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Day-ahead optimization model for renewable energy communities considering load shifting, electric vehicles and vehicle-to-grid technology

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HIGHLIGHTS

- Day-ahead load shifting for optimizing renewable energy use in communities.
- Integrates EVs, vehicle-to-grid, and time-of-use electricity rates.
- Considers members' flexibility to meet community goals.
- Achieves up to 99.27% self-sufficiency in the best-case scenario.
- Demonstrates a cost reduction from 8.54 € to −3.47 € per day.

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ABSTRACT

Renewable Energy Communities (RECs) represent a promising approach to accelerate the energy transition by enabling collective self-consumption and local energy management. However, the intermittent nature of renewable generation and the increasing integration of Electric Vehicles (EVs) pose significant challenges for optimal energy scheduling. This paper proposes a day-ahead multi-objective optimization model for RECs that simultaneously considers load shifting, EV charging coordination, and Vehicle-to-Grid (V2G) technology to minimize operational costs while maintaining user comfort. The model is formulated as a Mixed Integer Linear Programming (MILP) problem and implements the epsilon-constraint method to generate Pareto-optimal solutions, revealing trade-offs between economic efficiency and user preferences. Load shifting is modeled using a Multiple Knapsack Problem (MKP) approach with penalty functions to account for deviations from preferred time slots. Results from a case study composed of three different objectives demonstrated that, in the best case, self-sufficiency can be increased from 17.06% to 99.27%, and a significant reduction from 8.54 € to −3.47 € can be achieved in a single day.

1. Introduction

1.1. Motivation and related work

The transition to sustainable energy systems has accelerated the development of Renewable Energy Communities (RECs), which enable collective renewable generation, storage, and consumption. The European Union's Clean Energy Package defines an REC as a legal entity where participants voluntarily cooperate to generate, consume, store, or sell renewable energy [1]. However, the variability of renewable sources and the growing adoption of Electric Vehicles (EVs) create complex energy management challenges that require advanced optimization techniques and consideration of several aspects, including grid constraints [2].

Energy Communities are gaining an increasingly central role in European energy policies due to their ability to allow an association of consumers to promote local renewable energy generation and consumption to achieve a certain level of SS, giving them the ability to function autonomously from the power grid. EC also aim to achieve a good level of SC by maximizing the use of the renewables from their generation [3] and the coordination with flexible loads [4].

The shift towards EC implies that community members must take on responsibilities previously managed by centralized grids, particularly in

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Nomenclature

Sets and Indices

$b \in B$: Bin
$e \in E$: Electric vehicles
$i \in I$: Shiftable items (part of the duration of the consumption cycle of a specific device)
$t \in T$: Duration of the activities (consumption cycle of a specific equipment)

Parameters

$\eta^{ch(e)}$: Charging efficiency of EV e (%)
$\eta^{dch(e)}$: Discharging efficiency of EV e (%)
$av_(t,e)$: Availability for charge/discharge of EV e at time t
deg_cost_e : Battery degradation cost of the EV e(%)
exp_price_t : Price of exported energy at time t(%)
$f_{(b,i))}$: Maximum flexibility of device i and bin b
imp_price_t : Price of imported energy at time t(%)
$P^{max}_{ch(e)}$: Maximum power charge of EV e (kW)
$P^{max}_{dch(e)}$: Maximum power discharge of EV e (kW)
$P_{d(b,i)}$: Power demand in the bin b and device/load/household i (kW)
$P^{max}_{grid(t)}$: Maximum power imported/exported from/by grid at time t (kW)
soc^{max}_e : Maximum state-of-charge limit of EV e(kWh or %)
soc^{min}_e : Minimum state-of-charge limit of EV e(kWh or %)

Decision Variables

$P_{ch(t,e)}$: Power charge of EV e at time t (kW)
$P_{dch(t,e)}$: Power discharging of EV e at time t (kW)
$P_{exp(t)}$: Power exported from the grid at time t (kW)
$P_{imp(t)}$: Power imported from the grid at time t (kW)
$soc_{(t,e)}$: State of charge of EV e at time t (%)
$x_{t,b,i}$: Binary variable for device, load, household i shifting at time t and bin b (1 if load l starts at time t)

Acronyms

CM	Community Manager
CPLEX	Constraint Programming Language EXecutor
DES	Distributed Energy Systems
DSM	Demand Side Management
EC	Energy Community
ESS	Energy Storage System
EV	Electric Vehicle
GOA	Grasshopper Optimization Algorithm
LS	Load Shifting
MILP	Mixed Integer Linear Programming
OF	Objective Function
P2P	Peer-to-Peer
P2V	Prosumer-to-Vehicle
PPC	Peak Power Contract
PSO	Particle Swarm Optimization
PV	Photovoltaic Panel
REC	Renewable Energy Community
RES	Renewable Energy Sources
SC	Self Consumption
SOC	State of Charge
SS	Self Sufficiency
ToU	Tariff-of-Use
V2G	Vehicle to Grid

terms of balancing supply and demand within the EC, which can enhance the SC [5]. Unlike centralized grids, which can easily adjust fossil fuel power plant output to meet user demand, similar flexibility is often not possible with energy generated from renewable sources without wasting available resources.

As the energy generated from renewable resources increases, a new challenge is identified: the need to properly balance the supply and demand (power balancing) when the generation is completely dependent on weather conditions. Ultimately, when the EC demand is too high, the renewable energy sources can be insufficient to cover all the consumption needs, which means that the EC will need to buy electricity from the grid (which includes energy from non-renewable sources and leads to higher energy costs) to meet the demand. In contrast, if the EC production is too high, without the proper use of the energy storage systems, it will not be used by the members. In this case, excess renewables can be curtailed or fed into the grid without any financial return to the EC [6].

Recent research has addressed various aspects of REC optimization. The development of REC has gained momentum following the establishment of regulatory frameworks across Europe, with implementation accelerating since 2023 [7,8]. Gruber et al. [9] developed an energy community optimization model that assesses the difference between economic and technical resilience goals, demonstrating that cost optimization results in high demand peaks, while resilience optimization creates financial burdens on members. Rollo et al. [10] investigated load-shifting strategies at the appliance level in REC, comparing user-driven demand-side engagement with algorithmic optimization using genetic algorithms, achieving an optimal performance of over 94%. These works demonstrate the potential of collective energy management but require further integration with flexible resources, such as EVs.

In [11], the authors establish a MILP based optimal planning approach for renewable energy communities, where renewable energy can be transferred between the community participants, considering ToU electricity rates as well as multiple PV and ESS. It aims to minimize the total energy costs and CO_2 emissions of a REC. Then, a real case study for a small-scale REC testbed was conducted in a village in Carinthia, Austria, with nine participants (six consumers and three prosumers with existing PV systems). A similar approach is proposed in [12] to minimize the net energy cost (involving buying natural gas from the gas stations, buying electricity from the grid, and selling electricity to the grid) and the CO_2 emission cost, and uses the branch-and-cut method to solve the problem. Nevertheless, neither article considered the flexibility of loads and the management of EVs. In [13], the management of EVs in a company is proposed using a MILP approach based on the importance of the EVs for the company.

Faia et al. [14] extended the previous models by considering a P2V market where excess energy can be sold to EVs to minimize costs. It determines the best energy transactions between prosumers and EVs and allows them to buy electricity at lower prices than those offered by retailers. The authors evaluate the strategy in an energy community with different types of prosumers (household, commercial, and industrial) equipped with PV systems and batteries. Another approach is proposed in [15], where the authors explore cooperation between prosumers and consumers within a community in a P2P energy sharing trading system by proposing a two-stage optimization model to maximize utilities in the energy sharing trading. In this model, prosumers (individuals with renewable energy systems) can share energy with consumers (those who only consume electricity) and exchange energy between them. The authors start by determining who participates in the P2P trading and the amounts of exchanged energy in the first stage, followed by obtaining the optimal payments.

Sinha et al. [16] present a load-shifting approach for residential consumers which shifts the shiftable appliances from peak hours to off-peak hours to reduce the peak load and the energy costs, considering load priority and electricity prices without using any type of storage system. The aim of the proposed strategy is to bring the load consumption curve near the target load curve, considering two objectives: flattening the load consumption curve and reducing the cost of energy consumption. To test the efficacy of the proposed solution, the authors consider two test cases: one for a single house and one for three residential households. In both cases, a reduction in the peak demand and in the energy cost for consumers is verified.

The integration of EV charging coordination within communities has received growing attention, particularly with the rapid expansion of V2G technology. Kumar et al. [17] presented a comprehensive bibliometric review of 16,457 V2G articles from 1970 to 2023, revealing a significant increase in research after 2000, with a thematic evolution from “secondary batteries” to “smart grid” and “greenhouse gases.” Real-world implementations in 2024 demonstrated V2G’s grid-stabilizing capabilities, including Utrecht’s first large-scale car-sharing service and ChargeScape’s joint venture by BMW, Ford, Honda, and Nissan [18].

Advanced optimization approaches for V2G integration have emerged recently. Srihari et al. [19] developed an Artificial Neural Network combined with Particle Swarm Optimization for intelligent V2G management, ensuring precise energy extraction from solar power systems. Pang et al. [20] proposed a multi-level grouping-based competitive swarm optimizer for large-scale EV charging and discharging scheduling in V2G mode, focusing on load variance and user-side costs with real-time price constraints. Liu and Zhang [21] introduced a novel EV path optimization model integrating V2G technology with sophisticated slow charging and discharging management, achieving substantial cost reductions while balancing peak and off-peak loads. These studies highlight V2G’s potential but often lack integration with comprehensive demand-side management strategies.

Load shifting through DSM continues to evolve with sophisticated optimization techniques. Comprehensive frameworks for residential DSM with EV integration have been proposed, demonstrating that EVs can act as load-shifting devices during off-peak periods, flattening demand curves and establishing optimal energy utilization [22]. A novel probabilistic load shifting approach using particle swarm optimization has been developed for single-objective and multi-objective forms, integrating rooftop PV panels across 300 virtual residences [23]. Recent work on hybrid load shifting and curtailment policies for microgrids showed generation cost reductions from 707¥ to 676¥ when incorporating smart PHEV charging [24]. However, these works typically address REC and V2G separately rather than in an integrated framework.

Multi-objective optimization approaches for energy communities have emerged to balance conflicting objectives such as cost, emissions, reliability, and user satisfaction. Alzahrani et al. [25] proposed optimal sizing of REC using Multi-Objective Particle Swarm Optimization (MOPSO) with multiple swarms to foster solution diversity while ensuring non-dominated solutions defining a Pareto frontier. A multi-objective optimization framework for minimizing CO2 emissions and total annual costs in Alpine energy communities was developed, considering renewable energy sources within various constraints [26]. Alzahrani et al. [27] presented a multi-objective energy optimization approach that incorporates load and distributed energy source scheduling in smart power grids, aiming to optimize operation cost and pollution emission while utilizing renewable generation. Recent work by Abdulrazzaq [28] introduced an enhanced NSGA-II incorporating Monte Carlo simulation for meteorological uncertainties, achieving 18% improved convergence and 22% enhanced diversity compared to standard approaches. While these studies acknowledge multiple objectives, they typically do not simultaneously integrate load shifting, EV charging, and V2G technology with user comfort modeling. In [29], an Ant Colony search algorithm was proposed to solve the optimal power flow, including the management of EVs. In [30], a new load shifting approach is proposed to shift loads from off-peak hours to peak hours, thereby reducing peak demand and consumers’ energy bills, based on two optimization algorithms: PSO and GOA. The approach is then applied and evaluated in three different smart grid areas (residential, commercial, and industrial), and the results show that it can reduce peak demand and achieve substantial savings in the energy bill.

Few studies have simultaneously integrated load shifting, EV charging, and V2G operations while considering user comfort preferences within REC context. The consideration of user acceptance and comfort is crucial for practical implementation, as occupant behavior significantly impacts the effectiveness of demand-side management strategies, particularly in the smart grid environment where human decision-making under risk and uncertainty plays a paramount role [31].

Table 1 summarizes the key contributions from recent literature and positions the present work within this context.

As shown in Table 1, while individual aspects of REC optimization have been extensively studied in recent literature (2023-2025), there remains a significant gap for integrated frameworks that simultaneously address load shifting, bidirectional EV charging (V2G), multi-objective optimization, and user comfort considerations within the REC context. This work aims to bridge this gap by providing a comprehensive

Table 1
Comparison of recent literature on REC and EV optimization.

Reference	Load shifting	EV integration	V2G technology	Multi objective	User comfort	Modeling REC
Gruber et al. [9]	✗	✓	✗	✓	✗	✓
Rollo et al. [10]	✓	✗	✗	✗	✓	✓
Cosic et al. [11]	✗	✓	✗	✗	✗	✓
Yan et al. [12]	✓	✗	✗	✗	✓	✓
Morais [13]	✗	✓	✓	✗	✓	✗
Faia et al. [14]	✓	✓	✗	✗	✗	✓
Jiang et al. [15]	✓	✗	✗	✗	✓	✓
Sinha et al. [16]	✓	✗	✗	✗	✗	✗
Kumar et al. [17]	✗	✓	✓	✗	✗	✗
Srihari et al. [19]	✗	✓	✗	✗	✗	✓
Pang et al. [20]	✗	✓	✓	✗	✓	✗
Liu & Zhang [21]	✗	✓	✓	✓	✗	✗
Panda et al. [22]	✓	✓	✗	✓	✓	✗
Çakıl et al. [23]	✓	✗	✗	✓	✗	✗
Singh et al. [24]	✓	✓	✗	✓	✗	✗
Faria et al. [25]	✓	✗	✗	✗	✓	✓
Viesi et al. [26]	✓	✗	✗	✓	✗	✓
Alzahrani et al. [27]	✗	✗	✗	✓	✗	✓
Abdulrazzaq [28]	✓	✗	✗	✓	✗	✓
Soares et al. [29]	✓	✓	✓	✗	✗	✓
Jamil & Mittal [30]	✓	✗	✗	✗	✓	✗
Sharda et al [31]	✓	✗	✗	✗	✓	✗

day-ahead optimization model that captures the synergistic benefits of coordinating these elements.

1.2. Contributions and paper organization

This paper addresses the identified gaps by proposing an integrated optimization framework for day-ahead energy management in REC. The main contributions and novelty of this work are:

Integrated optimization approach: Unlike previous studies that address load shifting, EV charging, and V2G separately, this work proposes a unified framework that simultaneously optimizes all three elements, capturing their synergistic effects on community energy management. Multi-objective formulation with user comfort: The model explicitly incorporates user comfort through penalty functions that quantify deviations from preferred load operation times, enabling REC managers to explore trade-offs between cost savings and user satisfaction—a critical factor for the practical adoption of RECs. MKP-based load shifting: The load shifting problem is formulated using a Multiple Knapsack Problem approach with time-slot constraints, providing a computationally efficient method for scheduling flexible loads while respecting operational constraints. Comprehensive V2G modeling: The framework includes detailed EV battery dynamics, bidirectional power flows, and realistic constraints (SoC limits, charging/discharging rates, availability windows), providing a practical tool for communities with growing EV penetration. Pareto-optimal solution generation: The implementation of the epsilon-constraint method generates a complete Pareto front, enabling decision-makers to select solutions based on community-specific priorities and stakeholder preferences.

The remainder of this paper is organized as follows: Section 2 presents the mathematical formulation of the optimization model, including the load shifting approach (2.1), system constraints (2.2), and multi-objective framework (2.3). Section 3 describes the case study setup and presents results, including a discussion of the main findings and their practical implications. Section 4 concludes the paper, with the main insights and future research directions.

2. Optimization model

The optimization model presented in this paper aims to facilitate effective management of appliance usage in a community, enabling the utilization of renewable resources while balancing energy demand and supply. A general overview of the optimization model structure is provided in Fig. 1.

2.1. Renewable energy communities optimal scheduling methodology

To achieve optimal management of energy resources in a REC, the community manager, the entity responsible for managing all the community resources, has to indicate, based on the output of the developed strategy, what is the optimal time for the members to use the appliances, to avoid periods of the day with many appliances being used, and other periods without activities being done, allowing the maximization of the community resources as well as the minimization of the energy costs. Please note that this information is indicative and not mandatory. Users can always adjust the scheduling according to their needs. In this strategy, only the controllable/shiftable appliances can be shifted to any time period (such as washing machines, vacuum cleaners, dryers, water heaters, and dishwashers), and these appliances cannot be turned off. The total energy consumption should remain the same after the shift.

Furthermore, considering that sometimes it is not possible to fulfill all the community's needs solely with the community's own production, even with the scheduling of the appliances, the strategy also specifies when and how much energy should be imported and exported from the grid, or charged and discharged from the EVs, to contribute to better results and greater satisfaction of the members.

Regarding the implementation, based on the Multiple Knapsack problem, the following have been considered:

- The day is divided into 24 bins b, corresponding to the different hours of the day.
- There are T timeslots t (which correspond to the functioning of a device or load) divided into multiple items i depending on the activity duration. To clarify, consider the following example: The washing machine will run from 9:00 AM to 11:00 AM (for 2 hours), meaning that it will be divided into two items (one between 9:00 AM and 10:00 AM and another between 10:00 AM and 11:00 AM).
- The energy consumption of each item i is calculated according to the appliance consumption in that time period.
- The timeslots t should be placed inside the bins b according to the hour of the day that they will be used. An example of a timeslot allocation is shown in Fig. 2.

The optimization was developed in Python using the Pyomo library and the CPLEX solver. The code can be accessed at https://github.com/EV4EU/Energy_Community_Simulation.

2.2. Constraints

2.2.1. Unique bin costraint

The first constraint of this problem is represented in Eq. (1) and states that an item i of the asset (generic device, or load) of a timeslot t cannot be in more than one bin b. Considering that a timeslot of 2 hours is divided into two different subitems i, the first subitem can only occur in a specific hour and not in multiple hours. The binary variable x will represent the state of the item i in period t and in bin b.

$$\sum_{t=1}^{T} x_{(t,b,i)} \leq 1, x_{(t,b,i)} \in \{0,1\}, \forall b \in B, \forall i \in I \tag{1}$$

2.2.2. Placements constraints

This constraint (Eq. 2) indicates that all items i must be placed in a bin b. In other words, it guarantees that all requested appliances will be distributed to community members, regardless of the time of day. This constraint can be avoided if the load is not critical. In that case, Eq. (1) will be sufficient.

$$\sum_{t=1}^{T}\sum_{b=1}^{B} x_{(t,b,i)} = 1, x_{(t,b,i)} \in \{0,1\}, \forall i \in I \tag{2}$$

2.2.3. Item constraint

The item constraint is represented in Eq. (3) and states that a bin b cannot contain more than one item of the same timeslot (multiple items of the same timeslot cannot be in the same bin). Compared with a real scenario, it indicates that, for instance, a washing machine that runs for 2 hours cannot be replaced by two washing machines running for one hour each, and appliance usage cannot be divided into multiple tasks.

$$\sum_{i=1}^{I} x_{t,b,i} \leq 1, x_{(t,b,i)} \in \{0,1\}, \forall t \in T, \forall b \in B \tag{3}$$

2.2.4. Ascending order constraint

In addition, the Eq. (4) shows that the items of a timeslot t should be placed in consecutive bins ordered according to their positions (t and $t-1$). For instance, if the first subitem i is placed in the bin b, the second subitem $i+1$ has to be placed in the bin $b+1$, and the third subitem has to be placed in the bin $b+2$.

$$0 \leq t * x_{(t,b,i)} - (t-1) * x_{(t,b-1,i-1)} \leq 1, x_{(t,b,i)} \in \{0,1\}, \forall t \in T > 1, \forall b \in B, \forall i \in I > 1 \tag{4}$$

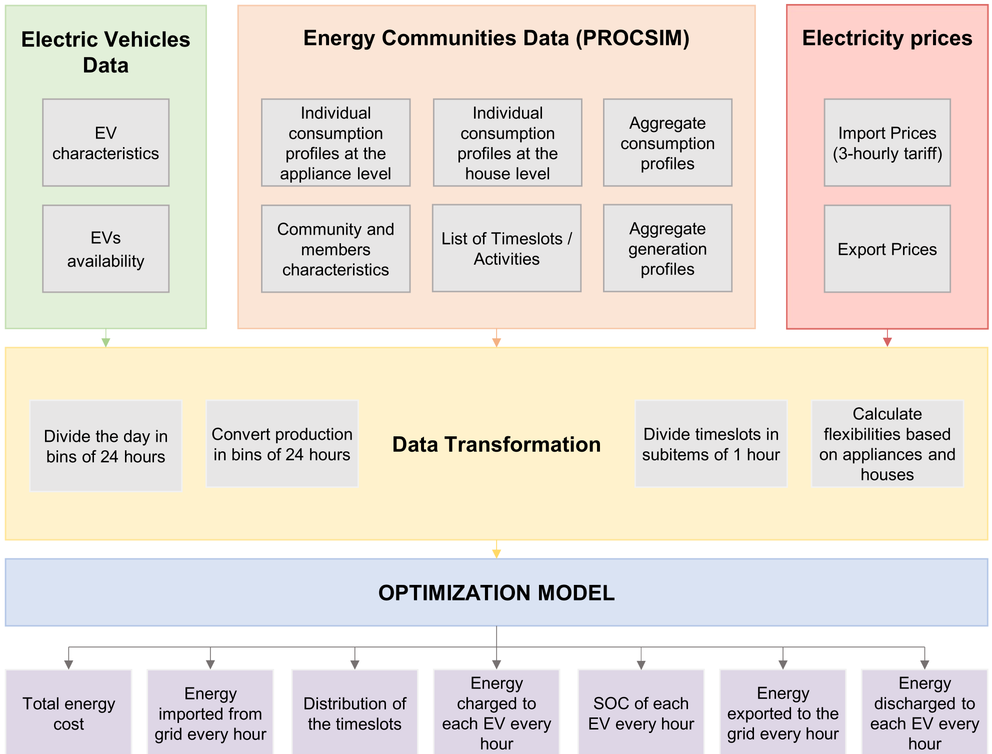


Fig. 1. Optimization model structure.

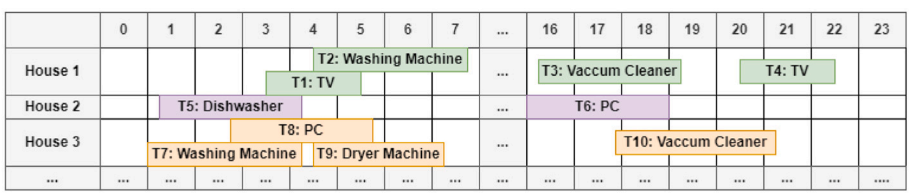


Fig. 2. Example of timeslots allocation.

2.2.5. Descending order constraint

Similar to the previous constraint, a descending order was also implemented to guarantee that the timeslots are consecutively placed, especially concerning the first bin. In the equation, t_{last} stands for the last timeslot of the simulation and b_{last} stands for the last bin.

This equation is represented in Eq. (5).

$$0 \leq (t+1) * x_{(t+1,b,i+1)} - t * x_{(t,b,i)} \leq 1,\ x_{(t+1,b,i+1)} \in \{0,1\}, \forall t \in T < t_{last}, \forall b \in B < b_{last}, \forall i \in I \tag{5}$$

2.2.6. Flexibility constraint

Regarding the flexibility of shifting activities, two constraints were created to impose the maximum Eq. (6) and minimum Eq. (7) flexibility. Concerning the maximum flexibility $f_{b,i}$, they limit the number of hours the timeslot can be moved from the requested time. In other words, flexibility is the maximum number of hours that can be subtracted or added to the original hour. This flexibility is calculated by multiplying the appliance flexibility by the house flexibility.

The constraint for the maximum flexibility can be observed in Eq. (6), where $f_{(b,i)}$ is the timeslot flexibility and $d_{(b,i)}$ is the real timeslot hour.

$$x_{t,b,i} * t - x_{t,b,i} * d_{b,i} \geq -1 * f_{b,i},\ x_{t,b,i} \in \{0,1\}, \forall t \in T, \forall b \in B, \forall i \in I \tag{6}$$

2.2.7. Minimum flexibility constraint

A similar constraint was defined to establish a minimum limit of hours during which appliance usage can be shifted based on the flexibility of the time slot and the desired date by the member. It is shown in Eq. (7).

$$x_{(t,b,i)} * t - x_{(t,b,i)} * d_{(b,i)} \leq f_{(b,i)},\ x_{(t,b,i)} \in \{0,1\}, \forall t \in T, \forall b \in B, \forall i \in I \tag{7}$$

2.2.8. Balance constraint

Regarding the balance of the active power P, a constraint was established to ensure that the load is balanced at any instant. Apart from the sum of the total power demand $P_{d(b,i)}$ and the sum of the total generation $P_{g(b,i)}$, it also includes the power imported $P_{imp(t)}$ and exported $P_{exp(t)}$ from the grid as well as the power charged $P_{ch(t,e)}$ and discharged $P_{dch(t,e)}$ by the EVs. It is represented in Eq. (8) where η is the efficiency of the batteries.

$$\sum_{b=1}^{B}\sum_{i=1}^{I} P_{d(b,i)} * x_{(t,b,i)} + P_{exp(t)} + \sum_{e=1}^{E} P_{ch(t,e)} == \sum_{b=1}^{B}\sum_{i=1}^{I} P_{g(b,i)} + P_{imp(t)} + \sum_{e=1}^{E} P_{dch(t,e)},\ x_{(t,b,i)} \in \{0,1\}, \forall t \in T \tag{8}$$

2.2.9. EV state of charge (SOC) constraint

For the calculation of EV SOC, a constraint (shown in Eq. (9)) was developed to ensure that the SOC $soc_{(t,e)}$ of each EV e is calculated as expected based on the power charge and discharge at any instant. In the formulation, it is assumed that time intervals are one hour. Based on the equation, the value of SOC is expressed in kWh. However, in the literature, the value should be expressed as a percentage by dividing the values by the battery capacity of the EVs.

$$soc_{(t,e)} = soc_{(t-1,e)} + P_{ch(t,e)} * \eta_{ch(e)} - P_{dch(t,e)}/\eta_{dch(e)}, \forall t \in T, \forall e \in E \tag{9}$$

2.2.10. Charge availability constraint

Considering that some information regarding the electric vehicles availability $av_{(t,e)}$ is obtained from the dataset, namely the hours of the day when the vehicle is connected (represented as 1) or not (represented as 0), this information is used to allow the cars to be charged only when they are connected (Eq. 10). Additionally, the maximum power that can be charged from the EV is limited according to the parameter P^{max}_{ch} (charger power).

$$P_{ch(t,e)} \leq P^{max}_{ch(e)} * av_{(t,e)}, \forall t \in T, \forall e \in E \tag{10}$$

2.2.11. Discharge availability constraint

The previous constraint was also applied to the vehicle discharge. The power discharged $P_{Dch(t,e)}$ by the EV is limited according to its availability in the different hours of the day and the maximum discharge power $P^{max}_{Dch(e)}$ imposed by the vehicle and charging station. The formula is presented in Eq. (11).

$$P_{dch(t,e)} \leq P^{max}_{Dch(e)} * av_{(t,e)}, \forall t \in T, \forall e \in E \tag{11}$$

2.2.12. Import limit constraint

Additionally, a new constraint was established to limit the power that can be imported $P_{imp(t)}$ from the grid at any instant, as shown in Eq. (12). This power is limited by the characteristics of the grid or the contracted power, which can vary over time. This limit is represented by the parameter $P_{grid(t)}$.

$$P_{imp(t)} \leq P^{max}_{grid(t)}, \forall t \in T \tag{12}$$

2.2.13. Export limit constraint

Not just limiting the imported power is important, but also limiting the exported power $Pexp(t)$, because it should not be possible to export more than allowed. It is represented in Eq. (13).

$$P_{exp(t)} \leq P^{max}_{grid(t)}, \forall t \in T \tag{13}$$

2.2.14. SOC minimum constraint

The SOC minimum constraint is used to guarantee that the SOC of the EV is never lower than the minimum established in the model parameter soc^{min}_{e} defined for each EV. It is extremely important to prevent over-discharge of the battery, which reduces the battery lifetime [32].

$$soc_{(t,e)} \geq soc^{min}_{e}, \forall t \in T, \forall e \in E \tag{14}$$

2.2.15. SOC maximum constraint

The last constraint (Eq. 15) is related to the overcharge of the EV battery. To prevent it, an upper limit soc^{max}_{e} was established to avoid having a SOC higher than this limit.

$$soc_{(t,e)} \leq soc^{max}_{e}, \forall t \in T, \forall e \in E \tag{15}$$

2.3. Objective functions

For this optimization problem, two distinct Objective Functions (OFs) were formulated (Eqs. 16 and 17): one aiming to maximize self-consumption and the other to minimize the overall energy cost. The second Objective Function (OF) explicitly incorporates the degradation cost of the batteries, represented as $deg_{c}ost(e)$, for each kilowatt-hour charged or discharged, ensuring that the model accounts for the long-term economic impact of using EV batteries as flexible assets.

The main aim is to evaluate whether it is possible to simultaneously increase the community's use of renewable generation and reduce the energy expenditures associated with grid imports. To this end, the approach considers both the flexibility offered by electric vehicles and the potential to shift appliance operation across time (LS). Considering both OFs, the model enables an evaluation of how far the community can reduce its reliance on external energy sources, increase self-sufficiency, and achieve a more cost-efficient operation without compromising the comfort or constraints of individual households. The formulation not only addresses immediate operational benefits—such as lowering peak imports—but also integrates broader considerations, such as asset longevity and user-centric flexibility, providing a comprehensive framework for managing energy flows in community-based energy systems.

$$minimize \sum_{t=1}^{T} P_{imp(t)} \tag{16}$$

$$\begin{aligned} minimize \sum_{t=1}^{T} & P_{imp(t)}/1000 * imp\_price_t - P_{exp(t)}/1000 * exp\_price_t \\ & + \left(\sum_{e=1}^{E} (P_{ch(t,e)} + P_{dch(t,e)})/1000 \right) * deg\_cost_e \end{aligned} \tag{17}$$

3. Results and discussion

To evaluate the designed load balancing strategy, three experiments were conducted using an EC dataset generated by PROCSIM tool [33] with five different houses and an EVs dataset with two electric vehicles. The data has been obtained in real houses in Portugal.

The first one relies on maximizing the use of renewable energy without considering the energy prices (import and export prices). On the other hand, in the second experiment, there are different prices for Low, Medium, and High Demand periods, and the low demand periods should be preferred. Ultimately, the last combines both to understand how they can be accomplished, corresponding to the ideal case. For the following experiments, the following parameters have been defined: $pch = 7200(W)$ and $n = 0.97$.

3.1. Model assumptions

The model input data includes information from community demand and production, as well as data from electric vehicles. Additionally, import and export prices are taken into consideration.

3.1.1. Community demand and production profiles

The community demand and production profiles as well as the community information (flexibility, Peak Power Contract (PPC), number of houses, etc.) are acquired from the PROCSIM [33] tool, which is an energy communities simulator. In addition to the aggregate consumption and production profiles, individual profiles at the appliance level and the household level were collected to enable the extraction of different activities, allowing timeslots to be created based on a schedule that fully meets members' own comfort. This data enables the model to understand when members plan to use the appliances the following day and, based on that, plan the community's energy management.

3.1.2. Electric vehicles availability

The information regarding the EV is taken from a computational tool [34]. It contains information about their initial, minimum, and maximum SOC (Table 2) and their availability throughout the day (Table 3). This information is especially useful for the model to know the times of the day when the different EVs can be charged or discharged, considering that sometimes the car may be on a road trip, and, in those situations, it is not available. Moreover, when the car is on a road trip, information regarding the energy used during the trip must be provided to allow the model to ensure that the vehicle will have at least that SOC before disconnecting.

3.1.3. Import and export prices

Regarding the electricity prices, this data was acquired from a retailer in Portugal. The export price is always the same (0.12), and the import prices are based on a three-hourly tariff (Off-peak hours, middle hours, and peak hours), as shown in Table 4. Concerning the selling price, the value is defined based on the average price of the spot market (MIBEL in Portugal) in the previous month of the simulation. This is why the value is constant and can be higher than the value of purchasing energy from the grid. Additionally, all the produced energy can be injected into the grid, creating an opportunity for remuneration.

3.2. Experiment 1: maximization of self consumption

The first experiment of the case study is related to the maximization of the SC to take, as much as possible, advantage of the renewable resources of the community. It is expected to decrease the power imported from the grid while increasing the power used from the PV generation.

Table 2
EVs characteristics (in kWh).

EV	Initial SOC	Minimum SOC	Maximum SOC
EV1	15	15	68
EV2	15	15	55

Table 3
EVs availability in the different hours of the day.

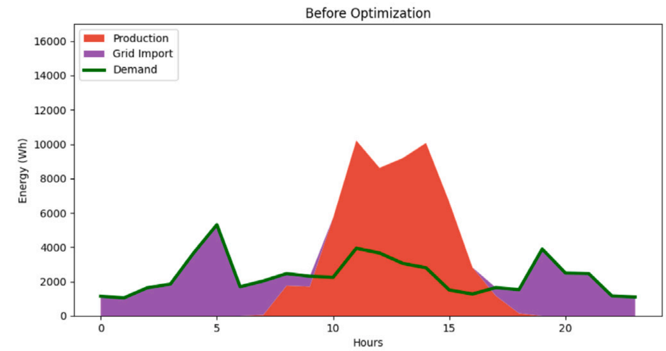
	1	2	3	4	5	6	7	8	9	10	11	12
EV1	0	1	1	1	1	1	1	1	1	0	0	0
EV2	0	1	1	1	1	1	1	1	1	0	0	0
	13	14	15	16	17	18	19	20	21	22	23	24
EV1	0	0	0	0	1	1	1	0	1	1	1	1
EV2	1	1	1	0	0	0	1	1	1	1	1	1

Table 4
Three-hourly tariff considered in the case study.

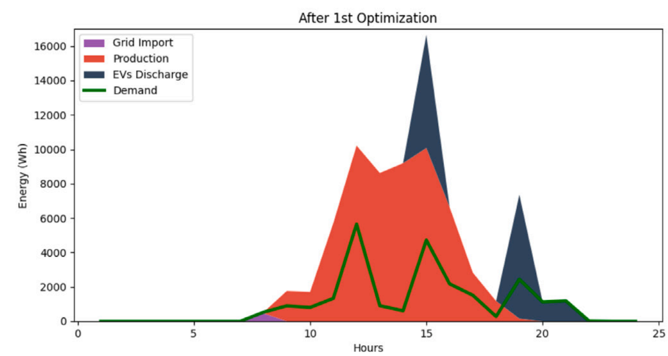
Period	0-7	8-10	11-17	18-20	21	22-23
€/kWh	0.0918	0.2417	0.1484	0.2417	0.1484	0.0918
Tariff	Off-peak	Peak	Middle	Peak	Middle	Off-peak

Table 5
Calculation of metrics for experiment 1.

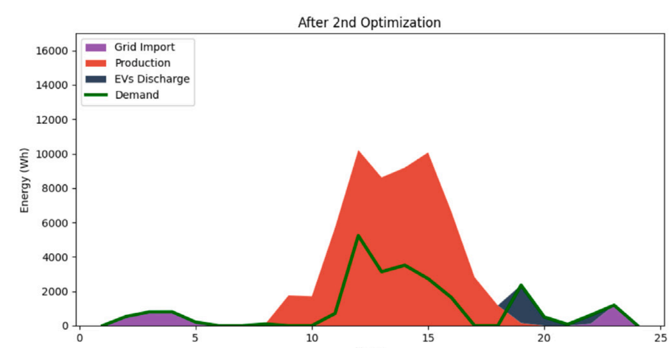
Metric	Before DSM	After DSM
Energy Consumed from Grid [kWh]	14.27	0.46
Energy Consumed from PV [kWh]	9.92	23.73
Energy Injected in the Grid [KWh]	48.23	34.42
Self Sufficiency [%]	17.06	99.02
Self Sufficiency (2) [%]	17.06	99.27
Self Consumption [%]	41.01	58.34
Energy Costs [€]	8.54	−1.18



(a) Before the Optimization.



(b) Optimization with OF 1.



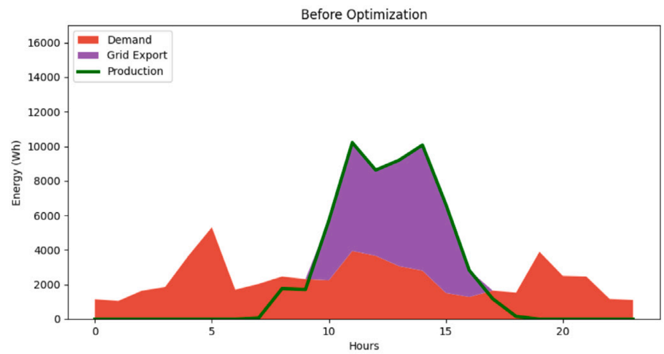
(c) Optimization with OF 2.

Fig. 3. Different sources of covering the community consumption (Grid Import, community Production, and EVs Discharge) in the different steps.

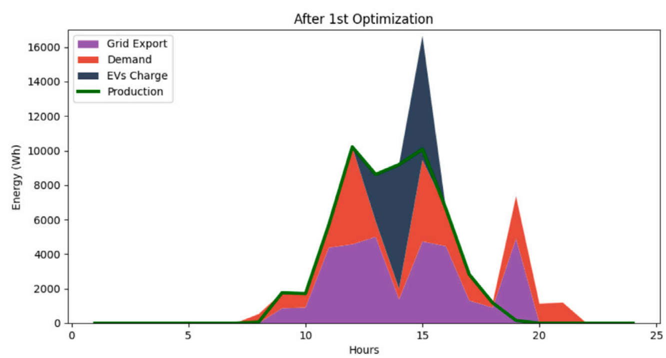
For this to happen, the optimization model shifts the shiftable appliances to periods of the day with higher production, and whenever this is not possible, it utilizes the battery of electric vehicles to store excess production, which can be used later when necessary.

In this specific case, since there are no electricity prices for different hours of the day, there is no difference in the hour of the day when power from the grid is acquired. The quantity of energy acquired is important for the objective.

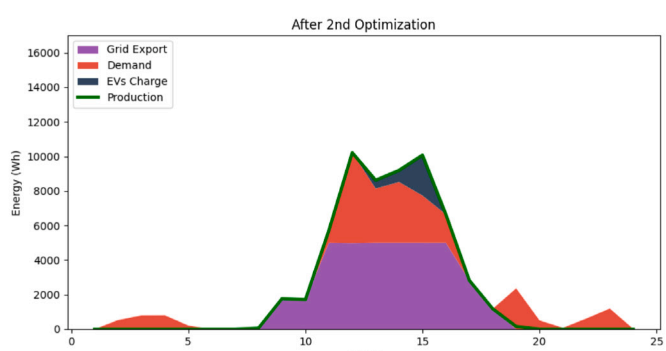
As shown in Table 5, there is a significant difference in the values obtained for the different metrics before and after applying the model. The model can effectively contribute to better management of renewable resources, importing, as little as possible, energy from the grid. In a single day, the energy acquired from the grid can be reduced by more than 13 kWh when using the model, corresponding to over 390 kWh in a



(a) Before the Optimization.



(b) After 1st Optimization.



(c) After 2nd Optimization.

Fig. 4. Different destinations of the community generation (Community Consumption, grid Export, and EVs Charge) in the different steps.

month and over 4.6 MWh in a year. The value of SS can also be increased from 17.06% to 99.02% when calculating through the traditional metric formula or from 17.06% to 99.27% when considering an equation defined for systems with energy storage, as addressed by the authors in [35]. It is important to note that the final cost is negative due to the quantity of energy sold to the grid, that is, in the present experiment, after DSM, 34.42 kWh.

Fig. 3(a) and (b) show the total energy consumption of the community for the following day before and after the load shifting strategy, where the total daily consumption when fulfilling the members' needs and when fulfilling the community goal can be seen. Before optimization, most consumption occurs during periods without solar production, necessitating the acquisition of energy from the grid (such as before 7 am and after 7 pm) and poor management of the PV resources. The appliance' operation is then rescheduled mainly between 10 am and 6 pm, where a better advantage of the existing renewable production can be taken, as shown in Fig. 3 and consequently reduces significantly the operation cost and increases self-consumption.

When the appliance operation cannot be rescheduled due to household or user constraints—either because the equipment is not flexible or the required runtime cannot be shifted—the model compensates by using energy stored in EV batteries (as observed at the end of the day) or, as a last resort, by importing electricity from the grid (notably around 8 a.m.). A similar representation is provided in Fig. 4(a) and (b). However, instead of illustrating how community consumption is supplied by different energy sources, these figures show how locally generated energy is allocated to various end uses. Before applying the optimization model, most of the locally produced energy is exported to the grid, with only a small share used to meet internal demand. After minimizing grid imports, although a significant amount of energy is still exported—due to production exceeding consumption—a considerably larger portion of the community's demand is supplied internally, as expected. Finally, Fig. 5 illustrates the rescheduled appliance operation across various household activities.

3.3. Experiment 2: minimization of the energy costs

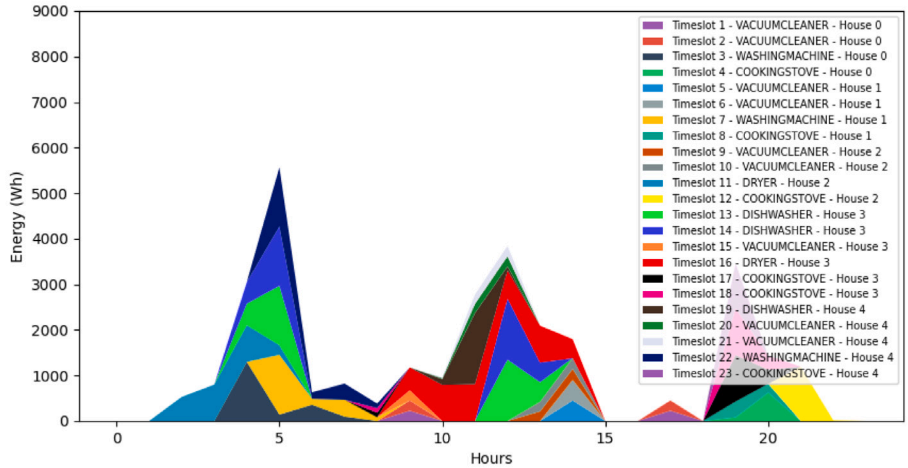
In this second experiment, a three-hourly tariff is used, divided into three periods. The primary goal is to minimize energy costs while using the desired appliances at the lowest prices. It can be achieved by shifting the appliances to hours of the day when prices are lower (middle hours or, especially, off-peak hours). Additionally, it can be used to generate some income by importing energy from the grid during off-peak hours (charging the EVs) and then exporting it to the grid during peak hours (discharging the EVs).

Table 6 shows that the objective is being achieved. When running the optimization model, considering that there are some time periods (especially during the night) where the import price is very low (it is lower than the export price), the battery is not just being used to fulfill the community needs but also to store the energy imported from the grid in the off-peak times to be sold to the grid in the peak times when the prices are higher. This means that the model allows the community to import all the energy from the grid during the day without any cost and additionally earn 3.47 €. When comparing the metrics, it is evident that the use of the strategy allows for the same energy consumption, saving 12.55 €, and also enables an increase in both SS and SC. This is equivalent to saving more than 360 €per month and more than 4320 €per year for the whole community.

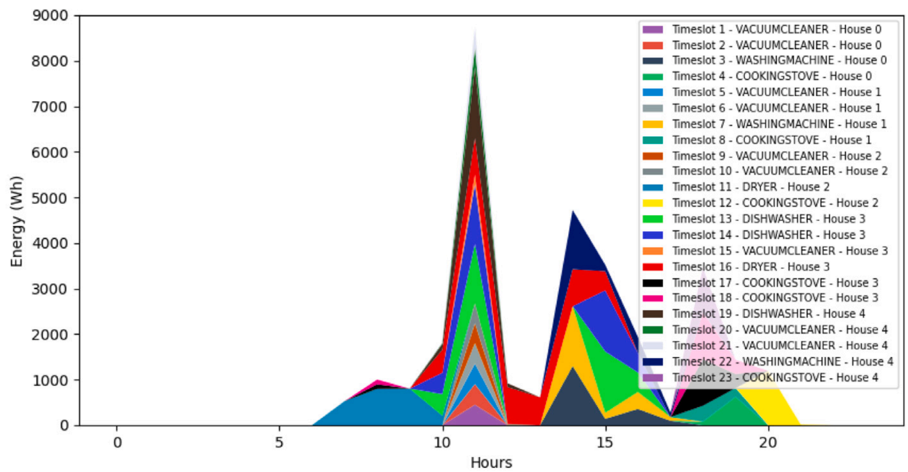
Fig. 3(c) illustrates how the community's energy consumption is supplied under the second model, enabling a direct comparison with Fig. 3(a). When analyzing both scenarios, substantial differences become evident. In particular, there is a clear reduction in the energy imported from the grid—even though this imported energy corresponds to the lowest-priced periods—and a significant increase in the share of consumption that is met by the community's own production. This shift highlights the model's effectiveness in prioritizing self-consumption and leveraging local generation to the fullest extent.

A similar trend can be observed when comparing Fig. 4(a) and (c). After applying the optimization strategy, the amount of energy exported to the grid is noticeably reduced, as more of the excess production is now redirected to internal uses. This includes the intentional charging of the community's EV batteries with surplus generation, contributing to higher overall self-consumption and improved use of flexible assets.

Regarding appliances' rescheduling, Fig. 5(a) presents the initial allocation of the twenty-three appliances across the five houses, reflecting the preferred operation times defined by the community members. In contrast, Fig. 5(b) depicts the updated schedule after the optimization model is applied. By comparing these two figures, it becomes possible to understand how the load shifting is performed throughout the day, identifying which appliances are moved to off-peak or higher-production



(a) Before the LS.



(b) After the LS.

Fig. 5. Timeslots allocation before and after the second experiment.

periods and how the aggregated flexibility contributes to reducing grid dependence. This visual comparison offers valuable insights into user-driven constraints, the potential flexibility of the community, and the effectiveness of the proposed scheduling strategy.

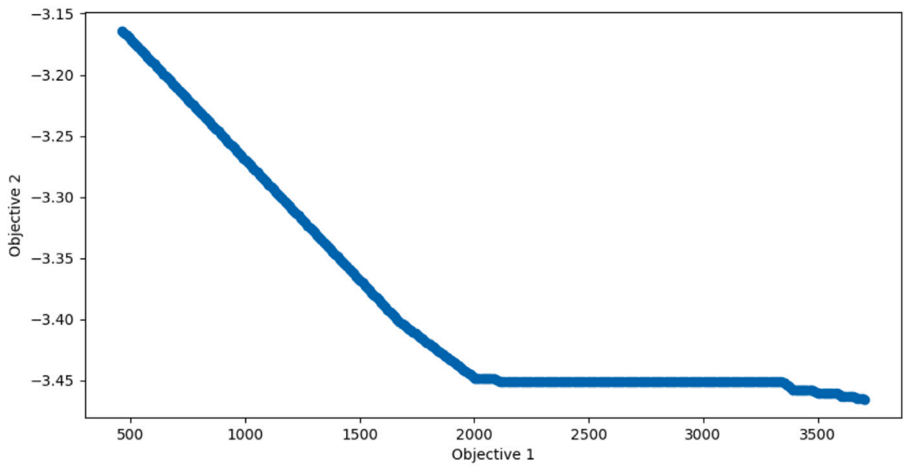
3.4. Experiment 3: multi-objective

The last experiment combines both objectives into a multi-objective approach, aiming to understand how they can be optimized simultaneously to achieve the best possible trade-off between maximizing the SC and minimizing costs using the Pareto Frontier [36].

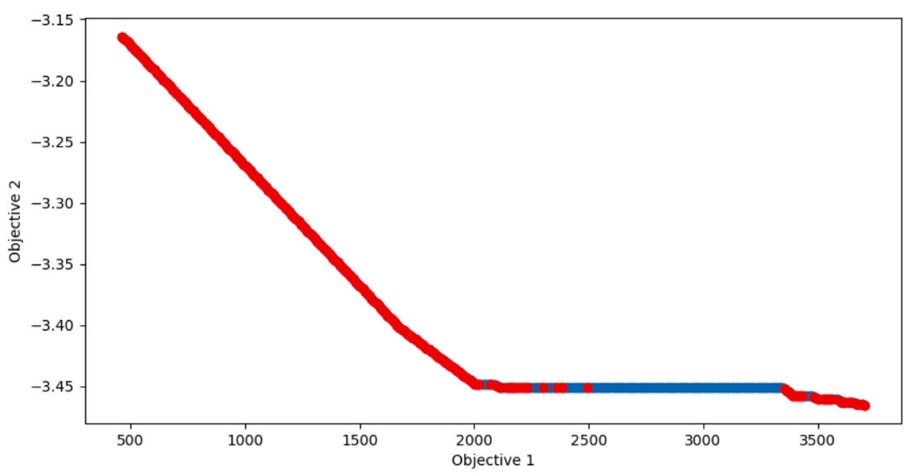
In this multi-objective model, after applying the Pareto Frontier, 201 optimal values were obtained (the ones with a higher trade-off between both objectives) from a total of 325 points in steps of 10W between the minimum (463.17W) and the maximum (3704.43W) obtained for both objectives, meaning that 124 dominated points have been removed from the initial set. The Pareto Frontier can be seen in Fig. 6, where the left side shows the representation of all the feasible points and the right side demonstrates the ones that are dominated by other solutions (in blue) and the ones that are not (in red). For each feasible point of the Pareto-optimal solutions set, the R-method [37] was used to rank the Pareto-optimal solutions based on the objective values of the multi-objective optimization and select the best solution. Dominated solutions are not presented in the figures for simplicity of analysis.

The results obtained for the 10 best solutions are displayed in Table 7. After obtaining the non-dominated alternative solutions to the problem, the two objectives are ranked based on their importance according to our perception (as shown in columns WO1 and WO2). For this step, it was decided that the first objective should have a higher rank than the second objective (specifically, 0.6 for maximizing the SS and 0.4 for minimizing the energy costs). Then, the Pareto optimal solutions were ranked based on the results obtained for both objectives (columns O1 and O2), and the results are provided in columns RO1 and RO2. After that, the ranks assigned to the objectives and the ones assigned to the solutions are converted into weights based on a formula provided by the authors in [37], and the values are shown in columns W1 and W2 for objectives 1 and 2, respectively.

Finally, the composite scores of the alternative solutions are calculated by summing up the products of the weights of the two objectives with the corresponding given weights, and their composite ranks are determined based on these values, where the best solution is the one with the highest composite score. The composite scores and the composite



(a) All the feasible points (634 points)



(b) The dominated (blue) and non-dominated (red) elements

Fig. 6. Pareto Frontier representation for the multi-objective optimization model.

Table 6
Calculation of metrics for experiment 2.

Metric	Before DSM	After DSM
Energy Consumed from Grid [kWh]	32.63	3.70
Energy Consumed from PV [kWh]	23.37	20.49
Energy Injected in the Grid [KWh]	34.78	37.66
Self Sufficiency [%]	17.06	86.72
Self Sufficiency (2) [%]	–	94.02
Self Consumption [%]	41.01	39.25
Energy Costs [€]	8.54	−3.47

ranks are shown in columns CS and CR, respectively. From this, it can be concluded that the best solution is solution 1, which has the best composite score value.

3.5. Summary

Finally, this subsection compares the results of the four presented scenarios, which are summarized in Table 8.

The importance of this optimization model is evident when comparing the metric values obtained for the first scenario with those of the remaining cases. In the first scenario, where no strategy is applied to manage the resources, more than 34 kWh of production is exported to the grid.

The results demonstrated that the first experiment, whose goal was to maximize the SS, was the one that obtained a lower amount of energy acquired from the grid in comparison to the results obtained in the remaining cases, allowing the maximization of the SS to about 99% (an increase of more than 80%). It means that less than 1% of the energy consumed comes from the grid, also leading to a reduction in the associated energy costs.

Regarding energy costs, the second experiment resulted in the lowest costs, with a cost of −3.47 €, indicating that the approach can enable one to save money by adjusting the periods of the day when appliances are used, without altering the total energy consumption.

Regarding the multi-objective model, the best solution obtained using the R-method was solution 1, which is the same solution as the one obtained in the first model. Taking this into account, it demonstrates that the first solution is not only the one that allows the minimum amount of energy to be imported from the grid, but also the one that permits the best trade-off between minimizing energy costs and minimizing the amount of imported energy.

Table 7
Application of R-Method to rank the Pareto-optimal solutions and select the best - the best 10 solutions. NDS: Non-Dominated solutions.

NDS	O1	O2	RO1	RO2	WO1	WO2	W1	W2	CS	CR
S1 (Min)	463.18	−3.164	1	201	0.6	0.4	0.023	0.004	0.015	1
S201 (Max)	3703.18	−3.465	201	1	0.6	0.4	0.004	0.024	0.012	2
S2	473.18	−3.166	2	200	0.6	0.4	0.015	0.004	0.011	3
S3	483.18	−3.168	3	199	0.6	0.4	0.012	0.004	0.010	4
S199	3683.18	−3.465	199	2	0.6	0.4	0.004	0.016	0.009	5
S4	493.18	−3.170	4	198	0.6	0.4	0.011	0.004	0.008	6
S5	503.18	−3.172	5	197	0.6	0.4	0.010	0.004	0.008	7
S6	513.18	−3.173	6	196	0.6	0.4	0.010	0.004	0.007	8
S200	3693.18	−3.465	200	2	0.6	0.4	0.004	0.012	0.001	9
S7	523.18	−3.176	7	195	0.6	0.4	0.009	0.004	0.007	10

Table 8
Comparison between the four scenarios.

Scenario	Objective	SS (%)	SS (2) (%)	SC (%)	Cost (€)
1	No Objective	17.06	17.06	41.01	8.54
2	Max. SS	99.02	99.27	58.34	−1.18
3	Min. Cost	86.72	94.02	39.25	−3.47
4	Multi	99.02	99.27	58.34	−1.18

4. Conclusion

This paper presents a day-ahead LS strategy developed for renewable energy communities, leveraging electric vehicles, V2G technology, and ToU electricity tariffs. The total daily energy consumption remains unchanged; however, appliance operation is shifted across the day according to household and device flexibility constraints. Through this optimization, the model identifies the most advantageous periods to operate each appliance, providing actionable scheduling recommendations that the CM can apply when coordinating community activities.

A study composed of three experiments is conducted to evaluate the methodology: one focusing on maximizing SC, another on minimizing energy costs, and a third combining both objectives. In the multi-objective scenario, the Pareto Frontier is constructed to identify non-dominated solutions, and the R-method is applied to rank and select the most suitable compromise solution.

The results show that the proposed model significantly improves the management of renewable energy within the community. By shifting appliance use to more favorable periods and using two electric vehicles as flexible storage units to absorb surplus production (whenever shifting is not feasible), the community achieves notable improvements in performance. The findings confirm that combining load-shifting techniques with dynamic electricity pricing, EV flexibility, and V2G capabilities can effectively reduce grid dependence and decrease total community energy costs.

Overall, the optimization demonstrates that self-sufficiency can increase dramatically—from 17.06% to 99.27%, when applying the first objective function. Additionally, substantial cost reductions can be achieved with the second objective, lowering community energy expenditure from 8.54 € to –3.47 € in a single day. In the multi-objective scenario, the selected Pareto-optimal solution coincides with that of the first objective, indicating that it provides the best trade-off between maximizing self-consumption and minimizing energy costs.

Future work will extend this strategy by incorporating additional constraints that better reflect real household preferences and comfort requirements. In the current formulation, flexibility is modeled solely as the maximum number of hours an appliance can be shifted. A more realistic approach could allow members to negotiate or approve a set of alternative scheduling options from which the CM selects one. It will also be important to integrate household occupancy patterns to prevent shifting appliances to periods when no one is available to use them. Furthermore, exploring alternative optimization techniques may facilitate timeslot exchanges between members, enabling more collaborative flexibility. Finally, the model will be tested with a larger number of households, appliances, and EVs to assess scalability and validate applicability under real operating conditions.

CRediT authorship contribution statement

Nuno Velosa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hugo Morais:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Lucas Pereira:** Writing – review & editing, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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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Data availability

The data will be made available upon request.

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