

RESEARCH ARTICLE

Optimal Photovoltaic Energy Allocation in Residential Renewable Energy Communities

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ABSTRACT Effective deployment of Renewable Energy Communities (RECs) is essential for the success of Europe's energy transition. However, there are no clear criteria for sharing energy generation among community members, which conditions the rhythm of RECs penetration. The lack of transversal legislation gave rise to different approaches in EU countries for solving this issue, with the calculation of 'a priori' and 'a posteriori' energy sharing coefficients being the most extended ones. Nevertheless, it is still necessary to develop better optimization algorithms to make the most of RECs, to minimize the surplus of energy, and improve payback among end-users and their impact on the energy system. This paper gives an overview of the state-of-the-art and proposes improvements to the linear programming (LP) methodologies devoted to obtaining an optimal calculation of renewable sharing coefficients; able to provide satisfactory results, no matter the size of the REC, while consuming affordable computation resources. The performance of the proposed method has been validated using real generation and consumption data collected from a Spanish DSO, considering both 'a priori' and 'a posteriori' remuneration schemes. The results prove the good behaviour of the proposed solution for different REC sizes and operating conditions.

INDEX TERMS Energy communities, electrical engineering, energy systems, energy transition, linear programming, optimization, renewable energies.

I. INTRODUCTION

The European Union (EU) has launched several initiatives over the last years to overcome the effects of climate change, such as the European Green Deal, which aims to achieve climate neutrality by 2050 and a 55% reduction of greenhouse gas emissions in the EU by 2030 [1]. Moreover, the latest geopolitical events in Europe have forced the EU to speed up the transition from oil and gas to renewable energy sources. Because of this, it was set as a target to increase 320GW the installed photovoltaic (PV) power by 2025 [2], an ambitious objective considering that nowadays the total installed PV power is around 260 GW [3].

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To reach these goals, the EU is promoting the creation of Renewable Energy Communities (REC), among others. This strategy aims to empower citizens to actively participate in the deployment of Distributed Energy Resources (DER) through the collective exploitation of small-scale renewable power plants to reduce their energy demand and consumption bills [4], decreasing at the same time the historical European dependence on external fossil fuel markets. RECs allow citizens to take advantage of renewable resources regardless of their dwelling characteristics or investment capacity and increase the exploitation of renewable energy resources [5], [6]. Moreover, RECs enable local generation, close to the end-users, to decrease costs and losses associated with energy transport and congestion of electrical networks, while increasing the self-sufficiency and economic benefits of communities using renewable sources.

Among European countries, Spain has an especially great potential to develop RECs, as 71,8% of the population lives in apartment blocks, sharing common spaces for PV deployment [7]. This feature, combined with its optimal irradiation conditions, gives rise to a scenario in which the deployment of RECs significantly impacts the energy system. Moreover, the Spanish network has already deployed an Advanced Metering Infrastructure (AMI), able to read the end user's hourly consumption since 2018 [8], [9]. Due to this, a Spanish study case has been selected for this paper, where the optimal energy management strategy for REC promoted by residential consumers with PV generation will be discussed.

The deployment of an AMI has enabled the implementation of a time-of-use (TOU) tariff and the correct retribution of RECs, allowing end-users to adapt their consumption profile to reduce energy costs. However, in the last years, both, the increase in energy prices from fossil fuels and the solar energy increase in the energy, mix have fostered a high variability in the daily energy market prices. This variable price profile makes the management of the REC even more relevant.

Even though the EU encourages its members to set up the necessary legal framework for fostering the deployment of RECs, there is still no consensus on the model to share the energy generated among users. For instance, France has implemented an 'a posteriori' methodology, where the energy is allocated hourly to the different clients once the energy has been produced [10]. Likewise, there is 'a posteriori' allocation in Portugal with a 15-min interval [11]. Following a different approach, Spain has chosen an 'a priori' methodology, where the energy allocation is defined before its production [7], [12]. At first glance, the 'a posteriori' methodology is the most suitable for sharing energy optimally. Moreover, it permits carrying out a more deterministic payback to all clients, as it is not necessary to predict either the energy cost, the production, or the consumption. On the other hand, the 'a priori' legislation provides fewer billing complications for energy companies since energy allocation is defined in advance. In the case of Spain, the current legislation requires setting the energy allocation of any community-shared generation plant 3 times a year. Therefore, an hourly-based distribution of the energy production for the following 4 months must be provided to the Distribution System Operator (DSO) [7], [13].

Some works available in the literature have studied in detail both energy allocation models, 'a priori' and 'a posteriori', focusing on their fitting inside different legal frameworks. For instance, an allocation improvement of the default methodology for the French legislation is proposed by Roy et al. [10], considering a REC with solar production. The proposed method improves the profits by optimizing the overall cost return instead of sharing the energy produced proportionally to the consumption of each time interval. Likewise, Orgando-Martinez et al. [14], and Villalonga Palou et al. [15] compare 'a posteriori' methodologies with 'a priori' methodologies.

Both conclude that 'a posteriori' allocation provides a better and a more fair return of the investment among the users. A comparison between a fixed parameter for allocating all the energy and one parameter for each hour with a static TOU tariff is presented in [16]. This work concludes that a parameter for each hour with a static TOU increases the whole community's profits. Martínez et al. in [17] study the impact of certain sharing allocation strategies and their effects on a REC with vulnerable consumers. In this case, the 'a posteriori' method is analyzed, and it is concluded that hourly variable coefficients are better for vulnerable clients. Eisner et al. [18] conducted a study over several years for 'a posteriori' methodologies that compares different strategies for energy sharing and concludes that the various strategies affect more on the sharing of the savings rather than the overall savings.

Other approaches of 'a posteriori' allocation are analyzed in RECs with different energy resources, like in [5] where energy allocation with batteries is studied and in [19], [20], and [21], where the energy resources can be individually owned. Fina [22] make an energy allocation 'a posteriori' with privately owned solar panels prioritizing the interaction between specific members.

Going one step further, Lazzari et al. [23] propose an 'a priori' methodology with a multi-objective cost function solved with a genetic algorithm (GA). The multi-objective function has two objectives: maximizing the resemblance of return of investment (ROI) between the different members while minimizing the energy surplus delivered to the grid. Despite the good results, the authors also refer to some issues associated with the GA convergence and the execution burden time. Hence, as shown in the validation, this methodology suits small energy communities with less than 20 clients.

This paper presents improvements to the linear programming (LP) methodologies to optimize the 'a priori' and 'a posteriori' allocation of energy and validates them using real data. In this work, the proposed method is evaluated with different community sizes, analyzing also the convergence and the speed of the algorithm. In addition, a comparison between different optimization goals is performed, evaluating their results with real data. Finally, in order to cover other scenarios in Europe, the same methodology is evaluated for 'a priori' and 'a posteriori' cases and analyzes the different performance of the same method in both cases.

The paper is organized as follows: Section II presents the framework of both the 'a priori' and 'a posteriori' allocation. In this case, the Spanish regulation is used, as it is necessary to determine a framework to set the necessary boundary conditions and constraints. In Section III, the methodologies are presented, and the KPIs' definitions are provided. Section VI details the origin of the datasets from real use cases and their main features. Finally, in Section V, the results of the methodology are presented and analyzed. In the last section, the conclusions extracted from this work are presented.

II. ENERGY ALLOCATION FRAMEWORKS

The Spanish regulation framework requires each REC to send a “sharing factor” list periodically to the Distribution System Operator (DSO), stating the percentage of generated energy allocated to each community member. This file is sent every 4 months and provides the renewable energy distribution of every hour for the following 4 months. In the Spanish case, the remaining surplus, the instantaneous difference between the allocated energy generation and demand, is sold to the grid at a significantly lower price than the consumer’s energy price. Moreover, the members cannot get profit from the monthly billing. The profit from selling the energy can only be used to compensate for the cost of buying energy. Therefore, the highest payback is achieved when community members cover their energy demand with renewables without delivering power to the grid. However, allocating these sharing coefficients is not straightforward.

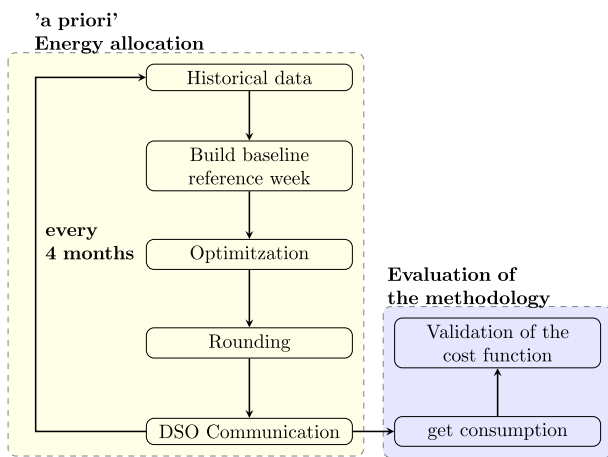


FIGURE 1. Flow chart of the ‘a priori’ energy allocation algorithm.

Allocating energy before its generation is the basis of the ‘a priori’ allocation system. Figure 1 presents the flow chart of ‘a priori’ energy allocation. As it is shown in the flow chart, three main steps are identified: baseline reference week configuration, optimization, and rounding. Therefore, good generation and consumption forecasts are essential to make a good match.

If compared with ‘a posteriori’ allocation, where forecasts are not necessary, ‘a priori’ methodologies are more complex. The ‘a posteriori’ methodologies use historical data, as the distribution is made once the energy is generated. Due to the monthly billing basis and the fact that no positive billings are allowed, the optimization uses the monthly energy consumption data to allocate solar energy to different users. Hence, in the ‘a posteriori’ case, just two steps of the previous flow chart are necessary: optimization and rounding. In this paper, both energy allocation frameworks, ‘a priori’ and ‘a posteriori’, will be considered for managing the energy assets of an REC. The REC proposed in this work has the structure presented in Figure 2 with one shared photovoltaic power plant and several dwellings.

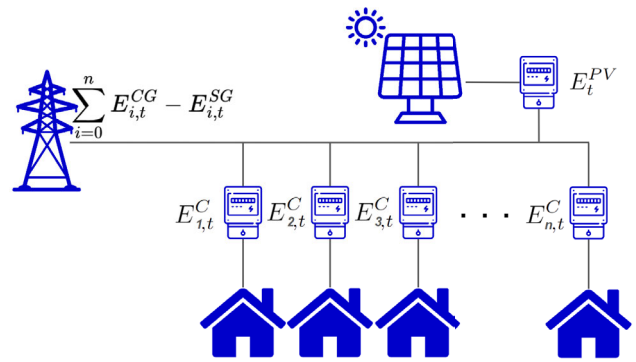


FIGURE 2. Energy community layout considering ‘n’ grid-connected members sharing a PV plant.

A. FORECAST OF CONSUMPTION, GENERATION, AND PRICE

For ‘a priori’ methodologies, some forecasting profiles must be defined to allocate energy. In the method presented in this paper, a weekly-based reference baseline is modelled using historical data. The creation of the baselines based on a simplified method enables the building of a forecast profile for each month. This strategy has been selected because the predicted time series consumption has a significant stochastic component. Also, weather conditions are usually significantly linked to consumption predictions. However, there are no reliable daily weather forecasts for long time periods, such as four months. Therefore, no weather data can be used to predict any of the time series, and only client patterns or assumptions based on previous years can be used. A significant prediction error is expected but it cannot be avoided.

Moreover, the price and consumption performances depend on inherent complexities. Likewise, prices cannot be estimated, as they depend on many factors. However, since the price mainly depends on the whole country’s demand, it can be estimated that the pattern will be the same, the cheapest and most expensive hours will remain the same, but the amplitude might change.

Considering all these statements, the baseline week approach seems fair enough for energy allocation. This baseline reference week is obtained by taking the mean of the hours of the week for consumption, generation, and price. This mean is calculated with the consumption of the same month of the previous year. Although this forecast approach might seem simple, it is the best option given the available information.

III. PROPOSED OPTIMIZATION ALGORITHM FOR ENERGY ALLOCATION IN REC

In the optimization step, energy can be allocated considering different objectives or, in other words, different cost functions (CFs) to be optimized. These CFs are evaluated with different key performance indicators (KPIs). In the case of RECs, and considering the boundary conditions of the study case, the CFs are proposed to achieve maximum energy savings

and minimum energy surplus supplied to the grid, while distributing the benefits fairly among the clients.

The following optimization models have been programmed in Python using Pyomo [24] and solved with the solver GUROBI [25].

A. COST FUNCTION DEFINITIONS

The cost function 1 (CF1) presented in Eq. 1 minimizes the overall cost of the REC and it has been already implemented in the literatures [14] and [16]. The cost of all consumers, n , is obtained by adding the cost of each time stamp, T . The cost of each time stamp has two parts. The first one is the energy consumed from the grid once the energy allocation is done, $E_{i,t}^{CG}$, multiplied by the grid energy price, $p_{i,t}^{CG}$. While the second one, which is subtracted from the first one, is the energy supplied to the grid once the energy allocation is done, $E_{i,t}^{SG}$, multiplied by the surplus energy price, $p_{i,t}^{SG}$. Γ represents all the decision variables in the optimization; in this case, they are: the energy allocated, $E_{i,t}^{SA}$, the energy supplied to the grid, and the energy consumed from the grid once the energy allocation is done.

$$CF1 = \min_{\Gamma} \sum_{i=1}^{n_{clients}} \left(\sum_{t=0}^T (p_{i,t}^{CG} E_{i,t}^{CG} - p_{i,t}^{SG} E_{i,t}^{SG}) \right) \quad (1)$$

An improvement of CF1 is proposed in CF2, written in Eq. 2. In this case the same CF is used, but the payback of all the members is forced to be equal, similar to that presented in [17]. Even though the cost function is the same, the inverse of the payback is forced to be equivalent between clients, and therefore, a change in the distribution is expected. For the sake of clarity, in the equation is written as $Payback_i$.

$$CF2 = \min_{\Gamma} \sum_{i=1}^{n_{clients}} \left(\sum_{t=0}^T p_{i,t}^{CG} E_{i,t}^{CG} - p_{i,t}^{SG} E_{i,t}^{SG} \right)$$

subject to:

$$Payback_i = Payback_{i+1} \quad \forall i \in members \quad (2)$$

Due to the gap between the price of buying energy from the grid and selling energy to the grid, the loss of savings in an REC comes from the surplus of energy sold to the grid instead of being consumed. This casuistic takes place when the energy is not correctly allocated. To avoid having problems due to prediction error, the CF3, presented in Eq. 3, minimises the injected cost of energy injected from the percentile 25.

$$CF3 = \min_{\Gamma} \sum_{i=1}^{n_{clients}} \left(\sum_{t=0}^T E_{i,t}^{SGP25} (p_{i,t}^{CG} - p_{i,t}^{SG}) \right)$$

subject to:

$$Payback_i = Payback_{i+1} \quad \forall i \in members \quad (3)$$

In the ‘a priori’ methodology, the model uses the resulting injected energy with respect to the 25 percentile of the consumption. Otherwise, consumption is used in the ‘a posteriori’ methodology. This element is multiplied by the

price difference between consuming and selling energy to the grid, to minimise the savings losses.

The CF4 is written in Eq. 4. The objective of CF4 is to find a solution with the maximum energy cost and the minimum payback deviation. Due to this, the deviation of the payback is penalised while the energy cost is forced to be equal or lower than the maximum cost, provided by the optimization in CF1 $cost_{min}$.

$$CF4 = \min_{\Gamma} \sum_{i=1}^{n_{clients}} \left| Payback_i - \sum_{i=1}^{n_{clients}} \frac{Payback_i}{n_{clients}} \right|$$

subject to:

$$cost_{min} \Rightarrow \sum_{i=1}^{n_{clients}} \left(\sum_{t=0}^T (p_{i,t}^{CG} E_{i,t}^{CG} - p_{i,t}^{SG} E_{i,t}^{SG}) \right) \quad (4)$$

Eq. 5 introduces a final cost function, the CF5. It uses the squared cost value, and the payback is forced to be equal for all the members. This cost function is similar to the CF2, and the results are expected to be identical in the ‘a posteriori’ case but different in the ‘a priori’ methodology, due to its non-linearity.

$$CF5 = \min_{\Gamma} \sum_{i=1}^{n_{clients}} \left(\sum_{t=0}^T p_{i,t}^{CG} E_{i,t}^{CG} - p_{i,t}^{SG} E_{i,t}^{SG} \right)^2$$

subject to

$$Payback_i = Payback_{i+1} \quad \forall i \in members \quad (5)$$

B. CONSTRAINTS OF THE OPTIMIZATION

Several constraints are the same regardless of the different cost functions, except those associated with linearizing the cost function’s terms and those introduced in the previous subsection. These constraints are set with various objectives, such as balancing the energy generated in the energy community or the energy allocated.

$$E_t^{PV} = \sum_{i=1}^{n_{clients}} E_{i,t}^{SA} \quad \forall t \in T \quad (6)$$

The first constraint, Eq. 6, limits the maximum energy allocated to the different clients in the REC. This constraint limits the addition of all the solar energy allocated to the members, $E_{i,t}^{SA}$, as each hour should be equal to the total generated energy E_t^{PV} .

$$E_{i,t}^{CG} - E_{i,t}^{SG} = E_{i,t}^C - E_{i,t}^{SA} \quad \forall i \in members, \forall t \in T \quad (7)$$

The energy balance inside each client should be met as well. This is considered in Eq. 7. Moreover, since the energy has a different price when it is bought than when it’s sold, the consumption from the grid, $E_{i,t}^{CG}$, and the energy surplus injected into the grid, $E_{i,t}^{SG}$, must be separated. The energy traded with the grid must be in balance with the energy

consumed, $E_{i,t}^C$, and the energy allocated, $E_{i,t}^{SA}$, from the REC.

$$0 \leq \sum_{i=1}^{n_{clients}} \left(\sum_{t=0}^T \left(p_{i,t}^{CG} E_{i,t}^{CG} - p_{i,t}^{SG} E_{i,t}^{SG} \right) \right) \quad \forall i \in members \quad (8)$$

Eq. 8 limits the minimum cost that a client can obtain to 0. This limit is set since the legislation prohibits making a profit in the monthly billing for injecting into the grid, and the surplus can only be used to cover expenses for purchasing grid energy.

For the definition of the inverse payback, a constraint is defined in Eq. 9. The inverse payback is calculated by dividing the savings by the investment of each client. The inverse payback, instead of the payback, is calculated so that the model stays linear.

$$Payback_i = \frac{\sum_{i=1}^n \left(\sum_{t=0}^T \left(p_{i,t}^{CG} (E_{i,t}^C - E_{i,t}^{CG}) - p_{i,t}^{SG} E_{i,t}^{SG} \right) \right)}{Investment_i} \quad (9)$$

All these constraints must also be combined with a restriction that avoids exploring unfeasible scenarios, such as selling and buying energy simultaneously. This is accomplished by limiting the energy consumed, $E_{i,t}^C$, from the grid to be equal to or smaller than the energy consumed by the members, as written in Eq. 10.

$$E_{i,t}^{CG} \leq E_{i,t}^C \quad \forall i \in members, \forall t \in T \quad (10)$$

C. ROUNDING THE SHARING COEFFICIENTS

Regarding the coefficients to be delivered to the DSO, the Spanish legislation asks for a list of numbers with no more than six representative values after the coma to divide the energy generated each hour among the REC members [13]. Therefore, the energy allocated in the optimization is transformed to fit within this threshold. To do so, for all hours of the optimized week, the energy allocated to each client is divided by all the energy produced by the solar panels. Afterwards, the numbers are rounded, and there's a verification that the sum of all the sharing coefficients doesn't exceed one. This is the last step of the algorithm before sending the file with the sharing coefficients for the next 4 months.

D. ASSESSMENT OF THE RESULTS

Four main indicators are used to evaluate the performance of the proposed methodology as presented in Table 1. The first is the percentage of energy generated from the solar panels sold to the grid. The second one is the members' payback standard deviation. The last two are the payback and the savings of the REC as a whole.

These KPIs are calculated after performing each optimization, considering the resulting coefficients that set how the generated energy is shared among the end users.

TABLE 1. Key performance indicators.

KPI name		Mathematical Expression
KPI1	Energy surplus	$\frac{\sum_{i=1}^n \left(\sum_{t=0}^T p_{i,t}^{SG} \right)}{\sum_{t=0}^T P_t^{PV}} \quad (11)$
KPI2	Payback dispersion	$\frac{std(Payback_i)}{mean(Payback_i)} \quad (12)$
KPI3	Mean payback	$\frac{\sum_{i=1}^n \left(\frac{Investment_i}{\sum_{t=0}^T \left(p_{i,t}^{CG} (E_{i,t}^C - E_{i,t}^{CG}) - p_{i,t}^{SG} E_{i,t}^{SG} \right)} \right)}{n} \quad (13)$
KPI4	Overall savings	$\sum_{i=1}^n \left(\sum_{t=0}^T \left(p_{i,t}^{CG} (E_{i,t}^C - E_{i,t}^{CG}) - p_{i,t}^{SG} E_{i,t}^{SG} \right) \right) \quad (14)$

IV. DEFINITION OF THE STUDY CASES

The validation of the proposed improvements with the different CFs is performed using real data from a local DSO that collects the REC consumption measurements through its digital metering network. Real-time data from solar-based generation plants and energy market information are also available. Considering the consumption profiles and the generation capacity, we build different REC scenarios, considering different numbers of end-users, production profiles, and optimization targets.

Following the proposed methodology, the performance of the proposed RECs is optimized using the consumption from the residential dwellings, the PV energy generated by the solar panels, and the energy price profiles.

This study used a database with one hour of sampling time for three years of measurements. The number of users involved in the REC was considered a configurable input, so different scenarios and conditions can be analyzed based on the community size.

The energy price has been extracted from the historical record of the Spanish market publicly available at [26].

This study case has considered some assumptions for building the REC models. For instance, the total investment has been considered as $1\text{€}/W_{peak}$ and this investment of the solar panels has been distributed proportionally between the members according to the consumption of the first year of data. As the second year with data availability is 2020, not all data has been considered, as the results could be altered due to the abnormal effects of the COVID crisis; only the latter months were used. The sharing coefficients for 'a posteriori' and the validation on the 'a priori' are performed with the data of the last 4 months of the third year.

To show the overall consumption profile of the community, as well as the power generation curve; both are presented in the plot available in Figure 3. Even though the consumption

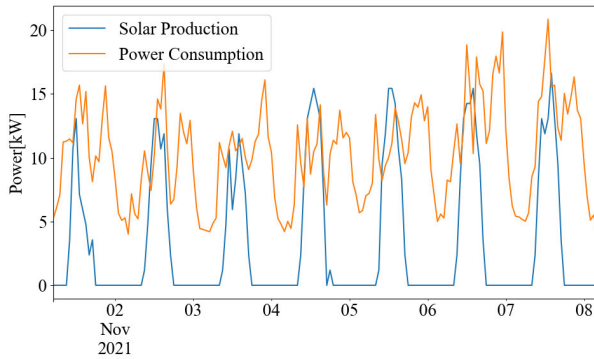


FIGURE 3. Energy generation and aggregated consumption of the 30 members REC.

is usually greater than the generation at first glance, an inadequate distribution of the generated energy can still give rise to a non-optimal exploitation of the resources.

Different community sizes have been defined to measure computational resources and convergence. Thirty household clients were used to benchmark the different cost functions. The solar generation is scaled as its mean power represents 40% of consumption, which is realistic considering the space constraints of urban areas.

V. EXPERIMENTAL RESULTS

This section presents the results obtained using the proposed methodology. It compares the performance achieved with the different cost functions, taking advantage of previously defined indicators. It is worth outlining that all validation for allocation is tested with data not seen by the optimizer when the ‘a priori’ approach is used.

In addition, the convergence of the results and the speed of the process, which depends on the number of clients or size of the REC, have been assessed. In all cases, the system’s convergence has proven to be consistent. There’s an obvious linear dependency between the number of clients and the computational costs, as the number of clients affects the optimization execution time. However, with 100 clients, the computational burden time is lower than 10 seconds when using an i9-11950H 2.60GHz computer. Therefore, the optimization time is found to be small if compared to other methodologies [23].

As introduced previously, for the sake of clarity, the results presented in this section are those obtained with a study case of an REC with 30 clients. Thus, the reader can easily follow the resulting plots and figures.

A. ‘A POSTERIORI’ ENERGY ALLOCATION

In this subsection, the KPIs introduced in section III-D will be calculated for different energy allocations from different optimization algorithms. These algorithms are based on previously presented cost functions and applied for the ‘a posteriori’ case. In addition, these indicators will also be evaluated considering the energy distribution resulting from applying the energy coefficients following the French methodology as a baseline. In this way, it will be possible

to determine whether the proposed algorithms introduce any advantage. It is worth outlining that the default French methodology shares the total solar production in such a way that the each time step the REC’s generated energy is shared proportionally to the instantaneous consumption of each member.

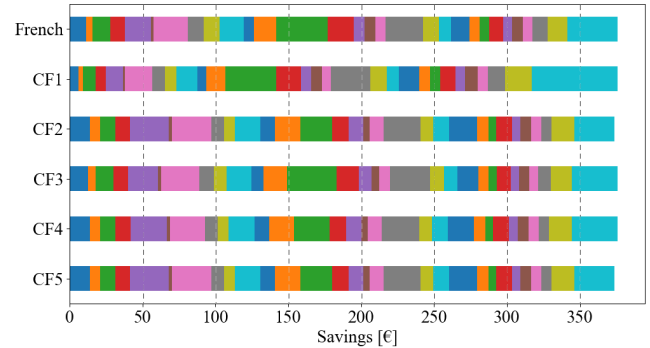


FIGURE 4. Four-month aggregated savings in Euros, KPI4, using ‘a posteriori’ methodology with different cost functions. Representing each member with a different color.

The bar chart in Figure 4 shows the mean monthly economic savings of all the REC in Euros, the KPI4 in Table 1. In this case, as well as in the following ones, the time period of the experiment has been set to four months to compare it later with ‘a priori’ strategies. In Figure 4, the different colors represent the savings of each member, while the overall length of each bar is the lump sum of all savings.

The first row in Figure 4 shows the savings achieved using the French market methodology. Likewise, the lengths of the other rows show that the savings obtained with all cost functions are almost equal to the French case. Moreover, it can be concluded that the savings obtained with CF2, CF3, CF4, and CF5 have similar distributions. However, analyzing the amount of energy excedents delivered to the grid in each case before evaluating these results will be helpful. In Figure 5, the excedents, or energy surplus, delivered using the different CFs is deployed.

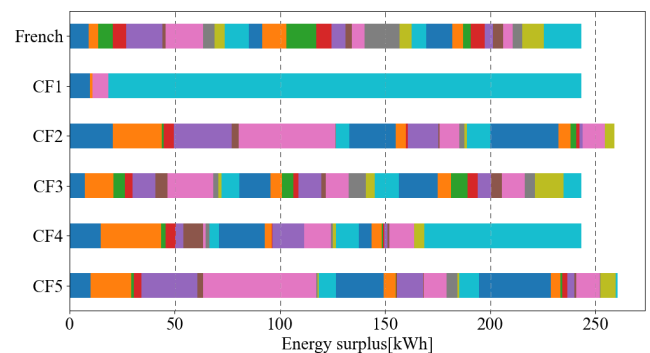


FIGURE 5. Energy surplus, KPI1, ‘a posteriori’ methodology with different cost functions. Representing each member with a different color.

Analyzing both Figure 4 and Figure 5, it is quite obvious that the French case is the one that distributes the most excedents among the users. On the other hand, the CF1 result shows a lack of balance in this indicator. This is due to the

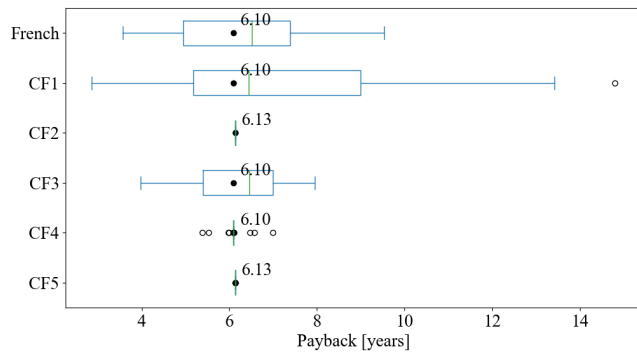


FIGURE 6. Mean payback, KPI3, and payback dispersion, KPI2, for the overall REC ‘a posteriori’ methodology with different cost functions.

fact that the distribution of the payback is not optimized in this strategy. Likewise, the results obtained with CF4 show a higher disparity in the surplus distribution compared to the French case. In the case of CF4, this imbalance is not that remarkable as REC members with a higher surplus are the ones with less consumption in proportion to their investment. In this case, a higher surplus is assigned to them to reduce the disparity in the payback periods of the different users. As the energy delivered to the grid generally has a low price, those strategies, such as CF2 and CF5, that give rise to higher surplus, are punished when savings are evaluated. In fact, it can be seen that the lump sum of both is slightly lower compared to the rest in Figure 4. In order to select among the CFs with better results, the return on the investment, as well as the balance of this return among the users, is evaluated. The distribution of the payback between the different clients changes depending on the selected cost function is depicted in Figure 6.

In Figure 6, the average value of the payback, with a black dot, and its dispersion among the users, are detailed. From the plot, it can be concluded that the CFs with lower dispersion are CF2 and CF5. This is reasonable, as in both cases, a constraint in the optimization limits this parameter. However, they have a slightly longer payback return period compared to the other CFs. On the other hand, the CF1, CF3, and the French cases show a greater dispersion. However, these three offer the shortest payback period for the overall REC together with CF4. CF4 is a compromise between the highest return and minimizing the dispersion of the payback. Therefore, it is necessary to consider whether the payback distribution is more important than the mean payback period or vice-versa. A balanced distribution among users is a criterion that has a bigger weight in the governance of RECs, an optimization based on CF2 and CF5 would be more suitable. On the other hand, CF3 and CF1 seem less appropriate for these KPIs, as they provide the worst results in this case. Finally, CF4 can be suitable for a REC that prioritizes the overall profit and penalizes the injection of energy to the grid.

All results have been summarized in Table 2, where the result of each strategy has been categorized. In this table,

the green cells are the ones with better results for each KPI, while the red ones outline the worst performances. The cells in orange are used for intermediate results.

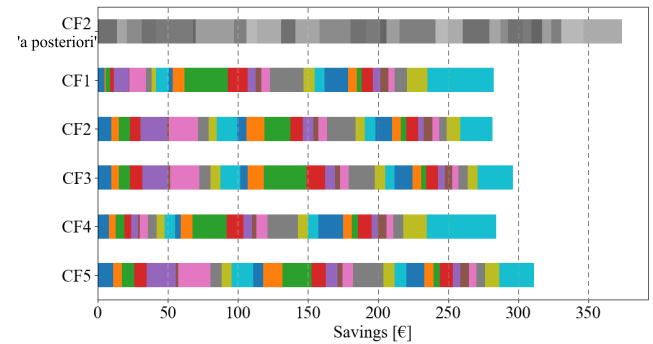


FIGURE 7. Four-month aggregated savings in Euros, KPI4, using ‘a posteriori’ methodology with different cost functions. Representing each member with a different color.

B. ‘A PRIORI’ ENERGY ALLOCATION

In this subsection, the results for the experiments with forecast data used in the optimization are evaluated using the KPIs introduced in section III-D. For all CFs, the forecasts are the same. Hence, only the CF affects the KPI variations.

As in the previous case, the energy cost savings is the first parameter to analyze. The results obtained with the different strategies are summarized in Figure 7. To compare the ‘a priori’ results with the ones obtained in the ‘a posteriori’ case, one of the best use cases of the previous section, CF2, is also included in the plot as a ‘ghost bar’ with the ‘a posteriori’ subindex.

In Figure 7, it can be clearly seen that the savings are lower in all cases if compared to the ‘a posteriori’ methodology using CF2. The CF3 and CF5 are the ones with higher savings within the ‘a priori’ methodologies.

Once again, in order to make a broader analysis, it is necessary to check the performance of energy surplus, or excedents generation, among the different strategies. Figure 8 details the mean energy surplus for 4 months.

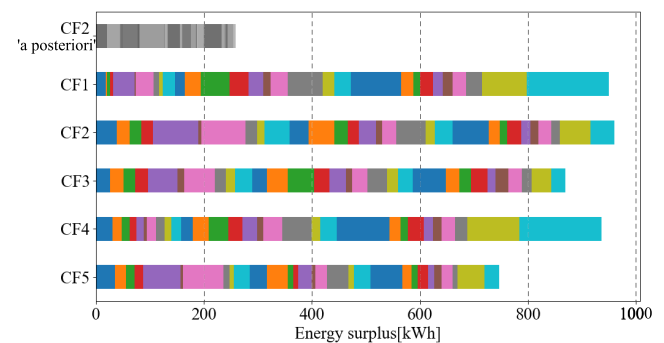


FIGURE 8. Energy surplus, KPI1, ‘a priori’ methodology with different cost functions. Representing each member with a different color.

As in the ‘a posteriori’ scenario, there’s an inverse dependency between the surplus energy sold to the grid

TABLE 2. Results summary for a REC of 30 members.

CF	Target of the CF	'a posteriori'				'a priori'			
		KPI1	KPI2	KPI3	KPI4	KPI1	KPI2	KPI3	KPI4
		[%]	[p.u.]	[years]	[€]	[%]	[p.u.]	[years]	[€]
CF1	Minimizing the energy cost	11.20	0.417	6.10	375.8	43.73	0.54	8.119	282.2
CF2	Minimizing the energy cost and balancing payback	11.92	0.000	6.13	373.7	44.16	0.08	8.143	281.4
CF3	Minimization of excedents	11.20	0.189	6.10	375.8	39.98	0.23	7.743	295.9
CF4	Minimizing payback deviation	11.20	0.043	6.10	375.8	43.09	0.40	8.063	284.2
CF5	Minimizing square energy cost	11.99	0.000	6.13	373.7	34.37	0.08	7.361	311.3

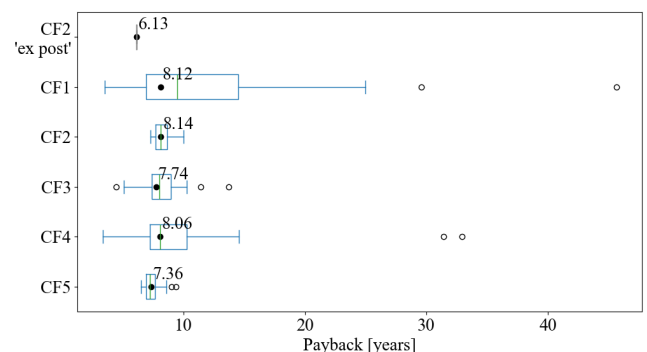
TABLE 3. Results summary for a REC of 100 members.

CF	Target of the CF	'a posteriori'				'a priori'			
		KPI1	KPI2	KPI3	KPI4	KPI1	KPI2	KPI3	KPI4
		[%]	[p.u.]	[years]	[€]	[%]	[p.u.]	[years]	[€]
CF1	Minimizing the energy cost	11.4	0.42	5.968	1605.8	43.43	0.63	7.919	1210.1
CF2	Minimizing the energy cost and balancing payback	11.8	0.00	5.986	1600.8	43.07	0.08	7.874	1217.1
CF3	Minimization of excedents	11.4	0.16	5.968	1605.8	39.41	0.18	7.535	1271.8
CF4	Minimizing payback deviation	11.4	0.03	5.968	1605.8	43.33	0.56	7.912	1211.3
CF5	Minimizing square energy cost	11.8	0.00	5.986	1600.8	31.96	0.07	7.035	1362.1

and the savings. However, no methodology can minimize the surplus as in the 'a posteriori' case. As it is clear in the plots, CF5, followed by CF3, produces smaller surplus, while the other three CFs have higher energy surplus levels. This directly impacts the cost savings, as higher surplus punish the profitability of the investment. Moreover, due to their uncertainty, the prediction errors are translated into higher surplus to be delivered to the grid instead of real-time consumption coverage, finally giving rise to lower cost savings. Even though CF3 and CF5 are the ones more advantageous, their performance is not comparable to the 'a posteriori' results. It is clear that there is no uncertainty linked to predictions in the 'a posteriori' case, hence the allocation is better, permitting minimizing the surplus and maximizing savings.

Finally, the dispersion of the payback and the mean payback, KPI2 and KPI3, respectively, are summarized in Fig. 9. From this figure, we can conclude that the 'a priori' methodologies obviously have longer paybacks and more dispersion if compared to 'a posteriori' cases. Among 'a priori' cases, the different CFs have different results; the shorter payback and the smallest dispersion are achieved with CF5, followed by CF3.

The other CFs provide a less balanced investment recovery among the users. This is due to the strategy for energy allocation provided by these CFs having a greater impact on

**FIGURE 9. Mean payback, KPI3, and payback dispersion, KPI2, for the overall REC 'a priori' methodology with different cost functions.**

the uncertainty of the forecast. Therefore, when validating with real data, the energy allocated is not so aligned with some members' consumption, resulting in a surplus of energy for those members.

C. DISCUSSION OF 'A PRIORI' AND 'A POSTERIORI' RESULTS

Those applications based on 'a posteriori' energy allocation provide better results without a shadow of a doubt. This is reasonable, as they do not depend on forecasts but work with real data. However, there is still some room for discussion on which CFs provide better performances.

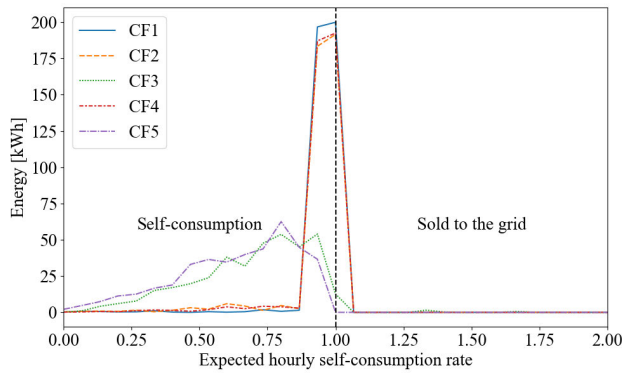


FIGURE 10. Expected self-consumption on the baseline reference week with the 'a priori' methodology.

Table 2 summarizes the different KPIs obtained in the validation for 30 users. Analyzing this table, it can be concluded that the values of KPI1, KPI3, and KPI4 have greater differences between 'a priori' and 'a posteriori', and the CFs that constrain the payback maintain this effect in both strategies. Among the CFs, it is clear that for 'a posteriori' CF2 and CF5 are the ones that achieved a better distribution of the savings among the end users. Taking into account also CF4, which offers the shortest return on investment while minimizing the dispersion of payback. On the other hand, CF5 has the best results in the 'a priori' case. From the results, it can be concluded that CF5 behaves similarly in the 'a posteriori' cases as in 'a priori' scenarios, but the other CFs do not.

Experiments have also been conducted for a REC with 100 members to validate these conclusions, introducing new energy consumption profiles. The results have been collected in Table 3. If the values are compared to Table 2 the matching is clear, as the heat map is the same cell by cell. Hence, the same conclusions can be scaled if the REC is larger.

D. SELF-CONSUMPTION VS EXCEDENTS RATE IN THE 'A PRIORI' CASE

In the Spanish study case, 'a priori' energy allocation prevails by force, as it is the methodology imposed by the electrical companies and the one set in the regulations. The previous results have proven that the higher the coverage of real-time demand by energy generation, the better. Hence, avoiding excedents as much as possible is highly recommended in RECs. The plot in Figure 10 is a histogram that shows the energy allocated with different CFs. The horizontal axis acts as a self-consumption rate bar. The values below one in the 'x' axis correspond to real-time demand coverage or self-consumption. The right side of the graph, for values greater than one, is reserved for excedents. It is important to note that this rate is calculated four months in advance; hence, it is a forecast.

The plot shows that CFs like CF1, CF2, and CF4 allocate energy in hours, covering a higher percentage of real-time consumption. On the other hand, CF3 and CF5 give rise to an

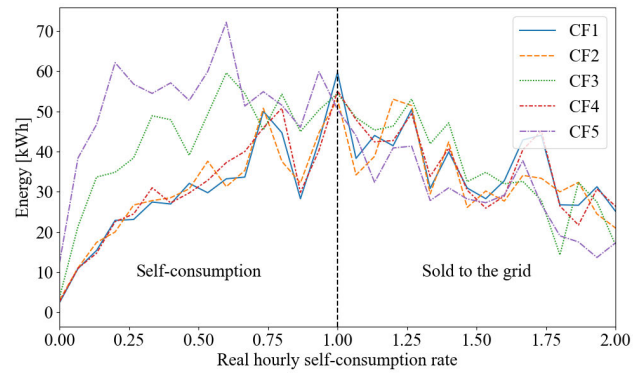


FIGURE 11. Power vs hourly self-consumption on the real data with the 'a priori' methodology.

energy allocation that does not fully cover the energy demand in those hours. Hence, the consumption is still higher, but all energy is self-consumed.

These differences are due to the fact that the first ones implement the L1 norm, which prioritizes the allocation of energy to a single member for each step of time, while CF5, since it's a quadratic cost function, follows an L2 norm, which gives rise to a broader number of results distributing the energy among different members [27]. CF3 lies in the middle since it works with the L1 norm but penalizes excedents with respect to the percentile 25. Considering this detail, results obtained with CF3 and CF5 seem safer, as they are less sensitive to consumption forecast uncertainties.

Figure 11 shows the real self-consumption rate calculated after the four-month period. In this case, no forecast interferes, as these calculations are made a posteriori, once the generation and consumption are historical curves. Of course, the mismatch between reality and forecast makes this graph quite different from the one in Figure 10.

It is quite clear in Figure 11 that there are greater excedents than the expected ones in Figure 10. This is especially remarkable in the cost functions based on the L1 norm (CF1, CF2, and CF4), as they are more sensitive to consumption forecast errors. Despite the fact that CF3 and CF5 also give rise to higher energy delivery to the grid, their performance ensures lower excedents. This can be seen as the area below the curves in both cases, on the left side of one in the x-axis, is clearly bigger if compared with the others.

VI. CONCLUSION

This paper presents improvements to the LP methodologies for allocating energy generation in RECs and evaluates their performance using real data obtained from a Spanish DSO. A straightforward conclusion that can be extracted from this paper is that 'a priori' energy allocation cannot compete with 'a posteriori' techniques, no matter the algorithm and CF used. This is due to the fact that the uncertainty of predictions significantly affects the 'a priori' calculation of the generation sharing coefficients, something that does not occur when they are calculated with all real data available. In a nutshell, four months ahead is too long to obtain reliable energy forecasts.

Therefore, legislation with ‘a posteriori’ methodologies is better for the members and would enable a higher REC penetration. At the same time ‘a priori’ legislation should evolve to shorter periods.

In the case of having an ‘a posteriori’ legislation, some specific CFs can achieve faster payback, while considering an equal return among the users, like CF2 and CF5. On the other hand, if a fast payback is combined with a limited dispersion among REC members the CF4 provides good results. These conclusions have been validated for different energy community sizes, from 30 up to 100 users, obtaining, in all cases, the same result.

This paper has considered the Spanish case based on its ‘a priori’ regulations, as it is one of the most representative cases in the EU. This case has inherent deviations between real energy consumption and forecast profiles. Also, in this scenario, CF5, which minimizes the squared costs, as in the ‘a posteriori’ case, provided a better performance as it is less affected by forecast errors. Moreover, since the CF is quadratic, it has proven to provide more reliable results, as the span of the optimization solutions covers a wider range of self-consumption coverage. This conclusion has also been scaled to other community sizes, which confirms these results.

In summary, this paper proposes an improvement for ‘a posteriori’ with CF5, prioritizing an equal distribution of the payback, and with CF4 ensuring the maximum overall saving while minimizing the payback dispersion. The improvements proposed are more significant in ‘a posteriori’, where the CF5 has better results since its non-linear behaviour.

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