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Including fairness and uncertainties in the design and operation optimization of local multi-energy systems

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To my family, friends, and girlfriend

To all my loved ones

Abstract

In the context of "local-to-regional" Multi-Energy Systems (MES), this Thesis aims to *i)* analyse the aspects influencing the optimal aggregation of end users in Energy Communities (ECs) and *ii)* evaluate the weight of uncertainties associated with Renewable Energy Sources (RES) and users' energy demand in the design optimization of local MES.

According to the first objective of this Thesis, the optimal aggregation of end users is studied in two different reference cases, neglecting uncertainties. In the first reference case, Mixed Integer Linear Programming (MILP) models are used to optimize the daily operation of the local power systems of the Citizen Energy Community (CEC) and the Renewable Energy Community (REC). Results shows that the complementarity between the energy demand and generation profiles of the EC members leads to relevant cost savings (e.g., daily cost savings are 15-20 % higher in ECs with a higher degree of complementarity between members). A novel cost allocation mechanism is also proposed to encourage end users using free-of-charge and non-dispatchable RES to join the EC. The second reference case examines the "fairness" of the distribution of the operational economic benefit among the members of an EC. A MILP model is used to optimize the daily operation of the local power system of a REC, and the "Shapley value" mechanism is applied to fairly allocate the optimal operational profit. This mechanism distributes higher economic benefits to the prosumers than to the consumers, as they contribute significantly to increasing the total economic benefit of the system.

The third case study, in line with the second objective of this Thesis, focuses on the weight of uncertainties associated with RES and energy demands in the design optimization of a local MES serving a REC. A novel framework is developed to perform the design-operation optimization of the system in the absence of and under uncertainties. The framework includes MILP and Stochastic Programming (SP) optimization models without and with uncertainties, solved for each day and for a set of daily stochastic scenarios of the uncertain parameters in one year, respectively. Different sets of stochastic scenarios are obtained by applying a clustering technique for each year of a training dataset. The "best" set of stochastic scenarios is then found by searching for the minimum standard deviation of errors between the solutions of the MILP and SP models without and with uncertainties, respectively, over the years of the training dataset. The SP model with the "best" set of stochastic scenarios is solved for each year of a testing dataset, resulting in "stochastic forecast" solutions. Finally, the "stochastic forecasts" are compared with the "deterministic forecast" solutions obtained by solving the MILP model in the absence of uncertainties for each year of the testing dataset. A key finding is that the "stochastic forecasts" predict the optimal life cycle cost of the system accurately, with an average error of 1.63 % compared to the "deterministic forecasts".

Overall, this Thesis shows interesting results in the design-operation optimization of local energy systems, despite some necessary assumptions such as the type of EC members and the uncertainties to be analysed. Several optimizations are performed to achieve general guidelines that lead to the optimal aggregation of end users in ECs, also ensuring a possibly fair distribution of the total economic benefit. The proposed framework for optimizing the design of local MES under uncertainties provides a reliable approach to assess the accuracy of the results under uncertainty with respect to those in the absence of uncertainty, allowing uncertainties to be weighted in the optimal design of the system.

Sommario

L’obiettivo di questa tesi è di *i)* analizzare i fattori che influenzano l’ottima aggregazione degli utenti finali in comunità energetiche e *ii)* valutare l’impatto delle incertezze associate alle fonti rinnovabili e alle domande di energia di diversi utenti nel problema di ottimizzazione della progettazione (cioè la scelta del tipo, del numero e delle capacità delle unità di conversione e di accumulo dell'energia) e del funzionamento di sistemi multi-energia locali. La motivazione alla base di questa tesi è di affrontare il problema generale di garantire l’accoppiamento ottimale tra domanda e produzione di energia nei sistemi sopra citati, considerando anche diverse incertezze.

In linea con il primo obiettivo di questa tesi, due diversi casi di studio di riferimento sono presentati per studiare l'aggregazione ottimale degli utenti finali, senza considerare alcun tipo di incertezza. Nel primo caso di riferimento, vengono usati modelli di tipo “Mixed Integer Linear Programming” (MILP) per ottimizzare il funzionamento di sistemi energetici locali associati ad una “comunità energetica dei cittadini” e ad una “comunità energetica rinnovabile”. I risultati delle ottimizzazioni condotte evidenziano che la complementarità dei profili energetici di domanda e di generazione dei membri porta a risparmi rilevanti (ad esempio, i risparmi economici totali sono del 15-20 % maggiori in comunità energetiche dove i membri presentano una maggiore complementarità tra curve di domanda e di generazione). Inoltre, viene proposto un nuovo meccanismo di allocazione dei costi totali per incoraggiare gli utenti finali che utilizzano risorse rinnovabili non programmabili ad entrare nella comunità energetica. Il secondo caso di riferimento valuta “l’equità" della distribuzione dei benefici economici tra i membri. Viene usato un modello MILP per ottimizzare il funzionamento del sistema energetico locale di una comunità energetica rinnovabile, ed il meccanismo di "Shapley value" è applicato per distribuire in modo equo l’ottimo profitto derivato dal funzionamento del sistema. Questo meccanismo alloca benefici economici maggiori ai prosumer rispetto che ai consumatori, per il loro maggiore contributo nell’aumentare il beneficio economico totale del sistema.

Il terzo caso studio, in linea con il secondo obiettivo di questa tesi, si concentra sul peso delle incertezze, associate alle fonti energetiche rinnovabili e alle domande di energia, nell'ottimizzazione della progettazione di un sistema multi-energia locale di una comunità energetica rinnovabile. Viene sviluppato un nuovo approccio metodologico per eseguire l'ottimizzazione della progettazione e del funzionamento del sistema analizzato in assenza e in presenza di incertezze. In particolare, questo approccio utilizza modelli di ottimizzazione MILP senza incertezza e di programmazione stocastica con incertezza, i quali sono risolti rispettivamente per ogni giorno e per un insieme di scenari stocastici giornalieri dei parametri incerti in un anno. Diversi gruppi di scenari stocastici sono ottenuti applicando una tecnica di “clustering” per ogni anno di un set di dati chiamato “training dataset”. Il “migliore” insieme di scenari stocastici viene identificato cercando la deviazione standard minima degli errori tra le soluzioni dei modelli MILP e di programmazione stocastica senza e con incertezze, rispettivamente, negli anni del “training dataset”. Il modello di ottimizzazione di programmazione stocastica con il "miglior" insieme di scenari stocastici viene risolto per ogni anno di un set di dati chiamato “testing dataset”, ottenendo soluzioni ottime chiamate "previsioni stocastiche". Infine, le "previsioni stocastiche" vengono confrontate con le soluzioni di "previsione deterministica" ottenute risolvendo il modello MILP in assenza di incertezze per ogni anno del “testing dataset”. Un risultato rilevante è che le soluzioni "previsioni stocastiche" predicono con una buona accuratezza il costo ottimale del ciclo di vita del sistema, con un errore medio del 1.63 % rispetto alle soluzioni "previsioni deterministiche".

Nel complesso, questa tesi mostra risultati interessanti nell'ottimizzazione della progettazione e del funzionamento di sistemi energetici locali, nonostante alcune ipotesi necessarie come il tipo di membri delle comunità energetiche e le incertezze analizzate. Sono state eseguite diverse ottimizzazioni per ottenere linee guida generali che portano all'aggregazione ottimale degli utenti finali in comunità energetiche, garantendo anche una distribuzione possibilmente equa del beneficio economico totale. La metodologia proposta per ottimizzare la progettazione di sistemi multi-energia locali in condizioni di incertezza fornisce un approccio affidabile per analizzare l'accuratezza dei risultati ottenuti in condizioni di incertezza rispetto a quelli in assenza di incertezza, consentendo così di valutare il peso delle incertezze nella progettazione ottimale del sistema.

Nomenclature

Acronyms

Agr	Agricultural
BM	Balancing Market
CEC	Citizen Energy Community
Com	Commercial
DA	Day Ahead
DLC	Direct Load Control
DR	Demand Response
EC	Energy Community
EES	Electrical Energy Storage
ES	Energy Storage
GB	Gas Boiler
HP	Heat Pump
IBDR	Incentive-Based Demand Response
ICE	Internal Combustion Engine
MES	Multi-Energy System
MILP	Mixed Integer Linear Programming
NB	Nash Bargaining
PBDR	Price-Based Demand Response
PDF	Probability Density Function
Pub	Public
PV	Photovoltaic
REC	Renewable Energy Community
RES	Renewable Energy Sources
Res	Residential
RMSE	Root Mean Squared Error
RO	Robust Optimization
RTP	Real Time Pricing

SP	Stochastic Programming
SW	Social Welfare
Ter	Tertiary
TES	Thermal Energy Storage
TOU	Time-of-Use
TSA	Time Series Aggregation

Symbols

A	Area, [m^2]
a	Interest rate, [%]
a_0, a_1	Coefficients of the linear characteristic curve of an energy conversion unit
c	Optimal cost of the system [€] or grid price [€/kWh]
cap	Capacity of an energy conversion or storage unit, [kW] or [kWh]
COP	Coefficient of performance, [-]
D^{var}	Maximum hourly shifting of the electricity load demand, [%]
E	Energy, [kWh]
El	Price elasticity
F	Power consumed by an energy conversion unit, [kW]
I	Global solar irradiance, [kW/m^2]
inc	Incentive, [€/kWh]
K	Number of stochastic scenarios
lt	Lifetime of an energy technology, [years]
M	Big-M parameter
N	Number of members of an energy community
$O\&M$	Operation and maintenance cost, [% of the investment cost]

P	Electrical power generated by an energy conversion unit, [kW]
Q	Thermal power generated by an energy conversion unit, [kW]
SC	Self-Consumption, [%]
w	Weight of a typical day in one year
Y	Total number of years in one dataset

Greek symbols

Δt	Time step of one hour in the optimization
δ	Binary variable indicating the on-off operational state of an energy conversion/storage unit, [-]
η	Efficiency, [-]
θ	Auxiliary variable

Subscripts and superscripts

c	Consumer
d	Day
el	Electricity
exp	Export
i	Member of an energy community
imp	Import
inv	Investment
k	Typical day used as stochastic scenario in the SP model
max	Maximum
min	Minimum
p	Prosumer
shift	Shifted electricity demand
t	Hour
th	Thermal

u	Energy technology
+/-	Charging/discharging state of an energy storage unit

Contents

1. Introduction

This Section introduces the main topics of this Thesis. Sub-Section 1.1 focuses on the background of this Thesis. Sub-Section 1.2 clarifies the motivation driving the work and the objective of this Thesis. Sub-Section 1.3 reports the literature review on “local-to-regional” Multi-Energy Systems (MES) and Energy Communities (ECs), with a particular focus on the design-operation optimizations of these systems in the absence of and under uncertainty. Sub-Section 1.4 specifies the methodology adopted and the contributions of this Thesis. Sub-Section 1.5 presents the general structure of this Thesis.

1.1. Background

The growth of the world population, the increase in global energy demand, the scarcity of fossil fuels and the environmental concerns require that the energy system configurations of the future be designed to achieve economic, environmental and social sustainability in energy demand and production [1]. In this direction, the European Union published the “Clean Energy Package” [2] to set energy and environmental targets in all European Countries. The new updated targets to 2030, which aim to achieve carbon neutrality by 2050 [3], refer to a 40-45 % share of Renewable Energy Sources (RES) in the final energy consumption, a 36 % increase in energy efficiency in the final energy consumption and a reduction of emissions by at least 55 % compared to the levels in 1990, according to the “Fit-for-55” [4] and the “REPowerEU” [5] plans. These targets are expected to bring greater economic, environmental and social benefits to all European citizens, without neglecting the most vulnerable ones with severe economic and social conditions [6]. In this context, the significant diffusion of distributed RES, fostered by the urgent need to face the environmental impacts of the climate change, has profoundly changed the way energy is used, in terms of generation, conversion, storage and consumption within the national, regional and local energy systems [7]. The traditional energy system, based solely on centralized power generation plants that adapted their operation according to the energy demands of end users, gave way to a system that integrates distributed energy generation and storage units owned by local users, who are increasingly required to match their energy demands with the availability of RES. However, the uncertainties associated with the variable RES and the energy demand profiles of local users, as well as the various aspects ensuring the optimal aggregation of local users, pose a major challenge in addressing the general issue of optimal matching of the energy demand and generation, thus also influencing the grid stability.

This Thesis attempts to address the optimization problem of the design (i.e., the choice of the type, number and size of the energy conversion and storage units) and operation of energy systems in “local-to-regional” configurations, also considering the uncertainties of the availability of RES and energy demand profiles of different end users. Both local and regional energy system configurations can be conceived as Multi-Energy Systems (MES), using renewable (e.g., solar irradiance, wind) and non-renewable (e.g., fuels as natural gas) energy sources to satisfy different types of energy demands (e.g., electricity, heating, cooling, fuels, etc.) through the interaction of multiple energy vectors at different geographical scales (e.g., neighbourhood, district, city, region, etc.). Energy Community (EC) configurations [8], which represent aggregations of end users of different consumption sectors (e.g., residential, commercial, tertiary, etc.) that share energy at the demand side, could use local power systems (i.e., managing only the demand and generation of electricity) or local MES to meet the different energy demands of their users. These aggregations in ECs could help the balance between energy generation and demand at the local level (i.e., in a neighbourhood or district connected to the distribution grid) and, in turn, also at the regional and national level (i.e., involving the transmission grid) in energy systems that include centralized plants (e.g., fuel-based power plants, centralized photovoltaic plants, etc.). Hence, the aggregation of final energy users within ECs could have an impact in economic (total economic cost or profit) and environmental (CO_2 emissions) terms on both local and regional MES. For example, regional systems encompassing groups of ECs [8] could achieve lower total costs by the optimal coordination between the distribution system operators (i.e., the operators of the distribution networks) and the community energy managers [9]. Figure 1 shows an example of a "local-to-regional" MES using RES (e.g., solar and wind energy) and fossil fuels to meet the electricity, heating/cooling and fuel demands of different types of end users. Note that the "local-to-regional" MES is composed of centralized power plants and local MES (and local power systems) that could serve ECs. For simplicity, Figure 1 shows only the electrical transmission and distribution grids, although the regional and local MES could include district heating networks and gas grids.

Two main issues arise in the effort to optimize the match between energy demand and generation in local power systems and MES. First, it is fundamental to choose the optimal aggregation between users characterized by different energy demands in local ECs and to ensure that each of these users receives a fair reward (e.g., economic cost saving or incentive) for being part of the community. This optimal aggregation is achieved by searching for the optimal match between the energy demand and generation profiles of different consumers and prosumers. Secondly, these energy systems are mainly driven by RES, which are characterized by seasonal intermittency, making their availability difficult to predict and therefore introducing uncertainty. In addition, when optimizing the design of such energy systems, the energy demand profiles of different users are one of the major sources of uncertainty.

The literature (sub-Section 1.3.2) has mainly focused on the economic benefits of end users in ECs, without clearly identifying the aspects that affect their optimal aggregation [10]. One of these aspects is the "fair" allocation of the total economic benefit of the EC to its members [11]. A cost/profit allocation mechanism that is perceived as fair by the members is essential to ensure the stability of the EC, e.g., by preventing members from leaving the EC. In addition, the mechanism of cost allocation can influence the formation of an EC (e.g., the types of end users that become members of the EC) by encouraging end users to join the EC only if they perceive the cost/profit allocation to be "fair". However, "fairness" is a subjective concept, and there is no common definition in the literature. Hence, this Thesis explores different cost/profit allocation mechanisms, such as the Shapley value and the Uniform pricing, to search for a fair distribution of the total economic benefit of the EC.

The literature (sub-Section 1.3.4) has presented several works that conduct the design optimization of local MES under uncertainty. However, there is an obvious lack in the evaluation of the weights of the uncertainties, associated with RES and energy demand profiles, in the optimal design and cost of local MES of ECs by comparing the optimal solution under uncertainties with that obtained without uncertainties. Neglecting the uncertainty of input data and boundary conditions in the design and operation optimization problem of a MES could lead to a solution (i.e., total economic cost or profit of the system, environmental CO_2 emissions, etc.) that is optimal only under the realization of a certain scenario and, consequently, non-optimal or sub-optimal decisions of the design of the system could follow [12]. Thus, the design and operation optimization of local and regional MES under uncertainty requires appropriate methods to obtain accurate and reliable predictions of the uncertain parameters that should be considered in the optimization, with the aim of achieving an optimal solution that takes into account the uncertainty. This Thesis adopts the Stochastic Programming (SP) method, based on stochastic scenarios representing the most likely realizations of the uncertain input data and boundary conditions, to carry out optimizations under uncertainty.

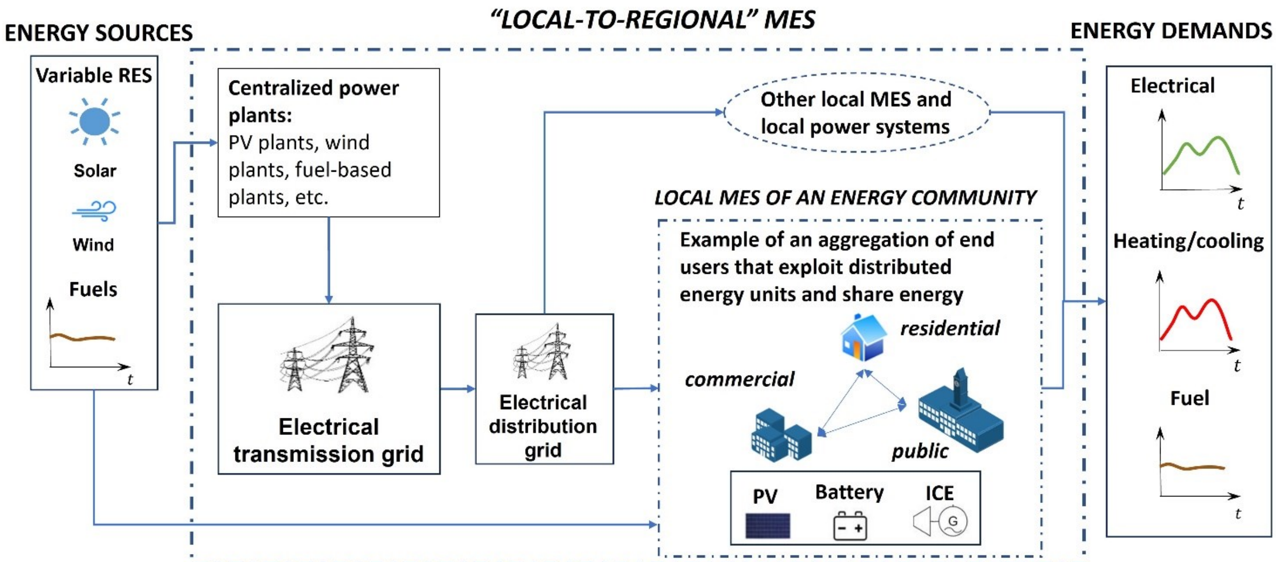


Figure 1. Layout of a "local-to-regional" MES including centralized power plants, local MES and local power systems, where a local MES or a local power system could serve an EC.

1.2. Motivation and objective of the Thesis

The main motivation of this Thesis is to address the general problem of ensuring the optimal match between energy demand and generation for different end users aggregated in Energy Communities (ECs) that could use local power systems or Multi-Energy Systems (MES), also considering uncertainties associated with the availability of Renewable Energy Sources (RES) and the energy demand profiles.

The research questions that have driven the work reported in this Thesis are formulated according to the research gaps identified in the state-of-the-art literature (see the next sub-Sections 1.3.2 and 1.3.4). The research questions are:

- What are the main aspects that ensure the optimal aggregation of end users in ECs and what are the weights of these aspects in terms of economic benefits to the EC and its members?
- What is the weight and impact of the uncertainty associated with RES and users' energy demands on the optimal design and cost of local MES meeting the energy demands of ECs?

Given these research questions, the aim of this Thesis is twofold, i.e., to *i)* analyse the aspects that influence the optimal aggregation of end users, representative of different consumption sectors, in ECs (that could use local power systems or local MES) and assess these aspects in economic terms and *ii)* evaluate the weight and impact of different uncertainties on the design optimization of local MES. To fulfil objective *i)*, the weights of the aspects influencing the optimal aggregation and cooperation of end users in ECs are assessed from an economic point of view for the EC and its members. To fulfil objective *ii),* two main uncertainties are considered on the generation and demand sides of the local MES, i.e., the solar irradiance and the electricity demands of end users, respectively.

The next sub-Section 1.3 introduces the literature review conducted in this Thesis.

1.3. Literature review

This Section focuses on the literature reviewed in this Thesis. Sub-Section 1.3.1 introduces the concept of "local-to-regional" Multi-Energy Systems (MES). Sub-Section 1.3.2 looks at Energy Communities (ECs) using local power systems or MES. Sub-Sections 1.3.3 and 1.3.4 focus on the state-of-the-art in optimizing such systems in the absence of and under uncertainty, respectively.

1.3.1. "Local-to-regional" Multi-Energy Systems (MES)

Favre-Perrod et al. [13] provided the first definition of a Multi-Energy System (MES), conceived as a multi-carrier energy system. Geidl and Andersson [14] and Geidl et al. [15, 16] pointed out that a MES uses several energy sources (renewable and not), which can be converted into energy carriers (e.g., electricity, gas, hydrogen, water, etc.), to satisfy the energy demands (e.g., electricity, heating, cooling, etc.) of different end users. In general, a MES includes different networks (e.g., electrical, gas, district heating/cooling, etc.), conversion units (solar photovoltaic plants, heat pumps, natural gas and electric boilers, fuel cells, etc.) and storage units (e.g., electrical energy storage, thermal energy storage, pumped hydro energy storage, etc.) [17]. Thus, a MES encompasses the production, conversion, storage and consumption of different energy carriers [7]. Mancarella [18] presented a comprehensive review of MES, classified according to their spatial location and extension, the multiple energy demands to be satisfied, the available renewable and non-renewable energy sources, and the different networks involved. The author highlighted the role of the optimal aggregation of end users in reducing the economic costs and carbon emissions of a MES, where users have characteristic energy demands representing typical consumption sectors. Guelpa et al. [17] reviewed the general status of electrical, thermal and gas energy systems (including energy conversion and storage units and energy networks) from a technological and modelling perspective and highlighted the recent trend to integrate these systems into MES. Vahid-Ghavidel et al. [19] reviewed the main Demand Response (DR) programs used in MES, which are flexibility strategies to optimally shift the electricity demand loads of users from one period to another, resulting in lower costs for end users and improved stability of the electrical grid.

In such a context, this Thesis embraces the vision of *"local-to-regional"* MES (see Figure 1 in sub-Section 1.1), i.e., energy system configurations with geographical extensions typical of buildings, districts, cities or regions [1, 7]. In general, a *local* MES meets the energy needs of users such as a building or an ensemble of buildings in a district by exploiting distributed energy conversion and storage units, while a *regional* MES also encompasses centralized power plants to meet the energy needs of several districts in a city or a region. Note that the aggregation of end users characterized by different energy demands (e.g., representative of different consumption sectors) may form an Energy Community (EC) at the local level (see next Sub-Section 1.3.2).

Klemm and Vennemann [20] reviewed the main modelling and optimization approaches for MES in city districts, highlighting that city districts include end users from different consumption sectors as the residential, commercial, industrial, agricultural and transportation ones.

Gabrielli et al. [21] studied a local MES in a residential neighbourhood in Zurich, which encompasses different energy conversion and storage units such as photovoltaic (PV) and solar thermal plants, electricity-driven heat pumps, micro-gas turbines, fuel cells and electrolysers, electrical and thermal energy storage units. The authors developed a Mixed Integer Linear Programming (MILP) model to optimize the design (i.e., the capacities of the energy units) and operation of the MES by simultaneously minimizing its costs and emissions.

Gao et al. [22] analysed a regional MES with electricity, heating and cooling demands. A two-stage optimization model is developed to optimize the capacities of the energy conversion and storage units (i.e., solar photovoltaic panels, wind turbines, boilers, absorption cooling units, electrical batteries, etc.) in the first day-ahead stage and the operation of the units in the second stage, respectively. Different objective functions such as the investment cost, the CO_2 emissions and the primary energy saving rate of the system are considered.

The next sub-Section 1.3.2 focuses on Energy Communities (ECs) that can use local power systems or local MES to meet the energy demands of their members.

1.3.2. Energy Communities as aggregations of end users

The concept of "Energy Community" (EC) was first introduced at the European level as a key driver of the energy transition. An EC is defined as a *"legal entity based on the voluntary participation of residential users, small and medium sized enterprises (SMEs) and local authorities, with the main purpose of providing environmental, economic or social benefits rather than attaining financial profits"* [23]. The recasts of the Internal Electricity Market Directive (IEMD) [24] and of the Renewable Energy Directive (RED II) [25] defined the Citizen Energy Community (CEC) and the Renewable Energy Community (REC), respectively. These two configurations differ in two main aspects: *i)* the use of Renewable Energy sources (RES) and *ii)* the inclusion of different energy demands [26]. In contrast to the CEC, the REC is obliged to use only RES and not fossil fuel energy. The CEC can only manage electricity demand, while REC also other demands such as heating and cooling. In general, ECs represent aggregations of end users from different consumption sectors (e.g., residential, tertiary, commercial, public, agricultural, etc.) with the possibility of exploiting the synergy between complementary energy demand and generation profiles [27], thus enabling energy sharing (see Figure 1). The aggregation in an EC leads to economic benefits in terms of cost savings for the members, social benefits in terms of access to energy for vulnerable energy users, and environmental benefits in terms of reduced CO_2 emissions of the energy system used [28].

ECs promote the aggregation of end users [29], with the aim of improving the match between energy demand and generation at the local level, thereby reducing the load on the energy networks. ECs also increase the self-consumption of distributed RES in neighbourhoods, districts, municipalities and cities [8, 18], by enabling members to share energy within the community [30]. Gjorgievski et al. [31] assessed the impact of regulated charges on the economic convenience of energy sharing within RECs. One finding is that different consumers and prosumers with heterogeneous and complementary demand profiles could obtain economic savings within RECs, even in the case where the energy sharing is taxed (with a lower price than for the energy purchased from the main electrical grid). The economic benefits of the members of an EC could increase by participating in Demand Response (DR) programs [32, 33], which are flexibility strategies that can further improve the local balance between energy generation and demand. Indeed, DR programs offer time-varying prices or incentives to end users to foster optimal shifting of their electricity demand loads from one hour to another, thus limiting the stress on the electrical grid. For example, Cai et al. [33] proposed a bilevel operation optimization model to minimize the energy expenditure of a residential EC and to achieve a flatter daily profile of its net electricity withdrawn from the grid. The model involves an electricity company that offers variable prices over time to the EC members to shift their loads from peak to off-peak hours, thus improving the renewable self-consumption of the EC (e.g., from 86 % to 91 % on a typical spring day) and leading to a reduction in annual energy costs of 20-60 $ for a group of at least 3/4 households.

Among the social advantages, RECs ensure access to distributed RES for different local energy users, including the most vulnerable ones [34] characterized by severe economic and social conditions [6], thus alleviating energy poverty. Balderrama et al. [35] and Li et al. [36] pointed out the role of ECs in supporting the rural electrification planning. For instance, the latter optimized the sizes of a fleet of PV plants, wind turbines and a biogas-fuelled diesel generator to ensure the sustainable electrification of an off-grid community in western China. Ceglia et al. [30] reviewed the main characteristics and the energy, economic, environmental and social goals of CEC and REC configurations, which show a relevant role in ensuring access to energy and mitigating energy poverty for vulnerable end users. Regarding the current situation of spread of ECs in individual Countries, Candelise and Ruggieri [37] highlighted the recent trend of fostering local and small citizen-led projects to establish ECs in Italy [38, 39].

ECs mainly use distributed RES to meet their energy demands, thus contributing to the reduction of the total environmental impact of regional and/or national energy systems. Liu et al. [40] carried out a multi-objective design-operation optimization and a sensitivity analysis on carbon tax, electricity price and equipment price, for a nearly-zero EC, achieving a 52-73 % reduction in annual carbon emissions. Kotagodahetti et al. [41] proposed a multi-criteria approach to evaluate different strategies of emission reduction in ECs. Ceglia et al. [42] conducted an energy, economic and environmental analysis of a REC in Benevento (Italy) and found that the energy sharing among the members of the REC could avoid 39.5 tons of CO_2 emissions per year compared to an energy system configuration without energy sharing.

A relevant issue of ECs consists of guaranteeing energy democracy and equity [43], which could be achieved, for example, by the fair allocation of the total economic benefit of the community to its members. The fair distribution of the total cost (or profit) among the members of an EC is fundamental to ensure its stability, thus avoiding that members drop out of the community, and this requires the formulation and implementation of a fair allocation mechanism [11, 44]. However, as reported by Berka and Creamer [44] and Gjorgievski et al. [11], the fair allocation of the total economic benefit of an EC is still not exhaustively addressed in the literature. Li et al. [45] presented different criteria of cost allocation in the design of tariffs for large power systems and they proposed approaches to adapt these criteria in ECs. Vespermann et al. [46] presented different cooperative allocation mechanisms, such as the Shapley value, to distribute the total benefit of an EC among its members and analysed some properties of these mechanisms (e.g., efficiency and individual rationality). Cremers et al. [47] reviewed different applications of Shapley value for ECs.

ECs utilizing local and distributed RES could rely on Multi-Energy Systems (MES) to satisfy the different types of energy demands of their members [48, 49]. Indeed, a MES consists of a set of energy conversion and storage units that make use of the interaction between multiple energy vectors, at different geographical scales (e.g., district, city, etc.), to find the best match between various energy sources and demands while limiting the environmental impact owing to the use of energy [18].

Barabino et al. [50] conducted a review of the main business models and objectives of optimization models for ECs. The review highlighted that most of the optimization models presented in the literature focus on economic objective functions such as the daily operational cost (e.g., Vespermann et al. [46]) and the total annual cost (e.g., Zatti et al. [51], Cosic et al. [52]). Nevertheless, although the literature has discussed the main economic benefits of being part of an EC, it fails to identify all the aspects that contribute to the optimal aggregation of end users in ECs (that could use local power systems or local MES), and to evaluate the weights of these aspects in the economic convenience of belonging to an EC [10]. These aspects are the complementarity of the energy demand and generation profiles, the fair allocation of the total cost/profit of an EC to its members, and the optimal modification of the energy demands of members through the application of DR programs. Wang et al. [53], Li et al. [54], and Li et al. [55] carried out design, operation, and design-operation optimizations of ECs, respectively, achieving optimal modifications of the total energy demands by applying different DR programs. However, the authors only considered the total energy demand of each EC, neglecting the complementarity of the energy demand and generation profiles of its members, and did not propose a cost allocation mechanism. Cosic et al. [52] developed a one-year Mixed Integer Linear Programming (MILP) model for the optimal planning and operation of a REC, where the optimal shifting of the electricity demands of members is driven by a Price-Based Demand Response (PBDR) with Time-of-Use (TOU) prices. However, the authors did not distribute the community cost among the members. Reis et al. [23] allocated the total cost of an EC to its members (e.g., residential houses, office, restaurant and school) according to their contributions to the total net electricity demand. However, they did not evaluate different DR programs and only modelled PV-equipped residential prosumers, neglecting potential complementarities between different types of end-users. Jiang et al. [56] presented an incentive-based mechanism to promote the optimal cooperation between prosumers equipped with PV and the energy community manager, without taking into account any DR program and without considering different types of prosumers. It clearly appears that none of the previous works have considered together all the aspects affecting the optimal aggregation of end users in ECs. On the contrary, to fill this gap, Sections 3 and 4 focus on these aspects and their impact on the economic benefits of the EC and its members.

1.3.3. Design and operation optimization of power systems and MES in absence of uncertainty

This sub-Section reports and discusses the works on the operation-only and on the design-operation optimization of power systems and MES that could satisfy the energy demands of end users aggregated in ECs, in the absence of uncertainties. It should be noted that Mixed Integer Linear Programming (MILP) models [21] are the most commonly used in the design and operation optimization of MES, due to the great simplification of the optimization problem obtained by linearizing the mathematical functions involved, with a reduced loss of accuracy (see sub-Section 2.1 for more details).

The first part of the analysed literature focuses on the optimization of *local* systems (see sub-Section 1.3.1), which only encompass locally distributed energy units.

Some works dealt with the operation-only optimization of local systems, thus considering the design of the distributed energy units as fixed. Reynolds et al. [57] optimized the operation of a multi-vector energy district (i.e., considering gas, electricity, heat), including as energy conversion and storage units a solar

PV plant, a combined heat and power unit, a gas boiler, a heat pump and a thermal storage, meeting the energy demands of different users from the building sector (i.e., hospital, hotel, school, office, apartment). The results highlighted that the simultaneous optimization of the operation of the conversion units and the flexible heating demands of the end users can lead to an increase in the economic profit of the district of about 53 % compared to a rule-based control without optimally modifying the heating demands of the users. Hurwitz et al. [58] carried out an operation optimization of a MES to minimize its operational costs and carbon emissions. The authors showed that the flexible electricity and heating demands of the MES could reduce the operational costs and carbon emissions by 3.5 % and 7.4 %, respectively, in a typical summer day. Ceglia et al. [59] analysed a Renewable Energy Community (REC) that aggregates a mixed-use building and an industrial wastewater treatment plant, both located in Benevento (Italy). Assuming the installation of one PV plant (size 466 kWp), the REC configuration, which benefits from energy sharing between the two users, is more economically viable than the configuration where the two users operate independently with two distinct PV plants (the total capacity is always 466 kWp) without sharing energy. Compared to a reference case where the two users purchase electricity from the grid to meet their whole demand, the REC configuration leads to a saving of annual operational costs that is 33 % higher than that obtained when the two users operate as two independent prosumers.

Other works focused on the design and operation optimization of local systems. Piazza et al. [60] presented a MILP optimization, performed on 12 typical days of one year, to achieve the optimal design and operation of a local multi-energy community at the University campus of Savona (Italy) with electricity, heating and cooling demands. After the optimization, CO_2 emissions and operational costs reduce by at least 33 % and 35 %, respectively, compared to a reference case in which electricity is withdrawn from the grid and the heating and cooling demands are met by natural gas boilers and heat pumps, respectively. Ceglia et al. [61] analysed a MES that satisfies the electricity, heating and cooling demands of a REC located in the municipality of Tirano (Italy). Several simulations are conducted to assess the benefits of integrating a small hydropower plant (77 kW), a cogeneration unit (thermal power of 2.9 MW) driven by a biomass-based boiler (thermal power of 4.38 MW), and distributed PV plants (1 MW) into the existing REC. The installation of these new facilities could lead to an increase in the electricity self-consumption and a reduction in the emissions of the REC by 49.7 % and 18.5 %, respectively. In a previous work by the author of this Thesis [62], multi-objective design-operation optimization models were developed for different EC configurations (CEC, REC and a hybrid configuration between CEC and REC), encompassing residential and commercial users with electricity and heating demands. The concurrent minimization of the total cost (i.e., investment and operational costs) and greenhouse gas emissions on four typical seasonal days leads to an average saving in economic costs of 14 % and a reduction in emissions of 24 % for the analysed configurations, with respect to the case where the users are simple consumers. Rech et al. [63] developed a MILP optimization model to select the optimal design configuration and operational strategy of a multi-energy hub located in Lisbon, which includes a university campus and an ensemble of residential buildings. The objective is to determine the optimal number and capacities of solar PV plants, solar thermal collectors and thermal storage units, to be installed on the rooftops of the residential buildings, with the total investment cost being fully covered by the university campus. The optimization results highlighted that the cooperation between the university campus and some selected residential buildings in the vicinity, after the installation of distributed PV plants, can achieve a yearly energy cost saving of 8 % for the university campus and 24-29 % for the residential buildings. Sousa et al. [64] conducted a one-year design optimization of a REC consisting of three members, one of which is a prosumer who can invest in PV and wind power plants. This prosumer benefits from individual self-consumption, energy sharing with other members and the sale of electricity surplus to the grid, contributing to a yearly net revenue of 87 k€ for the REC. Some works used typical days of a year to carry out an annual design-operation optimization. Fazlollahi et al. [65] carried out a one-year multi-objective optimization based on 8 typical days of input data (e.g., solar irradiance, energy demands, etc.) to achieve the optimal design and operation of a local MES consisting of thermal storage, cogeneration units and a solar thermal plant. The results show that thermal storage (with cyclic daily operation) contributes to a 4.7 % improvement in efficiency, a 5 % reduction in environmental emissions and a 2 % reduction in the total cost of the system. The typical days in [65] are obtained by applying a centroid-based clustering algorithm [66], which implements various indicators (based on daily and hourly demand, load curves) to compare each daily timeseries with its typical day. However, Fazlollahi et al. [65] did not perform the optimization based on a full year of historical input data and, in turn, the typical days are not selected by comparing the results of the full-year optimization with that based on typical days. On the other hand, the works of Bahl et al. [67, 68] highlighted the importance of selecting typical days and time steps for a design and operation optimization of a MES by taking the objective function as an indicator. They proposed an approach, based on a clustering technique, to identify typical days and time steps by minimizing the error between the optimal value of the total cost (annual investment and operational costs) found by solving the full-year optimization and that based on typical days. However, the authors did not assess the optimal sizes of the energy units obtained with the typical days and time steps compared to those found from the full-year optimization.

A few works in the literature focused on the optimization of *regional* MES (see sub-Section 1.3.1), which include centralized and distributed energy units. José et al. [8] pointed out that regional MES could include ECs organized as cooperatives.

Fischer et al. [69] carried out a multi-objective optimization to minimize the CO_2 emissions and the total annual costs (i.e., investment and operation) of a regional MES that meets the electricity and heating demands of a municipality in Sweden, representative of the Nordic countries. The system includes both centralized power plants (i.e., biomass-fired plants, hydropower plants and wind power plants) and distributed units (i.e., PV plants, biomass boilers, electric boilers and heat pumps). The optimization results showed that CO_2 emissions and peak electricity import from the electrical grid reduce by 60 % and 8 %, respectively, at a reasonable and not excessive cost increase. Li et al. [70] developed a master-slave game model to optimize the coordination between residential, commercial and industrial ECs with electricity, heating, cooling and gas demands within an urban system. Beyond the regional level, Danieli et al. [71] modelled and optimized the Italian energy system as a MES to find the optimal mix of wind, PV, biomethane and power-to-gas systems that minimizes the total investment and operational costs, while assessing the limits of the natural gas grid to accommodate green hydrogen for an increasing share of RES.

Other works investigated how to ensure a fair allocation of the total economic cost/profit of a local or regional system to its end-users aggregated in ECs, by implementing cooperative game-based [46] or other [72] approaches. The literature review reported here only covers the application of cooperative game-based approaches, since these can effectively represent the cooperation between the members of ECs.

“Shapley value” [73], “Nucleolus” [74], and “Nash bargaining” [75], which are the most commonly used allocation mechanisms based on cooperative game theory [76], were applied to attain the distribution of costs (or profits) among the members of an EC. Zatti et al. [51] optimized the capacities of different generation and storage units within an Italian EC consisting of three commercial and six residential users, and applied the Shapley value mechanism to fairly allocate the annual economic profit of the community to its members according to their economic contributions to the energy sold to the grid and to the energy shared with other members of the EC. De Souza Dutra and Alguacil [77] used a mechanism based on Shapley value to distribute incentives equitably among residential prosumers that benefit from an incentive-based demand response program. Fioriti et al. [78] solved a design-operation optimization problem of an EC and then implemented hybrid cooperative allocation mechanisms, such as the “Shapley-Nucleolus”, which ensures a fair cost allocation and stability in the sense of avoiding groups of users willing to leave the EC. Jiang et al. [56] developed a Nash bargaining model for a community made of five residential prosumers to fairly distribute the optimal increase in operational profit obtained by the cooperation between the prosumers and the energy community manager, compared to the case without cooperation. Zhao et al. [9] developed a two-level operation optimization model to maximize, in the first level, the revenue of a distribution system operator, and to minimize, in the second level, the operational costs of an alliance of ECs that are coordinated by the distribution system operator. Two mechanisms, based on the Nash bargaining theory, are implemented to fairly distribute the total operational cost of the alliance among ECs. Limmer [79] analysed the evolution over time of the distribution of the total costs among the prosumers of real residential ECs by implementing the Shapley value and Nucleolus mechanisms. The results of the simulations showed that the Shapley value and Nucleolus mechanisms are suitable for small and large ECs, respectively, and guarantee a fair and stable cost allocation in most of the time.

It is worth highlighting that the works analysed so far neglected any kind of uncertainty in the optimization problems. This aspect is the core of the next sub-Section 1.3.4.

1.3.4. Design and operation optimization of power systems and MES under uncertainty

Some works, such as that of Pilpola and Lund [80], analysed the impact of uncertainties on the values of different indicators (e.g., economic costs, CO_2 emissions and reliability) of an energy system, without carrying out an optimization procedure, but only simulating the model of the system. On the contrary, this Thesis focuses on the optimization under uncertainty, which requires the inclusion of uncertainties in the optimization problem. Frangopoulos [81] reviewed the main trends and challenges associated with the synthesis, design and operation optimization of energy systems, and highlighted the need for more research in the area of optimisation under uncertainty.

With regard to uncertainty in the long-term optimization of MES, Guelpa et al. [17] pointed out the need to develop methods and simplification approaches that allow to solve large-scale optimization problems. Kiani-Moghaddam et al. [82] presented an overview of the main modelling techniques for the assessment of uncertain techno-economic, environmental and social input parameters within the design and operation optimization of local MES. Liu et al. [83] and Mavromatidis et al. [12] identified “Stochastic Programming” (SP) [84] and “Robust Optimization” (RO) [85] as the main methods to optimize the design and operation of MES with different geographical scales under the uncertainty of input data and boundary conditions. SP is based on a set of stochastic scenarios to represent the possible realizations of the uncertain parameters, whereas RO relies on the definition of a possible range of values (named "uncertainty set") to describe the uncertainties. In the case of SP, the stochastic scenarios of the uncertain parameters can be obtained by sampling Probability Density Functions (PDFs) or by applying a clustering technique to a historical dataset containing daily profiles of the uncertain parameters.

This sub-Section deals with the optimization of power systems and Multi-Energy Systems (MES) under uncertainty. Specifically, the literature review is divided into works that consider uncertainty in the operation-only optimization and in the design-operation optimization of these systems.

The following works considered uncertainties in the operation-only optimization of power systems and MES. Veliz et al. [86] proposed a two-layer operation optimization model of a REC, where the first layer optimizes the energy shared among the members of the REC, while the second layer optimizes the operation of energy units and the net energy exchanged with the electrical grid. Confidence intervals, consisting of a set of forecast errors, are used to model the uncertainties associated with the initial state of charge of electric vehicles and with the net energy exchanged between the REC and the electrical grid. Dorahaki et al. [87] developed Mixed Integer Linear Programming (MILP) operation optimization models to maximize the economic profits of a CEC, a REC, and an operator of a multi-carrier energy network (consisting of electrical, water, gas and thermal networks) that acts as an intermediary player between the ECs and the upstream grids. A K-means clustering technique is applied to define stochastic scenarios of the renewable PV power generation and energy demands of the ECs. Kazemdehdashti et al. [88] developed a stochastic model to minimize the daily operational cost of purchasing electricity and natural gas for a residential MES under different uncertainties of RES, electricity and heating demands, energy prices and the traveling time for electric vehicles. The uncertainties of these parameters were modelled by different PDFs. Other works focused on systems bidding into electricity markets. Wang et al. [89] developed a three-stage model to optimize the operation of a regional system integrating multi-energy microgrids, under the uncertainties of the renewable power generation, the electricity and heating demands of end users and the prices in the real-time market. The first, second and third stages of the model refer to the operation in the Day-Ahead (DA) electricity market, the real-time operation and the allocation of the total economic benefit of the system to the individual microgrids through a Nash bargaining mechanism, respectively. Nobis et al. [90] formulated a two-stage SP model to optimize the operation of large-scale power plants in the DA and intra-day markets. Daneshvar et al. [91] formulated a two-stage SP model for the optimal scheduling and dispatching of a system (including hydro and thermal power plants, wind turbines and pumped storage) in the DA and Balancing Market (BM) stages, respectively, with stochastic scenarios of wind speed and electricity demand. The SP solution led to a 12.5 % increase in the total cost compared to an optimization without uncertainty. Schledorn et al. [92] developed a two-stage SP model to optimize the operation of a district heating system, based on cogeneration units, in the DA market under uncertainty of the DA market price. Gomes et al. [93], Moretti et al. [94], Zhang et al. [95] and Wang et al. [96] implemented different RO models to achieve the optimal DA scheduling and dispatching of distributed energy units in local microgrids, considering the variability of RES and electricity demands. Eventually, Siqin et al. [97] developed a distributionally-robust optimization model, based on an alternative method with respect to SP and RO, to achieve optimal day-ahead dispatching of a multi-community energy system consisting of three ECs with electricity, heating and cooling demands, under uncertainty of the power generated by PV plants. A Shapley value mechanism was proposed to allocate higher profits to the participants with higher solar PV consumption.

The following works considered uncertainties in the design and operation optimization of power systems and MES. As shown by Teichgraeber and Brandt [98], a two-stage SP model is suitable to optimize the design and operation of an energy system under uncertainties, where the design optimization is addressed in the first stage and the operation optimization in the second stage, the latter being influenced by the specific realizations of stochastic scenarios. Hafiz et al. [99] developed a SP optimization model to obtain the optimal sizes of electrical energy storage units in a residential EC under the uncertainty of solar PV generation and electricity demands of households, and they compared two investment options based on individual and shared energy storage. Zeng et al. [100] developed a two-stage SP model to optimize the design and operation of a local MES, taking into account the uncertainty of end-user electricity demand, RES generation supply and the sensitivity of end-user demand to price variations according to a demand response strategy. The authors found that the assessment of various uncertainties is fundamental to achieve a reliable design solution for a MES. Wang et al. [101] carried out a multi-objective optimization to minimize the total cost and emissions of a MES by first solving a deterministic model neglecting uncertainty and then solving a SP model considering uncertainty in energy demand and prices. The optimal SP solution results in a greater amount of power being purchased from the grid compared to the deterministic solution, leading to an improvement in the reliability of the MES. Gabrielli et al. [102] optimized the design of an urban MES by developing a RO model, which is based on a single robust scenario accounting for the uncertainty of weather conditions and energy demands.

Some works used SP optimization models with stochastic scenarios of the uncertain parameters that are defined from a set of typical days of a year, usually obtained by clustering techniques or other approaches [98, 103]. Li and Yang [103] used a two-stage SP model, based on typical days of solar irradiance and wind speed in one historical year, to optimize the design and operation of a hybrid energy system. Mansouri et al. [104] implemented a two-stage SP model to optimize the design and operation of a multi-energy hub. Uncertainty in energy demand and wind power generation is represented by daily stochastic scenarios generated by the Monte Carlo simulation and then reduced by a K-means clustering algorithm (resulting in a variable number from 5 to 20). Zheng et al. [105] applied a clustering technique to identify 6 typical days of PV power and residential electricity demand, which are used as stochastic scenarios in a two-stage SP model to optimize the design and operation of a grid-connected system consisting of PV and battery.

The literature indicates that the main uncertainties in the design-operation optimization of power systems and MES are related to the availability of energy sources as RES (i.e., generation side) and the energy demand profiles of end users (i.e., demand side) [106, 107]. Furthermore, most of the optimization models under uncertainty focus on optimizing economic objective functions (e.g., Dorahaki et al. [87], Kazemdehdashti et al. [88]), such as the total investment and operational costs in two-stage SP models (e.g., Teichgraeber and Brandt [98], Zheng et al. [105]). The in-depth analysis of the literature shows also that the stochastic scenarios of uncertain parameters are not usually defined according to the “best” forecasts based on historical input data [108], and that there is a lack of testing the optimization models under uncertainty with this “best” set of scenarios. Moreover, the literature does not clearly quantify the relative weight of the analysed uncertainties in the optimal cost/profit and design (optimal sizes of the energy units) of local MES of ECS. This can be achieved through the comparison between the optimization results under uncertainties, based on typical days of a year, and those without uncertainties, based on a full historical year of data [21]. To fill this gap, Section 5 focuses on the weighting of the uncertainties of RES and different energy demand profiles in the design optimization of a local MES.

1.4. Novel contributions of the Thesis

This Thesis has identified two main research gaps in the current literature (sub-Sections 1.3.2 and 1.3.4). A first gap is the evaluation of all the main aspects that lead to the optimal aggregation of end users in Energy Communities (ECs) and, in turn, have an impact on the economic convenience of forming and being part of an EC. Moreover, the weights of these aspects in the economic benefits of the EC and its members are not clearly assessed. These aspects relate to *i)* the complementarity of the energy demand and generation profiles in the aggregation of different end users in ECs, *ii)* the fair allocation of the total cost/profit of an EC to its members and *iii)* the optimal modification of the energy demands of members through the application of demand response programs. The second gap concerns the assessment of the weight of the uncertainties associated with RES and different energy demand profiles in the optimization of the design of a local Multi-Energy System (MES) serving an EC. The evaluation of the weight of uncertainties in the optimal system design consists in calculating the relative errors in the optimal system cost and sizes of the energy units under uncertainties (i.e., considering typical days of a year) compared to those obtained without uncertainties (i.e., considering a full historical year of data).

Hence, this Thesis aims to shed light, on the one hand, on the aspects that guarantee end users, representative of different consumption sectors, to achieve the optimal aggregation within ECs using local power systems or local MES and, on the other hand, on the weight and impact of uncertain input data and boundary conditions on the design optimization of local MES. This Thesis presents three case studies, where the first two reference case studies (Sections 3 and 4) and the third case study (Section 5) aim to fulfil the first and second objectives of this Thesis, respectively. In fact, the analysis of the main aspects that affect the optimal aggregation of end users in ECs is necessary before evaluating the weight of different uncertainties in the optimal design and cost of a local MES serving an EC.

This Thesis fills the above-mentioned gaps through the following contributions:

- The use of Mixed Integer Linear Programming (MILP) models in the absence of uncertainty to optimize only the operation of local power systems of different ECs (see Sections 3 and 4), comprising end users with representative demand profiles of different sectors, participating in demand response programs that improve the match of their energy demands with the availability of RES. Contrary to most of the optimization models in the literature, which only highlight the benefits of end users in ECs, the MILP models presented in Sections 3 and 4 are primarily used to evaluate the aspects that influence the optimal aggregation of users and to assess their weight in the economic benefits of the EC.
- The development of a general and novel optimization framework (see Section 5), based on a Stochastic Programming (SP) optimization model, to optimize the design and operation of a local MES under the uncertainties of the RES and the users' energy demands, which are representative of different sectors. The local MES meets the aggregated electricity demand of an EC, and the separate heating demands of its members. Unlike most of the current state-of-the-art works, the developed SP model is validated by selecting a set of stochastic scenarios that represent the best forecasts of the uncertainties from a training dataset, and this set of stochastic scenarios is used to test the SP model for each year of a testing dataset. In addition, the results from the testing of the SP model are compared to those obtained by solving a MILP model of the system without uncertainties in the same year to evaluate the weight of the main uncertain parameters in the design optimization of the system.

- The application of post-optimization allocation mechanisms to distribute the total economic benefits of the systems among their energy end-users. A novel allocation mechanism is formulated and proposed to reward more those end users exploiting free-of-charge RES (see Section 3), and an allocation mechanism based on the contributions of users to the optimal economic benefit of the system is applied to achieve and discuss fairness in the distribution of this optimal economic benefit (see Sections 4 and 5).

It should be noted that different optimization models are used throughout the Thesis in order to consistently achieve the twofold objective outlined. The main specifications of all models are stated in sub-Sections 3.1, 4.1 and 5.1, where sub-Section 5.1 clearly highlights the novelties of the MILP and SP models used in Section 5 compared to the MILP models in Sections 3 and 4.

The general assumptions of the Thesis are reported afterwards.

- The end users aggregated in ECs cooperate to achieve a common goal, which could be the minimization/maximization of the daily operational cost/profit (Sections 3/4) or the minimization of the annual life cycle cost of the system including investment and operational costs (Section 5). Thus, in line with most of the optimization models found in the literature (see sub-Sections 1.3.2 and 1.3.4), the daily operational cost/profit and the annual life cycle cost of the system are the objective functions in the implemented optimization models.
- In the search for a better match between the energy demand and generation in the analysed systems, the end users have shiftable electricity demands (i.e., represented by operational decision variables in the optimization problems). These can be practically obtained by optimally shifting the input hourly demands (i.e., parameters in the optimization problems) from one hour to another, while maintaining the same input daily demand in each day considered in the optimization problem.
- The dynamic operation of the local power systems and the MES is considered on each day evaluated in the optimization models, without taking into account the temporal relationship between consecutive days, resulting in a daily operation of the systems [68]. This assumption, which is quite common in the literature [68, 105], simplifies the mathematical formulation of the optimization models, leading to reduced computation times and to a lower number of decision variables and constraints compared to a model that allows the coupling of the different days. Moreover, neglecting the relationship between consecutive days does not compromise the achievement of global solutions for the optimal operation and design-operation of the local systems analysed, which encompass only energy units with a daily operation (e.g., energy storage unit).
- In line with the previous assumption, this Thesis only envisages the modelling and optimization of energy storage units with a daily operation [68, 105], while the design and operation optimization of seasonal storage (which would require more complex models that include the relationship between consecutive days) is beyond the scope of this Thesis.
- The local power systems of the ECs only cover the generation and demand of electricity.
- The optimization of the design of the energy networks (e.g., electrical grid) is outside the scope of this Thesis. Moreover, operational constraints of the electrical grid are not included in the developed optimization models.

- The optimization model under uncertainty (Section 5) is developed according to the Stochastic Programming (SP) method, where the stochastic scenarios are used to represent the possible realizations of the uncertain input parameters. SP is preferred to the Robust Optimization (RO) method because it ensures a solution that hedges against the uncertainty represented by a set of stochastic scenarios, as opposed to the RO solution that is optimal only under the realization of a specific scenario (i.e., the worst-case scenario). In line with the daily operation of the system (see the previous assumption), the SP model is based on typical days that are used as stochastic scenarios.
- In the developed optimization model under uncertainty, it is assumed that the information about the uncertain input data and boundary conditions does not change over consecutive time steps (e.g., hours) in the optimization problem [99]. This assumption is consistent with the SP method, which allows the introduction of the general concept of a temporal "stage" (see sub-Section 2.2) in which decisions are made or realizations of uncertain parameters become known (i.e., a stochastic scenario occurs, thus revealing itself).

1.5. Structure of the Thesis

This sub-Section presents the structure of the whole Thesis. Section 2 focuses on the methodology, i.e., the methods and approaches adopted to solve the optimization problems in the absence and presence of uncertainties, as well as the mechanisms implemented to achieve the allocation of the economic benefit of an EC to its members. Sections 3 and 4 report two reference case studies focusing on the operation optimization of local power systems associated with different EC configurations, in the absence of uncertainties. Section 3 identifies the aspects that affect the optimal aggregation of end users in ECs and weights these aspects in economic terms. Section 4 investigates the distribution of the economic benefit of an EC among its members in terms of fairness. Section 5 presents the design and operation optimization of a local MES serving an EC under different uncertainties, and finds the weights of these uncertainties in the optimal design of the system. Note that Sections 3 and 4, and Section 5 address the first and second objectives of this Thesis (see sub-Section 1.2), respectively. Section 6 highlights the critical remarks and presents the conclusions of this Thesis.

2. Methodology

This Section deals with the different methods and techniques used in this Thesis. Sub-Section 2.1 focuses on the Mixed Integer Linear Programming (MILP) optimization. Sub-Section 2.2 presents the Stochastic Programming (SP) optimization, highlighting the solution approaches and the step of generating stochastic scenarios. Sub-Section 2.3 presents the main mechanisms implemented to distribute the optimal economic benefit of an Energy Community (EC) among its members. It should be noted that some parts of this Section are derived from papers written by the author of this Thesis [10, 109, 110].

2.1. Mixed Integer Linear Programming (MILP) optimization

The Mixed Integer Linear Programming (MILP) optimization is the most common approach to solve design and operation optimization problems of various energy system configurations. The optimization of the design and operation of energy systems is based on a model of the system that includes equality and inequality constraints, which must be simple but at the same time accurate to describe the behaviour of each system unit at design and off-design conditions over the entire operating range. However, the optimization of the design and operation of complex energy systems, involving multiple units (i.e., energy conversion and storage units) and end-users, could require the formulation of a Mixed Integer Non-Linear Programming (MILNP) problem. The main issue is that state-of-the-art MINLP algorithms are not capable of optimizing the design and operation of complex systems including several units and their interconnections as well as multiple energy end-users, where thousands of decision variables may appear in the model and optimal global solutions are not guaranteed. Hence, it is convenient to transform the MINLP problem into a MILP problem by linearizing the non-linear constraints (e.g., the characteristic curves of some conversion units). In summary, a MILP formulation allows a great simplification of the design-operation optimization problem by linearizing the mathematical functions involved with a reduced loss of accuracy for most of the power plants, leading also to a reduction in the computational effort required to solve the optimization [111].

For the above reasons, this Thesis focuses on MILP optimization problems. Although all equality and inequality constraints of the developed MILP models will be described in detail in the following Sections, it may be useful for the reader to be introduced to the general formulation of a MILP optimization model at this point.

The MILP optimization [21] is usually formulated as follows:

$$\begin{gathered}\underbrace{\min}_{x,y}\ (\boldsymbol{c}^T\boldsymbol{x}+\boldsymbol{d}^T\boldsymbol{y})\\ s.t.\ \ \boldsymbol{A}\boldsymbol{x}+\boldsymbol{B}\boldsymbol{y}=\boldsymbol{b}\\ \text{where } \boldsymbol{x}\geq\boldsymbol{0}\in\mathbb{R}^{\boldsymbol{N_x}},\boldsymbol{y}\in\{0,1\}^{\boldsymbol{N_y}}\end{gathered} \tag{2.1}$$

in which $\boldsymbol{c}$ and $\boldsymbol{d}$ are the cost arrays associated with the continuous and binary decision variables, $\boldsymbol{x}$ and $\boldsymbol{y}$, respectively; $\boldsymbol{A}$ and $\boldsymbol{B}$ are the constraint matrices and $\boldsymbol{b}$ is the known term; $\boldsymbol{N_x}$ and $\boldsymbol{N_y}$ indicate the dimension of $\boldsymbol{x}$ and $\boldsymbol{y}$ (e.g., in an optimization with time horizon of one day and hourly time resolution, the decision variables assume one optimal value for each hour of the day), respectively. In the operation optimization problems of the systems analysed in this Thesis (i.e., the local power systems in Section 3 and 4), decision variables can refer to the real-time operation of the system units (e.g., the heating power provided by a heat pump, the charging/discharging power of a storage unit, etc.) and other operational variables (e.g., shiftable electricity demands, the electrical power of the system in excess or deficit that is exchanged with the external grid, etc.). In the design-operation optimization problem of the system analysed in this Thesis (i.e., the local MES in Section 5), in addition to the operational variables mentioned above, there are design decision variables related to the sizes of the energy technologies (e.g., the peak power of a solar PV plant, the maximum energy that can be stored in a storage unit, etc.). Binary variables are used in the operation optimization to select the optimal on/off state of a flexible energy unit (e.g., an internal combustion engine, a heat pump, a storage unit). An operational binary variable with optimal value equal to 1 or 0 indicates that a conversion unit is switched on or off (e.g., the internal combustion engine or the heat pump is producing or not producing power) or that a storage unit is charging or discharging, respectively. Note that binary/integer variables could also be used in the design optimization to include/exclude energy units in/from the optimal system configuration. However, as explained in sub-Section 5.1, in the optimization of the design and operation of local MES carried out in this Thesis, the type and number of the energy units are defined before the optimization and, therefore, binary/integer decision variables are not required in the design optimization.

The optimal values of the decision variables minimize (as in problem (2.1)) or maximize the value of an objective function. The objective functions of the MILP models could be various energy, economic, environmental and social indicators [112, 113], such as energy efficiency or primary energy consumption, total economic costs or profits, emissions of CO_2 or other pollutants, and job creation or welfare of the citizens, respectively. A single-objective or multi-objective optimization [114] could be performed, the latter consisting in optimizing with two or more conflicting objective functions by finding an optimal trade-off solution (e.g., minimizing simultaneously the investment cost of renewable-based energy technologies and carbon emissions). Nevertheless, in the case studies presented in this Thesis, only single-objective economic optimizations are carried out. This is in line with the twofold objective of this Thesis (sub-Section 1.2), i.e., to evaluate the aspects influencing the optimal aggregation of end users in ECs from an economic point of view, and to assess the weight of uncertainties in the optimal design of local MES serving ECs.

The equality constraints of the optimization problem (2.1) represent the energy balances of the overall system (i.e., only electricity balance for the analysed local power systems in Sections 3 and 4, electricity and heating balances for the analysed MES in Section 5), the characteristic curves describing the behaviour of the energy conversion units and the energy balances of the storage units. The characteristic curves of most of the conversion systems can be linearized in the usual range of operational loads, giving a simplified model with a negligible loss of accuracy [111, 115]. The inequality constraints are related to the technical, energetic, and economic limits of the decision variables. The energy balance for an energy carrier (e.g., electricity, thermal energy, etc.) in a system made of N end users can generally be expressed as:

$$\sum_{i=1}^{N}(E_{i,t}^{G} - E_{i,t}^{D}) + \sum_{i=1}^{N}(E_{i,t}^{-} - E_{i,t}^{+}) + \sum_{i=1}^{N}(E_{i,t}^{imp} - E_{i,t}^{exp}) = 0 \tag{2.2}$$

where $E_{i,t}^{G}/E_{i,t}^{D}$, $E_{i,t}^{-}/E_{i,t}^{+}$, $E_{i,t}^{imp}/E_{i,t}^{exp}$ is the energy generation/demand, the energy discharged/charged from/into the storage unit, the energy imported/exported from/to the external grid, respectively, for user

i at time step t. A general linear characteristic curve of an energy conversion unit (e.g., electrical heat pump) with one "fuel" stream and one "product" stream is described by the following constraints:

$$F_{i,t} = a_{0,i} \cdot P_{i,t} + a_{1,i} \cdot \delta_{i,t} \tag{2.3}$$

$$a_{2,i} \cdot min_{load} \cdot \delta_{i,t} \leq P_{i,t} \leq a_{3,i} \cdot max_{load} \cdot \delta_{i,t} \tag{2.4}$$

where $F_{i,t}$, $P_{i,t}$ and $\delta_{i,t}$ are the input power (e.g., electrical power consumed by a heat pump), the output power (e.g., the heating power provided by a heat pump) and the binary variable of the on-off operational state, at time step t for the energy conversion unit owned by user i. min_{load} and max_{load} are the minimum and the maximum loads of the conversion unit (the latter is equivalent to the size of the unit). $a_{0,i}$, $a_{1,i}$, $a_{2,i}$ and $a_{3,i}$ are input parameters depending on the type of the energy conversion unit. Note that for a cogeneration unit with two "product" streams, e.g., a combined heat and power engine producing electrical power and thermal power (the latter from exhaust gases), an additional equality constraint is needed with respect to Eq. (2.3) to represent the relationship between electrical and thermal power.

It is worth noting that the end users are assumed to have electricity demands that can be shifted (sub-Section 1.4), so all optimization models include Demand Response (DR) constraints to find the optimal shifted hourly demands, which can vary from the input hourly demands within a certain range, while keeping the total daily demands unchanged. The shifted electricity demands of end users are operational decision variables in the optimization models, while the input electricity demands are parameters. Furthermore, other constraints related to the national directives are introduced in all MILP optimization models, such as the calculation of the shared energy in the Renewable Energy Community (REC) according to the Italian legislation. The constraints related to the energy conversion and storage units of the analysed systems, the DR constraints and the constraints associated with the national policies are reported in detail in the next Sections for each case study.

Based on the methodology presented above, MILP models are used to optimize the operation of local power systems of Energy Community (EC) configurations (see Sections 3 and 4) and the design-operation of the local Multi-Energy System (MES) of an EC (see Section 5). In these case studies, the objective function to be minimized (maximized) is the daily operational cost (profit) of the local power system of an EC or the total life cycle cost (i.e., investment, operation and maintenance costs), actualized to one year of operation, of the local MES of an EC. Note that MILP optimization models may contain uncertainties associated with input data and boundary conditions (as in the case study in Section 5), thus requiring methods to perform the optimization under uncertainty, as discussed in the next sub-Section.

2.2. Stochastic Programming (SP) optimization

"Stochastic Programming" (SP) [84] and "Robust Optimization" (RO) [85] are the main methods to conduct the optimization under uncertainty [12]. SP considers a set of stochastic scenarios with the associated probabilities, while RO defines an interval of possible random realizations of an uncertain parameter. RO searches for a worst-case feasible solution, which is only optimal for a worst-case scenario, sometimes leading to overly conservative results [116]. On the contrary, SP is able to guarantee a well-hedged solution of the optimization problem under uncertainty, i.e., an optimal solution that takes into account multiple stochastic scenarios [117]. For the above reasons, this Thesis adopts Stochastic

Programming (SP). Sub-Sections 2.2.1 and 2.2.2 present the theory of the solution approaches and the generation of stochastic scenarios according to SP, respectively.

2.2.1. Formulation of the SP optimization and solution approaches

The Stochastic Programming (SP) method is suitable for solving optimization problems under uncertainties with different temporal "stages", which represent consecutive time intervals (not necessarily close in time) in which decisions are made or scenarios of uncertain parameters become known. In this Thesis, a SP model with a MILP formulation [118] is developed to optimize the design and operation of a local Multi-Energy System (MES) under uncertainties (see Section 5). The considered optimization under uncertainty addresses a two-stage design-operation problem, where the decisions related to the optimal sizes of the energy units are taken in the first stage (i.e., the design phase), while the operational decisions (i.e., the real-time power generated by the conversion units, the shifted electricity demands, etc.) are taken in the second stage (i.e., the operation phase). Note that the second stage, in which the real-time operation of the system takes place, is affected by the stochastic scenarios, i.e., the possible realizations of the uncertain parameters.

The general formulation of a two-stage SP optimization model is [101]:

$$\min[f(x) + E_s(\min g(y,s))] \qquad (2.5)$$
$$s.t. \quad h(x,y,s) \le 0$$

where x, y and s refer to the first stage decision variables, the second stage decision variables and one of the stochastic scenarios of the uncertain parameter (or parameters), respectively. $f(x)$ and $E_s(\min g(y,s))$ represent the part of the objective function that is independent of stochastic scenarios and the part that is dependent on them, the latter being the expectation value of a certain quantity (e.g., a cost $g(y,s)$) under the different stochastic scenarios. For example, in the design-operation optimization problem under uncertainties presented in Section 5, the first part of the objective function (i.e., $f(x)$) is the investment cost actualized to one year of operation of the system, and the second part (i.e., $E_s(\min g(y,s))$) is the expectation value of the annual operational cost. The investment cost depends on decisions, related to the optimal sizes of the energy units, taken before the realization of the stochastic scenarios (i.e., in the first stage), while the annual operational cost depends on decisions taken in the real-time operation of the system and influenced by the stochastic scenarios of the uncertain parameters. Note that the constraints $h(x,y,s)$, which depend on the decision variables in the second stage, are defined for each stochastic scenario. The objective function in problem (2.5) can be transformed into the following one if the set of stochastic scenarios is discrete:

$$\min\left[f(x) + \sum_{s=1}^{S} p_s \cdot g(y,s)\right] \qquad (2.6)$$
$$s.t. \quad h(x,y,s) \le 0$$

where p_s is the probability of the stochastic scenario s and the probability-weighted average (i.e., $\sum_{s=1}^{S} p_s \cdot g(y,s)$) replaces the expectation value in problem (2.5). The main solution approach to the problem (2.6) is called "Here and Now" (HN), where decisions are made "now" in the first stage (e.g., decisions about the optimal design of an energy system) before knowing which stochastic scenario will occur in a subsequent stage (e.g., in the second stage related to the real-time operation of an energy system). This means that all stochastic scenarios are considered simultaneously within one optimization and, consequently, the obtained SP solution consists of a unique set of optimal design decision variables and an optimal value of the objective function that hedge against the uncertainty represented by the stochastic scenarios. It is worth noting that the optimal value of the objective function for the minimization problem (2.6) according to the HN approach has a lower bound and an upper bound [98]. The lower bound is found by applying the "Wait and See" (WS) solution approach. Unlike HN, the WS approach solves the optimization model of the system for each stochastic scenario (e.g., one day) independently, under the utopic assumption that perfect information about each (daily) scenario is available prior to its realization. The optimal value of the objective function according to the WS approach is calculated by averaging, according to the scenario probabilities, the optimal values of the objective functions of the independent optimal solutions found for all scenarios. It should be stressed that the WS formulation follows a utopic approach, which is not feasible in practice, but it allows to understand how "far" the solution of the two-stage SP optimization with the HN approach is compared to that of the WS approach that assumes perfect information about the future. The upper bound of the solution to the minimization problem (2.6) is obtained by solving the model for a single average scenario, which is found by calculating a probability-weighted average of the stochastic scenarios before the optimization. Furthermore, in the case of a maximization problem instead of a minimization one (as in problem (2.6)), the WS solution and the solution based on the average scenario represent the upper and lower bound of the HN solution, respectively. An application and comparison of the HN and WS approaches to a two-stage SP optimization can be found in a paper by the author of this Thesis [110].

2.2.2. Generation of stochastic scenarios and probability definition

SP is a scenario-based method that requires the definition of a set of stochastic scenarios. According to the literature, stochastic scenarios of uncertain parameters can be generated by applying sampling techniques to Probability Density Functions (PDFs) [12] or by implementing clustering techniques on large datasets containing historical values of the uncertain parameters [119].

The uncertainty associated with input parameters can be represented by PDFs [120], which are usually assumed, available from the literature or constructed from historical or experimental data. For example, the uncertainty of the solar irradiance is usually represented by the Beta PDF, that of the wind speed/power by the Weibull or Rayleigh PDF, and that of the prices by the Normal PDF. Possible realizations of an uncertain parameter (i.e., its stochastic scenarios) are obtained by sampling its associated PDF, i.e., extracting values of the parameter from its PDF according to a particular technique. Random sampling and other sampling techniques are available in the literature [108, 121, 122], where a trade-off is sought between the high precision/accuracy of the sampling and the computational complexity of the implemented algorithm. It should be noted that the definition of a PDF to represent the uncertainty of a specific parameter is usually not straightforward due to the lack of experimental data or sufficient information from which to construct the PDF [12]. For this consideration, given the difficulty of defining a reliable PDF that covers the uncertainty of a parameter, this Thesis applies clustering techniques to generate stochastic scenarios of the uncertain parameters from historical data.

Hoffmann et al. [119] provided a comprehensive review of the main Time Series Aggregation (TSA) techniques used to reduce the complexity of energy system optimization models. The main objective of TSA is to reduce the amount of input data and timeseries while preserving their information in energy system optimization models and, in turn, to reduce the computational time to solve these optimization models [123]. In TSA, clustering techniques are used to aggregate timeseries based on the similarities of their features, i.e., the values of the parameters in the timeseries (e.g., weather parameters, energy demands, etc.). Clustering techniques group similar timeseries into a "cluster", where distinct clusters are generated by an iterative process that minimizes the "intra-cluster" distance between elements belonging to the same cluster, while maximizing the "inter-cluster" distance between elements of different clusters. Various metrics are available to calculate the distance between different timeseries, although the Euclidean distance [124], which represents the squared error, is the most commonly used by clustering algorithms. The main clustering techniques are K-means, K-medoids and hierarchical clustering [125]. K-means usually selects as representative the centroid, i.e., the average timeseries of a cluster, while K-medoids identifies as representative the medoid, i.e., the timeseries with the smallest value of the chosen distance metric with respect to all other timeseries of the same cluster. Hierarchical clustering initially considers each individual timeseries as its own cluster and then iteratively merges pairs of clusters until a desired minimum number of clusters is reached. In hierarchical clustering, the centroids or medoids are chosen as representative timeseries of the generated clusters. Clustering techniques are used to identify representative timeseries in typical time steps (e.g., minutes, quarter hours) for dispatch operation optimization problems with narrow time horizons, or in typical periods (e.g., days, weeks) for design and operation optimization problems of energy systems with longer time horizons [126].

In this Thesis (see Section 5), the stochastic scenarios are defined by taking an appropriate set of typical days that are representative of the uncertain parameters in a given year [98]. Hence, a K-means clustering technique is implemented on annual datasets, containing daily timeseries of the uncertain input data with hourly time resolution, to identify clusters (i.e., a cluster groups similar days) and their associated representative days, i.e., the typical days that are representative of that year. A typical day is taken as the representative day of a cluster with the lowest value of the Euclidean distance from the centroid of the cluster. Then each typical day is considered as a stochastic scenario in the SP optimization model (see sub-Section 2.2.1), and its probability is defined according to the frequency of the related cluster (i.e., the number of days in the cluster) for which the stochastic scenario is representative [105]. For the sake of completeness, the Appendix A to this Thesis presents an alternative method of defining scenario probabilities that take into account the time correlation between scenarios occurring on consecutive days.

2.3. Mechanisms to allocate the total economic cost/profit of an energy community

As highlighted in sub-Section 1.3.2, one of the main issues in Energy Communities (ECs) is to ensure a fair distribution of the total economic benefit (i.e., cost or profit) among the members, thus achieving what is called "energy distributive justice" [127]. Furthermore, the fair distribution of the total economic benefit is one of the relevant aspects that affect the optimal aggregation of end users in ECs and their economic costs or profits (see sub-Section 1.4). As one of the objectives of this Thesis is to evaluate these aspects (sub-Section 1.2), this sub-Section focuses specifically on the allocation of the total economic benefit of an EC. Since a unique definition of fairness in the allocation of the total economic benefit does not exist, this Thesis explores and applies different allocation mechanisms to distribute the total cost or profit of a system (e.g., a local power system or MES serving an EC) among its end users and assess whether it is fair.

Consider an EC configuration where the aggregator (also called the EC manager), which is assumed here to be a non-profit external agent, controls the economic revenues and expenditures within the governance model of the EC. Figure 2 shows how the daily operational costs of N end-users before cost allocation (block 1) are used by the aggregator to finance the total daily operational cost of the EC (block 2), which includes, for example, the costs of fuel consumption and net electrical power purchased from the grid (these costs are considered in the case study presented in Section 3). The remaining net revenue of the EC aggregator after deduction of costs (block 3) corresponds to a total cost distributed among the end users according to a cost allocation mechanism (block 4).

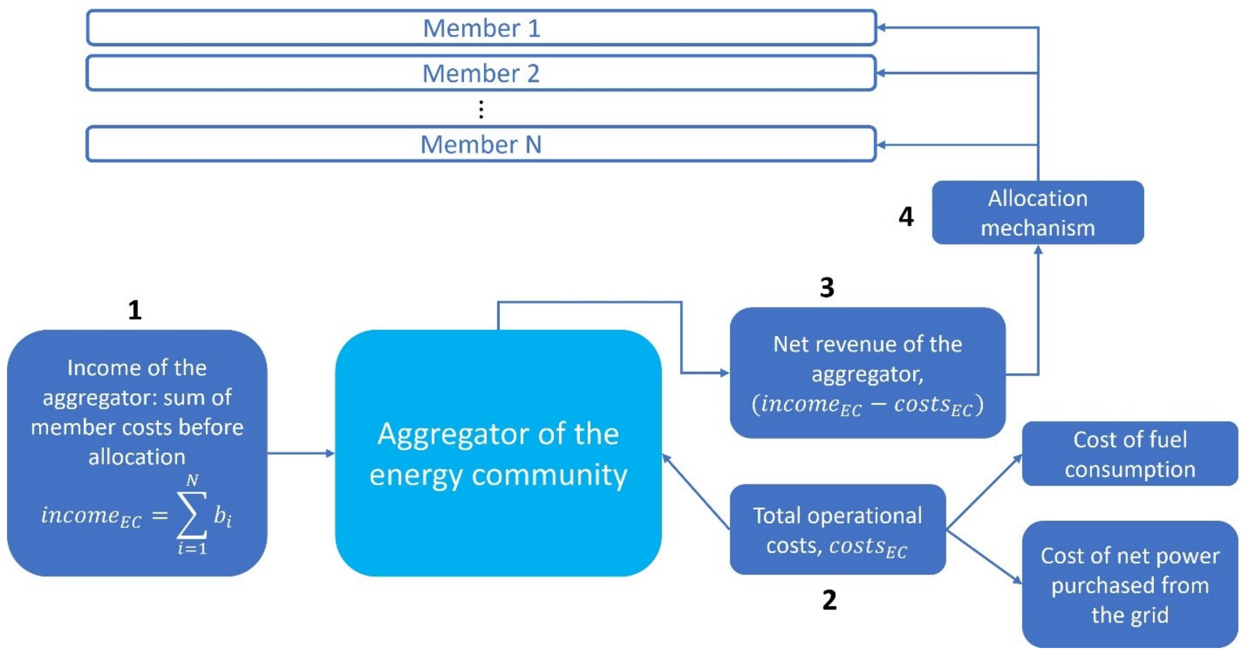


Figure 2. Economic flows managed by the aggregator of an energy community.

A first novel mechanism based on the procedure described above (see Figure 2) is formulated to encourage end users who have the higher advantage in becoming independent prosumers from the status of independent consumers to join the EC. The mechanism is applied after solving the optimization problem of the system associated with the EC (e.g., as problem (2.1) in sub-Section 2.1). The mechanism proposes that the daily cost allocated to each user i of an EC ($b_{i,new}$) is calculated as:

$$b_{i,new} = b_i - (income_{EC} - costs_{EC}) \cdot \frac{(b_{i,0} - b_{i,1})}{\sum_{i=1}^{N}(b_{i,0} - b_{i,1})} \tag{2.7}$$

where b_i is the daily cost of user i before cost allocation; $(income_{EC} - costs_{EC})$ is the net revenue of the EC aggregator, calculated as the difference between the income of the EC aggregator ($income_{EC}$, i.e., the sum of all the daily costs of the members before cost allocation) and the daily operational cost of the EC ($costs_{EC}$); $b_{i,0}$ and $b_{i,1}$ are the daily costs of user i when operating as an independent consumer and as an independent prosumer outside of the EC. The application of this mechanism results in a daily cost allocated to user i, which is calculated by subtracting from the cost before allocation the net revenue of the EC, multiplied by the ratio between the economic savings $(b_{i,0} - b_{i,1})$ obtained by user i by changing its status from independent consumer (with bill $b_{i,0}$) to that of independent prosumer (with bill $b_{i,1}$) and the sum of the economic savings of all users ($\sum_{i=1}^{N}(b_{i,0} - b_{i,1})$). The daily cost of user i before the cost allocation (b_i) is computed as the cost of purchasing electricity from the grid to meet the entire daily demand (which could be an input demand or an optimally shifted demand). It is worth observing that the daily operational cost of the EC is the objective function to be minimized in the MILP operation optimization model, which is solved before applying the cost allocation mechanism (see Section 3). In addition, note that in the case of application of Demand Response (DR) programs (see sub-Sections 3.2.3), the shiftable electricity demands affect the calculation of the daily cost allocated to each user i (in particular, the terms b_i, $income_{EC}$, $costs_{EC}$). The end users that find the greater advantage in becoming independent prosumers from the status of independent consumers are those achieving the better compromise between maximum renewable self-generation and minimum cost for it. Therefore, this mechanism is expected to mainly favour those members using energy conversion units driven by free-of-charge and non-dispatchable RES (e.g., using PV plants). This mechanism is applied in the first reference case study reported in Section 3, which deals with the operation optimization of a local power system meeting the aggregated electricity demand of an EC in the absence of uncertainties [10].

This Thesis also considers the allocation of the total cost or profit of an EC to its members through a cooperative game-based mechanism.

As highlighted by Fioriti et al. [78], after solving the operation or design-operation optimization problem of an EC, a cooperative game-based mechanism can be applied to distribute its optimal cost or profit among the members. A cooperative game model can effectively represent the cooperation among interacting players [128] of an EC, where the "players" (i.e., members of the EC) that form the "grand coalition" (i.e., the EC itself) cooperate to achieve a common goal (e.g., minimization of the total cost of the EC). A cooperative game model is defined by *N* players forming the "grand coalition" and by the "value" function *v* of any coalition *S* of players within the grand coalition [74]. For a cooperative game, the following formula applies:

$$v(S)\colon 2^N \to R \tag{2.8}$$

where $v(S)$ is the "value" function of coalition *S*, which is defined for each of the 2^N coalitions of players within the grand coalition (made of *N* players) and takes real values (R). The 2^N coalitions include the grand coalition itself and the empty coalition (i.e., the coalition with no players). For example, the value function of coalition *S* represents the total cost or profit associated with players cooperating in the coalition *S*. In the context of ECs, observe that the value of the grand coalition is equal to the total cost or profit of an EC, while the value of the empty coalition is zero.

Shapley value [73] is a cooperative game-based allocation mechanism, applied ex-post the optimization procedure, that allows to achieve a "fair" allocation of the optimal total cost or profit of the EC to its members. The cost or profit x_i allocated to an EC member *i*, called "payoff" afterwards, is calculated as follows:

$$x_i = \sum_{S \subseteq N, i \in S} \frac{(|S|-1)!\,(N-|S|)!}{N!} \big(v(S) - v(S \setminus \{i\})\big) \tag{2.9}$$

where $|S|$ is the size of the coalition S (i.e., the number of members in the coalition) and $\big(v(S) - v(S \setminus \{i\})\big)$ is the contribution of the member i to the value $v(S)$ of coalition *S*, i.e., the difference between the value $v(S)$ of coalition *S* including member *i* and the value $v(S \setminus \{i\})$ of coalition *S* without member i. Shapley value is "fair" in the sense that it succeeds in distributing the optimal cost/profit of an EC by weighting the contributions of members to the total benefits of the EC and each coalition (i.e., $v(S)$ in Eq. (9)) they participate in within the EC. However, the Shapley value requires the calculation of the value functions of 2^N coalitions, so the computational burden increases with the number N of members.

An example of the complete calculation related to the implementation of the Shapley value mechanism for a community of three members is reported below [109]. Table 1 shows the coalitions analysed, where the symbol () represents the empty coalition, and their corresponding "values", which could represent economic costs or profits in €. Although the values of the coalitions are assumed in the example below, note that in the optimization problem associated with an EC, the values of the coalitions can be obtained by solving the optimization problem for each coalition (see Section 4).

Table 1. Example of a grand coalition with three players, with the "values" of all coalitions.

Coalition	()	(1)	(2)	(3)	(1,2)	(1,3)	(2,3)	(1,2,3)
Value [€]	0	0	2	3	3	5	6	12

Eq. (2.9) is applied to compute the Shapley payoff for each of the three players. Player 1 appears in coalitions (1), (1,2), (1,3) and (1,2,3) and, therefore, its payoff is based on the weighted average marginal contribution to the values of these four coalitions:

$$\begin{aligned} x_1 = {} & \frac{(1-1)!\,(3-1)!}{3!}\big(v((1)) - v(())\big) + \frac{(2-1)!\,(3-2)!}{3!}\big(v((1,2)) - v((2))\big) \\ & + \frac{(2-1)!\,(3-2)!}{3!}\big(v((1,3)) - v((3))\big) + \frac{(3-1)!\,(3-3)!}{3!}\big(v((1,2,3)) - v((2,3))\big) \\ & = \frac{1}{3}(0) + \frac{1}{6}(3-2) + \frac{1}{6}(5-3) + \frac{1}{3}(12-6) = \frac{15}{6} \end{aligned}$$

Player 2 can participate in coalitions (2), (1,2), (2,3) and (1,2,3), and its payoff is:

$$\begin{aligned} x_2 = {} & \frac{(1-1)!\,(3-1)!}{3!}\big(v((2)) - v(())\big) + \frac{(2-1)!\,(3-2)!}{3!}\big(v((1,2)) - v((1))\big) \\ & + \frac{(2-1)!\,(3-2)!}{3!}\big(v((2,3)) - v((3))\big) + \frac{(3-1)!\,(3-3)!}{3!}\big(v((1,2,3)) - v((1,3))\big) \\ & = \frac{1}{3}(2) + \frac{1}{6}(3-0) + \frac{1}{6}(6-3) + \frac{1}{3}(12-5) = 4 \end{aligned}$$

Player 3 can participate in coalitions (3), (1,3), (2,3) and (1,2,3), and its payoff is:

$$
\begin{aligned}
x_3 = {} & \frac{(1-1)!\,(3-1)!}{3!}\big(v((3)) - v(())\big) + \frac{(2-1)!\,(3-2)!}{3!}\big(v((1,3)) - v((1))\big) \\
& + \frac{(2-1)!\,(3-2)!}{3!}\big(v((2,3)) - v((2))\big) + \frac{(3-1)!\,(3-3)!}{3!}\big(v((1,2,3)) - v((1,2))\big) \\
& = \frac{1}{3}(3) + \frac{1}{6}(5-0) + \frac{1}{6}(6-2) + \frac{1}{3}(12-3) = \frac{11}{2}
\end{aligned}
$$

This payoff allocation is defined as "imputation" because it simultaneously guarantees the properties of "efficiency" and "individual rationality" [74]. The property of efficiency ensures that the "value" of the grand coalition is allocated to all players, while the property of individual rationality means that each player benefits from participating in the grand coalition compared to operating as an independent player without cooperation with other players. In the example above, efficiency is ensured because the sum of the payoffs is equal to the "value" of the grand coalition (i.e., 12 €). Moreover, the payoff allocation satisfies the property of individual rationality, since the payoff allocated to each player is higher than the "value" of the coalition including only that player (e.g., for player 2, the payoff in the grand coalition is 4 € while its value *v((2))*, as an independent player, is 2 €). Note that the property of individual rationality for an allocation mechanism applied in an Energy Community (EC) ensures that each member achieves higher economic benefits within the community than acting as an independent end-user.

In this Thesis, the Shapley value mechanism is applied in the second reference case study (Section 4), which looks at the fair allocation of the operational profit of an EC to its members, neglecting any type of uncertainty. Having verified the effectiveness of the Shapley value mechanism, it is also applied in the case study focusing on the optimization of the design and operation of a local MES serving an EC under different uncertainties (Section 5). Moreover, for the sake of completeness, Appendix B of this Thesis presents the theory of another cooperative allocation mechanism based on the Nash bargaining optimization.

3. First reference case: operation optimization of a local power system with aggregation of different electricity demands in absence of uncertainty

This Section attempts to fulfil the first objective of this Thesis (see sub-Section 1.2), i.e., to clearly evaluate the aspects that influence the optimal aggregation of end users in an Energy Community (EC), and to quantify the weights of these aspects in the economic benefits of the EC and its members. Sub-Section 3.1 introduces the first reference case study of this Thesis, which deals with the operation optimization of local power systems of ECs in the absence of uncertainty. Sub-Section 3.2 focuses on the methodology, covering the aspects that affect the optimal aggregation of end users in ECs and presenting the Mixed Integer Linear Programming (MILP) operation optimization models of the ECs with their input data. Sub-Section 3.3 discusses the results of the optimizations carried out and the results of the distribution of the total economic benefit among the members. Sub-Section 3.4 outlines the conclusions of the Section. It should be noted that some parts of this Section are derived from a paper written by the author of this Thesis [10].

3.1. Case study: local power systems of the citizen and renewable energy communities

The problem addressed in Section 3 is the assessment of the main aspects affecting the optimal aggregation of end users in ECs and having an impact on the economic benefits of the EC and its members. Such a problem is analysed in a first case study that focuses on the optimization of the operation of two local power systems with fixed design (i.e., the sizes of the energy units are known), satisfying the aggregated electricity demand of two different Energy Community (EC) configurations, i.e., the Citizen Energy Community (CEC) and the Renewable Energy Community (REC), defined according to the European legislation [24, 25]. Figure 3(a) and Figure 3(b) show the two local power systems associated with the analysed CEC and REC configurations, respectively, each including a residential prosumer equipped with a solar Photovoltaic (PV) plant and an industrial, agricultural or tertiary prosumer equipped with an Internal Combustion Engine (ICE).

As anticipated in sub-Section 1.3.2, the REC uses only Renewable Energy Sources (RES) to potentially satisfy different types of energy demands (i.e., not only electricity), while the CEC can use both fossil fuels and RES to meet electricity demand only. Furthermore, these two EC configurations present two different ways of connecting to the main electrical grid. The CEC configuration represents an aggregation of members that form a single entity from the perspective of the distribution system operator and exchange energy with the low-medium voltage electrical distribution grid at a single point. This community configuration allows internal energy exchanges between its members, thus contributing to the "physical self-consumption" of the CEC. On the other hand, in the REC configuration, all members are directly and separately connected to the low-medium voltage electrical distribution grid under the same secondary (low-medium voltage) electrical cabin. In this way, the members of the REC share energy via the electrical grid, realizing what is called collective "virtual self-consumption". In the Italian context, the technical regulation of RECs follows the directives of GSE [39], the Italian Energy Services Operator, while the economic incentive for the shared energy among the members of RECs has been defined by ARERA [129], the Italian Regulation Agency for Environment, Network and Energy.

Figure 4 shows the three identified aspects that affect the optimal aggregation of end users in ECs, i.e., the complementarity of the energy generation and demand profiles of end users, the cost allocation mechanisms, and the Demand Response (DR) programs. Figure 4 also highlights the assumptions and boundary conditions in the development of the Mixed Integer Linear Programming (MILP) models (see optimization problem (2.1) in sub-Section 2.1, with fixed sizes of the energy units), which are used to optimize only the daily operation of the two local power systems associated with the CEC and REC configurations. Beyond some general assumptions already reported in sub-Section 1.4, the assumptions and boundary conditions in this case study are detailed in the following.

- In accordance with the European directives defining the ECs, only the production and demand of electricity are considered to allow a fair comparison between the CEC and REC configurations. Thus, the reference case study under analysis focuses on local power systems, i.e., managing only the production and demand of electricity in ECs, and not on Multi-Energy Systems (MES). Moreover, the REC configuration is modelled according to the Italian legislation [39]. The MILP models of the systems include only operational decision variables, while the design variables (sizes of the energy units) are input parameters.
- Any type of uncertainty is neglected in order to keep the used MILP optimization models as simple as possible. The reason for this choice is to clearly evaluate only the aspects that influence the optimal aggregation of end users in ECs and to quantify their weights in the economic benefits of the systems, without having to also assess the effects of uncertainties.
- The operation optimization is carried out, independently, for each characteristic day of April, December, and August, as representative of the mid, winter, and summer seasons of a year, considering the location of Padova (Italy). The operation optimization aims at minimizing the daily operational costs of the systems on the three characteristic days, also taking into account the incentive for shared energy of the REC according to the Italian legislation [39]. In addition, the renewable energy self-consumption of the CEC and REC are calculated to assess the aspects affecting the optimal aggregation of end users also from the energetic point of view.
- Four types of prosumers with different profiles of the daily electricity demand (shown in next Sub-Section 3.2.5) are considered, representing the industrial (Ind), agricultural (Agr), tertiary (Ter) and residential (Res) sectors. To better understand the logic behind the aggregation of prosumers in an EC and to maintain an acceptable computational time of the optimization procedure, only the coupling of two prosumers at a time is evaluated in both the CEC and REC configurations. Hence, the complementarity of prosumers is studied considering three different couplings, namely the residential prosumer with the industrial one (Ind-Res), with the agricultural one (Agr-Res) and with the tertiary one (Ter-Res). However, it should be noted that both prosumers in each coupling can represent a group of several prosumers, each of which has conversion units with smaller sizes. For example, a prosumer equipped with a solar PV plant with a peak power of 200 kW can represent 20 residential prosumers, each with an installed PV capacity of 10 kW (i.e., the maximum value of PV peak power at the residential level [130]).
- The yearly averaged daily profiles of the electricity demands of the four prosumers are taken from the literature [131] in the absence of more specific available data. However, it should be noted that the variability of the electricity demands over the seasons is already considered by analysing the combinations of these demands, which are characterized by different shapes representative of different prosumers. Hence, the evaluation of a set of several seasonal demands for each type of prosumer would not lead to different economic outcomes compared to those reported in sub-Section 3.3, but it would lead to significantly higher computation times.

- For simplicity and without loss of generality, in the local power systems of both the CEC and REC configurations, the industrial/agricultural/tertiary prosumer owns a dispatchable energy conversion unit (i.e., a biogas-fueled ICE) with a size of 200 kW_{el} and the residential prosumer owns a non-dispatchable unit (i.e., a PV system) with a maximum power generated of 200 kW_{el}. The choice of these sizes is in line with the Italian legislation for ECs [39]. Moreover, it is assumed that the users individually bear the investment costs of their energy units.
- The MILP optimization models can include DR constraints that allow the optimization of end users' electricity demands to seek a better match between energy demand and generation. DR programs optimally shift hourly electricity demands from peak to off-peak hours, thereby reducing peak demand and increasing demand during off-peak hours, while keeping the total input daily demand unchanged. Price-Based Demand Response (PBDR) and Incentive-Based Demand Response (IBDR) programs are implemented. PBDR sets time-of-use tariffs (base, intermediate and peak tariffs), i.e., prices for the electricity purchased from the grid that vary over time, with a maximum hourly variation in load demand of 10 %. IBDR programs offer an incentive to members who reduce their hourly electricity demand by at least 5 %, considering a maximum hourly variation in the load demand of 10 % or 20 % (referred to as IBDR1 and IBDR2 in Figure 4, respectively). The higher range of the hourly load variation for the IBDR is justified by the larger number of energy users who are typically inclined to participate in this type of program.
- Given the implementation of different DR programs as flexibility strategies, the use of electrical storage is not envisaged, since the perspective of this case study is to push towards the optimal matching of energy generation and demand (i.e., the optimal aggregation between prosumers) with the aim of achieving the minimum daily operational costs of the systems, limiting to the maximum the need for storage (which is an extra cost for the community).
- The optimal daily operational costs of the local power systems (with fixed design) of the CEC and REC are distributed among the members by implementing two different allocation mechanisms (C1 and C2 in Figure 4). Both allocation mechanisms are applied to distribute only the optimal daily operational costs and do not take into account the investment costs of the energy units. Moreover, considering that the users individually bear the investment costs of their energy units, and the daily cost of a member consists mainly of the operational costs, it is expected that the inclusion of investment costs in the daily cost allocation will not lead to significantly different results compared to the allocation of daily operational costs only. On the other hand, Section 5 presents a case study where the optimal annual investment and operational costs of a local MES are allocated to the end users.

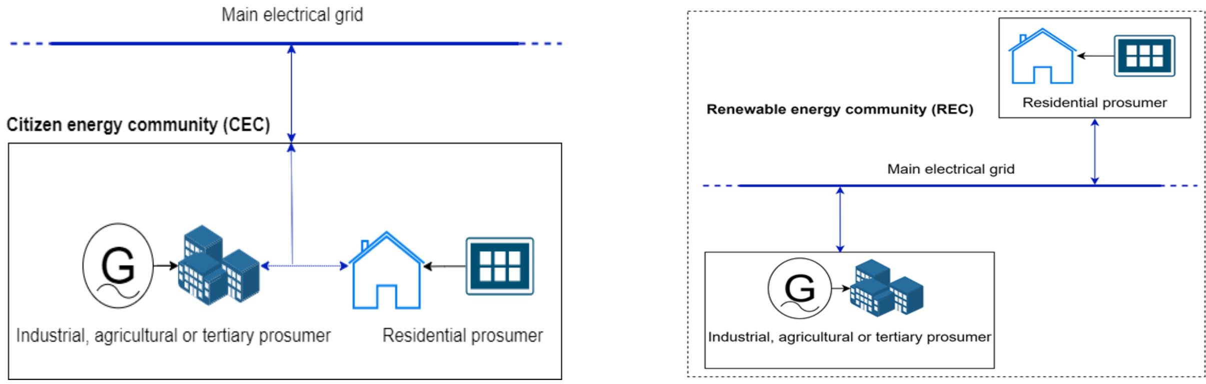


Figure 3. Local power systems of the a) Citizen and b) Renewable energy community, including an industrial, agricultural or tertiary prosumer and a residential prosumer equipped with an internal combustion engine (G) and a solar PV plant, respectively.

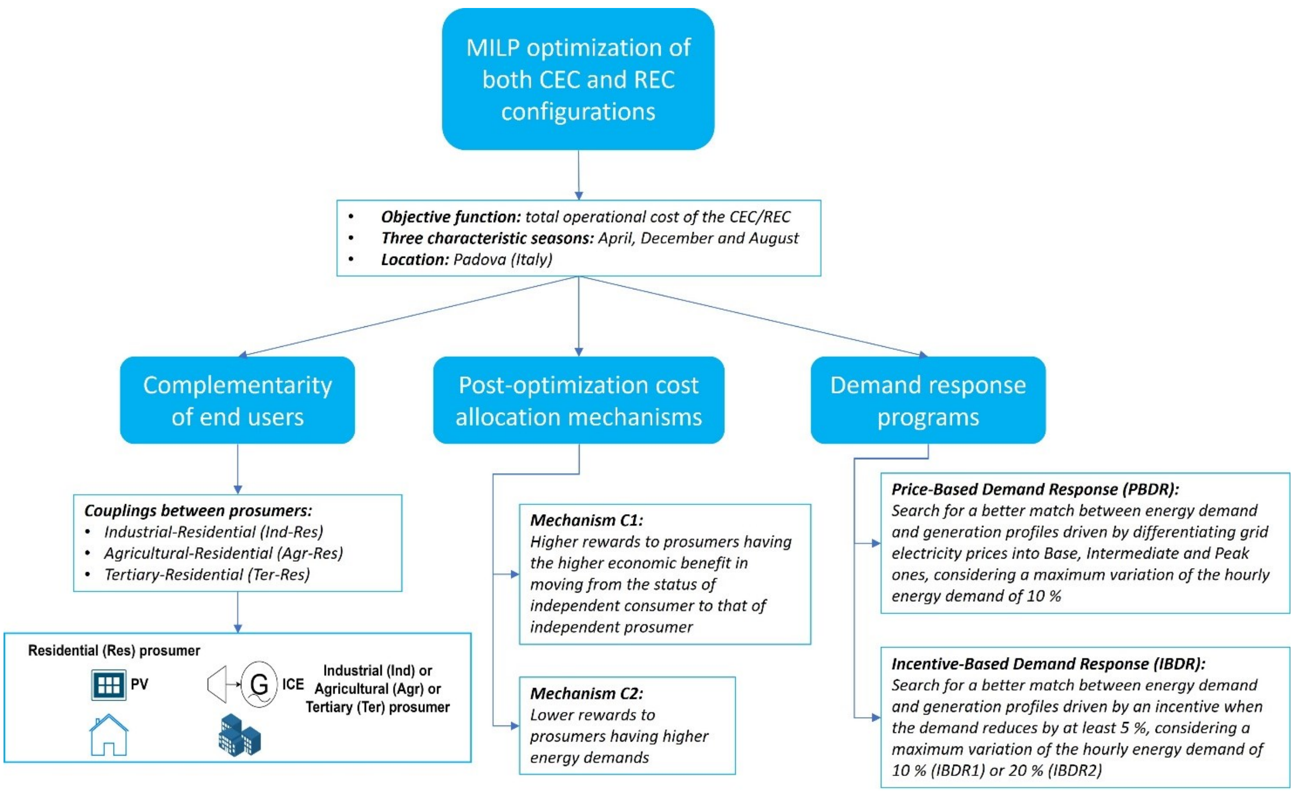


Figure 4. Optimization flowchart highlighting the couplings of end users, the cost allocation mechanisms and the demand response programs considered in the MILP optimization models of the CEC and REC configurations.

3.2. Methods

This sub-Section explains in detail the methodology used. Sub-Sections 3.2.1, 3.2.2 and 3.2.3 analyse the main aspects that influence the optimal aggregation of end users and their economic benefits in ECs, i.e., the degree of complementarity between the energy demand and generation profiles of different end users, the allocation of the total cost of the EC to its members, and the Price- and Incentive-Based Demand Response programs (PBDR and IBDR) as flexibility strategies. Sub-Section 3.2.4 presents the MILP operation optimization models of the local power systems associated with the CEC and REC configurations. Sub-Section 3.2.5 presents the input data of the optimization models.

3.2.1. Complementarity of end users in energy communities

The aggregation between different end users in ECs could bring economic benefits compared to their separate operation. Indeed, the power generated by one EC member can help meet the demand of a second member (i.e., a prosumer or a consumer) in case the latter faces high generation costs or is not provided with generation sources and storage units in the considered time frame (e.g., if the second member is a prosumer only equipped with PV, it cannot use PV power during the night). The most economically convenient aggregation between two members occurs when their generation and demand profiles are complementary. For example, consider the normalized electricity demand profiles shown in Figure 5. Suppose *prosumer 1* uses a dispatchable energy conversion unit (e.g., ICE with a size smaller than the peak demand) and has the electricity demand profile shown in blue, while *prosumer 2* uses a PV plant and has the electricity demand profile shown in green. In the case of separate operation, the ICE of *prosumer 1* cannot meet the peak load of its demand, while the PV of *prosumer* 2 cannot meet the constant load required in the morning and in the evening. On the contrary, in the case of a joint operation, the PV of *prosumer 2* could cover the peak demand of *prosumer 1* and the ICE of *prosumer 1* could cover the demand of *prosumer 2* in the absence of solar power. Thus, the complementarity of the generation and demand profiles of the two prosumers and the coordinated operation of their conversion units is a cost-effective solution with also an improved efficiency for the ICE (operating at constant load for most of the day instead of a few hours in the middle of the day). It should be noted that a similar reasoning also applies when considering the complementarity of energy demand and generation profiles in the aggregation between a prosumer and a consumer.

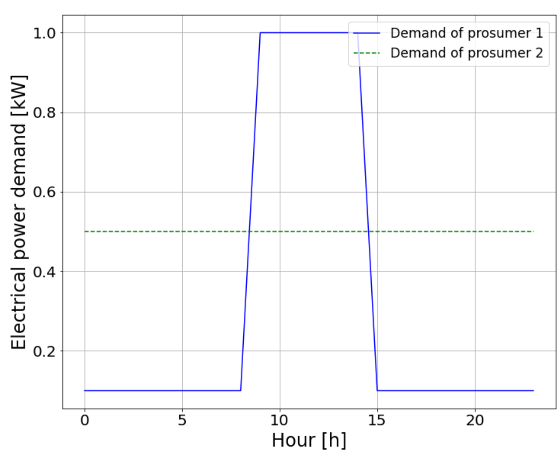


Figure 5. Normalized values of an electricity demand profile with a peak load in the middle of the day (blue line) and a constant electricity demand profile (dashed green line) for two prosumers.

3.2.2. Allocation of the total cost of the system

The optimal daily operational costs of the local power systems of the CEC and REC configurations need to be distributed among the members according to a specific allocation mechanism. Two different allocation mechanisms are implemented after solving the optimization (see sub-Sections 3.2.4). The first mechanism, labelled C1 in Figure 4 above (sub-Section 3.1), is based on Eq. (2.7) and has already been presented in sub-Section 2.3. The main idea of this mechanism is to reward more those end users who could achieve higher economic benefits by becoming independent prosumers starting from the status of independent consumers. The second mechanism, labelled C2 in Figure 4, is based on an average price [45] calculated as the ratio between the optimal daily operational cost and the total daily electricity demand of the system. Through this average price, C2 distributes the total benefit of the system among the members in proportion to the ratio between their individual electricity demand and the total demand. It should be noted that the electricity demands could be input parameters or decision variables (i.e., optimally shifted, see the optimization problem in sub-Section 3.2.4). In the case of application of Demand Response (DR) programs (see next sub-Section 3.2.3), the electricity demands of end users are optimally shifted, thus influencing both allocation mechanisms (e.g., see sub-Section 2.3 for mechanism C1).

3.2.3. "Demand response" programs as flexibility strategies

This sub-Section describes the two DR programs included in the MILP optimization models (reported in sub-Section 3.2.4) to promote optimal shifting of hourly demands, i.e., Price-Based Demand Response (PBDR) based on time-varying electricity prices and Incentive-Based Demand Response (IBDR) based on incentives [32].

The main PBDR programs rely on strategies of Time-of-Use (TOU) pricing, real time pricing and critical peak pricing, which present differences in the way grid purchase prices are defined. TOU sets two or three different hourly tariffs that are used throughout the day. Real time pricing is based on different hourly tariffs that track the daily profile of the day-ahead market price. Critical Peak Pricing sets high prices for a few hours of the year to prevent high demand during periods of extreme grid congestion. The PBDR program used in this work is based on a TOU strategy, which is the most socially accepted by the majority of end users [132], with three different hourly electricity tariffs for the power purchased from the grid (i.e., base, intermediate and peak electricity prices).

The base and peak electricity prices, c_{base} [€/kWh] and c_{peak} [€/kWh], are calculated as:

$$c_{base} = c_{inter} \cdot \left(1 + \frac{D^{var}}{El}\right) \tag{3.1}$$

$$c_{peak} = c_{inter} \cdot \left(1 - \frac{D^{var}}{El}\right) \tag{3.2}$$

where c_{inter} [€/kWh] is the intermediate price equal to the constant grid purchase price (see sub-Section 3.2.5), D^{var} is the maximum hourly fraction of the load that can be shifted [133] and El is the price elasticity of the electricity demand [134, 135]. Figure 6 shows an example of how the TOU strategy could affect the electricity demand profile of an end user from the agricultural consumption sector. The load partially shifts from periods with the peak price of 0.31 €/kWh (hours 5-9 and 18-20) to periods with the base price of 0.06 €/kWh (hours 0-4, 10-17 and 23) [136], while the intermediate price of 0.19 €/kWh is found when there is no significant load change after DR (hours 21-22). Thus, the PBDR programs with TOU tariffs allow the reduction of demand peaks (i.e., leading to peak shaving) and the increase of demand during periods of low load (i.e., leading to valley filling), thus improving the reliability of the power grid.

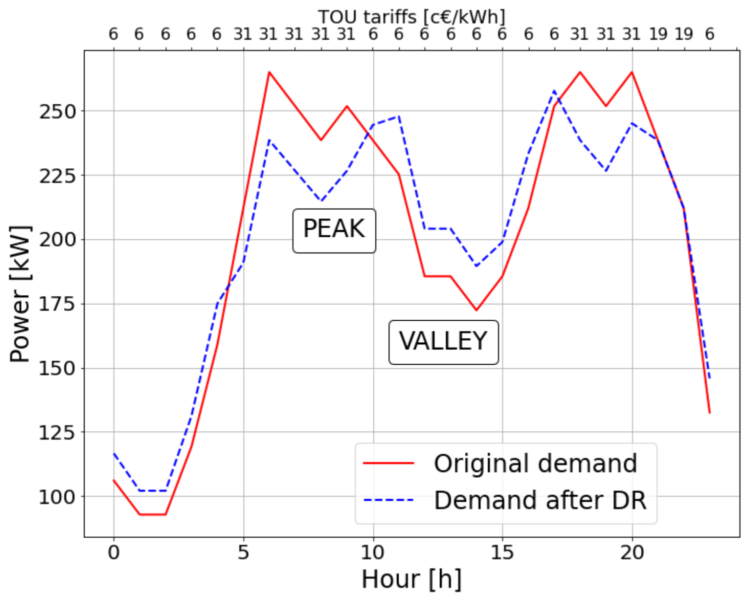


Figure 6. Peak, intermediate and base electricity prices according to the TOU strategy of the PBDR program. Peak and base prices (i.e., 0.31 €/kWh and 0.06 €/kWh) foster a decrease and increase, respectively, in the demand profile after the PBDR (blue dashed line) compared to the original one (red line).

The Incentive-Based Demand Response (IBDR) programs could be based on voluntary participation (e.g., Direct Load Control), mandatory participation (e.g., Interruptible Service strategy) or market-related participation (e.g., Demand Bidding strategy) [137]. In mandatory programs, contrary to the voluntary ones, end users are penalized if they do not comply with the load change requested by an agent such as a DR aggregator or the distribution system operator. In market-related programs, end users can offer load reductions to the distribution system operator at a profitable price. In general, end users accepting IBDR programs receive incentives when they reduce, shift or interrupt their load demands.

In this work the IBDR program adopts a Direct Load Control (DLC) strategy based on a unitary incentive. This incentive is given to member i only if it reduces the hourly energy demand by at least 5 %:

$$\frac{\left(E_{i,t}^{el} - E_{i,t}^{el,shift}\right)}{E_{i,t}^{el}} \geq 0.05 \tag{3.3}$$

where $E_{i,t}^{el}$ [kWh] and $E_{i,t}^{el,shift}$ [kWh] are the input electricity demand and the shifted electricity demand for the EC member i at hour t. The daily revenue of member i participating in the IBDR program is:

$$rev_{IBDR} = \left(\sum_{t=1}^{t=24} (E_{i,t}^{el} - E_{i,t}^{el,shift}) \right) \cdot inc_{IBDR} \tag{3.4}$$

where inc_{IBDR} [€/kWh] is the incentive for the IBDR program and $(E_{i,t}^{el} - E_{i,t}^{el,shift})$ is calculated only if constraint (3.3) is satisfied.

Figure 7 shows an example of the application of the IBDR program for an end user with an electricity demand representative of the residential sector, highlighting in light blue the energy reduction achieved in three hours of the day (namely, hours 8, 11 and 13) thanks to the IBDR. In this example, the presence of the IBDR encourages the user to modify its electricity demand appropriately in order to obtain the incentive foreseen by the IBDR. In any case, it should be noted that, unlike the PBDR case (with TOU electricity prices during the day), the EC members joining this IBDR program are charged a fixed electricity price for all hours of the day (i.e., the grid purchase price, 0.19 €/kWh, see sub-section 3.2.5). In addition, the maximum load variation in one hour (i.e., D^{var}), which usually represents the percentage of end users participating in the DR program, is assumed to be equal or higher with IBDR (i.e., 10 % or 20 %, see Figure 4) than with PBDR (i.e., 10%). Indeed, it is likely that final users prefer a voluntary DLC strategy, based on incentives, to a predefined TOU strategy, based on different electricity prices.

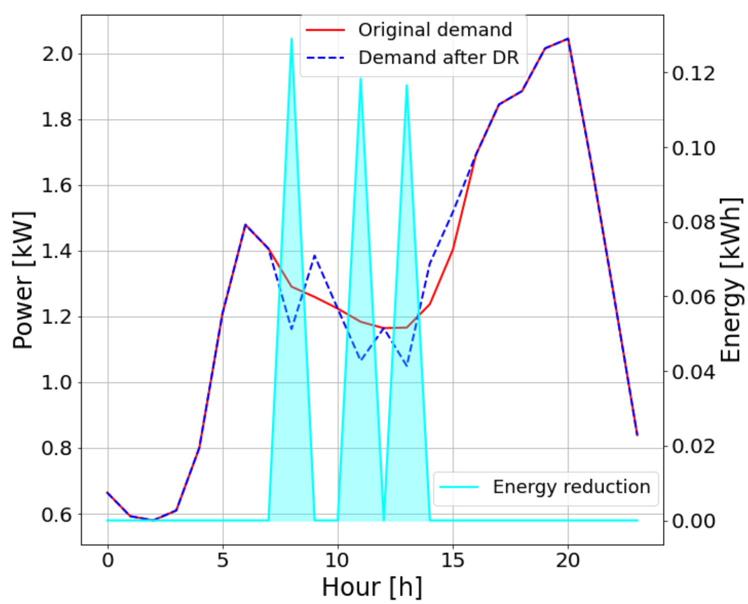


Figure 7. Example of energy reduction in three hours (8, 11, 13) due to the IBDR program with DLC strategy. The end user benefits from the incentive associated with IBDR if it reduces the hourly energy demand by at least a certain amount (e.g., 5 % in this work).

The general constraints [138] implemented in the MILP models for both the PBDR and IBDR are:

$$\sum_{t=1}^{24} E_{i,t}^{el} = \sum_{t=1}^{24} E_{i,t}^{el,shift} \tag{3.5}$$

$$E_i^{el,min} \leq E_{i,t}^{el,shift} \leq E_i^{el,max} \tag{3.6}$$

$$(1 - D^{var}) \cdot E_{i,t}^{el} \leq E_{i,t}^{el,shift} \leq (1 + D^{var}) \cdot E_{i,t}^{el} \tag{3.7}$$

where $E_{i,t}^{el}$ [kWh], $E_{i,t}^{el,shift}$ [kWh], $E_i^{el,min}$ [kWh] and $E_i^{el,max}$ [kWh] are the input electricity demand, the shifted electricity demand, the minimum and maximum of the input electricity demand for the EC member i at hour t. Eq. (3.5) states that the daily electricity demand after DR (i.e., $\sum_{t=1}^{24} E_{i,t}^{el,shift}$) is unchanged compared to that before DR (i.e., $\sum_{t=1}^{24} E_{i,t}^{el}$), which usually helps promote a high participation of end users in the DR program. Constraints (3.6) define the range of variation of $E_{i,t}^{el,shift}$ for member i at hour t. Constraints (3.7) avoid the presence of greater demand peaks after the DR compared to those before DR, thus ensuring the stability of the main electrical distribution grid.

3.2.4. MILP models for the operation optimization of the local power systems of the citizen and renewable energy communities

MILP models are used to optimize the operation of the local power systems of the Citizen Energy Community (CEC) and the Renewable Energy Community (REC), fixed the design of the energy units (i.e., the design variables are fixed as input parameters and do not represent decision variables). The decision variables in the operation optimization of both the CEC and REC are the power produced by the ICE (P_t^{ICE}), the binary variable associated with the operational state of the ICE (δ_t^{ICE}), the energy imported/exported from/into the grid (E_t^{imp}/E_t^{exp}, only for the CEC) and the shifted electricity demands of users in the case of application of PBDR or IBDR programs ($E_{i,t}^{el,shift}$, see the previous sub-Section). The models are developed and solved by means of the Gurobi software [139] with implementation of the linear-programming based branch-and-bound algorithm, which guarantees the global optimality of the solutions. The time horizon of the operation optimization is one day with a time resolution of one hour. The constraints and objective functions of the MILP operation optimization models are reported afterwards.

In the aggregation of prosumers considered in this work (see sub-Section 3.1), the industrial/agricultural/tertiary prosumer owns a biogas-fuelled Internal Combustion Engine (ICE). The operation of the ICE is modelled with the following constraints [111]:

$$F_t^{ICE} = a_0 \cdot P_t^{ICE} + a_1 \cdot \delta_t^{ICE} \tag{3.8}$$

$$P^{ICE,min} \cdot \delta_t^{ICE} \leq P_t^{ICE} \leq P^{ICE,max} \cdot \delta_t^{ICE} \tag{3.9}$$

where F_t^{ICE} [kW], P_t^{ICE} [kW$_{el}$] and δ_t^{ICE} [-] are the mechanical power consumed by the ICE, the electrical power produced by the ICE, and the binary variable describing the on/off operational state of the ICE at hour t, respectively. Eq. (3.8) represents the input-output relationship with one "fuel" stream and one "product" stream for the ICE, i.e., its linear characteristic curve. The values of the parameters a_0 and a_1 (equal to 2.008 [-] and 91 [kW], respectively) are taken from the data of the manufacturer reported in [140]. Constraints (3.9) are needed to fix the upper and lower bounds of P_t^{ICE}. As reported in [111], approximating the operating behaviour of the ICE with the linear characteristic curve introduces a small loss of accuracy, which is well compensated by the reduction in the computational time to solve the MILP optimization problem.

The residential prosumer owns a PV plant. The electrical power produced by the PV plant is:

$$P_t^{PV} = \eta^{PV} \cdot A^{PV} \cdot I_t \tag{3.10}$$

where P_t^{PV} [kW$_{el}$] is the hourly electrical power generated by the PV plant, η^{PV} [kW$_{el}$/kW] is the efficiency of the PV plant, A^{PV} [m^2] is the area of the PV panels and I_t [kW/m^2] is the hourly solar irradiance (on a tilted surface).

The energy balances and objective functions of the MILP models are different for the CEC and REC configurations. In fact, as explained in sub-Section 3.1, the CEC operates as a single entity, e.g., an electrical microgrid [24, 141], while the REC consists of different members that are directly and separately connected to the distribution grid according to the Italian legislation [39]. It should be noted that the members of the REC share energy using the main electrical distribution grid and therefore the shared energy is charged at grid prices. On the other hand, considering that the internal energy exchange between the members of the CEC takes place in a microgrid owned by the community, the shared energy is free of charge and therefore does not affect the total cost of the CEC.

The energy balance of the CEC is formulated as:

$$E_t^{ICE} + E_t^{PV} + E_t^{imp} - E_t^{exp} = \sum_i E_{i,t}^{el} \tag{3.11}$$

where E_t^{ICE}, E_t^{PV} and E_t^{imp}/E_t^{exp} are the energy [kWh] generated by ICE, the energy generated by PV and the energy purchased/sold from/to the grid.

The total daily operational cost of CEC is:

$$c_{CEC} = c_{ICE} + c_{imp,CEC} - c_{exp,CEC} \tag{3.12}$$

where c_{ICE} [€], $c_{imp,CEC}$ [€] and $c_{exp,CEC}$ [€] are the cost of ICE for fuel consumption (F_t^{ICE}, Eq. (3.8)), the cost for the energy purchased from the grid and the revenue for the energy sold to the grid, respectively. They can be expressed as:

$$c_{ICE} = \sum_{t=1}^{24} F_t^{ICE} \cdot c_{biogas} \cdot \Delta t \tag{3.13}$$

$$c_{imp,CEC} = \sum_{t=1}^{24} E_t^{imp} \cdot c_t^{imp} \tag{3.14}$$

$$c_{exp,CEC} = \sum_{t=1}^{24} E_t^{exp} \cdot c_t^{exp} \tag{3.15}$$

where c_{biogas} [€/kWh], Δt [h], c_t^{imp} [€/kWh] and c_t^{exp} [€/kWh] are the biogas price, the time step of one hour in the optimization, the grid purchase and sale prices, respectively. Note that c_t^{imp} is assumed to be constant over the hours of the day (see sub-Section 3.2.5) without a Price-Based Demand Response (PBDR) program (where different TOU tariffs are the hourly grid purchase prices) or when an Incentive-Based Demand Response (IBDR) program is applied.

According to the Italian legislation of the REC [39], two energy balances describe separately the total energy withdrawn from ($E_{withdrawn,t}$) and injected to ($E_{injected,t}$) the grid as reported by Eq. (3.16) and Eq. (3.17), respectively:

$$E_{withdrawn,t} = \sum_{i} E_{i,t}^{el} \tag{3.16}$$

$$E_{injected,t} = E_t^{ICE} + E_t^{PV} \tag{3.17}$$

For each hour t, Eq. (3.16) states that the total electricity demand of the REC is withdrawn from the grid, while Eq. (3.17) states that the total electrical production from RES (i.e., the electrical power produced by the biogas-driven ICE and the PV plant) is injected into the grid.

As shown by Eqs. (3.18) and (3.19), the economic costs/revenues of the energy exchanged with the grid now depend on the definitions of $E_{withdrawn,t}$ and $E_{injected,t}$:

$$c_{imp,REC} = \sum_{t=1}^{24} E_{withdrawn,t} \cdot c_t^{imp} \tag{3.18}$$

$$c_{exp,REC} = \sum_{t=1}^{24} E_{injected,t} \cdot c_t^{exp} \tag{3.19}$$

The Italian REC benefits from an incentive for the "shared energy" among its members, which is defined for each hour of the day as the minimum between the total energy withdrawn from the grid (i.e., $E_{withdrawn,t}$) and the total energy injected into the grid (i.e., $E_{injected,t}$):

$$E_{s,t} = min(E_{withdrawn,t}, E_{injected,t}) \tag{3.20}$$

The total daily operational cost of REC is:

$$c_{REC} = c_{ICE} + c_{imp,REC} - c_{exp,REC} - inc_{REC} \cdot \sum_{t=1}^{24} E_{s,t} \tag{3.21}$$

where inc_{REC} [€/kWh] is the incentive for shared energy and the last term of the daily operational cost represents the economic revenue due to this incentive.

The objective function to be minimized in the MILP optimization is the daily operational cost of the system, which is represented by Eq. (3.12) for the CEC and Eq. (3.21) for the REC. Although the objective function has a different form for the CEC and REC configurations, it includes the same terms as the cost of fuel, the cost of the energy purchased from the grid, the revenue from the energy sold to the grid and the revenue from any incentives provided by national policies (as in the case of the REC according to the Italian legislation).

In addition to the total daily operational cost of the system, the MILP models also include the calculation of the renewable energy self-consumption, which is an energy indicator that can be used to assess the optimal aggregation of end users in ECs. The renewable energy self-consumption is computed by the

Self-Consumption (SC) ratio, which is defined as the ratio of daily energy self-consumed to daily energy demand:

$$SC = \frac{\sum_{t=1}^{24} E_{self,t}}{\sum_{t=1}^{24} \sum_i E_{i,t}^{el}} \cdot 100\ \% \tag{3.22}$$

where each term $E_{self,t}$ is the minimum between the total hourly energy demand (i.e., $\sum_i E_{i,t}^{el}$) and the total hourly energy production (i.e., $E_t^{ICE} + E_t^{PV}$).

The above MILP optimization models can include constraints related to PBDR and IBDR programs (i.e., constraints (3.5)-(3.7) and (3.3)-(3.7), respectively, in sub-Section 3.2.3). Note that in the case a PBDR or IBDR program is applied, the input electricity demand of user i at hour t (i.e., $E_{i,t}^{el}$, which is an input parameter) is replaced by its shifted electricity demand (i.e., $E_{i,t}^{el,shift}$, which is an operational decision variable that is optimized) in the energy balances, represented by Eq. (3.11) for the CEC and Eq. (3.16) for the REC, and in Eq. (3.22) for the calculation of the energy self-consumption of the system. Furthermore, when PBDR is applied, the values of the peak, intermediate and base electricity prices (i.e., the TOU tariffs used as grid purchase prices) are input parameters, but the allocation of these prices to the different hours is managed by a set of integer decision variables introduced into the MILP optimization models.

3.2.5. Input data

The hourly data of global solar irradiance for a 30° south-facing surface in Padova (Italy) on the characteristic days of April, December and August (see sub-Section 3.1) are taken from the PVGIS database [142]. Figure 8 shows the input electricity demands of the considered prosumers, which are representative of the industrial, agricultural, tertiary and residential consumption sectors [131] (see sub-Section 3.1). Figure 9 shows the daily profiles of the grid sale price on the characteristic days of April, December and August in Italy considering the year 2019 [143]. Table 2 shows the values of all the input parameters associated with technologies, prices and incentives, and DR programs, in the MILP optimization models [129, 133, 135, 144]. Note that the size of the ICE and the maximum power generated by the PV plant are fixed to 200 kW to comply with the maximum allowed capacity of power plants in the REC according to the Italian legislation. The grid purchase price (c_t^{imp} in Table 2), without a PBDR program or when an IBDR program is applied, is assumed to be constant over the hours of each day, and equal to the average value of the electricity grid purchase price for customers in Italy [129]. On the other hand, when PBDR is applied, c_t^{imp} assumes the values of the TOU prices (see sub-Section 3.2.3). The incentive for shared energy in the REC is fixed at 0.12 €/kWh (similar to the Italian value), which is the sum of a feed-in premium (0.11 €/kWh) and a feed-in tariff (around 0.008-0.01 €/kWh) linked to the avoided grid losses within the REC [129].

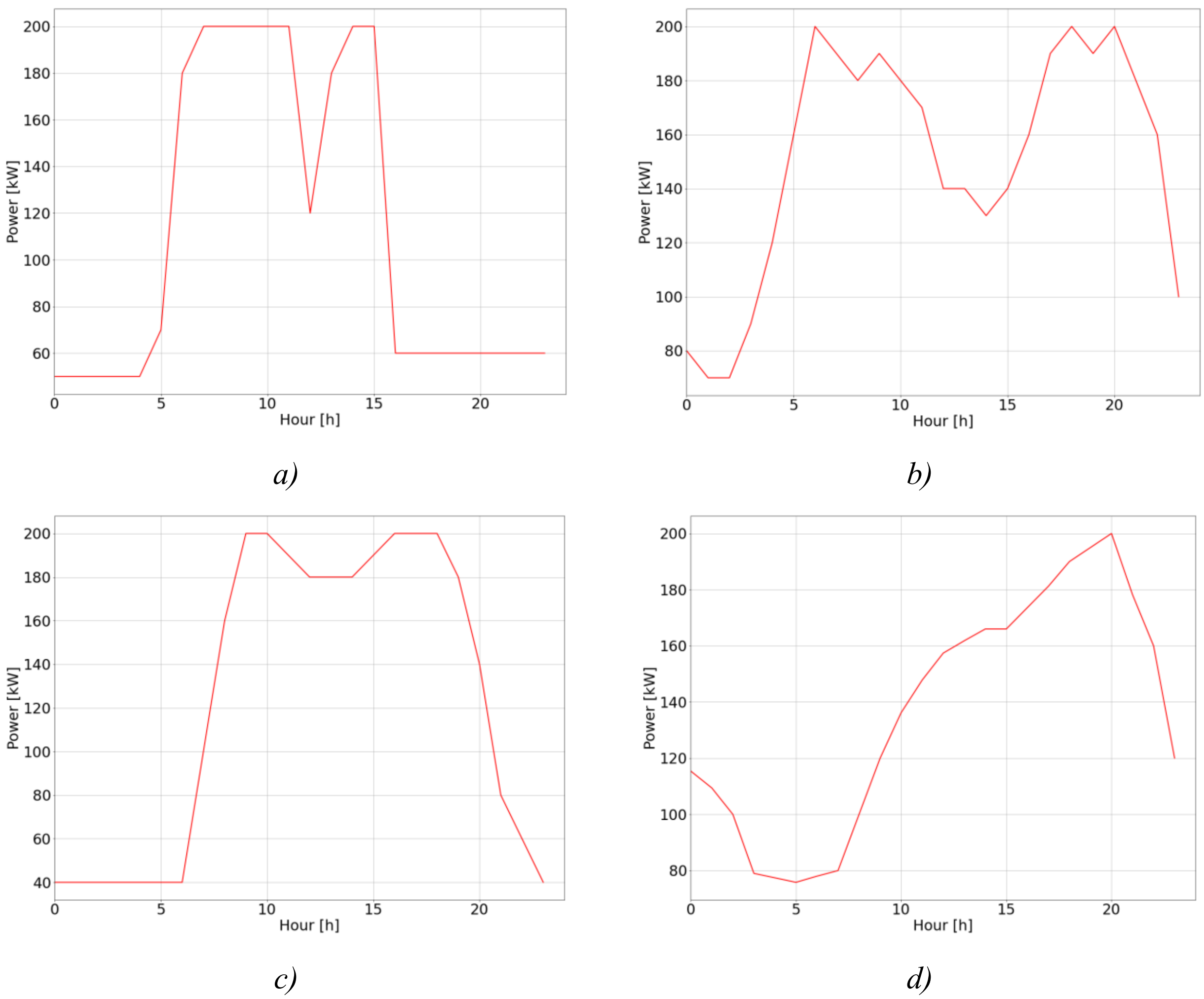


Figure 8. Daily profiles of the electricity demands of prosumers from four different sectors: a) industrial, b) agricultural, c) tertiary, and d) residential [131].

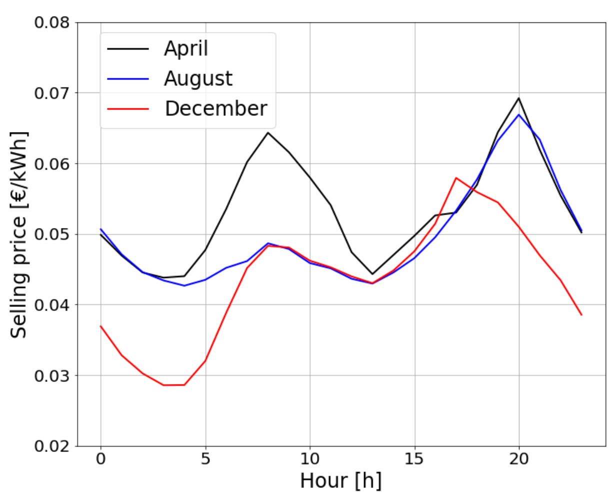


Figure 9. Daily profiles of the grid sale price for characteristic days of April, August and December in year 2019 in Italy [143].

Table 2. Input parameters associated with each technology, prices and incentives, and DR programs in the MILP optimization models [129, 133, 135, 144].

Type	Parameter	Value
Technology	A^{PV} [m^2]	2546 (200 kW_{el} is the maximum power produced)
	$P^{ICE,max}$ [kW_{el}]	200
	$P^{ICE,min}$ [kW_{el}]	50
	η^{PV} [kW_{el}/kW]	0.11
Prices and incentives	c_{biogas} [€/kWh]	0.055
	c_t^{imp} (without PBDR or with IBDR) [€/kWh]	0.19
	inc_{REC} [€/kWh]	0.12
DR	c_{base} [€/kWh]	0.06
	c_{peak} [€/kWh]	0.31
	c_{inter} [€/kWh]	0.19
	D^{var}	0.1
	El	-0.15
	inc_{IBDR} [€/kWh]	0.08

3.3. Results of the operation optimization and allocation of the total cost

Sub-Sections 3.3.1 and 3.3.2 present and discuss the results of the operation optimizations of the local power systems associated with the Citizen Energy Community (CEC) and the Renewable Energy Community (REC), respectively. Several optimizations are performed for the CEC and REC configurations, evaluating different aggregations of prosumers, and applying both Price-Based and Incentive-Based Demand Response programs (PBDR and IBDR, respectively). The complementarity of prosumers is studied considering three different couplings, i.e., the residential prosumer with *i)* the industrial one (Ind-Res), with *ii)* the agricultural one (Agr-Res) and with *iii)* the tertiary one (Ter-Res). The residential and the industrial/agricultural/tertiary prosumers are equipped with PV and ICE, respectively. The optimal daily operational costs of the systems are allocated to the members by implementing separately the two different cost allocation mechanisms, labelled C1 and C2, presented in sub-Section 3.2.2. It is worth recalling that mechanism C1 (based on Eq. (2.7) explained in sub-Section 2.3) can allocate lower costs to members who have a higher economic benefit in moving from the status of independent consumer to that of independent prosumer, while mechanism C2 allocates costs proportionally to the energy demand of members. Sub-Sections 3.3.1 and 3.3.2 report the outcomes obtained for the characteristic day of April, while the results referring to the characteristic days of December and August are summarized in Appendix C.

3.3.1. Citizen energy community

This sub-Section deals with the results of the CEC for the characteristic day of April. Figure 10 reports the optimal daily operational costs of the CEC and the costs allocated to its members (i.e., their bills), according to mechanisms C1 and C2, for all the couplings analysed (i.e., Ind-Res, Agr-Res and Ter-Res) in the basic "aggregation" case (i.e., without DR) and in the aggregations with DR programs as PBDR, and IBDR with a maximum hourly load change of 10 % (labelled IBDR1) and 20 % (labelled IBDR2). Table 3 displays the Self-Consumption (SC) values of the CEC without and with DR for all the couplings, and the economic savings achieved, compared to the basic aggregation case, when a DR program is implemented.

The highest degree of complementarity between prosumers is found with the Ind-Res coupling, which achieves the lowest cost (Figure 10) and the highest SC value (Table 3) of the system. For example, in the basic aggregation, the optimal daily operational cost and the SC of the system for Ind-Res (638.42 € and 94.07 %, respectively) are lower and higher than those for Agr-Res (807.68 € and 82.86 %) and Ter-Res (713.84 € and 85.12 %), respectively. Specifically, the optimal cost of the basic aggregation of Ind-Res is 21 % and 11 % lower than that of Agr-Res and Ter-Res, respectively. Ind-Res also shows lower costs and higher SC values compared to the other prosumer couplings in the operating conditions with DR programs. Note that in Figure 11 and in the following figures, the x-axis shows the hours of the day from 0 to 23, which represent one day. Figure 11 shows the separate daily operation of the industrial and residential prosumers, highlighting their input electricity demand (dashed black line), the power generated by PV or ICE (blue line) and the power exchanged with the grid (purchased in red and sold in green). The industrial prosumer can use the dispatchability of the ICE to help the residential prosumer meet its demand in the morning (e.g., hour 6) and part of the afternoon (e.g., hour 15), while the latter can partly satisfy the demand of the former by using PV production in the middle hours of the day, thus reducing the cost of biogas consumption for the industrial prosumer. The collaborative operation of the industrial and residential prosumers is therefore economically advantageous and highly recommended for the CEC configuration.

In each coupling, the specific cost allocation mechanism used (i.e., C1 or C2 in Figure 10) affects the individual costs (bills) of both prosumers, but not the total cost of the system. The application of the proposed allocation mechanism C1 results in lower daily costs for prosumers exploiting free-of-charge renewable sources (e.g., solar) compared to those using dispatchable sources (e.g., biogas). Specifically, with mechanism C1, the residential prosumer always obtains lower economic costs compared to the other prosumers due to the higher economic benefit obtained by changing its status from independent consumer to independent prosumer using a free-of-charge renewable source. For example, in the basic aggregation of coupling Ind-Res, the cost allocated to the residential prosumer is 28 % lower than that of the industrial prosumer with mechanism C1. As a result, the mechanism C1 proves to be favourable and fair to residential prosumers equipped with PV, thus encouraging them to participate in the EC, even though they cannot benefit from dispatchable power. Conversely, the application of mechanism C2 penalises the prosumer with the highest daily energy demand, i.e., the residential prosumer in the Ind-Res and Ter-Res couplings and the agricultural prosumer in the Agr-Res coupling (e.g., in Figure 10, with the Ind-Res coupling, the residential prosumer has a higher cost than that of the industrial prosumer overall the operating conditions when mechanism C2 is implemented).

As the Ind-Res coupling is the most convenient aggregation in economic and SC terms, the optimal power profiles of demand and generation are only shown for this case. Figure 12 shows the total electricity demand before and after DR (solid and dashed black lines, respectively), the power generated by ICE and PV (solid and dashed blue line, respectively) and the power exchanged with the grid (i.e., purchased in red and sold in green) for the CEC in the different operating conditions, i.e., the basic aggregation without DR (Figure 12(a)), the aggregation with the PBDR (Figure 12(b)), IBDR1 (Figure 12(c)) and IBDR2 (Figure 12(d)). Figure 12 shows that the power sold to the grid is close to zero in all the operating conditions, which means that the CEC has high values of renewable energy SC. Furthermore, the DR programs improve the SC of the system, which increases by about 2 % for PBDR and IBDR1, and by 6 % for IBDR2, with respect to the basic aggregation. Indeed, these DR programs reduce the net energy purchased from the grid and increase the PV consumption in the middle of the day (around hour 13), when the total power demand increases. Finally, Figure 12(d) shows that the IBDR2 represents the operating condition characterized by the most constant generation profile of the ICE, guaranteeing its optimal operation at maximum efficiency, and characterized by the minimum daily energy purchased from the grid, leading to the highest SC value of 99.68 % (Table 3).

It should be emphasised that the DR programs affect the individual demand profiles of EC members. For instance, Figure 13 shows the electricity demand before (solid line) and after (dashed line) the application of PBDR for both the industrial and residential prosumers in the Ind-Res coupling, where the TOU tariffs (i.e., peak, intermediate and base electricity prices, see sub-Section 3.2.3) are assigned to specific hours according to the optimal solution found (i.e., integer decision variables in the MILP optimization model allow to define a TOU tariff for each hour, see sub-Section 3.2.3). For both the residential and industrial prosumers, the PBDR leads to a general increase and decrease in the load demand in the morning and in the evening, in correspondence of the lowest and highest TOU tariffs of 0.06 €/kWh and 0.31 €/kWh, respectively. Moreover, Figure 13 shows that the application of the PBDR increases the electricity demand of both prosumers at hour 13, which explains the increase in the total demand of the CEC at the same hour, as shown in Figure 12(b).

The SC increase due to the DR strategies entails an increase in the economic savings for the whole CEC. For example, the total cost (Figure 10) with the IBDR1 program in the Agr-Res coupling (SC equal to 86.91 %) is 2.69 % lower (Table 3) than that in the basic aggregation (SC equal to 82.86 %). In all the couplings, the IBDR2 is the best DR program in economic terms (total costs and bills, Figure 10) and in terms of renewable energy self-consumption (SC, Table 3), due to the higher share of electricity demand that can be modified by the program (i.e., 20 %), whereas the PBDR and the IBDR1 show similar outcomes. For example, considering the Ter-Res coupling, the IBDR2 program leads to a SC of 92.74 % and to a total economic saving of 5.15 % (with respect to the basic aggregation), compared to the lower values of almost 89 % and 2.5 % obtained by both the PBDR and IBDR1 programs, respectively.

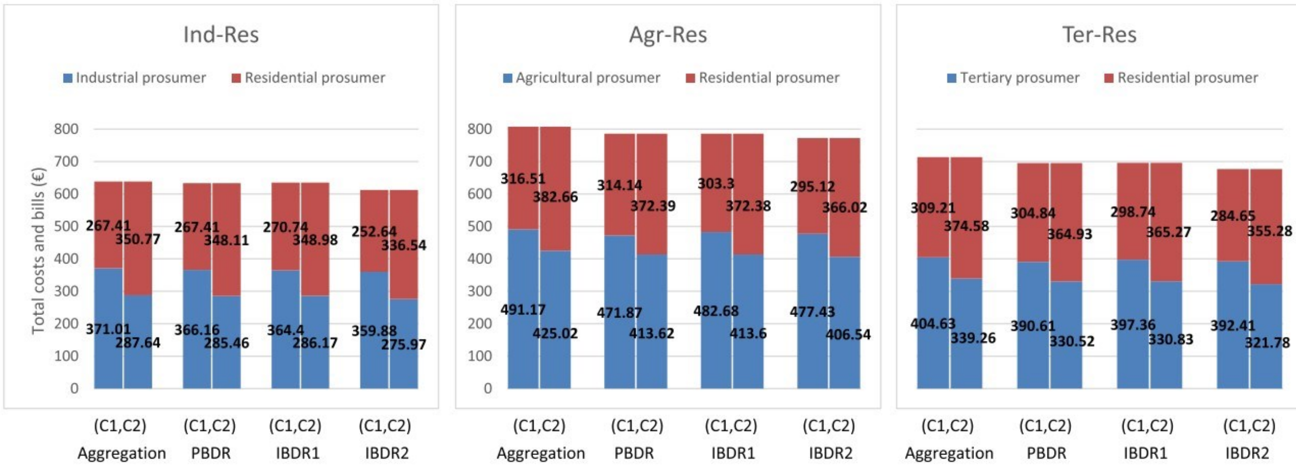


Figure 10. Economic results from the optimization of CEC in April. For each coupling of prosumers (i.e., Ind-Res, Agr-Res and Ter-Res), the optimal cost of the system and the costs allocated to the members (i.e., their bills) according to the allocation mechanisms C1 and C2 are shown in the basic "Aggregation" case without DR and in the aggregations with PBDR, IBDR1 and IBDR2. IBDR1 and IBDR2 refer to a maximum hourly load change of 10 % and 20 %, respectively.

Table 3. Self-consumption and total economic savings achieved through the application of the DR programs in the CEC.

	SC (%)			Economic savings compared to the basic aggregation (%)		
	Ind-Res	**Agr-Res**	**Ter-Res**	**Ind-Res**	**Agr-Res**	**Ter-Res**
Basic aggregation	94.07	82.86	85.12	-	-	-
PBDR	95.61	86.91	88.93	-0.76	-2.68	-2.58
IBDR1	96.11	86.91	88.8	-0.51	-2.69	-2.49
IBDR2	99.68	89.42	92.74	-4.06	-4.35	-5.15

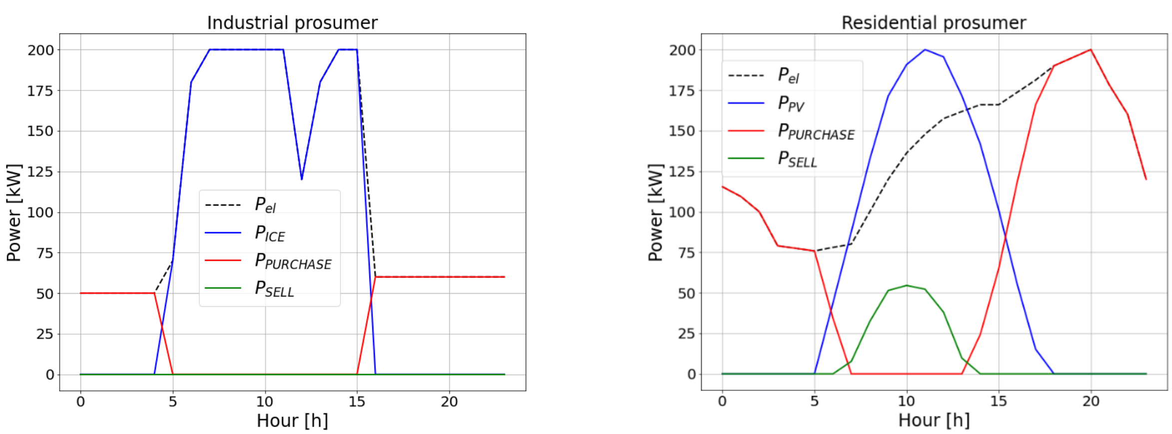


Figure 11. Electricity demand (P_{el}), power generated by ICE (P_{ICE}) or PV (P_{PV}) and power purchased from ($P_{PURCHASE}$) and sold to (P_{SELL}) the grid in the separate operation of the industrial (left) and residential (right) prosumers.

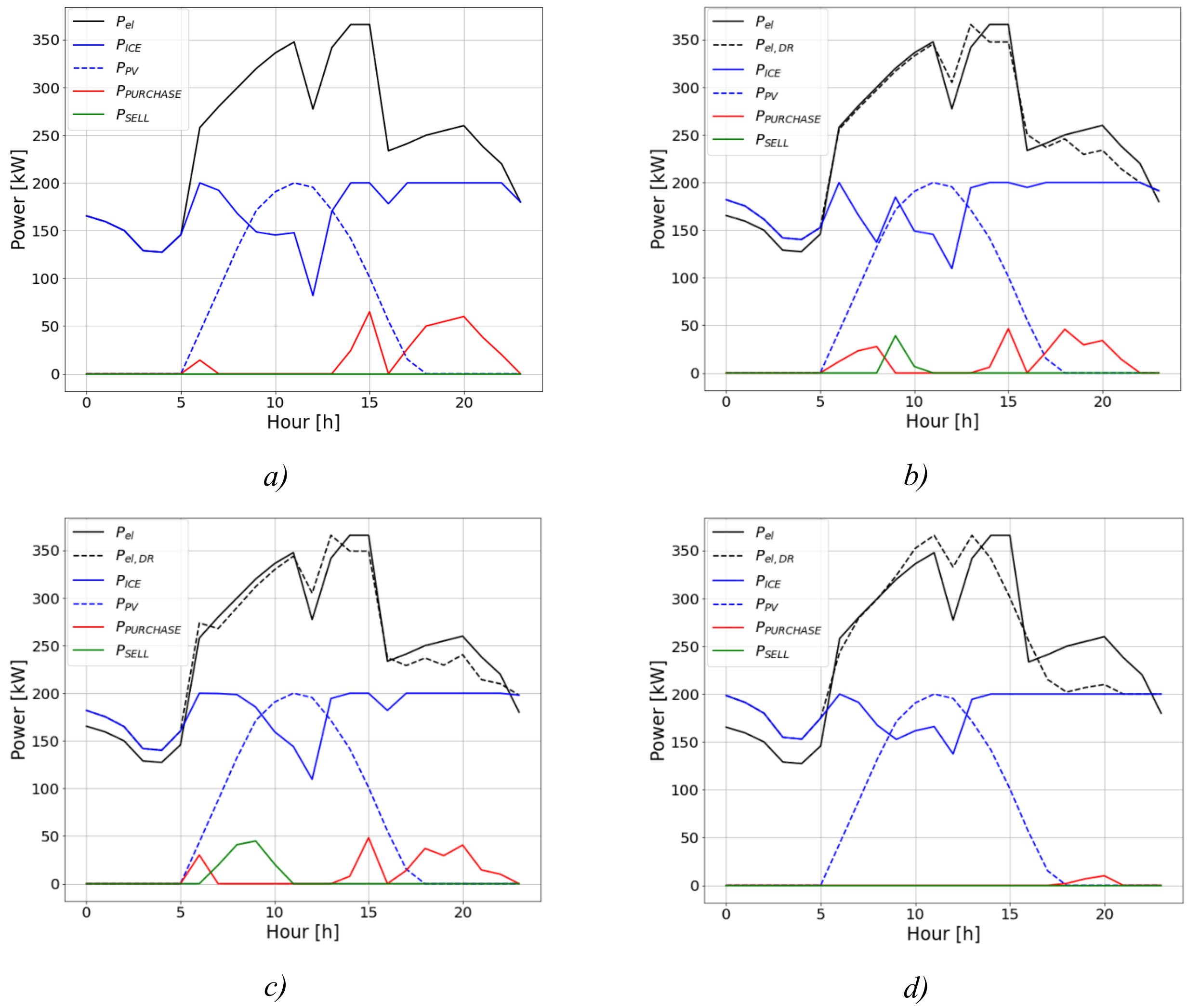


Figure 12. Electricity demand before (P_{el}) and after DR ($P_{el,DR}$), power generated by ICE (P_{ICE}) and PV (P_{PV}), and power purchased from ($P_{PURCHASE}$) and sold to (P_{SELL}) the grid for the CEC with the Ind-Res coupling a) in the basic aggregation without DR, with b) PBDR, c) IBDR1 and d) IBDR2.

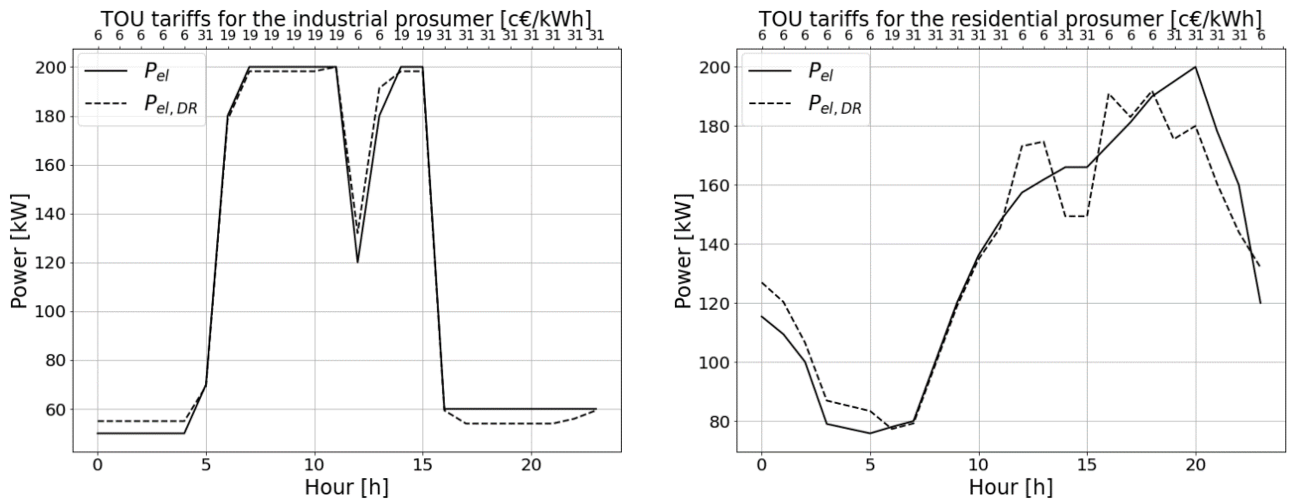


Figure 13. Electricity demand before (solid line) and after (dashed line) the application of the PBDR for the industrial (left) and residential (right) prosumers in the Ind-Res coupling. A TOU tariff is allocated to each hour according to the solution of the optimization problem.

3.3.2. Renewable energy community

This sub-Section presents and discusses the results of the REC, without and with the incentive for shared energy (see sub-Section 3.2.4), obtained for the characteristic day of April. Figure 14 displays the total costs of the REC and the costs allocated to its members, considering all the couplings and operating conditions described in sub-Section 3.3.1, now differentiating the case without and with the incentive for shared energy. Table 4 and Table 5 show the SC values of the REC and its economic benefits owing to the DR programs, without and with the incentive for shared energy, respectively.

In general, it is found that Ind-Res is the best coupling for the REC, except with the PBDR operating condition where Ter-Res coupling leads to lower costs as shown in Figure 14. In the REC with incentive, the optimal daily operational cost of the system with basic aggregation of Ind-Res is 722.65 €, which is 19 % and 9 % lower than that of Agr-Res (896.02 €) and Ter-Res (794.42 €), respectively. In the REC with incentive, the implementation of the PBDR program leads to a total cost of Ter-Res (339.41 €) that is 9 % and 14 % lower compared to that of Ind-Res (372.66 €) and Agr-Res (394.84 €), respectively. In fact, in this case, the tertiary prosumer is more successful than the other prosumers in profitably modifying its demand loads to match the lowest TOU electricity tariffs provided by the PBDR program.

In the case of REC without incentive, it is more cost effective to increase the purchase of power from the grid than to consume biogas, which leads to switch off the ICE during the optimal operation of the local power system of the REC. Consequently, a low and constant SC (from 21.83 % to 25.32 % for the different couplings, Table 4) is obtained due to the constant and low PV-only generation. Moreover, Figure 14 shows that in the case without the incentive for the REC, the proposed allocation mechanism C1 benefits the residential prosumer only if the PBDR is applied (regardless of the coupling) or in the Agr-Res coupling (without or with DR). For example, in the REC without incentive, considering the Agr-Res coupling and the PBDR program, the cost allocated to the residential prosumer (223.27 €) is 28 % lower compared to that of the agricultural prosumer (308.73 €) according to mechanism C1. The application of the cost allocation mechanisms C1 and C2 to the REC with incentive leads to similar findings compared to the CEC (see Figure 14 below and Figure 10 in sub-Section 3.3.1, respectively). For example, in the basic aggregation of coupling Ind-Res, the cost allocated to the residential prosumer is 17 % lower than that of the industrial prosumer with mechanism C1. Moreover, comparing Figure 14 (for REC) and Figure 10 (for CEC) and looking at the Ind-Res coupling with PBDR, the criterion C1 shows lower costs for the residential prosumer (125.88 € and 267.41 € for REC and CEC) compared to the industrial one (246.78 € and 366.16 € for REC and CEC).

Note that the SC of the REC with incentive (Table 5) decreases from the basic aggregation to the operating condition with PBDR (e.g., for Ter-Res the SC is reduced from 83.93 % to 81.09 %). Indeed, the TOU tariffs of the PBDR cause the hourly energy demand (i.e., the energy purchased from the grid for the REC, see sub-Section 3.2.4) to increase compared to the hourly energy production. Figure 15 shows that the difference between hourly energy demand and generation is almost the same for the basic aggregation (red bars) and PBDR (green bars) for all hours, except for hour 15, where this difference is much higher with PBDR. Consequently, when PBDR is applied to the REC, the overall effect could be an increase in the energy demand purchased from the grid in some hours, leading to a reduction in the SC compared to the basic aggregation, contrary to what happens in the CEC. On the other hand, the application of IBDR1 and IBDR2 to the REC bring higher values of the SC (for the REC with incentive) and lower values of the total costs compared to the basic aggregation, as reported in Table 5 and Figure 14. In the REC with incentive, considering the Ter-Res coupling, the application of the IBDR1 and IBDR2 programs increases the SC by 6 % and 10 %, respectively, and reduces the total costs by 5 % and 9 %, respectively. Figure 14 also shows that in the REC, both without and with incentive, the best DR program is PBDR, which approximately halves the total costs compared to the basic aggregation case without DR (e.g., in the REC with incentive, with Ter-Res coupling, PBDR significantly reduces the total cost by 57 % compared to the basic aggregation case).

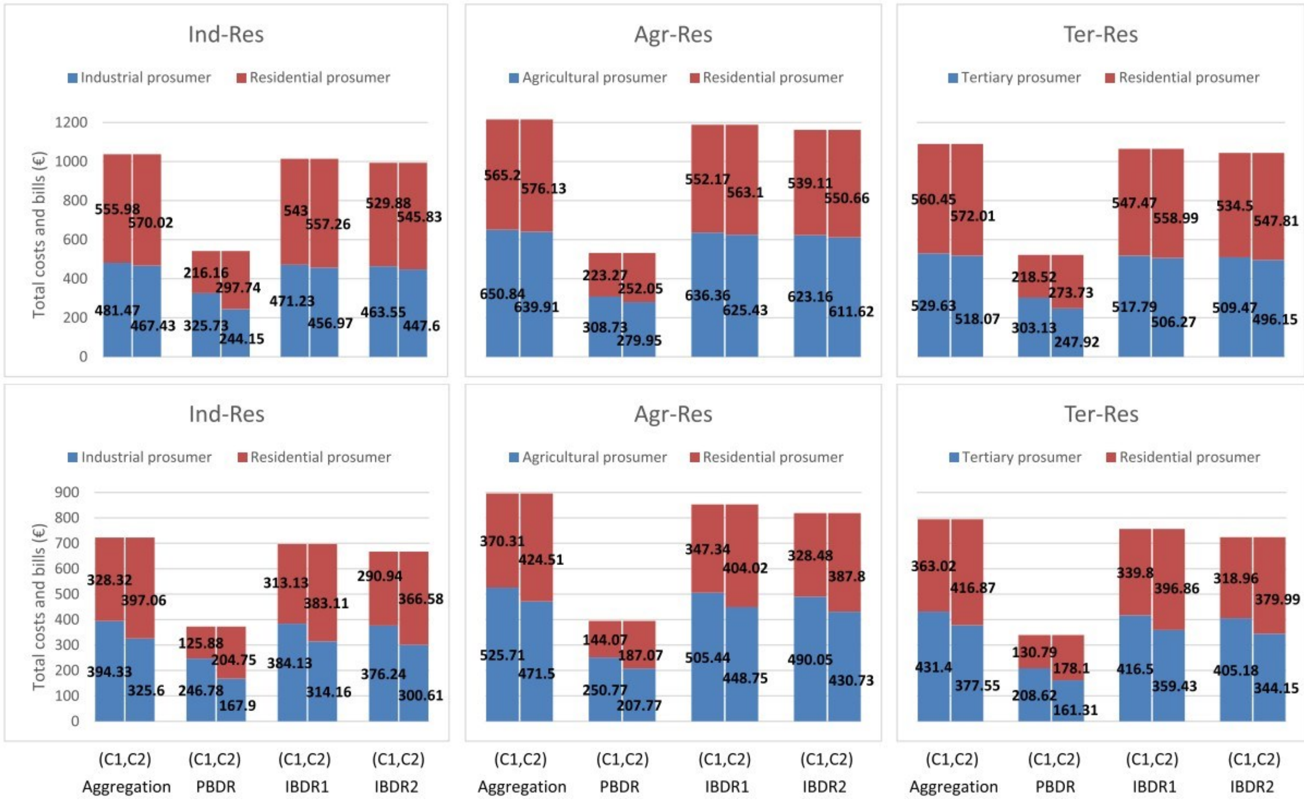


Figure 14. Economic results from the optimization of REC without (above) and with incentive (below) in April.

Table 4. Self-consumption and total economic savings achieved through the application of the DR programs in the REC without incentive.

	SC (%)			Economic savings compared to the basic aggregation (%)		
	Ind-Res	**Agr-Res**	**Ter-Res**	**Ind-Res**	**Agr-Res**	**Ter-Res**
Basic aggregation	25.32	21.83	24.18	-	-	-
PBDR	25.32	21.83	24.18	-47.77	-56.25	-52.15
IBDR1	25.32	21.83	24.18	-2.24	-2.26	-2.28
IBDR2	25.32	21.83	24.18	-4.24	-4.42	-4.23

Table 5. Self-consumption and total economic savings achieved through the application of the DR programs in the REC with incentive.

	SC (%)			Economic savings compared to the basic aggregation (%)		
	Ind-Res	**Agr-Res**	**Ter-Res**	**Ind-Res**	**Agr-Res**	**Ter-Res**
Basic aggregation	92.69	82.86	83.93	-	-	-

PBDR	88.9	76.8	81.09	-48.43	-55.93	-57.28
IBDR1	95.87	86.88	89.37	-3.51	-4.83	-4.8
IBDR2	99.05	89.35	92.47	-7.68	-8.65	-8.85

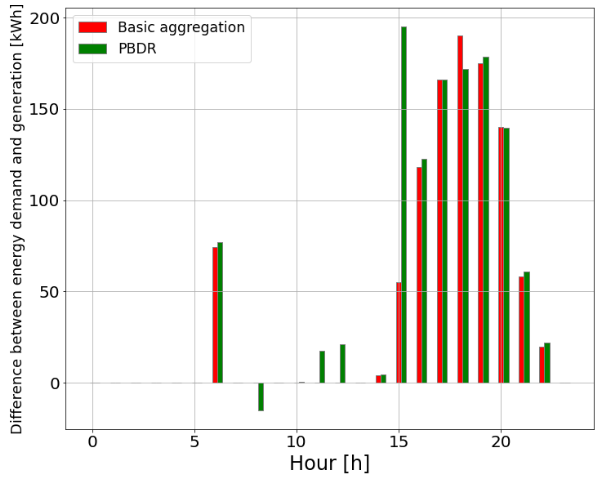


Figure 15. Hourly differences between energy demand and generation for the REC with incentive, considering the Ter-Res coupling in the basic aggregation (red bars) and with PBDR (green bars).

3.3.3. Main findings

This sub-Section summarizes the most relevant findings from the CEC and REC optimizations for the characteristic day of April (sub-Sections 3.3.1 and 3.3.2, respectively), while the findings for the characteristic days of December and August are summarized in Appendix C. The main findings are:

- In almost all cases (i.e., CEC and REC configurations with or without DR programs), *Ind-Res is found to be the prosumer coupling that leads to the lowest costs.* For example, in the basic aggregation (i.e., without DR) of CEC (REC with incentive) the optimal cost of Ind-Res is 21 % (19 %) and 11 % (9 %) lower than that of Agr-Res and Ter-Res, respectively.
- The cost allocation mechanism C1 successfully leads to lower costs for the residential prosumer (compared to the other prosumer in each coupling) in both the CEC and the REC with incentive, whereas in the REC without incentive only in the Agr-Res coupling or when the PBDR is applied. *Considering the basic aggregation of the best coupling Ind-Res, the application of the novel mechanism C1 to the CEC (or REC with incentive) results in a cost of the residential prosumer equipped with PV that is 28 % (or 17 % for the REC with incentive) lower than that of the industrial prosumer equipped with ICE, respectively.*
- *In the CEC, the PBDR and IBDR1 programs reduce the total costs by 0.6 %, 2.7 % and 2.5 % (Ind-Res, Agr-Res and Ter-Res), whereas the IBDR2 program by around 4-5 % across the different couplings. In the REC, PBDR is the most effective program with cost savings of 48 %, 56 % and 57 % (Ind-Res, Agr-Res and Ter-Res), while the IBDR programs do not allow to obtain savings higher than 8-9 %.* Moreover, in the CEC, the DR programs always improve the complementarity between prosumers and, in turn, the SC (by 2-6 %, 5-8 % and 4-9 % in Ind-Res,

Agr-Res and Ter-Res). On the other hand, in the REC with incentive, only the IBDR programs enhance the SC with respect to the basic aggregation (by 3-7 %, 5-8 % and 6-10 % in Ind-Res, Agr-Res and Ter-Res) contrary to the PBDR (-4 %, -7 % and -3 % in Ind-Res, Agr-Res and Ter-Res). In fact, the economically favourable TOU tariffs of the PBDR program promote the purchase of more electrical power from the grid in some hours, thus lowering the SC of the REC.

- *The CEC reports lower costs and higher self-consumption values compared to the REC in all couplings and operating conditions except for the PBDR case.* In fact, the CEC usually imports less power from the grid than the REC, leading to higher SC values. For example, in the basic aggregation of the Ind-Res coupling, the CEC (SC of 94.07 %) has total costs 12-38 % lower than the REC with-without incentive (SC of 92.69-25.32 %), respectively. Conversely, the application of PBDR allows REC to achieve lower costs than CEC through the optimal shifting of total electricity demand driven by the TOU tariffs of the PBDR program. Moreover, the CEC configuration presents the highest value of SC equal to 99.68 %, which is obtained with the Ind-Res coupling and with application of the IBDR2 program.

3.4. Conclusions

Section 3 fulfils the first objective of this Thesis (see sub-Section 1.2), i.e., to evaluate the main aspects affecting the optimal aggregation of end users, representative of different consumption sectors, in different Energy Community (EC) configurations, and to assess the weights of these aspects in terms of economic benefits for the whole system and its members. The first reference case study in this Section 3 deals with the operation optimization of the local power systems associated with the Citizen Energy Community (CEC) and the Renewable Energy Community (REC) in the absence of uncertainties. In this first reference case study, uncertainties are not considered in the optimization to identify and evaluate only the aspects that influence the aggregation of end users in ECs, thus keeping the optimization models as simple as possible without analysing the effect of uncertainties.

The innovative contribution of this work lies in the identification and comprehensive assessment of the main aspects affecting the aggregation of end users in ECs and their economic convenience, i.e.: the complementarity between the energy demand and generation profiles of different end users, the mechanisms to distribute the total cost of the EC among its members and the application of Demand Response (DR) programs (see Figure 4). Two Mixed Integer Linear Programming (MILP) models of the CEC and REC are used to conduct several optimizations considering different couplings of prosumers, equipped with PV plants or ICE (maximum generated power of 200 kW to comply with the Italian legislation), with electricity demand profiles that are representative of the residential (Res), industrial (Ind), agricultural (Agr) and tertiary (Ter) sectors. Price-Based Demand Response (PBDR) and Incentive-Based Demand Response (IBDR) programs can be introduced in the MILP models of the ECs to optimally shift end-user electricity demands through time-varying grid prices and incentives, respectively. In addition, two different mechanisms are implemented after the optimization to allocate the optimal daily operational cost of the system to its members. The proposed mechanism C1 rewards more those end users who achieve higher economic benefits by becoming independent prosumers compared to the status of independent consumers. Mechanism C2, based on an average price within the EC, distributes the total benefit of the system among the members in proportion to the ratio between their individual electricity demand and the total demand.

The main findings of this work allow to point out the following general guidelines, which include the weights of the analysed aspects in economic terms, to achieve an optimal aggregation of end users within an EC:

1) A good complementarity between different prosumers is crucial to exploit smartly the combination of dispatchable and non-dispatchable energy sources. For instance, coupling a PV-equipped residential prosumer with another ICE-equipped prosumer from the industrial-agricultural-tertiary sector allows the prosumer with PV to consume dispatchable power from the ICE when solar energy is not available, while covering the potential demand peaks of the prosumer with ICE through PV. Ind-Res and Agr-Res are the prosumer couplings characterized by the higher and lower degrees of complementarity, respectively, with the former having optimal daily costs 17-21 %, 14-15 %, 16-19 % (over the three characteristic days analysed) lower than the latter for basic aggregations (i.e., without DR) of CEC, REC without and REC with incentive.
2) In addition to complementarity, an effective cost allocation mechanism must be applied to distribute the optimal economic benefit of the EC among its members. In general, the novel allocation mechanism C1 results more successful in distributing lower costs to the more virtuous prosumer using a free-of-charge and non-dispatchable RES (i.e., solar), compared to the traditional mechanism C2, which allocates higher costs to prosumers having higher energy demands. The implementation of the mechanism C1 permits the residential prosumer equipped with PV to benefit from a daily cost that is 17-20 % and 28-30 % (April-August) lower compared to that of the industrial prosumer in the REC with incentive and in the CEC, respectively. Thus, C1 favours the residential prosumer, who achieves the better compromise between maximum self-generation from RES and minimum cost for it.
3) In addition to the complementarity and independently of the cost allocation mechanism, further economic savings are obtained at the community level by profitable changes of the demand profiles with DR programs. IBDR2 (i.e., with a maximum hourly shifting of the load demand of 20 %) and PBDR are the best DR programs for the CEC and REC, with economic savings of 4-5 % and 48-62 % (over the three characteristic days) respectively, compared to the basic aggregation.

In summary, the general guidelines show that: *1) the complementarity of end users may reduce the total cost of the local power system of an EC in the order of 15-20 %, 2) an effective cost allocation mechanism may reduce the costs of prosumers using free-of-charge renewables by 20-30 % compared to those using dispatchable sources, and 3) PBDR programs may reduce the total cost of the system even beyond 50 %.* The CEC is the best EC configuration in terms of lowest total costs (12-39 % lower than those of the REC) and highest self-consumption values (up to 99.68 %). On the other hand, the REC (supported by a government incentive) is economically preferred to the CEC when the PBDR program is applied.

These numbers provide a realistic quantitative indication of the economic advantages deriving from building an EC, and of the need to consider all the mentioned aspects together to correctly assess its positive economic impact. It is worth highlighting that the general guidelines are based on the results of several optimizations carried out considering different seasonal days, configurations of ECs, couplings of prosumers, DR programs and cost allocation mechanisms. Moreover, the general validity of the achieved guidelines relies on the strength of the global solutions attained by the optimization procedure, which is solved by the linear-programming based branch-and-bound algorithm ensuring the global optimality of the solutions. The general guidelines highlight the role of end users with complementary demand and generation profiles, which are typical of different consumption sectors (e.g., industrial and residential), in promoting the formation and spread of future ECs. The new cost allocation mechanism indicated as C1 could be proposed to foster the formation of ECs in locations with high availability of free-of-charge RES, thus attracting independent prosumers using these sources to join the EC. In addition, policy makers could develop energy policies to propose new market mechanisms, including tailored incentives and DR programs, with the aim of promoting the diffusion of RECs and enhancing their economic competitiveness with respect to CECs.

It should be noted that the allocation mechanism C1 could be only perceived as fair by prosumers using free-of-charge RES and might not be accepted by other types of prosumers in an EC (e.g., those using dispatchable sources such as the biogas). Moreover, mechanism C1 does not consider the contribution of each member of the EC to the total economic benefit of the system, which calls for further investigation of the concept of "fairness" in the allocation of the total cost/profit of an EC. The next Section 4 focuses specifically on the fair allocation of the total economic benefit of an EC through the application of a cooperative game-based mechanism.

4. Second reference case: operation optimization of a local power system with aggregation of different electricity demands in absence of uncertainty, and fair allocation of the operational economic profit

This Section presents the second reference case study of this Thesis, which deals with the fair distribution of the operational economic benefit of an Energy Community (EC) among its members. This is a prominent issue that has already been introduced and discussed in sub-Sections 1.1 and 1.3.2. The previous Section 3 has discussed two different mechanisms to distribute the operational costs of the local power systems of ECs among the members, but the fairness of this distribution has not been analysed. Hence, without claiming to provide a definitive and unique solution to the problem of the fair cost/profit allocation, which is probably pointless since there is no unique definition of fairness, this Section aims to provide a basic insight into how a possible fair allocation of the optimal economic benefit of an EC might look like. This is in line with the first objective of this Thesis (see sub-Section 1.2), i.e., to clearly evaluate the aspects (including the fair allocation of the economic benefit) that influence the optimal aggregation of end users in an EC, and to quantify the weights of these aspects in the economic benefits of the EC and of its members. Sub-Section 4.1 introduces the case study, which focuses on the operation optimization of a local power system of a Renewable Energy Community (REC) in the absence of uncertainty, with the successive application of allocation mechanisms to distribute the optimal operational economic benefit. Sub-Section 4.2 presents the developed Mixed Integer Linear Programming (MILP) model for the operation optimization of the system, the fair and unfair allocation mechanisms, and the input data. Sub-Section 4.3 summarizes the main results. Sub-Section 4.4 outlines the conclusions of the Section. It should be noted that some parts of this Section are derived from a paper written by the author of this Thesis [109].

4.1. Case study: local power system of the renewable energy community

The problem addressed in Section 4 is the assessment of the operational cost/profit allocation of an EC in terms of fairness to its members. Figure 16 shows the local power system with fixed design (i.e., the sizes of the energy units are known) of the Renewable Energy Community (REC) under analysis. It consists of three members, one consumer from the tertiary (Ter) sector and two prosumers representing the residential (Res) and commercial (Com) sectors (the electricity demands of these end users are reported in sub-Section 4.2.3), where the prosumers use solar Photovoltaic (PV) and Electrical Energy Storage (EES) units. The features of the REC configuration are not reported here as they have already been described in detail in sub-Sections 1.3.2 and 3.1.

A Mixed Integer Linear Programming (MILP) model is used to optimize only the daily operation of the local power system of the analysed REC (according to the formulation of the optimization problem (2.1) in sub-Section 2.1, with fixed sizes of the energy units). After finding the solution of the MILP operation optimization model, the Shapley value mechanism [73], based on a cooperative game model, is applied to fairly distribute the optimal economic benefit of the system among the end users. Finally, the fair allocation by Shapley value is compared with that obtained by applying a Uniform pricing mechanism [45, 72], which, unlike Shapley value, is not based on a cooperative game model and therefore does not consider the cooperation between the end users of the system in the process of cost/profit allocation.

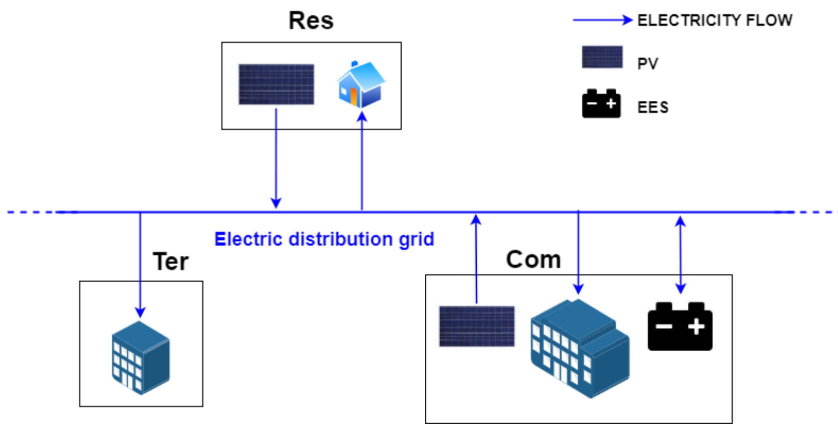


Figure 16. Local power system of the REC configuration comprising a tertiary (Ter) consumer, a residential (Res) prosumer equipped with a PV plant and a commercial (Com) prosumer equipped with a PV plant and an EES unit.

Beyond some general assumptions already reported in sub-Section 1.4, the main assumptions and boundary conditions considered in this case study are presented below.

- A local power system (i.e., managing only the production and demand of electricity) is considered for the REC, modelled according to the Italian legislation [39]. The MILP model of the system includes only operational decision variables, while the design variables (sizes of the energy units) are input parameters. For simplicity and without loss of generality, it is assumed that the residential prosumer owns only a PV plant (peak power of around 10 kW_{el}), while the commercial prosumer owns a PV plant (peak power of around 42 kW_{el}) and an EES unit (capacity of 50 kWh). Moreover, these users individually bear the investment costs of their energy units.
- As in the first reference case study in Section 3, uncertainty is neglected to keep the developed MILP optimization model as simple as possible, allowing only the fair distribution of the operational economic benefit of the system to be clearly assessed, which is the focus of this Section.
- The optimization aims at maximizing the daily operational profit of the system for a characteristic day of April, considering the location of Padova (Italy). According to the focus of this case study, the optimization of the operation of the system for one day is sufficient to subsequently conduct a basic and preliminary analysis of the fair distribution of the total economic benefit.
- The MILP optimization model includes Demand Response (DR) constraints to achieve the optimal shifting of the hourly load demands of the end users. Specifically, the DR implemented in this work is based on a Price-Based Demand Response (PBDR) program with a Real Time Pricing (RTP) strategy [32], which sets a daily profile of the grid purchase price that follows the daily profile of the Day-Ahead (DA) market price. In the RTP strategy, the grid purchase prices are usually different for each hour of the day, in contrast to the TOU strategy (see sub-Section 3.2.3), which sets two or three different hourly prices per day.
- The definition of fairness in the allocation of the economic benefit of the system to its members is consistent with that of the Shapley value mechanism (see sub-section 2.3), which allocates costs/profits to the members in proportion to their contributions to the costs/profits of the system

and its internal coalitions of members. As shown in the literature [78], the Shapley value ensures that the cost allocation is perceived as fair by the EC members. Other allocation mechanisms that do not meet this definition of fairness, such as Uniform pricing, are considered unfair. As the focus of this Section is on the daily operation optimization of a REC with fixed design, the analysis of fairness in allocating the optimal economic benefit is limited to the daily operational profit of the system. Hence, the investment costs of the energy units, which represent a small part of the daily costs to the members, are not evaluated in the daily benefit allocation (as assumed in the previous sub-Section 3.1).

4.2. Methods

This sub-Section focuses on the methodology used in this case study. Sub-Section 4.2.1 presents the Mixed Integer Linear Programming (MILP) model to optimize the operation of the local power system of the analysed REC. Sub-Section 4.2.2 specifies the implemented allocation mechanisms to distribute the operational economic benefit of the system. Sub-Section 4.2.3 lists the input data of the optimization models.

4.2.1. MILP model for the operation optimization of the local power system of the renewable energy community

This sub-Section presents the constraints and objective function of the MILP model used to optimize only the daily operation (with hourly time resolution) of the local power system of the REC (see Figure 16 in sub-Section 4.1), the design of which is fixed (i.e., the sizes of the units are input parameters). Hence, the decision variables in the operation optimization of the analysed system are the energy stored of EES ($E_{i,t}^{EES}$), its charging/discharging power ($P_{i,t}^{EES,+}$/$P_{i,t}^{EES,-}$), the binary variable indicating its state of charging/discharging ($\delta_{i,t}^{EES,+}$/$\delta_{i,t}^{EES,-}$), and the shifted electricity demands of users due to the application of the PBDR with RTP strategy ($E_{i,t}^{el,shift}$, see the assumptions in the previous sub-Section). The Gurobi software [139] is used to develop and solve the optimization model.

The operation of the PV plant for a member i of the REC (i.e., the residential or commercial prosumers, see sub-Section 4.1) is described by Eq. (4.1):

$$P_{i,t}^{PV} = \eta^{PV} \cdot A_i^{PV} \cdot I_t^{PV} \tag{4.1}$$

where $P_{i,t}^{PV}$[kW$_{el}$] is the electrical power generated by the PV plant at hour t, η^{PV} [kW$_{el}$/kW] is the efficiency of the PV plant, A_i^{PV} [m^2] is the available PV area and I_t^{PV} [kW/m^2] is the global solar irradiance (on a tilted surface) at hour t.

The operation of the Electrical Energy Storage (EES) unit for member i (i.e., the commercial prosumer, see sub-Section 4.1) is given by the following equations and constraints:

$$E_{i,t}^{EES} = E_{i,t-1}^{EES} + P_{i,t}^{EES,+} \cdot \eta^{EES,+} \cdot \Delta t - \frac{P_{i,t}^{EES,-} \cdot \Delta t}{\eta^{EES,-}} \tag{4.2}$$

$$E_{i,t}^{EES} \leq cap_i^{EES} \tag{4.3}$$

$$P_{i,t}^{EES,+} \leq P_i^{EES,peak} \cdot \delta_{i,t}^{EES,+} \tag{4.4}$$

$$P_{i,t}^{EES,-} \leq P_i^{EES,peak} \cdot \delta_{i,t}^{EES,-} \tag{4.5}$$

$$\delta_{i,t}^{EES,+} + \delta_{i,t}^{EES,-} \leq 1 \tag{4.6}$$

$$E_{i,24}^{EES} = E_{i,1}^{EES} \tag{4.7}$$

Eq. (4.2) describes the energy balance of the EES unit, where $E_{i,t}^{EES}$ [kWh], $P_{i,t}^{EES,+}/P_{i,t}^{EES,-}$ [kW$_{el}$], $\eta^{EES,+}/\eta^{EES,-}$ [-] and Δt [h] are, respectively, the hourly energy stored, the hourly charging/discharging power, the charging/discharging efficiency of the EES unit and the time step of the optimization, i.e., one hour. Constraint (4.3) states that the energy stored in the EES unit at hour t is bounded by cap_i^{EES} [kWh], which is the capacity of the EES. Constraints (4.4) and (4.5) bound the power charging and discharging of the EES unit by $P_i^{EES,peak}$ [kW$_{el}$], which is the maximum allowed power that can be charged/discharged into/from the EES. Constraint (4.6) avoids that the EES unit is charging and discharging at the same hour t, where $\delta_{i,t}^{EES,+}$ and $\delta_{i,t}^{EES,-}$ are the binary variables indicating the state of charging and discharging of EES at hour t (i.e., the optimal values of $\delta_{i,t}^{EES,+}$ and $\delta_{i,t}^{EES,-}$ are 1 and 0 respectively when the EES is charging, while the optimal values are 0 and 1 respectively when the EES is discharging). Eq. (4.7) states that the energy stored in the EES unit at the first hour of the day is equal to the energy stored at the last hour of the same day, which reflects the daily operation of the EES unit.

The members of the REC have shiftable electricity demands (see sub-Section 4.1) driven by a Price-Based Demand Response (PBDR) program with Real Time Pricing (RTP). The PBDR constraints are not reported here as they are equivalent to constraints (3.5)-(3.7) shown in sub-Section 3.2.3. It should be noted that the PBDR constraints are the same regardless of the pricing strategy used (i.e., Time-of-Use in Section 3 and RTP here), although the optimal values of the shifted electricity demands are affected by the different electricity prices set according to the chosen pricing strategy.

The REC configuration is modelled according to the Italian legislation (see sub-Section 4.1), which foresees that the shared energy among the members of the REC takes place within the electrical distribution grid. As introduced for the REC in Section 3, the total energy withdrawn from ($E_{withdrawn,t}$) and injected to ($E_{injected,t}$) the grid is calculated according to Eq. (4.8) and Eq. (4.9), respectively:

$$E_{withdrawn,t} = \sum_{i=1}^{N} (E_{i,t}^{el,shift} + E_{i,t}^{EES,+}) \tag{4.8}$$

$$E_{injected,t} = \sum_{i=1}^{N} (E_{i,t}^{PV} + E_{i,t}^{EES,-}) \tag{4.9}$$

where $E_{i,t}^{el,shift}$, $E_{i,t}^{PV}$, $E_{i,t}^{EES,+}/E_{i,t}^{EES,-}$ [kWh] and N are the shifted electricity demand, the energy generated by PV, the energy charged/discharged into/from the EES unit, for member *i* at hour t, and N is the number of members in the REC, respectively.

The shared energy among the members of the REC is:

$$E_{s,t} = min(E_{withdrawn,t}, E_{injected,t}) \tag{4.10}$$

The objective function to be maximized is the total daily profit of the local power system of the REC:

$$c_{REC} = \sum_{t=1}^{24} (E_{injected,t} \cdot c_t^{exp} - E_{withdrawn,t} \cdot c_t^{imp}) + inc_{REC} \cdot \sum_{t=1}^{24} E_{s,t} \tag{4.11}$$

where c_t^{exp} [€/kWh], c_t^{imp} [€/kWh] and inc_{REC} [€/kWh] are, respectively, the grid sale price, the grid purchase price and the incentive of the REC for the shared energy. The first summation represents the difference between the revenue from the energy sold to the grid ($E_{injected,t} \cdot c_t^{exp}$) and the cost for the energy purchased from the grid ($E_{withdrawn,t} \cdot c_t^{imp}$). The last term is the revenue due to the incentive for the shared energy.

4.2.2. Fair and unfair allocation of the total profit of the system

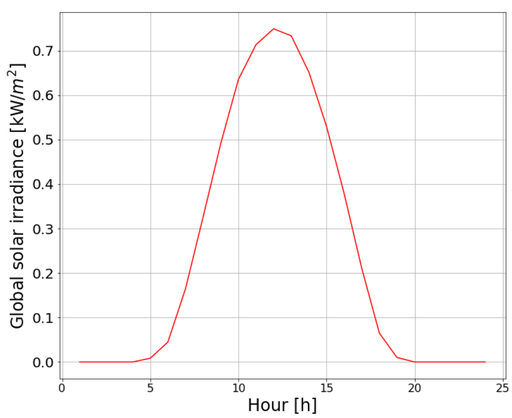
As shown in Section 3, the allocation of the total economic benefit of an EC is one of the main aspects affecting the optimal aggregation of end users and their economic costs/profits in ECs. In particular, the perception of fairness of the cost/profit allocation by the members of an EC is a factor that should not be neglected to ensure the correct formation and long-term stability of an EC. In this case study, Shapley value and Uniform pricing are applied as mechanisms to allocate the optimal economic benefit of the local power system of the REC.

The allocation mechanism of Shapley value [73], based on the cooperative game theory [128], is chosen to achieve a fair distribution of the total economic benefit of the system among its participants. Shapley value is considered a fair allocation mechanism because it allows the total economic benefit to be distributed among the members of the EC by weighting their contributions not only to the optimal economic benefit of the system, but also to the optimal economic benefits of all coalitions of the EC in which they participate. After solving the MILP optimization model of the system (sub-Section 4.2.1), the Shapley value is applied through Eq. (2.9) (reported in sub-Section 2.3) to fairly allocate the optimal daily profit of the system to its members. Note that in Eq. (2.9) the "value" function associated with a coalition of members within the REC corresponds to the optimal economic benefit achieved by only that coalition. The optimal economic benefit of a coalition is obtained by solving the optimization model (sub-Section 4.2.1) considering only the constraints associated with the energy units of the members in that coalition (see also the results in Section 4.3). Sub-Section 2.3 provides further details on the application of Shapley value.

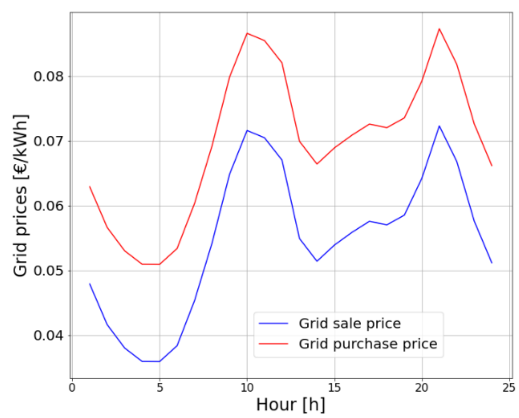
The allocation mechanism of Uniform pricing [45, 72] is simple to implement and well accepted by network regulators [145], but it does not adhere to the definition of fairness given by the Shapley value and is therefore considered an unfair allocation mechanism (see sub-Section 4.1). After the MILP optimization, Uniform pricing is applied to allocate the optimal economic benefit of the system to its members in proportion to the ratio between their individual electricity demand and the total demand. The mechanism charges the electricity demands of members with a uniform price, which is calculated as the ratio between the optimal economic benefit and the total demand of the system.

4.2.3. Input data

Figure 17(a) and (b) show, respectively, the profile of the global solar irradiance on an inclined surface (optimal tilted angle of 38°) for the location of Padova (Italy) derived from the PVGIS database [142], and the profiles of the grid purchase and sale prices [143], on a characteristic day of the spring season. It should be noted that the daily profile of the grid purchase price according to the PBDR program with RTP strategy is obtained by that of the grid sale price, which follows the day-ahead market price in Italy. Figure 18 reports the daily electricity demands of the end users, within the analysed REC, that are representative of the tertiary (consumer "Ter"), residential (prosumer "Res") and commercial (prosumer "Com") sectors [146]. Given the chosen electricity demands, it is worth highlighting that the REC has a heterogeneous composition, which improves its operational flexibility. Table 6 lists the values of other input parameters for the MILP model presented in sub-Section 4.2.1 [39, 129, 147-149], such as the incentive of the REC for shared energy [129].



a)



b)

Figure 17. a) Global solar irradiance on an inclined surface (optimal tilted angle of 38°) in Padova (Italy) [142] and b) grid purchase and sale prices [143], on a characteristic day of spring.

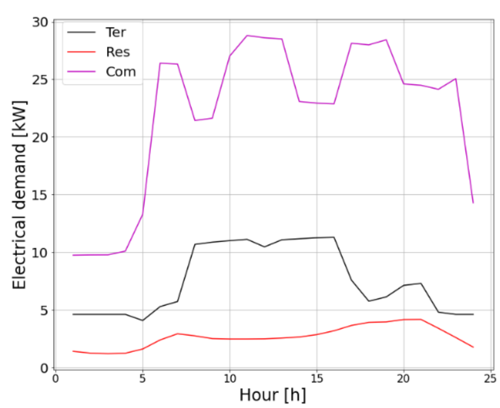


Figure 18. Daily profiles of the electricity demand of the tertiary consumer (Ter), residential (Res) and commercial (Com) prosumers [146].

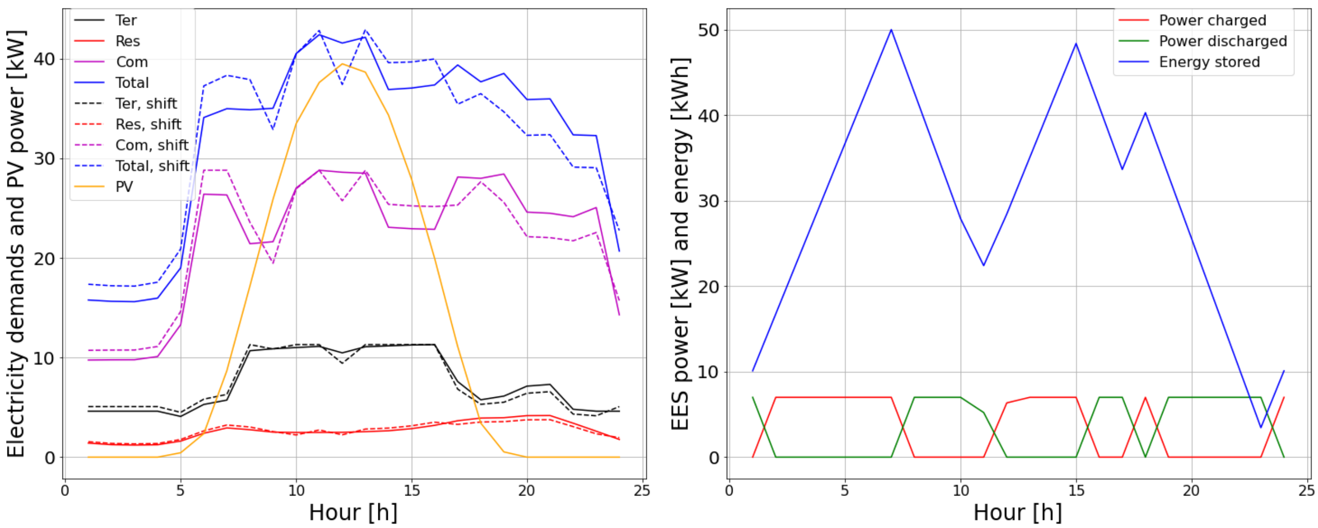
Table 6. Values of the input parameters in the MILP optimization model [39, 129, 147-149]. Some parameters refer to a specific member (e.g., Res, Com).

Parameter	Value
η^{PV} [kW$_{el}$/kW]	0.17
A_i^{PV} [m^2]	60 (Res, peak power of 10 kW$_{el}$), 250 (Com, peak power of 42 kW$_{el}$)
$\eta^{EES,+}$, $\eta^{EES,-}$ [-]	0.95
cap_i^{EES} [kWh]	50 (Com)
$P_i^{EES,peak}$ [kW$_{el}$]	7 (Com)
D^{var} [-]	0.1
inc_{REC} [€/kWh]	0.12

4.3. Results of the operation optimization and allocation of the total profit

This sub-Section presents and discusses the results obtained by solving the MILP operation optimization model of the system (sub-Section 4.2.1) and the results obtained by subsequently applying the allocation mechanisms of Shapley value and Uniform pricing (sub-Section 4.2.2) to distribute the optimal daily profit of the system among its members.

The outcomes from the operation optimization of the local power system of the REC are presented afterwards. Figure 19(a) shows the optimally shifted daily electricity demands of the tertiary consumer ("Ter"), the residential prosumer ("Res") and the commercial prosumer ("Com"), driven by the implementation of the PBDR program with RTP, as well as the total PV power generation of the two prosumers. The commercial prosumer shows larger load shifts of its optimal electricity demand (dashed purple line) compared to the other optimal demands (dashed black line for "Ter" and dashed red line for "Res"), as the commercial prosumer can exploit the Electrical Energy Storage (EES) unit and, thus, has a higher flexibility compared to the other members of the REC. Figure 19(b) shows the optimal daily operation of the EES unit of the commercial prosumer, in terms of power charged (red line), power discharged (green line) and energy stored (blue line). Note that all the shifted electricity demands (shown with dashed lines in Figure 19(a)) increase compared to the input demands (shows with solid lines) during hours 7-9, when the PV power generation is still low, thus requiring the discharge of power from the EES in the same period (Figure 19(b)). In the middle of the day, during hours 10-15, the total PV power generation is high (maximum value of 39 kW at hour 12), and this allows the EES to be charged to almost its maximum capacity (50 kWh) at hour 15. After hour 15, the available PV power decreases and, therefore, the power discharge of the EES helps meet the total electricity demand. Figure 20 shows the daily profile of the energy shared among the members of the REC. According to Eq. (4.11) in sub-Section 4.2.1, the shared energy is defined as the hourly minimum between the total energy withdrawn from the grid (i.e., the sum of the total shifted electricity demand of the system and the energy charged into the EES) and the total energy injected into the grid (i.e., the sum of the total PV energy generation and the energy discharged from the EES). At hour 12, the shared energy is equal to the maximum PV energy generated (i.e., 39 kWh), which is lower than the sum of the values of total shifted electricity demand (i.e., 37 kWh) and energy charged into the EES (i.e., 6.35 kWh). Hence, these outcomes outline that the local power system of the REC, equipped with renewable driven energy plants (as PV) and energy storage systems, can effectively take advantage of the shared energy among its end users and, in turn, obtain higher economic revenues due to the incentive for the shared energy provided by the Italian legislation.



a) *b)*

Figure 19. Daily profile of a) input and optimal shifted electricity demands of REC members and total PV power generation and b) power charged, power discharged, and energy stored for the EES unit.

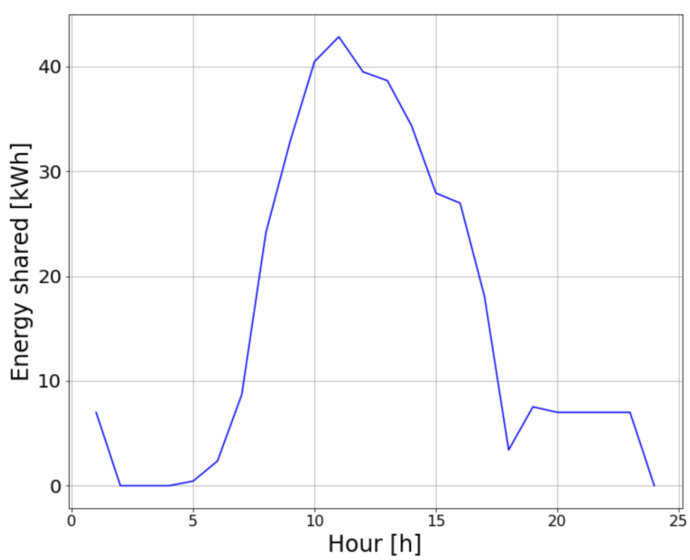


Figure 20. Daily profile of the optimal shared energy among the members of the analysed REC.

The optimal daily profit of the system, i.e., the optimal value of the objective function of the MILP optimization model (Eq. (4.11) in sub-Section 4.2.1), is equal to 8.61 €. This total profit is allocated to the members of the REC by applying, separately, the cooperative mechanism Shapley value and the Uniform pricing mechanism, described in sub-Section 4.2.2.

The calculation of the Shapley value, according to Eq. (2.9) in sub-Section 2.3, requires the identification of all coalitions of members within the REC and the computation of their "values" (i.e., the total costs/profits of coalitions, see sub-Section 2.3). The analysed REC encompasses three members, thus the 8 possible coalitions of members are *()*, *(Ter)*, *(Res)*, *(Com)*, *(Ter, Res)*, *(Ter, Com)*, *(Res, Com)* and *(Ter, Res, Com)*, where the first and last coalitions are, respectively, the empty coalition (i.e., with no member) and the grand coalition (i.e., the REC itself, which is the coalition that includes all members). *Ter*, *Res* and *Com* refer to the tertiary consumer, the residential prosumer and the commercial prosumer, respectively. It should be noted that the value of the empty coalition is 0, while the value of the grand coalition is the optimal daily profit found for the whole system (8.61 €). To obtain the value of a given coalition, it is sufficient to solve the MILP optimization model (sub-Section 4.2.1) considering only the equations and constraints associated with the members involved in that coalition. For example, the coalition *(Ter, Res)* consists of a consumer (Ter) and a prosumer (Res) equipped with only a PV plant, so the constraints of the EES unit (i.e., from (4.2) to (4.7) in sub-Section 4.2.1) associated with the commercial prosumer are not used in solving the problem of the operation optimization for coalition *(Ter, Res)*, and the decision variables of the EES appearing in Eqs. (4.8) and (4.9) are not considered as well. Moreover, for coalitions *(Ter)*, *(Res)*, *(Com)*, which represent the end users acting independently, and without cooperation with other community members, there is no energy shared with other members. Thus, when solving the optimization problems for coalitions *(Ter)*, *(Res)*, *(Com)*, the shared energy (Eq. (4.10)) is not calculated and the revenue term due to the shared energy is neglected in the objective function (Eq. (4.11)). Table 7 shows the "values" calculated for the 8 coalitions within the analysed REC, where negative and positive values refer to the net optimal daily costs and profits, respectively. For example, coalition *(Ter)* includes only one consumer, which leads to a daily cost of 12.85 €. On the other hand, the coalition *(Res, Com)* is based on the cooperation between the residential and the commercial prosumers and therefore presents the highest daily profit of 20.40 €. Once the values of all coalitions are obtained, the formula of the Shapley value (Eq. (2.9) in sub-Section 2.3) is applied to compute the Shapley payoff, i.e., the cost or profit allocated to each member of the REC. With the Uniform pricing mechanism (see sub-Section 4.2.2), the payoff allocated to each member of the REC is calculated as the product of its daily shifted electricity demand and the uniform price, which is defined as the ratio of the optimal total economic benefit (i.e., 8.61 €) to the total shifted electricity demand of the system.

Table 8 shows the payoffs (negative for costs and positive for profits) allocated to the members of the REC according to the Shapley value and Uniform pricing mechanisms. A first outcome is that both allocation mechanisms guarantee the properties of efficiency and individual rationality (see sub-Section 2.3). Efficiency is satisfied because the sum of the payoffs for both allocation mechanisms is equal to the optimal daily profit of the system (8.61 €), i.e., the value of the grand coalition represented by the community itself. Both Shapley value and Uniform pricing also guarantee the property of individual rationality, and therefore all members of the REC have higher economic gains (i.e., higher profits or lower costs) within the REC compared to the case in which they operate independently without cooperation. For instance, with the Uniform pricing allocation, the daily profits of the tertiary, residential and commercial members cooperating within the REC (profits of 2.01 €, 0.71 € and 5.89 €, respectively, in Table 8) are higher than when they operate independently in separate coalitions without cooperation (costs of 12.85 €, 1.03 €, 22.16 €, respectively, in Table 7). With Uniform pricing all members have daily profits, including the tertiary consumer, while the allocation by Shapley value results in daily profits for the prosumers and a daily cost for the tertiary consumer. It therefore appears that Uniform pricing is economically more profitable than Shapley value, at least for the tertiary consumer. However, the application of the Shapley value mechanism favours the prosumers of the REC, who contribute significantly to increase the daily economic profits of the REC and its internal coalitions, derived from the energy sold to the grid and the incentivised shared energy. For example, Table 8 shows that the residential prosumer receives the highest daily profit of 9.60 € according to Shapley value, highlighting the relevant contribution of this prosumer to the total profit of the system (8.61 €). Thus, the Shapley value is a fair allocation mechanism in the sense that prosumers, who promote self-consumption and shared energy within the REC, receive higher profits compared to consumers (who, in any case, have the economic convenience of being part of the REC rather than operating independently). On the contrary, with the Uniform pricing mechanism, the allocated economic benefits within the REC are more homogeneous (i.e., all members receive daily profits, but their contributions are not weighted equitably), without prosumers receiving higher rewards compared to consumers.

Table 7. Coalitions of the REC and their calculated "values", which represent daily operational profits (positive) or costs (negative).

Coalition	*()*	*(Ter)*	*(Res)*	*(Com)*	*(Ter, Res)*	*(Ter, Com)*	*(Res, Com)*	*(Ter, Res, Com)*
Value [€]	0	-12.85	-1.03	-22.16	-6.95	3.02	20.40	8.61

Table 8. Daily payoffs, i.e., costs (negative) or profits (positive), distributed to all members of the REC according to Shapley value and Uniform pricing.

	Payoffs [€]	
Member	***Shapley value***	***Uniform pricing***
Ter	-5.00	2.01
Res	9.60	0.71
Com	4.01	5.89
REC	8.61	8.61

4.4. Conclusions

Section 4 specifically analyses the fair allocation of the total economic benefit of a Renewable Energy Community (REC) to its members. It is worth recalling that the first objective of this Thesis is to evaluate all the main aspects that influence the optimal aggregation of end users in Energy Communities (ECs), including the distribution of the total economic benefit among the members. Thus, the aim of this Section is to propose a possible allocation of the total economic benefit that can be considered fair. The case study presented in Section 4 focuses on a REC with three users belonging to different sectors, i.e., a tertiary consumer, a residential prosumer and a commercial prosumer. The residential prosumer owns only a PV plant (peak power of around 10 kW), while the commercial prosumer owns a PV plant (peak power of around 42 kW) and an EES (capacity of 50 kWh). First, a Mixed Integer Linear Programming

(MILP) optimization model is used to optimize the daily operation of the local power system associated with the REC, and then two different allocation mechanisms are applied and their results are compared to assess the fairness of the distribution of the optimal economic benefit. Moreover, any type of uncertainty associated with input data and boundary conditions is disregarded to evaluate only the fairness of the allocation of the optimal economic benefit.

The mechanisms implemented to allocate the optimal economic benefit of the system are the Shapley value and the Uniform pricing, the former being one of the most widely used cooperative game-based models. As there is not a single definition of fairness in the distribution of the total economic benefit of an EC, this study considers the distribution given by the Shapley value mechanism as fair. In fact, Shapley value allows the optimal cost/profit of a system to be allocated to members by weighting their contributions to the costs/profits of the system and its internal coalitions in which they could participate. On the other hand, the Uniform pricing mechanism does not value the cooperation of the users of the system in the process of cost/profit allocation and is therefore considered an unfair allocation mechanism. This mechanism distributes the optimal cost/profit of the system by charging the electricity demands of the members of the REC through a uniform price (calculated as the ratio of the optimal economic benefit and the daily electricity demand of the system).

The solution of the operation optimization leads to an optimal daily profit of the system of 8.61 €, which is allocated to the members by separately applying the Shapley value and Uniform pricing mechanisms to evaluate their impact on the individual benefits of the members. From the payoffs (i.e., costs/profits) allocated to the members according to the Shapley value and Uniform pricing, it appears that the three members of the REC always find more economically convenient to participate into the community (i.e., obtaining higher profits or lower costs) compared to their separate operation, which is characterized by daily costs of 12.85 €, 1.03 € and 22.16 € for the tertiary consumer, residential prosumer and commercial prosumer, respectively. Uniform pricing allows to achieve daily profits of 2.01 €, 0.71 € and 5.89 € for the tertiary consumer, residential prosumer and commercial prosumer, respectively. On the other hand, the allocation by Shapley value leads to a daily cost of 5 € for the tertiary consumer and to daily profits of 9.60 € and 4.01 € for the residential and commercial prosumers, respectively. These results confirm that both Shapley value and Uniform pricing mechanisms guarantee individual rationality, i.e., that users have higher economic benefits in the REC than outside it. *Moreover, the application of Uniform pricing provides homogeneous payoffs among the members of the REC, but these payoffs are obtained without fairly weighting the contributions of the different members to the optimal economic benefit of the system. On the other hand, Shapley value is fairer to prosumers (in particular, the residential one), in the sense that "awards" the higher contributions of the prosumers to the optimal daily profit of the system by giving them higher payoffs than those of consumers.*

The results obtained show that the Shapley value is suitable to ensure a fair distribution of the optimal economic benefit of an EC characterized by a small size (e.g., with three members as in this case study). Moreover, the Shapley value seems to be an interesting option for ECs consisting mainly of prosumers. Policy makers and EC managers could also choose the Shapley value as cost/profit allocation mechanism to encourage independent prosumers to join the EC. Further research could focus on the factors that affect the temporal stability of the EC to avoid members willing to exit from the EC, which is beyond the scope of this Thesis. In addition, it should be noted that there are other cooperative game-based models that differ from the Shapley value, such as the Nash bargaining optimization model, the theory of which is briefly presented in Appendix B.

In the case study presented in Section 4, the design of the local power system of the REC is not optimized and, in addition, uncertainties associated with input data and boundary conditions are neglected. Hence, in the next Section 5, attention is given to the evaluation of the weight of uncertainties in the optimal design of a local Multi-Energy System (MES) serving a REC.

5. Design and operation optimization of a local multi-energy system with aggregation of electricity demands and separate thermal demands under uncertainties

Section 5 presents the third case study of this Thesis, which deals with the optimization of the design and operation of a local Multi-Energy System (MES) that meets the aggregated electricity demand of a Renewable Energy Community (REC), and the separate heating demands of its members, under different uncertainties. In the previous Sections 3 and 4, the uncertainties of the input data and boundary conditions in the optimization problems have been neglected to permit a clear evaluation of only the aspects affecting the optimal aggregation of end users in ECs. On the other hand, the aim of this Section is to fulfil the second objective of this Thesis (sub-Section 1.2), i.e., to quantify the weights of different uncertainties associated with the Renewable Energy Sources (RES) and the energy demand profiles of end users in the optimal design and cost of a local MES. Sub-Section 5.1 introduces the configuration of the analysed local MES serving a REC. Sub-Section 5.2 presents the developed framework to perform the design-operation optimization of a MES in the absence of and under uncertainties, the optimization models with or without uncertainties, and the input data. Sub-Section 5.3 presents and discusses the main results of the optimizations conducted, with the aim of defining the "best" set of stochastic scenarios associated with the uncertain parameters and then evaluating the weights of these uncertainties in the optimal design of the MES. Sub-Section 5.4 outlines the conclusions of the Section. It should be noted that some concepts introduced in this Section are derived from a paper written by the author of this Thesis [110].

5.1. Case study: Multi-Energy System (MES) of the renewable energy community

The problem addressed in Section 5 is the weighting of uncertainties associated with the RES and the energy demand profiles of end users in the optimal design and cost of a local Multi-Energy System (MES) of a Renewable Energy Community (REC). Hence, the third case study of this Thesis deals with the design and operation optimization of a local MES of a REC under uncertainties. Figure 21 shows the configuration of the system under analysis. The REC consists of four users representing the residential (Res), tertiary (Ter), commercial (Com) and public (Pub) sectors. The energy conversion and storage technologies that could be installed according to the solution of the design-operation optimization problem are solar Photovoltaic plants (PV), Heat Pumps (HP), natural Gas Boilers (GB), Electrical Energy Storage (EES) and Thermal Energy Storage (TES).

According to GSE (the Italian Energy Services Operator) [39], the maximum size of each energy conversion and storage unit of a REC is still set at 200 kW and all members of the community must be connected to the electrical distribution grid under the same secondary (low-medium voltage) electrical cabin. Thus, the members of the REC share electricity through the grid, so realizing that is called collective virtual self-consumption. However, ARERA (the Italian Regulation Agency for Environment, Network and Energy) [129] recently published a new document [150] that changes the previous restrictions, allowing the members of the REC to be connected under the same primary (medium-high voltage) electrical cabin and promoting not only the collective virtual self-consumption but also the individual physical self-consumption. In addition, the maximum size of energy systems belonging to RECs is likely to increase from 200 kW to 1 MW [151].

Given the above considerations, a novel framework is developed to optimize the design and operation of the analysed local MES of the REC, considering the uncertainties of solar irradiance and electricity demands of the different members. This framework includes design-operation optimization models of the system in the absence of and under uncertainties. The optimization aims at minimizing the life cycle cost (including investment, operation and maintenance costs) of the system actualized to one year of operation. The optimization model in the absence of uncertainties is formulated according to a MILP approach while that under uncertainties is formulated according to the Stochastic Programming (SP) method [84], which is one of the most commonly used methods to perform optimization under uncertainty (see sub-Section 2.2.1). In addition, the SP optimization model is based on a set of daily stochastic scenarios representing the most likely realizations of the uncertain parameters, identified by applying a K-means clustering technique on different annual datasets that contain values of the uncertain input parameters (see sub-Section 2.2.2).

It should be noted that the proposed framework does not claim to provide a definitive and general solution to the design-operation optimization problem of any MES under uncertainty. Rather, the aim of the framework is to provide a general and reliable approach to obtain optimal solutions under uncertainties and to assess their accuracy compared to optimal solutions in the absence of uncertainties (the latter relying on complete information about the uncertain input parameters), so weighting uncertainties. Beyond some general assumptions already reported in sub-Section 1.4, the specific assumptions and boundary conditions of this case study are presented below.

- It is worth noting that, unlike the MILP models used in Sections 3 and 4, the MILP and SP models used in this Section include both design and operational decision variables (and not just operational ones). When optimizing the design and operation of the local MES serving the REC, the type and number of the energy conversion and storage units are selected prior to the optimization. Thus, only the sizes of the energy units are design decision variables and are optimized in the design phase.
- It should be noted that the design-operation optimizations in the absence of and under uncertainties consider a time horizon of one year, assuming that the system behaviour is the same for each year of its life cycle. In other words, each year used in the design-operation optimization is assumed to be representative of the entire life cycle of the system (i.e., 20 years, see sub-Section 5.2.4) [105]. A one-year optimization is chosen to achieve a trade-off between the accuracy of the optimization results and acceptable computational times. Note that solving the MILP model for a full year without uncertainties requires a computational time of one day or even more (sub-Sections 5.3.1 and 5.3.2). On the other hand, the optimization for a multi-year period would require a computational time of several days, which is considered unacceptable for the purpose of this Thesis.
- The REC operates according to the latest legislation of ARERA [150], so both the individual physical self-consumption and the collective virtual self-consumption of electricity (which is the shared energy among the members) are considered in the REC [152], as also shown in Figure 21, and the optimal sizes of the energy technologies are not constrained to be lower than 200 kW_{el} [39]. Both the MILP model in the absence of uncertainties and the SP model under uncertainties of the analysed local MES consider the individual physical self-consumption of the community members, which is not evaluated in the MILP models used in Sections 3 and 4.

- To benefit from the complementarity between different and diverse curves of energy generation and demand, the members of the REC are chosen as representative of the residential, tertiary, commercial and public sectors. The residential and public members of the REC are prosumers who could invest in PV, HP, EES and TES units. Conversely, the tertiary and commercial users are consumers that could invest in natural GB units to satisfy their heating demands, while their electricity demands are met by purchasing electricity from the distribution grid. The electricity demands of end users can be optimally shifted according to a Price-Based Demand Response (PBDR) program with a Real Time Pricing (RTP) strategy.
- Although the REC analysed exploits a MES, the legislation of the REC only allows the sharing of electricity among the members of the community [150] and therefore these members satisfy their heating demands individually. According to the Italian legislation, *"the shared energy is, in each hour of the day, the minimum between the electricity withdrawn from the grid and the renewable electricity injected into the grid by each member of the community"*, and this shared energy (electricity) is incentivized at 0.12 €/kWh [129]. Moreover, the existence of a district heating network, which is necessary to allow the sharing of thermal energy among members, is not foreseen and is outside the scope of this Thesis.
- According to the literature review in sub-Section 1.3.4, the uncertainties considered are associated with the availability of solar irradiance and the profiles of electricity demand of end-users, given the high variability associated with RES and the likely incomplete information on the profiles of various end-user energy demands. Moreover, these uncertain parameters affect at most both the generation and demand sides of local MES serving ECs. It is also useful to note that the uncertainty in the energy demand profiles of different end users (i.e., residential, tertiary, commercial and public) may also take into account the uncertainty associated with the presence of different people in the buildings, although the modelling of the building loads (i.e., occupancy, lighting and appliances) is outside the scope of the Thesis. For the conversion and storage units included in the case study of this Section, average values of the investment costs are taken from the literature, given the technological maturity of the units and, therefore, the limited uncertainty of their costs [12]. On the other hand, the actual values of other input parameters, such as electricity prices, heating demands and ambient temperature, are taken from an available historical dataset.
- Daily timeseries with hourly values of the input parameters (i.e., solar irradiance, electricity demands, heating demands, ambient temperature and electricity prices) are available from a historical dataset covering the years from 2005 to 2020. This dataset is divided into a training dataset (years from 2005 to 2014), where the SP optimization model is validated to search for the "best" set of stochastic scenarios representing the most likely realizations of the uncertain parameters, and a testing dataset (years from 2015 to 2020), where the SP optimization model is tested in each year to achieve optimal solutions in terms of energy unit sizes and life cycle cost of the system under uncertainties (see sub-Section 5.2.1). According to the state-of-the-art in model training and testing [153], the complete dataset is divided into a larger training dataset (consisting of 10 years) and a smaller testing dataset (consisting of 6 years), which roughly corresponds to a ratio of 60:40 between the training and testing datasets (i.e., 60 % of the complete dataset is used for training while 40 % for testing).
- As the dynamic operation of the system and its units (e.g., daily storage) is modelled independently for each day [68] (sub-Section 1.4), typical days are selected as typical periods of

the input timeseries [126]. In addition, each typical day is represented by 24 typical time steps (i.e., hours) [154]. The typical days of the uncertain parameters are taken as the stochastic scenarios in the SP model, with probabilities corresponding to their weights in the specific year of the training dataset in which they are obtained (see sub-Section 5.2.1).

- The optimal life cycle cost of the system (including investment, operation and maintenance costs) predicted for one year of the testing dataset is fairly allocated to the members of the REC by applying the Shapley value mechanism (see sub-Section 2.3), which has already been used in the case study presented in Section 4. As in Sections 3 and 4, it is assumed that users individually bear the investment costs of their energy units. However, the cost allocation analysed here covers both the investment and operational costs of the system, i.e., the life cycle cost of the system actualized to one year, and not only the daily operational cost or profit as done in Sections 3 and 4. Considering both investment and operational costs allows for a comprehensive examination of the fairness of the total cost allocation to end users over a year, rather than a single day.
- The optimization of the design and operation of the system in the absence of uncertainties for each year of the training/testing dataset assumes complete knowledge of the input timeseries for each day of the year. On the contrary, the optimization under uncertainties for each year of the training/testing dataset only has knowledge of the input timeseries for a limited set of typical days (i.e., the stochastic scenarios) of the year.

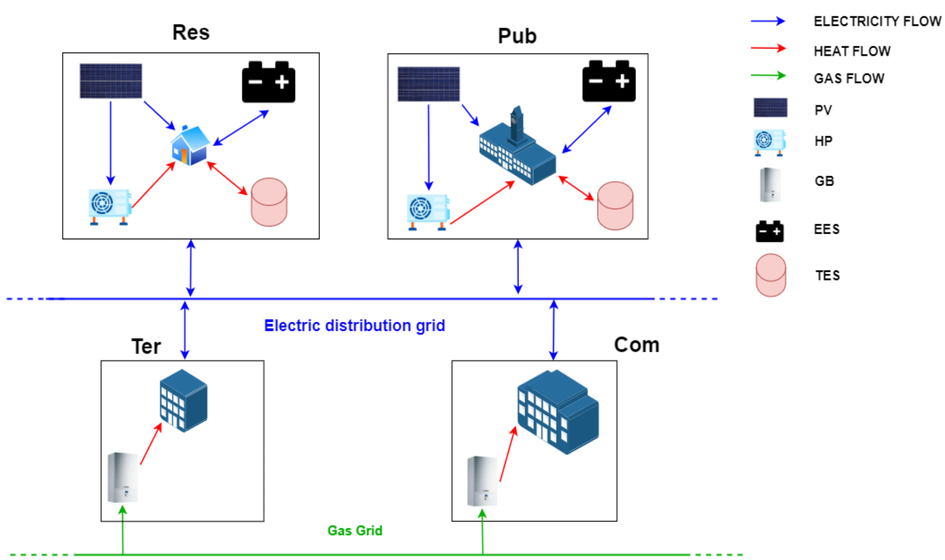


Figure 21. Local MES of a REC with residential (Res), tertiary (Ter), commercial (Com) and public (Pub) users. It is assumed that Res and Pub are prosumers that could install PV, HP, EES and TES units, while Ter and Com are consumers that could install only GB units.

5.2. Methods

This sub-Section presents the methodology used in this case study. Sub-Section 5.2.1 focuses on the optimization framework developed to address the optimization of the design and operation of the analysed system (see sub-Section 5.1) in the absence of and under uncertainties. Sub-Sections 5.2.2 and 5.2.3 present the Mixed Integer Linear Programming (MILP) optimization model in the absence of uncertainties and the Stochastic Programming (SP) optimization model under uncertainties, respectively. Sub-Section 5.2.4 specifies the input data of the optimization models.

5.2.1. Framework to carry out the optimization of the design and operation of the MES in absence of and under uncertainties

Figure 22 shows the novel optimization framework that is developed to solve the optimization of the design and operation of the local Multi-Energy System (MES) serving a Renewable Energy Community (REC) in the absence of and under uncertainties.

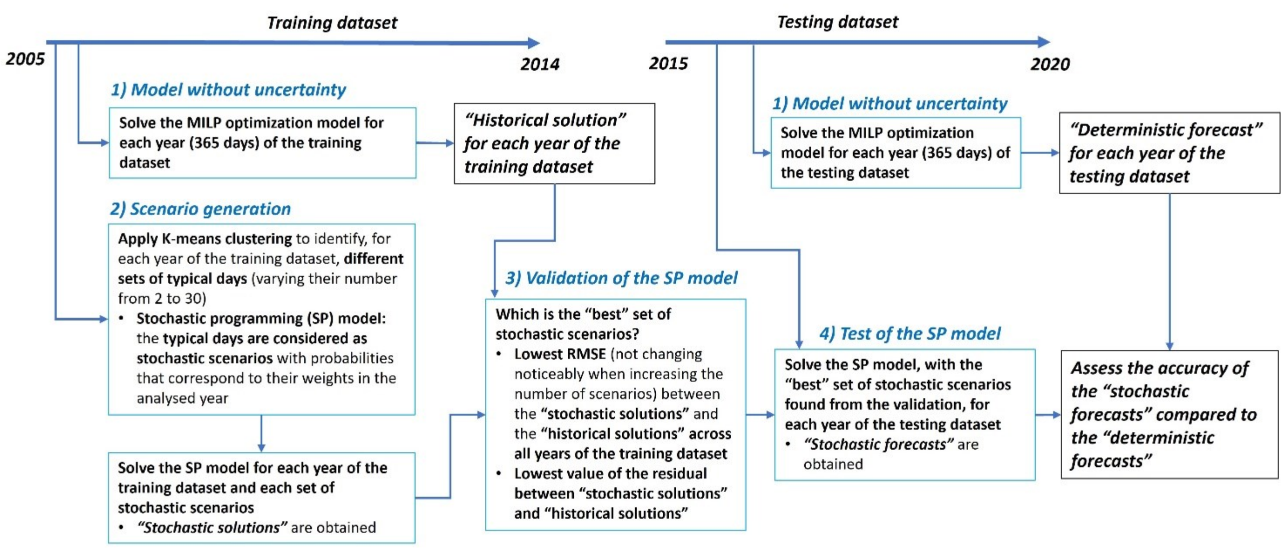


Figure 22. The developed optimization framework, including four steps called 1) Model without uncertainty, 2) Scenario generation, 3) Validation of the SP model and 4) Test of the SP model.

The aim of this framework is to propose a general approach to carry out the design-operation optimization of the local MES associated with the REC under the uncertainties of solar irradiance and users' electricity demand and, in turn, to assess the accuracy of the optimal solution under uncertainties compared to the optimal solution without uncertainty for each year of a testing dataset. The input timeseries (e.g., solar irradiance, electricity demands, etc.) are available in two datasets, i.e., a training dataset and a testing dataset covering the intervals of years 2005-2014 and 2015-2020 (see sub-Section 5.1), respectively. The optimization framework consists of four main steps:

1) Model without uncertainty: solving the Mixed Integer Linear Programming (MILP) optimization model in the absence of uncertainties, for each full year of the training and testing datasets, thus

obtaining the “historical solutions” (years 2005-2014) and the “deterministic forecasts” (years 2015-2020), respectively;
2) Scenario generation: generating different sets of stochastic scenarios of solar irradiance and electricity demands (varying the number of these scenarios) for each year of the training dataset;
3) Validation of the SP model: validating the Stochastic Programming (SP) optimization model, i.e., finding the “best” set of stochastic scenarios (from the training dataset) to be used in the test of the SP model;
4) Test of the SP model: testing the SP optimization model, based on the “best” set of stochastic scenarios, for each year of the testing dataset.

These four steps are described in more detail afterwards. *Step 1)* deals with achieving the solutions of the design-operation optimization problem without uncertainty. First, the MILP optimization model in the absence of uncertainties is solved for each year (considering 365 days) of the training dataset, thus obtaining a set of 10 *“historical solutions”* (one for each year of the training dataset). The same model is then solved for each year (considering 365 days) of the testing dataset, thus obtaining a set of 6 *“deterministic forecasts”* (one for each year of the testing dataset). Note that each optimal solution obtained includes the optimal value of the life cycle cost of the system (representing investment, operation and maintenance costs), which is the objective function of the design-operation optimization problem evaluated in this work (see next sub-Sections 5.2.2 and 5.2.3).

Step 2) deals with the generation of different sets of stochastic scenarios from the training dataset by applying a clustering technique. As reported in sub-Section 2.2.2, the main clustering techniques are K-means and K-medoids [119]. K-means usually selects as representative of the clusters (i.e., the representative days of groups containing similar days) the averaged typical days, called centroids, instead of the medoids (i.e., real typical days with timeseries having the smallest distance compared to all other timeseries of the same cluster) as done by K-medoids [125]. It should be noted that using the medoids could result in higher deviations compared to the average of the original timeseries [119], as the centroids are neglected. On the other hand, the centroids selected by K-means usually represent fictitious typical days, which could lead to a likely smoothing of the daily timeseries, thus neglecting their daily fluctuations. In the proposed framework, K-means is applied, where the clustering is driven by the formation of the centroids (as in K-means), but the typical day of each cluster is selected as the real day (as in K-medoids) with the lowest value of the Euclidean distance from the centroid (which is different from the medoid). This preserves the daily variations in the typical days, while minimizing their deviations from the whole original dataset of timeseries. K-means clustering is used to identify typical days of solar irradiance and electricity demands that are representative of each year of the training dataset. It is applied several times for each year of the training dataset, increasing the number of clusters generated from 2 to 30 and, thus, varying the number of typical days from 2 to 30. However, the design of a local MES under uncertainties represented by typical days also requires the inclusion of the extreme day where the highest daily electricity demands of users occur. Following the “replace representative period” approach presented by Kotzur et al. [125], clustering is first applied as described above, and then the extreme day becomes the new typical day of the cluster to which it was assigned to.

Each typical day (including the extreme day) is then considered as a stochastic scenario in the SP optimization model (see next sub-Section 5.2.3), with a probability defined as the frequency of the cluster (i.e., the number of days in the cluster) for which that typical day is representative. The frequency of the cluster also corresponds to the weight of the typical day in the year, i.e., the number of days in the year represented by that typical day. It should be noted that using the typical days as stochastic scenarios in the optimization of the system with a one-year time horizon is consistent with the assumption that the system operation is considered independently for each day of the year (sub-Section 1.4).

Step 3) deals with the validation of the SP optimization model. Note that among the different sets of typical days obtained by clustering and representative of a whole year, an appropriate set of typical days for a design optimization problem should be selected by comparing the optimal solution based on the typical days and that based on the yearly historical data (i.e., leading to the "historical solution" defined above), instead of only evaluating performance indicators of the clustering quality (e.g., average silhouette value) [124]. This type of comparison allows to validate the SP optimization model, i.e., to select the "best" set of stochastic scenarios of the uncertain parameters. The SP solution for a specific number of scenarios and a specific year of the training dataset is called *"stochastic solution"*. Note that 290 *"stochastic solutions"* are obtained by solving the SP model in the training dataset (i.e., for 29 sets for each of the 10 years). The optimal value of the life cycle cost of each *"stochastic solution"* in a year is then compared with that obtained from the *"historical solution"* (see *step 1)*) of the same year, and an error given by the residual (i.e., difference between the two) is calculated. This procedure is repeated for each year of the training dataset. It is worth noting that *step 3)* aims at defining the "best" set of stochastic scenarios by quantifying how far the *"stochastic solutions"* are from the "*historical solutions"*, which represent possible predictions and the target values of the life cycle cost of the system, respectively. For this purpose, the Root Mean Squared Error (RMSE) is used, which is one of the most popular indicators to quantify the error between predictions and target values of specific parameters or variables in the design of energy systems [155]. The RMSE calculates the *standard deviation of the errors* (using the residuals mentioned above) between the optimal life cycle costs of the system of the *"stochastic solutions"* and the *"historical solutions"* across all years of the training dataset. The "best" number of stochastic scenarios is taken to be the one that gives the lowest RMSE, after which the RMSE does not change significantly as the number of scenarios increases. The formula of the RMSE [155] is:

$$RMSE = \sqrt{\frac{\sum_{y=1}^{Y}(c_{SP,y,k} - c_y)^2}{Y}} \tag{5.1}$$

where $c_{SP,y,k}$, c_y, $(c_{SP,y,k} - c_y)$, and Y are the optimal value of the objective function (i.e., the life cycle cost of the system) found by solving the SP optimization model for year y with k stochastic scenarios (see sub-Section 5.2.3), the optimal value of the objective function found by solving the MILP model for the full year y without uncertainty (i.e., considering 365 days, see sub-Section 5.2.2), the residual, and the number of years (i.e., corresponding to the number of observations) considered in the analysed dataset, respectively. Note that when the formula of the RMSE is applied to select the "best" number of stochastic scenarios, y refers to a year of the training dataset, Y is equal to 10 (i.e., 10 years from 2005 to 2014 in the training dataset), $c_{SP,y,k}$ and c_y correspond to the optimal values of the objective function of the *"stochastic solution"* (with k stochastic scenarios) and the *"historical solution"* for year y of the training dataset, respectively. Subsequently, since for the "best" number of stochastic scenarios there are 10 sets of stochastic scenarios (i.e., one for each year of the training dataset, containing the same number but with different profiles), the "best" profiles of stochastic scenarios associated with the "best" number are taken in the year of the training dataset with the lowest value of the residual between the *"stochastic solution"* and *"historical solution"*.

Step 4) deals with the test of the SP optimization model. Once the "best" set of stochastic scenarios has been determined (i.e., both number and profiles of the stochastic scenarios), the SP optimization model is tested by solving it for each year of the testing dataset with the "best" set of stochastic scenarios as input, thereby providing *"stochastic forecasts"* that are optimal predicted solutions of the design-operation optimization problem. Finally, the accuracy of the *"stochastic forecast"* is assessed by calculating its errors with respect to the *"deterministic forecast"* (obtained in *step 1)*), in terms of differences in the optimal sizes of the energy units and values of the life cycle cost of the system, for each year of the testing dataset. This allows weighting uncertainties in the design optimization of a local MES.

5.2.2. Mixed Integer Linear Programming (MILP) optimization model of the MES in absence of uncertainties

This sub-Section presents the Mixed Integer Linear Programming (MILP) model to optimize the design and operation of the local MES of the REC in the absence of uncertainties. In the case of neglecting uncertainty, the timeseries of input data (e.g., solar irradiance, electricity and heating demands of end users, grid purchase and sale prices, etc.) are assumed to be known for each day of each year of the training and testing datasets. Thus, the MILP optimization model without uncertainty can be solved for all 365 days of a year of the training or testing datasets (as explained in sub-Section 5.2.1, see *step 1)* of the optimization framework), under the assumption that the year considered is representative of the entire life cycle of the system (see sub-Section 5.1).

It should be noted that in this case study the REC configuration complies with the latest legislation of ARERA [150] (see the boundary conditions in sub-Section 5.1), which foresees to take into account the shared energy among the members of the REC and also their individual physical self-consumption. Thus, the energy balances of each member of the REC appear in the MILP model used here to account for their individual physical self-consumption, which is a novel feature compared to the MILP models used in Sections 3 and 4.

The constraints and the objective function of the MILP model in the absence of uncertainties are reported afterwards. The following constraints refer to each hour t of each day d of a year (in the training or testing datasets) for a consumer c or prosumer p. The decision variables in the design and operation optimization of the system can be classified into design variables, i.e., the capacities (or sizes) of the energy units, and operational variables. The design variables are the capacities of the gas boiler (cap_c^{GB}), solar photovoltaic plant (cap_p^{PV}), heat pump (cap_p^{HP}), electrical and thermal energy storage units (cap_p^{ES} for a general storage unit). The operational variables are: the heating power generated by the heat pump ($Q_{p,t,d}^{HP}$) and the binary variable indicating its on-off operational state ($\delta_{p,t,d}^{HP}$); the energy stored by the energy storage unit ($E_{p,t,d}^{ES}$), its charging/discharging power ($P_{p,t,d}^{ES,+}/P_{p,t,d}^{ES,-}$) and the binary variable indicating its charging/discharging state ($\delta_{p,t,d}^{ES}$); the energy imported/exported from/to the electrical grid ($E_{p,t,d}^{imp}/E_{p,t,d}^{exp}$); the shifted electricity demands of the users due to the application of the PBDR with RTP strategy ($E_{c,t,d}^{el,shift}$ and $E_{p,t,d}^{el,shift}$). Each member of the REC has an electricity demand that can be optimally shifted according to the implemented PBDR program with a RTP strategy (see sub-Section 5.1). Hence, the constraints (3.5)-(3.7) reported in sub-Section 3.2.3 are also used in the model presented here.

For a consumer *"c"*, the constraints of the natural Gas Boiler (GB) are:

$$F_{c,t,d}^{GB} = Q_{c,t,d}^{GB}/\eta_{GB} \tag{5.2}$$

$$Q_{c,t,d}^{GB} \leq cap_c^{GB} \tag{5.3}$$

where $F_{c,t,d}^{GB}$ [kW] and $Q_{c,t,d}^{GB}$ [kW_{th}], cap_c^{GB} [kW_{th}] and η_{GB} [kW_{th}/kW] are the fuel power consumed and the heating power generated, the capacity (i.e., maximum heating power that can be generated) and efficiency of the GB, respectively. Eq. (5.2) represents the input-output characteristic curve of the GB and constraint (5.3) sets the capacity of the GB as upper bound of its generated heating power.

The electricity balance of a consumer *"c"* is:

$$E_{c,t,d}^{imp} - E_{c,t,d}^{el,shift} = 0 \tag{5.4}$$

where $E_{c,t,d}^{imp}$ and $E_{c,t,d}^{el,shift}$ [kWh] are the energy imported from the electrical grid and the optimally shifted electricity demand of consumer c.

The heating balance of a consumer *"c"* is:

$$Q_{c,t,d}^{GB} \cdot \Delta t - E_{c,t,d}^{th} = 0 \tag{5.5}$$

where Δt [h] is the time step of one hour in the optimization and $E_{c,t,d}^{th}$ [kWh] is the heating demand of consumer *"c"*.

For a prosumer *"p"*, the electrical power generated by a solar PV plant is calculated as:

$$P_{p,t,d}^{PV} = cap_p^{PV} \cdot I_{t,d} \tag{5.6}$$

where $P_{p,t,d}^{PV}$ [kW_{el}] is the electrical power generated by the PV plant, cap_p^{PV} [m^2] is the size of the PV plant (taking into account also the efficiency of PV) and $I_{t,d}$ [kW/m^2] is the global solar irradiance (on a tilted surface).

The characteristic curve of the HP of a prosumer *"p"* is expressed as:

$$P_{p,t,d}^{HP} = \frac{a_0 \cdot Q_{p,t,d}^{HP} + a_1 \cdot \delta_{p,t,d}^{HP}}{COP_{p,t,d}} \tag{5.7}$$

where $P_{p,t,d}^{HP}$ [kW_{el}], $Q_{p,t,d}^{HP}$ [kW_{th}], $\delta_{p,t,d}^{HP}$ [-], a_0 and a_1 [-], and $COP_{p,t,d}$ [kW_{th}/kW_{el}] are the electrical power consumed by the HP, the heating power generated by the heat pump, the binary variable indicating the on-off state of the HP during its operation, the constant coefficients that linearize the characteristic curve and the coefficient of performance in ideal conditions (using Carnot equation) calculated as reported in [156], respectively. Other constraints of the HP are:

$$\theta_{p,t,d}^{HP} \leq \delta_{p,t,d}^{HP} \cdot M \tag{5.8}$$

$$0 \leq cap_p^{HP} - \theta_{p,t,d}^{HP} \leq (1 - \delta_{p,t,d}^{HP}) \cdot M \tag{5.9}$$

$$min_{HP} \cdot \theta_{p,t,d}^{HP} \leq Q_{p,t,d}^{HP} \leq \theta_{p,t,d}^{HP} \tag{5.10}$$

where cap_p^{HP} [kW$_{th}$] is the capacity of the HP (i.e., the maximum value of the heating power $Q_{p,t,d}^{HP}$) and min_{HP} [% of the capacity] is the minimum part load of the HP. The "big M" method is applied by introducing the auxiliary variable $\theta_{p,t,d}^{HP}$ and the parameter M (with a high value, e.g., equal to 10^4) to avoid bilinear constraints, thus keeping a MILP formulation of the optimization model. Constraints (5.8) and (5.9) deal with the capacity of the HP and constraints (5.10) sets the lower and upper bounds of the heating power generated by the HP.

The energy balance equation of an Energy Storage (ES) unit, i.e., an Electrical Energy Storage (EES) or a Thermal Energy Storage (TES), of a prosumer *"p"* is:

$$E_{p,t,d}^{ES} = E_{p,t-1,d}^{ES} \cdot (1 - SD) + \left(P_{p,t,d}^{ES,+} \cdot \eta^{ES,+} - \frac{P_{p,t,d}^{ES,-}}{\eta^{ES,-}} \right) \cdot \Delta t \tag{5.11}$$

where $E_{p,t,d}^{ES}$ [% of capacity], SD [% of the state of charge at each hour], $P_{p,t,d}^{ES,+}/P_{p,t,d}^{ES,-}$ [kW] and $\eta^{ES,+}/\eta^{ES,-}$ [-] are the state of charge, the self-discharge, the charging/discharging power and the charging/discharging efficiency of the storage unit, respectively. Other constraints of the ES unit are:

$$\theta_{p,t,d}^{ES,+} \leq \delta_{p,t,d}^{ES} \cdot M \tag{5.12}$$

$$0 \leq cap_p^{ES} - \theta_{p,t,d}^{ES,+} \leq (1 - \delta_{p,t,d}^{ES}) \cdot M \tag{5.13}$$

$$\theta_{p,t,d}^{ES,-} \leq (1 - \delta_{p,t,d}^{ES}) \cdot M \tag{5.14}$$

$$0 \leq cap_p^{ES} - \theta_{p,t,d}^{ES,-} \leq \delta_{p,t,d}^{ES} \cdot M \tag{5.15}$$

$$E_{p,t,d}^{ES} \leq cap_p^{ES} \tag{5.16}$$

$$P_{p,t,d}^{ES,+} \leq C^{ES,+} \cdot \theta_{p,t,d}^{ES,+} \tag{5.17}$$

$$P_{p,t,d}^{ES,-} \leq C^{ES,-} \cdot \theta_{p,t,d}^{ES,-} \tag{5.18}$$

$$E_{p,t=1,d}^{ES} = E_{p,t=24,d}^{ES} \tag{5.19}$$

where cap_p^{ES} [kWh] is the capacity of the storage unit, $\delta_{p,t,d}^{ES}$ [-] is the binary variable associated with the charging or discharging state of the storage unit (where the optimal value of $\delta_{p,t,d}^{ES}$ is equal to 1 or 0, respectively), $C^{ES,+}$ and $C^{ES,-}$ [kW/kWh] are the specific input and output capacity. As in the case of the HP (Eqs. (5.8)-(5.10)), the auxiliary variables $\theta_{p,t,d}^{ES,+}$ and $\theta_{p,t,d}^{ES,-}$ and the M parameter are used to avoid bilinear constraints. Constraints (5.12)-(5.15) regard the capacity of the storage unit. Constraint (5.16) places the capacity of the storage unit as upper limit of its state of charge. Constraints (5.17) and (5.18) bound the charging and discharging power of the storage unit, respectively. Eq. (5.19) sets that the state of charge in the first hour of day *d* is equal to that in the last hour of the same day, according to the daily operation of the EES unit.

The electricity balance of a prosumer *"p"* is:

$$E_{p,t,d}^{imp} - E_{p,t,d}^{exp} + (P_{p,t,d}^{PV} + P_{p,t,d}^{EES,-} - P_{p,t,d}^{EES,+} - P_{p,t,d}^{HP}) \cdot \Delta t - E_{p,t,d}^{el,shift} = 0 \tag{5.20}$$

where $E_{p,t,d}^{imp}/E_{p,t,d}^{exp}$ [kWh], $P_{p,t,d}^{EES,-}/P_{p,t,d}^{EES,+}$ [kW] and $E_{p,t,d}^{el,shift}$ [kWh] are the energy imported/exported from/to the electrical grid, the power discharged/charged from/into the EES unit and the shifted electricity demand of prosumer p, respectively.

The heating balance of a prosumer *"p"* is:

$$(Q_{p,t,d}^{HP} + P_{p,t,d}^{TES,-} - P_{p,t,d}^{TES,+}) \cdot \Delta t - E_{p,t,d}^{th} = 0 \tag{5.21}$$

where $P_{p,t,d}^{TES,-}/P_{p,t,d}^{TES,+}$ [kW] and $E_{p,t,d}^{th}$ [kWh] are the power discharged/charged from/into the TES unit and the heating demand of prosumer *"p"*.

In this case study, the individual self-consumption of members is considered separately from the shared energy among members, according to the latest legislation of ARERA [150]. Hence, the total energy of the REC withdrawn from ($E_{t,d}^{imp}$) and injected to ($E_{t,d}^{exp}$) the grid at each hour t of day d are defined as:

$$E_{t,d}^{imp} = \sum_{i=1}^{N} E_{i,t,d}^{imp} \tag{5.22}$$

$$E_{t,d}^{exp} = \sum_{i=1}^{N} E_{i,t,d}^{exp} \tag{5.23}$$

where $E_{i,t,d}^{imp}/E_{i,t,d}^{exp}$ [kWh] is the energy imported/exported (exported only for prosumers *"p"*) from/to the electrical grid for member i at hour t of day d, and N is the number of members of the REC. The amounts of energy $E_{t,d}^{imp}$ and $E_{t,d}^{exp}$, net of the individual physical self-consumption of the members of the REC, contribute to the energy shared between them via the electric distribution grid. Indeed, the shared energy $E_{s,t,d}$ is defined as the hourly minimum between $E_{t,d}^{imp}$ and $E_{t,d}^{exp}$:

$$E_{s,t,d} = min(E_{t,d}^{imp}, E_{t,d}^{exp}) \tag{5.24}$$

and is incentivised according to the Italian legislation.

The objective function to be minimized in the MILP optimization model in the absence of uncertainties is the life cycle cost of the system, referring to one year of operation and encompassing all the 365 days:

$$c_{life\ cycle} = c_{design} + c_{operation} \tag{5.25}$$

where c_{design} and $c_{operation}$ [€] are the investment and operational (and maintenance) costs.

The investment cost is:

$$c_{design} = \sum_{u}\left(\left(\frac{a \cdot (1+a)^{lt_u}}{(1+a)^{lt_u} - 1} + O\&M_{fix,u}\right) \cdot c_{inv,u} \cdot \sum_{i=1}^{N} cap_i^u\right) \tag{5.26}$$

where u identifies a specific energy technology (e.g., PV), a [%] is the interest rate, lt_u [years] is the lifetime of the energy technology u, $O\&M_{fix,u}$ [% of the investment cost] is the fixed part of the operation and maintenance cost of the energy technology u, $c_{inv,u}$ [€/kW or €/kWh] is the investment cost and cap_i^u is the capacity [kW or kWh] of the energy technology u owned by member i. Notice that Eq. (5.26) represents the investment cost of the system actualized to one year of operation.

The yearly operational cost is:

$$c_{operation} = \sum_{d=1}^{365}\sum_{t=1}^{24}\left(\sum_{c}(F_{c,t,d}^{GB} \cdot c_{gas}) + E_{t,d}^{imp} \cdot c_{t,d}^{imp} - E_{t,d}^{exp} \cdot c_{t,d}^{exp} - E_{s,t,d} \cdot inc_{REC}\right) \quad (5.27)$$

where c_{gas} [€/kWh], $c_{t,d}^{imp}$ [€/kWh], $c_{t,d}^{exp}$ [€/kWh] and inc_{REC} [€/kWh] are the price of natural gas, the grid purchase price, the grid sale price and the incentive of the REC for the shared energy (equal to 0.12 €/kWh as specified in sub-Section 5.1), respectively. The first term of the summation represents the cost of natural gas that is consumed by the boilers of consumers *"c"*. The second and third terms are the cost for the electricity imported from the grid and the revenue for the electricity exported to the grid. The last term is the revenue due to the incentive for the shared energy. It is worth highlighting that the optimal value of the life cycle cost of the system found by solving the above MILP optimization model (i.e., $c_{life\ cycle}$ in Eq. (5.25)) is associated with the "historical solution" or "deterministic forecast" (i.e., the two types of optimal solutions without uncertainty, see Figure 22) depending on whether the MILP optimization model in the absence of uncertainties is solved for a year of the training or testing dataset (see sub-Section 5.2.1).

5.2.3. Stochastic Programming (SP) optimization model of the MES under uncertainties

A Stochastic Programming (SP) optimization model (see sub-Section 2.2.1) with a Mixed Integer Linear Programming (MILP) formulation [118] is used to optimize the design and operation of the MES associated with the REC, under the uncertainties of solar irradiance and electricity demands of users. The optimization of the design and operation of a MES under uncertainties is a two-stage problem. The decisions on the sizes of the energy units are made in the first stage that is assumed to occur before the realization of stochastic scenarios, while the decisions on the real-time operation of the system are made in the second stage that is influenced by the realizations of uncertainties represented by the stochastic scenarios. The "Here and Now" (HN) solution approach, described in sub-Section 2.2.1, is adopted to solve the SP optimization model. It should be noted that, according to the HN approach, optimal design and operational decision variables are achieved by considering all stochastic scenarios with their probabilities (i.e., the typical days with their weights in the year) simultaneously within the optimization. Hence, each SP solution consists of a unique set of optimal design decision variables (i.e., the sizes of the energy units) and an optimal life cycle of the system. The SP solution is not associated with a probability, but rather depends on the stochastic scenarios with their probabilities. Without assuming knowledge of each input daily timeseries in each year, as in the case of the MILP optimization model in the absence of uncertainties (sub-Section 5.2.2), a set of stochastic scenarios is defined to represent the uncertain parameters. As shown in sub-Section 5.2.1, different sets of typical days of solar irradiance and electricity demands are obtained for each year of the training dataset by clustering. Thus, the SP model relies on a set of stochastic scenarios corresponding to the typical days found. The SP model can be solved for a specific year (in the training or testing datasets), under the assumption that the year considered is representative of the entire life cycle of the system (see sub-Section 5.1).

The main difference between the MILP optimization model in the absence of uncertainties and the SP optimization model under uncertainties is that the former is formulated and solved for each day d of a year, whereas the latter for each typical day k of a year (where the typical days are defined by finding the representative timeseries of the uncertain solar irradiance and electricity demands in a year). Consequently, the optimization under uncertainty leads to different results than the optimization without uncertainty. Moreover, solving the SP optimization model for a given set of stochastic scenarios representative of a year, the number of which varies from 2 to 30 (see sub-Section 5.2.1), implies a lower computational effort compared to solving the optimization model in the absence of uncertainties in the same year with 365 days and corresponding input timeseries.

The decision variables, the constraints and energy balances of the SP optimization model do not change compared to those of the MILP optimization model in the absence of uncertainties (Eqs. (5.2)-(5.24) reported in sub-Section 5.2.2), except that the subscript associated with the day d is replaced by that of the typical day k. The formula of the design cost is equivalent to Eq. (5.26), whereas the operational cost is not calculated considering all the 365 real days of a year, but only the typical days with their weights in the year considered. The weight of a typical day is the number of days in a year represented by that typical day and corresponds to the frequency of the cluster (i.e., the number of days encompassed in the cluster) for which that typical day is representative. The yearly operational cost is:

$$c_{operation,SP} = \sum_{k=1}^{K} w_k \cdot \sum_{t=1}^{24} \left(\sum_{c} (F_{c,t,k}^{GB} \cdot c_{gas}) + E_{t,k}^{imp} \cdot c_{t,k}^{imp} - E_{t,k}^{exp} \cdot c_{t,k}^{exp} - E_{s,t,k} \cdot inc_{REC} \right) \tag{5.28}$$

where w_k is the weight of the typical day k (K is the number of typical days), which corresponds to the probability (value between 0 and 1) of a daily stochastic scenario multiplied by 365 to evaluate its contribution to the yearly operational cost. The objective function of the SP optimization model is given by the sum between Eq. (5.26) and Eq. (5.28). To make a comparison with problem (2.6) shown in sub-Section 2.2.1, the design cost (Eq. (5.26)) is the part of the objective function (containing the first stage decision variables) that is independent of stochastic scenarios, while the operational cost (Eq. (5.28)) is the part of the objective function (containing the second stage decision variables) that depends on stochastic scenarios. As explained in sub-Section 5.2.1 (Figure 22), the solution of the SP optimization model for a set of stochastic scenarios in one year of the training dataset is called "stochastic solution", whereas the test of the SP optimization model for a year of the testing dataset, where the "best" set of stochastic scenarios is fixed, leads to the "stochastic forecast" solution. Note that the optimal value of the objective function of the "stochastic forecast" is the life cycle cost of the system predicted for one year of the testing dataset.

Eventually, the Shapley value mechanism (see sub-Section 2.3) is applied to fairly distribute the optimal life cycle cost of the system (including investment, operation and maintenance costs), predicted for a year of the testing dataset ("stochastic forecast"), among the members of the REC by weighting their contributions to the total economic benefit of the system. Note that, in the calculation of the Shapley value (Eq. (2.9) in sub-Section 2.3), the "value" of each coalition S of the REC is the optimal life cycle cost of the system, predicted for one year of the testing dataset, that is attained by solving the SP optimization model considering only the members of coalition S. For example, in the SP optimization model for the coalition made of only the residential and tertiary users, only the constraints associated with these users are considered.

5.2.4. Input data

The main input data to the optimization models presented in sub-Sections 5.2.2 and 5.2.3 are the techno-economic parameters associated with the energy technologies and the daily timeseries of solar irradiance, electricity demands, heating demands, ambient temperature and prices of energy purchased/sold from/to the electrical grid. Table 9 shows the techno-economic parameters for each energy generation and storage technology (i.e., GB, PV, HP, EES and TES) and their input values to the optimization models [157, 158]. The interest rate a of the investment in the energy units and the lifetime lt_u of each energy technology u (Eq. (5.26)) are assumed to be 0.05 [-] and 20 years, respectively.

In the SP optimization model (sub-Section 5.2.3) typical days are used as stochastic scenarios. As seen in sub-Section 5.2.1, given the uncertainty of solar irradiance and electricity demands, K-means clustering is implemented to find the typical days of these uncertain parameters for each year of the training dataset. Then, the typical days of heating demands, ambient temperature and prices are associated (on the same chronological days) with the typical days of solar irradiance and electricity demands. For example, Figure 23, Figure 24, Figure 25, Figure 26(a) and (b) show the set of 29 typical days of solar irradiance, electricity demands, heating demands, ambient temperature and grid sale price in the year 2014, respectively. The data of solar irradiance and ambient temperature refer to the location of Padova (Italy) and are taken from the PVGIS database [142]. At each hour the grid sale price is assumed to be half of the day-ahead market price [143] in Italy, and the daily profile of the grid purchase price is obtained from that of the grid sale price by adding 0.2 €/kWh at each hour (thus obtaining different hourly values according to PBDR with RTP). The data of electricity and heating demands of different users are taken from [146]. Furthermore, the maximum hourly fraction of the load that can be shifted (i.e., D^{var}, see constraints (3.5)-(3.7) reported in sub-Section 3.2.3) is equal to 0.1. The price of natural gas is equal to 0.098 €/kWh.

The MILP optimization model in the absence of uncertainties (sub-Section 5.2.2) and the SP optimization model under uncertainties (sub-Section 5.2.3) are developed and solved using Gurobi software [139] with a minimum optimality gap (MIPgap) set at 2 % [67], which is found to be the best trade-off between sufficiently accurate results and acceptable computation times. The computer utilized is an Intel (R), Core (TM) i9-12900K with 3.20 GHz, 16 core, 24 threads and 64 GB of ram.

Table 9. Input techno-economic parameters of the optimization models [157, 158].

Technology "u"	Parameter	Value
GB	η_{GB}[kW$_{th}$/kW]	0.97
	$c_{inv,u}$ [€/kW$_{th}$]	300
	$O\&M_{fix,u}$ [% of $c_{inv,u}$]	4.9

PV	$c_{inv,u}$ [€/kW$_{el}$]	1250
	$O\&M_{fix,u}$ [% of $c_{inv,u}$]	1.1
HP	a_0, a_1 [-]	1.7961, 2.6527
	min_{HP} [% of capacity]	50
	$c_{inv,u}$ [€/kW$_{th}$]	1500
	$O\&M_{fix,u}$ [% of $c_{inv,u}$]	2.8
EES	SD [% of the state of charge in each hour]	0.04
	$\eta^{ES,+}, \eta^{ES,-}$ [-]	0.95, 0.95
	$C^{ES,+}, C^{ES,-}$ [kW/kWh]	0.5, 3
	$c_{inv,u}$ [€/kWh]	1500
	$O\&M_{fix,u}$ [% of $c_{inv,u}$]	1
TES	SD [% of the state of charge in each hour]	2.1
	$\eta^{ES,+}, \eta^{ES,-}$ [-]	0.99, 0.99
	$C^{ES,+}, C^{ES,-}$ [kW/kWh]	0.7, 0.7
	$c_{inv,u}$ [€/kWh]	400
	$O\&M_{fix,u}$ [% of $c_{inv,u}$]	4

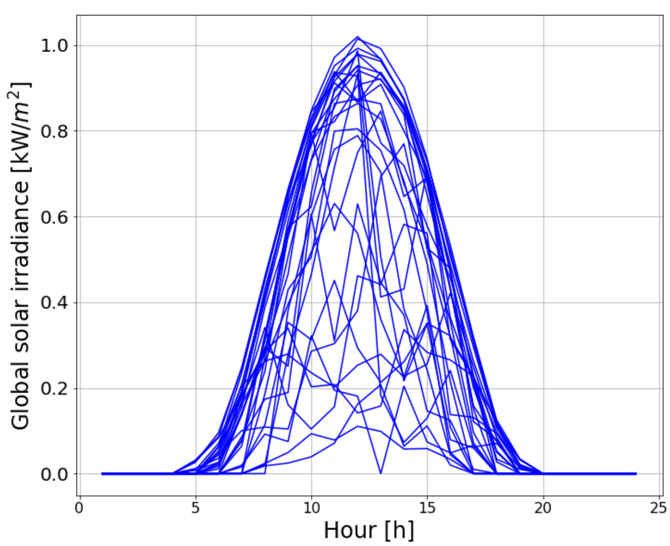


Figure 23. 29 typical days of solar irradiance representative of year 2014.

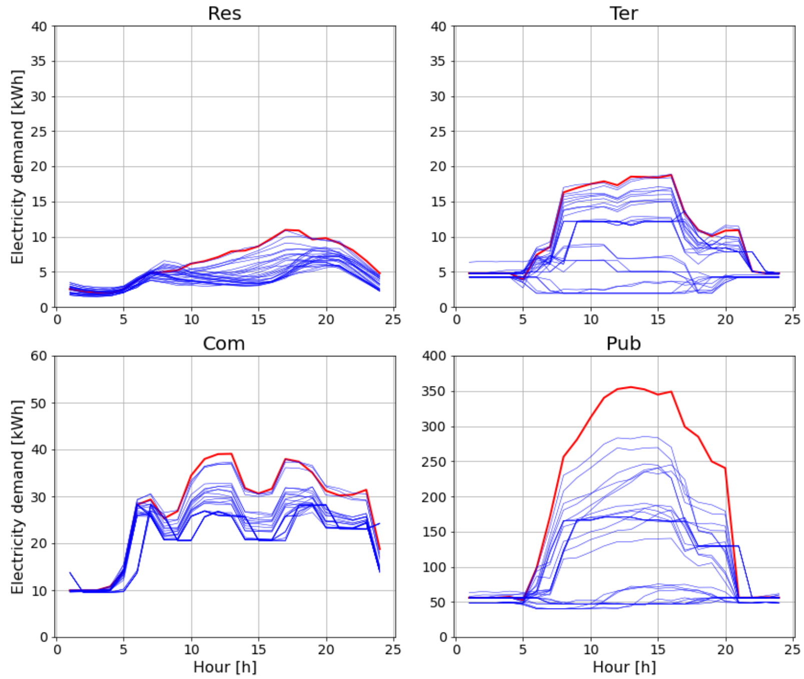


Figure 24. 29 typical days of electricity demands representative of year 2014 for the residential (Res), tertiary (Ter), commercial (Com) and public (Pub) members of the REC. The highest electricity demands of users, highlighted in red, account for the extreme day.

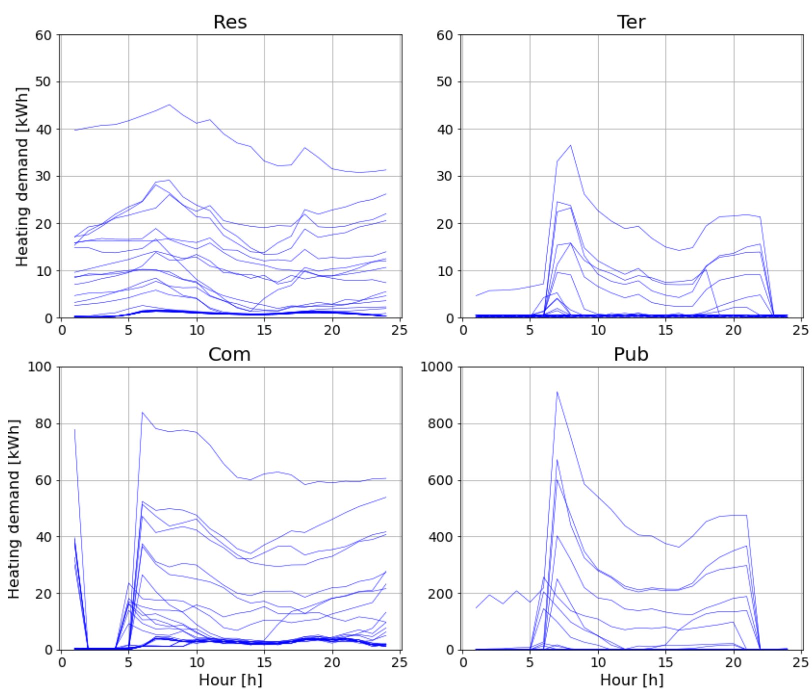
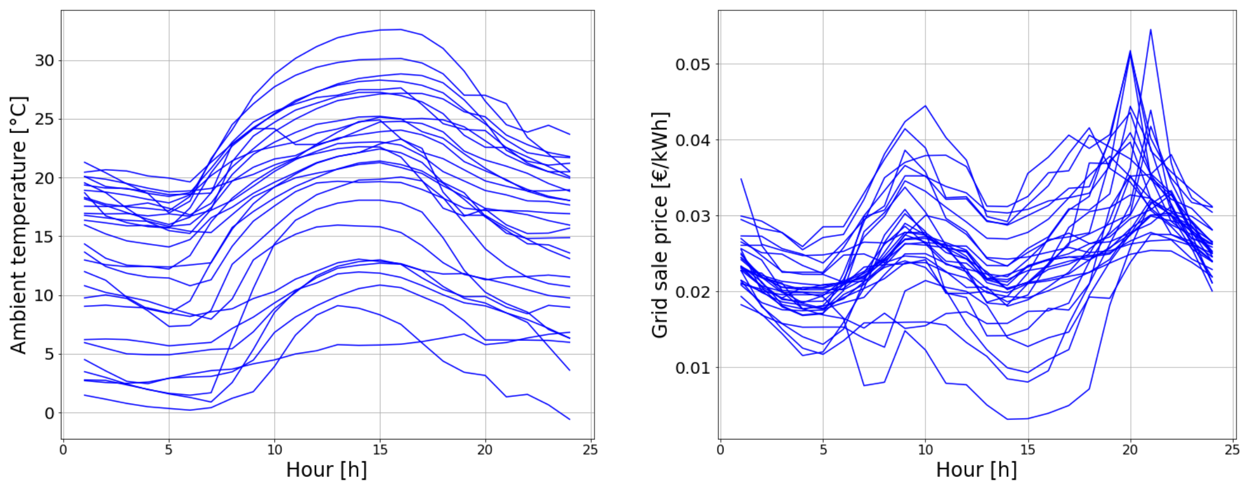


Figure 25. 29 typical days of heating demands representative of year 2014 for the residential (Res), tertiary (Ter), commercial (Com) and public (Pub) members of the REC.



a) *b)*

Figure 26. 29 typical days of a) ambient temperature and b) grid sale price, representative of year 2014.

5.3. Optimization results in absence of and under uncertainties

This sub-Section presents the results of the optimizations in the absence of and under uncertainties. Sub-Section 5.3.1 discusses the results of the optimizations that are performed to validate the Stochastic Programming (SP) optimization model, i.e., to select the "best" set of stochastic scenarios of the uncertain parameters from the training dataset. Sub-Section 5.3.2 discusses the results of testing the SP optimization model in the testing dataset, focusing on the weights of the uncertainties in the optimal design and cost of the analysed Multi-Energy System (MES).

5.3.1. Validation of the SP optimization model: definition of the "best" set of stochastic scenarios for the uncertain parameters

This sub-Section presents the findings that allow the validation of the Stochastic Programming (SP) optimization model, leading to the selection of a specific set of stochastic scenarios, i.e., the "best" set among the different sets generated. The results reported below are obtained by following the optimization framework presented in sub-Section 5.2.1 (see *step 1)* for solving the model without uncertainty, *step 2)* for scenario generation and *step 3)* for the validation of the SP model).

Figure 27 shows the optimal values of the life cycle cost of the system according to the "historical solutions" (blue dots) and the "stochastic solutions" (orange dots), which are obtained by solving the MILP model without uncertainty (sub-Section 5.2.2) and the SP model (sub-Section 5.2.3), respectively, for each year of the training dataset. In addition, the SP model is solved for 29 different sets of stochastic scenarios, containing a different number of stochastic scenarios ranging from 2 to 30 and different profiles. The choice of varying the number of scenarios from 2 to 30, which is a wider interval than those commonly used in the literature (i.e., no more than 20 scenarios approximately for one year, see e.g. [104]), is dictated by the need to evaluate how the stochastic solutions change over a sufficiently wide interval for each year of the training dataset. The minimum number of 2 scenarios corresponds to the minimum and meaningful number of clusters considered in a clustering technique (it is worth recalling that each stochastic scenario is the typical day of a generated cluster). The results outline that for a small number of stochastic scenarios (e.g., “k” equal to 2 or 3 in 2006, “k” equal to 2 in 2008 and 2010), the optimal value of the life cycle cost of the stochastic solution could be higher than that of the historical solution, given the high weight of the extreme day among the few scenarios in the SP model. For example, in 2006, the stochastic solution with 2 scenarios (where the extreme day represents 239 days of the year) and the historical solution lead to an optimal value of the life cycle cost of 492.41 k€ and 368.58 k€, respectively. It is interesting to note that in 2014 the stochastic solution with 29 stochastic scenarios is closest to the historical solution (the orange dot almost overlaps the blue one), with optimal values of 381.39 k€ and 382.65 k€ and with the lowest relative error of only 0.33 % across the different years, respectively.

The optimal life cycle cost of each “historical solution” is compared with that of each “stochastic solution” across all years of the training dataset and all generated sets of stochastic scenarios to calculate the Root Mean Squared Error (RMSE). According to Eq. (5.1) in sub-Section 5.2.1, the RMSE is used to calculate the standard deviation of the errors between the optimal values of the life cycle cost of the historical and stochastic solutions. Figure 28 shows the calculated RMSE for the 29 different sets of stochastic scenarios. The value of the RMSE shows a decreasing trend as the number of stochastic scenarios increases, with the highest and lowest values being approximately 78 k€ (for 2 scenarios) and 36 k€ (for 29 scenarios). This result is consistent with the fact that, in general, the optimal value of the objective function of the stochastic solution approaches that of the historical solution when the number of stochastic scenarios (i.e., typical days representative of a year) increases, thereby reducing the value of the RMSE. Since after 25 scenarios the RMSE remains almost constant around 40 k€ and the case with 29 scenarios presents the lowest value of the RMSE (i.e., 36 k€), the “best” number of stochastic scenarios is fixed to 29. In addition, the “best” profiles of the 29 stochastic scenarios are taken from the year 2014, which is characterized by the lowest value of the residual between the optimal values of the life cycle costs of the historical and stochastic solutions (i.e., a difference of 1.26 k€ is found). The choice of the 29 scenarios from year 2014 as the “best” set of stochastic scenarios seems the most appropriate, also considering the lowest relative error previously found between the historical and stochastic solutions (Figure 27). Note that Figure 23 and Figure 24 in sub-Section 5.2.4 show this “best” set of 29 stochastic scenarios of solar irradiance and electricity demands, respectively, found in the validation of the SP optimization model. This “best” set of stochastic scenarios will be used in the test of the SP optimization model in the next sub-Section 5.3.2.

It should be noted that the search for the solution of the SP optimization model allows not only to optimize taking into account uncertainty, but also to avoid the computational burden associated with the MILP optimization model without uncertainty. Indeed, the computational time to solve the MILP model without uncertainty for one year of the training dataset is on average 18 hours, in contrast to a few minutes to obtain a stochastic solution (i.e., in one year of the training dataset with a specific set of scenarios).

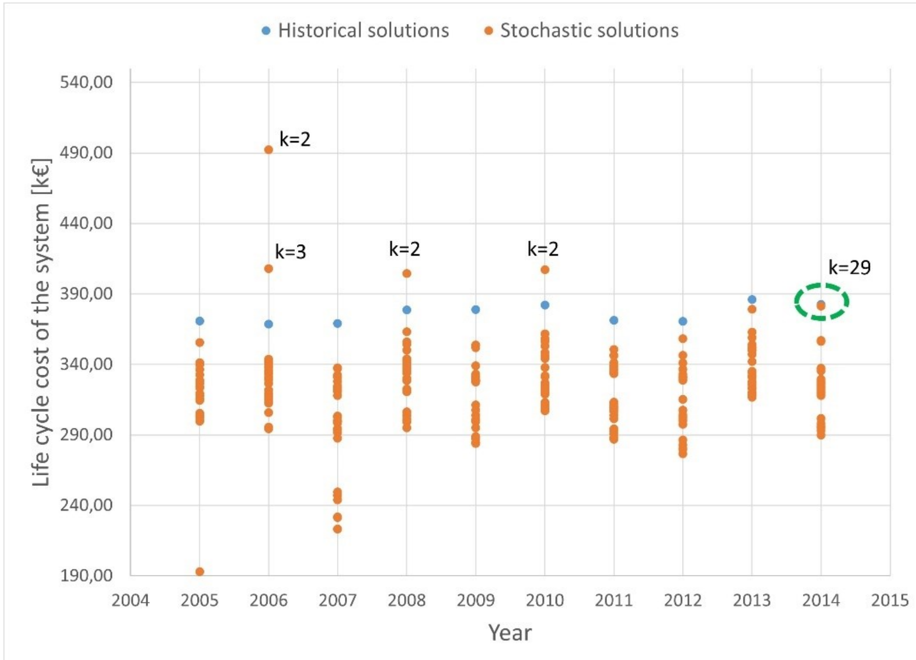


Figure 27. Optimal values of the life cycle cost of the system according to the historical solutions (blue dots) and the stochastic solutions (orange dots). For each year of the training dataset, 29 stochastic solutions are obtained, each based on a different number of stochastic scenarios (i.e., from 2 to 30). The dashed green circle indicates the stochastic solution with 29 scenarios that minimizes the relative error compared to the historical solution in year 2014.

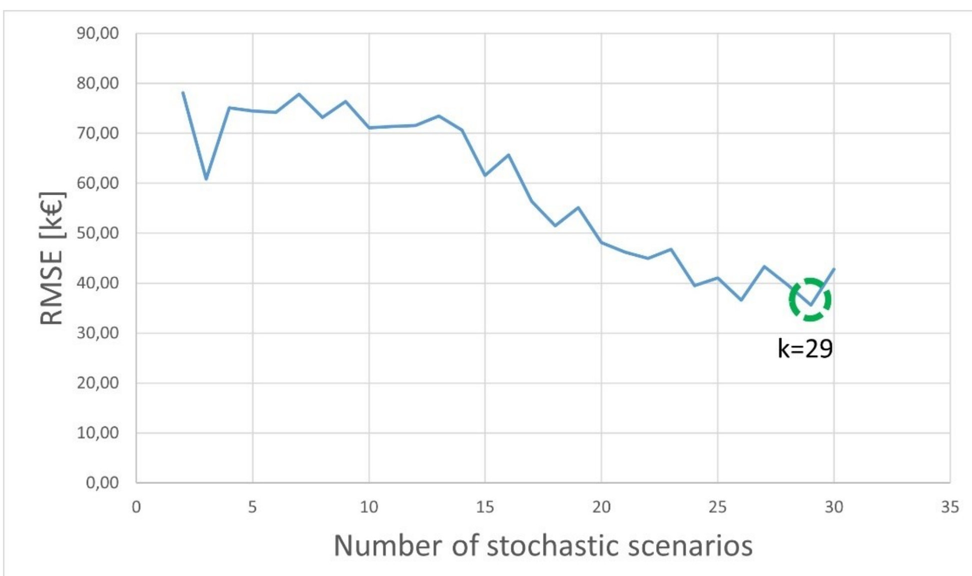


Figure 28. Trend of the Root Mean Squared Error (RMSE) as the number of stochastic scenarios increases from 2 to 30 in each year of the training dataset. The RMSE represents the standard deviation of the errors between the optimal values of the objective functions of the historical and stochastic solutions over the years of the training dataset (see sub-Section 5.2.1). The dashed green circle indicates the case with 29 scenarios leading to the lowest value of the RMSE of 36 k€.

5.3.2. Test of the SP optimization model: weights of uncertainties in the optimal design of the MES

This sub-Section presents the main findings obtained from testing the SP optimization model (see *step 4)* in sub-Section 5.2.1), which highlights the weights of the considered uncertainties in the optimal design and cost of the local MES associated with the REC. The test of the SP optimization model consists of solving this model with the "best" set of 29 stochastic scenarios of solar irradiance and electricity demands (i.e., the typical days found in sub-Section 5.3.1) as input data for each year of the testing dataset. The typical days of heating demand, ambient temperature and grid purchase/sale price in each year of the testing dataset are considered on the same chronological days associated with the 29 stochastic scenarios of solar irradiance and electricity demands. It is worth recalling that the MILP model in the absence of uncertainties solved for a year of the testing dataset relies on the assumption that the realizations of the scenarios of solar irradiance and electricity demands are known for each day of the year with zero prediction error. In other words, in the MILP model in the absence of uncertainties, there is complete knowledge of all timeseries in the 365 days, contrary to the SP model that is based on the "best" set of stochastic scenarios and attempts to predict the most accurate solutions possible for each year of the testing dataset. Finally, the "stochastic forecast", i.e., the solution of the tested SP model with the "best" set of 29 scenarios, is compared with the "deterministic forecast", i.e., the solution obtained by solving the MILP model in the absence of uncertainties, for each year of the testing dataset.

Table 10(a) shows the optimal sizes of the energy conversion and storage units of the system that are found in the stochastic forecasts and deterministic forecasts, while Table 10(b) shows the relative errors (in absolute value) of the optimal sizes according to the stochastic forecasts with respect to those of the deterministic forecasts. In both solutions, the Electrical Energy Storage (EES) units for the residential and public prosumers are not part of the optimal design of the system due to the high investment cost associated with this technology (in fact EES does not appear in Table 10). Note that the optimal sizes of the larger units, such as the PV and HP of the public user, are higher according to the stochastic forecasts than to the deterministic forecasts. This result is explained by the greater impact of the extreme day of the total electricity demand on the stochastic forecasts than on the deterministic forecasts, as the extreme day in the best set of 29 scenarios has a weight in the SP model of 7 days (i.e., w_k in Eq. (5.28)) instead of one single day as in the MILP model without uncertainties. Thus, the presence of the extreme day of the total electricity demand in the SP model leads to an increase in the optimal sizes of the PV and, in turn, of the HP (which could consume the electricity generated by the PV), compared to the optimal sizes found by solving the MILP model without uncertainties. Moreover, as the extreme day is mainly affected by the extreme electricity demand of the public user (with a peak of 350 kWh, see Figure 24), the overestimation of the PV and HP sizes mainly concerns the public user but not the residential one. As for the optimal sizes of the PV and HP units, the average of the relative errors over the years of the testing dataset is 13 % and 3 % (residential and public users, respectively) and 3 % and 10 % (residential and public users, respectively), respectively. Note that the error of 13 % in the optimal PV size for the residential prosumer can be neglected (look at the optimal sizes according to the stochastic and deterministic forecasts, Table 10(a)). It is worth noting that the optimal sizes of the TES units according to the stochastic forecasts present the highest relative errors compared to the deterministic forecasts (38 % and 23 % for the residential and public users, respectively, Table 10(b)). The reason for this result could be related to the fact that the temporal relationship between the typical days is neglected in the SP model and, therefore, the optimal size of TES reflects its daily operation and not a seasonal operation.

However, the largest relative error is found for the residential user, who has a TES unit with an optimal capacity much smaller than that of the public user (i.e., around 40-100 kWh for the residential user and more than 600 kWh for the public user, respectively, Table 10(a)). Hence, the weight of the optimal size of the TES unit for the residential user in the optimal life cycle cost of the system is lower than that for the public user, resulting in a higher acceptable error for the size of the TES unit of the residential user. Table 10(b) also shows that the stochastic forecasts result in optimal sizes of the GB units with no error with respect to those of the deterministic forecasts. In general, the above results show that the optimal sizes of PV, HP and GB according to the stochastic forecasts are quite accurate compared to the deterministic forecasts, while higher errors are found in the optimal sizes of the TES units.

Table 11 shows the optimal values of the life cost of the system (i.e., the objective function of the design-operation optimization problem) associated with the stochastic forecast and the deterministic forecast solutions, and the relative errors (in absolute value) of the life cycle costs according to the stochastic forecasts with respect to those of the deterministic forecasts. As expected, given the higher weight of the extreme day in the SP model than in the MILP model without uncertainties, the optimal life cycle cost of the stochastic forecast results higher than that of the deterministic forecast for all years of the testing dataset except for year 2016. For example, in 2015 the optimal life cycle cost of the system is 380.96 k€ with the stochastic forecast and 370.70 k€ with the deterministic forecast.

The highest and lowest relative errors of the life cycle cost according to the stochastic forecasts compared to those of the deterministic forecasts are equal to 2.77 % and 0.27 %, occurring in years 2015 and 2016, respectively. The average relative error over the years of the testing dataset is 1.63 %, which is lower than the optimality gap set for the optimization (i.e., 2 %) and is acceptable considering that the average computational time to solve the MILP model without uncertainty for one year of the testing dataset is 32 hours, as opposed to a few minutes to test the SP model in the same year. In addition, note that the use of the "best" set of 29 stochastic scenarios in the testing dataset leads to a lower value of the Root Mean Squared Error (RMSE) than that found in the training dataset for the same number of scenarios (i.e., 36 k€ in Figure 28). The formula of the RMSE, according to Eq. (5.1) in sub-Section 5.2.1, can also be used to calculate the standard deviation of the errors of the optimal life cycle costs according to the stochastic forecasts (based on the 29 stochastic scenarios) compared to the deterministic forecasts over the years of the testing dataset. The value of the RMSE obtained in the testing dataset is 7 k€, which is lower than the value of 36 k€ found in the training dataset. This confirms that the SP model with the "best" set of 29 stochastic scenarios predicts reliable cost solutions in the testing dataset, with a higher accuracy compared to that in the training dataset (i.e., the RMSE decreases by 81 %). This also confirms that the choice of dividing the historical input dataset (years from 2005 to 2020) into a training dataset of 10 years (2005-2014) and into a testing dataset of 6 years (2015-2020) is valid (as assumed in sub-Section 5.1).

As explained in sub-Section 5.2.3, the optimal life cycle cost of the system predicted for one year of the testing dataset (i.e., that associated with the "stochastic forecast") is equitably allocated to the members of the REC by applying the Shapley value mechanism (Eq. (2.9) in sub-Section 2.3). Table 12(a) shows the distribution of this optimal life cycle cost among the members of the REC for each year of the testing dataset. Table 12(b) shows the absolute annual cost savings achieved by the members by operating together in the REC compared to operating alone, and the shares of these cost savings in the total savings of the REC. It is worth noting that the annual cost savings of members are calculated as the differences between their annual costs when operating independently (i.e., outside the REC) and their annual costs obtained through the Shapley value allocation within the REC. Table 12(a) highlights that the annual costs allocated to the residential and tertiary users (approximately 18-20 k€ and 16-18 k€, respectively) are much lower than those allocated to the commercial and public users (approximately 53-54 k€ and 288-294 k€, respectively) over the years of the testing dataset. This is mainly explained by taking into account the higher daily electricity demands of the commercial and public users (Figure 24) and the high investment costs of the public user (due to the large optimal sizes of its units, Table 10(a)). However, Table 12(b) shows that, over the different years, approximately 41-57 % of the total annual cost savings of the REC (compared to the case where all members operate independently) are allocated to the commercial consumer, 21-34 % to the public prosumer, 10-20 % to the tertiary consumer and 3-15 % to the residential prosumer. For example, in year 2017, the total annual cost savings of the REC are 11.33 k€, of which 41 % and 32 % are distributed to the commercial and public users, respectively. As assumed in sub-Section 5.1, all users individually bear the investment costs of their energy units. Given the larger sizes of the units of the commercial and public users, they have to bear more expensive investments than those of the residential and tertiary users. Hence, the annual costs allocated to the commercial and public users by the Shapley value support their investments and provide them with higher annual cost savings compared to those of the residential and tertiary users.

The application of the Shapley value mechanism results in a fair distribution of the life cycle cost of the system, predicted for each year of the testing dataset, among its members. First, this mechanism rewards end users with low electricity demands, such as the residential and tertiary users, by allocating them low annual costs. In addition, the implementation of the Shapley value mechanism leads to higher annual cost savings for end users, such as the commercial consumer and the public prosumer, who make expensive investments, thus guaranteeing them a fair reimbursement. Therefore, the allocation by Shapley value can also encourage individual investments of members, with the aim of installing conversion and storage units that can be used to meet the energy needs of the whole REC.

Table 10. a) Optimal sizes of the energy conversion and storage units according to the stochastic forecast and the deterministic forecast (inside the brackets) solutions and b) absolute values of the relative errors of the stochastic forecasts compared to the deterministic forecasts, for each year of the testing dataset.

a)

	Stochastic forecasts (deterministic forecasts)					
	Years					
	2015	**2016**	**2017**	**2018**	**2019**	**2020**
$\boldsymbol{cap_{Res}^{PV}}$ **[kWel]**	25 (28)	20 (25)	23 (26)	25 (30)	25 (26)	20 (23)
$\boldsymbol{cap_{Res}^{HP}}$ **[kWth]**	41 (46)	40 (40)	39 (38)	40 (40)	41 (40)	39 (38)
$\boldsymbol{cap_{Res}^{TES}}$ **[kWh]**	126 (98)	42 (86)	46 (88)	50 (86)	106 (103)	39 (93)
$\boldsymbol{cap_{Ter}^{GB}}$ **[kW]**	36 (36)	36 (36)	36 (36)	36 (36)	36 (36)	36 (36)
$\boldsymbol{cap_{Com}^{GB}}$ **[kW]**	84 (84)	84 (84)	84 (84)	84 (84)	84 (84)	84 (84)
$\boldsymbol{cap_{Pub}^{PV}}$ **[kWel]**	537 (529)	489 (482)	521 (511)	585 (551)	521 (502)	469 (464)
$\boldsymbol{cap_{Pub}^{HP}}$ **[kWth]**	509 (481)	533 (479)	538 (463)	509 (499)	513 (475)	538 (461)
$\boldsymbol{cap_{Pub}^{TES}}$ **[kWh]**	790 (921)	694 (935)	666 (1021)	790 (849)	770 (955)	666 (1033)

b)

	Relative errors (absolute value, [%]) of the sizes of the stochastic forecasts with respect to the deterministic forecasts						
	Years						
	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**Average**
$\boldsymbol{cap_{Res}^{PV}}$	10.71	20.00	11.54	16.67	3.85	13.04	12.63
$\boldsymbol{cap_{Res}^{HP}}$	10.87	0.00	2.63	0.00	2.50	2.63	3.11
$\boldsymbol{cap_{Res}^{TES}}$	28.57	51.16	47.73	41.86	2.91	58.06	38.38
$\boldsymbol{cap_{Ter}^{GB}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\boldsymbol{cap_{Com}^{GB}}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\boldsymbol{cap_{Pub}^{PV}}$	1.51	1.45	1.96	6.17	3.78	1.08	2.66
$\boldsymbol{cap_{Pub}^{HP}}$	5.82	11.27	16.20	2.00	8.00	16.70	10.00
$\boldsymbol{cap_{Pub}^{TES}}$	14.22	25.78	34.77	6.95	19.37	35.53	22.77

Table 11. Optimal values of the life cycle cost of the system according to the stochastic forecast and the deterministic forecast solutions, and absolute values of the relative errors of the stochastic forecasts compared to the deterministic forecasts, for each year of the testing dataset.

	Years					
	2015	**2016**	**2017**	**2018**	**2019**	**2020**
Stochastic forecasts [k€]	380.96	376.44	383.39	380.16	381.38	375.72
Deterministic forecasts [k€]	370.70	377.46	375.75	375.65	374.90	367.15
Relative errors [%]	2.77	0.27	2.03	1.20	1.73	2.33

Table 12. a) Allocation of the optimal life cycle cost of the system, predicted for each year of the testing dataset (stochastic forecast), to the members of the analysed REC by Shapley value (the last line shows the annual life cycle costs that are distributed) and b) the annual cost savings of the members of the REC, compared to the case of independent operation, and their shares (in brackets) in the total annual cost savings of the REC (last line).

a)

	Costs allocated by Shapley value [k€]					
	Years					
Member	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Res	19.67	18.57	18.33	18.82	19.17	18.53
Ter	17.70	16.59	17.27	17.42	17.68	16.19
Com	54.26	52.79	53.31	54.38	53.93	52.55

Pub	289.34	288.50	294.48	289.54	290.61	288.45
REC	380.96	376.44	383.39	380.16	381.38	375.72

b)

	Absolute annual cost savings [k€] of members within the REC compared to the independent operation and their shares in the total annual cost savings of the REC [%]					
	Years					
Member	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Res	0.17 (2.81 %)	1.02 (12.12 %)	1.75 (15.43 %)	1.07 (12.85 %)	0.60 (9.73 %)	1.17 (14.58 %)
Ter	0.58 (9.63 %)	1.46 (17.28 %)	1.31 (11.59 %)	1.30 (15.5 %)	0.64 (10.41 %)	1.63 (20.43 %)
Com	3.25 (53.92 %)	3.81 (44.99 %)	4.65 (41.02 %)	4.17 (49.84 %)	3.49 (56.52 %)	3.53 (44.14 %)
Pub	2.03 (33.65 %)	2.17 (25.61 %)	3.62 (31.96 %)	1.82 (21.8 %)	1.44 (23.34 %)	1.67 (20.85 %)
REC	6.03	8.46	11.33	8.36	6.18	8.00

5.4. Conclusions

Section 5 fulfils the second objective of this Thesis, i.e., to evaluate the weight of the uncertainty associated with solar irradiance and end users' electricity demand in the optimal design and cost of a local Multi-Energy System (MES). This system satisfies the aggregated electricity demand of a Renewable Energy Community (REC) and the separate heating demands of its members. The analysed REC consists of four users with energy demands that are representative of the residential, tertiary, commercial and public sectors. The residential and public members are assumed to be prosumers who could install PV, HP, EES and TES units, while the tertiary and commercial users are assumed to be consumers who could install GB units.

A novel optimization framework is developed to carry out the design and operation optimization of the local MES of the REC. This framework includes a Mixed Integer Linear Programming (MILP) model and a Stochastic Programming (SP) model, which are used to optimize the system without and with uncertainties, respectively. The MILP model is solved for each day of a year, while the SP model for a set of typical days used as stochastic scenarios of the uncertain parameters in a year. In both models, the objective function to be minimized is the life cycle cost of the system actualized to one year of operation (including investment, operation and maintenance costs). The proposed framework relies on the availability of annual datasets containing daily timeseries of the input parameters, collected into a training dataset (from the years 2005 to 2014) and a testing dataset (from the years 2015 to 2020). The aim is to assess the accuracy of the optimal sizes and life cycle cost of the system obtained under uncertainties, compared to those obtained without uncertainties, for each year of the testing dataset.

Specifically, the optimization framework consists of four main steps. In the first step, the MILP model in the absence of uncertainties is solved for each year of the training and testing datasets, leading to the *"historical solutions"* (one for each year of the training dataset) and the *"deterministic forecasts"* (one for each year of the testing dataset), respectively. In the second step, different sets of typical days of the uncertain parameters are generated, including the extreme day with the highest electricity demand, by applying a K-means clustering technique several times (i.e., varying the number of typical days from 2 to 30 in the different sets) for each year of the training dataset. Note that the SP model, which is based on the typical days as stochastic scenarios, is solved for each year of the training dataset and each set of stochastic scenarios (i.e., for 29 sets for each of the 10 years, resulting in a total number of 290 optimization cases), and the SP solution for one year and one set of scenarios is called *"stochastic solution"*. In the third step of the proposed framework, the SP model is validated by identifying the "best" set of stochastic scenarios among the different ones generated over the years of the training dataset. The "best" set of stochastic scenarios is defined by choosing their number (i.e., from 2 to 30) and profiles (i.e., fixed one number of scenarios, there are 10 sets with different profiles over the years of the training dataset). The "best" number is chosen as the one that leads to the lowest value of the Root Mean Squared Error (RMSE), i.e., the standard deviation of the errors, between the optimal life cycle costs according to the stochastic and historical solutions over the years of the training dataset. After determining the "best" number of scenarios, the "best" profiles are taken from the year with the lowest value of the residual (i.e., the difference) between the optimal life cycle costs according to the stochastic and historical solutions. In the fourth step, the SP model is solved for each year of the testing dataset with the "best" set of stochastic scenarios as input data, resulting in *"stochastic forecasts"*. Finally, the accuracy of the optimal sizes and life cycle cost of the system according to the *"stochastic forecasts"* is assessed compared to the *"deterministic forecasts"* (found from the first step). This allows weighting uncertainties in the optimal design and cost of the system for each year of the testing dataset.

The validation of the SP optimization model suggests that the "best" set of stochastic scenarios contains 29 scenarios, found from the lowest value of the RMSE equal to around 36 k€, with profiles in the year 2014, which shows the lowest value of the residual equal to 1.26 k€. Given the "best" set of stochastic scenarios, the test of the SP optimization model leads to interesting outcomes regarding the weighting of uncertainties in the optimal design and cost of the local MES associated with the REC. The main outcomes in terms of optimal life cycle cost of the system, its fair allocation to the members and optimal sizes of the units are:

- *The average error in the optimal life cycle cost of the system according to the "stochastic forecasts" compared to the "deterministic forecasts" is 1.63 % over the years of the testing dataset*, which indicates the good accuracy of the *"stochastic forecasts"* in predicting the life cycle cost of the system in the testing dataset. In addition, the RMSE of the optimal life cycle costs between the "stochastic forecasts" and the "deterministic forecasts" (therefore in the testing dataset) is 81 % lower than that calculated in the training dataset (between the "stochastic solutions" and the "historical solutions"), showing an improved accuracy in predicting the optimal life cost of the system in the testing dataset compared to the training dataset.
- *The Shapley value mechanism fairly distributes the optimal life cycle cost of the system predicted for each year of the testing dataset*. This mechanism not only distributes lower annual costs to the residential and tertiary users characterized by low electricity demands (with allocated costs of around 18-20 k€ and 16-18 k€ over the years of the testing dataset, respectively), but also

ensures higher annual cost savings to the commercial and public users to support their expensive investments in the energy units (e.g., on average over the years of the testing dataset, 41-57 % and 21-34 % of the total annual cost savings of the REC are allocated to the commercial and public users, respectively).

- *The average errors in the optimal sizes of the units according to the "stochastic forecasts" (i.e., with uncertainties) compared to the "deterministic forecasts" (i.e., without uncertainties) vary between the different technologies*. For example, the average errors in the optimal sizes of PV are 13 % and 3 % for the residential and public prosumers respectively, while those in the optimal sizes of HP are 3 % and 10 % for the residential and public prosumers respectively, with absolute errors that are acceptable for both units. It is worth noting that the extreme day of the electricity demand mainly affects the optimal sizes of the PV and HP of the public prosumer (who has the highest daily electricity demand among the REC members), resulting in slightly higher sizes according to the "stochastic forecasts" than to the "deterministic forecasts". For the TES units, the "stochastic forecasts" lead to the highest relative errors in the optimal sizes compared to the "deterministic forecasts" (i.e., 38 % and 23 % for the residential and public prosumers, respectively). This could be explained by considering that the temporal relationship between the stochastic scenarios is neglected in the SP model. In addition, the optimal sizes of the GB units obtained with the stochastic forecasts are equal to those obtained with the "deterministic forecasts".

A first key result is that the stochastic forecasts (i.e., the optimal solutions under uncertainties) predict the optimal life cycle cost of the system with good accuracy, obtaining an average error of 1.63 %, which is good considering that it is lower than the optimality gap set for the optimization (i.e., 2 %) [67]. Moreover, note that in this Thesis the weight of uncertainties, which are represented by typical days in a year, is evaluated both in the optimal sizes of the units and in the life cycle cost of the system, and not only in the total cost as done in [67]. Another relevant result is that obtaining a "deterministic forecast" solution requires higher computational times (i.e., 32 hours on average) compared to obtaining a "stochastic forecast" solution (i.e., a few minutes on average), which indicates the advantage of time saving when solving the SP model under uncertainties compared to the MILP model without uncertainties for a one-year time horizon of the optimization.

A second key result is that the stochastic forecasts predict the optimal sizes of PV, HP and GB quite accurately, but show higher errors in predicting the optimal sizes of the TES units. In fact, a stochastic forecast is obtained by solving the SP model with the best set of stochastic scenarios, where the stochastic scenarios are typical days independent of each other. The temporal relationship between these typical days, neglected in this Thesis (see sub-Section 1.4), seems necessary to capture the seasonal operation of the TES units and, in turn, to reduce the errors in the optimal size of these units. Hence, the obtained stochastic forecast solutions are only reliable for the design of local MES that include storage units with a daily operation, neglecting their seasonal operation.

Given the local MES with a daily operation of the units (e.g., storage units), the SP method is suggested to conduct the one-year optimization of the design and operation of the system under uncertainties. Indeed, in a SP model, the uncertainty of input parameters with a daily variation (e.g., solar irradiance and end-user electricity demand) is intuitively represented by a set of stochastic scenarios, which could be obtained as typical days of a year. Moreover, the SP solution is achieved by considering all stochastic scenarios with their probabilities (i.e., the typical days with their weights in the year) simultaneously within the optimization. Hence, the SP solution is optimal for all scenarios considered and not for one scenario only, as the worst-case scenario in the robust optimization [102]. However, it is recommended to include an extreme scenario in the SP model (e.g., an extreme day of the electricity demand) to minimize the errors in the optimal sizes and cost with respect to an optimization without uncertainty (i.e., based on a full year with 365 daily timeseries).

The results obtained could be useful for policy makers and investors to make informed decisions, under the uncertainties of RES and users' energy demand, on the optimal design of a local MES (characterized by units with a daily operation) of a REC consisting of users representative of different consumption sectors. In addition, the Shapley value is an effective mechanism to fairly distribute the optimal life cycle cost of the system among the different users. This mechanism also fosters end users (e.g., commercial and public users) who have high demands and invest in units with large sizes to become members of the REC, as the cost allocation guarantees them a fair annual return on their investment.

Further research could address the improvement of the proposed optimization framework by increasing the number of years with available input timeseries in the training and testing datasets, as well as considering other uncertainties (e.g., heating demands, prices of technologies and energy carriers, etc.). In addition, the temporal relationship between different typical days used as stochastic scenarios in the SP model will be further investigated. Another possible direction of future work could focus on the evaluation of different objective functions (e.g., environmental and social objective functions such as the environmental emissions and the users' discomfort).

6. Critical remarks and Conclusions

Existing energy systems at different geographical scales (i.e., local, regional and national), referred to as "local-to-regional" Multi-Energy Systems (MES), can include local power systems and local MES, meeting different energy demands of end users by using various energy sources. These systems are undergoing a profound transformation, characterized by a relevant use of Renewable Energy Sources (RES) to counteract the harmful environmental effects of the climate change, as well as a strong integration of local consumers and prosumers using distributed energy units. In addition, local users can form Energy Communities (ECs), which are aggregations where different end users (e.g., coming from different consumption sectors) can share energy. Thus, the general problem of ensuring the optimal match between energy demand and generation in "local-to-regional" energy system configurations becomes quite challenging. In fact, the uncertainties associated with the variable RES and the profiles of energy demand of different end users, as well as the different aspects influencing the optimal aggregation of end users in ECs, complicate the achievement of an optimal solution to the problem of optimally matching energy demand and generation.

In such a context, this Thesis contributes to address the optimization problem of the design (i.e., the choice of the type, number and size of the energy conversion and storage units) and operation of energy systems in local configurations, also considering the possible uncertainty of RES and energy demand profiles.

In light of the above considerations, and as reported in sub-Section 1.2, this Thesis seeks to answer to the following research questions.

- What are the main aspects that ensure the optimal aggregation of end users in ECs and what are the weights of these aspects in terms of economic benefits to the EC and its members?
- What is the weight and impact of the uncertainty associated with RES and users' energy demands on the optimal design and cost of local MES meeting the energy demands of ECs?

These research questions have allowed to define the twofold objective of this Thesis. The first objective is to analyse all the aspects that affect the optimal aggregation of end users in ECs (that could use local power systems or local MES) and assess the weights of these aspects in the economic benefits of the whole system and its members. The second objective is to evaluate the weight of different uncertainties, on the generation and demand sides (i.e., RES and energy demand profiles), in the optimal design and cost of a local MES that meets the energy demands of an EC.

With the aim of assessing the weight of the uncertainty of RES and users' energy demands in the optimal design and cost of a local MES serving an EC, it is necessary to first analyse the main aspects that affect the optimal aggregation of end users in ECs. For this reason, this Thesis presents three case studies, where the first two reference case studies and the third case study aim to fulfil the first and second objectives of this Thesis, respectively. In the first two reference case studies, Mixed Integer Linear Programming (MILP) models are used to optimize only the operation of local power systems associated with different EC configurations in the absence of uncertainties. In the third case study, a novel optimization framework based on a Stochastic Programming (SP) model is developed to optimize the design and operation of a local MES serving an EC under uncertainties. The critical remarks associated with these case studies are summarized below.

The first reference case study (see Section 3), in line with the first objective of this Thesis, focuses on the main aspects affecting the optimal aggregation of end users and their economic benefits in different EC configurations, such as the Citizen Energy Community (CEC) and the Renewable Energy Community (REC). These aspects are the complementarity between the energy demand and generation profiles of the members of the EC, the allocation of the total economic cost of the EC to its members, and the application of Demand Response (DR) programs as flexibility strategies to optimally shift the electricity demands of the members. Two different MILP models are used to optimize the daily operation of the two local power systems associated with the CEC and REC configurations, in the absence of uncertainties. The optimization minimizes the daily operational cost of the system in three characteristic seasonal days.

Several optimizations are performed for the CEC and REC configurations, considering different prosumer couplings, Price-Based Demand Response (PBDR) and Incentive-Based Demand Response (IBDR) programs, and two different cost allocation mechanisms. The prosumers in the different couplings have electricity demand profiles that are representative of the residential (Res), industrial (Ind), agricultural (Agr) and tertiary (Ter) sectors, with the residential and the industrial/agricultural/tertiary prosumers equipped with PV and biogas-fuelled ICE, respectively. The optimal shifting of the electricity demands is driven by a PBDR program based on time-varying grid purchase prices according to a Time-of-Use (TOU) strategy, or by an IBDR program that incentivizes members who effectively reduce their hourly energy demand. After solving the operation optimization, two different cost allocation mechanisms are implemented to distribute the optimal daily operational cost of the system. A first mechanism, called “C1”, is proposed to reward more those end users who achieve the better compromise between maximum self-generation from RES and minimum cost for it. The second mechanism, called “C2”, distributes the total economic cost of the system among the members in proportion to the ratio between their individual electricity demand and the total demand, charging these ratios through an average price.

The main findings of this first reference case study highlight that:

- *The higher degree of complementarity between the energy demand and generation profiles of prosumers can reduce the daily cost of the system by 15-20 %. For example, Ind-Res is the best coupling in terms of complementarity between prosumers, with a daily cost that is up to 20 % lower than that of the Agr-Res coupling.*
- *The proposed mechanism C1, unlike mechanism C2, can reduce the daily costs of prosumers using free-of-charge renewables by 20-30 % compared to those using dispatchable sources, thus favouring the PV-equipped residential prosumer compared to the other prosumers equipped with the biogas-fuelled ICE.*
- *PBDR programs can reduce the daily cost of the local power system of the REC by more than 50 % when the optimal shifting of the total electricity demand is driven by the TOU grid prices.*
- *The local power system of the CEC achieves the lowest daily costs (12-39 % lower than those of the REC) and the highest self-consumption values (up to 99.68 %).*

It should be noted that the fairness of the cost allocation is not analysed in the first reference case study. Therefore, the second reference case study (see Section 4), in line with the first objective of this Thesis, focuses on the fairness in the distribution of the optimal operational economic benefit of an EC among its members. First, a MILP model is used to optimize the daily operation of the local power system of a Renewable Energy Community (REC) in the absence of uncertainties, maximizing the daily profit of the system. The REC consists of three members, one consumer from the tertiary sector and two prosumers representing the residential and commercial sectors. The residential prosumer owns a PV plant, while the commercial prosumer owns a PV plant coupled with an EES unit. In addition, the electricity demands of end users are optimally shifted by applying a PBDR program with a Real-Time Pricing (RTP) strategy, which sets different hourly grid purchase prices according to the daily profile of the day-ahead market price.

After solving the MILP operation optimization model, the Shapley value and the Uniform pricing mechanisms are applied separately to allocate the optimal daily profit of the system to its end users. It should be noted that the Shapley value mechanism, unlike the Uniform pricing mechanism, is based on a cooperative game model that takes into account the cooperation among the members of the REC in the process of allocating the total economic benefit. In other words, Shapley value is a fair allocation mechanism because it allocates costs/profits to the members in proportion to their contributions to the costs/profits of the community and its internal coalitions of members.

The main findings of this second reference case study highlight that:

- *The Uniform pricing mechanism can lead to a more homogeneous distribution of costs/profits among the members of the REC, although these costs/profits are obtained without fairly weighting the contributions of the different members to the optimal economic benefit of the system.*
- *The Shapley value mechanism rewards the prosumers (i.e., the residential and commercial users) by giving them higher economic benefits than the consumers (i.e., the tertiary user) for their major contributions to reducing (increasing) the costs (profits) of the system and its internal coalitions of members.*

The third case study (see Section 5) fulfils the second objective of this Thesis. The aim is to evaluate the weight of uncertainties associated with solar irradiance and end-user electricity demands in the optimal design and cost of a local MES, which meets the aggregated electricity demand of a REC and the separate heating demands of its members. The members have energy demands that are representative of the residential, tertiary, commercial and public sectors. The residential and public members are prosumers who could install PV, HP, EES and TES units, while the tertiary and commercial members are consumers who only invest in natural GB units. As in the second reference case study (Section 4), the electricity demands of end users are optimally shifted according to a PBDR program with a RTP strategy, which is implemented in the optimization models described below.

A novel optimization framework is developed to obtain optimal annual solutions to the design-operation optimization problem of the MES under uncertainties. The aim is not to provide a unique and general solution to the design-operation optimization problem of any MES under uncertainties, but rather to evaluate the accuracy of the optimal solutions under uncertainties compared to the optimal solutions in the absence of uncertainties. In the developed optimization framework, daily timeseries of the input data are available in two datasets, which are the training dataset (collecting the input timeseries in the years from 2005 to 2014) and the testing dataset (collecting the input timeseries in the years from 2015 to 2020). The optimization framework is implemented through four steps that are called 1) Model without uncertainty, 2) Scenario generation, 3) Validation of the SP model and 4) Test of the SP model. In the following, the objective function to be minimized in the optimization models is the life cycle cost of the system actualized to one year of operation. In the first step, a MILP model is used to obtain the optimal solution to the design-operation optimization problem of the system in the absence of uncertainties. The MILP model is solved for each day of each year of the training dataset, resulting in annual "historical solutions", and for each day of each year of the testing dataset, resulting in annual "deterministic forecasts". In the second step, different sets of stochastic scenarios of the uncertain parameters are obtained for each year of the training dataset. For this purpose, a K-means clustering is applied several times (i.e., varying the number of the generated clusters) for each year of the training dataset, and the representative days of the clusters, i.e., the typical days of each year (including the extreme day of the electricity demand), are taken as stochastic scenarios in the SP optimization model. The SP model is then solved for each year of the training dataset and each set of stochastic scenarios, resulting in "stochastic solutions". In the third step, the SP model is validated by searching for the "best" set of stochastic scenarios among the different sets generated. The "best" set of stochastic scenarios is found by looking for the lowest value of the Root Mean Squared Error (RMSE) between the optimal life cycle cost of the "historical solutions" and the "stochastic solutions", and by taking the lowest difference between these two solutions. In the fourth step, given the "best" set of stochastic scenarios as input, the SP optimization model is solved for each year of the testing dataset, resulting in annual "stochastic forecasts". Finally, the accuracy of the "stochastic forecasts" is quantified by a comparison with the "deterministic forecasts", leading to an evaluation of the weight of uncertainties (affecting the "stochastic forecasts") in the optimal design and cost of the local MES. In addition, the Shapley value mechanism is applied to fairly distribute the optimal life cycle cost of the system (according to the "stochastic forecast") among the members for each year of the testing dataset.

From the validation of the SP model, the "best" set of stochastic scenarios of solar irradiance and user electricity demands includes 29 scenarios from the year 2014. The test of the SP model with this "best" set of stochastic scenarios allows weighting the uncertainties in the optimal design and cost of the system. The key findings are:

- *The optimal predicted life cycle cost of the system according to the "stochastic forecasts" has an average error with respect to the "deterministic forecasts" of 1.63 % over the years of the testing dataset, which is acceptable considering the optimality gap (i.e., 2 %) and the higher computational times required to obtain the "deterministic forecasts" (i.e., 32 hours on average) compared to the "stochastic forecasts" (i.e., a few minutes). In addition, the accuracy of predicting the optimal life cycle cost of the system is higher in the testing dataset than in the training dataset, as the RMSE in the testing dataset is 81 % lower than in the training dataset.*
- *The errors obtained in predicting the optimal sizes of the PV, HP and GB units according to the "stochastic forecasts", with respect to the "deterministic forecasts", can be considered acceptable (relative errors in the range of 3-13 % for PV and HP, and zero error for GB). However, the higher relative errors for the optimal sizes of the TES units (in the range of 23-38 %) can be explained considering that the temporal relationship between the stochastic scenarios is neglected, thus losing the possibility of modelling the seasonal operation of the TES unit.*

To summarize, the optimal annual solutions obtained by testing the SP model (i.e., the "stochastic forecasts") well predict the optimal life cycle cost of the system and the sizes of PV, HP and GB (taking the solutions without uncertainties, i.e., the "deterministic forecasts", as reference). However, the errors found in predicting the sizes of the TES units require to introduce the temporal relationship between the stochastic scenarios in the SP model, which will be considered in future work. A last relevant result is that *the Shapley value mechanism fairly distributes the optimal life cycle cost of the system predicted for each year of the testing dataset.* Residential and tertiary users with lower demands receive lower costs, while commercial and public users, investing in energy units with large sizes, benefit from higher annual cost savings (up to 41-57% for commercial and 21-34% for public users).

In conclusion, this Thesis has evaluated the aspects affecting the optimal aggregation of end users in ECs and the weight of the uncertainties associated with solar irradiance and users' electricity demands in the optimal design and cost of a local MES serving an EC. Regarding the optimal aggregation of end users in ECs, future work could explore cost/profit allocation mechanisms based on different definitions of fairness compared to the Shapley value mechanism. Concerning the optimization of the design and operation of local MES under uncertainties, future work will certainly focus on improving the proposed optimization framework. For example, the training and testing datasets where the SP optimization model is validated and tested could be extended, other uncertainties (e.g., related to energy demands other than electricity) could be considered and the temporal relationship between the stochastic scenarios will be investigated. In the context of "local-to-regional" MES, there is the need to design the energy systems of the future to be economically, environmentally, and socially sustainable, with the aim of ensuring energy security and affordability for a wide range of end users. In this direction, a challenging development of this Thesis could be to optimize the design and operation of a regional MES under uncertainties. A regional MES includes, in addition to local power systems and local MES meeting the energy demands of ECs, also centralized generation plants that satisfy, e.g., the energy needs of large end users (e.g., from the industrial sector). Furthermore, the models of different energy networks (e.g., electrical, district heating, gas, etc.) could be included in the design-operation optimization model of a regional MES. Optimizing the design and operation of this complex system requires the assessment of various uncertainties, such as those related to boundary conditions, e.g., the ability of the system to meet environmental and social targets set by European and national legislation. An example of an environmental target to be achieved is the minimum share of RES in the total final energy consumption of a regional MES. Therefore, future work will aim at formulating and implementing the model for optimizing the design and operation of a regional MES, under uncertainties such as the future minimum share of RES in the total final consumption of the system.

Scientific publications

The author of this Thesis is author or co-author of the following scientific publications:

- Papers published in journals: [159], [160], [10], [62], [161], [162]
- Papers published in conference proceedings: [109], [156], [110], [163], [164]

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Appendix

A. Method for defining probabilities of time-correlated stochastic scenarios

This sub-Section presents an alternative method for defining the probabilities of stochastic scenarios, which differs from the method based on the frequency of the cluster (see sub-Section 2.2.2) used in the third case study of this Thesis (see Section 5). The method presented below is taken from a paper [110] written by the author of this Thesis.

In [110] a two-stage problem (see sub-Section 2.2.1) is considered for an electricity retailer that has to choose the optimal amount of energy to exchange in the Day-Ahead (DA) market in the first stage, and the optimal amount of energy to exchange in the Balancing Market (BM) in the second stage, which is affected by the uncertainty of the RES. Thus, a two-stage SP optimization model is developed to optimize the operation of the local power system of the retailer in the two electricity markets that occur in subsequent days. The two-stage SP optimization model is based on a set of stochastic scenarios of RES generated by applying a K-means clustering technique on a dataset containing multiple daily timeseries of the uncertain parameter. It is worth reminding that, according to state-of-art clustering approaches, the representative timeseries of a cluster can be considered as a stochastic scenario in the SP optimization model. The probability of the stochastic scenario can be defined as the relative frequency of the cluster, which is calculated as the ratio between the number of timeseries in this cluster and the total number of timeseries [90, 98, 165]. However, this approach to defining the scenario probabilities does not consider the possible temporal correlation between the stochastic scenarios occurring on the consecutive days of the DA and BM stages.

To address this issue, a method based on the "conditional probabilities" is proposed.

For clarity, we assume that the first and second stages, associated with the DA and BM stages, refer to two subsequent days denoted d and $d+1$, respectively. For each scenario i in day d, there is a scenario j in day $d+1$, where both i and j refer to scenarios found by the clustering. The method presented here assigns to each scenario j in day $d+1$, given the scenario i in day d, the conditional probability defined as expressed by Eq. (A.1):

$$p(j|i) = \frac{\#(i,j)}{\#(i,*)} \tag{A.1}$$

where the numerator is the number of pairs of subsequent days d and $d+1$ in which scenarios i and j occur respectively, while the denominator is the number of pairs of subsequent days in which scenario i in day d occurs independently of the scenario in the following day $d+1$. The denominator also corresponds to the number of timeseries in a specific cluster. According to the proposed method, each representative timeseries j in day $d+1$, chosen as a stochastic scenario in the SP model, has different probability values (i.e., the conditional probabilities) depending on the representative timeseries i in day d.

B. Nash bargaining optimization

This sub-Section aims to present the general mathematical formulation of a Nash bargaining cooperative optimization model, which allows the optimal economic benefit of a system, e.g., an Energy Community

(EC), to be fairly distributed among its members in a different way with respect to the Shapley value (sub-Section 2.3).

B.1. Mathematical optimization model

In a Nash Bargaining (NB) cooperative problem, N players cooperate to optimize their individual economic benefits while achieving an optimal solution for the system. The NB optimization solution satisfies the properties of individual rationality (i.e., each player has an economic benefit derived by cooperation, see sub-Section 2.3) and Pareto optimality, the latter ensuring that a player cannot increase its optimal benefit without decreasing the benefits of other players (i.e., this ensures an optimal solution for the whole system). Contrary to the Shapley value mechanism, which is applied after the optimization of a system, NB is an approach that incorporates the distribution of the total economic benefit into the optimization problem.

In the Nash bargaining theory, the economic benefits of the players (i.e., their economic costs or profits) are represented by mathematical functions called "utility functions". Nash bargaining optimization aims at simultaneously maximizing the "incremental utility functions" of all cooperating players, i.e., their increases (decreases) in profits (costs) obtained by cooperating within a grand coalition (e.g., an EC) with respect to the case without cooperation. The NB solution is the set of decision variables x that maximizes the Nash product given in Eq. (B.1):

$$max \prod_{i=1}^{N} u_i^{incr}(x_i) \tag{B.1}$$

$$u_i^{incr}(x_i) = u_i(x_i) - u_i' \tag{B.2}$$

$$u_i^{incr}(x_i) \geq 0 \tag{B.3}$$

where $u_i^{incr}(x_i)$ is the (hourly or daily) incremental utility function of player i (here referring to an increase in the economic profit), i.e., the difference (shown in Eq. (B.2)) between the utility $u_i(x_i)$ when a cooperative agreement is reached between the players and the utility u_i' without agreement (here considered as an input parameter), the latter hereinafter referred to as the "disagreement outcome". In the context of an EC, the utility with agreement and the disagreement outcome of member i correspond, respectively, to the economic benefit of cooperating with other members of the EC and to that of a reference case without cooperation, for example when each energy end-user operates independently. Note that the incremental utilities in Eq. (B.2) are defined with opposite signs when the utilities refer to costs. Constraint (B.3) guarantees individual rationality, so that cooperation between players never penalizes any individual player. In fact, the value of the utility with agreement is higher than or equal to the disagreement outcome (on the other hand, the value of the utility is lower than or equal to the disagreement outcome when the incremental utility represents a decrease in cost).

Note that the objective function of the Nash bargaining optimization (Eq. (B.1)) is non-convex and non-linear, which makes it difficult to find the optimal solution. However, the works [75, 166-168] showed that the above problem is equivalent (i.e., in terms of optimal solution), under certain assumptions, to a convex problem based on logarithmic utility functions. These works also demonstrated that the NB solution is a "proportional" fair solution according to the definition of Kelly et al. [169, 170]. Another relevant aspect to highlight is the comparison between the NB optimization and the traditional "Social

Welfare” (SW) optimization, which maximizes (minimizes) the total profit (cost) of a system. The objective function of the NB optimization problem depends on the individual objectives of the players (due to the product of the incremental utility functions), in contrast to the case of the SW optimization (where the objective function could be a sum of the incremental utility functions). For this reason, NB optimization is capable of achieving a “proportional fair” solution, which is optimal not only for the individual members but also for the whole system (i.e., this solution is also a solution of the SW problem where the sum of the incremental utility functions is maximized [168, 171]). On the other hand, in SW optimization, different optimal utilities (e.g., profits/costs) of the players can be obtained until the total utility (e.g., profit/cost) of the system is maximized (or minimized), thus likely leading to an unfair solution in terms of the distribution of the total benefit of the system.

C. Other results of sub-Section 3.3

Sub-Sections 3.3.1 and 3.3.2 present the results of the operation optimizations and total cost allocation for the local power systems of the Citizen Energy Community (CEC) and the Renewable Energy Community (REC), respectively, considering a characteristic day of April. This sub-Section summarizes the results obtained for two other characteristic days of December and August. Figure C.1, C.2 and C.3 show the optimal daily operational costs of the systems and the costs (bills) allocated to the members in the CEC, REC without incentive and REC with incentive, respectively, for the two characteristic days of December and August. The main findings obtained are in line with those referring to the characteristic day of April (see sub-Sections 3.3.1-3.3.2-3.3.3).

The Ind-Res coupling achieves the highest degree of complementarity between the generation and demand profiles of its prosumers. For example, in December, Ind-Res has 17 %, 14 %, 16 % (19 %, 15 %, 19 % in August) lower costs compared to Agr-Res in the basic aggregation of CEC, REC without incentive and REC with incentive, respectively. In terms of cost allocation, the proposed mechanism C1 for the basic aggregation of Ind-Res coupling leads in August to a cost of the PV-equipped residential prosumer that is 20 % (in the REC with incentive) and 30 % (in the CEC) lower than that of the ICE-equipped industrial prosumer, whereas C1 does not benefit the residential prosumer in December due to the low solar irradiance (it is worth reminding that mechanism C1 favours the users exploiting free-of-charge RES). The IBDR2 and PBDR programs are the most profitable flexibility strategies in the CEC and REC, with maximum economic savings in total costs of 2.3-4.7 % (December-August) and 57.8-61.8 % (August-December), respectively. Comparing CEC and REC with basic aggregation, the optimal costs of the CEC are 14 % and 29 % lower than those of the REC with and without incentive in December (12 % and 39 % in August), respectively. Eventually, it should be noted that the optimal costs of the CEC and the REC with incentive decrease significantly from December to April due to the increase in solar irradiance and grid sale prices (Figure 9 in sub-Section 3.2.5). Conversely, these optimal costs slightly decrease from April to August because the decline of the grid sale prices counteracts the effect of the increase in solar irradiance.

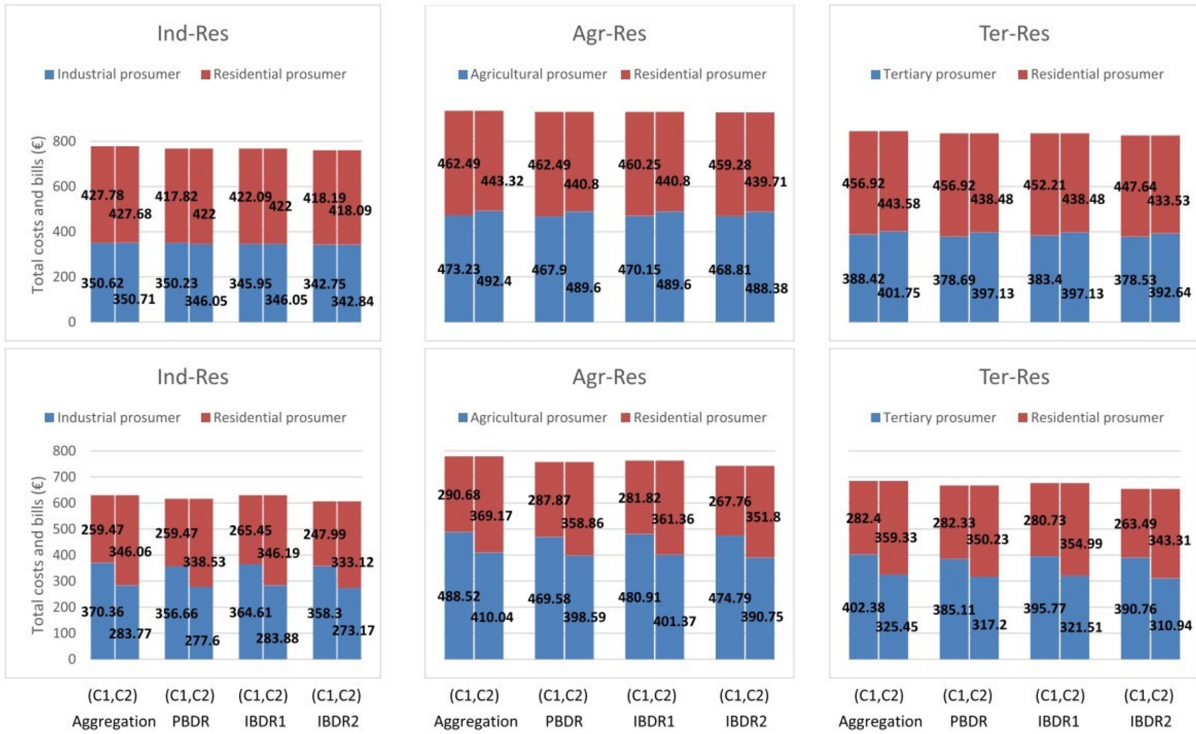

Figure C.1. Economic results from the optimization of CEC in December (above) and August (below).

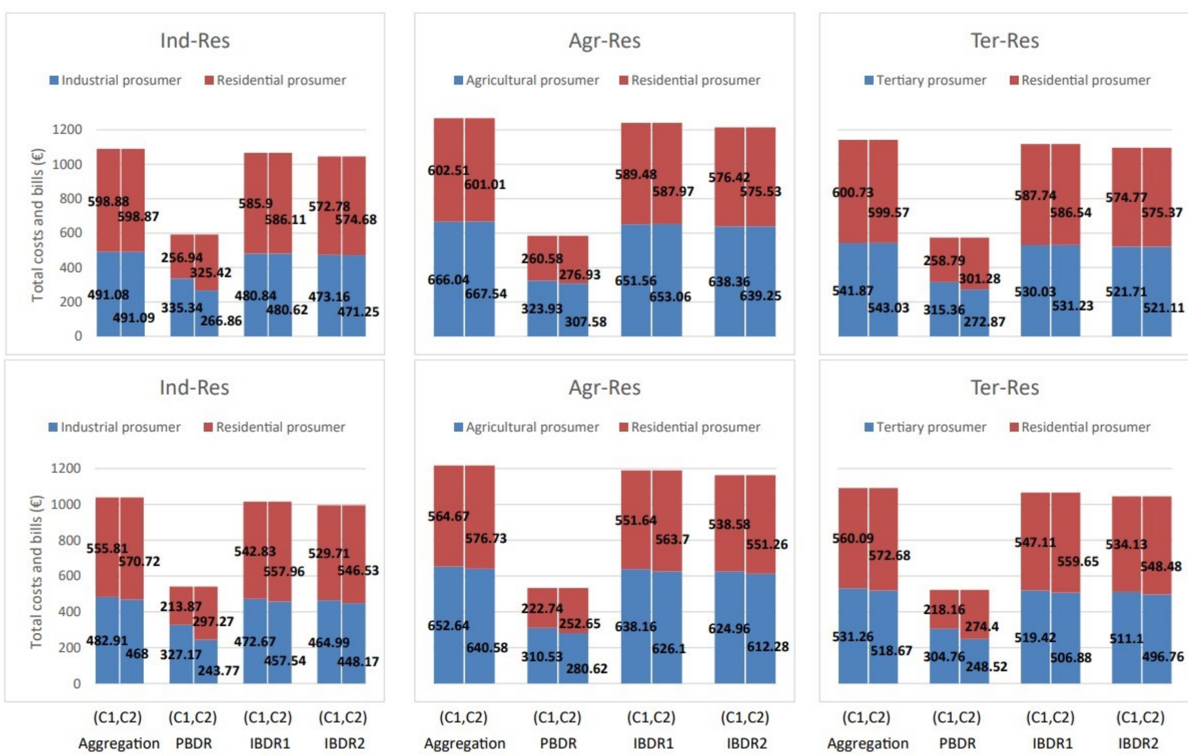

Figure C.2. Economic results from the optimization of REC without incentive in December (above) and August (below).

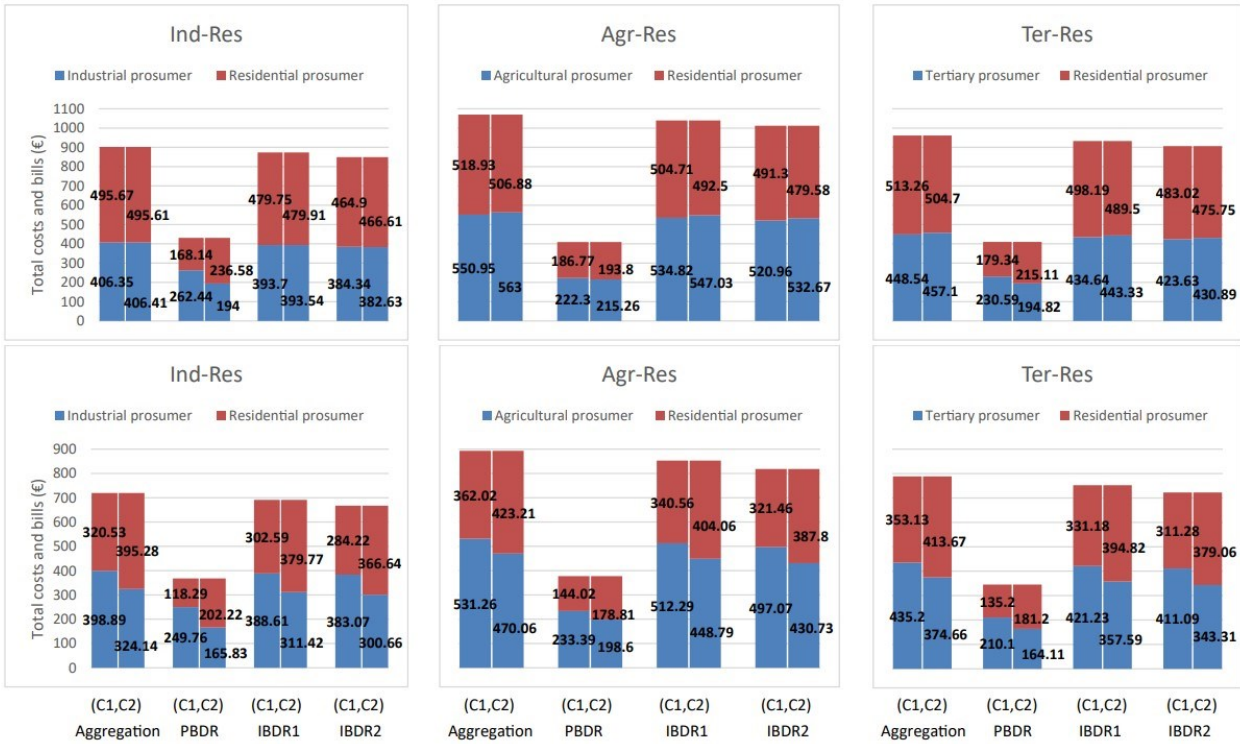

Figure C.3. Economic results from the optimization of REC with incentive in December (above) and August (below).