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Neural-assisted HVACs optimal scheduling for renewable energy communities

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ABSTRACT

Renewable energy communities (RECs) show a high potential for the efficient use of distributed energy technologies at local levels according to the Clean Energy Package of the European Union. Nevertheless, many problems are encountered during the planning phase of a REC because a large number of decision variables should be considered depending on the types of community participants and their load profiles. Moreover, the load schedule is fundamental with the aim of maximizing the energy shared within the community and the economic revenue of the REC. This is the main objective of this work that deals with the problem of optimal scheduling for electrical heating and cooling systems in a university lecture building included in a renewable energy community. The conditioning systems are significant electrical loads that can be scheduled both to reduce the energy requirements of the buildings and to synchronize energy injection and withdrawal from the grid, achieving energy self-consumption. The energy demand for the building is estimated using a specific simulation environment (EnergyPlus) which is experimentally validated with a campaign of measurements. From this software, a training dataset is created and used to implement a computationally lean neural network to represent through a black-box model the thermal-electrical behavior of the lecture building. Through the use of this neural model, the building thermal set points are processed by an optimization algorithm to maximize the economic revenue of the REC, while retaining the comfort boundaries of the building. The innovative proposed strategy is applied on a yearly simulation of the REC resulting in reduced energy required for thermal conditioning, higher cash-flows associated with the energy market and a smaller carbon footprint of the community.

1. Introduction

Commercial and residential buildings energy consumptions represent more than 40 % of the global energy worldwide produced: about the 50 % of this amount of energy is consumed for heating, cooling, and air conditioning (HVAC) [1,2]. Efficient management of electrical loads in the grid system is an actual and recent problem with the increased penetration of renewable-based distributed generation [3,4]. In the recently introduced scenario of Renewable Energy Communities (RECs), economic incentives can be acquired by the community members when they share electricity among their fellow members. These incentives are given when simultaneous (i.e., in the same hour slot) energy withdraw and injection is performed. Unfortunately, injection and withdraw exhibit peaks at different times of the day [5,6]. In fact, the supply of power from renewable energy sources like wind and solar is much volatile due to the variability of atmospheric conditions: it is a weakness in the power system that represents an obstacle to the continued expansion of renewables [7,8]. From an energetic point of view, the load and generation profiles of the prosumers and consumers should be clustered with a combinatory analysis to find the optimal assignment of the prosumers considering the synergy of their load and electricity generation profiles with the aim of achieving maximum economic revenue. Moreover, lacks in capacity, induced by high rises in demand during peak hours of consumption, are responsible for vulnerabilities in the

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electricity system and expensive improvements in infrastructure are therefore required.

In this context, the present paper presents the implementation of a demand-response tool able to optimize the economic and energetic profiles of RECs considering simultaneously the thermal/electrical demands of the buildings, the indoor thermal comfort conditions maintenance, the thermal inertia features of the buildings envelope. The study proposes an innovative method for the optimization of the HVAC scheduling, and it is applied to a reference case study belonging to a present REC. The case study is composed by many residential prosumers and a single public building (a university center in central Italy). The university building is simulated by means of EnergyPlus software [9] to model the building's thermal behavior and to evaluate the electrical energy demand for different configurations of the HVAC system, equipment loads, people that occupy the room, and the lighting system. To validate this simulation tool, a preliminary experimental campaign was carried out in order to calibrate the simulation model, above all in terms of thermos-hygrometric behavior. The zonal thermal response of the building was evaluated using the simulation model for different profiles of HVAC heating and cooling throughout the year. This allowed the formulation of a large dataset, with the final purpose of creating a black-box model to be used in the electrical load optimization. This model was implemented using an Artificial Neural Network (ANN) able to estimate the electrical load given an internal temperature profile. This allowed the embedding of the neural model for the building HVAC system in a larger optimization process, aimed at reducing the electricity consumption and maximizing the economic revenue of the REC. The objective of the paper is to exploit modelling and optimization techniques that belongs to the literature (such as building geometrical thermal modelling, black box fitting through ANN, and algorithmic non-linear optimization) for a recent topic, namely renewable energy communities. The resulting simulation and design tool is innovative and fills a gap in the literature due to its computational characteristics (obtained by the black-modelling approach, which is faster than a geometrical thermal modelling of a building) and the optimization towards economic cost functions, which are novel due to the recent introduction of monetization for shared energy among REC members. Interesting results derive from this analysis in terms of optimization strategies to be adopted in the REC domain.

The paper is structured as follows. First, an overview of the state of the art for technologies and management techniques aimed at renewable energy communities will be discussed. Then, the materials and methods section will describe the thermal model and its experimental validation, the implementation of the neural model of the building and the formalization of the optimization problem towards the REC. The optimization results in terms of both daily and yearly improvements are then presented. Conclusions and final remarks close the paper.

1.1. State of the art

Renewable Energy Communities (RECs) are supported by the European countries due to the necessity to involve citizens as active participants in the energy transition for climate neutrality. They include shareholders or members which are individual subjects, small-medium enterprise or companies, local authorities, or municipalities. The principles on which a REC is founded are the decentralization and localization of energy production by means of Renewables; the economic incentive recognized to the REC for quotas of shared energy, which is defined as the minimum value between the withdrawn energy valued at the national price (by the deficit prosumers) and the injected energy (by prosumers that are producing more than they are consuming) evaluated at the zonal price evaluated on hourly basis. Among the solutions that are available to increase the efficiency of a REC, Demand Side Management (DSM) measures contribute to motivate users to shift their electricity usage [10]. DSM can be implemented by residential as well as commercial users, but residential loads are much more flexible than commercial ones and they can deploy DSM techniques more easily. Not only the Load Shifting technique could be implemented (load relocation from peak usage periods to off-peak usage periods), but also Load Reduction techniques (increasing of the loads reduction during every period through cyclic operation and using more efficient appliances [11,12]); Load Growth and Flexible Load Shaping actions could be also applied (the customers are encouraged to increase the electricity use to participate to power system balancing in the first case, in the second one the consumers disposed to modify their load usage pattern are rewarded with incentives) [3,11,13,14,15].

Among the DSM measures, an important issue for the design of efficient energy management and building thermal control concerns Demand Response (DR) [16–18]: the key strategy is that the end users play an active role in the electricity system by adapting their consumption profiles on the basis of renewable energy production trends and dynamic energy pricing policies [19,20]. The shifting of HVAC electric loads according to a smart strategy allows the participation in DR services. Therefore, the tenant can be considered the fundamental component for demand flexibility achievement because he should find convenient to schedule some tasks in order to obtain a reward.

Another technology developed for smart monitoring and controlling of home appliances is the so-called Home Energy Management System (HEMS) [21]: smart plug systems are used to schedule and control the home appliances [22]. Both DR and HEMS create new challenges and opportunities for the smart grids and the active prosumers in the market, thanks to the important goals that can be reached [23]: the distributed energy generation management brings to increase the sustainability and wellbeing of residents in Renewable Energy Communities [24]. Many other advantages are obtainable through the implementation of these strategies, such as cost reductions in energy consumption, environmental benefits, the mitigation of voltage issues on the distribution feeder, the reduction of the peak demand and of the load profiles that could be intelligently handled in this way [25,26].

In this scenario, different case studies can be analyzed and solved through numerical optimization algorithms and by formulating multi-objective problems, for the purpose of maximizing the revenue for the incentives. In particular, classical optimization algorithms, *meta*-heuristic or evolutionary computation, soft-computing based optimization algorithms (Fuzzy Logic, Artificial Neural Network), and game theory are widely used in DSM applications; moreover, different objective functions are implemented. Among the models strategies, *meta*-heuristic algorithms are easy to be applied and they are able to solve highly complex computational problems, although premature convergence and time-consuming concerns (above all when the number of variables and constraints are high) may happen.

The problem could be faced up by considering a simple aggregation of users or a real Energy Community. Considering the first case, in [2] the optimal use of a building heating system under the hypothesis of participation in a Demand Response program was firstly analyzed. The DR setup is based on price volume indications sent by an aggregator to the building energy management system. A maximum volume of energy to be consumed during a specific time-period and a monetary reward assigned to the participant if the conditions are ensured, were fixed: the optimization algorithm efficacy was tested both on a simplify model and on a realistic building model in EnergyPlus.

The balancing problem of the community grid and of the building energy management should be solved by creating optimal adaptable scheduling strategies that consider both community-level factors (distributed energy resources shared in the community) and building-level factors (as, for example, the demand balance with potential load flexibilities) [27–29]. In [27] the model proposed by the authors consider minimum-cost optimization problems by considering both these aspects: the building is designed to optimize zonal temperature setpoints in response to day-ahead weather conditions, occupancy, and electricity price estimations to ensure comfortable conditions; the community involves several onsite distributed energy resources and joint flexibilities among the connected buildings. A test community network with four EnergyPlus building models is implemented for representing a real building cluster at Qatar University. It is observed that the community's operation cost can be reduced up to 21 % when the community operators strategically reschedule the identified potential joint-flexibilities among the connected buildings. Aly Elhefny et al. [30] consider five simple residential community composed by 100 dwellings with different control settings and distribution infrastructure: building simulations by means of EnergyPlus program, a solar photovoltaic (PV) model, and the power flow model are implemented. Simulation test results show that the voltage regulation strategies by using flexible loads could help to reduce the number of operations of the voltage regulators. Also, in [31] a co-simulation tool is developed to simulate a residential community of about 500 houses and the combined effects of Energy Efficiency techniques HEMS, and battery systems are investigated at the aggregation scale. In [32] a bottom-up model for managing the flexibility in residential electric load profiles is presented. The user behavior, all the relevant technologies, and the controller settings are considered; moreover, a linear electrical storage equivalent model is taken into account. The results show that PV battery systems offer the largest values of switchable power and storage capacity, but Heat Pumps (HPs) and PV battery systems flexibility shows seasonal and daily variations. Bianchini et al. [33] consider the problem of cost-optimal operation of smart buildings with a centralized HVAC system, PV generation, and both thermal and electrical storage devices. Demand-Response program is also considered for the buildings occupants. The proposed solution is based on a Model Predictive Control strategy to optimally manage the HVAC system and the storage devices considering both the thermal comfort and possible technological constraints.

When a real Energy Community (EC) is analyzed, the modelling procedure and the steps to be followed should be different: many studies aim at finding the optimal solution in terms of environmental and efficiency benefits but they overlook that the creation of an energy community may lead to concerns regarding the ownership of common assets, the risks that users could decide to leave the community, the fair distribution of profits, and possible barriers for users to join [34,35]. In this scenario, another important role could be assigned to an intermediary subject that is responsible for the aggregation of the several consumers: the aggregator. Fioriti et al. [34] propose a custom business model for ECs that aims at stimulating the cooperation among users and the optimal operation of the community by an aggregator, also including exit clauses to establish how and when users can leave the community itself. Also Cornélusse et al. [36] present a community microgrid architecture, with an internal market which distributes the benefits of the community among the participants, by ensuring that none of them is penalized with respect to acting individually. Nikita Tomin et al. [37] aim at presenting a unified approach to optimally managing the community microgrids with an internal market, considering the social, environmental, and economic benefits of a community in a particular location. Also in this case, a Pareto efficiency condition guarantees that nobody is penalized for participating in the community, with respect to individual actions, since this is the fundamental requirement for developing a strong and resilient community.

2. Materials and methods

2.1. Description of the case study and simulation model

The case study is a university center built in the 1970s–1980s period in Perugia (center of Italy) [38]. The climatic zone is type E (considering the Italian Law classification) that correspond to a temperate climate and an inner low altitude area. It is a modern building with a total surface of about 4000 m^2 with an external envelope composed by an insulated masonry with redbrick as outer finishing (outer surface 7160 m^2). It has good thermal insulation properties, with an estimated thermal transmittance of the opaque envelope of about 0.34 W/(m^2 K). Lecture halls are located at the ground floor of the building, at the first floor both lecture hall and offices are positioned. Large aluminum windows are present in all the rooms all around the building (U_w equal to 3.0 W/(m^2 K)); a double layer laminated glazing is installed with a total thickness of 22 mm (glass layer 4 mm, air 12 mm, glass layer 6 mm, U_g of 2.8 W/(m^2 K)).

An experimental campaign was carried out in a lecture hall at the ground floor of the building. The room has a rectangular shape (12 m × 8 m with a 3.6 m ceiling height), with a total volume of about 350 m^3 (Fig. 1).

Only the south-west facade is an external wall (with a surface of 29 m^2) and it has a large window installed (total surface of 15 m^2, about half of the whole external surface). The window has curtains that can be used for shielding. The WWR (Window-to-Wall Ratio) of the building envelope is equal to 43 % (for the only lecture hall it is equal to 52 %). The first floor is a clay/cement mix floor with a total thickness of 0.35 m and a thermal transmittance of about 2.0 W/(m^2 K), while the ground floor is insulated from the soil thanks to an insulated layer 8 cm-thick. The building performance was evaluated by means of EnergyPlus simulation code and the geometry was implemented by means of Google SketchUp plug-in (Fig. 2). EnergyPlus software [9] is able to model the buildings' thermal performance and the energy consumption demands concerning the HVAC, equipment/plug loads, and lighting system. The simulations were conducted by considering the actual building characteristics such as the geometry, the opaque and glazing envelope thermal insulation properties, the ventilation rate, the lighting, equipment/plug loads, and the occupancy features. The model was calibrated from the thermal behavior point of view by means of a preliminary experimental campaign, as described below. The walls between the tested room and the other contiguous rooms were modelled as adiabatic surfaces, considering all the building at the same temperature as they are all air-conditioned. The south-west wall was considered as a heat exchanging surface with the outside boundary air conditions; the ground floor also allows the heat transfer with the soil.

Internal gains from people (65 W per person with an occupancy of about 15 persons) and lights/equipment (10 W/m^2) were considered as heat sources based on daily occupancy schedules that are different in the several period of the year. For the calibration period (June 2022) the lights were considered off, except for the first hours of the day (8.00–10.00 a.m.) thanks to the significant contribution of the sun through the windows. The tested room has a single thermal zone. No air-conditioning system was modelled but only the heating and cooling energy demand of the room was evaluated: the corresponding consumptions associated to a heat pump installed inside the building were evaluated in post-processing phases by considering the efficiency of the selected model (both in terms of COP – Coefficient of Performance and EER – Energy Efficiency Ratio). To this aim a room air set point temperature fixed at 20 °C in winter and 26 °C in summer was fixed during the occupancy periods. The site location chosen for the building is Italy because of the high temperatures reached in the spring-summer period in the country: the efficacy of a PV plant installation in this case is higher because of the increasing electricity consumptions for the cooling.

All the simulations were carried out considering as geographical location the Italian region, where the investigated building belongs. To make this study consistent with legislation, no case studies were considered outside the national limit. Inside this limit, four cities were chosen: Milan, Perugia, Rome, and Catania that represent different latitudes (north, center, and south) and different climates (inner high altitude, inner low altitude, mild Mediterranean climate, and warm weather at seaside, respectively for Milan, Perugia, Rome, and Catania).

Annual simulations were carried out with a time step of one hour and four different scheduling profiles were considered: case 1 and case 2 are quite similar with a large ON-period, typical of intermediate/temperate climatic zones (Milan and Perugia, respectively); case 3 considers a lower ON period in winter and the system OFF during the lunch period (reference city is Rome) and case 4 is typical of south Italy climatic zones

Fig.1. Photo images of the selected case study (ouside and inside view) [38].

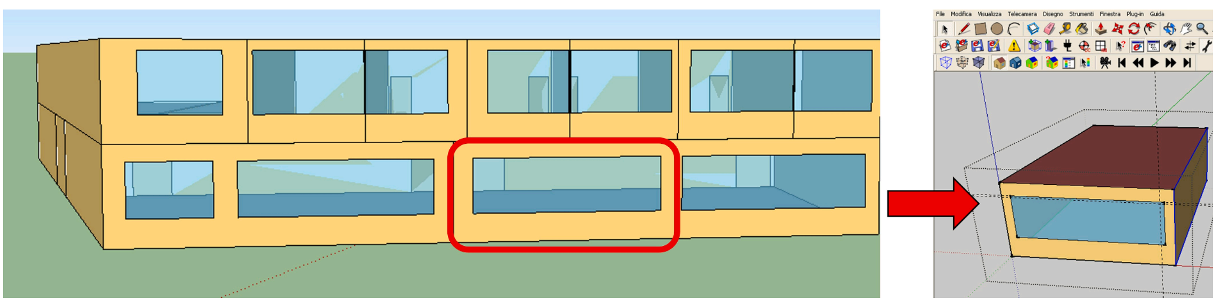

Fig.2. 3D model implemented in Google SketchUp for EnergyPlus code.

(such as Catania) with a limited ON-period of the HVAC system, above all in autumn–winter seasons (see Table 1). The weather files of these places were taken from EnergyPlus databases (EPW – Energy Plus Weather data). The chosen ON-OFF profiles are coherent to the intended use of the lecture halls of the University.

2.2. The co-simulation method

The paper aims at investigating an optimal HVAC scheduling strategy suited for a smart building with a set of potential flexible set-points to be rescheduled under different operation conditions. In the proposed framework, the building-level optimization model, which aims at minimizing the electricity cost of an individual building, is intended to find the best zonal temperature setpoints in response to the weather conditions, occupancy, and electricity price estimations. The EnergyPlus model of the building generated a large amount of time-series data that was used to relate the zonal thermal capacity in increasing/decreasing indoor temperature and the building electricity consumption of the heating/cooling system where a distributed zonal control strategy is programmed, on the basis of the outside weather conditions. In theory, since the purpose of the neural model is to recreate the functional relationship between the thermal response of the building and the climatic conditions, an exhaustive, gridded dataset considering all possible climatic and internal conditions should be used. However, creating such dataset is impossible due to the large number of variables. Moreover, several zones of that grid would be meaningless (e.g., very cold air temperature during a fiery sunny day). For this reason, to teach the ML the building thermal response for the largest variety of conditions, the dataset was augmented considering climatic profiles (Milano, Roma, Catania) that are not only the ones that will be used for the final application (Perugia). This way, only sensible combinations of the climatic conditions are considered, albeit in a larger scope.

2.2.1. Building neural model

The purpose of the neural model is to embed in a computationally light black-box the energetic estimation performed by the EnergyPlus environment. For this purpose, the simulations are used to create a machine-learning dataset for training and validation of an Artificial Neural Network (ANN) able to estimate the energetic demand (either in cooling or heating) of the building for a given set of inputs that completely defines the thermal conditions. The ANN works on hourly blocks, predicting the energy demand in kWh of the building.

Table 1
Simulated case studies considered for the analysis.

	Case 1		Case 2		Case 3		Case 4	
	Heating Period	Cooling Period	Heating Period	Cooling Period	Heating Period	Cooling Period	Heating Period	Cooling Period
	Climatic zone E (Milano)		Climatic zone E (Perugia)		Climatic zone C (Roma)		Climatic zone B (Catania)	
Annual ON - Period	15/10-15/04	01/06–30/09	15/10-15/04	01/06–30/09	15/11–15/03	01/06-30/09	01/12–15/03	01/06–30/09
Daily ON - Period	7am–6 pm	8am–6 pm	9 am–7 pm	9am–7 pm	7 am–1 pm 5 pm–6 pm	8 am–1 pm 5 pm–6 pm	9 am–5 pm	9 am–5 pm

The input considered for the ANN model are:

- The temperature at the beginning of the hourly block t_0
- The temperature at the end of the hourly block t_1
- The following environmental quantities averaged over the hour:
  1. *Normal and diffuse solar irradiance*
  2. *Wind speed and direction at 10 m altitude*
  3. *Relative humidity*
  4. *Air temperature at 1 m altitude*

The output of the ANN is the kWh necessary to achieve the temperature change from t_0 to t_1 over the hour. To use a single ANN for both heating and cooling, the output is mapped considering a positive value for heating, and negative for cooling. It should also be noted that the ANN can output very low values of energy in case the environmental conditions lead to a natural passage between the two temperatures (e.g. natural cooling during the evening). For the purpose of the simulation, the quasi-zero output of the ANN will be rounded at zero and interpreted as the non-necessity of either cooling or heating. The interaction between the building thermal model and the building neural model is shown in Fig. 3.

The chosen architecture is a Deep Multilayer Perceptron. The choice of this architecture is related to the simple sizing procedure of its hyperparameters (for which techniques used in training classic MLP can be exploited) and the large learning capabilities obtainable even with few hidden layers. The dataset for the ANN training is composed of 35,040 samples, divided into an 80 to 20 ratio for training and validation. Optimal size for the training was investigated considering a two-hidden-layer ANN in Fig. 4 (a). Training performance is shown in Fig. 4 (b). An example of validation performance of the ANN on four days is shown in Fig. 5. As can be seen, the ANN is able to represent correctly both the heating demand during cold days (November and February) and the cooling one during hot days (June and August).

2.2.2. Optimization of REC thermal profile

The neural model of the building is embedded in a larger optimization process aimed at maximizing the economic revenue of a Renewable Energy Community (REC). The community is composed of prosumers for which, often, electrical power production and demand are non-synchronous events. REC regulation provides economic incentives for the synchronization of the hourly injections operated by some prosumers and the energy withdrawals made by other members of the community in the same hour. A good strategy aims at shaping the load curve of the prosumers as similar as possible to the production curve. A possible approach lies in the management of controllable loads such as storage elements, electric vehicles and, as in the case of this study, HVAC. These loads absorb a considerable amount of power, and the thermal inertia of the building can be exploited to introduce a degree of freedom in arranging the scheduling of heating and cooling systems. This is of course bounded by the acceptable comfort conditions inside the building. The purpose of the optimization is to find a heating–cooling profile for the REC members that results in the larger economic revenue.

The problem is posed as an optimization problem with boundaries, as shown in Fig. 6.

The solution space feature 24 dimensions, each variable representing the set-point for the temperature during a specific hour of the day. According to the season, the solution space is bounded to ensure comfort for the building occupants. The total generated and demanded power during the 24 h is given by Eq. (1):

$$INJ_H = \sum_{m=1}^{72} inj_h[m]; WTH_h = wth_{LB,h} + hvac_{LB,h} + \sum_{m=1}^{72} wth_h[m] \tag{1}$$

Where $inj_h[m]$, $wth_h[m]$ are respectively the injected and withdrawn energy for the m-th member of the community at the hour h. The lecture building baseline hourly load profile is $wth_{LB,h}$ and the lecture building total HVAC related hourly load is $hvac_{LB,h}$. The hourly, cumulative generation and loads are INJ_h and WTH_h. To properly compute this energy balance is of course necessary to consider the variable heating–cooling energy demand (which changes according to the set-points). This task, which would require a complete simulation of the building for each functional evaluation, is leanly performed by the trained ANN.

From the energy profiles, an economic cost-function is computed (*cf*), considering the total cost for energy of the community and the lecture building (BUY_h), reduced by the energy sale ($SELL_h$), and the self-consumption incentives (INC_h):

$$BUY_h = WTH_h \bullet buyprice_h \tag{2}$$

$$SELL_h = INJ_h \bullet sellprice_h \tag{3}$$

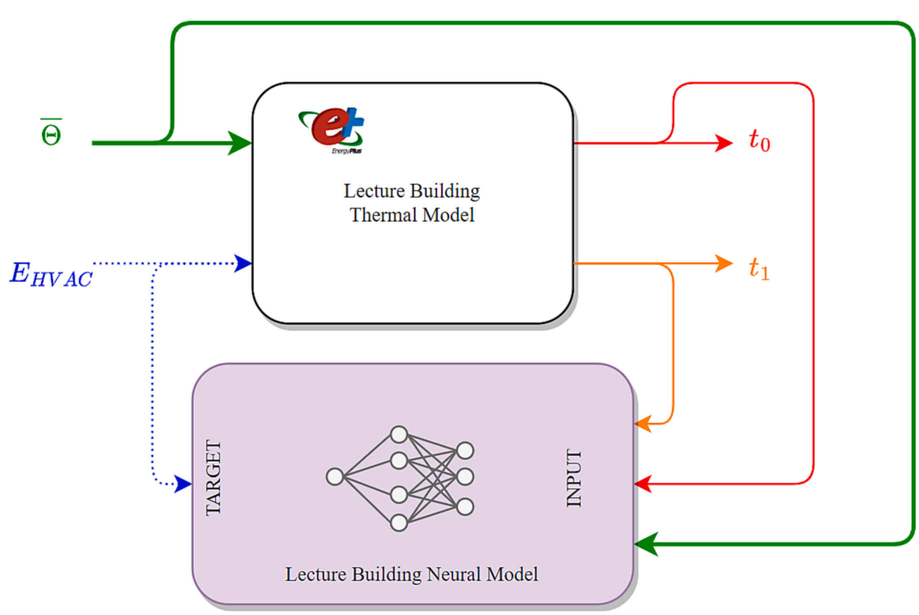

Fig. 3. Building thermal model – Building Neural model interaction represented by means of a blocks diagram.

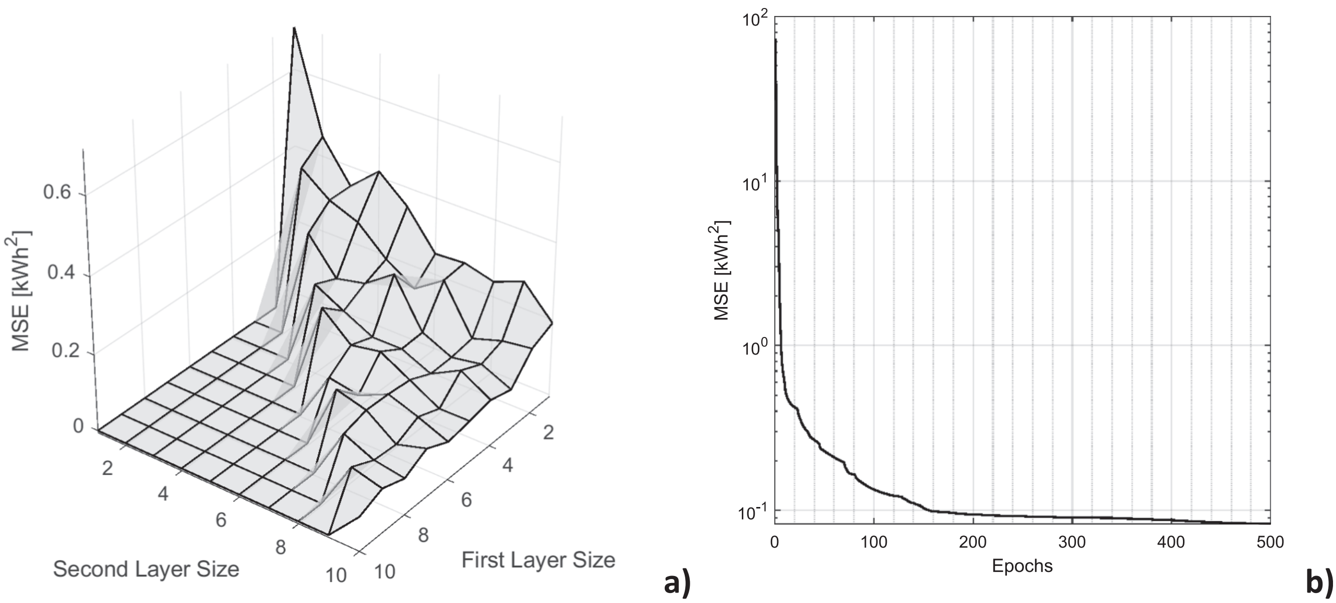

Fig. 4. a) investigation of the optimal size for the two layers ann; b) training performance of the ann, saturating at an optimal performance of 0.0785 after 500 epochs.

$$INC_h = \min(INJ_h, WTH_h) \bullet incprice \tag{4}$$

$$cf = -\left(\sum_{h=1}^{24} BUY_h - SELL_h - INC_h\right) \tag{5}$$

Where $sellprice_h$ is the average national unitary price (PUN) shown in Fig. 7, considered as remuneration for the electricity injected in the grid, and $buyprice_h$ is the energy price on the market calculated considering a 10 % markup on the PUN.

The cost function aims at minimizing the total energy expense of the REC over the 24 h. The optimization algorithm is composed of a cascade of a genetic algorithm for initial exploration of the solution space, and a local search algorithm based on trust region for the refinement of the solution.

The behavior of the algorithm was analyzed for numerous days during the yearly period, but for the sake of brevity, only two days were selected and shown. Therefore, the simulations of the energetic and economic optimization are shown considering the following three tests. In Test 1, a simulation of a February day is reported, thus considering the heating of the building during a very cold day. In the second (Test 2), a simulation of August is shown, thus considering the cooling of the building during a very hot day. The chosen of these two tests is due to the importance to observe the behavior of the community during both heating and cooling periods, considering also a low renewable energy production and a consistent distributed energy production, respectively. Lastly, a yearly simulation of the community will show the cumulative effects of the optimization strategy (Test 3).

3. Results and discussion

3.1. Preliminary experimental campaign and calibration results

For the sake of completeness, a simple experimental campaign was carried out in June 2022: it was useful to calibrate the model developed in EnergyPlus and to evaluate its effectiveness. An environmental monitoring stations was set-up in the room [38,39]: the measured parameters are air temperature (1 m high from the floor), air relative humidity, and air velocity.

The sampling rate was 10 min for each probe. Concurrent to the internal experimental campaign, a weather station installed on the roof of the Engineering Department (University of Perugia) was considered for the monitoring of the external parameters (outside air temperature, outside relative humidity, wind air speed, global solar radiation on horizontal pane). The parameter that was considered for the calibration of the model is the air temperature inside the room. For the validation of the model, the weather database was modified for the reference location by using the data measured hourly for air temperature, solar radiation, and relative humidity by the weather station in June 2022: these data were used for developing a weather file legibly by EnergyPlus. Fig. 8 shows the difference between the indoor air temperature measured on-site and the ones calculated by EnergyPlus taking into account the new weather file data (a typical spring week in June); also the outside air temperature and the global solar radiation values were reported. The cooling plant was maintained “off” from June 22nd to 26th and on 27th and 28th of June it was powered “on”. Moreover, the curtains were not considered in the simulations because they were maintained open during the experimental campaign. Many adjustments and upgrades of the boundary conditions were applied to the model to obtain a simulated building that could be considered calibrated. The glazing parameters and the boundary conditions to be assigned to the internal walls, pavement, and ceiling were changed until the mean air temperature trend was aligned with the measured one. Both solar and visible transmittance and reflectance were modified to evaluate the exact solar radiation supplied in the room; concerning the thermal exchanges with the neighboring rooms, the best calibration was obtained when the two internal walls and the ceiling were considered adiabatic (no exchange with spaces at the same inside air temperature). The wall between the lecturing hall and the hallway and the pavement were considered not adiabatic.

The trend in Fig. 8 is the final result of the calibration process. It can be observed a good correspondence of the two trends with maximum differences on 0.5 °C close to the maximum/minimum temperature values of a day. A rather good consistence was also observed when the outside parameters are related and compared to the correspondent inside values: the lower air temperatures are shown on June 26th when the external air temperatures and global solar radiation were lower. In the

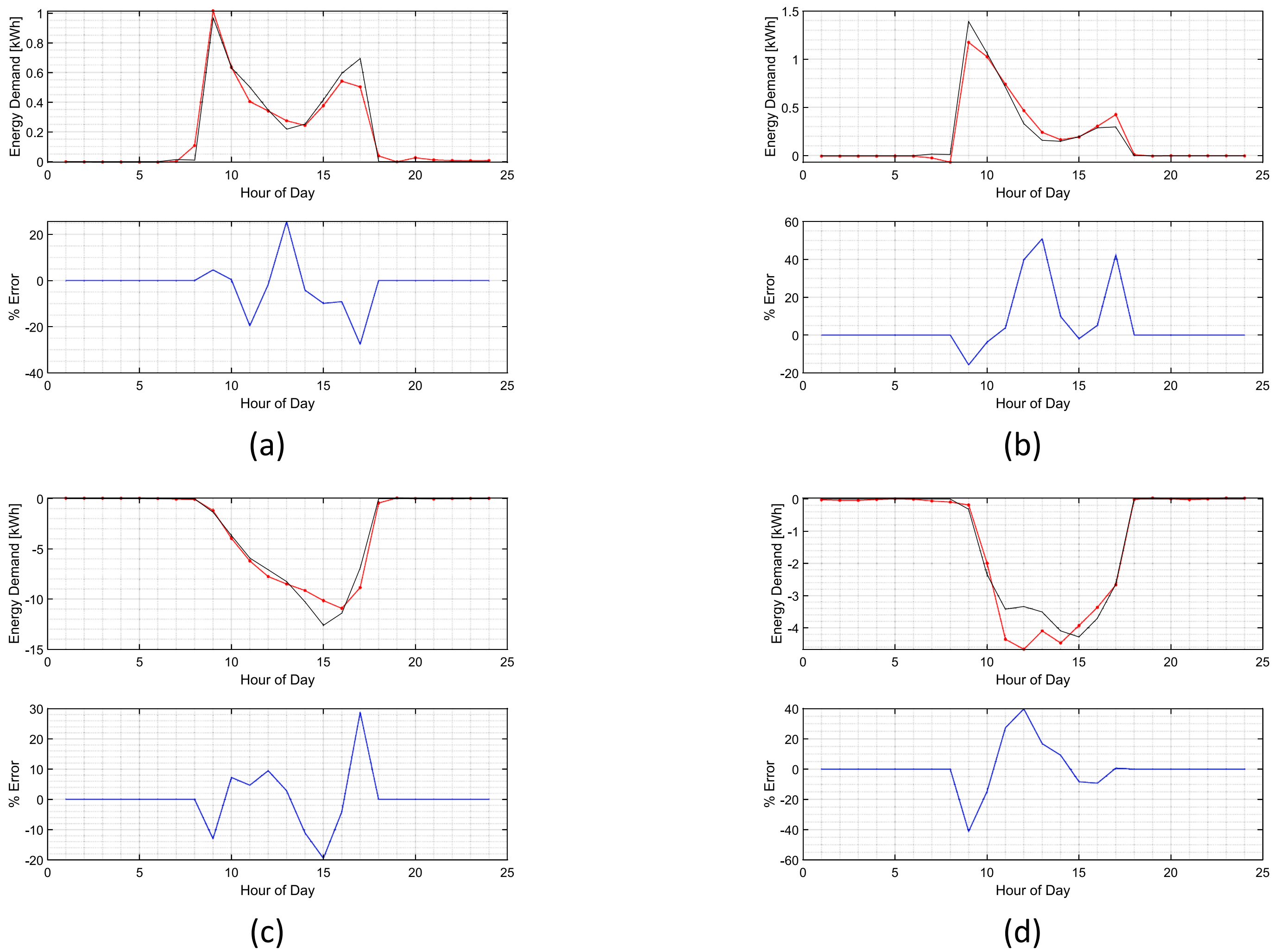

Fig. 5. Neural Network predicted energy demand (red trace) Vs. energy plus simulations (black trace) for different days of the year. Negative energy demands are cooling loads, positive energy demands are heating loads. Heating in (a) 27th of November, (b) 4th of February. Cooling in (c) 30th of June, (d) 15th of August. Percentage error for magnitudes over 100Wh are shown in blue.

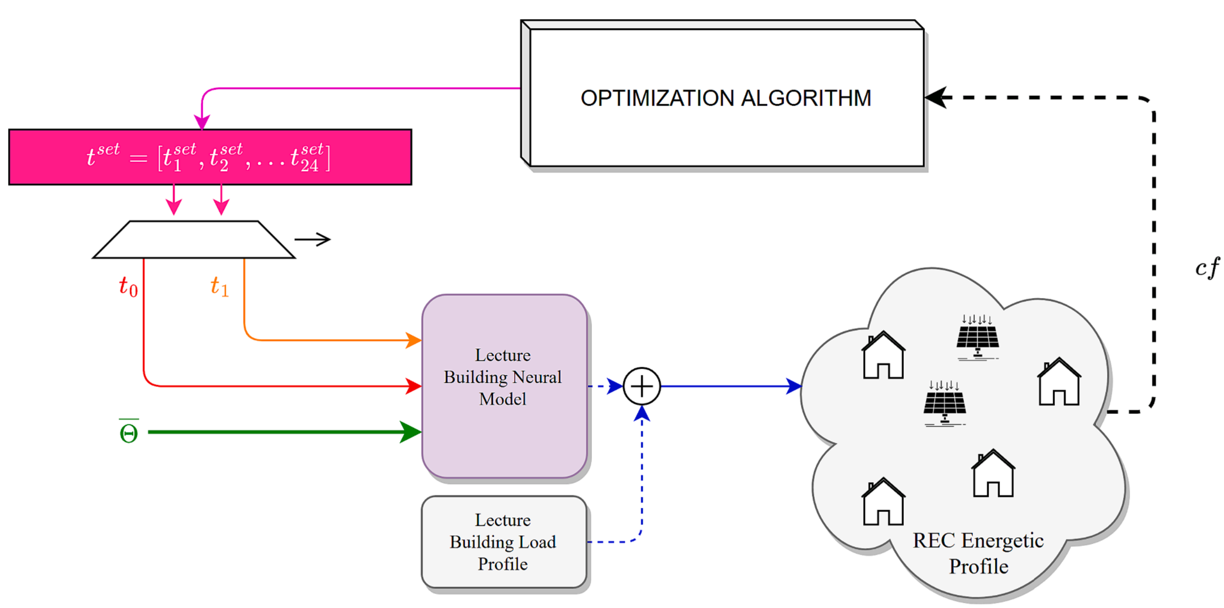

Fig. 6. Blocks diagram representation of the Optimization algorithm structure.

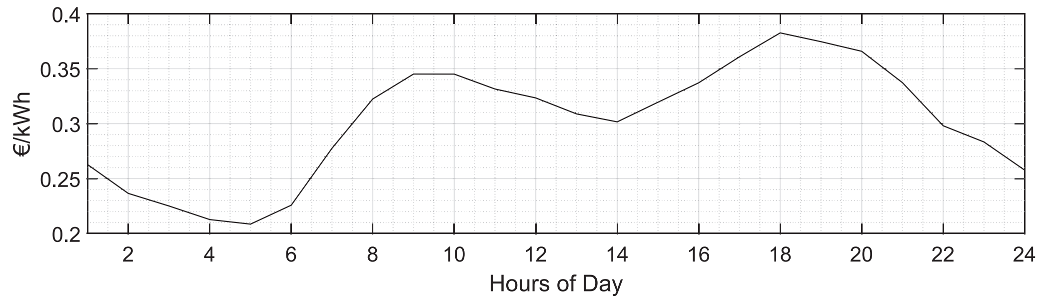

Fig. 7. Cost function trend over 24 h.

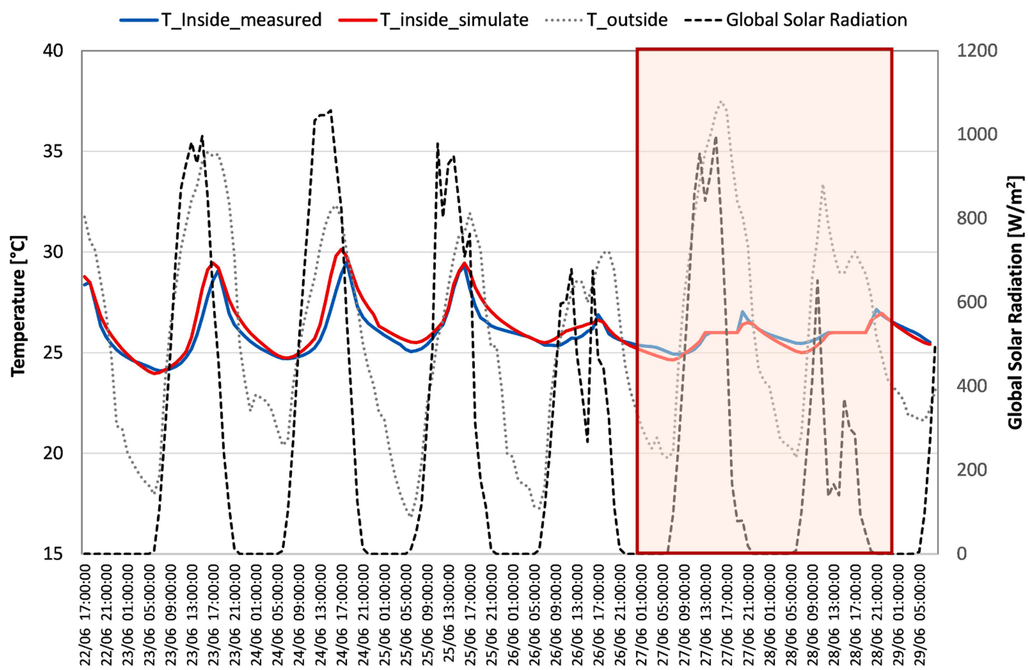

Fig. 8. Comparison between the measured air temperature inside the room and the simulated values during the experimental campaign (also the outside air temperatures and the global solar radiation are shown); the red rectangle highlights the days with the cooling system "on").

last two days the schedule considered the cooling system on from 8.00 am to 07.00 pm. After 07.00 pm the inside air temperatures increased because of the solar radiation contribution and the outside air temperatures that were still high in the evening. The simulation trends also followed this profile. Finally, the mean values measured every day were represented in Table 2: also in this case the differences are quite low (maximum differences of 0.6 °C for the air temperatures and 3 % in terms of relative humidity) and in general the simulated results are always slightly higher than the measured ones. Some validation indexes were used to quantify the calibration of the model: Normalized Mean Bias Error (NMBE), Coefficient of Variation of the Root Mean Square Error (CV(RMSE)), and coefficient of determination (r^2). In particular, the ASHRAE Guide- line 14 [40] recommendations were considered, and the following criteria (hourly criteria) were used:

- NMBE: from − 10 % to + 10 %;
- CV(RMSE) < 30 %;
- $r^2 > 0.75$.

In terms of indoor air temperatures, the NMBE mean value is about 4 %, the coefficient of determination value is always very high ($R^2 > 0.91$), and the Coefficient of Variation of the Root Mean Square Error

Table 2
Comparison between measured and simulated mean daily values.

	Measured		Simulated	
	Mean Inside Air Temperature [°C]	Mean Relative Humidity [%]	Mean Inside Air Temperature [°C]	Mean Relative Humidity [%]
23/06/2022	25.6	47.0	26.0	49.6
24/06/2022	26.1	43.1	26.6	45.5
25/06/2022	26.4	47.9	26.8	48.8
26/06/2022	25.8	46.9	26.0	49.9
27/06/2022	25.6	51.0	25.5	52.1
28/06/2022	26.0	53.6	25.8	54.0

(CV(RMSE)) is within the range suggested by the ASHRAE guidelines (less than 30 %).

3.2. Results of simulations and optimization model

In the following the simulations of the energetic and economic optimization is shown considering the three tests beforehand explained.

3.2.1. Heating in winter (Test 1)

For this test the date of February 7th, 2022 was used for the simulation. This date was chosen due to the particularly rigid climate, to assess the optimization capabilities of the approach in a condition where consistent heating is required to ensure the comfort boundaries defined for the building. The simulation is reported in Fig. 9: a strong pre-heating of the building during the early hours of the day can be observed with a consequent reduction of the overall energy required for heating. The hourly cost of energy for the whole community is computed using eq. (5), resulting in an end-of-day saving of 224€.

3.2.2. Cooling in summer (Test 2)

For the second test, the date of August 24th, 2022 was used for the simulation. This date was also chosen due to the severe heat present during the day and the necessity of using HVAC for refrigeration starting from the early hours of the day. At the same time, the intense sunlight resulted in high PV production during the hottest hours that could compensate for the higher power demand due to heating. In this case, the strategy found by the algorithm was to accept a smaller heat rise during the early morning and compensate by lowering the temperature during the hours with the highest PV production (Fig. 10). The hourly cost of energy for the whole community is computed using eq. (5) resulting in a net positive cash flow of 106€.

3.2.3. Yearly simulation (Test 3)

This last test performed the simulation and the optimization of the temperature setpoints throughout the year to evaluate the effects in different seasons. Results of the daily energy costs savings are shown in Fig. 11, showing both the daily results and a weekly moving average. As can be seen from the figure the two sets of points (optimized and non-optimized) overlaps during spring and late-summer and early-winter, due to the absence of both heating and cooling to be optimized. The same data is shown in the histogram reported in Fig. 12 in order to observe the average variations. The optimized configuration has average end-of-day energy costs almost close to zero (-10.61€) and a small standard deviation (215.69€), whereas the non-optimized solution features both higher average costs (-128.72€) and larger standard deviation (285.82€). A summary of the annual data is reported in Table 3. Interestingly, since the optimization of problems is obtained by reducing the HVAC loads, the overall incentives received by the REC are lower. This is expected since the self-consumed energy of the community is, in general, lower. However, the introduction of a storage system able to synchronize the prosumers could lead to higher incentives for the community as well.

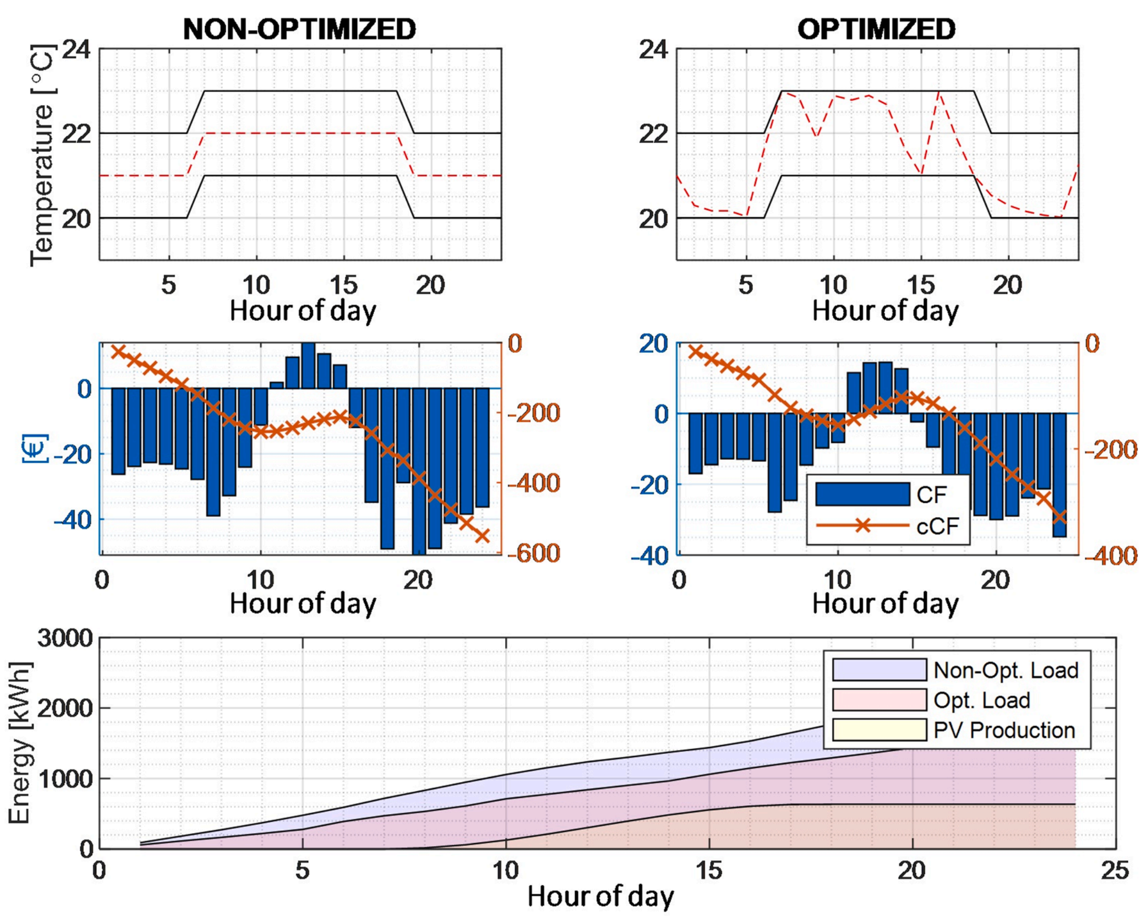

Fig. 9. Test of the optimization strategy during a winter day in February. From top to bottom rows: temperature set points, hourly cash flow and cumulative cash flow, cumulative energy produced and consumed during the day. Left column shows non-optimized set points, right column shows optimized set points. Optimization leads to an end of the day saving of 224€.

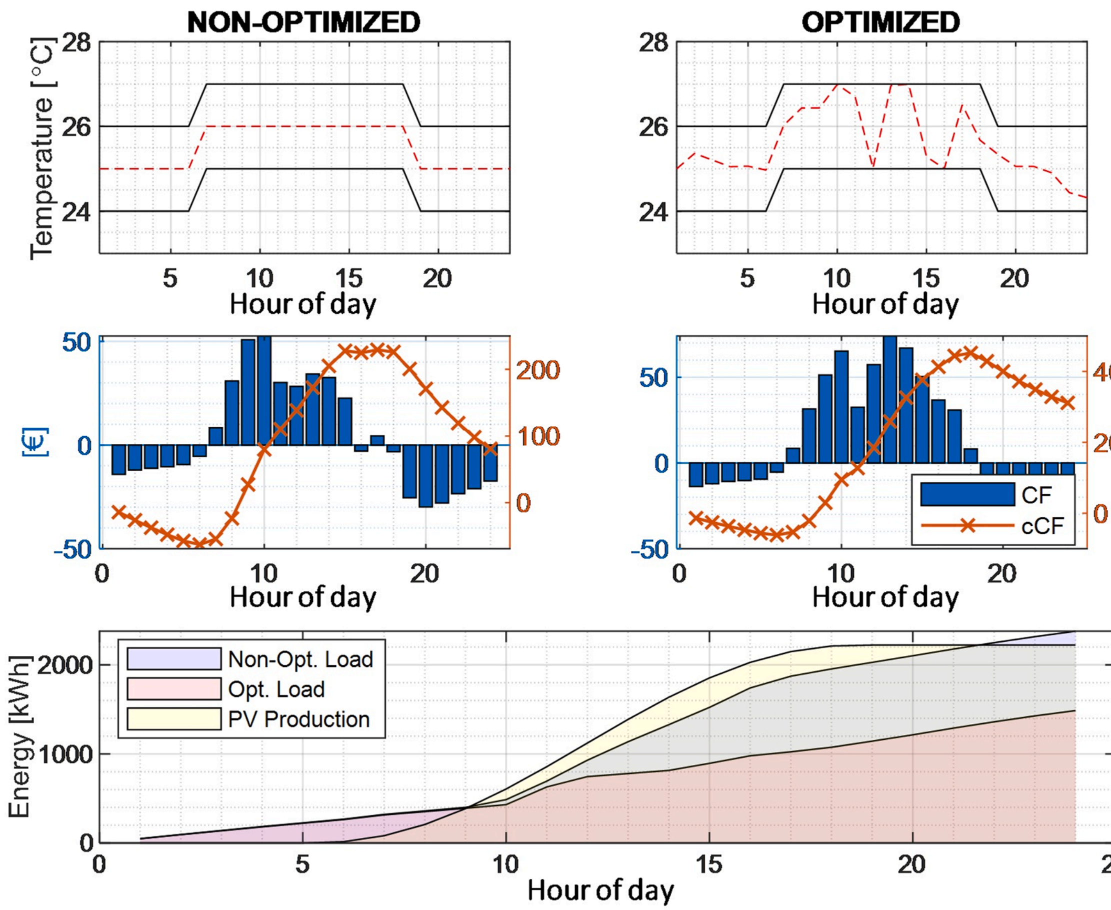

Fig. 10. Test of the optimization strategy during a summer day in August. From top to bottom rows: temperature set points, hourly cash flow and cumulative cash flow, cumulative energy produced and consumed during the day. Left column shows non-optimized set points, right column shows optimized set points. Optimization leads to positive cash flow of 106€.

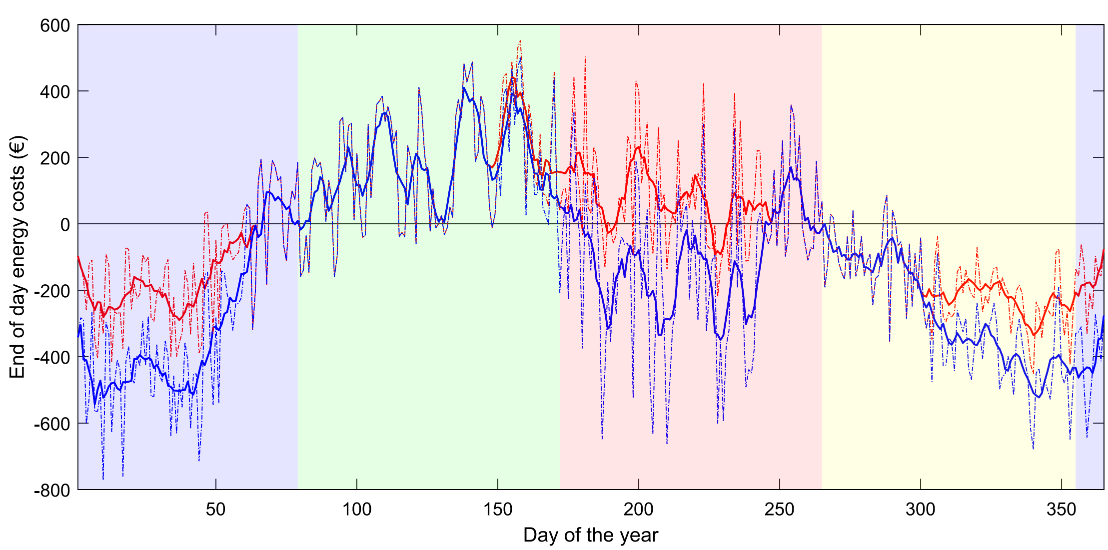

Fig. 11. Yearlong simulation of the optimized (red traces) and non-optimized (blue traces) HVAC systems in terms of resulting end-of-day energy cost savings. Dotted lines are daily data, full lines are 7 days moving averages. The two lines overlaps in the periods where the HVACs systems are usually not used for heating or cooling. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

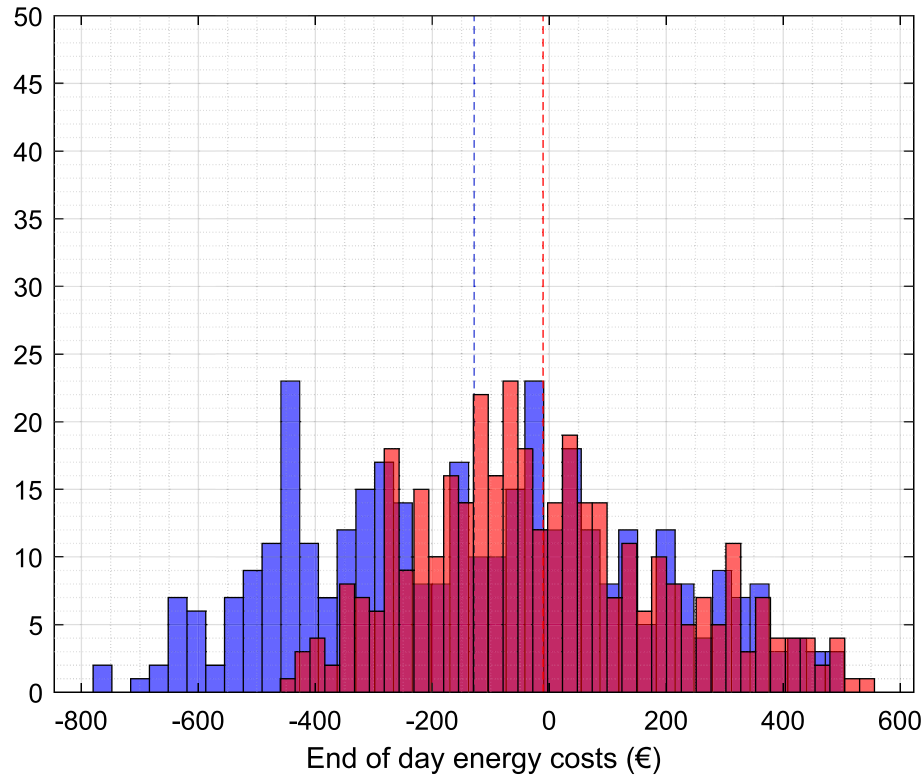

Fig. 12. Histogram representation of the results obtained from the year-long simulations: in blue the non-optimized configuration, in red the optimized one. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Energy and economic annual results for the optimized and non-optimized configurations.

	Non-Optimized	Optimized
Total HVAC Energy for heat (MWh)	115.44	33.20
Total HVAC Energy for cooling (MWh)	89.45	27.92
Total Incentives (€)	28501	23671
Equivalent HVAC CO_2 Emissions (ton)	49.63	14.27
End of Year Cumulative Cash Flow (€)	−46984	−38756

4. Conclusions

This work presents a modelling and optimization technique applied for a recent important topic, namely Renewable Energy Communities (RECs). The proposed simulation and design tool is new with respect to the literature studies due to its faster computational characteristics that are obtained by black-modelling approach and thanks to the optimization towards economic cost functions, which are novel due to the recent introduction of monetization for shared energy among REC members. In particular, the novel approach was used to optimize the scheduling of a HVAC system for a public lecture building that belongs to the REC case study. The necessity for the scheduling arises to minimize the costs associated to the energy purchase and to maximize the incentives relative to the shared energy in a REC in which the educational building is included. The energy demand of the HVAC loads for the lecture buildings were modelled by EnergyPlus software. The model was also experimentally validated by using a campaign of measurements. Thanks to the simulations derived from the validated model, a neural model able to quickly assess the energy demand from the thermal profile of the building was implemented. This neural model was included in an optimization problem framework to compute, on a daily basis, the optimal set points of the HVAC system, with the aim of reducing the end-of-day total energy costs on the community. The achieved results shows that a smart modulation in the HVAC system allows to fully exploit the PV production, resulting both in lower and more regular daily energy costs. The proposed approach confirms the importance of approaching a demand-response strategy in a REC scenario and the critical role of the HVACs systems due to their energy demand. The methodology proposed can be further expanded by considering more complex economic interactions between the members of the REC, such as inclusions of fair-share policies, and by considering the HVAC contribution of the individual members of the REC.

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.

Data availability

Data will be made available on request.

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