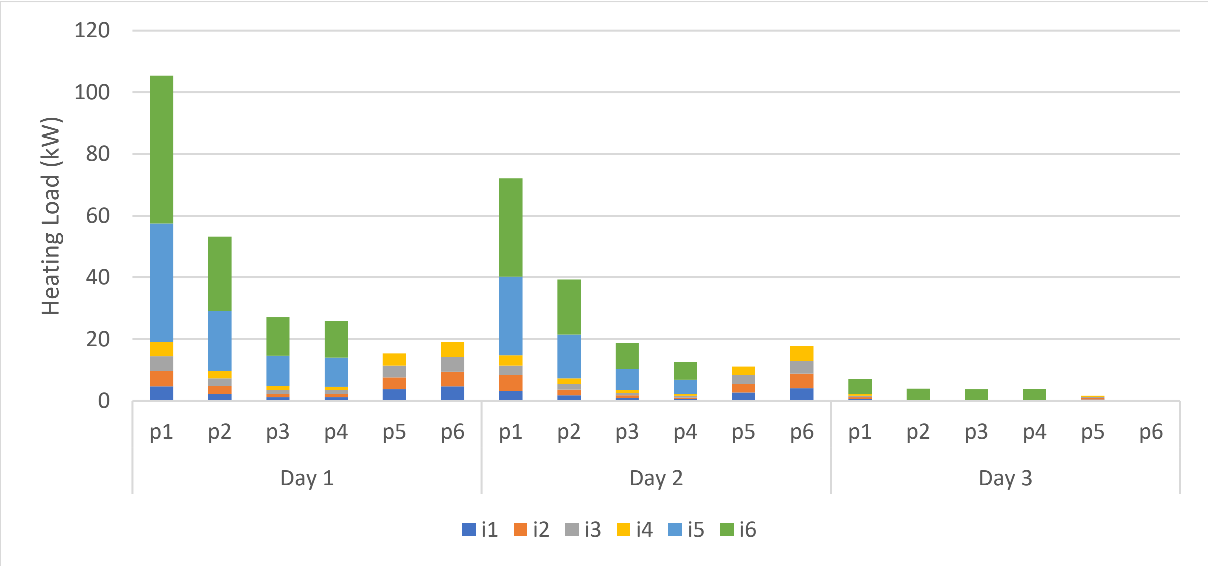


Fig. 5.2. Heating demand of district buildings for the three typical days (Day1: Winter, Day 2: Mid-season, Day 3: summer)

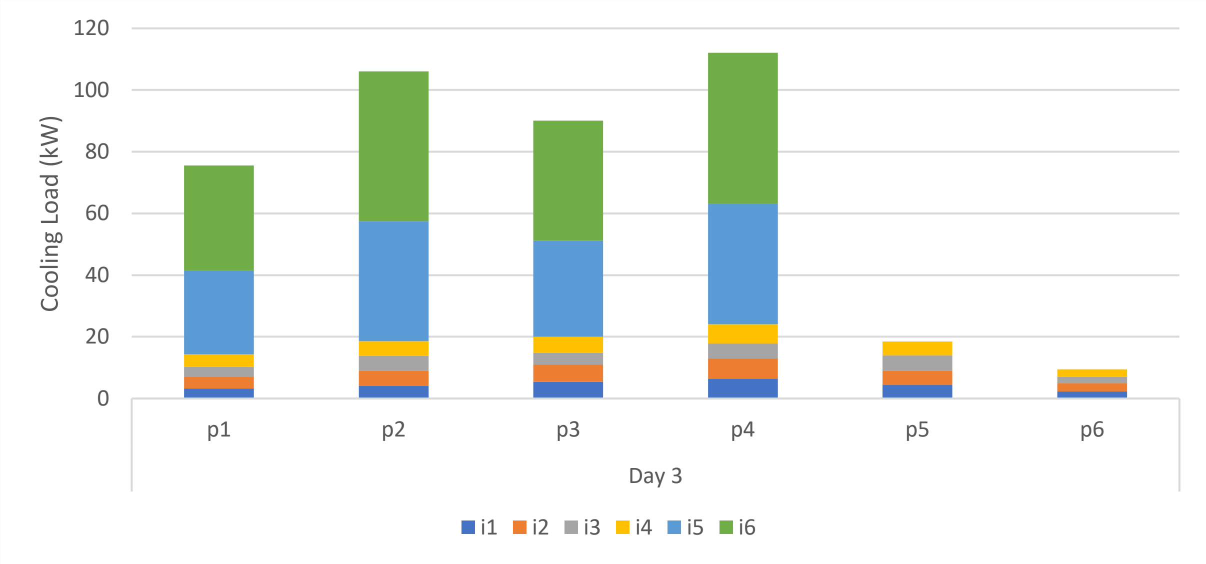


Fig. 5.3. Cooling demand of district buildings for Day 3: Summer.

The candidate technologies and their respective capacities are presented in Table 5.2. The economic characteristics of candidate technologies (capital and maintenance costs) are presented in Table 5.3. Each technology has a different lifetime, specifically CHP, heat pumps, chillers, boilers, wind turbines, photovoltaics and solar thermal collectors have a lifetime of 20 years whilst electric and thermal storage units have a lifetime of 15 and 30 years, respectively, and pipes have a lifetime of 30 years.

Regarding the two candidate wind turbines, their power curves have been constructed as described in subsection 2.6. The power curves and the relevant technical characteristics of the wind turbines are described in Appendix A.

The cost of natural gas in Greek market is set to 0.054 €/kWh [96]. The cost of buying electricity from the grid is calculated for each period based on the residential tariff provided by the Public Power Corporation [143]. However, the hours of the residential tariff do not match with the periods of this test case, therefore the tariffs were calculated as weighted averages of the hours of each respective period and the respective tariff. Electricity prices are presented in Table 5.4. The price for selling excess electricity to the grid is different for each electricity generation technology, specifically 0.55 €/kWh for electricity generated from photovoltaics, 0.08785 €/kWh for electricity from CHP, and 0.25 €/kWh for electricity generated from wind turbines, respectively [144]. The carbon emission factor for natural gas consumption is 0.184 kg/kWh [96]. The carbon emission factor for electricity generation from the grid is 1.12kg/kWh [143]. Finally, discount rate is set to be 7.5%.

Table 5.2. Candidate technologies and their respective technical characteristics.

Technology	Method "A"		Method "B"	
	Capacity Bounds	Efficiency	Capacity	Efficiency
CHP	5 – 50 kW	0.25 (*el.*) 0.50 (*th.*)	10 kW 50 kW	0.25 (*el.*) 0.50 (*th.*)
Heat Pumps	5 – 50 kW	COP^h=3.5 COP^c=3.0	10 kW 50 kW	COP^h=3.5 COP^c=3.0
Chillers	5 – 50 kW	0.87	10 kW 50 kW	0.87
Boilers	5 – 50 kW	0.9	10 kW 50 kW	0.90
Wind Turbines	6 kW 10 kW	-	6 kW 10 kW	-
Photovoltaics	≤ 10 kW	0.16	≤ 10 kW	0.16
Solar Thermal	-	0.6	-	0.6
Thermal Storage	≤100	-	≤100	-
Electricity Storage	≤100	0.9 *(in)* 0.85 *(out)*	≤100	0.9 *(in)* 0.85 *(out)*

Table 5.3. Economic data of the available technologies

Technology	Capital cost	Maintenance cost
CHP	$C_{fix:}$ 1000 € $C_{lin:}$ 500 €/kW	0.027 €/kWh
Heat Pumps	545 €/kW	0.001 €/kWh
Chillers	850 €/kW	0.001 €/kWh
Boilers	100 €/kW	0.0027 €/kWh
Wind Turbines	3000 €/kW	0.01 €/kWh
Photovoltaics	2000 €/kW	14 €/kW/year
Solar Thermal	700 €/kW	18 €/m^2/year
Thermal Storage	60 €/kWh	0.01 €/kWh
Electricity Storage	500 €/kWh	-
Pipe	100 €/m	-
Microgrid controller	1500 €	-

Table 5.4. Electricity purchase price in (€/kWh) for each typical day and time period.

Electricity purchase price (€/kWh)	p1	p2	p3	p4	p5	p6
d1: Winter	0.0804	0.0946	0.0946	0.0832	0.0946	0.0946
d2: Mid-season	0.0875	0.0946	0.0946	0.0889	0.0946	0.0818
d3: Summer	0.0946	0.0946	0.0946	0.0946	0.0946	0.0693

Solar irradiance and wind speed values were taken from available data for the year 2015 from a meteorological station operated by NTUA. The data were provided as hourly values but calculated as averages for each respective day and period. In Fig. 5.4 solar irradiance and wind speed are depicted.

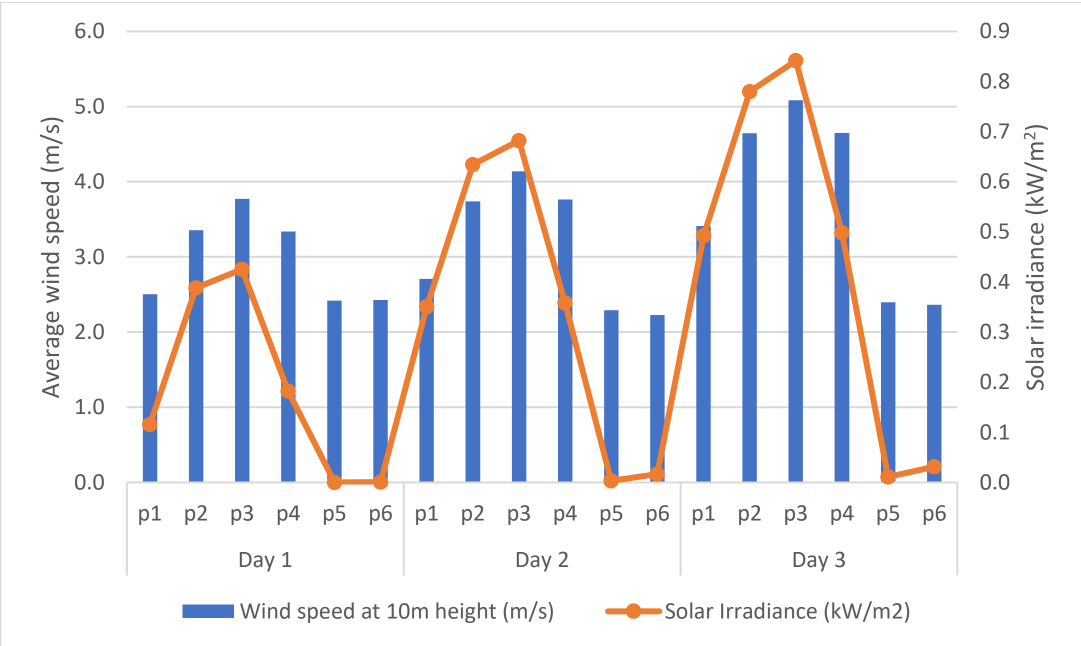


Fig. 5.4. Average wind speed and solar irradiation for the three typical days, for all periods

Table 5.5 presents the available roof area for installing solar photovoltaics and/or solar thermal collectors, and the value of parameter d_i^{WT} which indicates if a wind turbine could be installed at a building.

Table 5.5. Area for solar technologies and parameter for wind turbines (d_{iWT}=1 means suitable for WT).

Building	A_i (m^2)	d_i^{WT}
i1	75	0
i2	80	1
i3	67	1
i4	70	1
i5	90	0
i6	100	0

The following assumptions are made:

- The minimum part load of CHP units is assumed to be 50%. It is considered that above this value the efficiency of the CHP remains constant, and it is consistent with literature [109]. Also, CHP can be turned on and off without constraints.
- Start-ups and shut-downs of technologies are controlled, which means they can operate without any time delay.
- Heat pumps are assumed to have a constant COP for all typical days. Typically, COP is calculated based on external temperatures, however for the purposes of this work it is assumed to be constant.
- National grid has a large capacity and can integrate electricity injected from technologies (renewables or CHP) without any stability problems. The same assumption applies to microgrid Also, national grid can satisfy the energy demand if required.
- Photovoltaics are installed and operate at an optimal angle.
- Heating losses are proportional to the distance between buildings and are equal to 0.00015 m^{-1} [106].
- Transmission losses between microgrid are equal to 1% [96].
- Capital costs include investment and installation cost.

5.2 Scenarios for the optimal design of DES (Deterministic)

In order to assess the advantages of a DES and analyse the impact they can have in terms of costs and carbon emissions; three scenarios are depicted as follows:

- *Scenario 1 – Business-as-usual (BAU):* This is the conventional scenario where heating demand in buildings is satisfied by boilers and cooling by air condition units. Also, solar thermal collectors are considered as candidate technology as they are widely used in Greece and are assumed to be a conventional technology. Electricity consumption is satisfied from the national grid.

- *Scenario 2 – Renewables:* The same as Scenario 1, plus renewables (pv and wind turbines), absorption chillers and cogeneration technologies. Heat pumps are assumed to be air/water. Also, electricity exchange with the grid (buying/selling) is available.
- *Scenario 3 – Green:* The same as Scenario 2, plus the storage technologies, the ability to form a microgrid to exchange electricity and a DHN to exchange thermal energy.

Each of these scenarios is applied to both “Method A” and “Method B” to provide a comparison between each method, regarding values of TAC, carbon emissions, selected technologies and operational profiles of technologies. This case study was based on [145], with changes on the location of the problem and some technical characteristics of the candidate technologies.

5.3 Scenarios for the optimal design of DES under uncertainty

The scenarios used for each method of optimization under uncertainty are which were defined in subsection 4.5 are described here analytically. The methodology for this part of the case study was based on [146].

5.3.1 Objective-wise uncertainty

For the objective-wise worst-case optimization, it is assumed that the worst-case value of the uncertain parameters is as follows:

- Interest rate is 10%;
- Electricity prices are 10% higher;
- Natural gas price is 20% higher;
- Energy demand is 10% higher;
- Solar radiation is 10% lower;
- Wind speed is 20% lower.

5.3.2 MMR and MER

Prices of electricity and gas vary by ±20% for the high and low scenario, respectively. It is further assumed that the interest rate varies by ±2.5%. Regarding the application of MER, which is based on the knowledge of probabilities, it is assumed that there is a 50% probability that Scenario R1 will occur, 20% probability for Scenario R2 and 10% for scenarios R3 to R5, respectively. The upper bound of CO_2 emissions (which are applied as constraint) has been considered to be 100,000 kg/year.

5.3.3 Monte Carlo simulation

For Monte Carlo simulations uncertain parameters follow specific probability distributions. It is assumed that electricity prices follow a uniform distribution, natural gas price triangular distribution, interest rate, solar radiation and energy demand follow a normal distribution, and wind speed follows a Weibull distribution. In Table 5.6 the values for probability distributions are depicted. Moreover, regarding the range of electricity price value, and the standard deviation in interest rate, energy demand and solar radiation, respectively, distributions are applied to a percentage factor by which the respective value of the parameters changes (e.g. energy loads vary between ±10%). This formulation is made for convenience due to the variations of these values at each respective day *d* and period *p*.

Weibull distribution has been converted using the inverse transform method into eq. (5.1) as described in [147]. A similar cumulative Weibull distribution function has been applied in [119]. In addition, it is assumed that the shape parameter (k) is equal to 2. This assumption can be considered sufficient for a preliminary estimation, and accordingly, the value of *c* (which represents the characteristic wind speed) is equal to $1.13 \times v_{d,p}^{w}$ [148]. Moreover, it is noted that normal distribution is defined as $\theta \sim N(\mu, \sigma)$, where μ represents the value of each parameter at the deterministic scenario and σ is the standard deviation.

$$X = c \cdot (-\ln R)^{1/k} \tag{5.1}$$

where,

c is the scale parameter, *k* the shape parameter and *R* a uniform distribution random number in the interval [0,1].

Table 5.6. Parameters and distributions used in Monte Carlo simulations

Parameter	Distribution
Electricity price (€/kWh)	Uniform(0.8μ,1.2μ)
Natural gas price (€/kWh)	Triangular(0.0432, 0.06, 0.0648)
Interest rate (%)	Normal(μ, 0.11μ)
Energy demand	Normal(μ, 0.03μ)
Solar radiation	Normal(μ, 0.03μ)
Wind speed	Weibull(k, $c_{d,p}$)

Chapter 6: Results of DES optimization (deterministic case)

In this Chapter the results of the test case application of DES are presented for the two methods regarding the deterministic application, and also for the optimization under uncertainty. The multi-objective optimization problem has been solved using AUGMECON2 method. The MILP models have been formulated in GAMS [149] and solved using GUROBI solver on a PC with a 3 GHz processor and 12 Gb RAM.

6.1 Multi-objective optimization results

The results for the multi-objective optimization problem are presented and compared for each scenario. In Fig. 6.1 a flowchart regarding the application of "Method A" and "Method B" is presented.

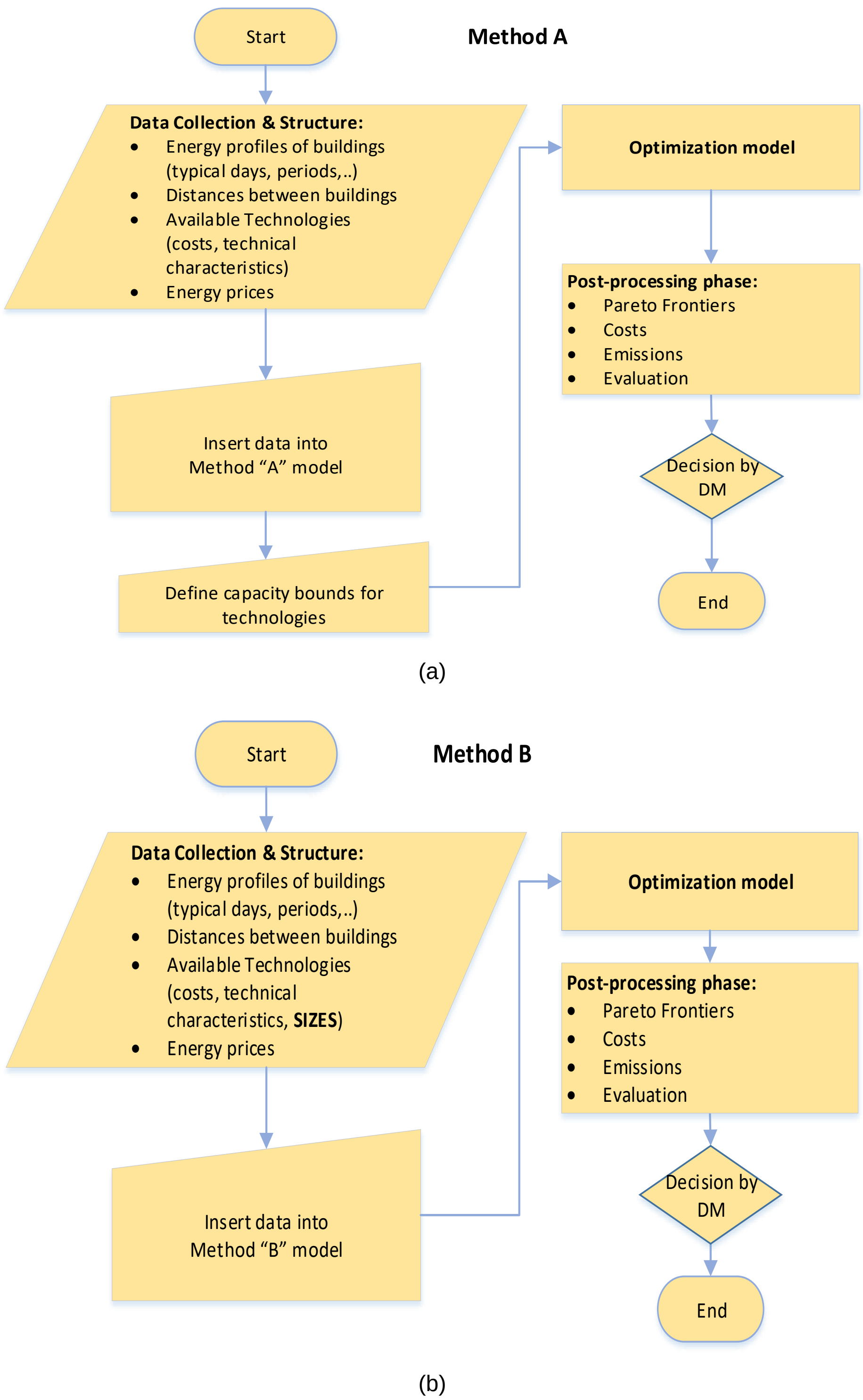


Fig. 6.1. Technical route diagram for applying: (a) "Method A" and (b) "Method B"

The Pareto front of the results from the application of multi-objective optimization problem are depicted in Fig. 6.2. The results show clearly that TAC and carbon emissions are conflicting objectives, i.e. the higher the TAC is the lower the carbon emissions are. The most expensive solution, both in terms of costs and carbon emissions is Scenario 1 (BAU). However, it can be observed that Scenario 1 does not offer a typical Pareto frontier, which can be attributed to the absence of degrees of freedom. Moreover, comparing Scenario 2 and Scenario 3, it can be observed that scenario 3 offers the most attractive solutions; specifically, Scenario 3 has the lowest TAC and carbon emissions in both methods.

Analytically, regarding results of “Method A”, Scenario 2 TAC has a range between 16,284 – 25,503 €/year and carbon emissions between 75,082 – 149,980 kg/year. On the other hand, in scenario 3 TAC ranges between 15,294 – 43,395 €/year and carbon emissions between 11,249 – 155,282 kg/year. In “Method B”, results follow a similar pattern compared to “Method A”. Specifically, Scenario 1 provides the solutions with the higher TAC and carbon emissions, followed by Scenario 2 and Scenario 3, which has the most attractive results. In scenario 2 of this method, TAC is between 18,110 and 29,927 €/year, while carbon emissions are between 78,412 and 143,546 kg/year. In Scenario 3 TAC is lower and between 16,930 and 44,583 €/year, and carbon emissions between 11,657 and 155,200 kg/year.

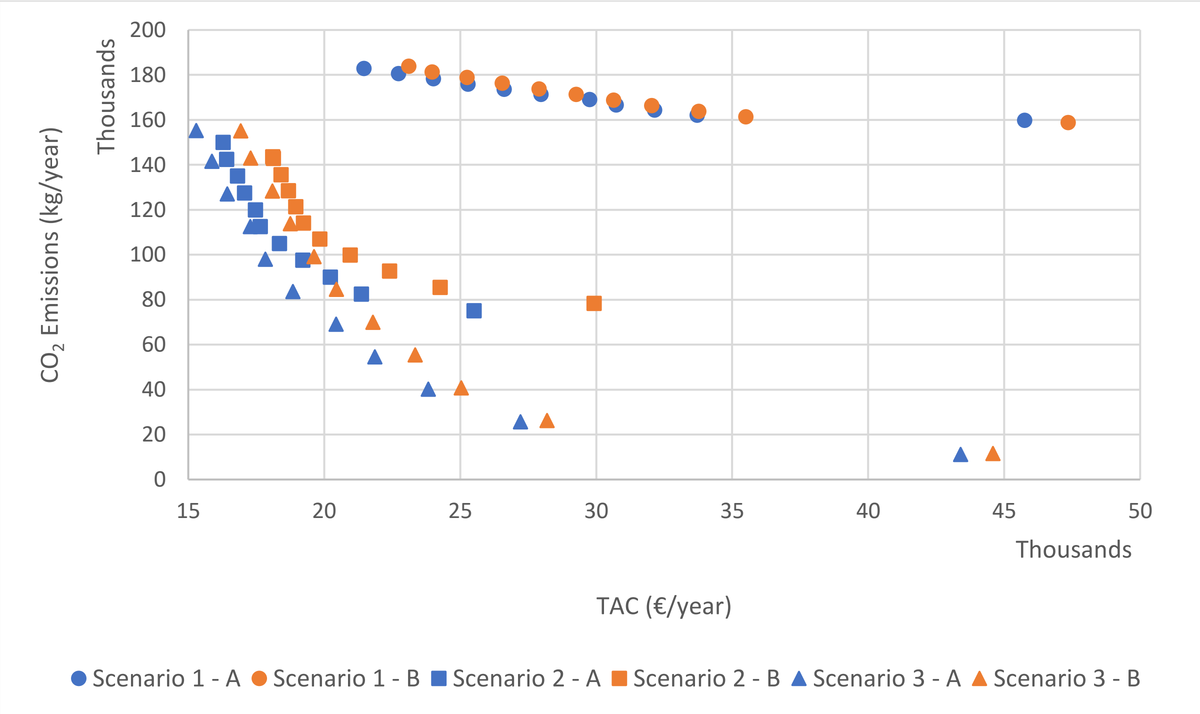


Fig. 6.2. Pareto front of “Method A” and “Method B”, for scenarios 1 – 3 respectively.

In “Method A”, TAC at Scenario 2 is between -24% and -44% compared to Scenario 1, and at Scenario 3 between -6% and 70% compared to Scenario 2. Similarly, in “Method B” TAC at Scenario 2 is between -22% and -37% compared to Scenario 1, and at Scenario 3 between -7% and 49% compared to Scenario 2. Regarding carbon emissions, there is a significant reduction in Scenario 3 compared to Scenarios 1 and 2, in both methods. Specifically, in “Method A” carbon emissions are up to 53% lower in Scenario 2 compared to Scenario 1 and up to 85% in Scenario 3 compared to Scenario 2. In “Method B”, carbon emissions are up to 51% lower in Scenario 2 compared to Scenario 1, and up to 85% lower in Scenario 3 compared to Scenario 2. Therefore, it can be concluded that the inclusion of storage units, microgrid and the DHN network further drives emissions down, and more particularly can provide solutions in which carbon emissions are approximately up to seven times lower (referring to the best-case solution of carbon emissions in scenario 2 compared to scenario 3 for both methods), which is noteworthy. Moreover, to provide a more thorough comparison between the two methodologies, the Pareto fronts for scenario 3 – DES are depicted in Fig. 6.3. It is shown more clearly that “Method A” provides more attractive solutions compared to “Method B” in terms of TAC and carbon emissions.

Computational time for scenario 3 is 2 hours and 14 minutes in “Method A” and 3 hours and 50 minutes in “Method B”, respectively. Computational times for Scenario 1 and 2 are much lower for both methods. Specifically, 4 and 6 seconds for “Method A”, and 4 and 7 seconds for “Method B”, respectively. The computational time increases dramatically due to the addition of more technologies and especially storage, DHN and microgrid which make the models more complex and leads to a remarkable increase of computational time from the order of some seconds to the order of a few hours. It is noted that the optimality gap in the model is 3%, which can be considered small. It is further noted, that regarding Scenario 3 in “Method A”, the model consists of 6,182 equations, 6,176 variables and 583 binary variables, whereas in “Method B” the model consists of 7,604 equations, 9,020 variables and 1,399 binary variables.

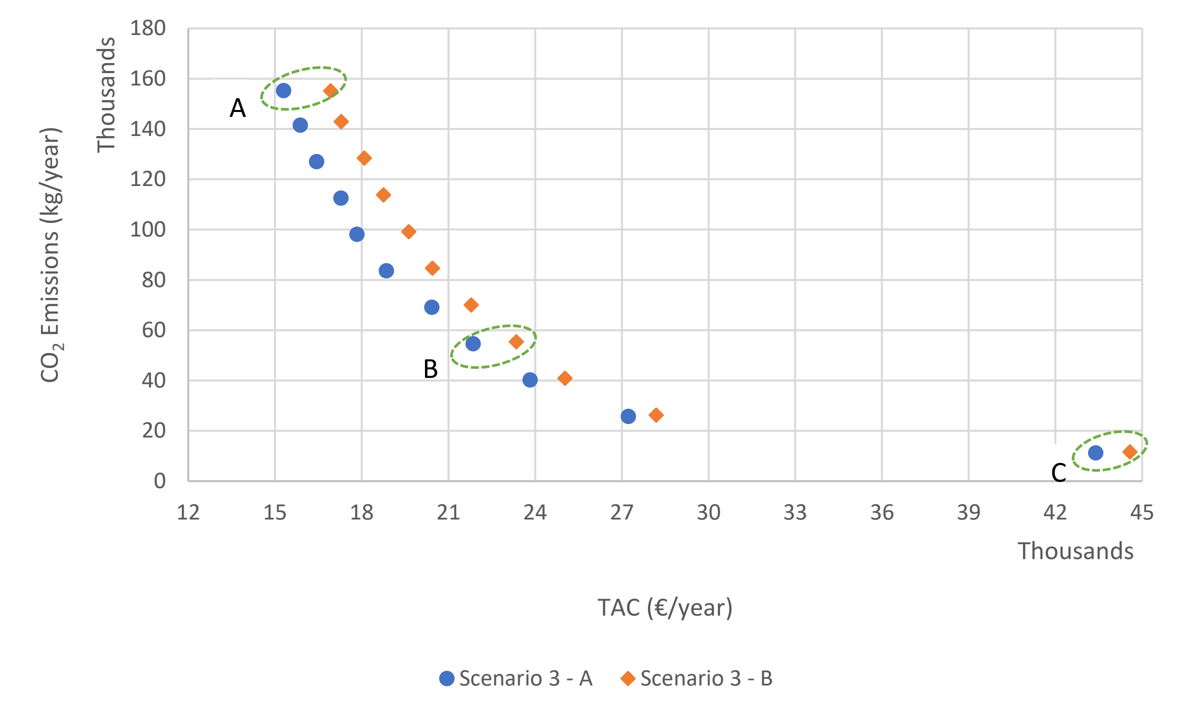


Fig. 6.3. Pareto fronts for Scenario 3 in “Method A” and “Method B”.

6.2 Detailed breakdown of solutions

A comparison of the results of objective functions for both methods is presented analytically in Fig. 6.4 and Fig. 6.5 for TAC and CO_2 emissions, respectively. The most notable differences between the two methods are in terms of TAC. Specifically, at the first solution (minimizing TAC), “Method B” has an 11% higher cost compared to “Method A”. As solutions move towards the minimization of carbon emissions both methods seem to offer similar results, with a small difference of approximately 3% in the final solution. As for the comparison of carbon emissions values, results show that the two methods have very small differences. At the last solution (minimizing emissions) carbon emissions in “Method B” are 4% higher compared to “Method A”.

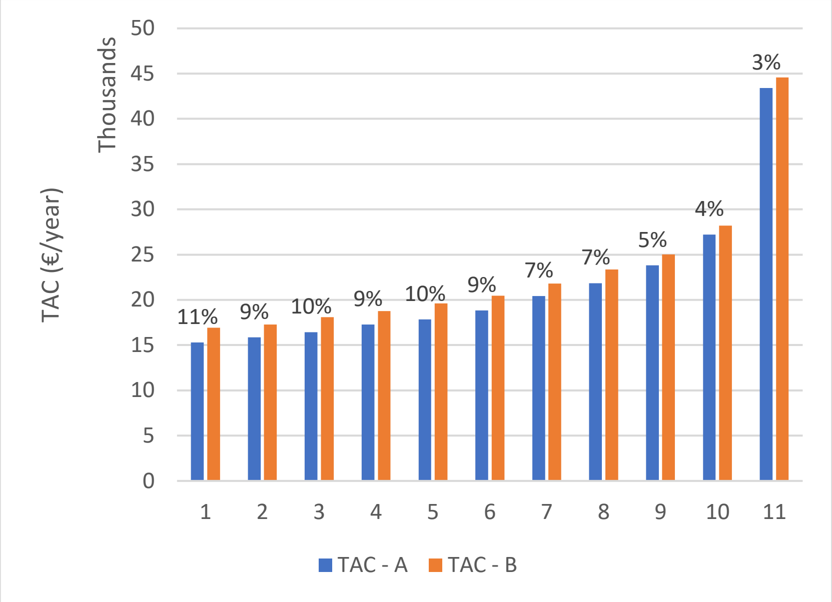


Fig. 6.4. Comparison of TAC for "Method A" and "Method B", respectively.

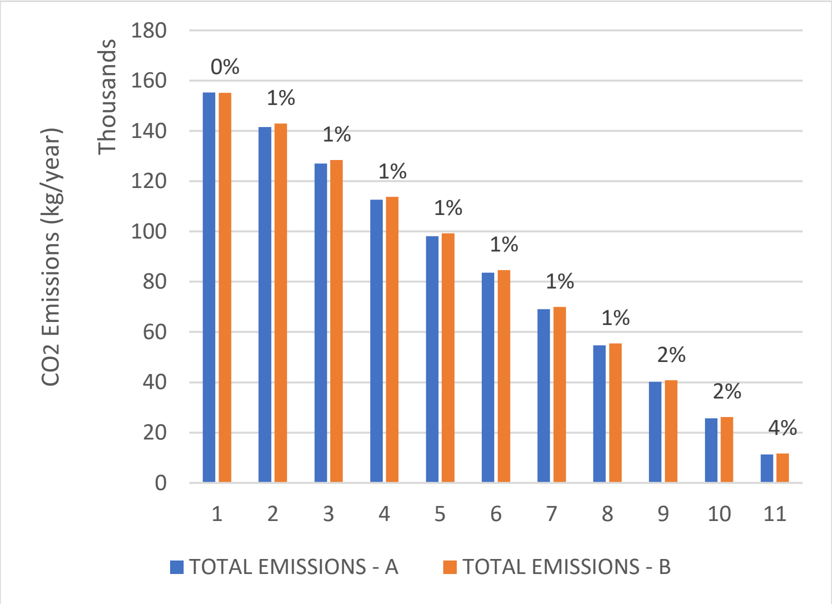


Fig. 6.5. Comparison of CO_2 emissions for "Method A" and "Method B", respectively.

In Fig. 6.8 - Fig. 6.8 a detailed breakdown of the components of TAC is depicted to present the differences analytically between each method, for Scenarios 1 – 3 respectively. It can be observed that the pattern of solutions is similar for each scenario. For instance, in Scenario 1, operational cost has the largest impact in both methods. On the other hand, in Scenarios 2 and 3, capital cost is the largest component whereas operational cost is negative. This shift can be attributed to profit from selling excess electricity generated from renewables and/or CHP units. Moreover, results show that as solutions move towards the last solution (minimizing CO_2) capital cost gets higher due to the selection of more expensive technologies which increase the value of TAC.

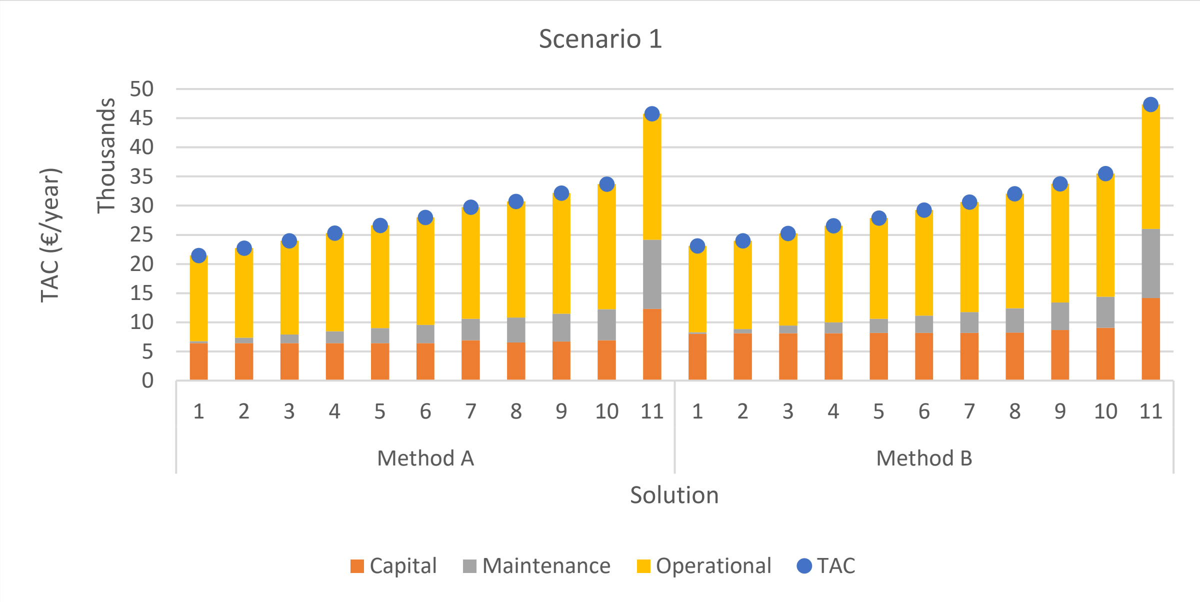


Fig. 6.6. A detailed breakdown of TAC equation components for Scenario 1, for Method A" and "Method B", respectively.

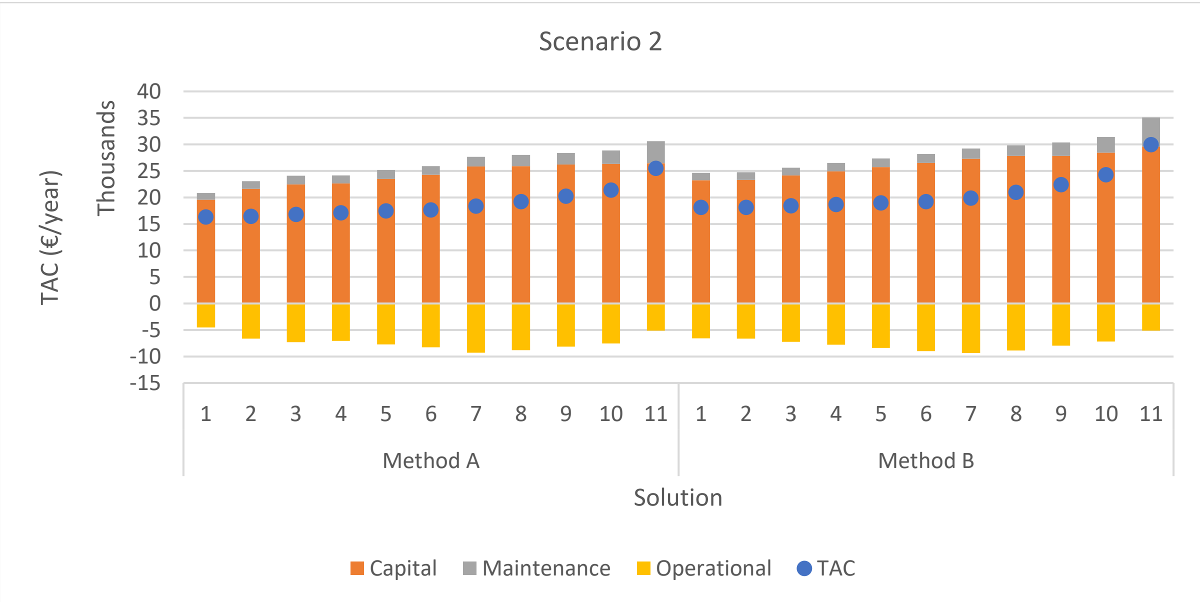


Fig. 6.7. A detailed breakdown of TAC equation components for Scenario 2, for Method A" and "Method B", respectively.

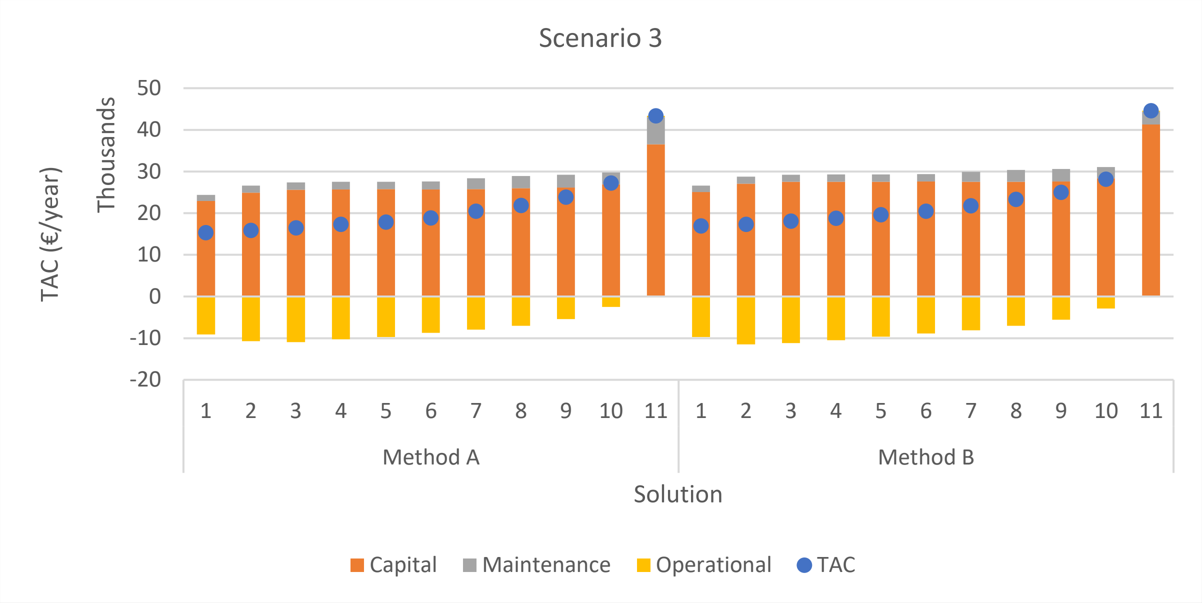


Fig. 6.8. A detailed breakdown of TAC equation components for Scenario 3, for Method A" and "Method B", respectively.

In addition, a detailed breakdown of the solutions regarding carbon emission equation components of each method is presented in Fig. 6.9 - Fig. 6.11, for Scenarios 1 – 3 respectively. It can be seen that the main source of emissions in all three scenarios of both methods is electricity from the grid. However, as solutions move towards the area of minimizing carbon emissions natural gas plays a more significant role. Specifically, in Scenario 3, from solution 8 towards solution 11, natural gas is the main source of emissions in both methods. This can be attributed to the lower emission factor of natural gas, compared to the Greek national grid emission factor.

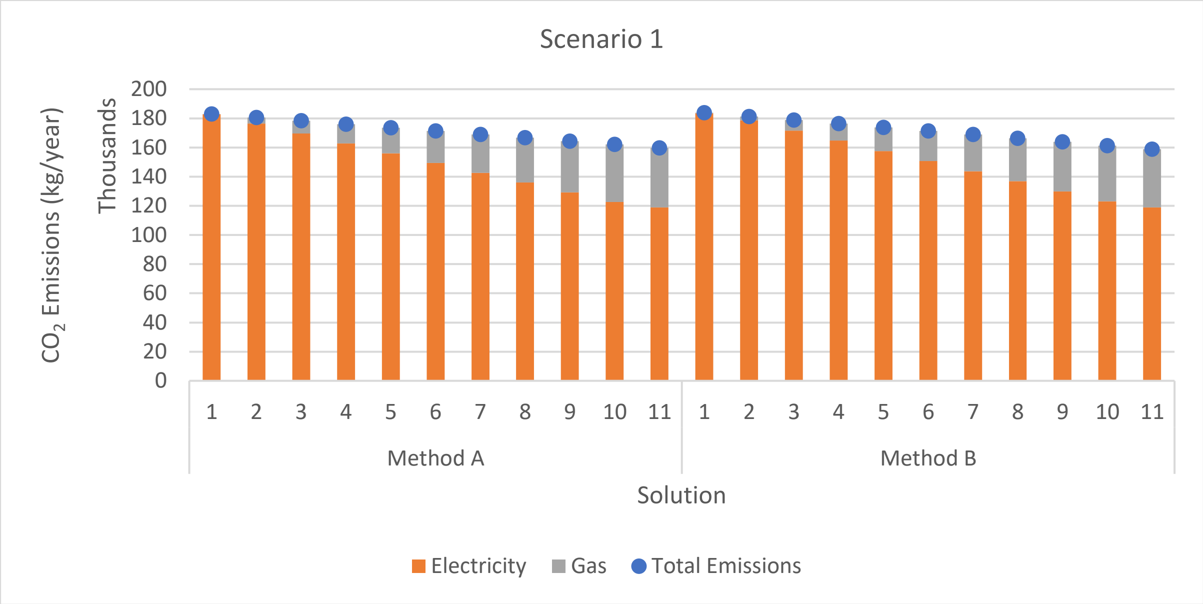


Fig. 6.9. A detailed breakdown of carbon emission equation components for Scenario 1, for Method A" and "Method B", respectively.

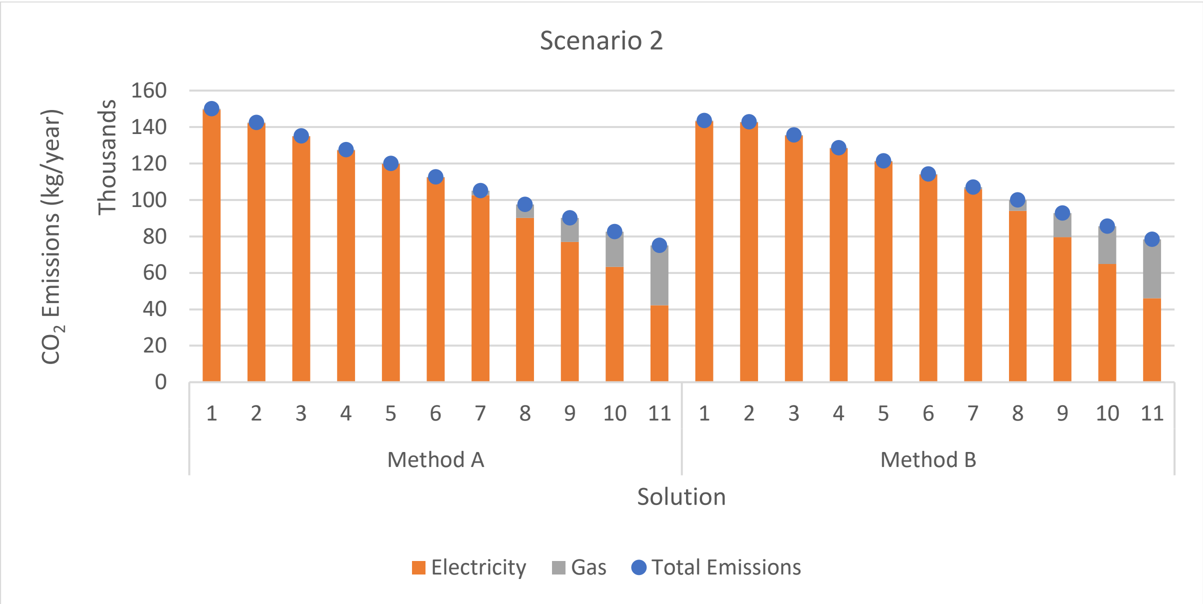


Fig. 6.10. A detailed breakdown of carbon emission equation components for Scenario 2, for Method A" and "Method B", respectively.

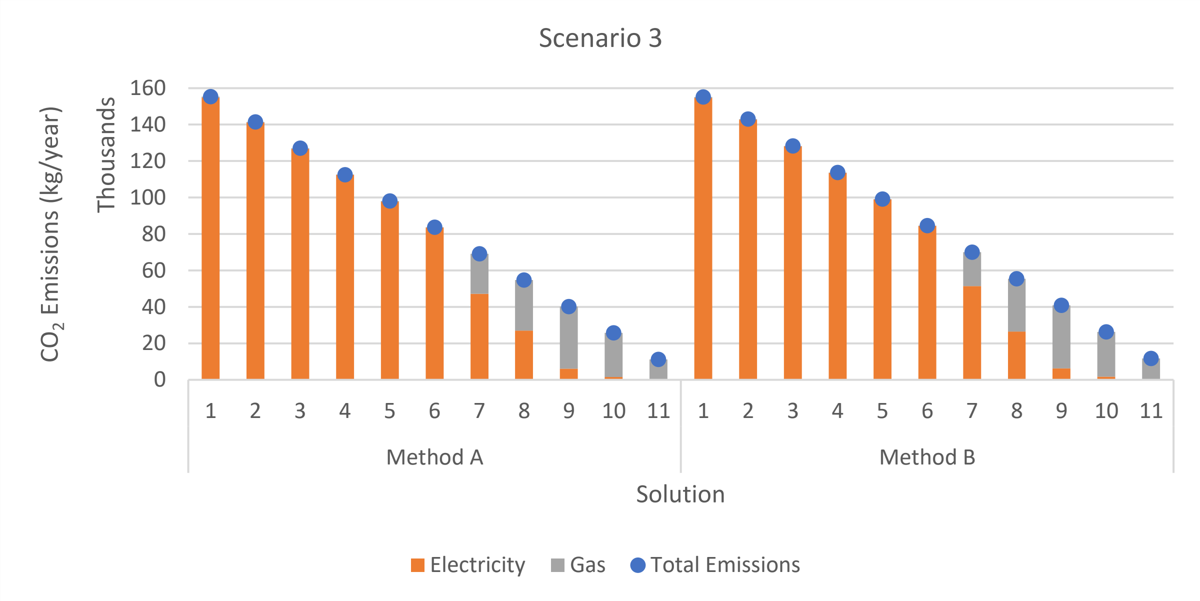


Fig. 6.11. A detailed breakdown of carbon emission equation components for Scenario 3, for Method A" and "Method B", respectively.

6.3 Comparison between Scenarios and Methods

Each solution of each method the configuration of the DES and the operational profile of the installed technologies is different for the respective Scenario. In Table 6.1 - Table 6.3 a detailed analysis of the configuration of the system for each Method is presented, for Scenarios 1 – 3 respectively, with the following results: (a) total capacity of each selected technology, (b) the number of DHN links and (c) the installation (or not) of a microgrid.

It is observed that in Scenario 1 the configuration of the system is similar in both methods. A notable difference is the increased capacity of solar thermal collectors in solution 11 (minimizing CO_2). The similar structure of the system is attributed to the small number of candidate technologies, which leads to less degrees of freedom. On the other hand, in scenarios 2 and 3 the differences at optimal configuration of the systems are notable. A common trend is the selection of renewables at every solution. Specifically, the larger wind turbines are installed at all three available buildings at every solution in both scenarios. Photovoltaics are installed at full capacity after solution 7, in Scenario 2, and after solution 2 in Scenario 3. Solar thermal collectors are also selected to provide hot water. Regarding CHP units, those are selected from solution 7 up to solution 11, in both Scenarios 2 and 3, and in both "Method A" and "Method B", respectively. It can be observed that the capacity of CHP units increases as solutions move towards minimizing CO_2, showing the benefits of cogeneration technologies regarding increased energy efficiency and lower carbon emissions. The same applies for absorption chillers which are not installed at any solution in Scenario 2 but are selected at a few solutions in Scenario 3. Boilers are installed at every solution in both Scenarios 2 and 3, and both methods. It is noted that the capacity of boilers is significantly higher at “Method B”, as there is no flexibility regarding the size of the units. Heat pumps which can satisfy both cooling and heating demand are the preferred technology in Scenario 2, and also installed at high capacity in Scenario 3. Moreover, as for the energy storage technologies selection in Scenario 3, it is noted that electricity storage is selected only at the last solution (minimizing CO_2) in both methods (with the exception of solution 5 in “Method B”, where a storage unit with very small capacity is selected), most probably due to the higher initial cost, whilst thermal storage is selected at solutions 7 up to 11 in “Method A”, and at every solution in “Method B”.

Regarding the design of DHN in Scenario 3 it can be noted that there are network links at every solution of both methods (except solutions 3 and 4 in “Method A”). However, in “Method B” there are more links compared to “Method A”. The installation of pipes for the design of a DHN depends on the availability of surplus heat to supply the network. Therefore, it can be implied that the available technologies supplying heat in “Method B” are “oversized”, and can generated larger amount of thermal energy, and subsequently higher cost. As for the microgrid, it can be noted that it is selected at every solution, at both “Method A” and “Method B”, respectively.

Table 6.1. Detailed configuration of optimal solutions at Scenario 1 for “Method A” and “Method B”, respectively

	HP (kW)		B (kW)		ST (m2)	
#	**A**	**B**	**A**	**B**	**A**	**B**
1	112	140	25	50	12	5
2	112	140	20	40	16	16
3	112	140	20	40	16	16
4	112	140	25	40	13	16
5	112	140	25	50	13	13
6	112	140	25	50	13	13
7	112	140	75	50	13	13
8	112	140	38	60	13	13
9	112	140	50	100	13	13
10	112	140	74	140	13	13
11	112	140	102	140	362	362

Table 6.2. Detailed configuration of optimal solutions at Scenario 2 for "Method A" and "Method B", respectively

	CHP (kW)		HP (kW)		ACH (kW)		B (kW)		WT (kW)		PV (kW)		ST (m2)	
#	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
1	0	0	112	140	0	0	25	50	30	30	30	40	5	5
2	0	0	112	140	0	0	25	50	30	30	40	40	7	7
3	0	0	112	140	0	0	20	50	30	30	44	44	16	7
4	0	0	112	140	0	0	25	50	30	30	45	48	7	7
5	0	0	112	140	0	0	20	50	30	30	49	52	16	7
6	0	0	112	140	0	0	25	50	30	30	54	57	7	7
7	5	0	112	140	0	0	25	50	30	30	60	60	8	13
8	5	10	112	140	0	0	20	50	30	30	60	60	16	10
9	10	10	112	140	0	0	25	50	30	30	60	60	8	11
10	11	20	112	140	0	0	20	40	30	30	60	60	16	16
11	13	20	112	140	0	0	29	100	30	30	60	60	13	60

Table 6.3. Detailed configuration of optimal solutions at Scenario 3 for "Method A" and "Method B", respectively

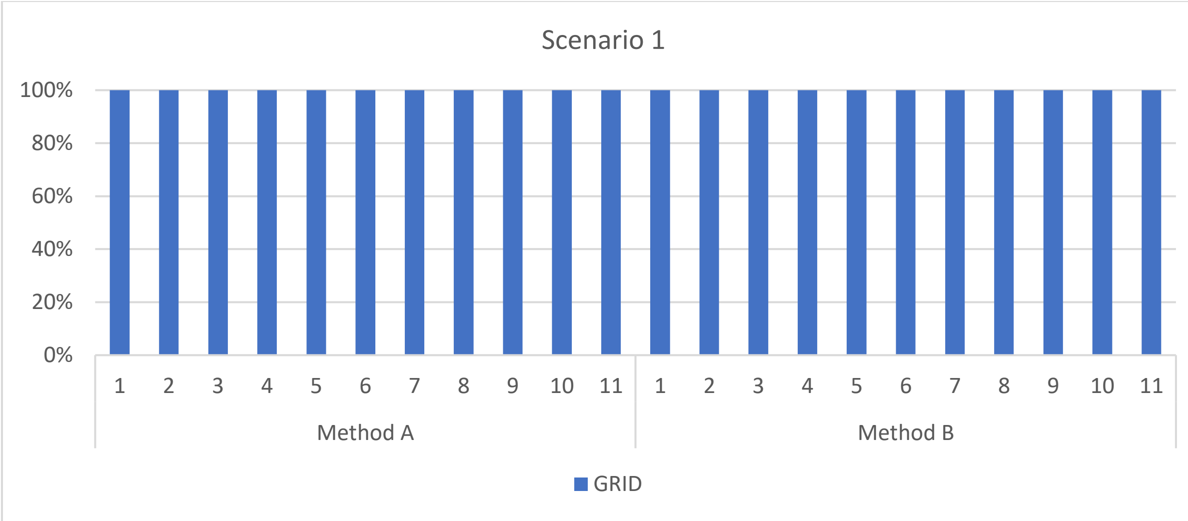
	CHP (kW)		HP (kW)		ACH (kW)		B (kW)		WT (kW)		PV (kW)		ST (m2)		ES (kWh)		TS (kWh)		DHN		MG	
#	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
1	0	0	112	140	0	0	25	30	30	30	46	48	5	5	0	0	0	0	2	3	1	1
2	0	0	112	140	0	0	20	30	30	30	56	58	7	7	0	0	0	0	2	3	1	1
3	0	0	112	140	0	0	30	30	30	30	60	60	8	8	0	0	0	0	0	3	1	1
4	0	0	112	140	0	0	25	30	30	30	60	60	16	8	0	0	0	0	0	3	1	1
5	0	0	112	140	0	0	25	30	30	30	60	60	8	8	0	1	0	0	2	3	1	1
6	0	0	112	140	0	0	20	20	30	30	60	60	16	8	0	0	0	0	1	4	1	1
7	5	10	101	110	11	30	25	20	30	30	60	60	8	8	0	0	9	19	1	4	1	1
8	6	10	100	110	13	30	15	20	30	30	60	60	10	8	0	0	20	17	2	3	1	1
9	10	10	95	110	18	30	25	30	30	30	60	60	10	10	0	0	1	36	3	3	1	1
10	17	20	104	120	11	20	25	0	30	30	60	60	11	16	0	0	21	52	2	3	1	1
11	24	30	152	220	0	0	20	80	30	30	60	60	59	59	87	87	190	223	5	5	1	1

In Fig. 6.12 - Fig. 6.14 the supply mix of electricity, heating and cooling for "Method A" and "Method B", are presented for the whole neighbourhood for Scenarios 1 – 3, respectively. In Scenario 1, electricity is supplied through the grid. However, in Scenarios 2 and 3 where more options for electricity supply exist, the results are different. In Scenario 2, electricity supply from the grid has the largest share, which is gradually reduced at solutions towards minimizing CO_2, and electricity share from CHP and renewables increases. It is noted that in "Method A", the share of renewables and CHP is higher compared to the solutions of "Method B". In

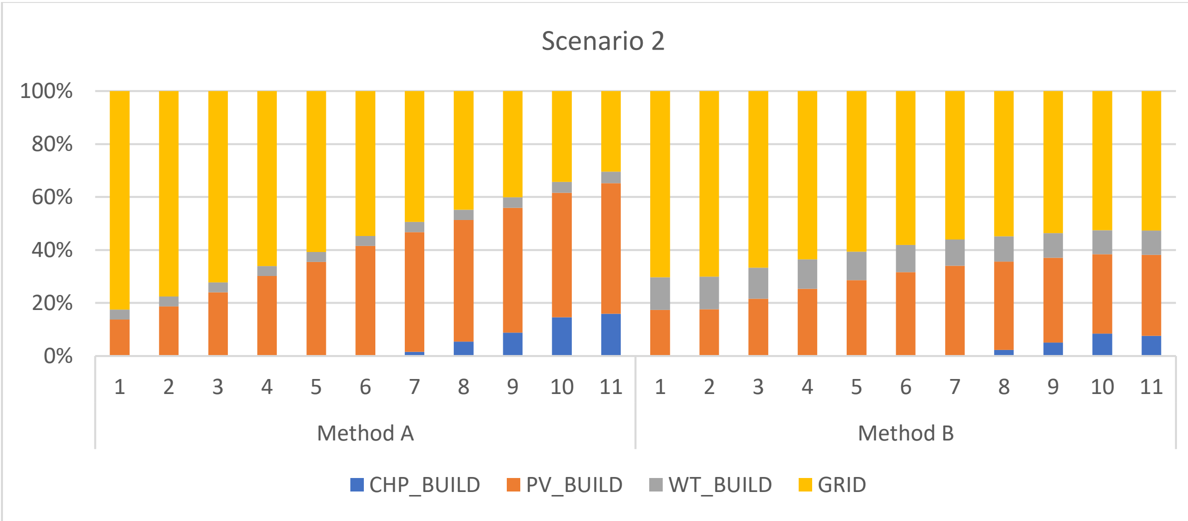
Scenario 3, electricity from the grid is the dominant source at first, but gradually is reduced. At the last solution, no electricity from the grid is used at either method. It is noted that the electricity exchange through microgrid and renewable energy, specifically from photovoltaics have a large share. Overall, results from both methods in Scenario 3 are similar.

Regarding heating generation, in Scenario 1 the results from both methods are similar, with heat pumps being the main source of heating up until solution 6, after which the boilers have the largest share. In Scenario 2 heat pumps have the largest share of heating supply in both methods. CHP units are also installed and generate heat at solutions 7-11 and 8-11, at “Method A” and “Method B”, respectively. In Scenario 3 results are similar to those of Scenario 2. Both methods follow a similar pattern with heat pumps having the largest share of heat generation. CHP units supply heat from solution 7 until solution 11 for both methods. Moreover, boilers have a small share of heat supply, in both Scenarios 2 and 3, and “Method A” and “Method B”. Finally, solar thermal collectors supply a small percentage of heat at all Scenarios and at both methods.

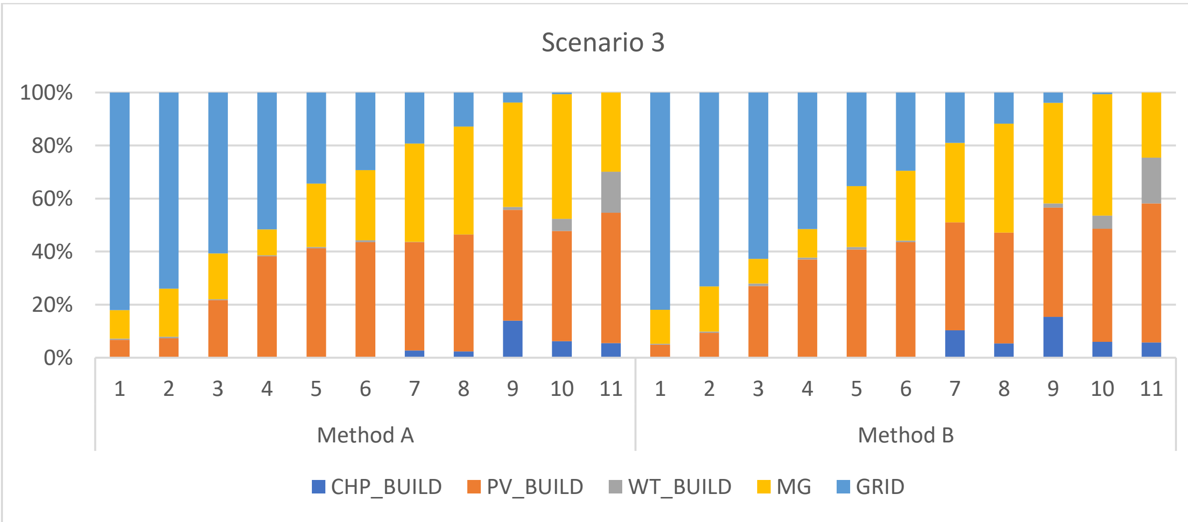
As for cooling energy supply, in Scenarios 1 and 2 cooling is satisfied only by heat pumps. In Scenario 2 where absorption chillers are also available as a candidate technology they are not selected at any solution. However, in Scenario 3, absorption chillers are selected at solutions 7 – 10, but overall heat pumps have the largest share of cooling energy supply.



(a)

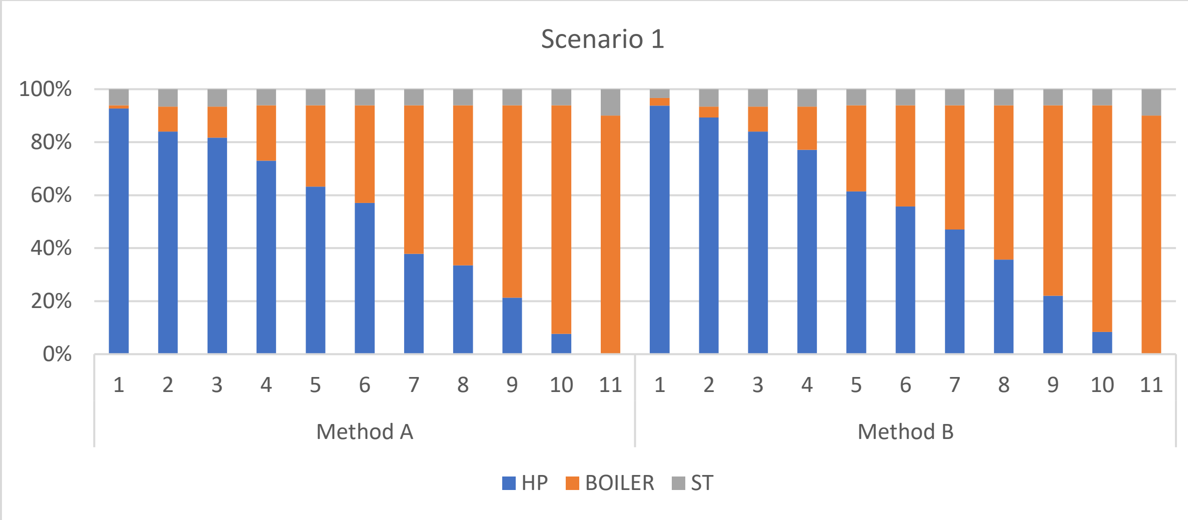


(b)

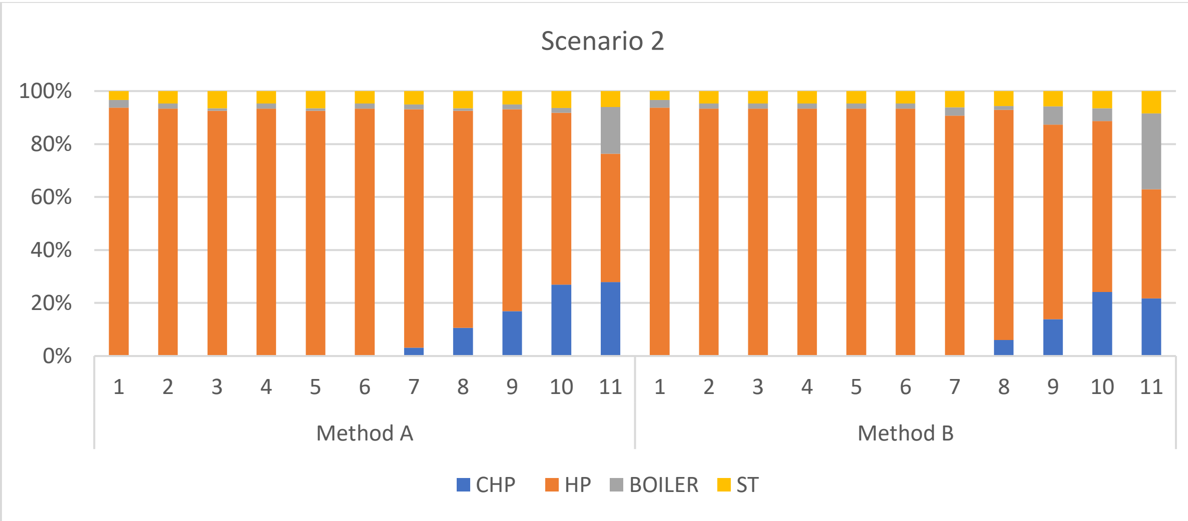


(c)

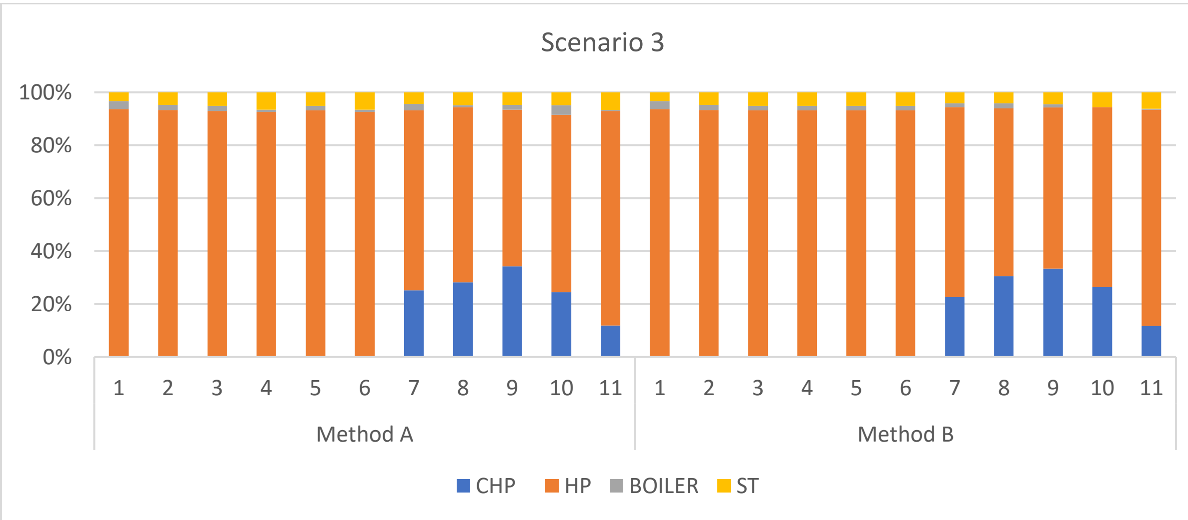
Fig. 6.12. Electricity supply mix for "Method A" and "Method B" for: (a) Scenario 1, (b) Scenario 2 and (c) Scenario 3, respectively.



(a)

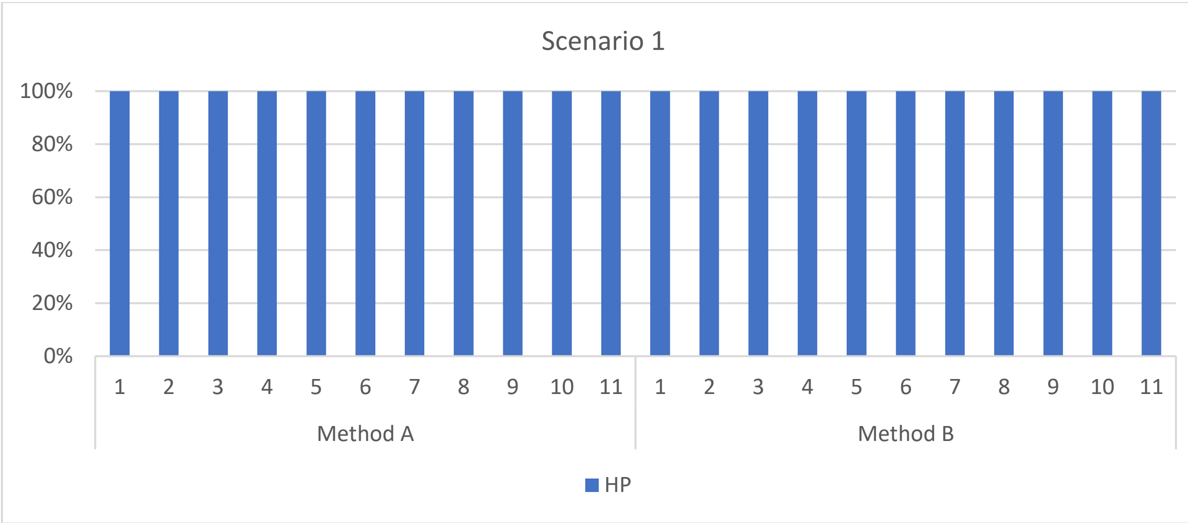


(b)

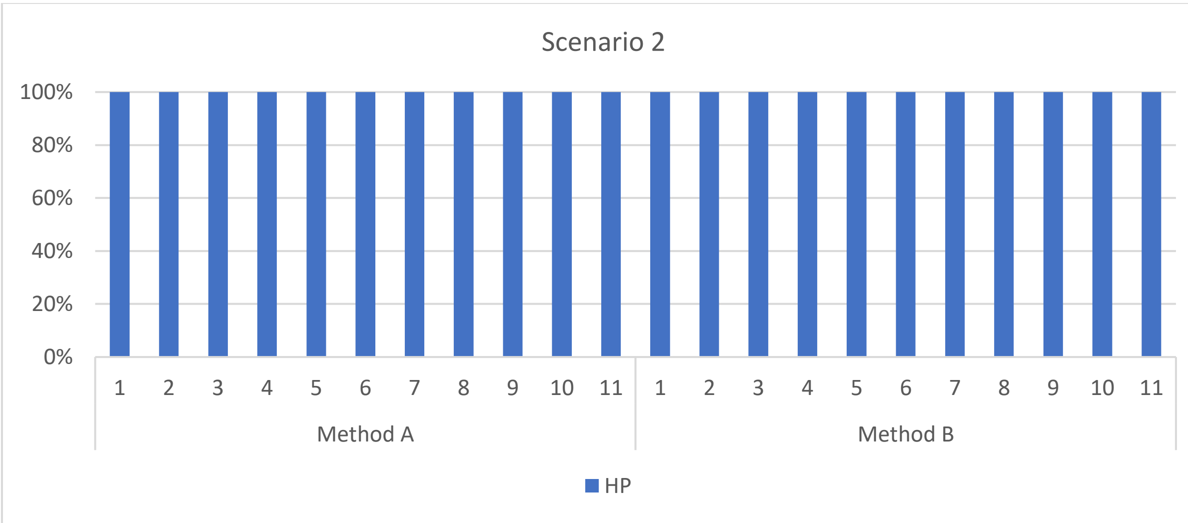


(c)

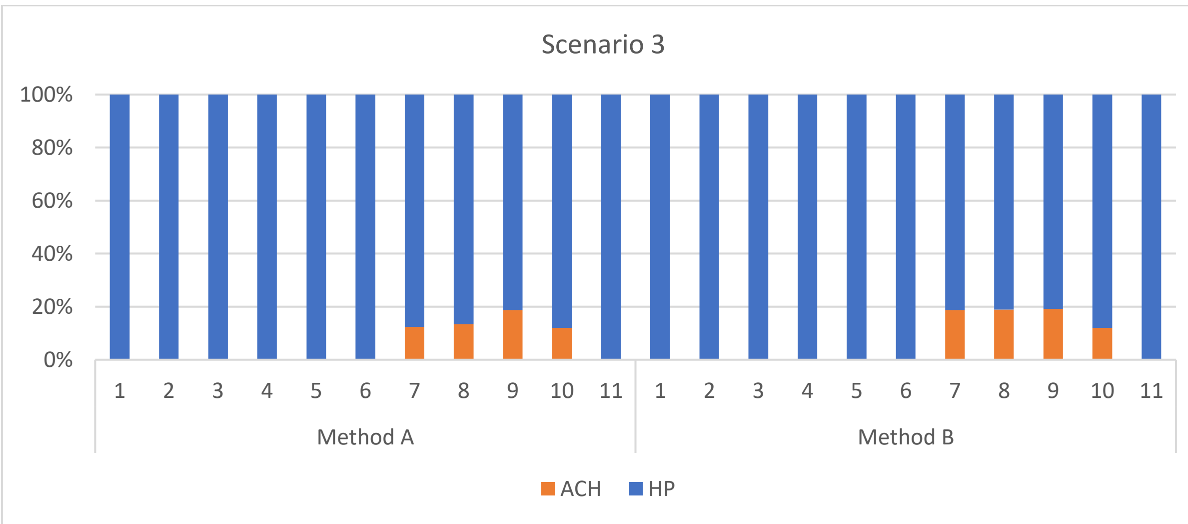
Fig. 6.13. Heating supply mix for "Method A" and "Method B" for: (a) Scenario 1, (b) Scenario 2 and (c) Scenario 3, respectively.



(a)



(b)



(c)

Fig. 6.14. Cooling supply mix for “Method A” and “Method B” for: (a) Scenario 1, (b) Scenario 2 and (c) Scenario 3, respectively.

Fig. 6.15 illustrates how the electricity generated by CHP units, photovoltaics and wind turbines is used throughout the year in Scenario 3, for "Method A" and "Method B" respectively. For CHP units, it can be seen that most of the generated energy is supplied to the respective buildings for local use or supplied to the microgrid, in both methods. For photovoltaics, at solutions 1 – 3 (where cost objective function has largest impact) most of generated electricity is sold to the grid, taking advantage of the high selling prices, and the rest is used locally or supplied to the microgrid. For solutions 4 – 11, most of generated electricity is used locally or supplied to the neighbourhood microgrid. Regarding wind turbines, most of the produced electricity is sold to the grid for solutions 1 – 9, where for the last two solutions a large share of electricity is used for satisfying local needs or exported to the microgrid. Overall, electricity generation follows a similar pattern for both methods.

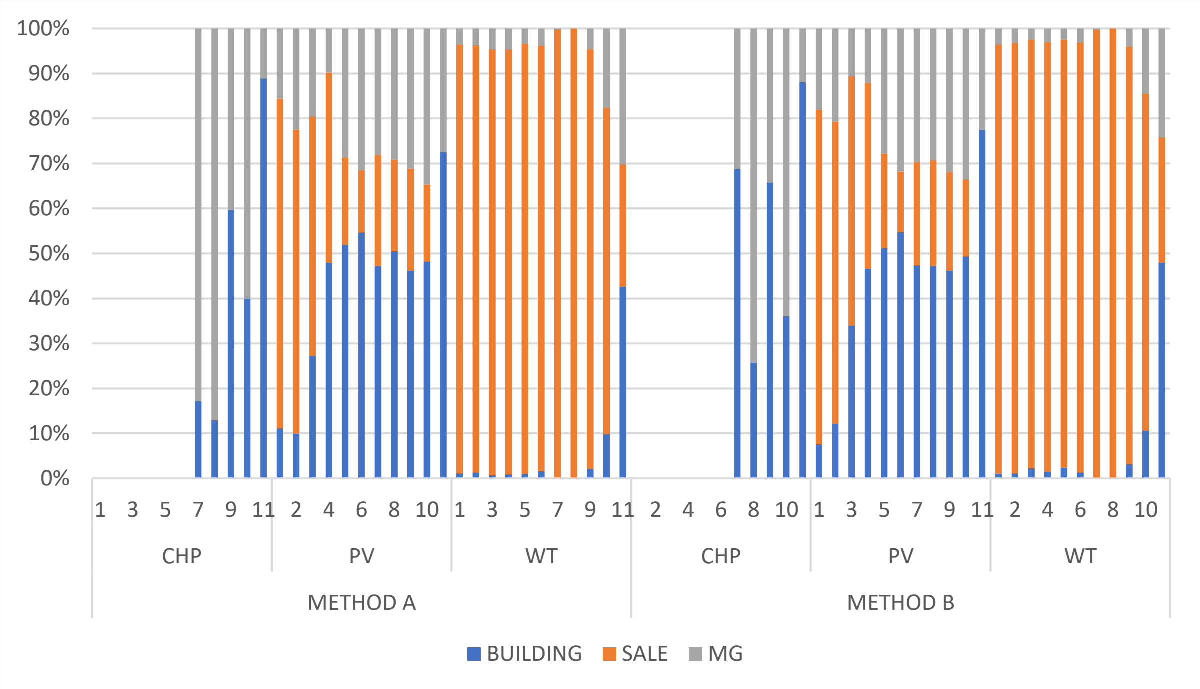


Fig. 6.15. Electricity generation from CHP, photovoltaics, and wind turbines for Scenario 3, for "Method A" and "Method B"

Although it can be seen in Fig. 6.11 - Fig. 6.14 that many solutions follow a similar structure in both methods, the differences between "Method A" and "Method B" are notable. In general, "Method A" can provide solutions which are more attractive in terms of TAC and carbon emissions due to the higher degrees of freedom it incorporates which does not influence the direction of optimization. Therefore, a larger set of design solutions can be provided [109]. However, despite the advantage of "Method A" to generate a larger set of solutions, the sizes of technologies that occur as outcome might not be available commercially. An argument could be made that some technologies are eligible for custom-making (e.g. CHP). However, this is not considered a viable option as it does not apply to all technologies. On the other hand, “Method B” relies on commercially available technologies with specific technical characteristics (i.e. capacity). Nevertheless, for the design of a DES the task of selecting technologies with predefined capacity is complex, especially when the set of buildings is large. Moreover, the complexity increases in case there is the option to form a microgrid or a DHN as outputs or having the ability to install energy storage technologies. Designing a DES for a single building is a much easier task compared to the design of a DES for an urban area.

In Fig. 6.16 - Fig. 6.21 an illustration of the system’s structure is depicted for solutions “A”, “B” and “C” shown in Fig. 6.3, for Scenario 3 of “Method A” and “Method B”, respectively. The installed technologies at each building, the heat flow through DHN and electricity exchange with microgrid and national grid are illustrated for comparison. At first glance it is obvious that the solutions vary significantly between each point and each method; different technologies are installed at each building and the structure of the DHN is different at each solution. Specifically, at point “A” (the solution with the lowest TAC) in “Method A” a boiler is installed at buildings i1, i2, i5 and i6 while in “Method B” a boiler is installed at buildings i1, i4, i5 and i6. Heat pumps are installed at each building in both methods, and photovoltaics at buildings 1 – i5. Differences also exist in DHN interconnections, in “Method A” building i5 supplies heat to building i3, which supplies heat to building i4, on the other hand in “Method B” building 1 supplies heat to building i2, building i5 supplies heat to building i4, which supplies heat to building i3. Moreover, buildings i1 – i5 exchange electricity with microgrid and with national grid and building i6 only purchases electricity from the grid in both methods.

At point “B”, there are more differences between each method. For instance, in “Method A” a CHP unit is installed at building i3, while in “Method B” a CHP unit is installed at building 4. In “Method A”, heat pumps are installed at buildings i1, i3, i5 and 6 and absorption chillers at buildings i2 and i4, while in “Method B” heat pumps are installed at buildings 4, 5 and 6, and absorption chillers at buildings i1 – i3. In “Method A” boilers are installed at buildings i1 and i6, and in “Method B” at buildings i2 and i6. Photovoltaics are installed at all buildings and solar thermal collectors at building i6. Thermal storage is also installed at buildings i1 and i2 in “Method A”, while in “Method B” only at building i2. Regarding DHN connections, in “Method A” building i3 supplies heat to buildings i2 and i4 and at “Method B” building i4 supplies heat to buildings i1 and i3, and building i1 supplies heat to building i2. In addition, all buildings exchange electricity with the microgrid, although operational differences exist between each method. Operational differences also exist regarding buying and selling electricity from the grid, where in “Method A”, building i1 buys and sell electricity to the grid, buildings i2, i3 and i4 only export electricity, and buildings i5 and i6 only buy electricity. In “Method B” results are similar except at building i6, which buys and sells electricity.

Furthermore, regarding Point “C”, which is the optimal solution in terms of minimizing carbon emissions, it can be noticed that several technologies are installed at each building in both methods. In “Method A”, CHP units are installed at buildings i1, i4, i5 and i6, while in “Method B” at buildings i1, i5 and i6. Heat pumps are installed at all buildings in both methods to satisfy cooling and/or heating demand. Boilers at “Method A” are installed at buildings i3 and i4, while at “Method B” at buildings i1 – i4. Solar photovoltaics are installed at all each building in both methods, and solar thermal collectors at buildings i1, i2, i3, i4 and i6. Thermal storage units are also selected in both methods, and are installed at buildings i1, i2, i3, i4 and i6 in “Method A” and at buildings i1 – i5 in “Method B”. It is noted that at point “C”, electrical storage units are installed at all buildings. Moreover, in both methods DHN interconnections exist, in “Method “A” building i4 and i5, building i4 and i6 and i3, building i3 and i2, and building i2 and i1 are connected, and in “Method B”, building i2 and i1, building i3 and i2, i6 and i4, and building i4 and i5. Finally, it is noteworthy that at illustration points “A”, “B” and “C” wind turbines are installed at buildings i2, i3 and i4, in both methods. Also, in both methods all buildings exchange electricity with the microgrid. Regarding, electricity exchange with the grid in both methods buildings only sell excess electricity, specifically buildings i2, i3 and i4. Therefore, these illustrations show the differences between each method, and each respective point at the Pareto front, which are important in terms of system’s configuration and design, and also for the optimal operation of the selected technologies.

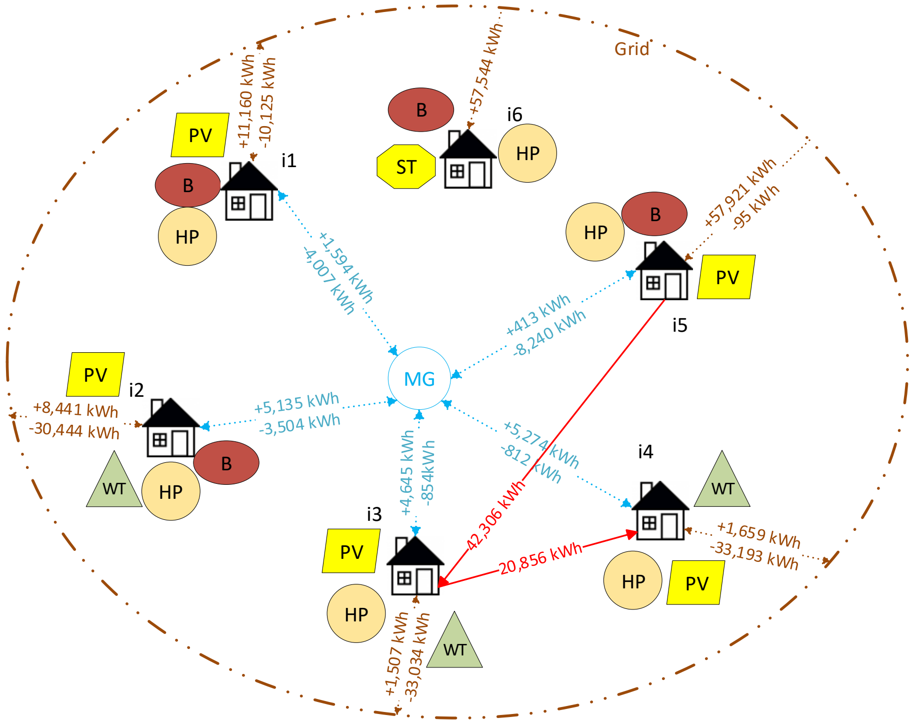


Fig. 6.16. Layout of DES for solution "A" of "Method A" with heat flow through DHN and electricity exchange through microgrid and national grid throughout a year.

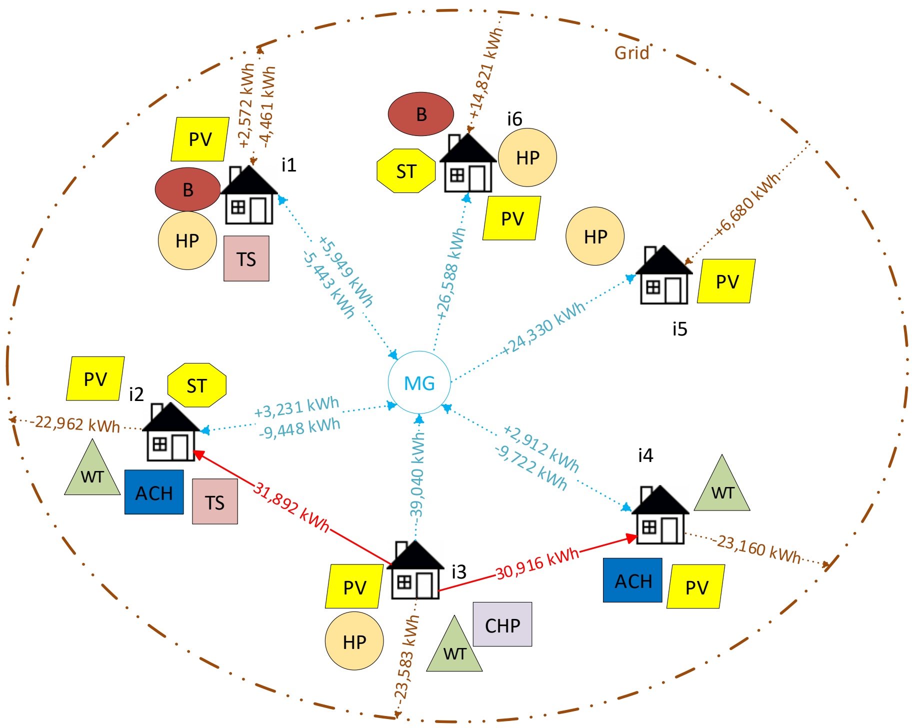


Fig. 6.17. Layout of DES for solution "B" of "Method A" with heat flow through DHN and electricity exchange through microgrid and national grid throughout a year.

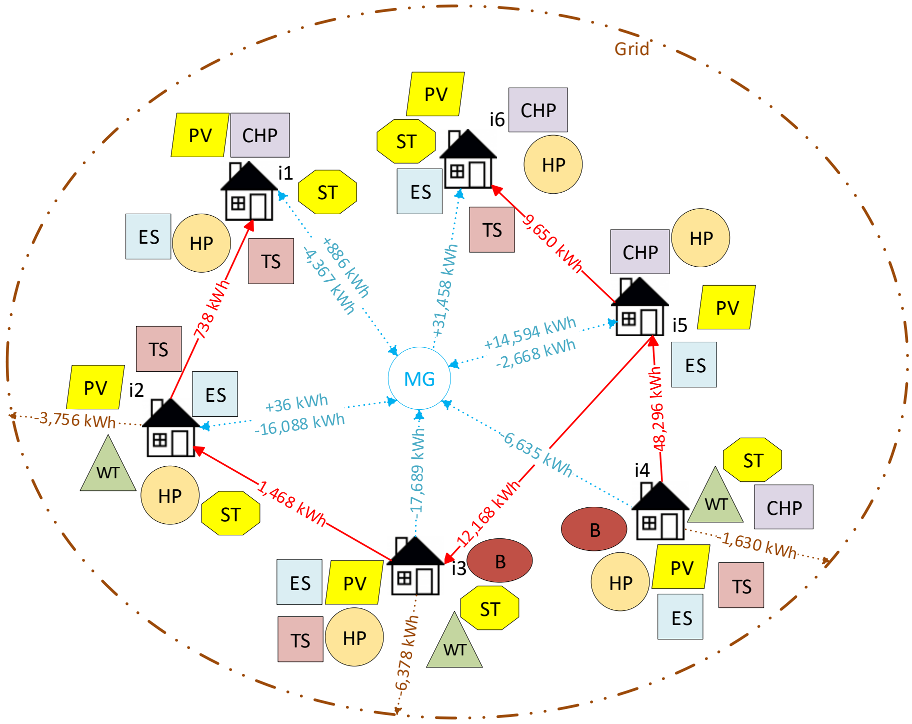


Fig. 6.18. Layout of DES for solution "C" of "Method A" with heat flow through DHN and electricity exchange through microgrid and national grid throughout a year.

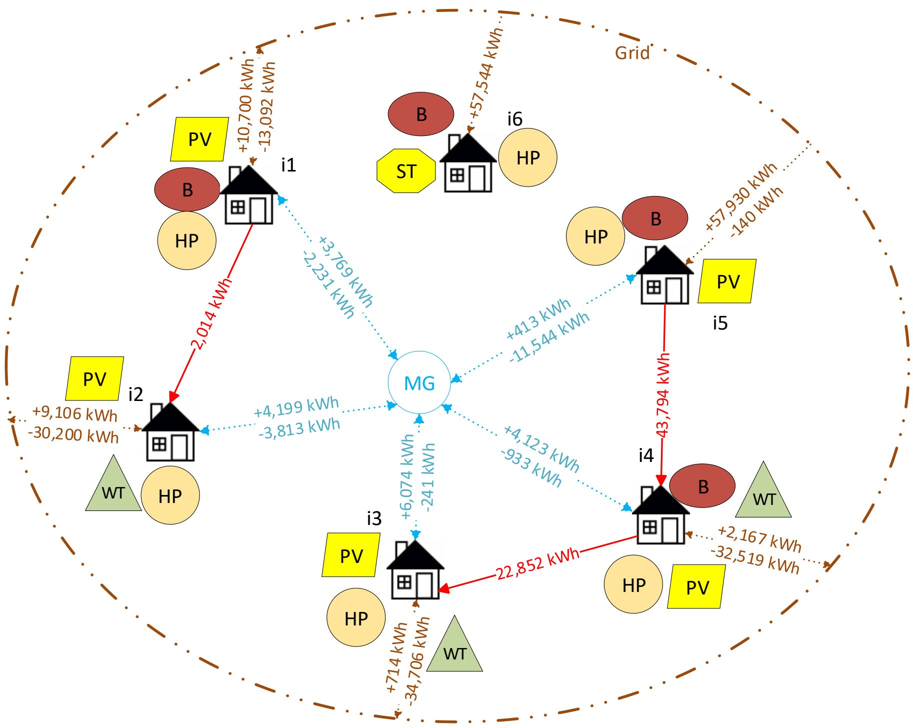


Fig. 6.19. Layout of DES for solution "A" of "Method B" with heat flow through DHN and electricity exchange through microgrid and national grid throughout a year.

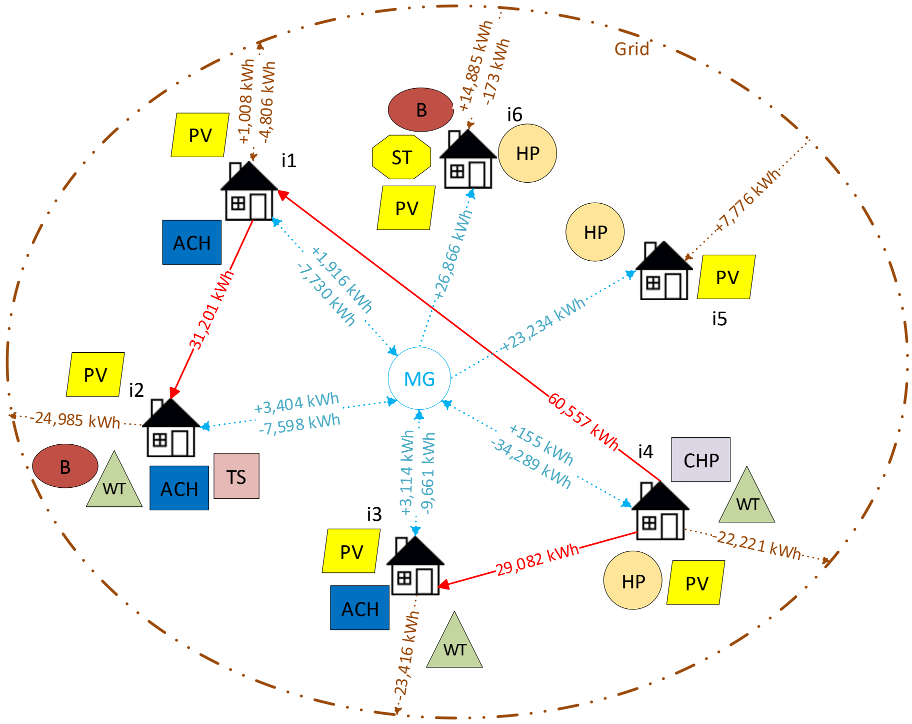


Fig. 6.20. Layout of DES for solution "B" of "Method B" with heat flow through DHN and electricity exchange through microgrid and national grid throughout a year.

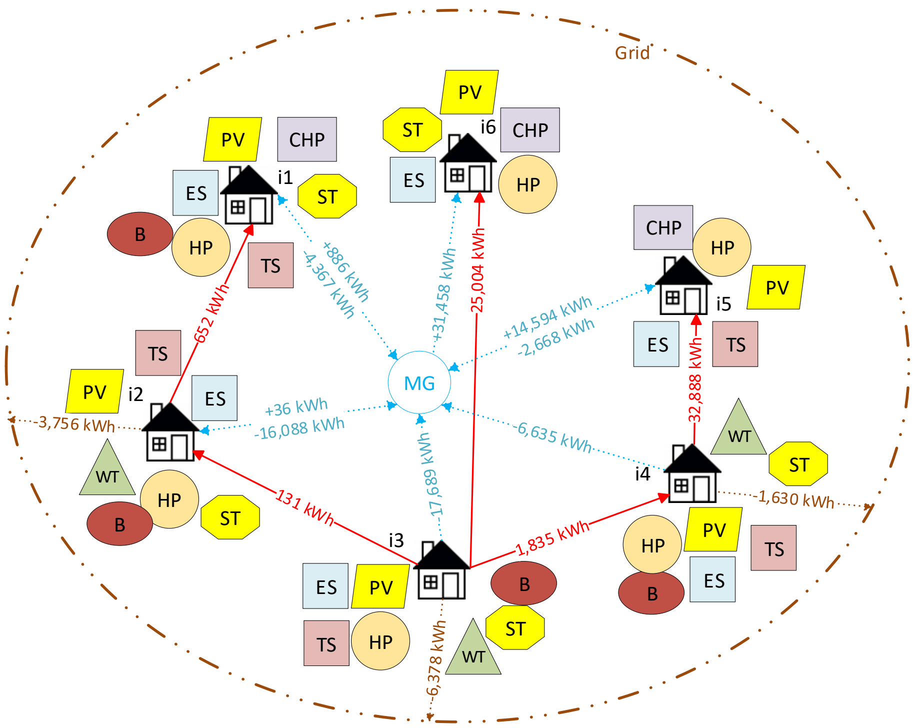
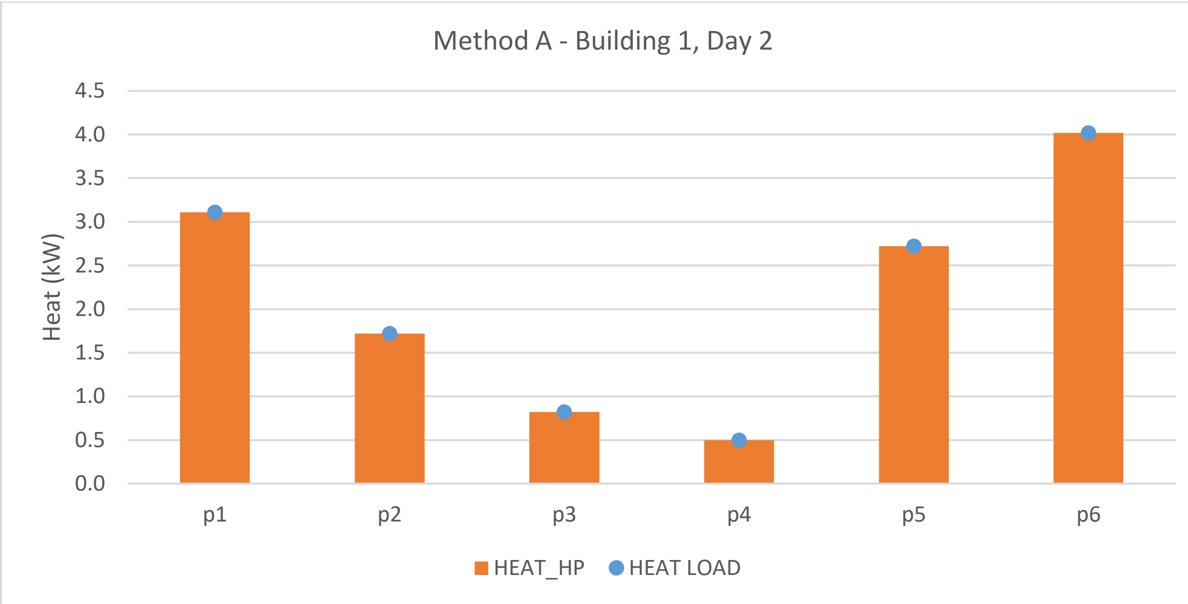


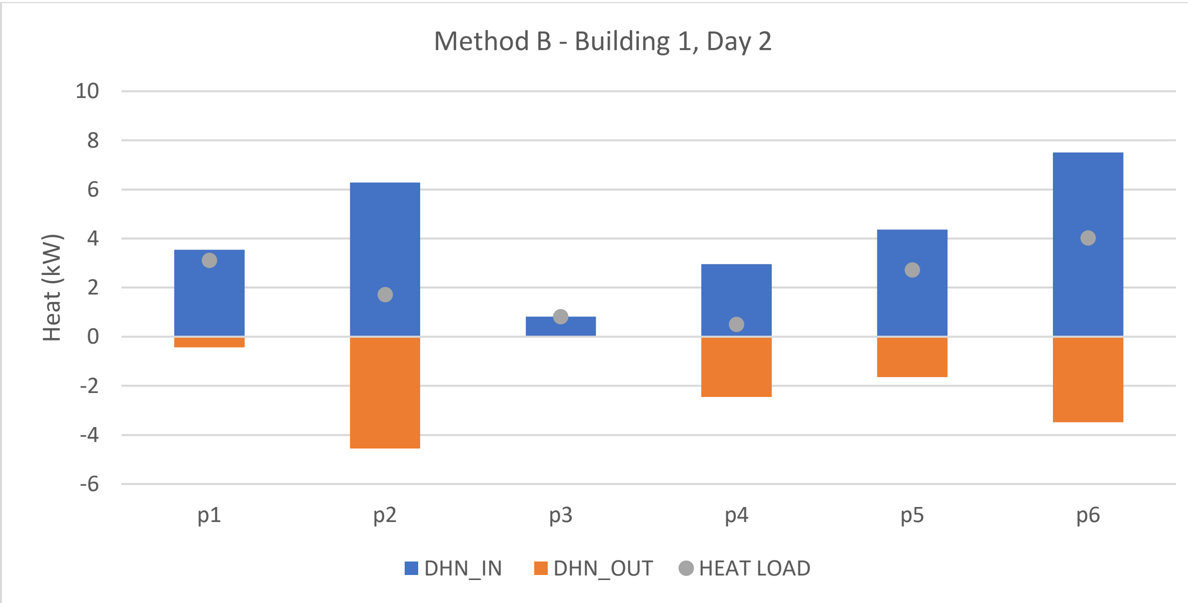
Fig. 6.21. Layout of DES for solution "C" of "Method B" with heat flow through DHN and electricity exchange through microgrid and national grid throughout a year.

In Fig. 6.22 and Fig. 6.23 the heat and electricity balances at building i1 of solution "B" Scenario 3, are depicted as illustrative examples for a typical mid-season day (day 2), for

"Method A" and "Method B" respectively. Heat demand in "Method A" is satisfied exclusively with heat pumps for all the periods of day 2. On the other hand, in "Method B" heat demand is satisfied via heat transfer from DHN. Specifically, building i4 supplies heat to building i1, which is used partially to satisfy local demand and the remaining heat is exported to the network to satisfy heat demand at building i2 (for periods p1, p2, p4, p5 and p6). Regarding electricity, in "Method A" demand is satisfied by local generation from photovoltaics for periods p1 – p4. At period p5 electricity is bought from the grid and also received through the microgrid, while at period p6 electricity demand is mainly satisfied from the microgrid, and a small portion from photovoltaics. Also, at all periods electricity is consumed for heat pumps operation. At period p1, excess electricity from photovoltaics is exported to the microgrid while at periods p2 and p3 excess electricity is sold to the grid. At period p4 a large portion of excess electricity is sold, and a small portion is exported to the microgrid. Similarly, in "Method B", photovoltaics supply electricity to satisfy local demand, however there is no electricity import from the microgrid. At periods p5 and p6 electricity is bought from the grid. Excess electricity is either exported to the microgrid or sold to the grid.

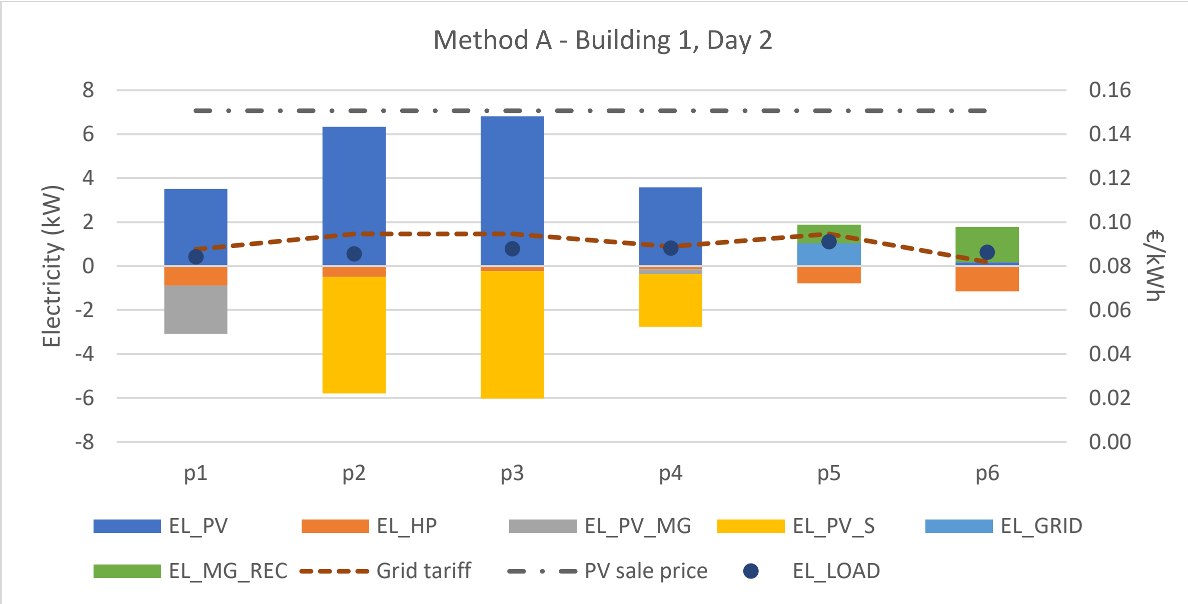


(a)

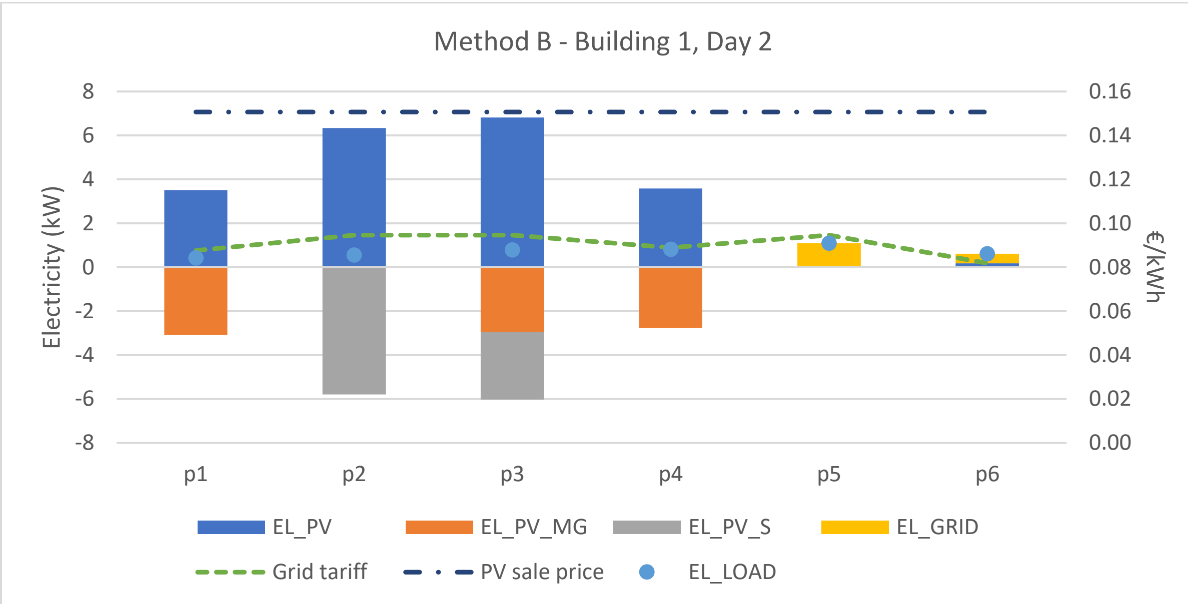


(b)

Fig. 6.22. Heat balance for mid-season at building i1 (Scenario 3, solution "B"), for: (a) "Method A" and (b) "Method B", respectively.



(a)



(b)

Fig. 6.23. Electricity balance for mid-season at building i1 (Scenario 3, solution “B”), for: (a) “Method A” and (b) “Method B”, respectively.

6.4 Summary of Results and Discussion

The results show that the selection of the design method plays a significant role. The results between each method vary, not only in terms of system’s configuration but also in terms of capacity of technologies and operation. Both methods present optimal solutions which can be used by a DM to choose amongst many available options, with each one of them having different TAC and carbon footprint. The choice of the preferred solutions relies on several factors that can influence the decision, such as the available budget for the project or specific environmental policy targets for carbon emissions reduction.

Furthermore, as mentioned previously, “Method A” has the advantage of providing a larger set of design solutions, but those solutions might not correspond to commercially available technologies. Hence, it is suggested these two methods to be used in parallel, as shown in the diagram depicted in Fig. 6.24. A DM could first use “Method A” to get a preliminary idea of the optimal configuration of the DES in terms of design variables. Then, “Method B” could be applied, in which candidate technologies have sizes close to those provided by “Method A”. The appropriate definition of the capacity of candidate technologies (or bounds) is a very important task, which becomes even more important when a DES at an urban level is designed, and also when multi-objective optimization is applied.

In addition, the differences regarding the results of TAC between the two methods, (as shown in Fig. 6.9) further show the importance of selecting a design method. A high TAC value affects the financial viability of a project and could lead a DM to reject it. Therefore, combining these two methods could be used in real applications, e.g. designing a DES for apartment blocks, where the capital and operational costs could affect the financial characteristics of the project.

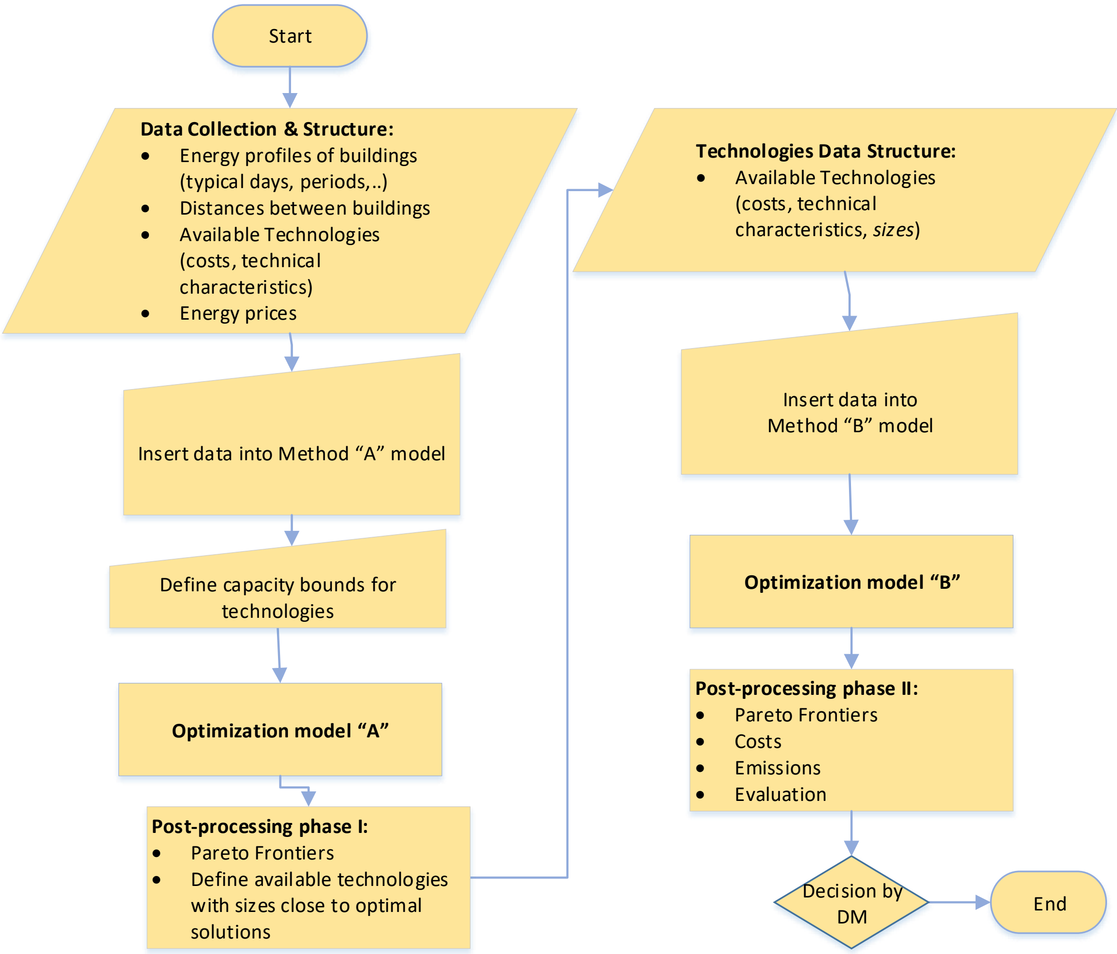


Fig. 6.24. Illustration of the possible combination of "Method A" and "Method B"

Chapter 7: Results of DES optimization under uncertainty

This Chapter provides the results of optimization under uncertainty for the test case. The results of the application of each method described in subsection 4.5 are presented, discussed and compared. Uncertainty analysis is based on Scenario 3 of "Method A" which is referred from now on as the deterministic scenario.

7.1 Results of objective-wise uncertainty

The first method examining the optimal design of DES under uncertainty is objective-wise worst-case uncertainty. Scenarios OW1 and OW2 have been applied to the test case, as described in subsection 5.3 and the results are depicted in Fig. 7.1. Results show that uncertainty in parameters in Scenario OW1 provides worse solutions compared to the deterministic scenario. Scenario OW2, in which all uncertainties are taken into account, provides the worst solutions compared to all scenarios. Nevertheless, solutions are characterized as robust because they represent the best solutions of the worst-case scenarios. Scenario OW1 was solved in 50 seconds and Scenario OW2 in 2 minutes, which are much lower compared to Scenario 3 in "Method A". This highlights the significance of parameters' values in optimization and its effects in computational load. Analytically, in Scenario OW1 TAC ranges between 22,155 and 44,462 €/year and carbon emissions between 12,879 and 156,030 kg/year. In Scenario OW2, TAC is between 28,163 and 53,604 €/year and carbon emissions are between 35,103 and 203,448 kg/year.

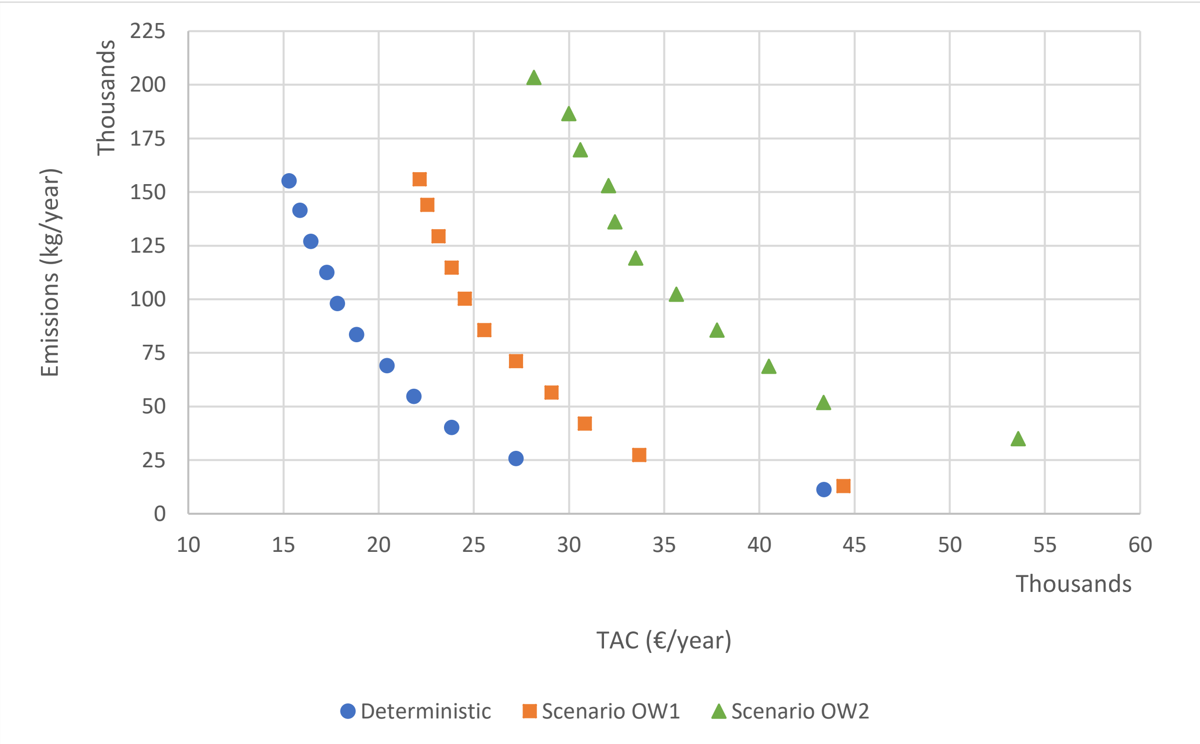
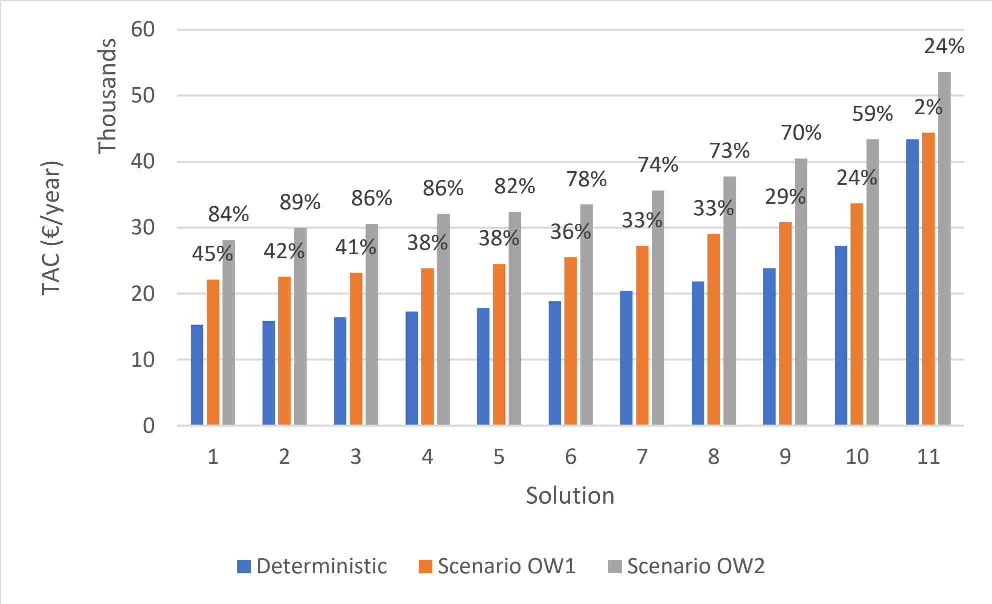
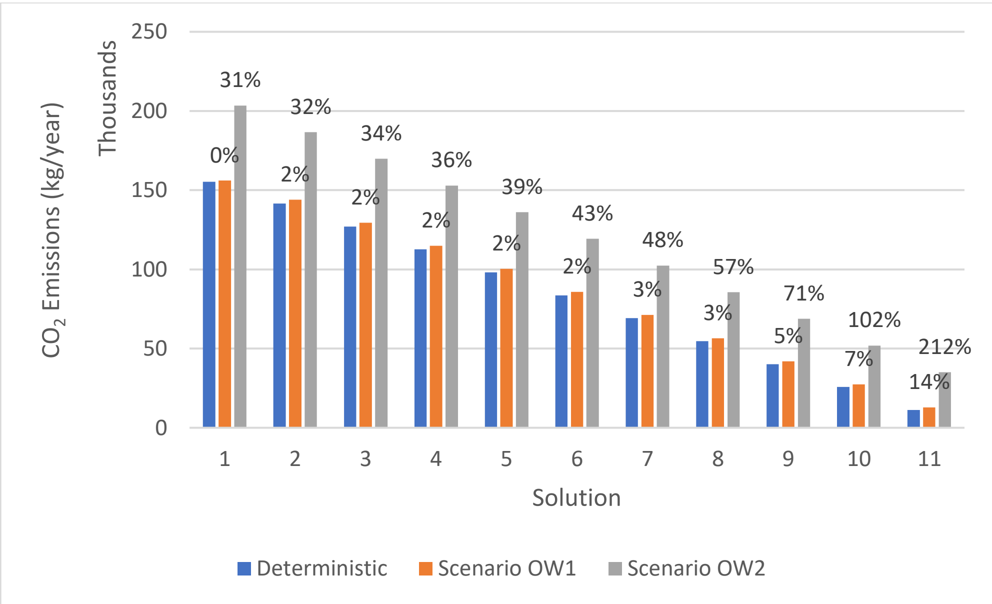


Fig. 7.1. Pareto frontiers for the deterministic scenario, Scenario OW1 and Scenario OW2.

Values of TAC and carbon emissions are presented in Fig. 7.2 for comparison. Compared to the deterministic scenario, Scenario OW1 has 45% higher TAC at the first solution (minimizing TAC), reaching a low 2% at the last solution (minimizing carbon emissions). Regarding Scenario OW2, it has 84% higher TAC at the first solution and 24% at the last. As for carbon emissions it is noted that Scenario OW1 has small differences compared to the deterministic scenario, reaching as high as 14%. On the other hand, in Scenario OW2 differences in results are more noticeable, with the increase of carbon emissions being between 31% and 212%, for the first and last solution, respectively.



(a)



(b)

Fig. 7.2. Differences in values of objective functions for Scenario OW1 and Scenario OW2 of: (a) TAC and (b) Carbon emissions, respectively, compared to the deterministic scenario.

A detailed breakdown of TAC and carbon emissions for each solution is shown analytically in Fig. 7.3 and Fig. 7.4, respectively, to better assess the differences of each scenario. Compared to the deterministic scenario, the main differences of Scenario OW1 and Scenario

OW2 are in terms of capital and operational cost. Especially in Scenario OW2 operational cost is significantly higher, indicating not only differences in structural decision variables, but also in operational ones (e.g. lower sales of excess electricity to the grid). It is obvious that uncertainties in parameters affect the components of TAC objective function significantly. Regarding carbon emissions, results follow a similar pattern in all scenarios. Specifically, electricity is the main source of emissions in most solutions, with natural gas having the largest share at solutions towards minimization of carbon emissions, due to its lower carbon emissions' factor. It is noted that in the last solution of all three scenarios no carbon emissions are from electricity use (grid).

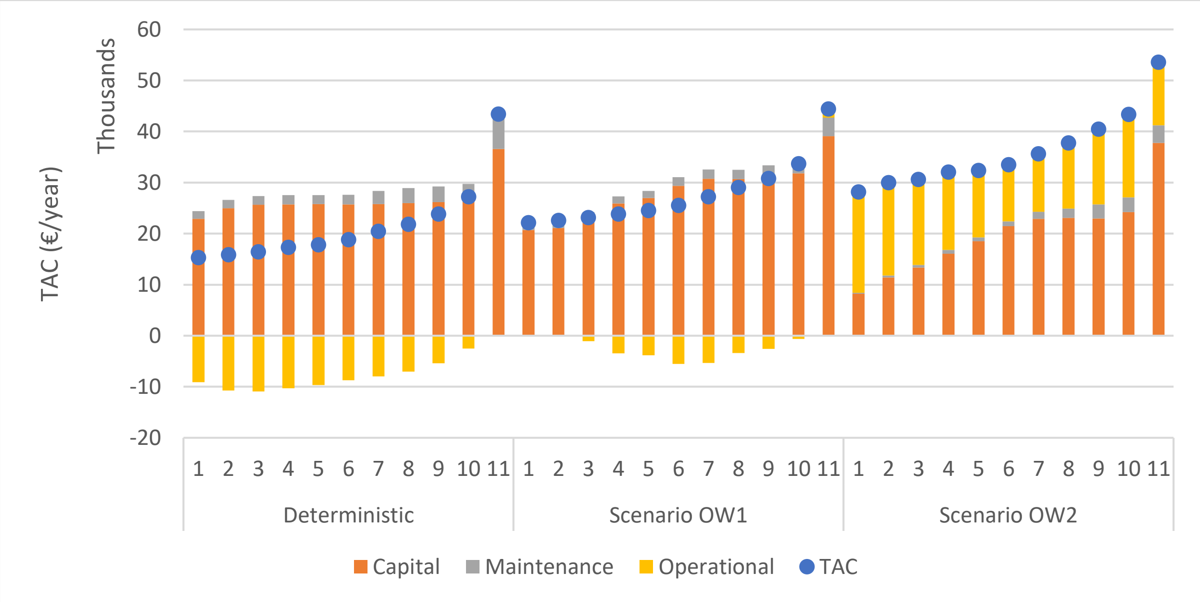


Fig. 7.3. TAC components for the deterministic scenario, Scenario OW1 and Scenario OW2, respectively.

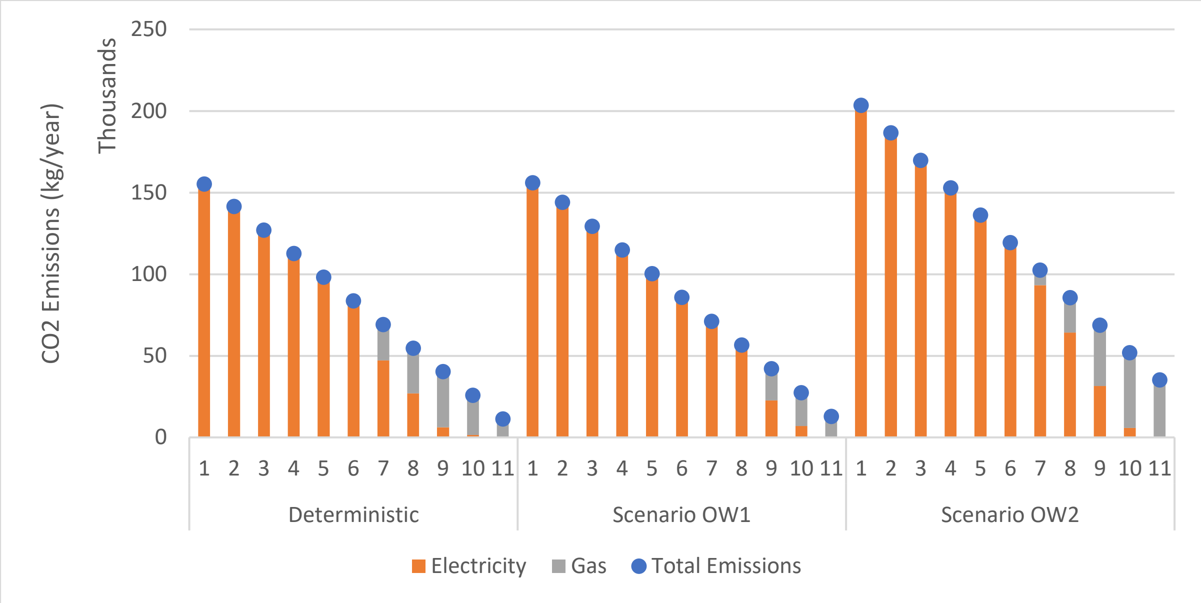


Fig. 7.4. Carbon emissions components for the deterministic scenario, Scenario OW1 and Scenario OW2, respectively.

In Table 7.1 the DES configuration for the deterministic scenario, Scenario OW1 and Scenario OW2 is presented and the structural differences between each scenario are shown. For instance, the total capacity of CHP units and heat pumps in Scenario OW2 is higher compared to Scenario OW1. This can be attributed to the increase of energy demand, hence technologies with larger capacity are required to satisfy the loads. Also, wind turbines are selected in Scenario OW1, but not in Scenario OW2 (except in the last solution). A 20% reduction of wind speed made wind turbines a less attractive choice. Generation from wind turbines is based on the value of wind speed, which must also be above a specific cut-in speed. In addition, the total capacity of photovoltaics is lower compared to the deterministic scenario. Solar thermal collectors are not selected in any solution. Also, the total capacity of storage technologies is lower compared to the deterministic scenario. Moreover, several differences exist regarding the configuration of the DHN and the formation of a microgrid. It is noted that the microgrid is not selected as an optimal choice in the first three solutions of Scenario OW2.

Table 7.1. Detailed DES configuration of optimal solutions for Scenario OW1 and Scenario OW2.

	CHP (kW)	HP (kW)	ACH (kW)	WT (kW)	B (kW)	PV (kW)	ST (m2)	ES (kWh)	TS (kWh)	DHN	MG
	Deterministic										
1	0	112	0	30	25	46	5	0	0	2	1
2	0	112	0	30	20	56	7	0	0	2	1
3	0	112	0	30	30	60	8	0	0	0	1
4	0	112	0	30	25	60	16	0	0	0	1
5	0	112	0	30	25	60	8	0	0	2	1
6	0	112	0	30	20	60	16	0	0	1	1
7	5	101	11	30	25	60	8	0	9	1	1
8	6	100	13	30	15	60	10	0	20	2	1
9	10	95	18	30	25	60	10	0	1	3	1
10	17	104	11	30	25	60	11	0	21	2	1
11	24	152	0	30	20	60	59	87	190	5	1
	Scenario OW1										
1	0	112	0	30	20	18	0	0	0	1	1
2	0	112	0	30	20	20	0	0	0	1	1
3	0	112	0	30	20	28	0	0	0	1	1
4	0	112	0	30	20	39	0	0	0	2	1
5	0	112	0	30	25	45	0	0	0	0	1
6	0	112	0	30	25	55	0	0	0	0	1
7	0	111	6	30	22	60	0	0	0	1	1
8	0	111	5	30	22	60	0	0	0	1	1
9	5	107	5	30	15	60	0	0	21	1	1
10	9	106	6	30	12	60	0	0	46	4	1
11	17	112	0	30	20	60	0	87	121	3	1
	Scenario OW2										
1	0	123	0	0	25	0	0	0	0	0	0
2	0	123	0	0	8	11	0	0	2	5	0
3	5	123	0	0	20	21	0	0	0	0	0
4	5	123	0	0	20	31	0	0	13	0	1
5	0	123	0	0	25	43	0	0	0	0	1
6	0	123	0	0	25	56	0	0	0	0	1
7	5	118	5	0	20	60	0	0	0	2	1
8	6	120	7	0	10	60	0	0	6	2	1
9	10	104	19	0	15	60	0	0	12	2	1
10	18	104	21	0	10	60	0	6	46	3	1
11	21	111	14	30	17	60	0	59	95	3	1

7.2 Results of Robust Optimization (MMR and MER)

As described in subsection 5.3.2, the robustness of the problem is examined by taking TAC as the objective function and the CO_2 emissions as a constraint with upper bound 100,000 kg/year, according to Scenarios R1 – R5. The optimal value of TAC for each *s-th* scenario is calculated and the results are presented in Table 7.2. The TAC value varies significantly between each scenario, ranging from a low 11,337 up to 24,332 €/year, i.e. the values of scenario R2 and scenario R5 respectively.

Table 7.2. Results of TAC at each scenario

Scenario	Energy Prices	Interest Rate	TAC_s (€/year)
R1	BAU	BAU	17,734
R2	High	High	24,322
R3	High	Low	14,608
R4	Low	High	20,846
R5	Low	Low	11,337

In the next step, the MMR criterion is applied using eq. (3.7) with the optimal value for MMR calculated to be 0.018 (approximately 2%). The values of each TAC_s when MMR is minimized, are shown in Table 7.3. The application of MMR leads to a very small increase of approximately 27 €/year in the total annual cost, compared to the BAU solution (Scenario R1).

Table 7.3. Results of TAC at each scenario when MMR is applied

Scenario	Energy Prices	Interest Rate	TAC_s (€/year)
R1	BAU	BAU	17,761
R2	High	High	24,378
R3	High	Low	14,702
R4	Low	High	21,215
R5	Low	Low	11,538

Moreover, the configuration of the whole neighbourhood for each scenario *s* is presented in Table 7.4. The structure of the DES for each scenario is different. For instance, when Scenario R1 and MMR are compared it can be seen that a boiler is installed at buildings i1, i2, i5 and i6 in Scenario R1 and at buildings i1, i2, i4 and i6 when MMR is applied. Also, minor differences exist regarding the capacity of photovoltaics in building i1 and the solar thermal collectors' area at building i6. It is noted that in Scenarios R4 and R5, CHP units and absorption chillers are installed due to the lower price of natural gas. An interesting remark is the installed capacity of photovoltaics at some buildings in Scenarios R2 and R4, which is lower than the maximum upper bound of 10 kW.

Table 7.4. DES configuration for each scenario and MMR criterion.

Building	CHP (kW)	HP (kW)	CHILLER (kW)	BOILER (kW)	PV (kW)	ST (m2)	ES (kWh)	TS (kWh)	WT (kW)	DHN (Yi,j)	MG
	Scenario R1										
i1	0	6.4	0	5	10	0	0	0	0	0	1
i2	0	6.6	0	5	10	0	0	0	10	0	
i3	0	5.0	0	0	10	0	0	0	10	0	
i4	0	6.2	0	0	10	0	0	0	10	3	
i5	0	39.1	0	5	10	0	0	0	0	4	
i6	0	48.9	0	5	10	8.4	0	0	0	0	
	Scenario R2										
i1	0	6.4	0	5	3.5	0	0	0	0	0	1
i2	0	6.6	0	5	6.6	0	0	0	10	0	
i3	0	5.0	0	5	9	0	0	0	10	4	
i4	0	6.2	0	0	10	0	0	0	10	0	
i5	0	39.1	0	0	10	0	0	0	0	3	
i6	0	48.9	0	5	10	8.4	0	0	0	0	
	Scenario R3										
i1	0	6.4	0	5	10	0	0	0	0	0	1
i2	0	6.6	0	5	10	0	0	0	10	0	
i3	0	5	0	0	10	0	0	0	10	4	
i4	0	6.2	0	0	10	0	0	0	10	0	
i5	0	39.1	0	5	10	0	0	0	0	3	
i6	0	48.9	0	5	10	8.4	0	0	0	0	
	Scenario R4										
i1	0	6.4	0	5	3.5	0	0	0	0	0	1
i2	5.2	6.6	0	5	4.4	0	0	0	10	3	
i3	0	0	5	0	3.5	0	0	0	10	4	
i4	0	0	6.2	0	2.4	0	0	0	10	0	
i5	0	39.1	0	0	10.0	0	0	0	0	0	
i6	0	48.9	0	5	10.0	7.4	0	0	0	0	
	Scenario R5										
i1	0	6.4	0	5	10	0	0	0	0	0	1
i2	0	6.6	0	5	10	0	0	0	10	0	
i3	0	0	5	5	10	0	0	0	10	0	
i4	5.1	0	6.2	0	10	0	0	0	10	3	
i5	0	39.1	0	0	10	0	0	0	0	4	
i6	0	48.9	0	5	10	8.4	0	0	0	0	
	MMR										
i1	0	6.4	0	5	8.3	0	0	0	0	0	1
i2	0	6.6	0	5	9.8	0	0	0	10	0	
i3	0	5	0	0	10	0	0	0	10	0	
i4	0	6.2	0	5	10	0	0	0	10	3	
i5	0	39.1	0	0	10	0	0	0	0	4	
i6	0	48.9	0	5	10	7.4	0	0	0	0	

The solutions generated from the application of MMR are considered to be robust as the risk is minimized from the extreme values of scenarios. Also, the small value of the MMR indicates that perturbations in economic parameters do not affect TAC significantly, when the resulting configuration and operational profiles of technologies are selected.

Nevertheless, if the probabilities of each scenario to occur came to be known, results could change. Therefore, the application of MER using eq. (3.8) has been also examined by assigning probabilities to each scenario. A 50% probability was assumed for Scenario R1, 20% probability for Scenario R2 and 10% for Scenarios R3 to R5, respectively. These probabilities are depended on estimations of the DM. The resulting value of MER is 0.002, which is considerably lower compared to the classic MMR method, which is an indication that the estimation of probabilities could lead to less conservative results. The results of the DES configuration when the MER criterion is applied are presented in Table 7.5. The comparison of the results between MMR and MER shows minor differences regarding the installed capacity of photovoltaics at building i1 and the solar thermal collectors at building i6, where the results match those occurring from Scenario R1. In addition, it is noted that electric and thermal storage units are never installed. Finally, both MMR and MER are not computationally intensive methods, taking a total of 6 minutes 18 seconds and 2 minutes and 54 seconds, respectively. Those values refer to the application of MMR and MER only, not taking into account the time to solve each Scenario R1 – R5.

Table 7.5. DES configuration for each probability scenario when MER is used with probabilities (0.5, 0.2, 0.1, 0.1, 0.1).

<table>
<tr><th>Building</th><th>CHP (kW)</th><th>HP (kW)</th><th>CHILLER (kW)</th><th>BOILER (kW)</th><th>PV (kW)</th><th>ST (m2)</th><th>ES (kWh)</th><th>TS (kWh)</th><th>WT (kW)</th><th>DHN (Yi,j)</th><th>MG</th></tr>
<tr><td>i1</td><td>0</td><td>6.4</td><td>0</td><td>5</td><td>10</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td rowspan="6">1</td></tr>
<tr><td>i2</td><td>0</td><td>6.6</td><td>0</td><td>5</td><td>10</td><td>0</td><td>0</td><td>0</td><td>10</td><td>0</td></tr>
<tr><td>i3</td><td>0</td><td>5</td><td>0</td><td>0</td><td>10</td><td>0</td><td>0</td><td>0</td><td>10</td><td>0</td></tr>
<tr><td>i4</td><td>0</td><td>6.2</td><td>0</td><td>5</td><td>10</td><td>0</td><td>0</td><td>0</td><td>10</td><td>3</td></tr>
<tr><td>i5</td><td>0</td><td>39.1</td><td>0</td><td>0</td><td>10</td><td>0</td><td>0</td><td>0</td><td>0</td><td>4</td></tr>
<tr><td>i6</td><td>0</td><td>48.9</td><td>0</td><td>5</td><td>10</td><td>8.4</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
</table>

The configuration of the DES for Scenario R1 (BAU) and Scenario R4 is depicted in Fig. 7.5, and for the application of MMR and MER in Fig. 7.6, for illustrative purposes and to show their differences analytically. Despite small differences in system's structure, the application of RO techniques leads to different results of operational variables such as heat flow transfer through the DHN, transfer of electricity to and from microgrid, and also to and from national grid.

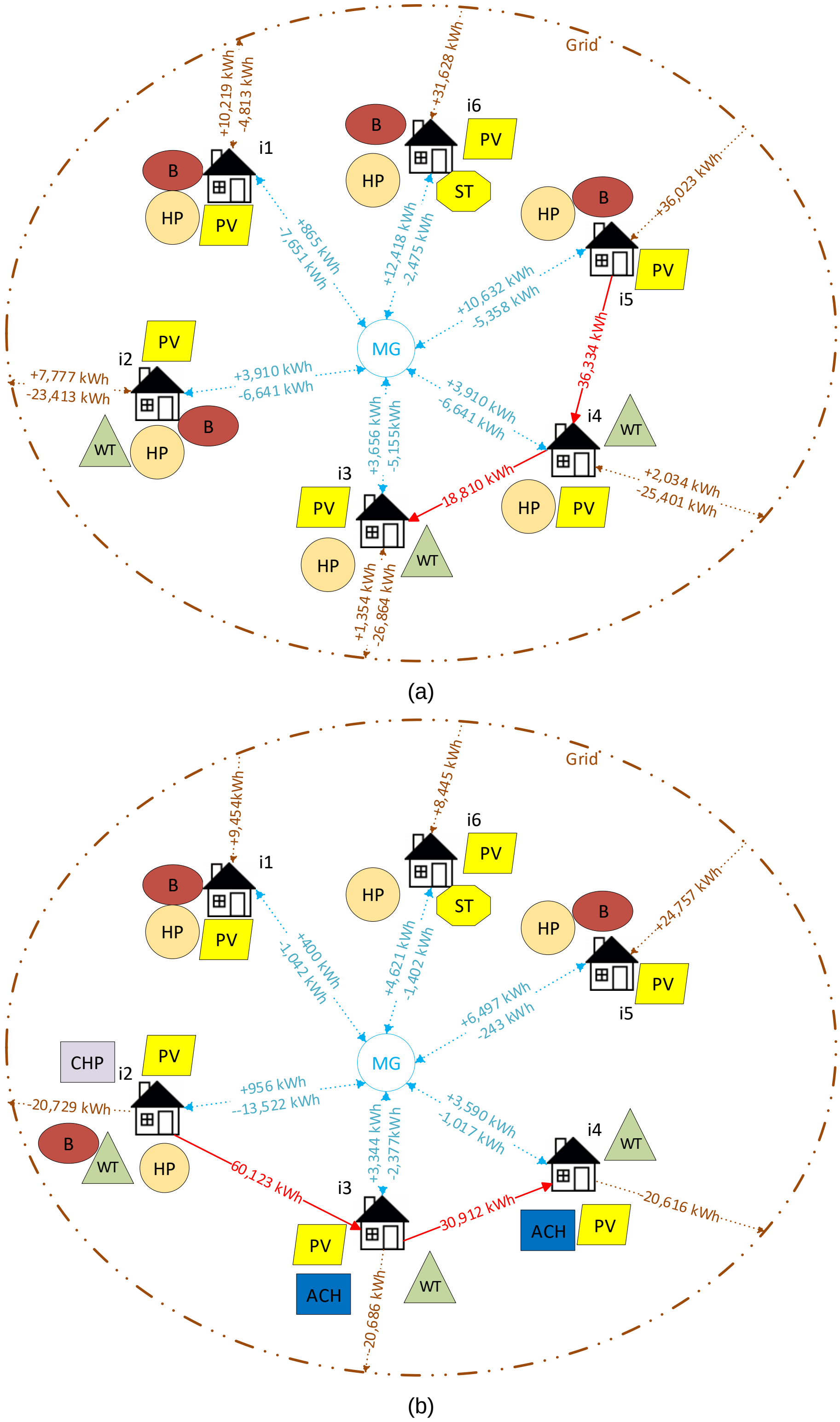


Fig. 7.5. Configuration of DES for: (a) Scenario R1 (BAU) and (b) Scenario R4, respectively.

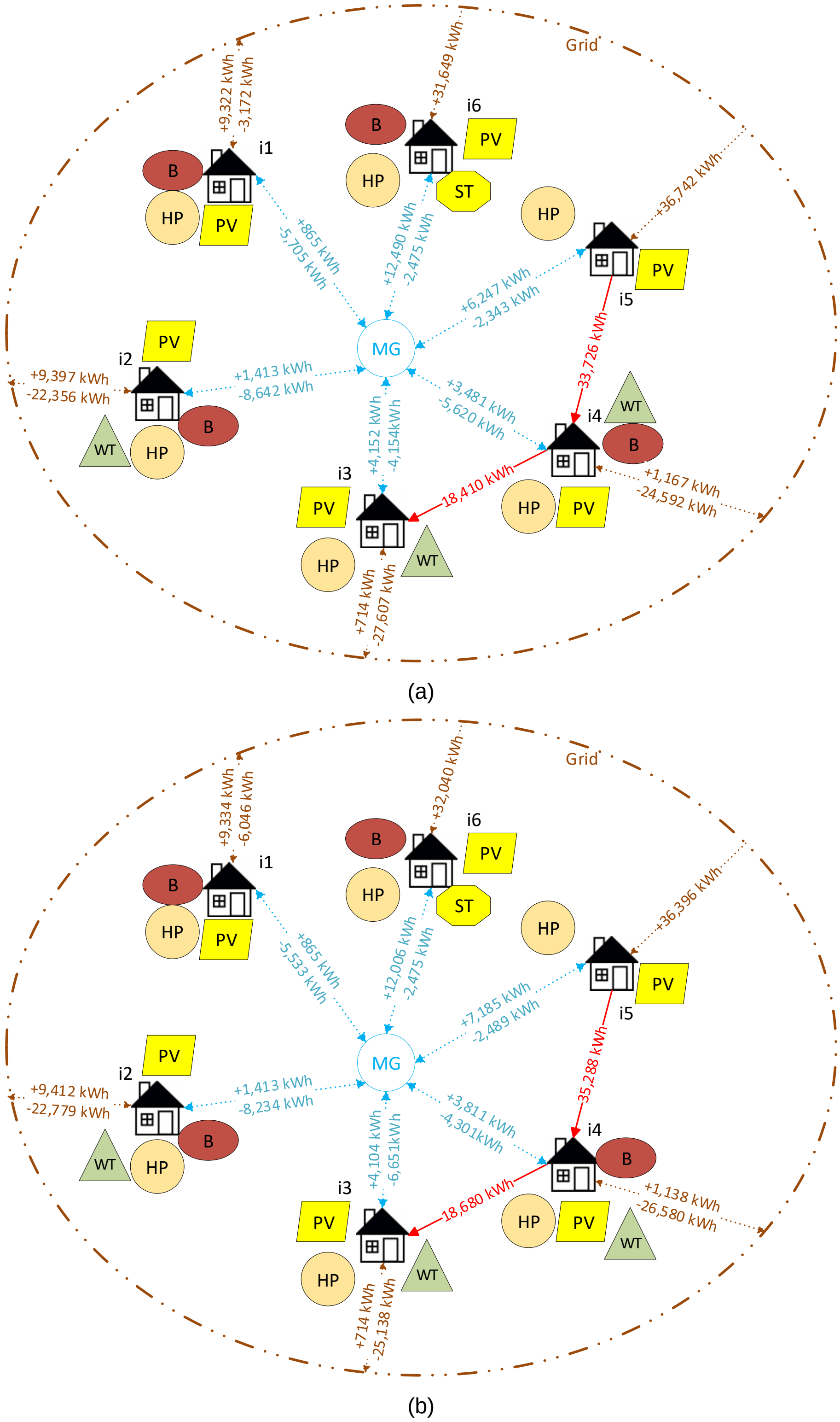


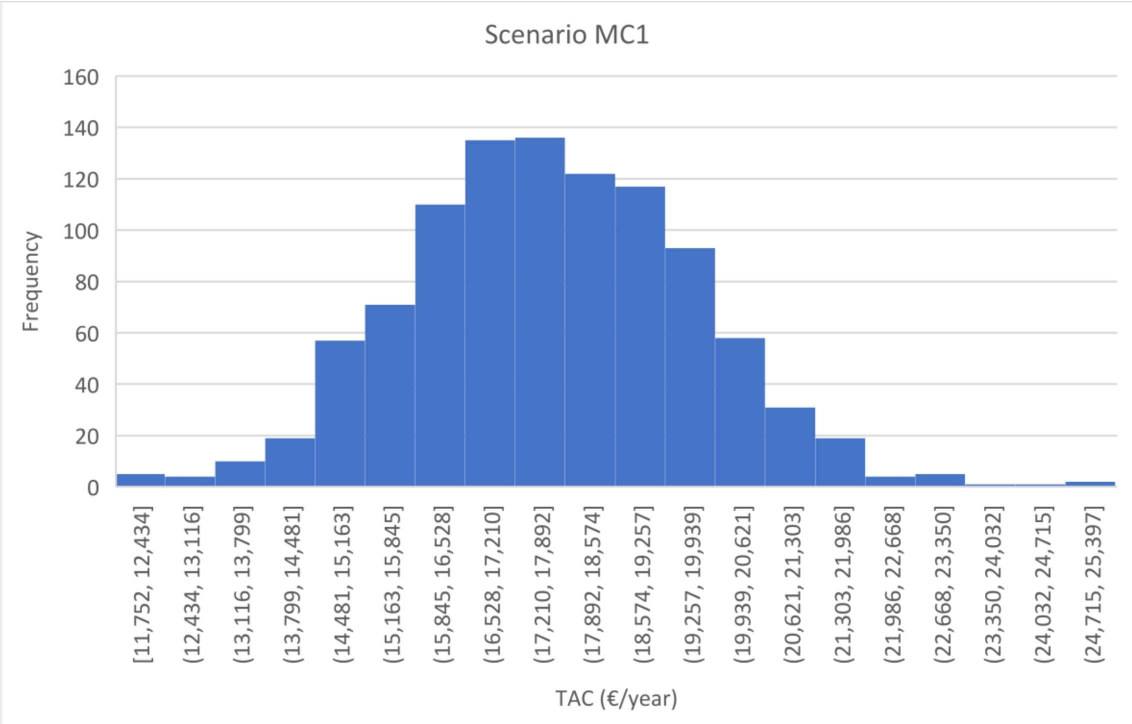
Fig. 7.6. Configuration of DES for: (a) MMR and (b) MER, respectively.

7.3 Results of Monte Carlo simulation

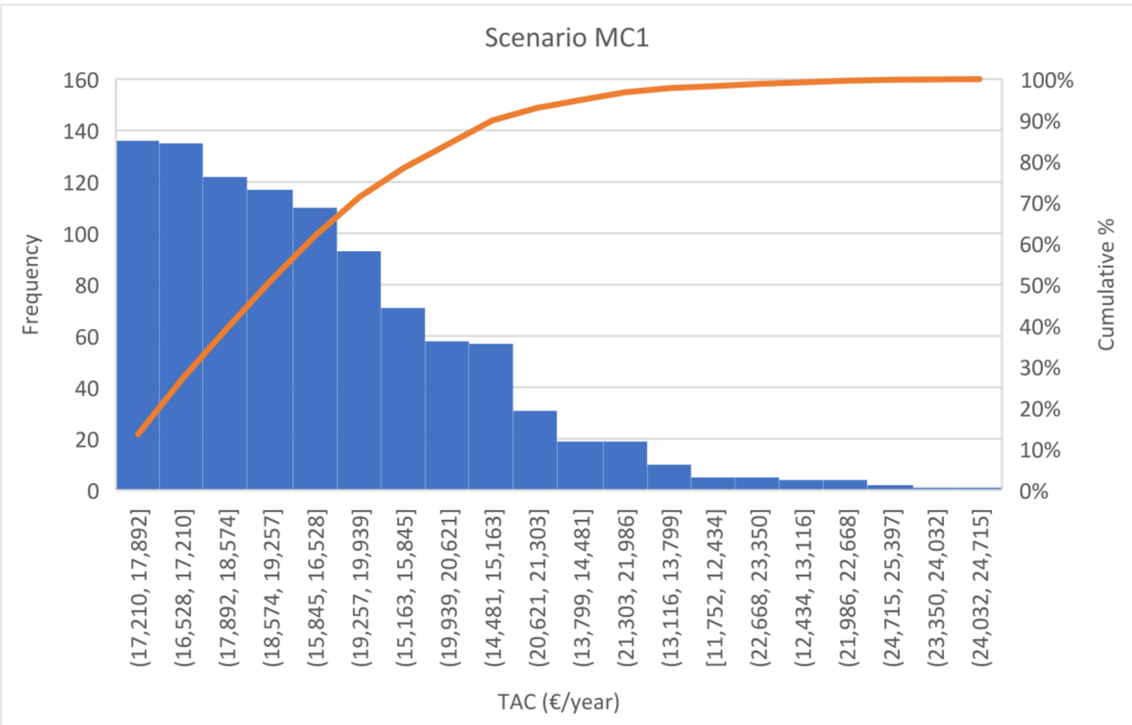
The last method used for optimal design of DES under uncertainty was Monte Carlo simulations, as described in subsection 5.3.3. Monte Carlo simulation was also applied on the single-objective optimization problem, with carbon emissions as a constraint having an upper bound of 100,000 kg/year. The number of iterations has been set to 1000, for both scenarios MC1 and MC2, taking a total of 2 hours 24 minutes and 3 hours 24 minutes, respectively. The results of Monte Carlo simulations are illustrated in Fig. 7.7 and Fig. 7.8, for Scenario MC1 and Scenario MC2, respectively. For each solution the values of TAC, the optimal configuration of the system and the operational variables of the technologies are calculated. The values of TAC are separated into bins, where each column represents the generation frequency of each solution. In Scenario MC1 the range of TAC is between approximately 12,000 and 25,000 €/year. On the other hand, in Scenario MC2 the values of TAC vary significantly, ranging between approximately -33,000 and 32,000 €/year. However, these "extreme" values are only generated for very few solutions and are attributed to the probability of very high or very low wind speeds, respectively.

In addition, Pareto charts are depicted to sort the data from the most common to the least common value (from left to right). This kind of charts is useful as the Pareto line shows the cumulative percentage of the probability that these results will occur. For instance, in scenario MC1 where uncertainty exists only in economic parameters, there is a 70% probability that TAC will be between approximately 16,000 and 20,000 €/year. On the contrary, when all parameters are uncertain in Scenario MC2, a cumulative probability of 50% is calculated that the TAC will be between approximately 21,000 and 27,000 €/year.

Furthermore, it is shown that the value of TAC is considerably higher in scenario MC2. It can be deduced that TAC is underestimated when uncertainty is considered to be only in economic parameters. In other words, the values of energy demand, solar radiation and wind speed have a major impact on the results and uncertainty of these parameters must be always taken into consideration. Therefore, a DM must examine in detail the uncertain parameters and be sure to consider all scenarios in order to assess the results properly and identify the most robust solutions.

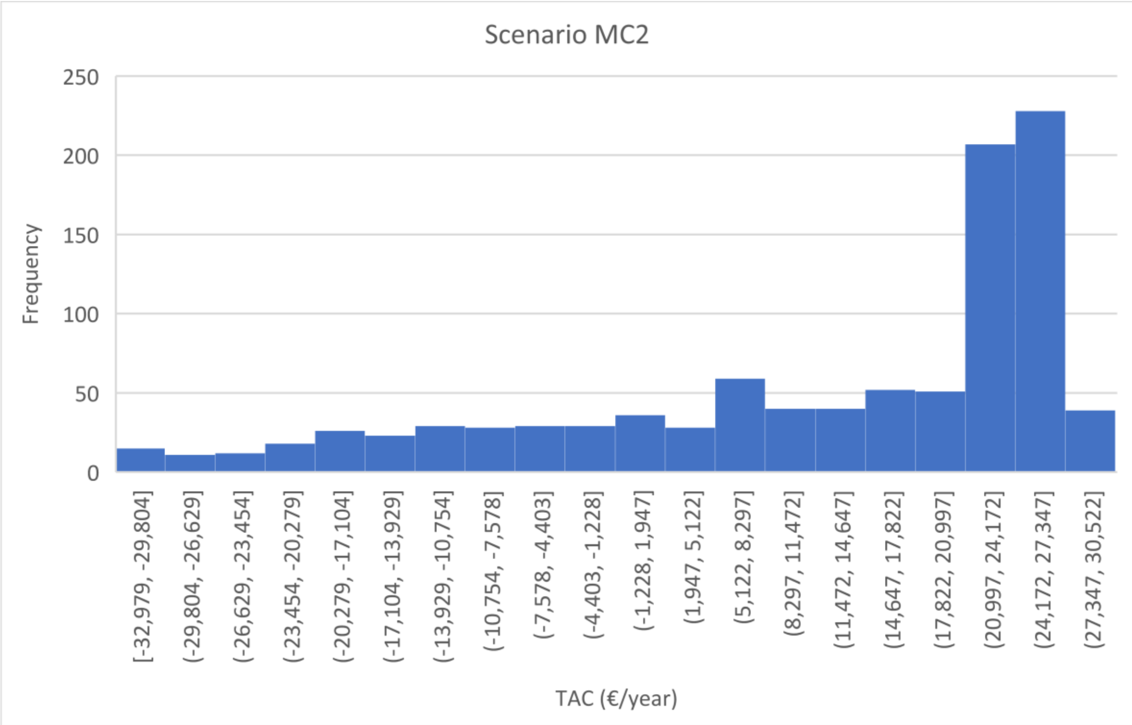


(a)

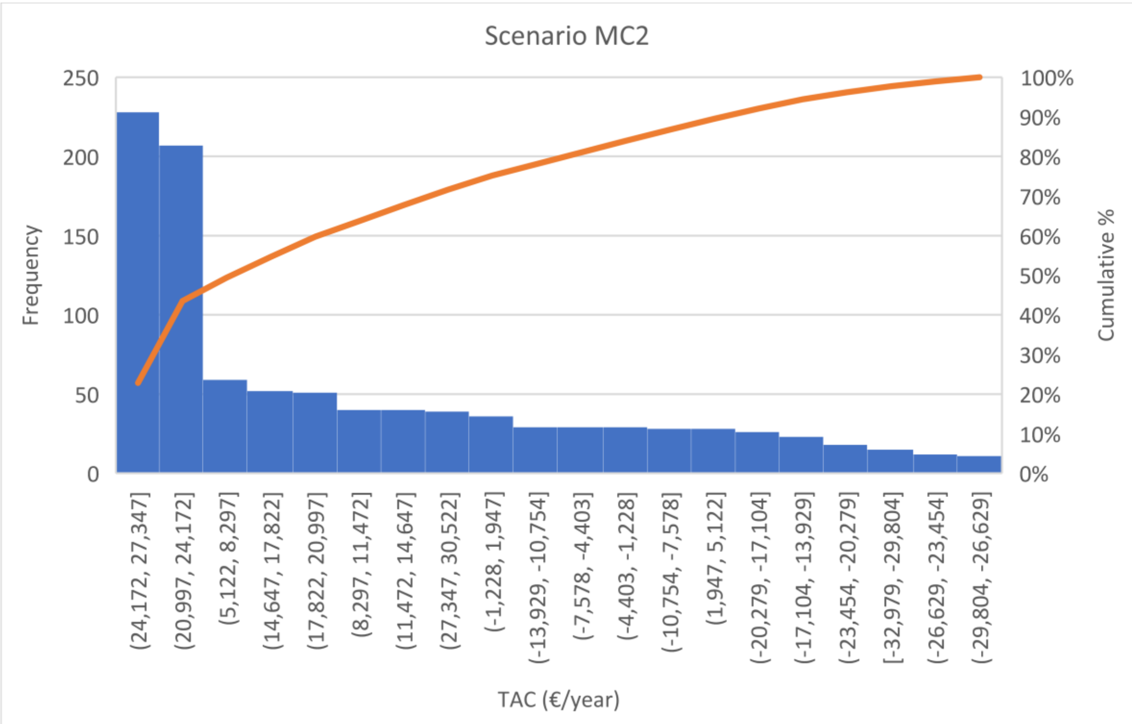


(b)

Fig. 7.7. Results of Monte Carlo simulation for Scenario MC1: (a) Histogram and (b) Pareto Chart, respectively.



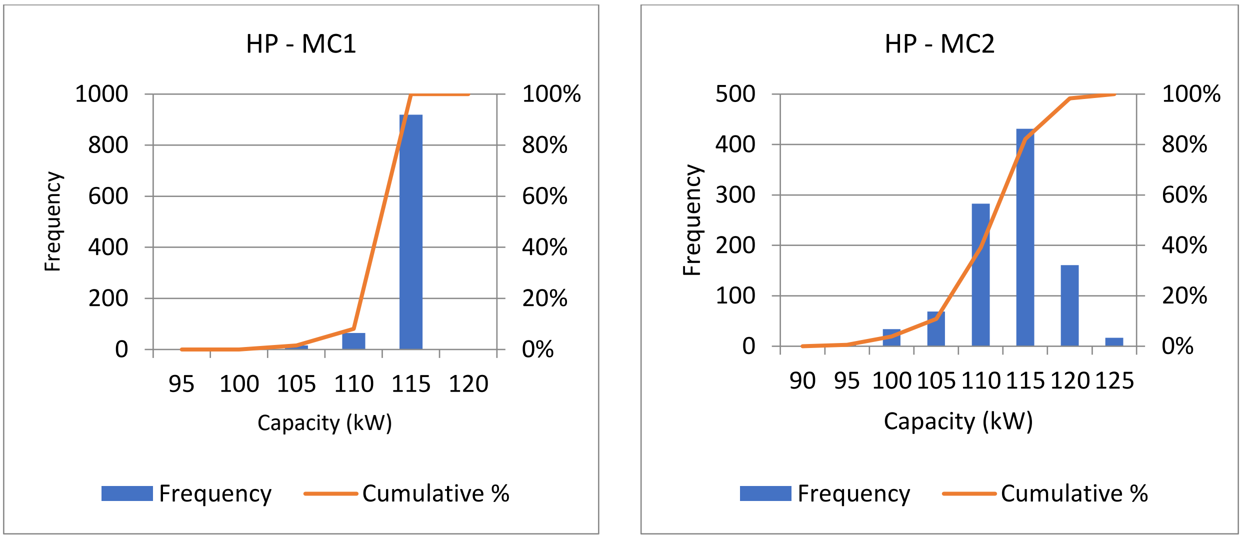
(a)



(b)

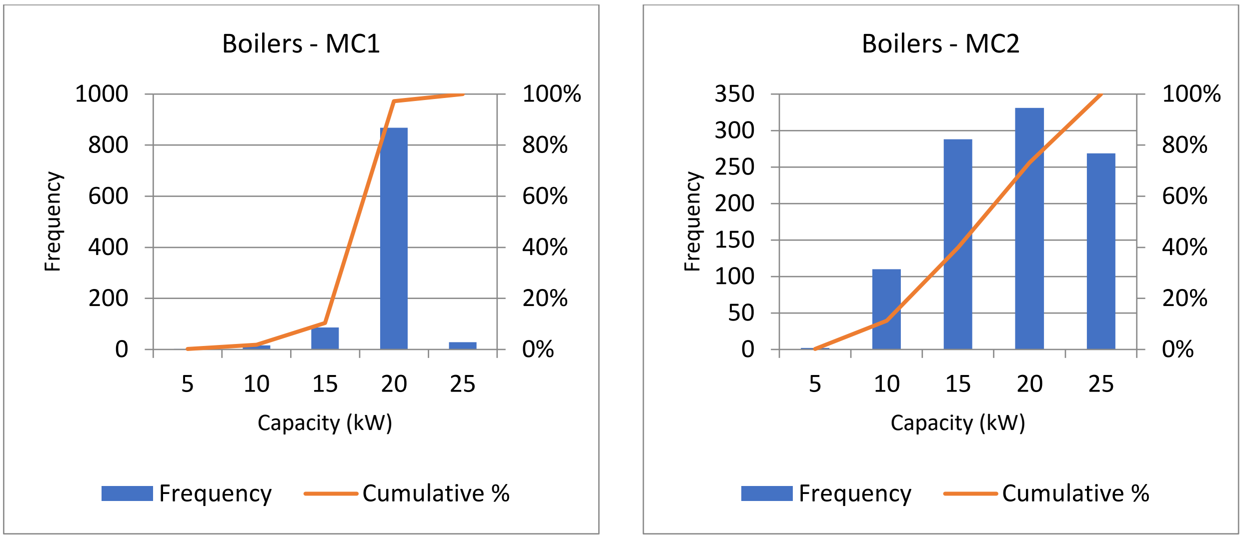
Fig. 7.8. Results of Monte Carlo simulation for Scenario MC2: (a) Histogram and (b) Pareto Chart, respectively.

Moreover, the configuration of the system in each scenario could offer fruitful conclusions, specifically about some important key decision variables. The results regarding the installation of heat pumps and boilers are presented for illustration purposes in Fig. 7.9 and Fig. 7.10, for scenario MC1 and MC2, respectively. There is a high probability that heat pumps and boilers will be installed in both scenarios. Their respective installed total capacity is more likely to be higher in Scenario MC2, which can most probably be attributed to the higher energy loads. Furthermore, the effects of variations in wind speed can be seen in Fig. 7.11 which presents the total capacity of wind turbines in Scenario MC2. Results show a 60% probability of wind turbines to be installed, which means that a 40% probability exists where wind turbines are not installed. This value is not negligible and must be examined carefully by the DM. A low probability reveals the uncertain characteristics of wind speed and the relative low wind potential of the respective area. On the other hand, the high solar radiation of the area and its low variability leads to the selection of photovoltaics at every solution.



(a) (b)

Fig. 7.9. Total installed capacity of heat pumps at: (a) Scenario MC1 and (b) Scenario MC2, respectively.



(a) (b)

Fig. 7.10. Total installed capacity of boilers at: (a) Scenario MC1 and (b) Scenario MC2, respectively.

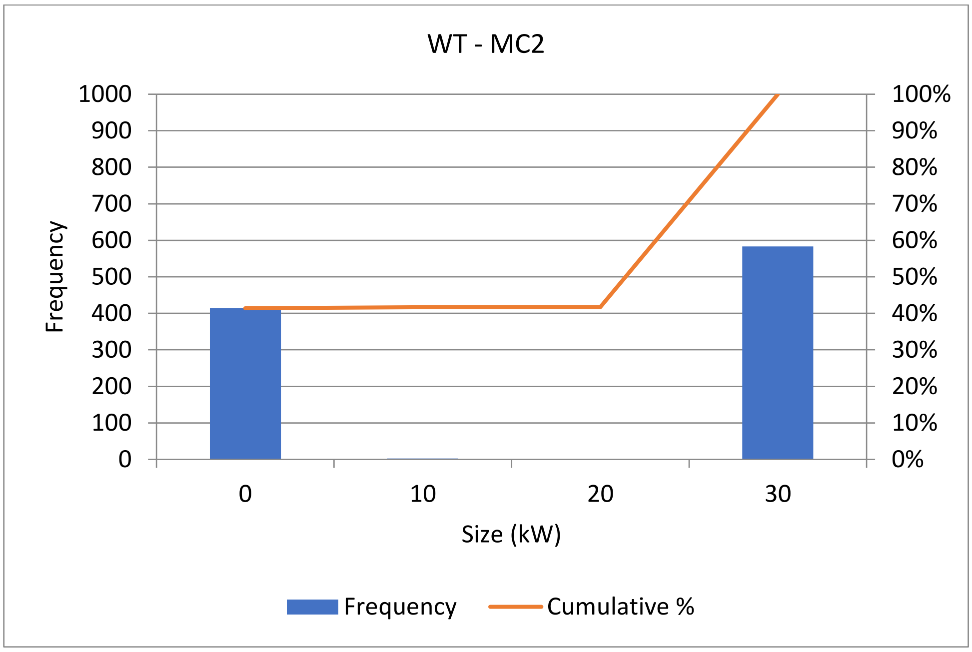


Fig. 7.11. Total installed capacity of wind turbines at Scenario MC2, respectively

7.4 Summary of results and discussion

This chapter showed the effect that uncertainty in parameters has on the design of a DES. Several methods were examined, namely objective-wise uncertainty, MMR, MER and Monte Carlo simulation, based on the construction and examination of respective scenarios for each method. Energy prices, interest rate, solar radiation, wind speed and energy demand were chosen as the uncertain parameters.

Although results between each method vary, several conclusions can be drawn. Firstly, the application of MMR when considering uncertainty only in economic parameters can provide robust solutions with minimum risk and a small increase of TAC. If probabilities are known applying MER can provide less conservative results. In the case of Monte Carlo simulations when all parameters are considered uncertain (not only the economic parameters, but also energy demand, wind speed and solar radiation) the results show a significant increase of TAC. However, the most pessimistic results are taken when objective-wise worst-case optimization is used as the worst values of the uncertain parameters are considered for the optimization.

Moreover, it is shown that uncertainty affects the structure and operation profile of technologies of the DES. Therefore, a DM should examine uncertainty in detail and select the appropriate tool in order to make an informed decision and identify robust solutions. Hence, it can be concluded that the optimal design of a DES using the deterministic approach is not a good choice and could result in bad solutions.

Chapter 8: Conclusions

This Chapter presents the main findings of the thesis. The results regarding the application of mathematical programming for both deterministic methods and for the techniques for optimization under uncertainty are summarized and the conclusions are highlighted. Also, the benefits occurring from the development of DES are clearly shown. The thesis concludes with a small discussion of future research ideas.

8.1 Innovation

This thesis examined the optimal design of a distributed energy system, using mathematical programming, with a focus on robust solutions. DES could play a major role in future energy systems, especially in urban areas, therefore methods for designing such systems need to be developed. The advantage of local generation, which minimizes losses can have a major impact in reducing primary energy consumption and associated carbon emissions of energy generation.

This thesis has made several contributions in the field of designing DES. Two approaches for the modelling of technologies have been presented, expanding previous relevant work from the literature and modelling more candidate technologies. Those approaches have been compared as they offer different solutions and a new strategy regarding the design of a DES has been presented. These approaches were examined through a case study applied in a Greek area, offering insights into how such methods could be applied in Greece and the benefits that could occur. Moreover, this thesis has focused on the robustness of solutions and has combined multi-objective optimization with several techniques used to provide robust solutions. Four techniques for optimization under uncertainty have been modelled and applied in the case study.

8.2 Main Findings

An MILP optimization framework for the design of a DES has been developed, in which the total annual cost and carbon emissions are the two objective functions to be minimised. The scope of the current thesis was to present a methodology for the design of DES using single- and multi-objective mathematical programming, with the following candidate technologies: (a) cogeneration units, (b) heat pumps, (c) absorption chillers, (d) boilers, (e) solar thermal collectors, (f) solar photovoltaics, (g) wind turbines, (h) thermal energy storage, (i) electric thermal storage, (j) district heating network (DHN) and (k) microgrid. In this context, the decision-making tool developed, provided as outputs the selected technologies and their respective capacity, the layout of the DHN, the operational profile of installed technologies and the electricity exchange through the microgrid and national grid.

For the optimal design of DES two multi-objective optimization methodologies have been developed in GAMS, namely “Method A” and “Method B”. The first method can perform simultaneous sizing of available technologies, while the second selects technologies with a specific predefined size from available sets. The methods are based on a generic framework and could be adapted for application in different districts. The results provide the DM with the Pareto frontier of the optimal solutions so they could make the best choice according to their preferences and budget restrictions. The solutions provide the configuration of the DES (which candidate technology is installed at each building), the capacity of the respective technologies and its operational profile.

Furthermore, a case study was carried out for a neighbourhood of six buildings in an area in Attica and three scenarios were depicted to examine the benefits of DES compared to conventional methods of energy supply in buildings. Scenario 1 was the BAU, in which conventional technologies were used to supply heating and cooling, with electricity bought only from the grid. In Scenario 2, heat pumps, absorption chillers and cogeneration technologies were introduced, along with electricity exchange with the grid (buying/selling). Scenario 3 was an expansion of Scenario 2 with the addition of storage technologies, microgrid and DHN.

The results showed that Scenario 3 provided the most attractive solutions, compared to the other two scenarios, in both methods. Also, it was shown that TAC and carbon emissions are conflicting objectives. The integration of renewables, CHP units, storage technologies, the availability to form a microgrid for electricity exchange and the installation of DHN leads to the reduction of carbon emissions and to an increase of the total annual cost. Specifically, in "Method A" TAC has a range between 16,284 and 25,503 €/year and carbon emissions between 75,082 and 149,980 kg/year in Scenario 2, while in Scenario 3 TAC has a range between 15,294 and 43,395 €/year and carbon emissions between 11,249 and 155,282 kg/year. In "Method B", in Scenario 2 TAC is between 18,110 and 29,927 €/year, and carbon emissions are between 78,412 and 143,546 kg/year. In Scenario 3 TAC is between 16,930 and 44,583 €/year, and carbon emissions between 11,657 and 155,200 kg/year. Also, Scenario 3 in "Method A" was solved in 2 hours and 14 minutes, while in "Method B" it took 3 hours and 50 minutes, showing that "Method B" is more computationally intensive, which is expected as it is based on a combinatorial approach and has less degrees of freedom compared to "Method A".

Comparing the results of the two methods it is shown that "Method A" is the one that offers the most attractive solutions as it is more flexible compared to "Method B". Results showed that regarding total annual cost "Method B" provides solutions between 3% and 11% higher compared to "Method A" in Scenario 3. Regarding carbon emissions for Scenario 3, "Method A" provides solutions with relatively better results, a small difference of up to some 4% was calculated between the two methods. Also, in most solutions a DHN was formed between buildings to exchange heat and at all solutions a microgrid to exchange electricity. The addition of storage technologies, microgrid and DHN leads to a significant reduction of carbon emissions.

However, there is a significant drawback in "Method A". The solutions generated with this method might not be available commercially. In this aspect "Method B" which relies on technologies with predefined sizes could provide more accurate results. In addition, the comparison of the two methods showed that solutions in each method regarding system configuration and operational profile of the technologies are different. Therefore, the combination of the two methods is suggested as an alternative design methodology. Specifically, applying "Method A" as a first step in the design process to detect the promising range for each technology, followed by "Method B" with a narrower range for the capacity of technologies in order to get optimal and simultaneously realistic results.

Subsequently, the second step was to examine the optimal design of DES under uncertainty, which was the main goal of this thesis. Uncertainty in designing a DES lies in many parameters, such as energy prices (electricity and natural gas), interest rates, climate data and energy loads. Several techniques were applied to deal with uncertainty, belonging either in the field of robust optimization or stochastic optimization. Specifically, four methods were used, namely: (a) objective-wise uncertainty, (b) minimax regret criterion, (c) minimax expected regret criterion and (d) Monte Carlo simulations. Moreover, the application of MER is a technique applied for the first time for the design of a DES. These techniques were applied to "Method A" and were furthermore distinguished between single- and multi- objective optimization. Objective-wise worst-case optimization was applied to the multi-objective problem, using two scenarios, namely:

- Scenario OW1 which considers uncertainty only in economic parameters, and
- Scenario OW2 which considers all parameters are considered uncertain.
- On the other hand, the other three methods were applied to a single-objective problem with TAC as the objective function and carbon emissions transformed into a constraint with a respective upper bound of 100,000 kg/year. For each technique several scenarios were constructed as follows:
    - For MMR and MER five scenarios were depicted, namely Scenario R1 to Scenario R5, in which only economic parameters were uncertain with ranges between a low and a high value for each respective parameter.

- For Monte Carlo simulations, two Scenarios were depicted, namely Scenario MC1 with only economic parameters as uncertain and Scenario MC2 with all parameters as uncertain.

The most pessimistic results occurred when objective-wise uncertainty was applied, due to the characteristics of the method. The objective-wise method was based on “Method A” of the deterministic approach and it considers the worst-case values of uncertain parameters. The concept of the method is that by considering the worst-case values of the uncertain parameters a DM could get robust solutions as they will always considered to be optimal. From a computational perspective, it took 50 seconds and 2 minutes, to solve Scenario OW1 and Scenario OW2, respectively. It was observed that both scenarios were solved at a much lower computational time compared to Scenario 3 in “Method A”, which shows the effects of parameters’ values in computational load of optimization problems. Regarding the results, compared to the deterministic scenario, in Scenario OW1 TAC was higher between 2% and 45%. In Scenario OW2 the differences at TAC were more obvious, between 24% and 84%. Regarding carbon emissions, differences between Scenario OW1 and deterministic are small, reaching up to 14%, and between Scenario OW2 and deterministic case were between 31% and 212%. Objective-wise uncertainty method might offer robust solutions, but it does increase the TAC dramatically. This is expected as the worst values of the parameters are considered in the calculations. However, from a DM perspective might not be the best approach as these values might never occur. It could be argued that the results of the objective-wise method are the more robust, but might be “unrealistic”, increase the cost of the project significantly, and might lead a DM to a “wrong” conclusion.

As for MMR and MER methods, they can be used when scenarios regarding the evolution of the respective parameters can be depicted. Those methods are based on the calculation of the regret between the optimal value and the extreme values of each scenario. The MER method assumes probabilities for those scenarios, offering a less conservative approach for the DM. Those methods can provide fruitful results to a DM, as they can calculate the regret (i.e. cost) between the deterministic approach and optimization under uncertainty, what the robust technologies are and their respective operational profiles. This is very important in energy planning problems as installed technologies will operate for years and is also important to operate them at the most appropriate way to have the lowest cost.

Specifically, the results of MMR method showed differences between each respective scenario. MMR was calculated to be equal to roughly 2%, which corresponds to approximately 27 €/year compared to the BAU solution. Also, differences were shown regarding DES structure and operational profiles of technologies. The configuration of the system at MMR showed that the preferred technologies were mainly heat pumps, boilers, photovoltaics and wind turbines. A comparison between Scenario R1 (deterministic scenario) and MMR shows minor differences regarding the configuration of the DES. It was revealed that most technologies selected in Scenario R1 are robust, except the boiler at building i5, which at MMR is installed at building i4. Also, there are differences exist regarding the capacity of photovoltaics at building i1 and solar thermal collectors' area at building i6. The application of MER showed that less conservative results can occur if the respective probabilities of each scenario are known. The probabilities for each scenario were assumed to be 0.5, 0.2, 0.1, 0.1 and 0.1 for each Scenario R1 to R5, respectively. The resulting value of MER was calculated to be approximately 0.002. The configuration of the system was similar to MMR, with minor differences for photovoltaics and solar thermal collectors at building i1 and building i6. MMR was solved in 6 minutes 18 seconds and MER in 2 minutes 54 seconds, showing that they are not computationally intensive methods. Nevertheless, the application of MMR and MER showed that despite the fact they can offer risk-averse solutions, considering uncertainty only in economic parameters does not affect TAC significantly.

Finally, for Monte Carlo simulations each uncertain parameter is considered to follow a specific probability distribution, interest rate, energy demand and solar radiation follow normal distribution, electricity prices follow uniform distribution, natural gas price triangular distribution and finally, wind speed follows Weibull distribution. Monte Carlo simulation was the most computationally demanding method for the optimization under uncertainty, taking for 1000 iterations a total of 2 hours 24 minutes and 3 hours 24 minutes, to solve Scenario MC1 and Scenario MC2 respectively. The results showed significant variations between Scenario MC1 and MC2, specifically in Scenario MC1 TAC is calculated to be between 12,000 and 25,000 €/year and in Scenario MC2 between -33,000 and 32,000 €/year. It was shown that the application of Monte Carlo simulations generates some extreme solutions which are attributed to the very high and very low values of some uncertain parameters (specifically wind speed was shown to affect results significantly). Another significant aspect of applying Monte Carlo simulations is that important conclusions can be deduced about the candidate technologies. Monte Carlo simulations do not offer a unique solution, rather a set of solutions based on the range of the probability distributions of uncertain parameters. Therefore, the values of decision variables are calculated based on the respective probabilities. For instance, heat pumps and boilers are selected at both scenarios with a high probability. Also, results show a relatively low probability for wind turbines which is attributed to the relatively low wind energy potential of the area of the case study.

All these techniques highlighted the importance of considering uncertainty in designing DES and it was shown that each parameter affects results differently. The results from all techniques showed that considering uncertainty only in economic parameters does not affect results significantly. Taking into account uncertainties in energy demand, solar radiation and wind speed caused significant changes in system's structure and operational profiles of technologies. Therefore, it can be concluded that it is important to take into account the whole range of uncertainties. Overall, all these techniques provided solutions characterized as robust, which are different compared to the deterministic model. When all parameters were treated as uncertain results showed differences regarding technologies selection and their respective capacities at each building. This is very important in long-term problems, especially for the system's performance and for the financial viability of the project. Making calculations based only in the deterministic model (current input data) could lead to system's failure in case of increased demand or revenue losses if a technology cannot operate (e.g. wind turbines). Hence, a DM can use the outcome of optimization under uncertainty to make a more informed decision by considering the long-term aspects of the problem.

In conclusion, the thesis showed the importance of DES as an economically and environmentally friendly alternative concept of designing future energy systems. The generic mathematical programming frameworks developed in this thesis could be applied at an urban level and redesign energy systems, leading to a reduction of energy consumption and carbon emissions which can be beneficial to the environment and to society. The significant reduction of carbon emissions and the local supply of energy could lead urban energy systems towards sustainability.

8.3 Proposals for future work

There are several areas for directing future research regarding the design of DES or urban energy systems in a more general context. For instance, in this thesis only two objective functions have been used in the multi-objective optimization framework. Those objective functions could be increased by considering sustainability criteria in order to provide robust and sustainable solutions. Sustainability is a general term considering many aspects besides cost and carbon emissions, such as the creation of jobs, air pollution etc. A multi-criteria assessment for the design of DES using sustainability indicators could be very useful in the context of sustainable development [150–152]. Also, the effects of energy loads and their variability, considering state-of-the-art techniques for energy management of buildings, and/or the introduction of energy efficiency measures regarding buildings' envelope could be examined.

Moreover, the increase of electric vehicles could be examined as they could be considered electric storage units. Also, the concept of grid stability needs to be examined. Assumptions regarding the capacity of the grid to always receive electricity generated locally might need careful examination. This is more important when renewables are also used as they are intermittent energy sources. Some work was carried out towards this direction, but it is a field requiring a more detailed analysis [110,111,153].

Another area for future research is the legal framework regarding the introduction of energy communities, and the allocation of cost and profits in the implementation and operation of DES [154]. Finally, another direction for future research is a more detailed analysis regarding uncertainty, for instance examining the effects of the national grid's emission factor based on the scenarios for national energy planning.

In general, the proposed methods can be applied with other building and climate characteristics, while the uncertainty can be extended to other parameters. The flexibility of the formulation is suitable for application in different cases of DES examining the robustness of the solutions across various parameters.

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Appendix A. Wind turbines

The first wind turbine is a 6 kW wind turbine with the following specifications described in Table A. 1. The power curve is depicted in Fig. A. 1.

Table A. 1. Technical characteristics of the 6kW wind turbine [155]

Rated output power	6 kW at 11.5 m/s, measured after inverter
Cut-in / survival wind speed	2.7 m/s / 60 m/s
Rotor diameter / swept area	5.6 m / 24.6 m^2
Blades	2 fiberglass-epoxy blades, aluminium root inserts
Power and overspeed regulation	Centrifugal pitch regulator, stalls blades to limit rotational speed
Brake	Dynamic brake, optional tower base forced blade stall brake
Rotational speed	80 - 245 rpm

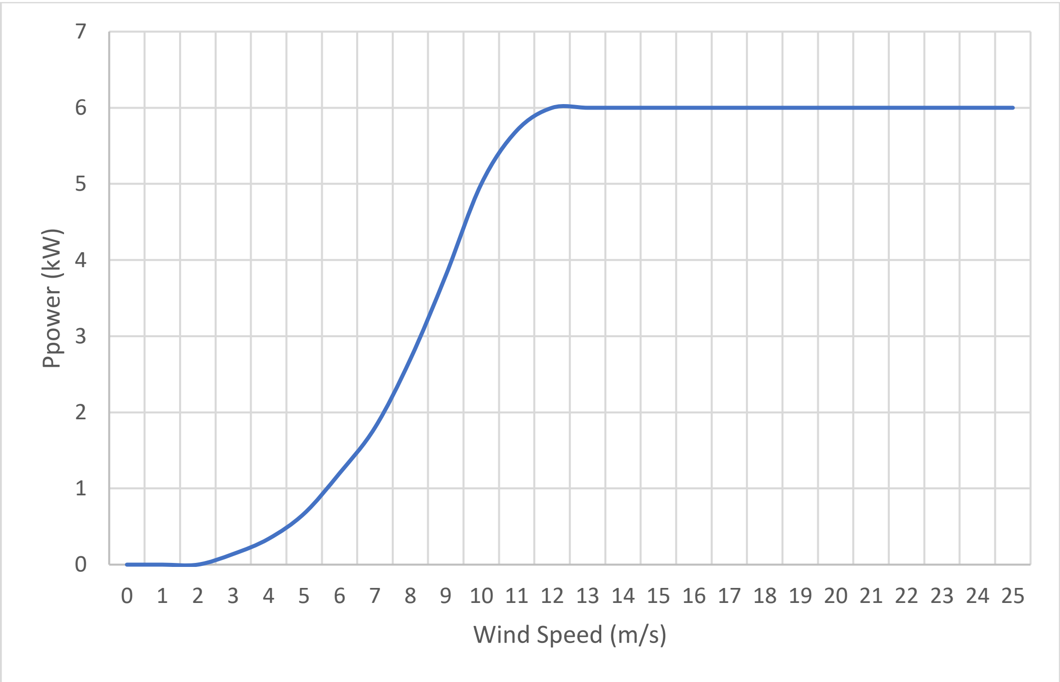

Fig. A. 1. Power curve of the 6kW wind turbine.

The second wind turbine is a 10 kW wind turbine with the following specifications described in Table A. 2 The power curve is depicted in Fig. A. 2.

Table A. 2. Technical characteristics of the 10 kW wind turbine [156].

Rated output power	10kW, limited by software
Cut-in / cut-out wind speed	1.85 m/s / 30 m/s
Rotor diameter / swept area	9.8 m / 75.4 m^2
Blades	3 blades, horizontal axis, Fiberglass, flex resin with polyurethane
Power and overspeed regulation	Variable pitch with active control By wind and power
Brake	Electromechanical safety brake
Rotational speed	120 rpm

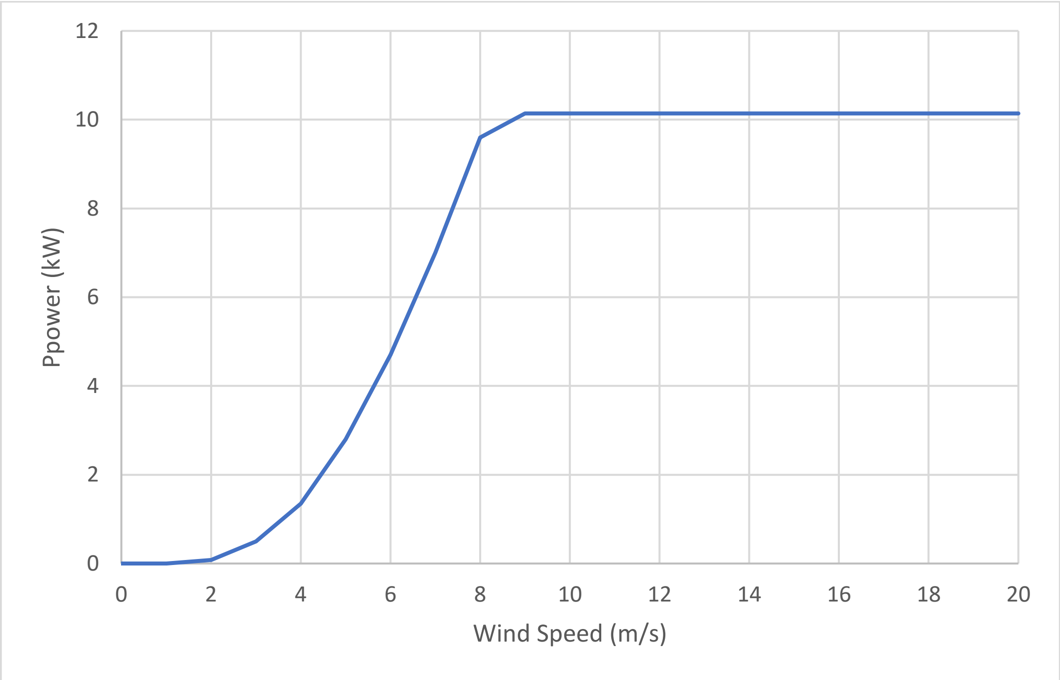

Fig. A. 2. Power curve of the 10 kW wind turbine.