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A stochastic optimization procedure to design the fair aggregation of energy users in a Renewable Energy Community

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ABSTRACT

Optimizing unit sizes and operation within a Renewable Energy Community (REC) can match intermittent renewable energy generation with variable user energy demands. These uncertain variables are often represented by pre-defined stochastic scenarios, without searching for the "best" scenarios and testing the optimization models with these scenarios. Moreover, little work both optimized RECs under uncertainty and distributed optimal life-cycle costs (investment and operation) among members. Thus, the objectives are: *i)* identifying the "best" set of stochastic scenarios of solar irradiance and user electricity demands and *ii)* assessing the accuracy of the "stochastic forecasts" of the total system costs and unit sizes, obtained by solving a stochastic programming model based on the "best" scenarios. The proposed novel procedure shifts the "present moment" back in time to split historical data into "past" and "future" periods used to identify the "best" scenarios and compare the "stochastic forecasts" with the utopic "perfect forecasts" based on the perfect knowledge of real data, respectively. The small errors between these forecasts in the optimal life-cycle costs (less than 2 %) and sizes (3–13 %) indicate good effectiveness of the suggested procedure. Also, the optimal life-cycle costs of "stochastic forecasts" are fairly distributed among users by applying the Shapley value mechanism.

1. Introduction

Creating a greener and more equitable society requires increased utilization and consumption of distributed Renewable Energy Sources (RES). Recently, the European Union updated the energy and environmental targets of the "Clean Energy Package" [1], according to the "Fit-for-55" [2] and the "REPowerEU" [3] plans, with a view to achieving the carbon neutrality by 2050 [4].

Energy Communities (ECs) are innovative energy system configurations that could help achieve the energetic and environmental targets set by the European Union [5]. ECs promote the aggregation of local users [6] to improve the match between energy demand and generation at the local level, thereby reducing the burden on the energy networks. ECs also increase the self-consumption of distributed RES in neighbourhoods, districts, municipalities and cities [7,8], by enabling members to share energy within the community [9]. The European legislation [10, 11] defined the Citizen Energy Community (CEC) and Renewable Energy Community (REC) [12]. Contrary to CEC, REC is constrained to use only RES and not fossil fuel energy. CEC can manage only the electricity demand, while REC also other demands such as heating and cooling.

1.1. Literature review

ECs may exploit the synergy between different types of energy users [13] from different consumption sectors, leading to several economic (e.g., cost savings) [14], environmental (e.g., emission reductions) [15] and social (e.g., access to distributed RES for low-income users) [16] benefits to its members. As demonstrated in a work of the authors (Volpato et al. [17]), the aggregation of various users with complementary demand and generation profiles in ECs results in economic savings for both the community and single members. Gjorgievski et al. [18] found a similar result for the members of a REC, also when the energy sharing is taxed (with a lower price than that for the energy

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purchased from the grid). RECs ensure access to distributed RES to different local energy users, including the most vulnerable ones [19] characterized by severe economic and social conditions [20], thus mitigating energy poverty. Balderrama et al. [21] and Li et al. [22] pointed out the role of ECs in promoting the rural electrification planning. As the case for Italy, Candelise and Ruggieri [23] found that local and small citizen-led projects foster the spread of ECs [24]. ECs also encourage final users to participate in Demand Response (DR) programs [25,26] to improve the local balance between energy generation and demand and, in turn, limit the stress on the electric grid. Cai et al. [26] minimized the energy expenditure of a residential EC while achieving a flatter daily profile of its net electricity withdrawn from the grid. Mariuzzo et al. [27] optimized the design of an EC, reducing the annual CO_2 emissions while, at the same time, ensuring economic savings and limited social discomfort to users with shiftable loads.

According to Lowitzsch et al. [28] and Bartolini et al. [29], RECs could rely on Multi-Energy Systems (MES) to satisfy the various energy demands of their members. A MES consists of a set of energy conversion and storage units that exploit the interaction between multiple energy vectors (e.g., electricity, heat, cooling, fuels, etc.), at different geographical scales (e.g., neighbourhood, district, municipality, city, etc.), to find the best match between energy demand and generation. Two main issues arise in the design and operation optimization of local MES of ECs. First, the intermittent RES and the various energy demands of end-users might be difficult to be predicted, thus invoking the need of proper design-operation optimization models under uncertainties [30]. Sakki et al. [31] proposed a novel method to account for different sources of uncertainty in the design-operation optimization of renewable-driven energy systems. Coignard et al. [32] found that the calculation of total cost, self-sufficiency and self-consumption of an EC are highly affected by the forecasts of energy demands. Simoiu et al. [33] developed a multi-agent model of an EC, where the willingness of members to shift their energy demands is evaluated by a stochastic approach. Another relevant issue for ECs is guaranteeing the fair allocation of the total economic benefit to its members, thus satisfying energy democracy [34]. A fair allocation of economic benefits should also ensure that each member finds it more economically convenient to participate in the EC rather than to operate independently, thus preventing members from dropping out of the community [35,36].

In such a context, this paper focuses on the design and operation optimization of a local MES meeting the energy demands of a REC under uncertainties in solar irradiance and users' electricity demand. The fairness in the allocation of the total cost of the system to its end users is also analysed. Thus, the literature below mainly focuses on the design and operation optimization of MES of ECs without uncertainty, with uncertainty, and on the fair allocation of the total economic cost/profit within ECs.

Some works neglected any uncertainty. Piazza et al. [37] presented a Mixed-Integer Linear Programming (MILP) model to optimize the design and operation of an EC. The optimal CO_2 emissions and operational costs are 33 % and 35 % lower compared to a reference case in which electricity is withdrawn from the grid and the heating and cooling demands are satisfied by natural gas boilers and heat pumps, respectively. In a work of the authors (Dal Cin et al. [38]), multi-objective design--operation optimization models of different EC configurations are developed, encompassing residential and commercial users with electricity and heating demands. Results show an average economic cost saving of 14 % and a reduction of emissions by 24 % for the analysed configurations, with respect to the case in which users are simple consumers. Sousa et al. [39] conducted a design optimization of a REC that comprises two consumers and a prosumer using PV and wind power plants. Ceglia et al. [40] analysed the MES of the municipality of Tirano (Italy), supplying a REC with electricity, heating and cooling demands. Bahl et al. [41,42] selected an appropriate set of typical days for a design-operation optimization of a MES by finding the minimum error between the optimal objective function based on typical days and that based on the full annual data.

The main uncertainties in the design-operation optimization of MES are related to the RES (i.e., generation side) and the energy demand profiles (i.e., demand side) [43,44]. Some works applied Monte Carlo based techniques to assess how the optimal capacity planning [45] and the optimal operational management [46] of ECs change under different scenarios of the uncertain parameters. However, these techniques do not allow to obtain optimal design and operational decisions (i.e., the choice of unit sizes and loads) under uncertainty, since the optimization is solved for each scenario independently. On the other hand, Stochastic Programming (SP) [47] and Robust Optimization (RO) [48] are the main methods to conduct the optimization under uncertainty [49]. SP considers a set of stochastic scenarios with the associated probabilities, while RO defines an interval of possible random realizations of an uncertain parameter. One example of application of RO to optimize the day-ahead operational scheduling of an EC under the uncertainty in solar PV power generation and load demand can be found in Ref. [50]. RO searches for a worst-case feasible solution, which is only optimal for a worst-case scenario, sometimes leading to overly conservative results [51]. 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 [52]. Di Somma et al. [53] used a SP optimization model to maximize the shared energy within an Italian REC, represented by a condominium equipped with a PV plant of known capacity, and thus maximize the associated economic benefits provided for by the Italian legislation, under the uncertainty in PV power generation and user demands. Zakaria et al. [54] reviewed SP for two-stage design-operation problems, 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 are taken in the second stage (i.e., the operation phase) that is affected by the stochastic scenarios. Some works used SP models with typical days of a year as stochastic scenarios of the uncertain parameters [55,56]. Li and Yang [56] 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. [57] 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 was represented by daily stochastic scenarios, the number of which (variable from 5 to 20) is found by applying K-means clustering. Zheng et al. [58] optimized the design and operation of a system consisting of PV and battery, considering 6 typical days of PV power and residential electricity demand, found by clustering, as stochastic scenarios in the two-stage SP model. Narayan and Ponnambalam [59] included the risk of uncertainty associated with energy demands and RES in the formulation of a two-stage SP model for the optimal design of a microgrid. In the previous works, the stochastic scenarios of uncertain parameters are often selected a priori, without validating the optimization models under uncertainty on historical input data to identify the "best" set of stochastic scenarios, and without testing the optimization models under uncertainty with the preliminarily identified "best" scenarios. In addition, the weight of the uncertain parameters in the optimal design of the systems (e.g., in the optimal cost/profit and sizes of the energy conversion and storage units) is not assessed. It is also worth highlighting that the works cited above did not consider any allocation of the total cost/profit of the EC to its members.

Some works investigated how to ensure a fair cost/profit allocation to the EC members by implementing cooperative game-based [60,61] or other [62] approaches. The literature reported here covers only the cooperative game-based approaches, such as "Shapley value" [63], "Nucleolus" [64], and "Nash bargaining" [65], which can effectively represent the cooperation among the members of ECs. Zatti et al. [66] optimized the design of an EC, which comprises three commercial and six residential users, and applied the Shapley value mechanism to fairly allocate the total economic profit to the members in accordance with their economic contributions to the energy sold to the grid and to that shared with other members. De Souza Dutra and Alguacil [67] used a mechanism based on Shapley value to distribute incentives equitably among residential prosumers participating in an incentive-based demand response program. Fioriti et al. [68] optimized the design and operation of an EC and, subsequently, implemented hybrid cooperative allocation mechanisms based on Shapley value and Nucleolus. Jiang et al. [69] developed a Nash bargaining model to fairly distribute the operational profit of a community made of five residential prosumers. Zhao et al. [70] used a Nash bargaining model to fairly allocate the optimal operational cost of an alliance of ECs. Volpato et al. [71] applied the Shapley value and the Nucleolus allocation criteria and the Nash bargaining optimization approach to comprehensively compare three different distributions of the total cost of a general EC (consisting of both consumers and prosumers) based on the different notions of "individual", "collective" and "proportional" fairness, respectively. Although the previous works focused on the allocation of the cost/profit of an EC, they disregarded the uncertainty of input parameters in the design-operation optimization of the system.

Few works considered both the optimization of MES supplying ECs under uncertainties and the fair distribution of the total economic benefit. Siqin et al. [30] optimized the day-ahead dispatch of three ECs under the uncertainty in the PV power. A Shapley value mechanism is applied to fairly allocate the total economic cost saving to the ECs. However, this work did not optimize the design of the system and, besides, did not distinguish the individual energy demands of the community members. Ye et al. [72] minimized the operational cost of a residential EC (including the cost of purchasing electricity from the main grid and the cost of charging/discharging electrical storage units) under the uncertainty in RES, user energy demands and electricity prices. The authors also used a Nash bargaining model to fairly distribute the total cost among users, but neglected to optimize the energy generation (i.e., PV and wind power plants) and storage capacities. Tomin et al. [73] optimized the design and operation of an EC comprising three microgrids. They implemented a bi-level model to minimize total costs under the uncertainty in the choice of the EC configuration in the upper level, and to minimize operational costs, emissions and power shortage of each microgrid in the lower level. They also allocated the total economic cost to the microgrids, although they neglected the users' electricity demand in each microgrid, thus disregarding the cost distribution among individual users.

1.2. Research gap, goal and novelty

The literature review pointed out two evident gaps.

- The validation and successive test of the optimization models under uncertainty. Indeed, the common practice in the literature is to select in advance and arbitrarily the stochastic scenarios in these optimization models (e.g., Refs. [56–58]), without validating and testing them.
- The lack of a comprehensive case study in which the weight of different uncertainties are quantified in the design-operation optimization of a local MES associated with an EC [39,70,74,75], also considering the fair allocation of the total cost of the system to the EC members [73].

This work fills in the above-mentioned gaps in the design and operation optimization of a local MES of a REC under the uncertainties in solar irradiance and users' electricity demand. The goal is twofold.

i. Identifying the "best" set of stochastic scenarios (i.e., the most representative) that represent the most accurate predictions of the uncertain parameters in a "past" training dataset (2005–2014).
ii. Assessing the accuracy of the optimal "stochastic forecasts" of the system total cost and unit sizes, based on the previously found "best" set of stochastic scenarios, in a "future" testing dataset (2015–2020).

Fig. 1 shows the novel procedure developed to achieve the twofold goal, which shifts the "present moment" back in time, using the input data of the period prior to the "present moment" as the "past" training dataset (2005–2014), and the data of the subsequent period as the "future" testing dataset (2015–2020).

The procedure is based on MILP and SP [47] models to optimize the design-operation of the system with, respectively, perfect knowledge of input timeseries and under uncertainties, with the aim of minimizing the life cycle cost of the system (investment, operation and maintenance costs). SP is chosen over RO because the former's formulation is more appropriate for the considered uncertainties represented by stochastic scenarios [76]. The procedure is organized according to the four points below, where points 1) to 3) contribute to goal i) and points 1)-4) to goal ii).

1) <u>Model with perfect knowledge</u>: the MILP model is solved for each year, first using the training and then the testing datasets, so leading to the *"historical solutions"* and *"perfect forecasts"*, respectively, the latter based on the utopic assumption of perfect knowledge of the "future".
2) <u>Scenarios generation</u>: different sets of stochastic scenarios of the uncertain parameters are generated by applying K-means clustering in the training dataset.
3) <u>Validation of the SP model</u>: the SP model, solved for each year and set of stochastic scenarios, leads to different *"stochastic solutions"*. The "best" set of stochastic scenarios is identified considering the lowest Root Mean Squared Error (RMSE) and residual between the optimal life cycle costs according to the *"stochastic solutions"* and *"historical solutions"*.
4) <u>Test of the SP model</u>: the SP model is solved for each year of the testing dataset with this "best" set of scenarios, resulting in different *"stochastic forecasts"*, the accuracy of which is assessed compared to the *"perfect forecasts"* in terms of the optimal life cycle cost of the system and the optimal sizes of the units.

To the best of the authors' knowledge, this paper is the first to present such a novel procedure to find the "best" set of stochastic scenarios and test the associated "stochastic forecasts".

Furthermore, the optimal life cycle cost according to the *"stochastic forecast"* obtained for each year of the testing dataset is fairly allocated to the EC users by applying the Shapley value mechanism. This ensures a fair allocation of the optimal economic benefit of an EC by distributing lower costs to members who contribute more to the cost reduction of the community and its internal coalitions of members. Contrary to Nucleolus [64] and Nash bargaining [65] mechanisms, Shapley value does not require an optimization problem dedicated to the cost allocation.

The remaining part of the paper is organized as follows. Section 2 presents the local MES of the REC, the novel optimization procedure and the Shapley value mechanism. Section 3 reports the MILP and SP optimization models, and the input data. Section 4 discusses the results obtained from the implementation of the procedure. Section 5 draws the Conclusions of this work.

2. Methodology

Section 2.1 introduces the Renewable Energy Community (REC) associated with a local Multi-Energy System (MES). Section 2.2 describes the novel stochastic optimization procedure. Section 2.3 explains the Shapley value mechanism to fairly distribute the optimal cost of the system.

2.1. Renewable Energy Community configuration

Fig. 2 shows the system analysed. To benefit from the complementarity between diverse curves of energy generation and demand, the members of the REC are chosen as representative of the residential (Res),

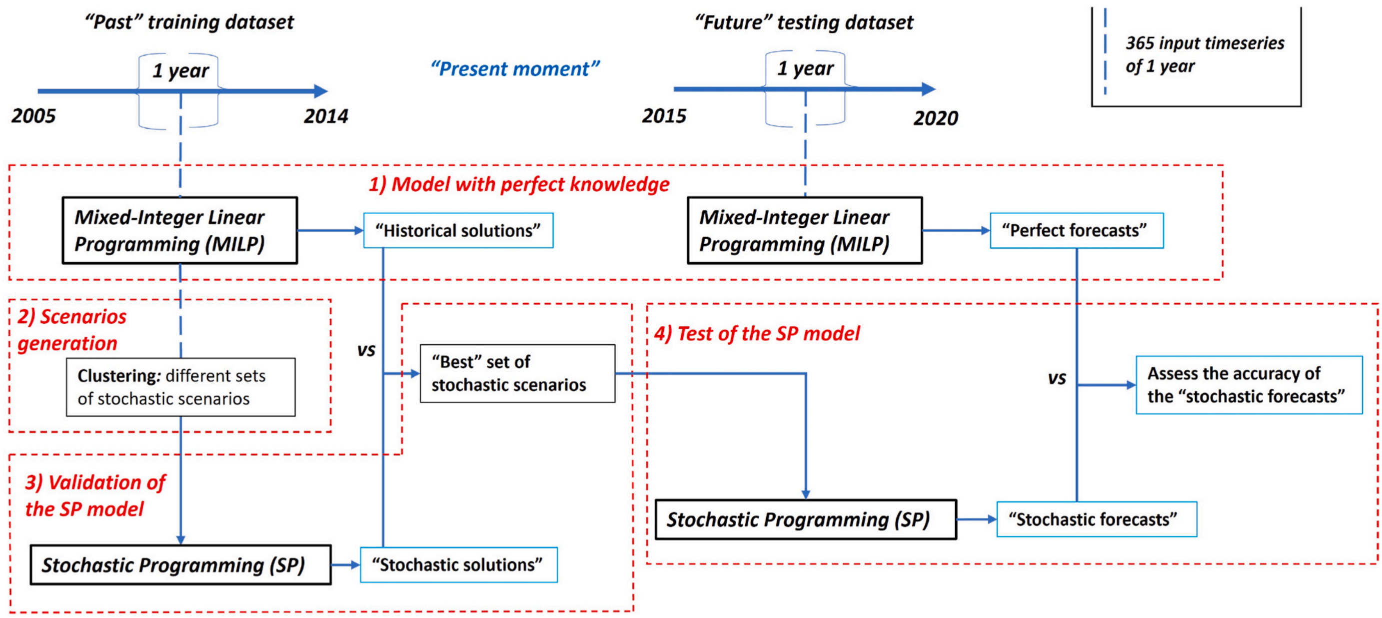

Fig. 1. Structure of the novel optimization procedure to obtain the "best" set of stochastic scenarios (left) and assess the "stochastic forecasts" based on the "best" set compared to the "perfect forecasts" based on real data (right).

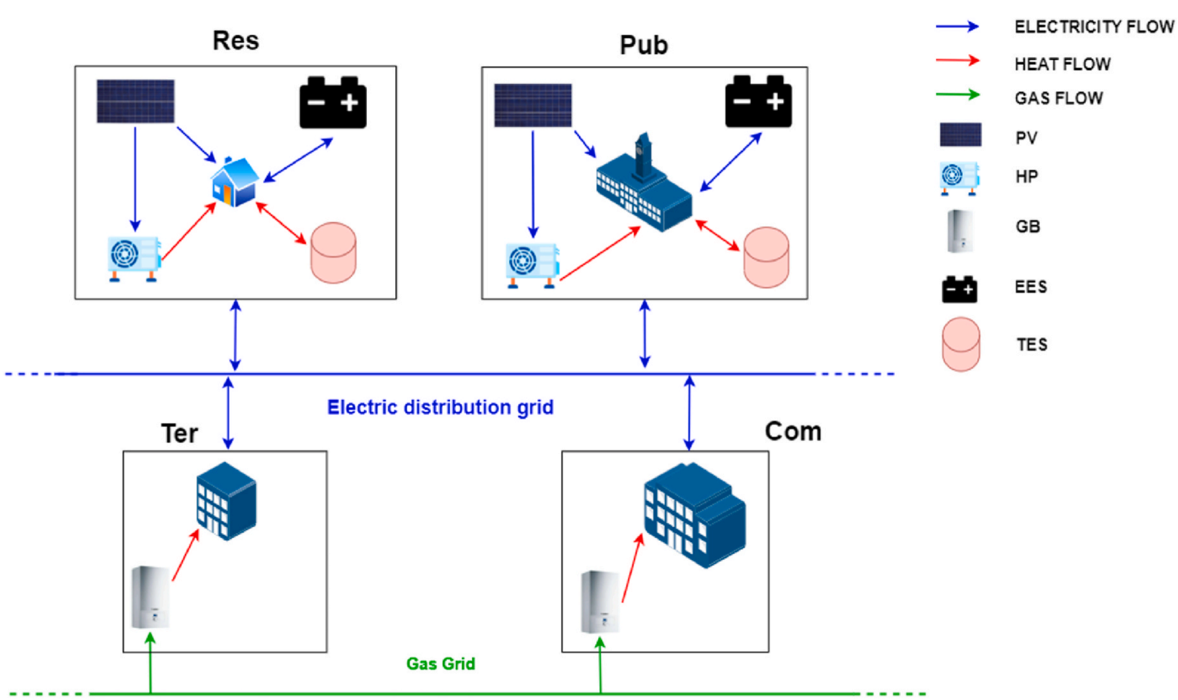

Fig. 2. Local MES of a REC with residential (Res), tertiary (Ter), commercial (Com) and public (Pub) users.

tertiary (Ter), commercial (Com) and public (Pub) sectors. The residential and public members are prosumers who could invest in solar PhotoVoltaic plants (PV), Heat Pumps (HP), Electrical Energy Storage (EES) and Thermal Energy Storage (TES). Conversely, the tertiary and commercial members are consumers that could invest in natural Gas Boilers (GB) to satisfy their heating demands, while their electricity demands are met by purchasing electricity from the distribution grid.

According to the Italian legislation, the members of the REC under the same primary cabin share electricity through the grid, realizing that is called collective virtual self-consumption.

The assumptions and boundary conditions of this work are reported afterwards.

- The legislation of the REC only allows the sharing of electricity among the community members [77], who individually satisfy their heating demands. The *shared energy, net of the individual physical self-consumption of members* [78], *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* [77, 79].
- The users' electricity demands can be optimally shifted according to a Price-Based Demand Response (PBDR) program with a Real Time Pricing (RTP) strategy [25], which sets a daily profile of the grid purchase/sale price following that of the day-ahead market price.

- The input dataset containing daily timeseries is divided into a larger training dataset (2005–2014), representing the "past" period, and a smaller testing dataset (2015–2020), representing the "future" period, 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) [80]. The representation of uncertainty in solar irradiance and electricity demands is assumed to be the same in the "past" and "future" periods.
- The time horizon of the optimization is one year, assuming that the system operation is the same for each year of its life cycle. This leads to a trade-off between the accuracy of the optimization results and acceptable computational times.
- Optimizing the design and operation of the system with perfect knowledge of input timeseries requires the input timeseries for each day of the year. In the testing dataset, this corresponds to the utopic assumption of perfect knowledge of the "future". On the contrary, the optimization under uncertainties only has knowledge of the input timeseries for a set of days of the year, i.e., the stochastic scenarios. In addition, the temporal relationship between consecutive stochastic scenarios is disregarded, which does not compromise the achievement of global optimal solutions in exchange for a higher model simplicity [42,58].

2.2. Novel stochastic optimization procedure

Fig. 3 shows in detail the four steps of the novel procedure to carry out the design-operation optimization of the system under uncertainties in solar irradiance and users' electricity demand. The "present moment" is set at the beginning of year 2015, so using the "past" period (2005–2014) and the "future" period (2015–2020) as training and testing datasets, respectively. The aim is to identify the "best" set of stochastic scenarios in the "past" dataset and then assess the accuracy of the "stochastic forecasts", based on the "best" set of stochastic scenarios, compared to the "perfect forecasts" with perfect knowledge in the "future" dataset. In the optimization models, the time horizon is one year, and the life cycle cost of the system actualized to one year (investment, operation and maintenance costs) is the objective function to be minimized. The optimization procedure and the related assessment consist of four steps.

1) Model with perfect knowledge: solving the Mixed-Integer Linear Programming (MILP) optimization model with perfect knowledge of input timeseries for each year of the training and testing datasets;
2) Scenarios generation: generating different candidate sets of stochastic scenarios of solar irradiance and electricity demands for each year of the training dataset;
3) Validation of the SP model: finding the "best" set of stochastic scenarios, extracted from the training dataset, to be used in the SP model;
4) Test of the SP model: solving the SP model, based on the "best" set of stochastic scenarios, for each year of the testing dataset.

Step 1) deals with the optimization problem knowing all input timeseries. First, the MILP model with perfect knowledge is solved for each year (considering 365 days) of the training dataset, thus obtaining a set of 10 *"historical solutions"* (2005–2014). The same model is then solved for each year of the testing dataset, based on the utopic assumption of perfect knowledge of the "future" (Section 2.1), thus obtaining a set of 6 *"perfect forecasts"* (2015–2020).

Step 2) deals with the generation of different sets of stochastic scenarios. K-means clustering [81] is applied for each year of the training dataset to identify typical days of solar irradiance and electricity demands, increasing the number of clusters generated (i.e., groups containing similar days) from 2 to 30. Thus, the number of typical days (i.e., the representative of clusters) is varied from 2 to 30, resulting in 29 alternative sets, each made of 2 up to 30 typical days. K-means usually selects as representative the averaged typical days (centroids), instead of the real typical days as done by K-medoids [82]. Taking the centroids as typical days could lead to a smoothing of the daily timeseries, thus neglecting the peaks of the solar irradiance and electricity demands in each year. To avoid this issue, the typical day of each cluster is selected as the real day with the lowest value of the Euclidean distance from the centroid of the cluster. In addition, the design of a MES also requires the inclusion of the extreme day where the highest electricity demands occur. Following the "replace representative period" approach [82], 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 is considered as a stochastic scenario in the SP model, with a probability corresponding to the frequency of its cluster (number

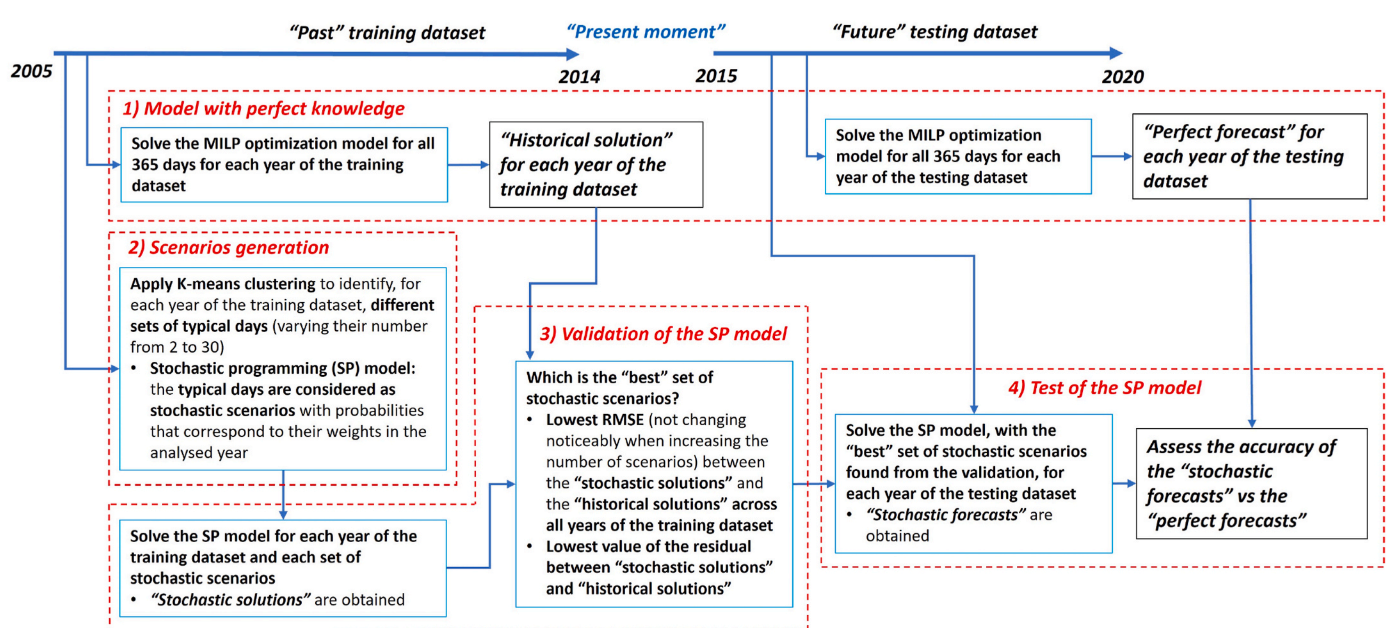

Fig. 3. Details of the four steps of the novel optimization procedure: 1) Model with perfect knowledge, 2) Scenarios generation, 3) Validation of the SP model and 4) Test of the SP model.

of days in the cluster), that is equivalent to the weight of the typical day (number of days in a year represented by that typical day). The daily timeseries of heating demands, ambient temperature and prices are considered on the same days of the typical days of solar irradiance and electricity demands to preserve the chronological correlation between the daily timeseries of uncertain parameters and non-uncertain parameters.

Step 3) deals with the validation of the SP model. An appropriate set of typical days for a design optimization problem should be selected by comparing the optimal solution based on the typical days with that based on the annual historical data (i.e., leading to the "historical solutions" defined above) [83], for example taking the optimal value of the objective function as indicator [41,42]. This comparison allows to validate the SP model, i.e., to select the "best" set of stochastic scenarios of the uncertain parameters. The SP solution for a set of scenarios and a year of the training dataset is named *"stochastic solution"*, with 290 *"stochastic solutions"* obtained in the training dataset (i.e., for 29 sets for each of the 10 years). The value of the objective function of each *"stochastic solution"* in a year (based on the typical days) is compared with that of the *"historical solution"* (based on the perfect knowledge of input timeseries, see *step 1)*) of the same year, and an error given by the residual (i.e., difference between the two) is calculated. This computation is repeated for each year of the training dataset to select the "best" set of stochastic scenarios with their number and profiles. The Root Mean Squared Error (RMSE) is used to calculate the *standard deviation of the errors* (using the residuals) between the values of the objective functions of the *"stochastic solutions"* and *"historical solutions"* across all years of the training dataset. A RMSE is calculated for each number of stochastic scenarios, and the lowest RMSE, after which it does not change significantly as the number of scenarios increases, gives the number of the "best" set of stochastic scenarios. The formula of the RMSE is [84]:

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

where $c_{SP,y,k}$ and c_y, $\left(c_{SP,y,k} - c_y\right)$, and Y are, respectively, the optimal values of the objective function found by solving the SP model for year y with k stochastic scenarios (see Section 3.2) and the MILP model for year y with perfect knowledge of input timeseries (see Section 3.1), the residual, and the number of years considered, respectively. 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 in the training dataset), $c_{SP,y,k}$ and c_y correspond to the optimal values of the objective function of a *"stochastic solution"* and the *"historical solution"* for year y of the training dataset, respectively. Since for the "best" number of stochastic scenarios there are 10 sets containing different profiles, the "best" profiles of stochastic scenarios 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 model. This is solved for each year of the testing dataset with the "best" set of stochastic scenarios, thereby providing *"stochastic forecasts"*. Finally, the accuracy of the *"stochastic forecasts"* is assessed by calculating its errors with respect to the *"perfect forecasts"* (see *step 1)*) in terms of optimal life cycle cost of the system and units' sizes for each year of the testing dataset.

2.3. Allocation of the optimal cost of the Renewable Energy Community

A cooperative game model can effectively represent the cooperation between interacting players [85] of an EC, where the "players" (i.e., members of the EC) constituting the "grand coalition" (i.e., the EC itself) cooperate to achieve a common goal (e.g., minimization of the total cost of the community). A cooperative game model is defined by N players forming the "grand coalition", which includes 2^N coalitions as the grand coalition itself and the empty coalition (i.e., the coalition without players) [64]. Each coalition S is associated with a "value" function, which represents the benefit of the players in cooperating together. In the context of ECs, the value of the grand coalition could correspond to the total cost/profit of an EC, while the value of the empty coalition is zero. This work applies Shapley value [63], a cooperative game-based allocation mechanism applied ex-post the optimization, to achieve a fair distribution of the optimal economic benefit of the EC among its members. The cost/profit x_i allocated to a member i is calculated as:

$$x_i = \sum_{S \subseteq \{1,\dots,N\}, i \in S} \frac{(|S|-1)!(N-|S|)!}{N!} \left(v(S) - v(S\backslash\{i\})\right) \tag{2}$$

where $|S|$ is the size of the coalition S (i.e., the number of members of the coalition) and $(v(S) - v(S\backslash\{i\}))$ is the contribution of the member i to the value $v(S)$ of coalition S, i.e., the difference between the value $v(S)$ with member i and the value $v(S\backslash\{i\})$ without member i. Shapley value assigns to each member a cost/profit that represents its weighted average marginal contribution to the cost/profit of each coalition it takes part in within the grand coalition. In other words, Shapley value is fair in the sense that it succeeds in distributing the optimal cost/profit of an EC by weighting the individual economic contributions of its members [86].

The Shapley value mechanism is applied after testing the SP model to distribute the optimal life cycle costs according to the annual "stochastic forecasts" (Section 2.2). The choice of the four users of different consumption sectors in the REC (Fig. 2) is a good compromise between the search for the best match among different generation and demand curves and the need of limiting the computational time required to solve the SP model for each of the 16 (2^4) coalitions of members in the REC.

3. Optimization models

Sections 3.1 and 3.2 present the Mixed-Integer Linear Programming (MILP) and Stochastic Programming (SP) models to optimize the design-operation of the system with perfect knowledge of input timeseries and under uncertainty, respectively. Section 3.3 specifies the input data.

3.1. Mixed integer linear programming optimization model of the system with perfect knowledge

The MILP model is solved for all days of a year of the training or testing datasets (Section 2.2), assuming to know the input timeseries (e.g., solar irradiance, electricity and heating demands, ambient temperature, grid purchase and sale prices) for each day.

The constraints refer to each hour t (i.e., $T=\{1, \dots,24\}$) of each day d (i.e., $D=\{1, \dots,365\}$) of a year for a consumer c (i.e., $C=\{Ter,Com\}$) or prosumer p (i.e., $P=\{Res,Pub\}$). The decision variables in the design and operation optimization of the system can be classified into design variables and operational variables. The design variables are the capacities of the PV (cap_p^{PV}), HP (cap_p^{HP}), EES and TES (cap_p^{ES} for a general storage unit), while the capacity of GB (cap_c^{GB}) is fixed by the heating demand. The operational variables are: the heating power generated by the HP ($Q_{p,t,d}^{HP}$) and the binary variable indicating its on-off operational state ($\delta_{p,t,d}^{HP}$); the energy stored by the ES 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 users due to the application of the PBDR with RTP strategy ($E_{c,t,d}^{el,shift}$ and $E_{p,t,d}^{el,shift}$). Energy and power variables have, respectively, [kWh] and [kW] as units of measurement.

Each member *"i"* of the REC has an electricity demand that can be optimally shifted:

$$\sum_{t=1}^{24} E_{i,t,d}^{el} = \sum_{t=1}^{24} E_{i,t,d}^{el,shift} \tag{3}$$

$$E_{i,d}^{el,min} \le E_{i,t,d}^{el,shift} \le E_{i,d}^{el,max} \quad (4)$$

$$(1 - D^{var}) \cdot E_{i,t,d}^{el} \le E_{i,t,d}^{el,shift} \le (1 + D^{var}) \cdot E_{i,t,d}^{el} \quad (5)$$

where $E_{i,t,d}^{el}$, $E_{i,t,d}^{el,shift}$, $E_{i,d}^{el,min}$, $E_{i,d}^{el,max}$, and D^{var} are, respectively, the input electricity energy demand, the shifted electricity energy demand of member i in hour t of day d, the minimum and maximum of the input electricity energy demand in day d, and the hourly maximum fraction of the load that can be shifted (the value assumed here is 0.1). Eq. (3) states that the daily electricity demand of member i does not change after shifting the hourly loads. Both constraints (4) and (5) set upper and lower bounds to the shifted electricity demand $E_{i,t,d}^{el,shift}$.

For a consumer *"c"*, the constraints of the GB are:

$$F_{c,t,d}^{GB} = Q_{c,t,d}^{GB} \Big/ \eta_{GB} \quad (6)$$

$$Q_{c,t,d}^{GB} \le cap_c^{GB} \quad (7)$$

where $F_{c,t,d}^{GB}$ and $Q_{c,t,d}^{GB}$, cap_c^{GB} and η_{GB} [−] are the fuel power consumed and the heating power generated, the capacity and efficiency of the GB, respectively. Eq. (6) represents the input-output characteristic curve of the GB and constraint (7) sets the capacity as upper bound of the heating power.

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

$$E_{c,t,d}^{imp} - E_{c,t,d}^{el,shift} = 0 \quad (8)$$

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

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

$$Q_{c,t,d}^{GB} \cdot \Delta t - E_{c,t,d}^{th} = 0 \quad (9)$$

where Δt is the time step of 1 h in the optimization and $E_{c,t,d}^{th}$ is the heating energy demand of consumer *"c"*.

For a prosumer *"p"*, the electrical power generated by PV is:

$$P_{p,t,d}^{PV} = cap_p^{PV} \bullet I_{t,d} \quad (10)$$

where $P_{p,t,d}^{PV}$ is the power generated, cap_p^{PV} [m^2] is the capacity (considering 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:

$$P_{p,t,d}^{HP} = \frac{a_0 \bullet Q_{p,t,d}^{HP} + a_1 \bullet \delta_{p,t,d}^{HP}}{COP_{p,t,d}} \quad (11)$$

where $P_{p,t,d}^{HP}$, $Q_{p,t,d}^{HP}$, $\delta_{p,t,d}^{HP}$, a_0 and a_1, and $COP_{p,t,d}$ are the electrical power consumed, the heating power generated, the binary variable indicating the on-off operational state of the HP, the constant coefficients [−] that linearize the characteristic curve and the coefficient of performance in ideal conditions (Carnot equation) calculated as reported in Ref. [87], respectively. Other constraints of the HP are:

$$\theta_{p,t,d}^{HP} \le \delta_{p,t,d}^{HP} \bullet M \quad (12)$$

$$0 \le cap_p^{HP} - \theta_{p,t,d}^{HP} \le \left(1 - \delta_{p,t,d}^{HP}\right) \bullet M \quad (13)$$

$$min_{HP} \bullet \theta_{p,t,d}^{HP} \le Q_{p,t,d}^{HP} \le \theta_{p,t,d}^{HP} \quad (14)$$

where cap_p^{HP} [kW] is the capacity 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 (equal to 10^4) to avoid bilinear constraints, thus keeping a MILP formulation of the optimization model. Constraints (12) and (13) deal with the capacity of the HP and constraint (14) sets the lower and upper bounds of the heating power generated by the HP.

The energy balance of an ES (i.e., EES or TES) of a prosumer *"p"* is:

$$E_{p,t,d}^{ES} = E_{p,t-1,d}^{ES} \cdot (1 - SD) + \left(P_{p,t,d}^{ES,+} \cdot \eta^{ES,+} - \frac{P_{p,t,d}^{ES,-}}{\eta^{ES,-}}\right) \cdot \Delta t \quad (15)$$

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

$$\theta_{p,t,d}^{ES,+} \le \delta_{p,t,d}^{ES} \bullet M \quad (16)$$

$$0 \le cap_p^{ES} - \theta_{p,t,d}^{ES,+} \le \left(1 - \delta_{p,t,d}^{ES}\right) \bullet M \quad (17)$$

$$\theta_{p,t,d}^{ES,-} \le \left(1 - \delta_{p,t,d}^{ES}\right) \bullet M \quad (18)$$

$$0 \le cap_p^{ES} - \theta_{p,t,d}^{ES,-} \le \delta_{p,t,d}^{ES} \bullet M \quad (19)$$

$$E_{p,t,d}^{ES} \le cap_p^{ES} \quad (20)$$

$$P_{p,t,d}^{ES,+} \le C^{ES,+} \bullet \theta_{p,t,d}^{ES,+} \quad (21)$$

$$P_{p,t,d}^{ES,-} \le c^{ES,-} \bullet \theta_{p,t,d}^{ES,-} \quad (22)$$

$$E_{p,t=1,d}^{ES} = E_{p,t=24,d}^{ES} \quad (23)$$

where cap_p^{ES} [kWh] is the capacity, $\delta_{p,t,d}^{ES}$ is the binary variable associated with the charging (1) or discharging (0) state of ES, $C^{ES,+}$ and $C^{ES,-}$ [kW/kWh] are the specific input and output capacity. 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 (16)-(19) regard the capacity of ES. Constraint (20) places the capacity of ES as upper limit of its state of charge. Constraints (21) and (22) bound the charging and discharging power of ES. Eq. (23) 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.

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

$$E_{p,t,d}^{imp} - E_{p,t,d}^{exp} + \left(P_{p,t,d}^{PV} + P_{p,t,d}^{EES,-} - P_{p,t,d}^{EES,+} - P_{p,t,d}^{HP}\right) \cdot \Delta t - E_{p,t,d}^{el,shift} = 0 \quad (24)$$

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

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

$$\left(Q_{p,t,d}^{HP} + P_{p,t,d}^{TES,-} - P_{p,t,d}^{TES,+}\right) \cdot \Delta t - E_{p,t,d}^{th} = 0 \quad (25)$$

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

The total energy of the REC withdrawn from ($E_{t,d}^{imp}$) and injected to ($E_{t,d}^{exp}$) the grid are defined as:

$$E_{t,d}^{imp} = \sum_{i=1}^{N} E_{i,t,d}^{imp} \quad (26)$$

$$E_{t,d}^{exp} = \sum_{i=1}^{N} E_{i,t,d}^{exp} \quad (27)$$

where $E_{i,t,d}^{imp}$/ $E_{i,t,d}^{exp}$ is the energy of member i, net of the individual physical self-consumption, imported/exported from/to the electrical grid in hour t of day d, and N is the number of REC members. The shared energy $E_{s,t,d}$ is defined as the hourly minimum between $E^{imp}_{t,d}$ and $E^{exp}_{t,d}$:

$$E_{s,t,d} = min\left(E^{imp}_{t,d}, E^{exp}_{t,d}\right) \tag{28}$$

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

$$c_{life\ cycle} = c_{design} + c_{operation} \tag{29}$$

where c_{design} and $c_{operation}$ are the investment and operational costs.

The investment cost of the system actualized to one year of operation is:

$$c_{design} = \sum_{u\in U}\left(\left(\frac{a\cdot(1+a)^{lt_u}}{(1+a)^{lt_u}-1} + O\&M_{fix,u}\right)\cdot c_{inv,u}\cdot \sum_{i=1}^{N} cap^u_i\right) \tag{30}$$

where u identifies a specific energy technology (i.e., $U=\{GB,PV,HP,EES,TES\}$), a [%] is the interest rate, lt_u [years] is the lifetime of the technology u, $O\&M_{fix,u}$ [% of the investment cost] is the fixed part of the operation and maintenance cost of the technology u, $c_{inv,u}$ [€/kW or €/kWh] is the investment cost and cap^u_i is the capacity [kW or kWh] of the technology u owned by member i.

The annual operational cost is:

$$c_{operation} = \sum_{d=1}^{365}\sum_{t=1}^{24}\left(\sum_{c\in C}\left(F^{GB}_{c,t,d}\cdot c_{gas}\right) + E^{imp}_{t,d}\cdot c^{imp}_{t,d} - E^{exp}_{t,d}\cdot c^{exp}_{t,d} - E_{s,t,d}\cdot inc_{REC}\right) \tag{31}$$

where c_{gas} [€/kWh], $c^{imp}_{t,d}$ and $c^{exp}_{t,d}$ [€/kWh], and inc_{REC} [€/kWh] are the price of natural gas, the grid purchase and sale prices, and the incentive of the REC, respectively. The first term of the summation represents the cost of natural gas consumed by the boilers. 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 with perfect knowledge (i.e., $c_{life\ cycle}$ in Eq. (29)) is associated with the "historical solution" or "perfect forecast" depending on whether the MILP model is solved for a year of the training or testing dataset (Section 2.2).

3.2. Stochastic programming optimization model of the system under uncertainty

The main difference between the MILP model with perfect knowledge (Section 3.1) and the SP model under uncertainty is that the former is formulated for each day d of a year, whereas the latter for each typical day k of a year. Thus, given the reduced model size of the SP model, solving it implies a lower computational effort compared to solving the MILP model with perfect knowledge.

The decision variables, constraints and energy balances of the SP model are those of the MILP model with perfect knowledge (Eqs. (3)–(28), Section 3.1), 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. (30), whereas the operational cost is not calculated considering all the 365 days of one year but only the typical days with their weights in the year considered (Section 2.2). The annual operational cost is:

$$c_{operation,SP} = \sum_{k=1}^{K} w_k\cdot\sum_{t=1}^{24}\left(\sum_{c\in C}\left(F^{GB}_{c,t,k}\cdot c_{gas}\right) + E^{imp}_{t,k}\cdot c^{imp}_{t,k} - E^{exp}_{t,k}\cdot c^{exp}_{t,k} - E_{s,t,k}\cdot inc_{REC}\right) \tag{32}$$

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 annual operational cost. The objective function of the SP model is given by the sum between Eq. (30) and Eq. (32).

The SP solution for a set of stochastic scenarios in one year of the training dataset is called "stochastic solution", whereas the test of the SP model with the "best" set of stochastic scenarios for a year of the testing dataset leads to the "stochastic forecast" (Section 2.2). The optimal life cycle cost of the system according to a "stochastic forecast" is fairly allocated to the members of the REC by implementing the Shapley value mechanism. In Eq. (2) (Section 2.3), the "value" of each coalition S of the REC is the optimal life cycle cost, predicted for one year of the testing dataset, that is attained by solving the SP model considering only the members of coalition S.

3.3. Input data

Table 1 shows the values of the techno-economic parameters for each technology [88,89]. The interest rate a of the investments and the lifetime lt_u of each technology u (Eq. (30)) are assumed to be 0.05 [-] and 20 years, respectively.

Figs. 4–6 and 7(a) and (b) show, respectively, the 29 typical days of solar irradiance, electricity demands, heating demands, ambient temperature and grid sale price in the year 2014. The typical days of solar irradiance and electricity demands represent the "best" set of stochastic scenarios found from the validation of the SP model (next Section 4.1). Solar irradiance and ambient temperature refer to the location of Padova (Italy) and are taken from PVGIS [90]. According to the implemented PBDR with RTP strategy (Section 2.1), in each hour the grid sale price is assumed to be half of the day-ahead market price [91] in Italy, and the grid purchase price is calculated as the grid sale price plus 0.2 €/kWh. The electricity and heating demands of different users are taken from Ref. [92]. Moreover, the maximum hourly fraction of the load that can be shifted (constraints (5) in Section 3.1) is equal to 0.1. The price of natural gas is equal to 0.098 €/kWh. The incentive for shared energy is 0.12 €/kWh.

The models are developed and solved using Gurobi software [93] with a maximum optimality gap set at 2 % [41], which is found to be the best trade-off between 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 1
Input techno-economic parameters of the optimization models [88,89].

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

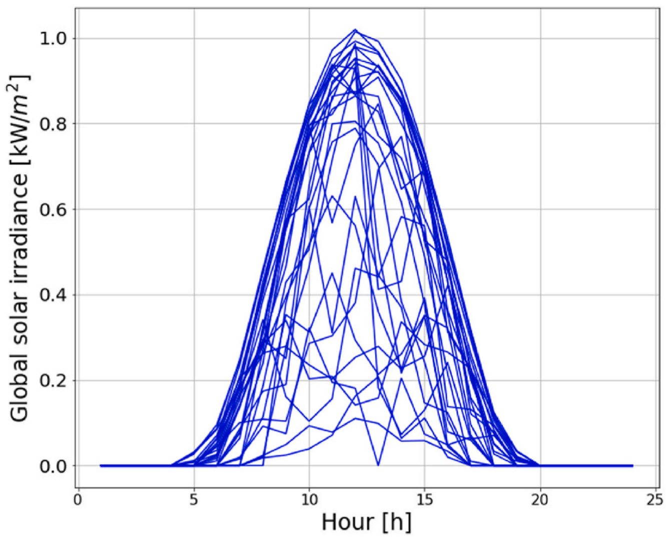

Fig. 4. 29 typical days of solar irradiance in 2014.

4. Results

Sections 4.1 and 4.2 discuss the results of the validation and test of the Stochastic Programming (SP) optimization model, respectively. Section 4.3 summarizes the critical remarks of the proposed novel stochastic optimization procedure.

4.1. Validation of the stochastic programming optimization model

This Section presents the validation of the SP model, leading to the selection of the "best" set of stochastic scenarios from the "past" period (Section 2.2). Fig. 8 shows the calculated RMSE for 29 different cases, each with a different number of stochastic scenarios ranging from 2 to 30 in each year of the training dataset. 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., not more than 20 scenarios approximately for one year), is dictated by the need to evaluate how the RMSE changes over a sufficiently wide interval. The minimum number of 2 scenarios corresponds to the minimum and meaningful number of clusters considered in a clustering technique. 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 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, the "best" number of stochastic scenarios is fixed to 29 (dashed green circle in Fig. 8). In

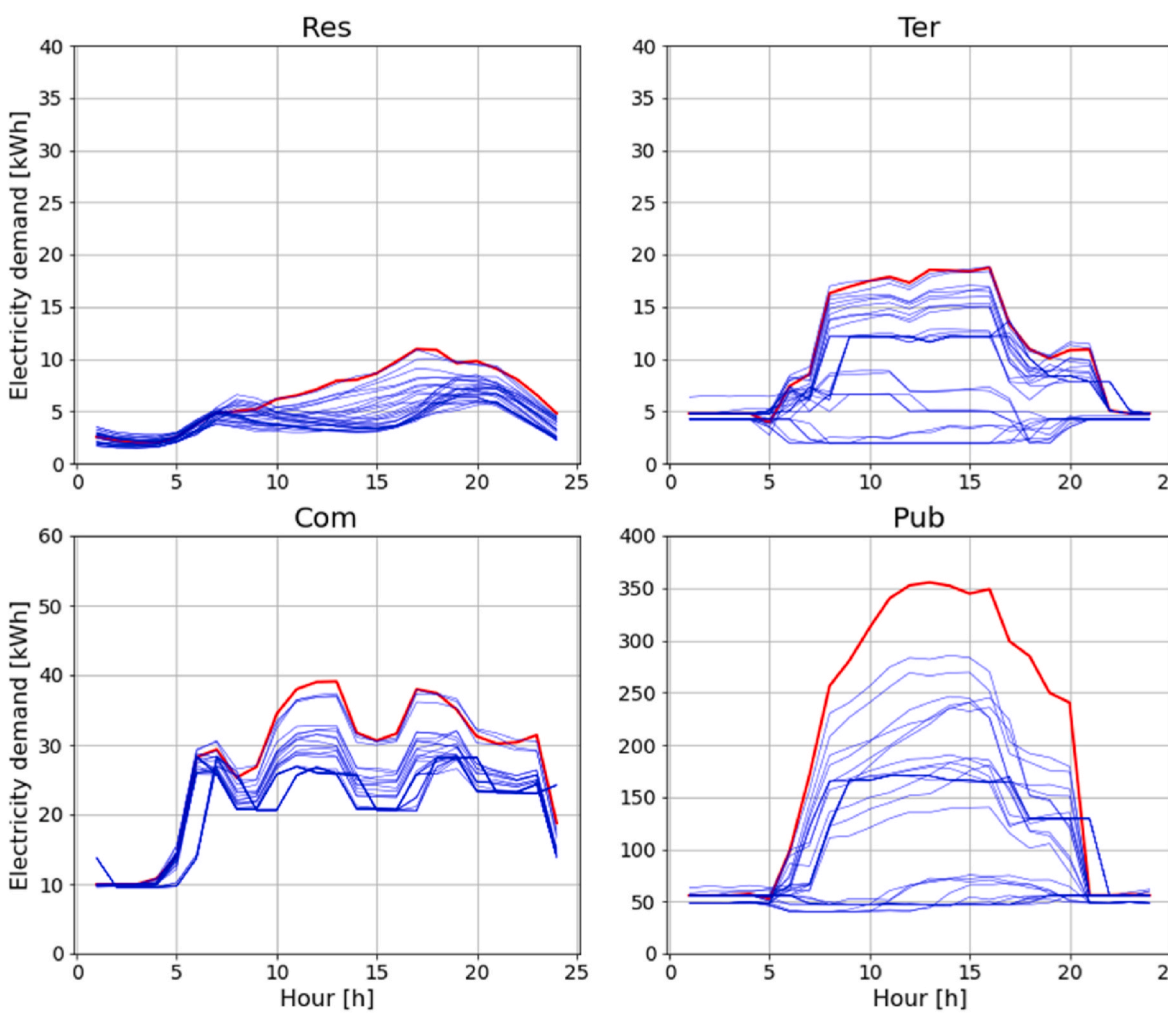

Fig. 5. 29 typical days of electricity demands in 2014 for the residential (Res), tertiary (Ter), commercial (Com) and public (Pub) members of the REC. The highest electricity demands of users, highlighted in red, account for the extreme day.

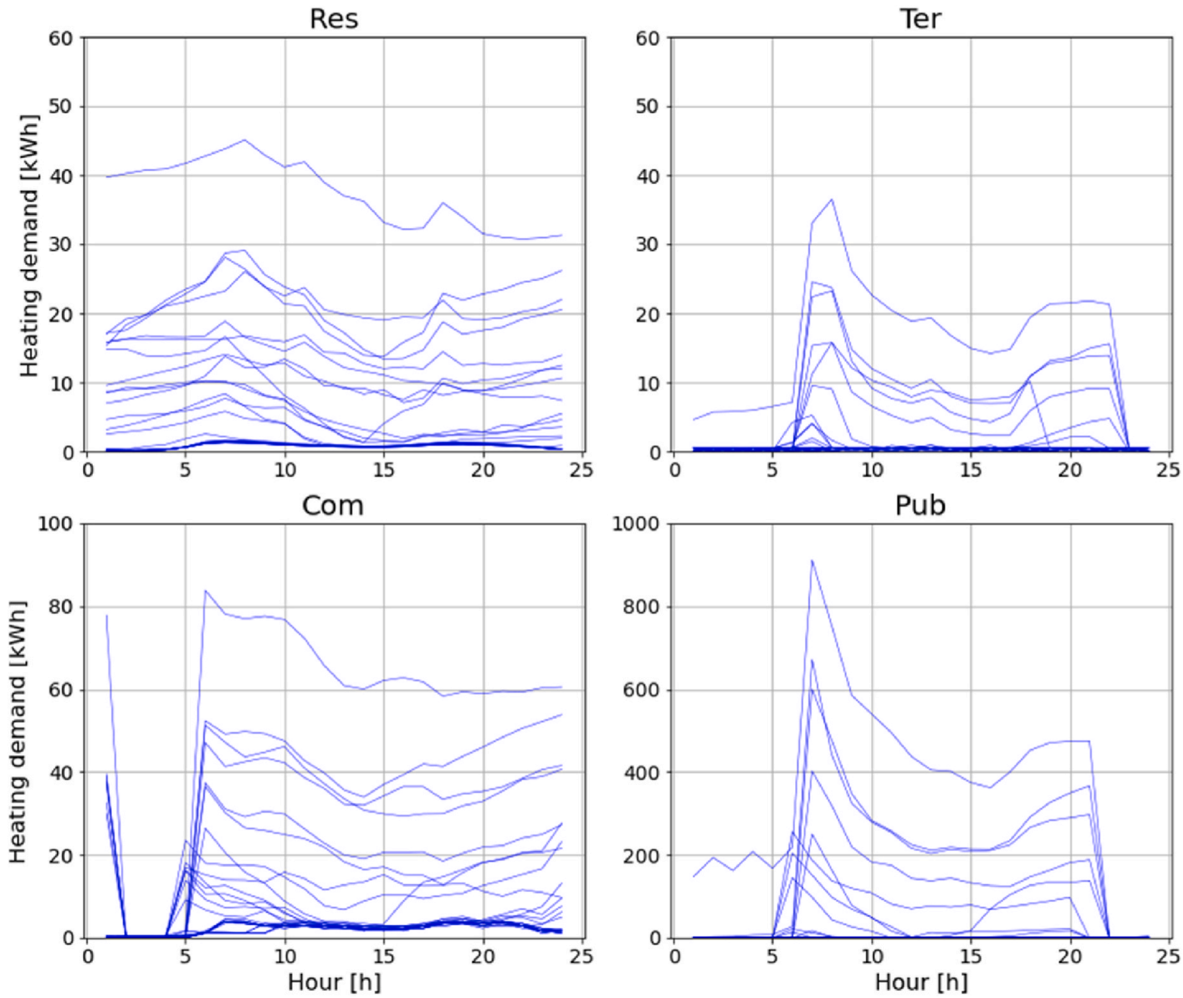

Fig. 6. 29 typical days of heating demands in 2014 for the residential (Res), tertiary (Ter), commercial (Com) and public (Pub) members of the REC.

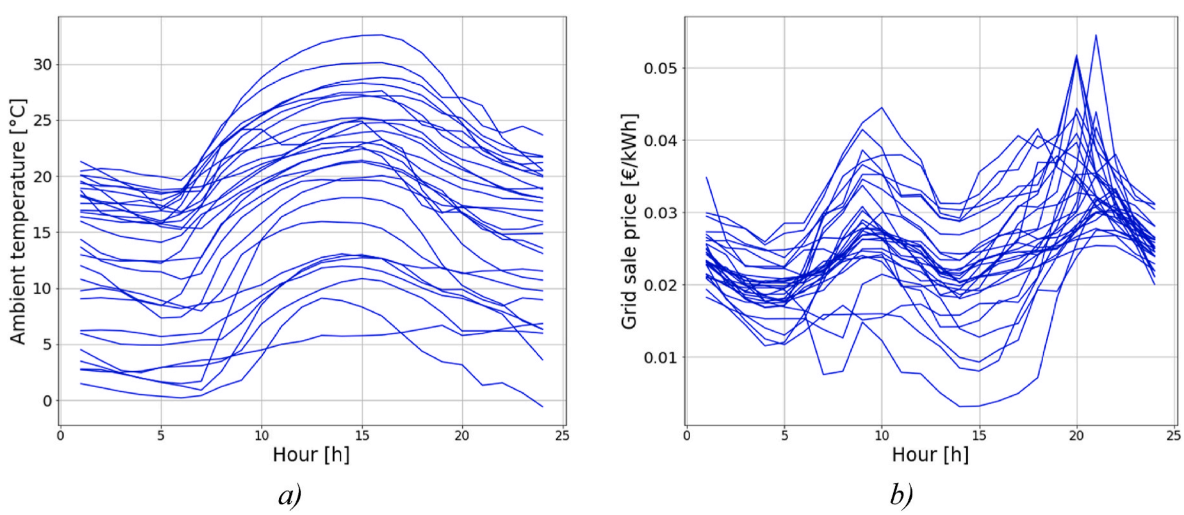

Fig. 7. 29 typical days of a) ambient temperature and b) grid sale price in 2014.

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 of 1.26 k€ (error of 0.33 %) between the optimal values of the objective functions of the historical and stochastic solutions. Note that Figs. 4 and 5 in Section 3.3 show this “best” set of 29 stochastic scenarios of solar irradiance and electricity demands, respectively.

4.2. *Test of the stochastic programming optimization model*

This Section presents the test of the SP model in the “future” period

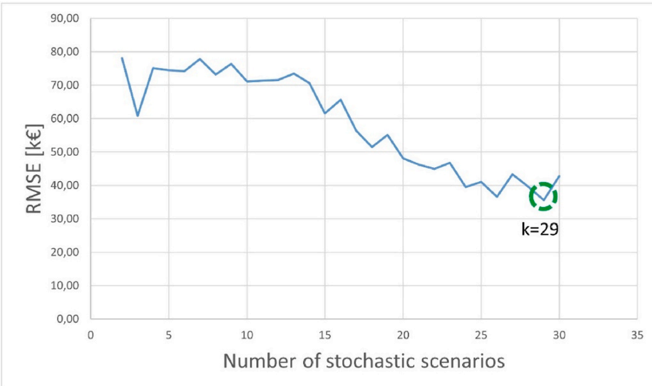

Fig. 8. Trend of the Root Mean Squared Error (RMSE) as the number of stochastic scenarios increases from 2 to 30 in each year of the training dataset. The dashed green circle indicates the case with the "best" set of 29 scenarios leading to the lowest value of the RMSE of 36 k€.

(Section 2.2). Table 2(a) shows the optimal sizes of the units according to the stochastic forecasts and perfect forecasts, while Table 2(b) shows the relative errors according to the stochastic forecasts with respect to the perfect forecasts. In both solutions, the 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. However, note that the absence of EES is not harmful for the operational flexibility of the system, which is already ensured by the PBDR program that optimally shifts the users' electricity demands. 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 perfect forecasts. This is explained by the greater impact of the extreme day of the total electricity demand on the stochastic forecasts than on the perfect forecasts, as the extreme day has a weight in the SP model of 7 days (in the "best" set of 29 scenarios) instead of one single day as in the MILP model with perfect knowledge. Thus, the extreme day in the SP model leads to an increase in the optimal sizes of PV and, in turn, of HP (which could consume the electricity generated by the PV), compared to those found by solving the MILP model. Moreover, the overestimation of the PV and HP sizes mainly concerns the public user as the extreme day is mainly affected by its high electricity demand (peak of 350 kWh, see Fig. 5). As for the optimal sizes of the PV and HP units, the average relative error over the years of the testing dataset is 13 % and 3 % (residential and public users) and 3 % and 10 % (residential and public users), respectively. Looking at the optimal sizes according to the stochastic forecasts (Table 2(a)), the relative errors (Table 2(b)) in the conversion units can

Table 2
a) Optimal sizes of the energy conversion and storage units according to the stochastic forecast and the perfect forecast (inside the brackets) solutions and b) absolute values of the relative errors of the stochastic forecasts compared to the perfect forecasts, for each year of the testing dataset.

a)

	Stochastic forecasts (perfect forecasts)					
	Years					
	2015	2016	2017	2018	2019	2020
cap^{PV}_{Res} [kW]	25 (28)	20 (25)	23 (26)	25 (30)	25 (26)	20 (23)
cap^{HP}_{Res} [kW]	41 (46)	40 (40)	39 (38)	40 (40)	41 (40)	39 (38)
cap^{TES}_{Res} [kWh]	126 (98)	42 (86)	46 (88)	50 (86)	106 (103)	39 (93)
cap^{GB}_{Ter} [kW]	36 (36)	36 (36)	36 (36)	36 (36)	36 (36)	36 (36)
cap^{GB}_{Com} [kW]	84 (84)	84 (84)	84 (84)	84 (84)	84 (84)	84 (84)
cap^{PV}_{Pub} [kW]	537 (529)	489 (482)	521 (511)	585 (551)	521 (502)	469 (464)
cap^{HP}_{Pub} [kW]	509 (481)	533 (479)	538 (463)	509 (499)	513 (475)	538 (461)
cap^{TES}_{Pub} [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 perfect forecasts						
	Years						
	2015	2016	2017	2018	2019	2020	Average
$\mathbf{cap}^{PV}_{Res}$	10.71	20.00	11.54	16.67	3.85	13.04	12.63
$\mathbf{cap}^{HP}_{Res}$	10.87	0.00	2.63	0.00	2.50	2.63	3.11
$\mathbf{cap}^{TES}_{Res}$	28.57	51.16	47.73	41.86	2.91	58.06	38.38
$\mathbf{cap}^{GB}_{Ter}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{cap}^{GB}_{Com}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbf{cap}^{PV}_{Pub}$	1.51	1.45	1.96	6.17	3.78	1.08	2.66
$\mathbf{cap}^{HP}_{Pub}$	5.82	11.27	16.20	2.00	8.00	16.70	10.00
$\mathbf{cap}^{TES}_{Pub}$	14.22	25.78	34.77	6.95	19.37	35.53	22.77

Table 3
Optimal values of the life cycle cost of the system according to the stochastic forecast and the perfect forecast solutions, and absolute values of the relative errors of the stochastic forecasts compared to the perfect 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
Perfect 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

be considered acceptable (with no error for GB). Conversely, the optimal sizes of the TES units according to the stochastic forecasts present higher relative errors compared to the perfect forecasts (38 % and 23 % for the residential and public users, respectively, Table 2(b)). The reason for this is mainly related to the neglected temporal relationship between the typical days in the SP model, resulting in optimal sizes of TES being suitable only for the daily operation and not for the seasonal operation. In other words, while in the MILP model with perfect knowledge the daily operation of TES units is evaluated for each day of each year of the testing dataset, in the SP model the daily operation of TES units is only considered in the "best" set of 29 stochastic scenarios that are independent of each other, leading to a neglected temporal relationship between typical days. In addition, the higher relative errors in the TES sizes in specific years (e.g., for the residential user in 2016, 2017, 2018 and 2020) are explained by the considered typical days of ambient temperature taken from the "past" period, which are very different from those really occurring in the years of the testing dataset. In fact, it is worth reminding that the uncertainty in the ambient temperature is not considered in this work, and therefore the "best" set of 29 stochastic scenarios from the "past" period is mainly representative only of solar irradiance and user electricity demands. Finally, the residential user shows the highest relative errors in the TES size. These are more acceptable than those for the public user because the optimal design of the system is more affected by the optimal TES size of the public user (hundreds of kW) than that of the residential user (tens of kW). However, the errors in the TES sizes do not compromise the validity of the proposed novel procedure, as demonstrated by the low errors in the optimal life cycle costs obtained according to the stochastic forecasts and the lower RMSE in the testing dataset than in the training dataset (see the results below).

Table 3 shows the optimal life cycle costs of the system associated with the stochastic forecasts and the perfect forecasts, and the relative errors according to the stochastic forecasts with respect to the perfect forecasts. The highest and lowest relative errors are 2.77 % and 0.27 % in years 2015 and 2016, respectively, with an average relative error of 1.63 %. It is acceptable given that the average computational time to solve the MILP model with perfect knowledge for one year of the testing dataset is 32 h, as opposed to a few minutes to test the SP model in the same year. Moreover, the RMSE between the optimal life cycle costs according to the stochastic forecasts and perfect forecasts is 7 k€, which is lower than 36 k€ (Fig. 8) found in the training dataset for the same number of scenarios. This confirms that the SP model with the "best" set of 29 stochastic scenarios predicts reliable solutions in the testing dataset, with a higher accuracy than in the training dataset (the RMSE decreases by 81 %), suggesting that the SP model does not overfit training data. This also confirms the validity of splitting the input dataset (2005–2020) into a "past" training dataset (2005–2014) and a "future" testing dataset (2015–2020).

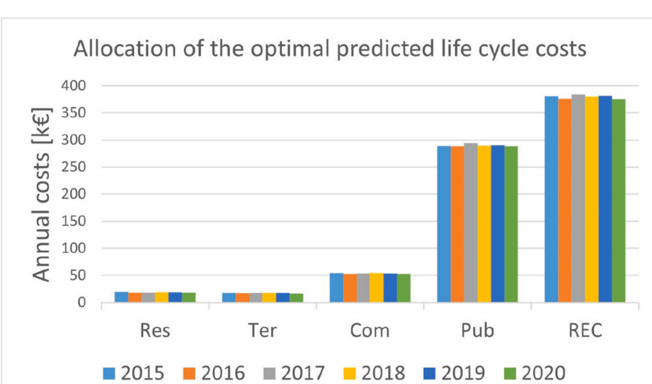

Fig. 9. Allocation of the optimal life cycle cost of the system, predicted for each year of the testing dataset, to the REC members by Shapley value.

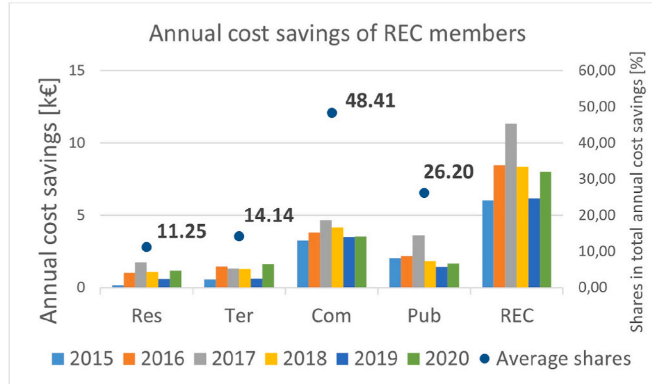

Fig. 10. Annual cost savings of the REC members compared to the case of independent operation (left axis) and their average shares (dark blue dots) in the total annual cost savings of the REC (right axis).

Fig. 9 shows the fair distribution of the optimal life cycle cost among the REC members for each year of the testing dataset by the Shapley value mechanism. Fig. 10 shows the annual cost savings of members achieved by operating together in the REC compared to operating alone (left axis), and the average shares (dark blue dots) of these cost savings in the total savings of the REC (right axis). In addition, Table 4(a) and Table 4(b) in the Appendix show in detail the values of these costs associated with Figs. 9 and 10, respectively. Table 4(a) (Fig. 9) highlights that the annual costs allocated to the residential and tertiary users (18–20 k€ and 16–18 k€, respectively) are much lower than those allocated to the commercial and public users (53–54 k€ and 288–294 k€, respectively). This is mainly explained by the higher daily demands of the commercial and public users (Figs. 5 and 6) and the high investment costs of the public user (due to the large optimal sizes of its units, Table 2 (a)). Indeed, the Shapley value allocation depends on the weights of the users' demand and the energy generation of prosumers in the calculation of the individual contributions of members to the values (i.e., life cycle costs) of all 16 coalitions considered within the REC by the Shapley value mechanism (Eq. (2), Section 2.3). However, Table 4(b) shows that, over the different years, approximately 41–57 % of the total annual cost savings 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 (48.41 %, 26.2 %, 14.14 % and 11.25 % on average, respectively, in Fig. 10). For example, in year 2017, the total annual cost savings are 11.33 k€, of which 41 % and 32 % are allocated to the commercial and public users, respectively. The commercial and public users bear more expensive investments than the residential and tertiary users, so the Shapley value supports these investments by fairly distributing higher annual cost savings to the commercial and public users.

4.3. Critical remarks

This Section summarizes the main findings from the results presented in Sections 4.1 and 4.2, highlighting the advantages and limitations of the proposed novel stochastic optimization procedure.

- The presented procedure can be used to optimize the sizes and operation of units within a REC under uncertainties in solar irradiance and members' electricity demand. To fill the gaps identified in the literature, the procedure successfully identifies the "best" set of stochastic scenarios of the uncertain variables in a "past" training

dataset, and then evaluates the accuracy of the optimal "stochastic forecasts" solutions, based on the "best" set of stochastic scenarios, compared to the "perfect forecasts" with perfect knowledge in a "future" testing dataset. For the analysed REC, the "stochastic forecasts" based on the "best" set of 29 stochastic scenarios lead to acceptable errors in the optimal life cycle cost and sizes of less than 2 % and in the range of 3–13 % for conversion units, respectively.
- However, a limitation of the proposed procedure is that it disregards the temporal relationship between consecutive typical days used as stochastic scenarios in the SP model. While this choice improves the computational efficiency of the SP model, resulting in a few minutes to obtain the optimal "stochastic forecasts", it reduces the model accuracy, leading to higher errors in the predicted sizes of TES units (i.e., 38 % and 23 % on average for the residential and public users, respectively) than the other units. It should be noted that these errors could be further reduced by searching for the "best" set of stochastic scenarios that is also representative of the uncertainty in the ambient temperature, which affects the TES operation and therefore its optimal size.
- The proposed procedure is general and flexible. In fact, the SP model under uncertainty and the MILP model with perfect knowledge could be adapted to different REC settings characterized, for example, by a different geographical location and a higher number of members than those considered. However, given a REC with a higher number of members (e.g., tens or hundreds), greater computational resources would be required to solve the MILP model with perfect knowledge and to fairly allocate the optimal predicted life cycle cost to the REC members using the Shapley value. In fact, for large RECs, the number of user coalitions increases dramatically and so does the computational time to solve the SP model for each coalition to achieve the fair economic allocation of the predicted life cycle costs. The procedure could also integrate and use different techniques to generate alternative sets of stochastic scenarios, such as clustering techniques other than K-means (e.g., K-medoids, hierarchical clustering) and artificial neural networks, with the aim of improving the accuracy in predicting the "best" set of stochastic scenarios and thus reducing the errors in the "stochastic forecasts" of sizes of both conversion and storage units.

5. Conclusions

This paper searches for the optimal sizes and operating conditions of energy conversion units of a Multi-Energy System (MES) within a Renewable Energy Community (REC) under uncertainties in solar irradiance and users' electricity demand. The twofold objective is to *i)* find the "best" set of stochastic scenarios associated with the analysed uncertainties and *ii)* assess the accuracy of the "stochastic forecasts", based on the "best" set of stochastic scenarios, in terms of optimal cost and design of the system by comparison with the utopic "perfect forecasts" based on the perfect knowledge of real data. The analysed REC consists of two residential and public prosumers who could install PV, HP, EES and TES units, and two tertiary and commercial consumers who could install GB units.

A novel optimization procedure is presented that shifts the "present moment" back in time to divide an available dataset into "past" (2005–2014) and "future" (2015–2020) periods, which are used as training and testing datasets, respectively. The procedure is based on Mixed-Integer Linear Programming (MILP) and Stochastic Programming (SP) models to carry out the design-operation optimization of the system minimizing its life cycle cost. The MILP model is solved for each day of each year, first using the training and then the testing datasets, leading to the *"historical solutions"* and *"perfect forecasts"*, respectively, the latter based on the utopic assumption of perfect knowledge of the "future". Subsequently, different sets of stochastic scenarios of the uncertain parameters are obtained by applying K-means clustering in the training dataset. At this point, the SP model, solved for each year and set of stochastic scenarios, leads to different *"stochastic solutions"*. The "best" set of stochastic scenarios is identified considering the lowest Root Mean Squared Error (RMSE) and residual between the optimal life cycle costs obtained according to the *"stochastic solutions"* and *"historical solutions"*. The last step consists in solving the SP model for each year of the testing dataset with this "best" set of scenarios, resulting in different *"stochastic forecasts"*, the accuracy of which is assessed compared to the *"perfect forecasts"*.

In the presented case study, the validation of the SP model shows that the "best" set of stochastic scenarios contains 29 scenarios from the year 2014. Given this "best" set of scenarios, the test of the SP model leads to the following outcomes in terms of optimal life cycle cost, its fair allocation and optimal sizes of the units.

- *The average relative error in the optimal life cycle cost of the system according to the "stochastic forecasts" with respect to the "perfect forecasts" is 1.63 %*, which indicates the good accuracy of the SP model in predicting the optimal life cycle cost over the years of the testing dataset.
- *The Shapley value mechanism fairly allocates the optimal life cycle cost predicted for each year of the testing dataset.* In fact, this mechanism not only distributes lower annual costs to the residential and tertiary users characterized by low electricity demands (18–20 k€ and 16–18 k€ over the years of the testing dataset, respectively), but also guarantees users with expensive investments (e.g., commercial and public users) higher reimbursements (41–57 % and 21–34 % of the total annual cost savings, respectively) encouraging them to stay within the REC.
- *The average relative errors in the optimal sizes according to the "stochastic forecasts" compared to the "perfect forecasts" are 3-13 % for PV and HP (with acceptable errors), while the optimal sizes of the GB units are predicted with no error.* Note that the presented procedure neglects the temporal relationship between consecutive typical days defining the stochastic scenarios in the SP model, thus disregarding the seasonal operation of the storage units. This choice was dictated by the search for the best compromise between model accuracy and computational times. The errors between "stochastic forecasts" and "perfect forecasts" in the optimal sizes of the storage units are therefore higher than those of the other units (i.e., 38 % and 23 % for the residential and public prosumers, respectively).

In summary, we can state that the proposed procedure succeeds in identifying the "best" set of stochastic scenarios representing uncertain parameters because the errors in the optimal life cycle costs (less than 2 %) and sizes of conversion units (3–13 %) according to the "stochastic forecasts" can certainly be considered acceptable in the common practice of MES design. The implicit assumption is that the representation of uncertainties in the "future" will remain the same as in the "past". Moreover, the SP model proves to be computationally efficient, taking only a few minutes to obtain a "stochastic forecast", compared to the 32 h on average required to achieve a "perfect forecast".

The proposed procedure could be useful for policy makers and investors because *i)* it helps make informed decisions, based on the "stochastic forecasts", on the optimal design of MES supplying RECs under uncertainties in RES and users' energy demand, *ii)* it can be adapted to optimize the design-operation of MES having different characteristics (e. g., type and number of users, additional units, etc.) from those considered in this work and *iii)* it has the possibility of including an allocation mechanism (e.g., the Shapley value) to fairly distribute the total economic benefit of the REC among its members.

The good accuracy and the low computational times of the SP model pave the way to future developments of the proposed procedure. Further research could analyse the impact of changing the temporal position of the "present moment" on the "stochastic forecasts", which would require larger training and testing datasets. Other directions of future work could focus on considering other uncertainties (e.g., ambient temperature, heating demands, prices of technologies and energy-related costs, etc.) and further investigating the temporal relationship between consecutive typical days used as stochastic scenarios in the SP model.

CRediT authorship contribution statement

Gabriele Volpato: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Data curation, Conceptualization. **Gianluca Carraro:** Writing – original draft, Validation, Supervision, Formal analysis, Conceptualization. **Luigi De Giovanni:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Enrico Dal Cin:** Writing – review & editing, Formal analysis, Conceptualization. **Piero Danieli:** Writing – review & editing, Visualization. **Edoardo Bregolin:** Writing – review & editing, Visualization. **Andrea Lazzaretto:** Writing – original draft, Supervision, Methodology, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

Acronyms		**Symbols**	
Com	Commercial	a	Interest rate, [−]
EC	Energy Community	a_0, a_1	Coefficients of the linear characteristic curve of an energy conversion unit
EES	Electrical Energy Storage	c	Optimal cost of the system [€] or grid price [€/kWh]
ES	Energy Storage	cap	Capacity of an energy conversion or storage unit, [kW] or [kWh]
GB	Gas Boiler	COP	Coefficient of performance, [−]
HP	Heat Pump	D^{var}	Maximum hourly shifting of the electricity load demand, [−]
MES	Multi-Energy System	E	Energy, [kWh]
MILP	Mixed-Integer Linear Programming	F	Power consumed by an energy conversion unit, [kW]
PBDR	Price-Based Demand Response	I	Global solar irradiance, [kW/m^2]
Pub	Public	inc	Incentive, [€/kWh]
PV	Photovoltaic	K	Number of stochastic scenarios
REC	Renewable Energy Community	lt	Lifetime of an energy technology, [years]
RES	Renewable Energy Sources	N	Number of members of an energy community
Res	Residential	$O\&M$	Operation and maintenance cost, [€]
RMSE	Root Mean Squared Error	P	Electrical power generated by an energy conversion unit, [kW]
RTP	Real Time Pricing	Q	Thermal power generated by an energy conversion unit, [kW]
SP	Stochastic Programming	w	Weight of a typical day in one year
Ter	Tertiary	Y	Total number of years in one dataset
TES	Thermal Energy Storage		
Greek symbols		**Subscripts and superscripts**	
Δt	Time step of 1 h in the optimization	c	Consumer
δ	Binary variable indicating the on-off operational state of an energy conversion/storage unit, [−]	d	Day
η	Efficiency, [−]	el	Electricity
θ	Auxiliary variable	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
		u	Energy technology
		$+/-$	Charging/discharging state of an energy storage unit

Appendix

Table 4
a) Allocation of the optimal life cycle cost of the system, predicted for each year of the testing dataset, to the members of the REC by Shapley value (the last line shows the annual life cycle costs) 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€]						
Member	Years					
	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)

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 [%]						
Member	Years					
	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

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