OPTIMIZING ENERGY COMMUNITIES DESIGN AND SIZING FOR BATTERY OPERATION AND ENERGY TRADING

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ABSTRACT

Energy communities have proven to be a key enabler in managing distributed renewable production that involves citizens in the energy transition. While there are tools in the market to address the optimization of energy communities, there is a lack of design tools that comply with current legislation, which imposes significant restrictions such as pre-establishment of energy sharing coefficients to distribute the renewable production within the community. This paper presents the *Energy Community design optimization* solution, which consists of two combined tools: (1) *Energy trading optimization tool*, to calculate the optimal energy sharing coefficients, and (2) *Battery sizing tool*, to optimise the sizing and operation of a battery within the energy community to optimise the energy use. These tools are applied to the case study of La Balma energy community in Spain. The results show that more than half of the annual PV production is injected into the grid when no battery is considered, even if the energy sharing coefficients are optimised. On the other hand, the use of a battery improves the renewable utilisation factor from 45.42% up to 68.66%. The study is complemented by a simple economic analysis of the return on investment in a new battery.

Keywords: energy community, battery, design optimization, renewable production, modelling.

INTRODUCTION

Cities and buildings have a crucial role in the energy transition towards cleaner energy sources and a reduced carbon footprint as cities are responsible for more than two thirds of global energy consumption and more than 70% of carbon dioxide emissions (World Economic Forum, 2022). The number of self-consumption installations in cities and buildings, especially photovoltaic (PV) systems, have increased significantly in Europe during the last few years (International Energy Agency, 2023). This implies that consumers are becoming prosumers, which poses some challenges such as the integration of distributed energy sources and storages. One of the main solutions to address this challenge is the Energy Communities (EC) (Kojonsaari & Palm, 2021). An EC is a legal entity which is based on voluntary and open participation, effectively controlled by its users who are natural persons, cooperatives, local authorities, or small- and microenterprises (European Parliament, Council of the European Union, 2018). EC users play an active role in producing, consuming and sharing energy to meet community-level objectives such as maximising community self-consumption through on-site renewable production, reducing grid dependency or minimising overall energy cost (European Commission, 2024). For the design and operation of ECs, advanced energy management solutions are required, including tools for optimally 1) sizing the renewable energy production & storage system (mainly, batteries), and 2) establishing how the surplus energy should be shared among the EC users (Papadimitriou et al., 2023). Some examples can be found in the literature. (Faria, Marques, Pombo, Mariano, & Calado, 2023) develops an optimal sizing solution for the production and battery within an

EC, (Sousa et al., 2023) focuses on the design to support investment decisions and (Zanvettor, Casini, & Vicino, 2024) focuses on the design of the optimal operation of the storage units. These studies present tools framed in a dynamic market context, which implies that the energy flows within the EC are determined at real-time depending on the production and demand (Cruz-De-Jesús, Martínez-Ramos, & Marano-Marcolini, 2022). However, current legislation framework in Europe is more restrictive in this sense. In countries such as Spain, Italy or France, static energy sharing coefficients need to be predefined in advance to regulate the energy distribution within the community (Gruber, Bachhiesl, & Wogrin, 2021). In consequence, the utilisation of the renewable energy locally produced will depend on the value assigned to the coefficients. However, there is a lack of tools focusing on this specific current legal scenario in which energy sharing coefficients need to be defined in advance to the operation (Ahmed, Ali, & D'Angola, 2024).

This work proposes an EC design tool that complies with the current Spanish legislation, which can be extended to countries with a similar legal framework for EC. The proposed tool calculates the optimal energy sharing coefficients and studies the advantages of integrating a battery to significantly improve the utilisation factor of the PV system, minimising the negative effect of the mismatch between production and demand due to both renewable intermittency and the stationarity of the energy sharing coefficients.

METHOD

The proposed *Energy Community design optimization* solution consists of two tools:

- The *Energy trading optimization tool*, which calculates the energy sharing coefficients to establish the distribution of PV production among the users. These coefficients are determined to minimise the excess PV production that is not self-consumed within the community.
- The *Battery sizing tool*, which calculates the optimal capacity of the battery and its operation in order to maximise the self-consumption and avoid excess PV production.

The excess PV production concept used in this paper refers to the PV production that is not utilised by the EC members and needs to be injected into the grid.

The configuration of the *Energy Community design optimization* is presented in Figure 1. The inputs for both tools are the hourly PV production profile for a year and the hourly consumption profile for each consumer.

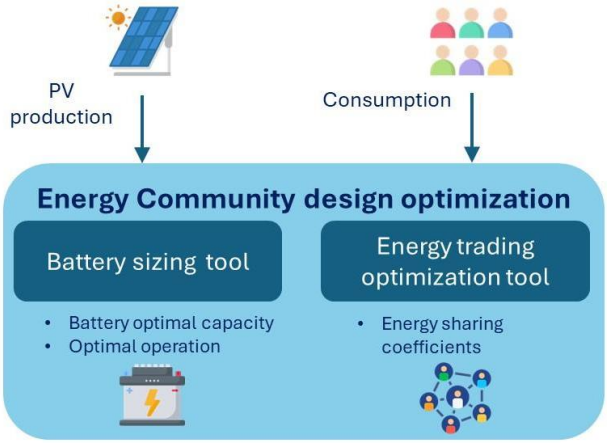

Figure 1: Energy Community design optimization: component tools and inputs.

The global optimization (minimization of the energy injected into the grid) is disaggregated into two simpler optimization problems instead of considering the whole design together, dividing the solution into two tools. This makes the solution more scalable for EC with a high number of users. Solving the original global problem implies clustering optimization for the sharing coefficient calculation and dynamic optimization for the battery sizing which may pose an intractable problem for cases with many users.

Energy trading optimization tool

The *Energy trading optimization tool* aims at calculating the energy sharing coefficients of each consumer that maximise the self-consumption of the locally produced energy, that is, minimise the excess PV production that is not consumed within the community and is injected into the grid. The energy sharing coefficients are calculated subject to the current Spanish legislation that allows, in the more flexible scenario, the definition of hourly energy sharing coefficients for the consumers along the year. Consequently, 8.760 values need to be defined in advance for the whole year, and for each user.

The optimization is performed using historic consumption and production data for a whole year. As a first step, the days of each month are clustered by identifying days that have similar consumption patterns for each user. Then, the energy sharing coefficients are calculated for these clustered days. This approach reaches a trade-off between a generic solution in which a unique energy sharing coefficient is defined for each user for the whole year, and a model with a minimum of generalisation with energy sharing coefficients calculated for each hour of the year. In this last case, the model will adjust perfectly accurately for the year of data used for the design, but it will be overfitted and result in a poor extrapolation when other years are considered. In addition, the proposed approach results in a simplification of the optimization problem as the number of optimization variables is reduced.

The clustering process is conducted considering the following assumptions: 1) it is performed for every month assuming that the difference in consumption between days of the week are due to circumstantial factors and not due to significant changes in users' behaviour, 2) the energy sharing coefficients are calculated only for the hours with PV production, which are updated every month, and 3) the maximum number of clusters each month is eight (corresponding to the days of the week and a holiday) and the minimum is two.

The days of the year are classified according to the day of the week, additionally indicating the regional holidays. The clustering of the days is conducted using the *K-means* method, and it is applied for each consumer independently and for each month of the year. The optimal number of clusters for each consumer and month is identified through the *silhouette coefficient* technique, which checks the distance between the clusters and the distance of the points within the cluster to the centre, assigning a score that can be compared to different clustering groups. The optimal clusters identified for each consumer and month are combined, determining the resulting clusters that need to be considered in the EC and associating energy sharing coefficients for each of them. The total number of clusters will be between 24 (a minimum of two clusters for each month) and 96 (a maximum of eight clusters each month).

Once the days are clustered, the optimization problem is solved to determine the energy sharing coefficients, that is, the decision variables. The optimization is defined by the group of equations (1):

$$\min_{\alpha} P_{exc}^{PV}(\alpha) \;\; where\; \alpha = [\alpha_0, \dots, \alpha_N] \tag{1.a}$$

subject to:

$$P_{exc}^{PV}(\alpha) = P_{pro}^{PV} - C_{self}^{cons}(\alpha) \tag{1.b}$$

$$0 \leq \alpha_i \leq 1 \tag{1.c}$$

$$\sum_{i=1}^{N} \alpha_i(t) = 1 \;\; for\; t = 0, \dots, 8760h \tag{1.d}$$

where $P_{exc}^{PV}(\alpha)$ represents the total excess PV production in the EC, α denotes the energy sharing coefficients for the N total number of users in the EC, P_{pro}^{PV} is the total PV production and $C_{self}^{cons}(\alpha)$ refers to the total self-consumption coming from the PV production. Eq. (1.a) represents the objective function to be minimised in the optimization problem. Eq. (1b) is an equality constraint that defines how the excess PV production is calculated. The energy sharing coefficients' limits are established through the inequality constraints in eq. (1.c). Finally, an additional equality constraint is included through eq. (1.d) to assure that the sum of all the coefficients at each hour is equal to 1. The objective function is linear, as well as all the equality and inequality constraints, resulting in a Linear Problem (LP). The optimization problem is implemented and solved using the GEKKO framework in Python (Beal, Hill, Martin, & Hedengren, 2018).

Battery sizing optimization tool

There exist two sources of mismatch that cause that the entire PV production is not self-consumed in the EC: (1) the production hours of the PV system do not match the consumption hours, and (2) the hourly energy sharing coefficients do not assure that all the PV production is consumed, even if there is enough demand. As the hourly energy sharing coefficients need to be predefined in advance, once they are applied, they may allocate a PV production for a consumer with a lower demand, generating an excess PV production for that user that is not utilized and is injected into the grid. The proposed solution to avoid this mismatch and improve self-

consumption is the use of a battery to shift the total energy load for the EC. The *Battery sizing tool* calculates the optimal operation of a given battery, considering all the energy and economic flows. This operation tool can be used for design purposes by modifying the battery capacity (in terms of energy and hours for full charge/discharge) and other characteristics.

The model integrated into the optimization tool considers the following components: *grid*, *producer* (PV production), *storage* (battery) and *consumers*. An energy balance is performed in each component, establishing the connections among all of them. These connections can be removed depending on the considered scenario. The connection between the storage and the grid represents the option to use the battery for arbitrage.

The key component to model is the storage, in this case, an electric battery. First, an energy balance in the battery is formulated in equation (2).

$$\frac{dE_{bat}}{dt} = \eta_c \cdot P_{in}^{bat} - \frac{P_{out}^{bat}}{\eta_d} \quad (2)$$

where P_{in}^{bat} is the power entering the battery, P_{out}^{bat} denotes the power discharged by the battery, η_c is the charging efficiency and η_d the discharge efficiency.

The state of charge (SOC) represents the available normalized energy accumulated in the battery and is calculated as the percentage of accumulated energy based on the battery's nominal capacity (Waag & Sauer, 2009). Equation (3) represents the SOC calculation.

$$SOC = \frac{E_{sto}^{bat}}{C_{bat}} \cdot 100\% \quad (3)$$

where E_{sto}^{bat} is the stored energy in the battery and C_{bat} is the energy capacity of the battery. The SOC constraints are defined in equation (4):

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (4)$$

where SOC_{max} represents the upper limit of SOC that is defined to avoid reaching a 100% charge that would derive into high operation temperatures that favor degradation. On the contrary, SOC_{min} denotes the lower limit, called the *depth of discharge*, that is defined by the manufacturer.

An additional constraint is introduced in eq. (5) to limit the number of daily battery cycles:

$$n_{cyc}^{day} \leq n_{cyc}^{max} \quad (5)$$

Where n_{cyc}^{day} are the daily number of cycles that the battery conducts, and n_{cyc}^{max} is the maximum limit, defined by the manufacturer. The cycle of the battery n_{cyc} is calculated according to equation (6):

$$n_{cyc} = \left[\frac{d(\eta_c \cdot P_{in}^{bat})}{dt} - \frac{d\left(\frac{P_{out}^{bat}}{\eta_d}\right)}{dt} \right] / 2 \quad (5)$$

Finally, the battery degradation is also introduced, which is defined as a percentage of capacity loss per year. This is applied proportionally during the year simulation and introduces a loss x in equation (2) when the different simulation points are considered.

The *Battery sizing tool* includes an optimal operation for the battery, which is built using a Model Predictive Control (MPC). The objective function of the MPC is defined in equation (7), and the constraints are eq. (2-6).

$$\min E_{grid}^{PV}(C_{bat}) \quad (7)$$

Where $E_{grid}^{PV}(C_{bat})$ is the PV production that is not stored or consumed and is sent to the grid. This assures that the self-consumption is maximized.

In this case, the proposed optimization problem is nonlinear. It is solved for a whole year, considering a prediction horizon for the MPC.

Assessment indicators for comparison

The objective of the EC design is to optimally exploit the PV production and minimise the excess PV production that is not utilised within the EC. The Key Performance Indicator (KPI) used for assessing the results is the **on-site renewable energy utilisation factor (RUF)**. This indicator refers to part of the renewable energy produced locally that is used by the EC, either directly from the PV system (instantly used) or the battery (stored and used a posteriori). The RUF is calculated as the ratio of renewable energy produced and used or stored on-site along the considered timeframe, and the renewable energy produced in the same timeframe. The on-site RUF shall be calculated using equation (8):

$$RUF = \frac{E_{REU} + E_{ETS}}{E_{REP}} \quad (8)$$

where E_{REU} is the total renewable energy produced and used to cover a final energy use, E_{ETS} is the total renewable energy produced and stored, and E_{REP} accounts for the total renewable energy produced on-site.

Case study description

La Balma is a housing cooperative in Poblenou (Barcelona, Spain). It was established as a Citizen Energy Community in 2023, with the aim of promoting the consumption of renewable energy in the community, while reducing dependence on large electric utilities. The installation has 31 panels of 560Wp, giving a total capacity of 17.36kWp. This is divided into 9.52kWp used for consumption in the common areas of the building, and 7.84kWp to be shared between the 20 co-livings that confirm the EC. The PV production data is estimated using PVGIS (European Commission, 2024), and the historic consumption data from 2023 for each user is obtained from (DATADIS, 2024).

The *Energy Community design optimization* is used in this case study using the approach shown in Figure 2. The design of the EC is conducted considering as the aim to maximize the self-consumption of the PV production. The battery is not allowed to do arbitrage for the current case study to focus on the use of energy inside the community. The steps of the case study can be summarised as:

(1) Optimised scenario: battery sizing. The *Battery sizing tool* is used to determine the optimal capacity of the battery to minimise the excess PV production that is not utilized. For that, the results from the baseline scenario are used, as indicated in Figure 2: the excess PV production that is not utilised in the EC and that can still be used to cover the demand is considered as the available production, and the grid consumption from the baseline scenario is the consumption to be covered in this scenario by the PV system or battery systems. A first simulation is performed assuming an unlimited energy and power capacity for the battery, and the resulting maximum charge energy is determined. Then, discretized values of battery capacity are defined and simulated based on it, and the RUF is calculated for each battery size.

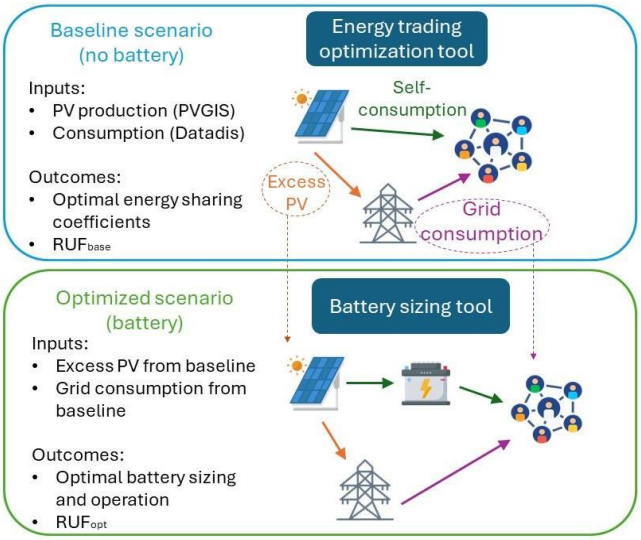

Figure 2: Case study approach to optimise La Balma EC design and operation.

(2) Analysis of the scenario with the optimal battery. Once the optimal battery capacity is selected from step 2, the whole system is simulated considering the battery operation and how the PV production directly consumed, and the PV production stored in the battery are shared among the users. Two possibilities are simulated: (1) an ideal scenario in which the available energy stored in the battery can be distributed among users without having to apply the energy sharing coefficients and (2) a scenario in which the energy sharing coefficients are also applied at the battery outlet. The RUF for each scenario is calculated: $RUF_{bat,ideal}$ and $RUF_{bat,EC}$ respectively.

(3) An economic feasibility study is performed. For that, the return of investment (ROI) is calculated for selected scenarios. The ROI is accounted using equation (9), considering that the energy saved by the storage is self-consumed.

$$ROI = \frac{Pr_{net}}{I} = \frac{E_{saved} \cdot p_{€} - I}{I} \quad (9)$$

Pr_{net} is the net profit, which is calculated as the difference between the revenue and the investment I. The revenue accounts for the cash received, which is computed considering the energy saved E_{saved} and the purchase price of electricity $p_{€}$.

For the *Battery sizing tool*, the following assumptions are taken to define the battery parameters based on values provided by La Balma suppliers: the battery degradation each year is 1.5%, the charge efficiency is 93%, the discharge efficiency is 95% and the discharge depth is 95%. For the economic feasibility study, the battery investment is considered to be of 600€/kWh and a purchase price of 0.15€/kWh. In addition, a financing aid of 35% of the initial price is considered.

RESULTS AND DISCUSSION

The baseline scenario is optimised and simulated considering the optimal energy sharing coefficients and no battery in the EC. Figure 3 shows the PV production that is self-consumed and the excess PV production that is injected into the grid each month as a total in the EC. Each bar represents the total PV production.

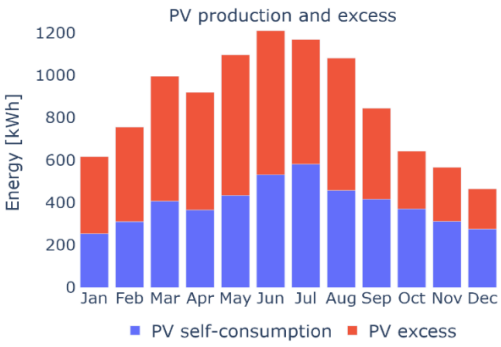

Figure 3: PV self-consumed, and excess PV production not utilised in the community.

Figure 3 shows the excess PV production that is not utilised throughout the whole year, ranging from 41% to 60% depending on the month.

Figure 4 represents the grid consumption of each user in the EC and the associated excess PV production to each user, understood as the assigned PV production to that user that is not utilised.

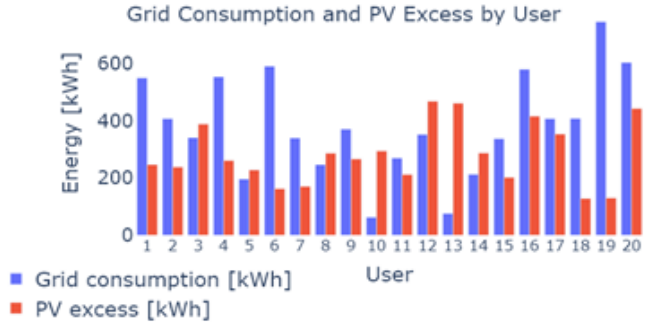

Figure 4: Grid energy and excess PV production by user.

Figure 4 provides evidence that there is an important mismatch due to the energy sharing coefficients: all users consume from the grid, but there is an excess PV production that is not used by all of them. This justifies the use of a battery to better match the production and demand. Table 1 presents a summary of the yearly total consumption in the EC, indicating how much is consumed from each source.

Table 1: Yearly energy consumption, PV production and renewable utilisation factor in the EC.

Yearly EC consumption	18.03 MWh
Yearly PV production	10.37 MWh
Yearly EC self-consumption	4.71 MWh
Yearly grid consumption	13.31 MWh
Yearly EC excess PV production	5.65 MWh
RUF_{base}	45.42%

The RUF_{base} indicates that more than half of the PV production is not consumed by the EC and is sent to the grid. This indicator shows the limitation of having to settle hourly energy sharing coefficients.

The optimised scenario considers a battery. A first optimization is performed without any limitation for the battery capacity for neither the energy storage nor the discharge power, which results in an optimal charging profile that establishes that a battery with an approximate capacity of 50kWh would improve the RUF to almost 100%. Based on this, a set of discretized capacities of the battery are optimized and simulated. The calculated RUF for the ideal and restrictive EC scenarios are plotted together with the baseline RUF as a function of the battery capacity in Figure 5.

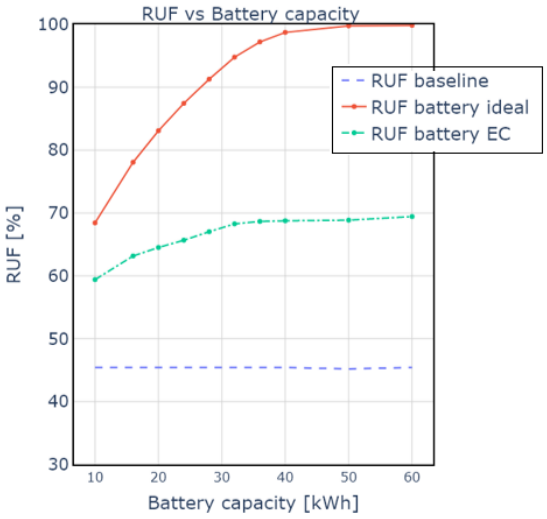

Figure 5: Evolution of the RUF with battery capacities.

Considering an ideal scenario, the integration of a battery above 40kWh would result in a RUF close to 100%. However, if the energy from the battery is distributed according to the energy sharing coefficients, the RUF is considerably reduced and the difference of RUF depending on the battery capacity is not so different. A battery with a capacity of 10kWh results in a RUF of almost 60%, while for a capacity of 36kWh it increases up to almost 70%. These two scenarios are compared in detail in Table 2.

Table 2: Yearly consumption metrics for a battery of 10kWh and a battery of 36kWh.

Battery capacity	**10kWh**	**36kWh**
Yearly EC consumption	18.03 MWh	
Yearly PV production	10.37 MWh	
Yearly self-consumption	6.16 MWh	7.12 MWh
Yearly grid consumption	11.87 MWh	10.91 MWh
Yearly excess PV prod.	4.21 MWh	3.25 MWh
$RUF_{bat,ideal}$	68.43%	97.22%
$RUF_{bat,EC}$	59.40%	68.66%

It is important to notice that when considering an ideal scenario, the RUF differs significantly depending on the battery capacity. On the contrary, the change in the RUF for the two battery capacities is smaller in the other scenario.

Finally, the economic feasibility of these two scenarios is studied. Table 3 represents the return of investment for the purchase of a battery of 10kWh and 36kWh.

Table 3: ROI of 10kWh and 36kWh battery.

Battery of 10kWh			
Year	**Revenue**	**Net profit**	**ROI**
1	352.56€	-3547.44€	90.96%
5	2037.60€	-2189.30€	56.14%
10	3296.89€	-603.11€	15.46%
12	3898.56€	-1.44€	~0%
Battery of 36kWh			
Year	**Revenue**	**Net profit**	**ROI**
1	735.56€	-14.864.44€	95.28%
10	6909.41€	-8690.59€	55.71%
20	12916.59€	-2683.41€	17.20%
25	15622.11€	22.11€	~0%

In the case of the 10kWh battery, it takes 12 years to recover the investment. For the battery of 36kWh, the revenues are more relevant than for the 10kWh battery, but as the investment is also higher, the ROI increases up to 25 years. In consequence, even if the battery of 36kWh could be considered as the best solution from the technical point of view (it has a higher RUF), it is not economically interesting. The battery of 10kWh trades off RUF improvement against ROI. The ROI of the 10kWh battery is 12 years, close to 10 years which is usually considered convenient for batteries.

The battery technically presents a solution to better exploit the RES production in an EC and improves the RUF. However, the economic feasibility of the solution is more uncertain at this moment (due to high costs of battery projects) and depends on the financing aid. For the case study, 35% of financing aid was considered, which is a standard figure in the market of the EC, La Balma. Nevertheless, this may not be the case for other markets. A key aspect for enhancing economic viability is the optimisation of the battery sizing and operation. This includes leveraging the battery for arbitrage, thereby capitalizing on variable electricity market prices and increasing the revenues.

CONCLUSIONS

Energy communities have emerged as a solution to favour the integration of RES at local level and actively involve citizens in the energy transition. Current legislation in many European countries requires pre-establish energy sharing coefficients to systematically share the locally produced energy among the community's users. This paper presents a tool to optimise the design and operation of an EC, which is simulated for La Balma EC in Spain. When considering the scenario of the EC without a battery and optimising the energy sharing coefficients, there is a large mismatch between PV production and demand, further increased by the limitation of the sharing coefficients that does not allow readjustment according to the real hourly demand of each user. Consequently, the RUF for this scenario is around 45%. This indicator can ideally be improved up to 100% if the restriction of sharing coefficients at the battery output is not considered, and almost 70% when including it. Finally, an economic feasibility study is presented, giving a solution that balances the technical and economic optimum.

FUTURE WORK

As a preliminary verification, the same dataset was used for design and simulations for performance assessment; next steps will include more rigorous cross-validation with new data to enhance robustness and optimize PV production. Future work will explore the potential of the battery to complement the use of locally produced RES. To this end, it will be considered that the battery can arbitrage with the grid and take advantage of variable prices of the electricity market. For this purpose, the *Battery sizing tool* will be adapted to optimise the design and operation of the battery not only based on energy objectives but also with economic goals. Future research will study how these arbitrage capabilities can reduce the ROI of battery integration in an EC.

ACKNOWLEDGEMENTS

This work has been developed in the context of the project *'DE-RISK the adoption of Local Flexibility Markets to unlock the safe and reliable mass deployment of Renewable Energy Systems (DE-RISK)*', which has received funding from European Union's Horizon EUROPE Programme under **grant agreement No. 101075515**.

REFERENCES

(2018). *Directive (EU) 2018/2001 of the european parliament and of the council of 11 december 2018 on the promotion of the use of energy from renewable sources (recast) (text with EEA relevance.)*

Faria, J., Marques, C., Pombo, J., Mariano, S., & Calado, M. D. R. (2023). *Optimal sizing of renewable energy communities: A multiple swarms multi-objective particle swarm optimization approach* MDPI AG. doi:10.3390/en16217227

Gruber, L., Bachhiesl, U., & Wogrin, S. (2021). The current state of research on energy communities. *E & i Elektrotechnik Und Informationstechnik, 138*(8), 515-524. doi:10.1007/s00502-021-00943-9

International Energy Agency. (2023). *Renewables 2023*

Kojonsaari, A., & Palm, J. (2021). *Distributed energy systems and energy communities under negotiation* Springer Science and Business Media LLC. doi:10.1007/s40866-021-00116-9

Papadimitriou, C., Di Somma, M., Charalambous, C., Caliano, M., Palladino, V., Cortés Borray, A. F., et al. (2023). *A comprehensive review of the design and operation optimization of energy hubs and their interaction with the markets and external networks* MDPI AG. doi:10.3390/en16104018

Sousa, J., Lagarto, J., Camus, C., Viveiros, C., Barata, F., Silva, P., et al. (2023). Renewable energy communities optimal design supported by an optimization model for investment in PV/wind capacity and renewable electricity sharing. *Energy, 283*, 128464. doi:10.1016/j.energy.2023.128464

Waag, W., & Sauer, D. U. (2009). SECONDARY BATTERIES – LEAD– ACID SYSTEMS | state-of-charge/health. In J. Garche (Ed.), *Encyclopedia of electrochemical power sources* (pp. 793-804). Amsterdam: Elsevier. doi:10.1016/B978-044452745-5.00149-0

World Economic Forum. (2022). *These are the world's most sustainable cities*

Zanvettor, G. G., Casini, M., & Vicino, A. (2024). *Optimal operation of energy storage facilities in incentive-based energy communities* MDPI AG. doi:10.3390/en17112589