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Integrating load profiling and multi-objective optimisation: an open-source tool for the design of renewable energy communities

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Abstract. The increasing interest in Renewable Energy Communities (RECs) has prompted stakeholders to gain greater confidence in simulating electric energy flows among different consumers and prosumers within the community. Within the framework of the SACER project, an open-source numerical tool was developed to design the optimal configuration of a REC. First, the trends of electric energy consumption for a series of typical days can be determined for a generic REC member at three levels of accuracy. When hourly consumption data are available, typical profiles can be defined. In this work, two algorithms were used and compared for this purpose: the Aggregate approXimation method and the Self-Organising Map (SOM) model. If the aforementioned data are unavailable, representative patterns are reconstructed from monthly data, which are typically available from energy bills for existing buildings. If no data are available, the profiles can be estimated as a function of the building intended use and floor area. Then, the optimal configuration of the REC can be assessed using a multi-objective mixed-integer linear programming model (Analytic Hierarchy Process). Given the relative importance of each user-defined objective function, the revenues for REC components can be maximized by optimizing investment costs in new renewable energy generators and batteries while minimizing energy costs. To test the proposed methodology, the optimal configuration of a new REC comprising 23 residential and 2 tertiary buildings was determined.

1 Introduction

In recent years, the energy power system has undergone a deep transformation, shifting from a centralised generation paradigm toward distributed energy production, primarily driven by the widespread deployment of renewable energy generators. Within this evolving context, a

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new model of energy sharing has emerged: Renewable Energy Communities (RECs), in which end-users play a central and active role in energy consumption, generation, storage, and sharing. Among the benefits of this scenario, it is worth noting enhanced user engagement and the ability to enable more flexible, resilient energy systems.

Within this framework, the SACER project [1] aims to investigate and optimize a new generation of RECs in which users can share not only electricity but also thermal energy. While the foundational principles of energy communities remain unchanged, this new concept enables the deployment of additional renewable energy sources, the integration of more decentralised energy generators, and the recovery of waste heat, such as that rejected in industrial districts. Interest in energy communities capable of sharing thermal energy is growing across Europe, as numerous studies highlight their significant environmental and economic benefits [2]. However, the main barrier to their widespread deployment is not technological but linked to regulatory issues, with authorization processes posing significant challenges in many countries. Previously published papers suggest that the development of these innovative energy communities is facilitated in regions where public or private energy infrastructure already supports the exchange of thermal energy among users, such as local district heating networks [3]. Indeed, current research agrees that these next-generation RECs can significantly improve renewable energy deployment beyond the capabilities of conventional energy-sharing models. Within this topic, the SACER project was conceived to foster the development of next-generation RECs and Collective Self-Consumption Groups (CSGs) at the municipality level. Specifically, the project aims to contribute to the definition of optimal operational rules for second-generation energy communities by investigating innovative thermal and electrical storage systems that can serve as key elements for energy exchange in these emerging concepts when coupled with heat pumps.

Designing and modelling an efficient energy community requires maximizing the overall self-consumption of the community members while complying with local technical requirements and regulatory constraints [4]. In a more recent paper [5], the authors provided a comprehensive overview of the modelling approaches adopted for REC simulations, highlighting that such models typically integrate economic objectives, such as CAPEX, OPEX, and total cost minimization, together with technical goals related to efficiency, reliability, and system stability. Furthermore, environmental criteria, including emissions reduction and renewable energy penetration, are also commonly considered, and several studies adopted multi-objective optimization frameworks to balance these objectives. To reduce model complexity and computational costs, representative days are often identified for each period of the year, allowing an accurate yet tractable representation of prosumers behaviour.

Various approaches can be found in the literature for reconstructing energy demand profiles of the different actors within a REC. For example, Novoa, Flores, and Brouwer [6] modelled a set of buildings with different intended uses (i.e., residential, commercial, and industrial) using EnergyPlus to obtain hourly energy demand profiles for different periods of the year. These annual trends were subsequently reduced using a k-medoids clustering method, yielding three representative days per month. Fleischhacker et al. [7] employed both K-means clustering on synthetic and real measured data to cluster temporal demand profiles; due to the limited ability of clustering algorithms to capture peaks and outliers in time series, this approach was combined with peak-detection algorithms to exclude extreme events from the dataset. Other works also accounted for uncertainty in building energy demand, emphasising that accurate models must consider not only average energy behaviour but also potential fluctuations related to unpredictable factors such as occupant behaviour [8] and weather conditions [9]. In this work, we present and compare two methodologies for defining the energy consumption trend of members of a REC under design. The typical energy consumption profiles are then used to simulate energy fluxes with high accuracy within a

REC. In Sections 2 and 3, we provide detailed descriptions of the methodologies used to reconstruct member energy demand and generation trends. Section 4 focuses on the mathematical model used to analyse and optimize the REC configuration. The outcomes of these two sections are then used in Section 5, where a case study is presented.

2 Energy consumption profile definition

As discussed in the introduction, accurately simulating a REC requires defining a series of typical hourly consumption trends for each community member. In this paper, we present three different methodologies based on the temporal resolution of the available data for the simulation. If hourly or sub-hourly values of electric and thermal energy consumption are available for a specific period (at least one year), it is possible to use this information directly to define the profiles. For this task, we present and compare two methodologies based on the Symbolic Aggregate approXimation (SAX) [10] and the Self-Organising Map (SOM) [11] algorithms, both suitable for identifying the most common trends in energy consumption data. However, in some cases, hourly data are not available. Therefore, every time the data are aggregated at monthly intervals (e.g., in energy bills), it is necessary to redistribute the monthly energy consumption to an hourly basis to recreate a finer profile. In order to demonstrate the effectiveness of this method, we have analysed a series of buildings with different intended uses, such as offices, light industry, cinemas, and educational facilities. Starting from energy bill data, we have generated a set of typical hourly curves for each category, which can be used to model the performance of a REC.

2.1 Symbolic Aggregate Approximation (SAX) method

Symbolic Aggregate approXimation (SAX) algorithm is a time-series representation technique designed to reduce data dimensionality while preserving the essential temporal structure of the original dataset. This method operates by transforming a continuous numerical time series into a sequence of discrete symbols, thus enabling efficient comparison operations and pattern recognition. The SAX methodology has already been used for similar tasks, including analyzing building performance and detecting faults [12].

The first step of the SAX algorithm is the normalization of the input dataset. Subsequently, the time series is divided into segments of equal duration using the Piecewise Aggregate Approximation (PAA) method. In this work, a 6-hour segment duration is adopted. For each segment, the data mean value is computed and used as a compact indicator of the data within that interval. To convert these average values into symbols, the SAX method relies on a predefined alphabet and a set of breakpoints that partition a Gaussian distribution into equiprobable regions. Then, each segment's mean value is mapped to a symbol based on the area it falls in. It is worth mentioning that this methodology is well-suited for tasks such as motif discovery and anomaly (discord) detection in time-series data. By tuning a limited number of parameters, namely the alphabet size and number of segments, the algorithm provides a flexible and computationally efficient framework capable of capturing both magnitude and shape characteristics of temporal patterns.

In this study, the SAX methodology was initially tested on data collected from a demonstrator building, located in Bologna (Italy). The building selected for the analysis is a light laboratory of the University of Bologna. The data collected is the electric energy consumption of the building sampled at a frequency of 15 minutes. The main objective was to identify a set of representative days that accurately describe the building energy behaviour. To this end, the days of the year are first classified into four distinct categories: summer and winter weekdays, weekends, and holidays (i.e., the Christmas break).

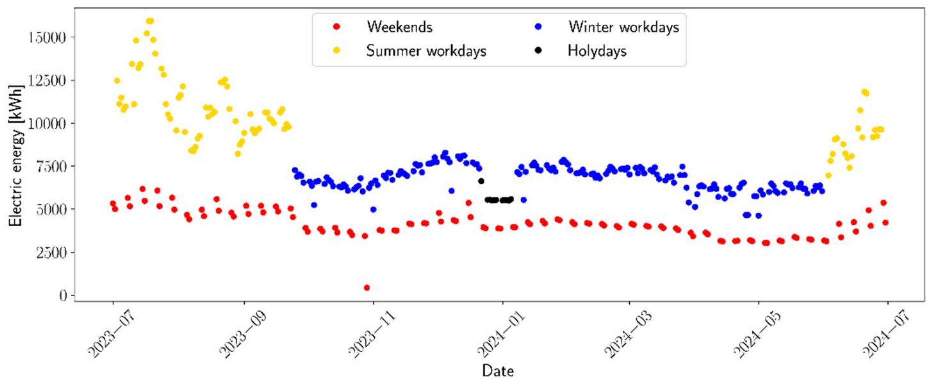

Fig. 1. Subdivision 'a priori' of the different days of the year into subcategories. Weekends are shown in red, summer weekdays in yellow, winter weekdays in blue, and the Christmas holidays in black.

The dataset of daily electric energy consumption data is reported in Fig. 1 for the considered day categories. It is possible to appreciate that the building daily energy demand during the weekend days (red dots) is always lower compared to the consumption occurring during the working days. This is due to the building occupancy profile, since no occupants are present. Therefore, electric energy consumption is only related to base electrical loads (e.g., equipment always connected to the grid, such as servers, emergency lights, and other machinery). Another interesting outcome of the analysis concerns the summer period (yellow points). Due to the presence of an electric-driven chiller, higher consumption, by up to 100%, is observed compared to the winter period (blue dots).

For each day cluster, the SAX algorithm is applied independently. As an illustrative example, the analysis of winter weekdays is discussed in detail. The daily electric energy consumption profiles for days in this cluster are shown in Fig. 2, along with the four 6-hour segmentations implemented by the SAX method.

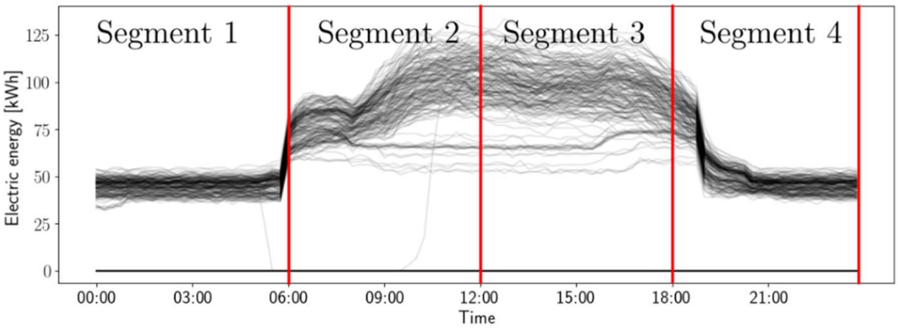

Fig. 2. Daily electric energy consumption trends for all winter working days. The four 6-hour segments used in the SAX algorithm are also highlighted.

A clear similarity across most of the daily profiles can be observed in this cluster. As described above, each daily time series is encoded into a sequence of symbols representing its temporal evolution (namely, 'a', 'b', 'c'), where each symbol captures the characteristic trend within a segment. For instance, in this case, the symbol 'a' denotes a flat consumption trend over the corresponding segment. Fig. 3 shows the frequency of occurrence of the different symbolic patterns identified by the numerical algorithm. The most frequent pattern corresponds to the symbolic sequence ‘acca’. In contrast, the remaining sequences (i.e., ‘abca’, ‘abba’, ‘accb’, ‘aaaa’, and ‘aaca’) represent less common behaviours, likely associated with atypical operating conditions or system malfunctions. These outlier patterns are therefore excluded from the construction of the representative daily profile of winter working days. By applying this filtering logic to all identified periods, daily consumption curves with similar shapes are identified. For each cluster, the most frequently occurring set of curves is selected, and the representative daily consumption profile is then obtained by averaging all the curves within this set. As a result, a profile that captures the typical consumption behaviour of the cluster is obtained.

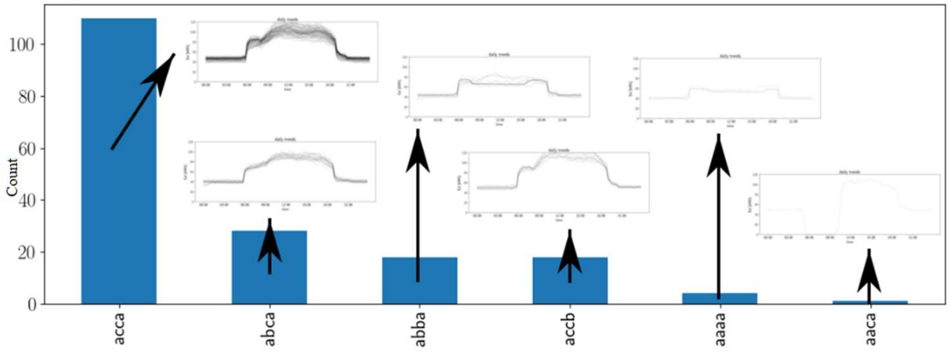

Fig. 3. Frequency of occurrence of daily energy consumption patterns identified by the SAX algorithm, with the corresponding time series.

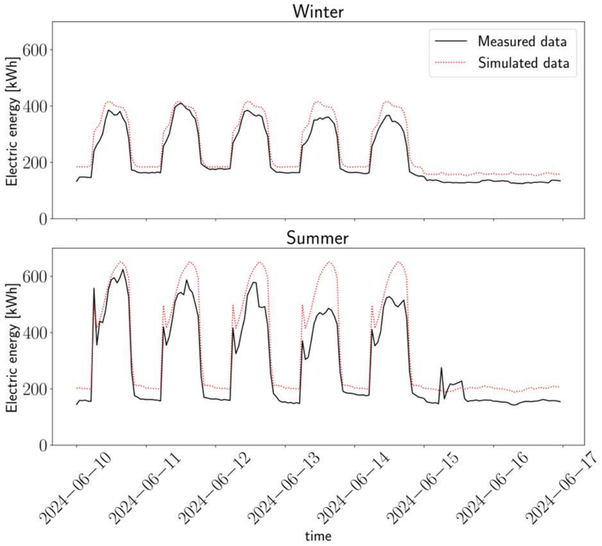

Fig. 4. Weekly electric energy consumption profile obtained numerically (red dashed line) and effective electric energy consumption profile (black solid line) for the two considered seasons (Winter and Summer)

The typical annual electric energy consumption of the building can then be reconstructed by repeating the representative daily profiles. As shown in Fig. 4, the trend determined by the SAX algorithm (red dashed line) closely follows the measured building effective energy consumption (black solid line). The main discrepancies occur during the summer period, when the building overall electric energy consumption is strongly influenced by cooling systems and, consequently, depends significantly on ambient climatic conditions. The

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reconstructed profile obtained in this way represents the average summer behaviour; however, on a seasonal basis, the observed differences are negligible.

2.2 Self-Organising Map (SOM) method

A limitation of the SAX-based methodology is the need to predefine the number and typologies of representative day clusters, thereby constraining the algorithm expected outputs. To overcome this issue, a machine learning approach based on Self-Organising Maps (SOMs) was adopted. This algorithm is an unsupervised learning technique widely used for exploratory data analysis, clustering, and dimensionality reduction. More in detail, artificial neural networks are used to project high-dimensional data onto a two-dimensional map while preserving, as much as possible, the topological structure of the original dataset. In the context of time-series analysis, SOMs are particularly effective at identifying groups of series exhibiting similar behaviours, facilitating visual interpretation and pattern recognition. Moreover, the SOM learning process relies on a competitive-cooperative mechanism among neurons. For each input vector, the most similar neuron, referred to as the Best Matching Unit (BMU), is identified. The BMU and its neighbouring neurons are then updated, allowing the map to progressively self-organise.

In this work, the SOM algorithm was applied in two steps. During the first stage, days characterised by nearly constant daily electric energy consumption (e.g., weekends) were isolated from days with significant intraday variability in the energy demand (e.g., working days). The outcome of the first SOM run is shown in Fig. 5 for the same demonstrator building considered in the previous section.

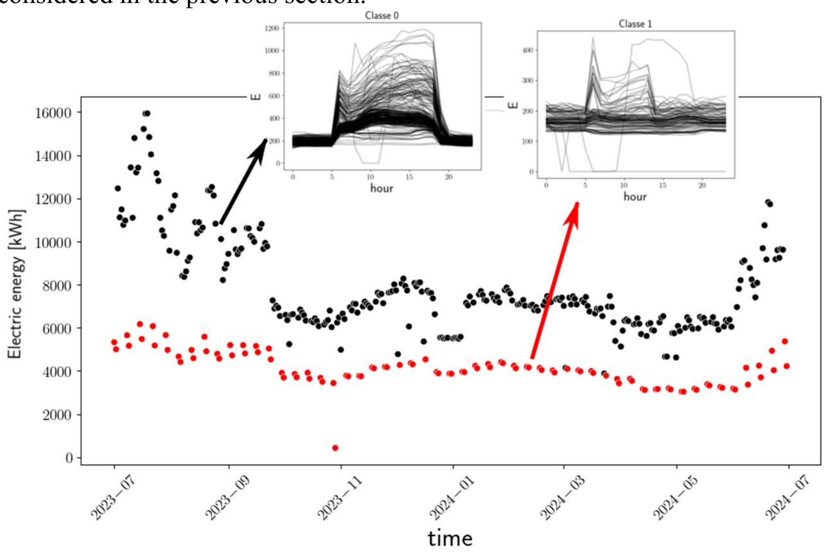

Fig. 5. Outcomes of the first SOM algorithm run: days with nearly constant electric energy consumption (red points) separated from days with variable electric energy demand (black points).

Subsequently, the algorithm was applied again only to the first cluster (black point), which contained samples with variable consumption patterns, to identify sub-order patterns. During this second stage, the outputs of the first numerical run were combined with the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm. This numerical method uses a density-based clustering, which enables the identification of clusters with arbitrary shapes and variable sizes, while explicitly labelling isolated points as outliers. When applied to time-series data projected onto a SOM, the

HDBSCAN method exploits the two-dimensional topological representation to improve cluster separation and reduce noise, without requiring the number of clusters to be specified a priori.

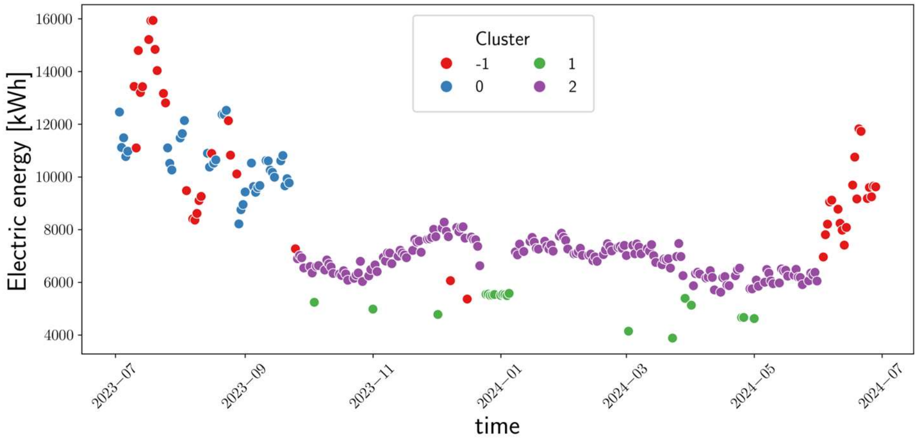

Fig. 6. Outcomes of the HDBSCAN algorithm to cluster days with variable consumption profiles identified by the first run of the SOM method.

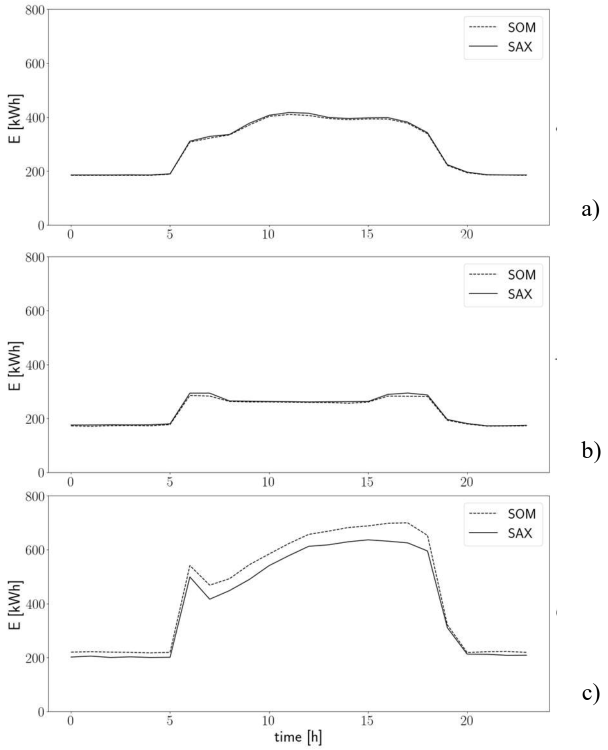

Fig. 7. Comparison between the hourly values of electric energy consumption for winter working days (a), weekend (b), and summer working days (c) of representative days for the demonstrator building obtained by the SAX and SOM algorithms

The results of this second clustering step are shown in Fig. 6. Three clusters were automatically identified: summer working days (cluster 0), winter working days (cluster 2), and the Christmas break period (cluster 1). An additional ensemble of days, labelled as -1, groups all days classified as outliers. With this combined approach (SOM and HDBSCAN), it is possible to easily identify the different days that describe the yearly behaviour of a building, reducing the user's manual intervention.

A comparison of the representative daily profiles obtained using the SAX and SOM methodologies is shown in Fig. 7. Both algorithms yielded very similar results; however, the SOM-based method offers the advantage of not requiring a priori assumptions on the number of representative days, thus reducing the number of inputs and user effort.

3 Generation of representative profiles for different building intended uses

The ultimate goal of the SACER project is to develop a numerical tool capable of simulating energy fluxes between the members of an energy community. A fundamental prerequisite for this purpose is the generation or estimation of typical consumption and production profiles for each community member. The implemented code operates at three levels of detail, depending on the granularity of the available consumption data. The highest level of detail allows the reconstruction of daily consumption trends by applying algorithms such as SAX or SOM methods to hourly or sub-hourly data, which are typically available from recently installed smart energy meters. This approach enables the identification of representative daily patterns specific to each building and, therefore, REC member.

When detailed temporal data are unavailable, the code can generate hourly profiles from aggregated consumption values. In this case, the REC design requires the use of predefined consumption and production profiles typical of different building use categories, derived from real measurement data. Moreover, in the early design phases of an energy community, it may be the case that no consumption data are available. In such cases, the tool estimates energy profiles based on the building intended use and floor area. For this reason, a library of typical energy consumption profiles is generated and used whenever detailed consumption data are missing. To this end, more than 50 buildings belonging to the University of Bologna, with different intended uses such as offices, educational buildings, laboratories, and recreational facilities, were analyzed. For each building category, normalized representative curves were generated for the typical days identified according to the methodology described in the previous section. For residential buildings, internal data were unavailable; therefore, reference curves from the ARERA portal were adopted.

Regarding renewable energy production, a dual approach was proposed. When production data were available, they were used directly to derive representative generation profiles for different periods of the year. When such data are unavailable or when assessing the installation of new photovoltaic systems within the energy community, a Python-based tool can be employed. The tool is based on the Perez [13] transposition model. It uses solar irradiance data from the Typical Reference Year (TRY) of the REC location, along with information on available roof or other surface area, panel orientation, and tilt angle. This approach allows the estimation of electrical energy production for photovoltaic systems under arbitrary geometric configurations.

4 . Numerical model for the optimization of RECs

In this paper, the planning phase of REC design is solved using a multi-objective mixed-integer linear programming (MILP) model developed in Pyomo [14]. The model selects REC's participants (i.e., prosumers and consumers) while suggesting additional photovoltaic and electrical storage systems. The optimization algorithm aims to design a REC that balances investment costs, energy performance (i.e., maximizing the shared energy flux), and community size.

In the numerical methodology, a REC is composed of a set of consumers ($c \in C$), prosumers ($p \in P$), renewable energy generators ($r \in R$), electric energy storage systems (i.e., batteries) ($b \in B$), and discrete time periods ($t \in T$). Binary decision variables determine whether a consumer participates in the REC (δ_c^C), whether a prosumer (δ_p^P), a renewable generator (δ_r^R), or a battery (δ_b^B) is activated, and whether each battery operates in charging or discharging mode at time t ($\sigma_{b,t}$). Continuous decision variables describe the electric energy fluxes among the REC's members, including energy supplied by prosumers to consumers ($P_{p,c,t}^P$), energy delivered by renewable generators to consumers ($P_{r,c,t}^R$), energy used to charge batteries ($P^{ch} * b, r, t$), and energy discharged from batteries to consumers ($P^{dec} * b, r, c, t$). Additional variables account for the electricity imported from the national grid by each consumer ($G_{c,t}$) and the state of charge of each battery associated with each renewable source ($S_{b,r,t}$).

More in detail, the model optimizes three conflicting objective functions. The first one minimizes the total cost (Z_1), accounting for grid energy purchases, new investments in renewable energy systems and batteries, and revenues for shared energy linked to incentives (Eq. 1). In particular, (α) represents the unit cost of electricity imported from the grid, (K_r^R) and (K_b^B) are the fixed investment or activation costs. Moreover, the parameters (γ_p^P) and (γ_r^R) represent the incentive tariffs and the battery discharge, respectively, adjusted by the efficiency factor (η^{-1}). The second objective function maximizes the total amount of energy shared within the community (Z_2, see Eq. 2). Lastly, Eq. 3 shows the third objective function, by means of which the number of participating consumers (Z_3) can be restricted to limit the subdivision of benefits to too many of participants.

$$min\, Z_1 = \alpha \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} G_{c,t} + \sum_{r \in \mathcal{R}} K_r^R \delta_r^R + \sum_{b \in \mathcal{B}} K_b^B \delta_b^B - \sum_{p \in \mathcal{P}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} \gamma_p^P P_{p,c,t}^P \tag{1}$$

$$\max Z_2 = \sum_{p \in \mathcal{P}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} P_{p,c,t}^P + \sum_{r \in \mathcal{R}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} P_{r,c,t}^R + \sum_{b \in \mathcal{B}} \sum_{r \in \mathcal{R}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} \eta^{-1} P_{b,r,c,t}^{dec} \tag{2}$$

$$\min Z_3 = \sum_{c \in \mathcal{C}} \delta_c^C \tag{3}$$

The numerical model constraints are adapted from Neri et al. [15]. Specifically, the algorithm includes: demand balance constraints ensuring that consumer demand is met at each time period; prosumer and renewable generation constraints limiting energy production according to availability and activation decisions; battery state-of-charge constraints governing energy evolution, storage capacity, and discharge feasibility; battery activation and operational constraints enforcing installation requirements and mutually exclusive charging and discharging modes; and community aggregation and participation constraints ensuring that shared energy does not exceed the demand of participating consumers and that only selected consumers receive shared energy.

The multi-objective optimization problem is solved through the weighted-sum scalarisation technique [16]. This approach employs the Analytic Hierarchy Process (AHP) method to formulate preferences a priori. Once the weights are calculated, they can be used as the relative significance of each objective function. Initially, each objective function is solved individually to find the ideal (Ij) and nadir (AIj) solutions (for each j objective function) with a payoff-table approach. Ideal solutions are the maximum values for benefitoriented objectives (i.e., maximization) and minimum values for cost-oriented objectives (i.e., minimization), while nadir solutions are the opposite. A linear normalization technique is then employed to synthetize a single objective function as in Eq. 4.

$$\min Z^M = w_1 \frac{Z_1 - I_1}{AI_1 - I_1} - w_2 \frac{Z_2 - AI_2}{I_2 - AI_2} + w_3 \frac{Z_3 - I_3}{AI_3 - I_3} \quad (4)$$

The objective function weights are calculated using the AHP method, a multicriteria decision-making approach that assesses the relative importance of each criterion through pairwise comparisons [17]. By applying the standardized nine-point Saaty scale, decision-makers can systematically express their preferences. First, a pairwise comparison matrix $P = [p_{i,j}] \forall i, j = 1, \dots, m$, with m the number of criteria, representing the importance of criterion i over criterion j. The criteria weights vector W is obtained by solving the eigenvalue problem $(P - \lambda_{max} I)W = 0$, where λ_{max} is the maximum eigenvalue of matrix P and I is the identity matrix. The consistency of the pairwise comparisons is evaluated using the Consistency Index $CI = (\lambda_{max} - m)/(m - 1)$ and Consistency Ratio $CR = CI/RI$, where where RI is the Random Index. A consistency ratio $CR < 0.10$ indicates acceptable judgments.

5 Case study

To test the capabilities of the numerical methodology presented in this paper, a simple case study was analysed. We have considered the following group of buildings belonging to the same primary electrical substation: 2 industrial prosumers (P_0 and P_1), that generate and require electric energy; 3 photovoltaic (PV) systems (R_2, R_3, R_4), whose electric energy yield can be shared with the community members or stored in batteries, a single battery (B_0), and a maximum of 50 potential residential consumers, where multiple condominium apartments are located within the same building envelope. All of these buildings are connected to the AC001E00817 substation, located in Bologna, Italy.

To reduce computational effort, only four representative days are used to cluster the trends in electric energy consumption/production throughout the year: winter working day (W-W), winter weekend (W-WE), summer working day (S-W), and summer weekend (S-WE). The algorithm tries to minimize the net system cost (Z1), maximize the shared energy within the community (Z2) and determine the optimal number of members to reduce the energy absorbed from the national grid (Z3). It is important to emphasize that this last parameter provides only a suggestion during the REC design phase regarding the optimal number of consumers. It should not be considered a constraint, since RECs remain open and publicly accessible.

The numerical results show that the best configuration is achieved with the following values of the aforementioned parameters: Z1 = 3766.24 €, Z2 = 10306.6 kWh and Z3 = 23 residential blocks of flats, each with around 30 apartments, for a total net floor area of 58510 m2. The total electric energy required by consumers is approximately 21350 kWh. It is worth noting that only 52% of the REC electric energy demand is met by the national grid, with the remaining 48% supplied by shared energy flows. If we also consider the energy demand of the two prosumers, the total energy required by the REC increases to 51963 kWh, highlighting the strong effects of large-dimension prosumers within the system.

Furthermore, it is interesting to show the energy mix of the residential buildings inside the REC. In fact, the two prosumers self-consume 25140 kWh directly from the PV systems installed on it. In Fig. 8, the energy sources for the electric energy demand of each consumer are shown, with the energy delivered by the grid shown in grey.

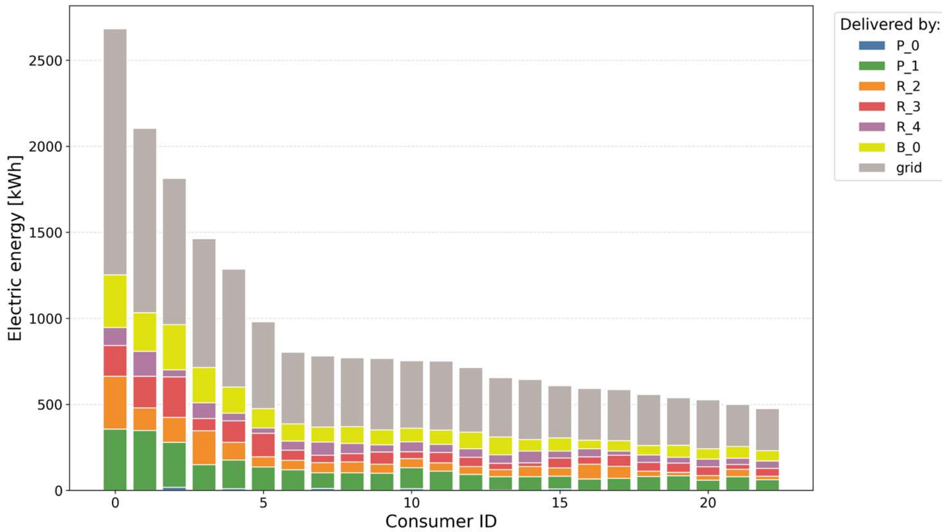

Fig. 8. Sources for the electric energy demand of the 23 consumers of the REC.

To better understand the energy flows among the REC members, all the energy production and consumption profiles are reported in Fig. 9.

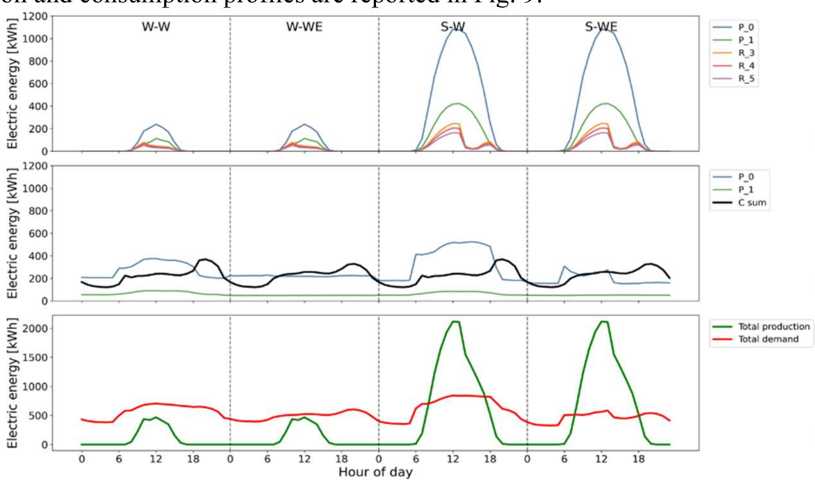

Fig. 9. Energy production trend for the 2 prosumers and 3 PV systems within the REC (a), electric energy demand of the two prosumers and cumulative energy demand of the REC members (b) and trend of the global energy demand and production within the REC (c).

6 Conclusions

This paper presents an integrated and flexible methodology, based on numerical algorithms, for the design and optimization of Renewable Energy Communities (RECs) developed within the framework of the SACER project. The proposed method combines load profile reconstruction techniques, photovoltaic energy production estimation, and a multi-objective optimization algorithm into a single open-source numerical tool aimed to support both early-stage planning and detailed design of energy communities.

A key contribution of the work is the development and comparison of alternative methods for generating representative electrical load profiles for each REC member, depending on data availability. When high-resolution consumption data are available, both Symbolic Aggregate approXimation (SAX) and Self-Organising Maps (SOM) methods proved effective in identifying typical daily patterns while filtering out anomalous outliers. The SOM-based approach, in particular, demonstrated greater flexibility by automatically detecting representative clusters without requiring a priori assumptions. On the other hand, a library of normalized profiles for different building use categories was developed, enabling the tool to remain applicable and ensuring robustness across different design contexts when only aggregated or no consumption data are available.

On the renewable energy production side, a numerical code was implemented to evaluate the yield of photovoltaic systems installed within the REC. This modelling approach allows both the direct use of measured data and the estimation of new installation performance through physically based models. This dual strategy enhances the applicability of the tool to both existing and prospective RECs.

The planning and design of the REC configuration are addressed through a multi-objective mixed-integer linear programming (MILP) formulation that simultaneously considers economic performance, energy-sharing maximization, and community size. The integration of the Analytic Hierarchy Process (AHP) with a weighted-sum scalarization enables decision-makers to explicitly incorporate preferences and priorities, thus increasing the transparency and adaptability of the optimization process.

The effectiveness of the numerical code described in this paper was assessed in a case study. Numerical results demonstrated the capability of the tool to identify a balanced REC configuration, highlighting the significant roles of large prosumers and shared renewable generation systems in reducing grid dependency and increasing local self-consumption. Overall, the outcomes confirm that the proposed concept can effectively support the design of optimized RECs across different data availability scenarios, while maintaining a reasonable computational burden by using representative days for annual simulations.

Future developments will focus on extending the model to include thermal energy flows, valorizing shared heat among REC members, implementing temperature-dependent electrical and thermal load corrections, and conducting an uncertainty analysis to further enhance the realism and applicability of the tool for next-generation efficient energy communities.

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References

1. SA-CER, https://www.sa-cer.it/ (2023).
2. J. Fouladvand, Behavioural attributes towards collective energy security in thermal energy communities: Environmental-friendly behaviour matters. Energy **261**, 125353 (2022). https://doi.org/10.1016/j.energy.2022.125353
3. K. Hartmann, J. Palm, The role of thermal energy communities in Germany's heating transition. Frontiers in Sustainable Cities **4**, 1027148 (2023). https://doi.org/10.3389/frsc.2022.1027148

4. Z. Huang, H. Yu, Z. Peng, M. Zhao, Methods and tools for community energy planning: A review. Renewable and sustainable energy reviews **42**, 1335–1348 (2015). https://doi.org/10.1016/j.rser.2014.11.042
5. V.Z. Gjorgievski, S. Cundeva, G.E. Georghiou, Social arrangements, technical designs and impacts of energy communities: A review. Renewable Energy **169**, 1138–1156 (2021). https://doi.org/10.1016/j.renene.2021.01.078
6. L. Novoa, R. Flores, J. Brouwer, Optimal renewable generation and battery storage sizing and siting considering local transformer limits. Applied Energy **256**, 113926 (2019). https://doi.org/10.1016/j.apenergy.2019.113926
7. A. Fleischhacker, G. Lettner, D. Schwabeneder, H. Auer, Portfolio optimization of energy communities to meet reductions in costs and emissions. Energy, **173**, 1092–1105 (2019). https://doi.org/10.1016/j.energy.2019.02.104
8. G. Naim, C. Naldi, M. Dongellini, G.L. Morini, Dynamic Energy Simulation of a Student Residence Including the Occupant Behavior Influence. REHVA HVAC World Congress. Springer, 164–173 (2025). https://doi.org/10.1007/978-3-032-06810-1_17
9. B. Pickering, R. Choudhary, District energy system optimization under uncertain demand: Handling data-driven stochastic profiles. Applied energy **236**, 1138–1157 (2019). https://doi.org/10.1016/j.apenergy.2018.12.037
10. J. Lin., E. Keogh, S. Leonardi, Experiencing SAX: a novel symbolic representation of time series. Data Mining and Knowledge Discovery. **15**, 107-144 (2007). https://doi.org/10.1007/s10618-007-0064-z
11. T. Kohonen, Self-organized formation of topologically correct feature maps, Biological Cybernetics 43, 59–69 (1982). https://doi.org/10.1007/BF00337288
12. C. Miller, Z. Nagy., A. Schlueter, Automated daily pattern filtering of measured building performance data. Automation in Construction **49**, 1–17 (2015). https://doi.org/10.1016/j.autcon.2014.09.004
13. R. Perez, P. Ineichen , R. Seals, J. Michalsky, R. Stewart, Modeling daylight availability and irradiance components from direct and global irradiance. Solar Energy**, 44(5**), 271-289 (1990). https://doi.org/10.1016/0038-092X(90)90055-H
14. M.L. Bynum., G.A. Hackebeil, W.E. Hart, C.D. Laird, B.L. Nicholson, J.D. Siirola, J.P. Watson, D.L. Woodruff, Pyomo – optimization modeling in Python, 3rd Edition. Vol. **67**. Springer (2021). https://doi.org/10.1007/978-3-030-68928-5
15. A. Neri, M.A. Butturi, F. Lolli, R. Gamberini, Inter-firm exchanges, distributed renewable energy generation, and battery energy storage system integration via microgrids for energy symbiosis. Journal of Cleaner Production **414**, 137529 (2023). https://doi.org/10.1016/j.jclepro.2023.137529
16. A. Neri, M.A. Butturi, F. Lolli, R. Gamberini, Enhancing Waste to-Energy and Hydrogen Production through Urban–Industrial Symbiosis: A Multi-Objective Optimisation Model Incorporating a Bayesian Best-Worst Method. Smart Cities **7.2**, 735–757 (2024). https://doi.org/10.3390/smartcities7020030
17. R. Saaty, The Analytic Hierarchy Process—What It Is and How It Is Used. Mathematical Modelling **9.3-5**, 161–176 (1987). https://doi.org/10.1016/0270-0255(87)90473-8