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ECoSIM: Decision support system for energy communities

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Abstract. This paper introduces ECoSIM, a decision support simulator designed to assist the planning and optimization of Energy Communities (ECs). ECoSIM integrates a multi-objective optimization model to support communities to determine the optimal configurations for their local renewable energy systems (RES). The simulator considers three decision variables: photovoltaic (PV) rated power, wind turbine (WT) rated power, and battery energy storage system (BESS) capacity. Through the optimization model, these variables are optimized based on the community-specific parameters such as community type (residential or mixed), number of members, and total annual energy demand (including electric heating, cooling and electric transportation). The optimization process models the energy, economic and environmental goals of the community through multiple objective functions as follows: maximizing self-sufficiency, cost savings, self-consumption and minimizing the payback period. By enabling trade-off analysis among conflicting objectives, ECoSIM assists communities to make informed and sustainable investment decisions that balance energy, economic and environmental goals. Preliminary results demonstrate the performance of the decision support system to find the best optimal solution for ECs within budget and technical constraints, aiming to accelerate the adoption of decentralized energy systems through customized, data-driven planning.
Keywords: Energy Communities; Decision support systems; multi-objective optimization; differential evolutionary optimization; Renewable Energy Systems.

1. Introduction

The transition towards low-carbon and decentralized energy systems has led to the growing interest in Energy Communities (ECs) as a viable and sustainable alternative to conventional energy supply models. Energy Communities empower consumers and prosumers who also generate electricity, to collectively invest in and manage renewable energy sources (RES), such as solar photovoltaic (PV) and wind power, supported by energy storage systems. By enhancing local energy self-sufficiency, reducing reliance on centralized grids, and creating cost-effective solutions, ECs have the potential to contribute significantly to the decarbonization of the energy sector and to increase resilience at the local level. However, the design and operation of ECs pose multiple challenges, particularly related to optimal resource sizing, investment planning, and ensuring a balance between technical performance and financial viability.

To support the planning and decision-making process for EC deployment, this paper proposes a simulation-based optimization framework that models the load and generation profiles of the community based on weather conditions, evaluates the technical and economic performance, and identifies the optimal configuration of PV rated power, wind turbine, and the capacity of the energy storage systems. The proposed framework is implemented as an interactive web-based simulator, ECoSIM, that integrates weather data, tariff schemes, community preferences and generates consumption profiles. A multi-criteria optimization approach is used to balance key objectives such as self-sufficiency, self-consumption, cost savings, and payback period. The methodology is applied to a case study in Constanța, Romania, demonstrating how digital tools facilitates the creation of energy-resilient communities.

2. Literature review

A systematic literature review on the concept of energy communities was performed (de São José et al., 2021) using six databases and carefully selected keywords. It found that overlapping definitions created confusion among researchers and readers, highlighting the need for standardized terminology. The review also emphasized the importance of studying synergistic improvements in multi-purpose energy communities and exploring energy islands as models for developing adaptable solutions for land-based communities. Also, (Kubli & Puranik, 2023) conducted a morphological analysis of 90 energy communities and pioneering companies to explore business model design options applicable to energy communities. It identified 25 emerging design options and developed a typology that supports the configuration of tailor-made business models. The analysis showed potential for further development of energy communities and contributed to the literature by offering one of the first business model perspectives through a morphological approach, providing a practical tool for community developers.

Another research aimed to enhance understanding of the social arrangements, technical designs and impacts of energy communities (Gjorgievski et al., 2021). It discussed the roles and interactions of different actors, reviewed the technical design of local energy systems based on community goals and benchmarked the literature by methods, modelling objectives, and design constraints. Furthermore, (Dudka et al., 2023) analyzed 164 French energy communities to examine how increasing involvement of businesses and state authorities has impacted citizen engagement. It identified four configurations of energy citizenship: full citizen ownership, shared citizen ownership, citizen crowdfunding, and civic participation. The results showed that strong citizen engagement and community logic remained dominant across the models.

Additionally, (Ahmed et al., 2024) reviewed the shift from centralized to decentralized energy systems, emphasizing the role of renewable energy communities (RECs) in advancing local resilience, efficiency, and carbon neutrality. It highlighted the European Union's support for energy communities and explored the global progress, benefits, and key activities of RECs. The review found varying levels of adoption across countries and identified challenges alongside recommendations to support REC growth. Another research conducted an economic feasibility analysis of energy communities considering two investment options: third-party investment and self-investment by households, along with various cost allocation methods (Li & Okur, 2023). An optimization model was developed to determine the optimal operation of the energy community. The results showed that third-party investment was economically feasible under appropriate energy prices and payback periods, with the highest profits achieved at a 15-year payback time. Households, however, benefited more from joint self-investment despite the high initial costs. The research highlighted that energy costs for households were significantly influenced by payback time and cost allocation methods, providing valuable insights for investment and cost-sharing decisions.

Also, (Petrovics et al., 2024) examined the scaling of energy communities by analyzing 28 cases using a fuzzy set Qualitative Comparative Analysis (QCA). It identified eight necessary conditions or combinations of conditions that support actionable scaling mechanisms. The research provided concrete insights for policymakers on the types of capacity support, structures and tools needed to connect and expand energy communities. By empirically identifying crucial leverage points, the article contributed to strategies for upscaling the impact of energy communities, positioning them as a key component in global climate governance. Moreover, (Bielig et al., 2022) analyzed the social impact of Energy Communities in Europe by clarifying key concepts such as community empowerment, social capital, energy democracy and energy justice. A systematic literature review was conducted, and an evidence gap map was developed to classify existing studies by methods and constructs measured. The findings revealed a lack of rigorous evidence, particularly from quantitative, experimental, longitudinal and counterfactual studies.

A novel modeling framework to support energy systems planning for remote communities was proposed (Quitoras et al., 2021) by incorporating decision-maker attitudes toward multiple uncertainties and energy solution philosophies. Using a multi-objective optimization approach, the study evaluated various configurations to minimize the levelized cost of energy and fuel consumption, with a case study in the Northwest Territories, Canada. The inclusion of uncertainties reduced the renewable energy penetration from 69% to 51% and increased diesel consumption. The analysis also demonstrated that retrofitting building enclosures could significantly lower heating demand. The study provided actionable recommendations to enhance energy security, affordability and sustainability, while supporting Indigenous-led energy initiatives. Moreover, (Fangjie et al., 2022) proposed a multi-objective optimal scheduling model for community integrated energy systems under uncertainty and demand response constraints. It developed a source-load uncertainty model, a comprehensive demand response model, and constructed satisfaction and utility models based on supplier profit, resident cost, carbon treatment and renewable energy use. Using the entropy weight method and Muirhead mean operator, the best strategy was determined. Case studies showed improved robustness, a 7.59–9.84% reduction in resident cost, a 17.71–95.64% reduction in carbon treatment and increases in supplier profit and renewable energy use.

3. Materials and methods

The main objective of the simulator is to provide decision support for creating and developing Energy Communities. Thus, the proposed methodology provides a framework that collects input data, requirements, models the load and generation profiles, optimizes the rated power of the PV and wind systems, including the storage capacity and finally, assesses the energy sufficiency and financial viability of the results. Figure 1 depicts the steps of the methodology that are described in the following subsections.

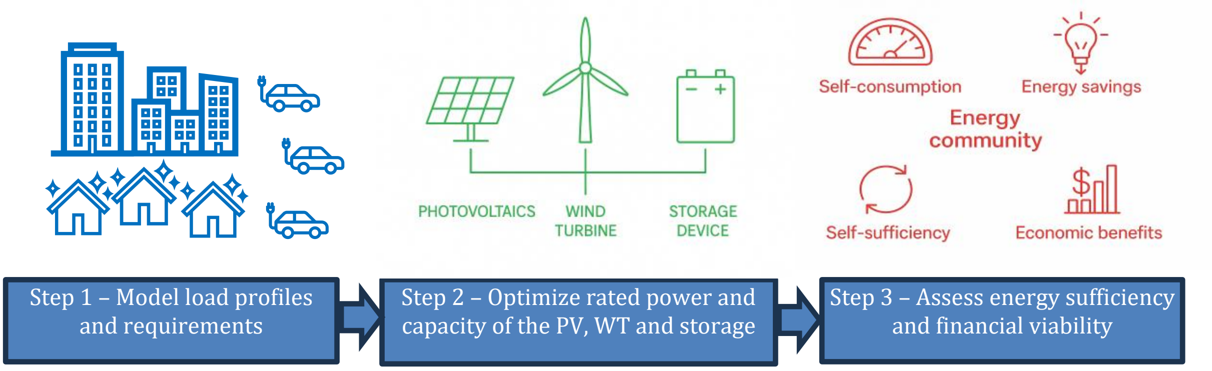

Figure 1. Steps of the proposed methodology

3.1. Modelling EC profiles and requirements

For creating energy communities, the following aspects related to the electricity consumption should be considered: size and structure of the community (number of members, type of members – residential, commercial, public or industrial consumers), typical load curves, load requirements (public consumption, individual consumption, heating and cooling, EV transportation), electricity tariffs (Time of Use – ToU and Feed-In Tariff – FiT). Also, budgetary constraints and restrictions related to the available surface for installation of the PV and wind turbines are modelled. Let's denote by m the number of members; C^t the total electricity load of the community for each time interval t; ToU^t, FiT^t the tariff rates for ToU and FiT; B_{RES} the maximum available budget for the initial investment in RES and by $Cost_{PV}, Cost_{WT}, Cost_{SD}$ the specific costs for PV, WT and storage systems, including equipment and installation. These input parameters are provided by the EC based on its requirements and consumption records. In case the load records with low granularity (t) are not available, the values can be estimated based on historical weather records extracted from the open weather APIs (for e.g., Open-meteo[1]) using eq. (1) and (2):

$$Lf^t = \min\left(1, (\mathrm{w}_0 + \mathrm{w}_1 \times |\mathrm{temp}^t - 20| - \mathrm{w}_2 \times sr^t + \mathrm{w}_3 \times \mathrm{ws}^t) \times \tau^t\right) \quad (1)$$

$$C^t = \frac{Lf^t}{\sum_t Lf^t} \times CT \quad (2)$$

Where: Lf^t – load factor; $\mathrm{w}_0, \mathrm{w}_1, \mathrm{w}_2, \mathrm{w}_3$- set of weights between 0.0005 and 0.01; temp^t – temperature; sr^t – solar radiation; ws^t – wind speed; τ^t- hourly multiplier; CT – total annual load of the community.

3.2. Optimize the rated power of the PV and wind turbine and the capacity of the storage system

A multi-optimization model is used to determine the optimum values of the rated power of the PV and WT and the capacity of the storage device. The decision variables of the model are set as follows: P_{PV} – rated power of the PV system; P_{WT} – rated power of the wind turbine; Cap_{SD} – capacity of the storage system. The aim of the community is to increase self-sufficiency and self-consumption to achieve energy independence or reduce as much as possible the grid dependence. Also, financial aspects are considered when creating an EC such as cost savings of the members and payback period of the initial investment. Therefore, the following objective functions are modelled:

O1: Self-sufficiency is determined as the ratio between the self-generated energy consumed locally and the total consumption of the community for each time interval. It expresses the degree of independence since a greater value indicates that the community mainly covers its load from the local generation.

$$\max SS = \frac{\sum_t \min(G^t, C^t)}{\sum_t C^t} \quad (3)$$

Where G^t represents the self-generated energy by the PV (G_{PV}^t) and WT (G_{WT}^t) and discharged by the storage device ($P_{SD,dis}^t$).

$$G^t = G_{PV}^t + G_{WT}^t + P_{SD,dis}^t \quad (4)$$

The potential energy generated by each subsystem is determined based on the weather records and deterministic models of the photovoltaics and wind turbines as described in (Oprea & Bâra, 2023), (Manwell et al., 2010) and summarized in the following equations:

$$G_{PV}^t = P_{PV} \times \eta_{STC} \times [1 + \gamma \times (T_{cell}^t - T_{STC})] \times \frac{sr^t}{sr_{STC}} \quad (5)$$

$$G_{WT}^t = \begin{cases} 0, ws^t < ws_{cin} \text{ or } ws^t < ws_{cout} \\ P_{WT} \times \left(\frac{ws^t - ws_{cin}}{ws_r - ws_{cin}}\right)^3, ws_{cin} \le ws^t \le ws_r \\ P_{WT}, ws_r \le ws^t \le ws_{cout} \end{cases} \quad (6)$$

Where:

- η_{STC} - efficiency under standard test conditions (STC), between 15% and 22%
- γ - temperature efficiency coefficient, between -0.004 to -0.005 per °C
- T_{STC} - standard temperature (25°C)
- T_{cell}^t - cell temperature (°C)
- sr^t - solar irradiation at time *t*
- sr_{STC} - solar irradiation under standard test conditions (1000 W/m²)
- ws_{cin} - minimum wind speed for wind generation (3 m/s)
- ws_r - wind speed for rated power (10 m/s)
- ws_{cout} - maximum wind speed for wind generation (25 m/s)

[1] https://open-meteo.com/

The operating model of the storage system is determined based on the SD capacity, rated power and surplus or demand in the community. For charging, $P_{SD,cha}^{t}$ is calculated as the minimum available power between the surplus (difference between the generated power and load), rated power and the remaining capacity of the SD.

$$P_{SD,cha}^{t} = \min\left(G_{WT}^{t} + G_{PV}^{t} - C^{t}, P_{SD}, \frac{SOC_{max} - SOC^{t}}{\eta_{SD}}\right), if\ G_{WT}^{t} + G_{PV}^{t} - C^{t} > 0 \quad (7)$$

Where:

- P_{SD} – rated power of the storage device considered as a fraction of its capacity
- SOC_{max} – maximum state of charge, around 97-98% of Cap_{SD}
- η_{SD}- charging/discharging efficiency, between 90 and 95%
- SOC^{t}- current state of charge (SOC) of the storage device

For discharging, $P_{SD,dis}^{t}$ is calculated as the minimum available power between the deficit (difference between the load and local generation), rated power and the available state of charge.

$$P_{SD,dis}^{t} = \min(C^{t} - G_{WT}^{t} - G_{PV}^{t}, P_{SD}, \eta_{SD} \times SOC^{t}), if\ C^{t} - G_{WT}^{t} - G_{PV}^{t} > 0 \quad (8)$$

O2: Self-consumption is defined as the ratio between the self-generated energy consumed locally and the total self-generated energy for each time interval. A greater value indicates that the energy is consumed locally, thus reducing the exported energy into the main grid.

$$\max SC = \frac{\sum_t \min(G^{t}, C^{t})}{\sum_t G^{t}} \quad (9)$$

O3: Cost savings of community is determined as the ratio between the savings of the members and the initial payment (before affiliation with the EC). The payment of the community is calculated as the difference between the cost of energy consumed from the grid and the revenue for the energy injected into the grid. The initial payment is calculated as the cost of energy consumed exclusively from the grid.

$$\max CS = \frac{\sum_t C^{t} \times ToU^{t} - \sum_t\left(\max(C^{t} - G^{t}, 0) \times ToU^{t} - \max(G^{t} - C^{t}, 0) \times FiT^{t}\right)}{\sum_t C^{t} \times ToU^{t}} \quad (10)$$

O4: Payback period is calculated based on the initial investment cost ($CapEx$) for the equipment and installation of the RES systems, including storage. This metric indicates the duration (years) necessary to recoup the initial investment, taking into account the total annual savings from self-consumption as well as the revenue generated from energy injected into the grid.

$$\min PB = \frac{CapEx}{\sum_t \min_t(C^{t}, G^{t}) \times ToU^{t} + \max(G^{t} - C^{t}, 0) \times FiT^{t}} \quad (11)$$

Where $CapEx = P_{PV} \times Cost_{PV} + P_{WT} \times Cost_{WT} + Cap_{SD} \times Cost_{SD}$

The following constraints are imposed on the optimization model:

C1: Surface constraints for PV and wind turbine installation. The size of the PV power plant and the WT should be less than or equal to the available surface for RES installation:

$$P_{PV} \times A_{PV/kWp} + P_{WT} \times A_{WT/kWp} \leq A_{RES} \quad (12)$$

Where $A_{PV/kWp}$ and $A_{WT/kWp}$ are specific areas for PV and WT per kWp and A_{RES} represents the maximum available surface for RES installation.

C2: Budget constraints. The initial investment cost for the RES components should be less than or equal to the available budget of the community:

$$P_{PV} \times Cost_{PV} + P_{WT} \times Cost_{WT} + Cap_{SD} \times Cost_{SD} \leq B_{RES} \quad (13)$$

C3: Operational constraints of the storage system. The current state of charge of the SD should be greater than or equal to a minimum SOC and less than or equal to its maximum SOC and the charging/discharging power should be less than the rated power of the SD:

$$SOC_{min} \leq SOC^{t} \leq SOC_{max} \quad (14)$$

$$0 \leq P_{SD,cha}^{t}, P_{SD,dis}^{t} \leq P_{SD} \quad (15)$$

Also, the following constraint is imposed to avoid simultaneous charging and discharging:

$$P_{SD,cha}^{t} \times P_{SD,dis}^{t} = 0 \quad (16)$$

For the decision variables the minimum bounds are set to zero and the maximum bounds are set based on the budget constraints.

The multi-objective model is transformed into a multi-criteria objective function that aims to maximize self-sufficiency, self-consumption, and cost savings, while minimizing the payback period. The term $PB/10$ normalizes the payback period to align the scale with other terms.

$$\min fobj = -\theta_1 \times SS - \theta_2 \times SC - \theta_3 \times CS + \theta_4 \times PB/10 \quad (17)$$

Where $\theta_1, \theta_2, \theta_3, \theta_4$ are weighing factors reflecting the relative importance of each objective.

The problem is solved using the Differential Evolution (DE) algorithm, a population-based, stochastic global optimization method suitable for non-linear, non-differentiable, and multi-modal objective functions. DE uses an iterative approach performing the following steps: i) mutation - donor vector is generated for each candidate by adding the weighted difference of two randomly selected population vectors to a third vector; ii) crossover - the donor vector is combined with the target vector to produce a trial vector; iii) selection - the trial vector replaces the target vector if it yields a better objective value. DE is a robust solver due to its ability to avoid local minima, and simplicity of implementation without the need for gradient information.

3.3. Assess the energy sufficiency and financial viability

To evaluate the optimization results and the viability of the EC project, several key performance indicators (KPIs) are calculated that reflect the self-sufficiency, energy independence and financial performance.

From the energy perspective, Grid Dependency Index (GDI) is calculated that quantifies the extent to which an energy community relies on electricity imported from the external grid. It is calculated as the ratio of imported energy to the total energy demand over a given period. A lower GDI indicates a higher degree of energy autonomy, while a higher value suggests greater dependency on the external power system.

$$GDI = \frac{\sum_t \max(C^t - G^t, 0)}{\sum_t C^t} \quad (18)$$

From the financial perspective, Net Present Value (NPV), Internal Rate of Return (IRR) and Return on Investment (ROI) are calculated to assess the financial viability of the EC project.

NPV is a financial metric that evaluates the profitability of an investment by calculating the difference between the present value of cash inflows and outflows ($CashFlow^t$) over the project's lifetime (T) adjusted with a discount rate (r). A positive NPV indicates a financially viable project.

$$NPV = -CapEx + \sum_{t=0}^{T} \frac{CashFlow^t}{(1+r)^t} \quad (19)$$

IRR is the discount rate at which the NPV of all cash flows (both incoming and outgoing) equals zero. It represents the project's expected annual rate of return and is used to assess investment attractiveness.

$$0 = -CapEx + \sum_{t=0}^{T} \frac{CashFlow^t}{(1+IRR)^t} \quad (20)$$

ROI measures the gain or loss relative to the initial investment cost, typically expressed as a percentage. It provides a simple indication of overall profitability.

$$ROI = \frac{\sum_{t=0}^{T} CashFlow^t}{CapEx} \times 100 \quad (21)$$

4. Results and discussions

The methodology is implemented as an online simulator called ECoSIM[2] developed in Python with Streamlit[3] that provides an easy interface to input data and visualize the results of the optimization model. For simulations, a mixed community with 100 residentials and 2 commercial consumers located in Constanta, Romania (latitude 44.177269 and longitude 28.652880) is considered, having an annual

[2] https://smart-optim-energy.ase.ro:80/ecosim/

[3] https://streamlit.io/

consumption of 250000 kWp. The community intends to switch from conventional heating/cooling to Heat Pumps (HP), therefore an average rated power of 7kWp/member is added to simulations and the operation of the HP are modelled based on the weather conditions. Also, several EV stations are added to allow members to charge their electric vehicles. The annual distance that needs to be covered by EV charging is set to 500000 km per year. The maximum budget is €150000 and the available surface for RES installation is 1000m^2. Based on the location of the community, historical weather records are extracted from the weather API and the load for each time interval is generated using eq. (1-2). The community intends to invest in a PV power plants and a storage system and uses the optimizer to determine the optimum values of the rated power and the SD capacity. The optimal PV rated power is 197.69 kWp and storage capacity is 323.23 kWh, obtained using DE algorithm by setting the weights of the objective function as follows: $\theta_1 = 0.5, \theta_2 = 0.2, \theta_3 = 0.2, \theta_4 = 0.1$. Figure 2 illustrates the hourly load profile of the community, including baseline consumption, HP consumption for heating/cooling and water heating, EV charging consumption. Between 8:00 and 16:00 the load is covered by the PV generation and after 16:00 until 2:00 the storage device covers between 50% and 20% of the demand.

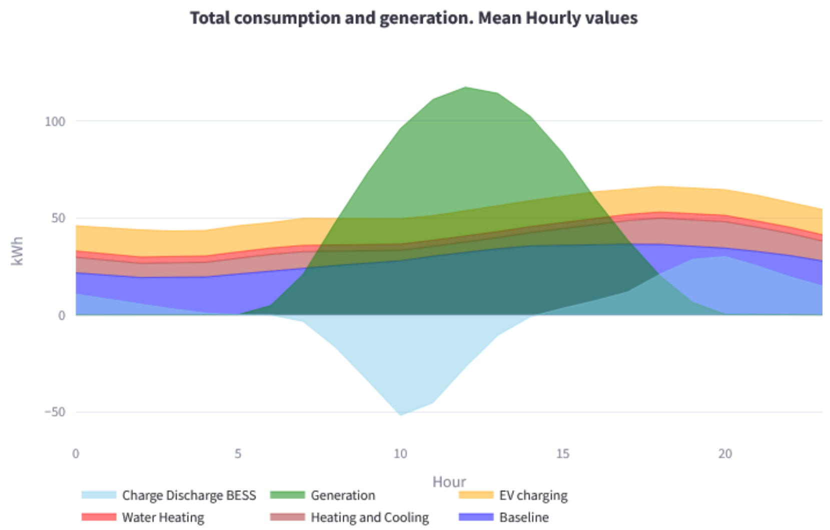

Figure 2. Hourly load profile and generation

In Figure 3, the energy distribution between self-generation, self-consumption, gird consumption and feed-in energy reflect a high self-consumption (71%) and a relatively moderate grid reliance (49%). There is room for optimization (shifting the consumption when the generation exceeds the demand) since the feed-in energy is 29% of the total generated energy.

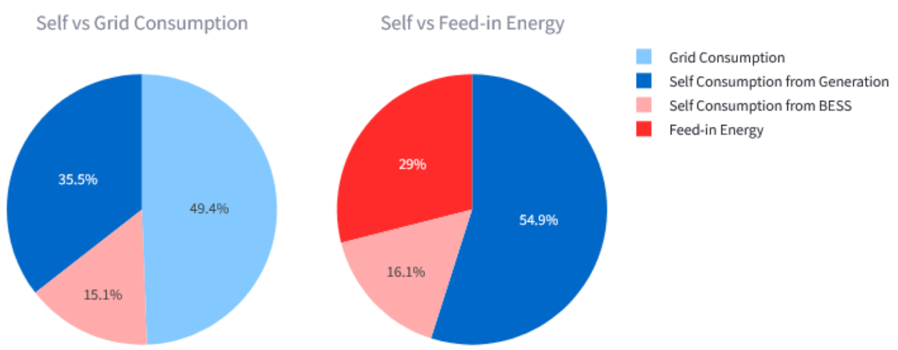

Figure 3. Energy distribution between self-consumption, gird consumption and feed-in

The monthly costs and revenues are depicted in Figure 4. The self-consumption revenue varies between €2000 and €3000 during winter months when the feed-in revenue is almost zero, increases up to €4500 during spring and autumn and exceeds €5000 in summer when the feed-in revenue increases up to €2000. The total payment of the community decreases from €8000 in winter months to -€2000 in summer months, when the community has a net revenue from feed-in energy.

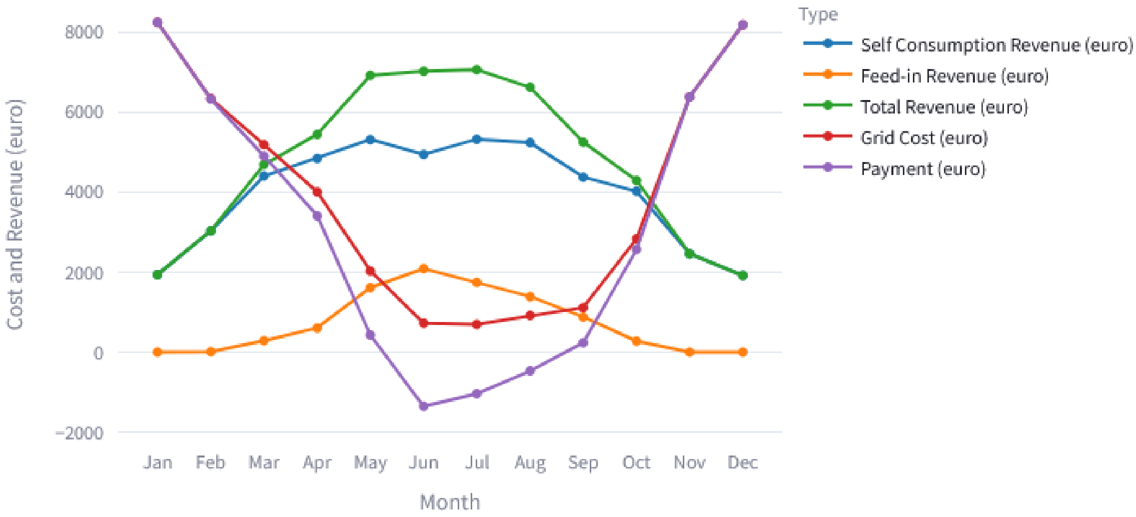

Figure 4. Monthly cost and revenue of the community

To assess the viability of the project, the KPIs are calculated, and Monte Carlo analysis is performed to evaluate the risks of the project for its lifetime of 25 years, considering a discount rate of 3%. The risk analysis is performed by varying the tariff rates with ±50%, the generation decrease with 35% due to degradation and the operational costs increase with 50%.

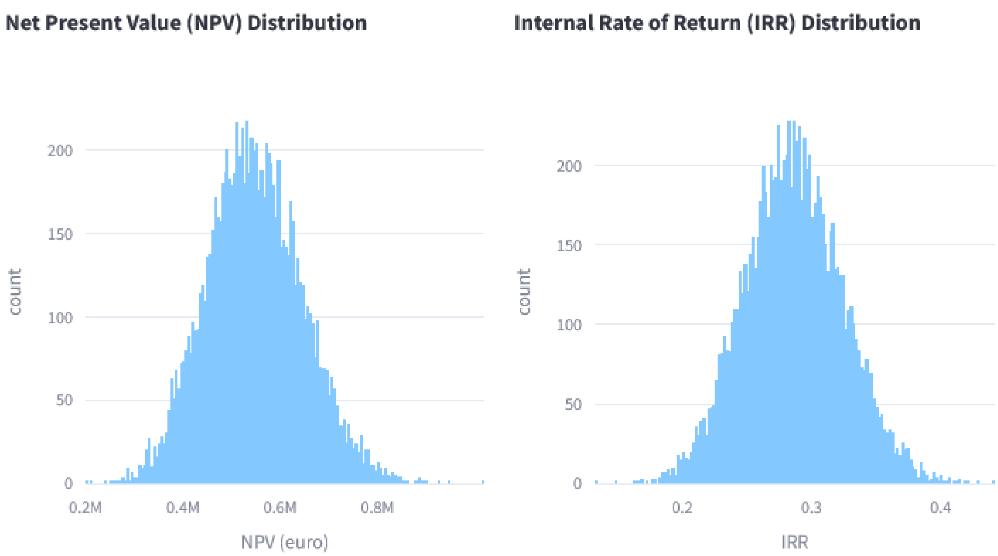

Figure 5. Monte Carlo analysis

In the case of NPV, the mean value is 548,459.54 € (5th percentile: 390,258.19 €, 95th percentile: 715,413.11 €). The project is financially viable, as the average NPV is positive. As for the IRR, the mean value is 28.66% (5th percentile: 22.53%, 95th percentile: 34.99%), indicating that the project is attractive, as the average IRR is higher than the discount rate.

The KPIs for the EC for the entire project lifetime are centralized in Table 1.

Table 1. KPIs for the EC project lifetime

KPI	**Value**
Self-Sufficiency (SS)	50.6%
Self-Consumption (SC)	71.0%
Grid Dependence Index (GDI)	49.4%
Cost Savings (CS)	59.9%
Net Present Value (NPV)	€680591
Internal Rate of Return (IRR)	70.88%
Payback Period (PB)	1.4 years
Return on Investment (ROI)	1676.39%
Initial payment per member	Residential €471.5
	Commercial €23573
Final payment per member	Residential €188.7
	Commercial €9433

The energy community achieves a self-sufficiency rate of 50.6%, meaning that over half of its electricity demand is met by local generation (PV and discharging of the SD), while the self-consumption rate of 71.0% indicates efficient utilization of generated energy within the community. A GDI of 49.4% reflects a moderate reliance on the external grid, in line with the achieved self-sufficiency. Economically, the project is highly attractive, with cost savings of 59.9% over its lifetime, a NPV of €680,591, and an IRR of 70.88%, significantly exceeding typical investment benchmarks. The payback period is just 1.4 years, suggesting a rapid return on the initial investment. The high value of ROI of 1676.39% further confirms the project's profitability. From a member perspective, the initial electricity cost per residential unit is €471.5 and €23,573 per commercial member, while the final cost drops to €188.7 for residential and €9,433 for commercial members, indicating high benefits and incentivising participation in the community energy project.

5. Conclusions

This paper proposed a decision-support framework implemented as a simulator called ECoSIM for optimizing the design and operation of Energy Communities based on local renewable generation and energy storage. The framework integrates data-driven load modeling, deterministic energy system simulations, and multi-objective optimization to evaluate both energy performance and economic feasibility. Applied to a mixed residential-commercial community in Constanța, the optimized configuration resulted in a PV installation of 197.69 kWp and a battery storage capacity of 323.23 kWh, achieving a self-sufficiency of 50.6% and self-consumption of 71.0%. Financial results are equally promising, with a net present value of €680,591, an internal rate of return of 70.88%, and a payback period of just 1.4 years. The Monte Carlo analysis further confirmed the robustness of the project against uncertainties in tariffs, generation, and operational costs.

ECoSIM provides stakeholders, such as municipalities, cooperatives, or private inverstors, a practical solution to evaluate and optimize EC configurations in a location-specific and user-centric manner. Future work will focus on expanding the simulator's capabilities by integrating real-time data feeds, incorporating behavioral modeling of end-users, and supporting additional flexibility assets such as demand response.

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