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Multi-Method Simulation and Optimisation for Maximising Benefits in Renewable Energy Communities: A Real-World Case Study from Italy

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Abstract. This paper introduces a novel multi-method modelling framework for Renewable Energy Communities (RECs), integrating agent-based modelling, discrete-event simulation, and system dynamics. This hybrid approach enables a comprehensive assessment of RECs, capturing both their technical and economic dynamics. The work's key contributions are twofold: (i) a flexible technical modelling framework adaptable to diverse geographical and regulatory contexts, and (ii) an advanced optimisation model aimed at minimising costs and maximising benefits for decision support.

The optimisation model has been built upon the modelling framework and can be adjusted to various REC configurations, allowing for variations in photovoltaic capacity, demand patterns, energy price structures, and regulatory schemes. This flexibility enables a policy-aware and context-sensitive simulation and optimisation of REC operations. The model enables the evaluation of a wide range of scenarios, helping stakeholders assess both short-term and long-term technical and economic performance, making it a robust tool for forecasting and strategic planning.

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A real-world case study in Val d'Aosta, Italy, demonstrates the model's applicability and effectiveness. The study highlights the framework's ability to incorporate country-specific REC regulations while optimizing REC configurations. Results show a reduction in external energy reliance and an increase in shared energy, leading to enhanced energy autonomy and economic benefits. These findings validate the model's robustness and scalability, establishing it as a pioneering framework for REC planning and policy innovation.

Keywords: Renewable Energy Communities, Modelling Approach, Multi-method Simulation, Agent-based modelling, Discrete-event Simulation, System Dynamics, Meta-heuristic Optimisation, Flexibility, Replicability, Scalability, Economic Benefits

1 Introduction

The Clean Energy for All Europeans package, introduced by the European Commission in November 2016 (Capros et al., 2018), includes key directives such as the Renewable Energy Directive (RED II) and the Internal Market for Electricity. These directives aim to promote distributed energy generation, enhance the role of Renewable Energy Sources (RES) (Frieden et al., 2020), and empower citizens as active participants in the energy transition (Sokolowski, 2018). As a result, new energy management systems have emerged, including microgrids (Sanfilippo and et al., 2023), smart cities (Zacepins et al., 2019), and Renewable Energy Communities (RECs).

A REC is a legally recognized entity that operates independently while complying with national regulations. It is characterized by open and voluntary participation, with governance controlled by its members—individuals, small and medium-sized enterprises, or local authorities such as municipalities. Unlike traditional energy entities, RECs prioritize environmental, economic, and social benefits over financial profit (Vetrò and Brignoli, 2025; Lode et al., 2022).

Figure 1 illustrates the general concept of a REC, which can include different types of participants. Pure producers, represented by photovoltaic (PV) panels, generate electricity that is shared among community members. Consumers, depicted as individual houses, rely on this shared energy for their needs. Additionally, prosumers—buildings equipped with rooftop PV systems—can generate electricity locally. These prosumers have the flexibility to consume the energy they produce, share surplus electricity with other REC members, or feed excess power into the main grid, contributing to a more balanced and efficient energy distribution within the community.

The adoption of RECs is accelerating across Europe, supported by regulatory frameworks and financial incentives. A recent study identified nearly 4,000 energy communities in the EU, involving approximately 900,000 members, with Germany, the Netherlands, and Denmark leading the movement (Koltunov et al., 2023). Figure 2 presents an overview of the transposition status of REC definitions in different European countries.

However, the widespread deployment of RECs, combined with the increasing integration of variable renewable energy sources, presents challenges for efficient and sustainable electricity grid management. Among the different RES technologies adopted within RECs, PV systems are the most prevalent due to their modularity, cost-effectiveness, and ease of integration into buildings and ground installations (Gianaroli et al., 2024).

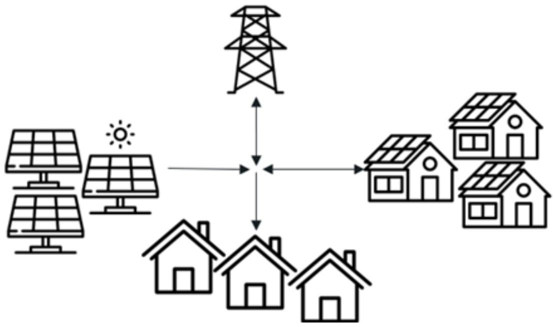

Fig. 1. Renewable Energy Community concept.

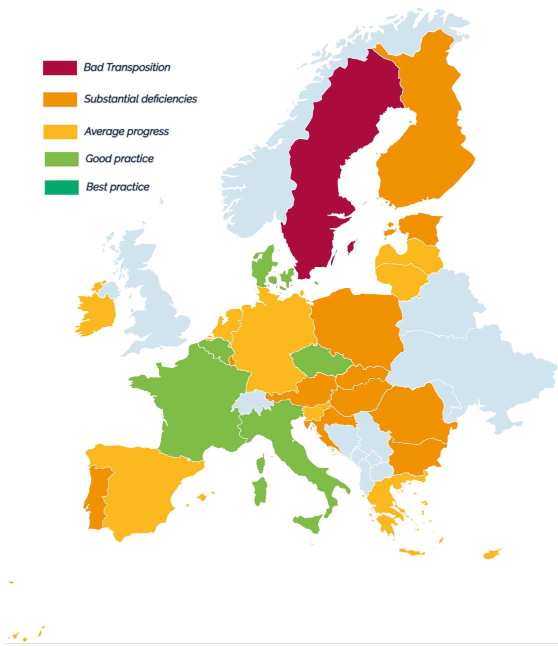

Fig. 2. Transposition map of REC and Citizen Energy Community definitions – April 2024, sourced from (REScoop Website, 2024).

Despite the rapid growth of RECs, there is a need for advanced optimisation strategies to enhance their economic, environmental, and operational performance. Several business models for RECs have been proposed, differing in governance structures, pricing mechanisms, and energy distribution strategies (Barabino et al., 2023). Furthermore, the complexity of REC management necessitates sophisticated optimisation approaches that account for diverse technologies, including PV systems, energy storage, electric vehicles, and heating/cooling systems. Existing studies have addressed optimisation from two key perspectives:

- Real-time energy management considers optimisation methods that support real-time control of energy assets to minimise costs, enhance flexibility, and ensure grid stability. These approaches include demand response programs, local flexibility markets, and multi-objective energy management frameworks (Cruz-De-Jesús et al., 2023; Caliano et al., 2022).
- Strategic planning and system design encorporating optimisation techniques which aid in the long-term planning of RECs by determining optimal infrastructure deployment and energy-sharing mechanisms. Notably, mathematical models incorporating geographical, meteorological, and demographic data have been developed to optimize PV installation and maximise economic and environmental benefits (Orlando et al., 2023; Lazzari et al., 2023).

From an operational perspective, REC members — producers, consumers, and prosumers — can be modeled as agents within a distributed multi-agent system (Listopad, 2019). Additionally, dynamic system modelling is crucial for simulating complex interactions among energy assets (Mihailovs and Cakula, 2020). In this regard, recent research has explored methods for assessing REC feasibility under economic and regulatory uncertainty (Pagnini et al., 2024; Cutore et al., 2023).

As shown, various works proposed modelling and optimisation approaches in the context of RES optimal design for REC application. Mathematical modelling in REC, considering the optimisation, is used to maximise profit based on the number of prosumers and consumers, finding the profitability by comparing the optimal REC and without REC case (Sassone et al., 2024) however, the optimisation models, do not consider the overall useful time of the investment, as in this work.

2 Objectives

This research is driven by the objectives and broader framework of the PROBONO project (PROBONO Project, 2022), which aims to foster the development of sustainable, energy-positive, and zero-carbon Green Building Neighborhoods across Europe. The PROBONO project, funded by the European Union's Horizon 2020 program, focuses on aligning the interaction between buildings, communities, and stakeholders, leveraging digitalisation and smart technologies to achieve net-zero emissions and energy-positive environments.

In this context, the goals of PROBONO closely align with the challenges faced by RECs, particularly in the transition to renewable energy. One of the critical issues in this transition is optimising the performance of decentralized energy production systems, especially PV installations. Achieving these objectives involves not only determining the optimal size and configuration of PV systems — considering factors such as fluctuating energy demand, variable PV output, and differing regulatory frameworks and incentives — but also balancing capital expenditures (CAPEX) and operational expenditures (OPEX) with the economic benefits of reducing electricity purchases and increasing energy sales within the REC. Additionally, navigating the complex landscape of local regulations and incentive schemes, which can greatly impact the economic viability of RECs, presents further challenges. Without adaptable models, stakeholders often lack the tools needed to make informed decisions that consider the unique legal and economic conditions of their specific locations.

Optimally sizing PV systems not only enhances economic performance but also minimises excess electricity production, reducing the need to export surplus power to the grid. This improves self-consumption and resilience while helping to mitigate grid congestion by preventing overproduction, which can strain local distribution infrastructure. When PV systems are tailored to match energy demands and grid capacity, they boost energy efficiency and contribute to a more stable and reliable electrical grid.

The primary objective of this research is to develop a model that can be used both in a simulation and optimisation tool for RECs. This model is designed to help stakeholders make informed decisions regarding PV system sizing and energy management strategies, ultimately supporting the growth and success of sustainable energy communities. By optimising the performance of RECs, this research directly aligns with PROBONO's mission to demonstrate how Green Building Neighborhoods can achieve energy-positive outcomes while benefiting both society and the environment through innovative, decentralized energy solutions.

The model requires to be adaptable and replicable to various locations and scalable to different scenarios, if relevant data regarding PV production, budget requirements, electricity consumption, and local regulations related to shared energy incentives are available. Through its application, the model will provide valuable insights into how the integration of REC within local communities can be optimised to enhance both economic and environmental outcomes.

3 Proposed Approach

This section introduces a model for RECs designed to conduct comprehensive techno-economic analyses and optimise their benefits. This work builds upon and extends the findings presented in the conference paper delivered at the 15th Conference on Data Analysis Methods for Software Systems in November 2024. A REC is a complex system, that requires dynamic management of various interconnected components, including buildings and their production and consumption. To address this complexity, a multi-method modelling approach is adopted, combining Agent-Based Modelling (ABM), Discrete Event Simulation (DES), and System Dynamics (SD):

- Each PoD is modelled as an agent with specific attributes, such as installed renewable energy systems, electricity generation and electricity demand, and the ability to inject or withdraw electricity from the grid. ABM allows for the detailed representation of individual behaviours and decision-making processes, capturing their interactions and contributions to the REC.

– DES considers the dynamic interactions and adjustments among PoDs at each time step, allowing the system to adapt to real-time changes, such as fluctuations in energy demand, production, or grid conditions.
– At the community level, SD synthesizes the results from individual agents, treating the REC as an interconnected system. This approach captures aggregated trends (e.g., total energy shared, overproduction, overconsumption) and long-term economic impacts on the REC.

This model serves dual purposes of simulation and optimisation, offering a robust framework for analysing and enhancing REC performance over its entire lifetime. It ensures that the proposed solutions are not only effective in the short term but also sustainable and economically viable over time.

The simulation lays the foundation for the optimisation process, which determines the optimal configuration of nominal PV capacities at each PoD. It analyses electricity exchanges at both PoD and REC levels, evaluates financial metrics such as costs, revenues, incentives, and net benefits under both REC and non-REC scenarios, and identifies the optimal sizing of PV systems to maximise economic and environmental benefits. The primary objective is to minimise costs while ensuring uninterrupted electricity demand coverage within the REC.

4 Model Definition

The aim of the model is to capture the state within a REC consisting of n PoDs in a generic area. A PoD is a specific location within a REC where electricity is either consumed, generated, or both. It represents a physical or virtual point in the electrical grid where energy flow is monitored and managed. It typically corresponds to a building, household, or any unit equipped with its own electricity meter, which can either consume electricity from the grid or supply electricity back to it, using a PV system.

The energy demand of the *i-th* PoD, $e_i^D(t)$, must be determined for each time period t. In addition, the PV production at the *i-th* PoD during each time period t, $e_i^P(t)$, is calculated by multiplying the PV production profile for 1 kW, $\phi(t)$, by the nominal power of the PV system installed at that PoD, P_i^{PV} as shown in equation 1.

$$e_i^P(t) = \phi(t) \times P_i^{PV} \tag{1}$$

The net energy exchange, $e_i^X(t)$, represents the net energy flow at PoD i during a specific time period t. It is calculated as the difference between the energy produced, $e_i^P(t)$, and the energy demanded, $e_i^D(t)$, at the same PoD and time interval, as expressed in equation 2.

$$e_i^X(t) = e_i^P(t) - e_i^D(t) \tag{2}$$

The energy exchange $e_i^X(t)$ at the *i-th* PoD during a given time period t can either result in energy being injected into the grid or withdrawn from it. The energy injected, denoted as $e_i^I(t)$, represents the surplus energy exported to the grid when the production exceeds the demand. Conversely, the energy withdrawn, denoted as $e_i^W(t)$, represents the energy imported from the grid to cover the demand when it exceeds the production.

If $e_i^X(t)$ is positive, it is considered as energy injected, $e_i^I(t)$, and $e_i^W(t)$ is set to zero. Conversely, if $e_i^X(t)$ is negative, it is considered as energy withdrawn, $e_i^W(t)$, and $e_i^I(t)$ is set to zero. This ensures that, for any given time period t, the energy exchange is exclusively categorized as either injected or withdrawn. Mathematically, this can be expressed as shown in equation 3.

$$e_i^I(t) = \max(e_i^X(t), 0) \qquad e_i^W(t) = \max(-e_i^X(t), 0) \tag{3}$$

The energy shared by the *i-th* PoD, $\bar{e}_i(t)$, during a given period corresponds to the energy made available from the PoD i for the REC. This is calculated as shown in equation 4.

$$\bar{e}_i(t) = \min(e_i^I(t),\, e_i^W(t)) \tag{4}$$

This equation is essential because it quantifies the actual contribution of each PoD to the shared energy pool of the REC. By using the minimum between the energy injected and the energy withdrawn, the model ensures that only the surplus energy, which is effectively available for sharing, is accounted for. This avoids overestimating the shared energy, as it limits the contribution to the actual availability of energy at the PoD. This calculation is critical for balancing the energy flows within the REC. It determines the total energy shared, directly influencing the financial benefits derived from shared incentives or reduced energy costs. Furthermore, it ensures the equitable distribution of shared energy across all PoDs, aligning individual contributions with the overall objectives of the REC. By accurately representing the energy available for sharing, this equation promotes efficient energy management and supports the collective operation of the REC. It also serves as a foundational component for aggregating and analysing energy contributions across all PoDs in the REC.

By aggregating the energy contributions from all PoDs, the REC quantifies the total energy shared and exchanged during a period t. This includes the aggregated energy injected into the grid, withdrawn from the grid, and shared within the REC. The total values are calculated by summing the respective energy components across the number of PoDs n, as represented in equation 5.

$$e^I(t) = \sum_{i=1}^{n} e_i^I(t), \quad e^W(t) = \sum_{i=1}^{n} e_i^W(t), \quad \bar{e}(t) = \sum_{i=1}^{n} \bar{e}_i(t) \tag{5}$$

This aggregated perspective allows the REC to evaluate its collective energy performance, effectively balancing energy flows between injection, withdrawal, and sharing. It provides a comprehensive view of the energy dynamics within the community, serving as a foundation for accurate accounting and reporting of energy exchanges.

The financial transactions associated with energy exchanges in the REC include both the revenue from selling injected energy and the cost of buying withdrawn energy. The revenue from selling the injected energy, denoted as $r(t)$, is calculated by multiplying the energy injected into the grid, $e^I(t)$, by the market sell price at time t, $p^S(t)$.

Similarly, the cost of buying the withdrawn energy, denoted as $c(t)$, is calculated by multiplying the energy withdrawn from the grid, $e^W(t)$, by the purchase price at time t, $p^B(t)$. These relationships are expressed in equations 6.

$$r(t) = e^I(t) \times p^S(t) \qquad c(t) = e^W(t) \times p^B(t) \tag{6}$$

The equations formalized so far express the dynamics of energy and financial exchanges as continuous functions of time, enabling detailed analysis at any specific moment within the study duration. However, for practical and comparative purposes, these time-dependent equations need to be annualized, in order to align the analysis with standard accounting practices. This ensures that the CAPEX and the OPEX are appropriately accounted for the financial statements. Specifically, CAPEX is reflected in the balance sheet as an asset and is typically amortized or depreciated over its useful life. In contrast, OPEX is included in the income statement, representing the periodic operational costs incurred during the study duration. This involves aggregating the results over each year of the study to obtain yearly metrics such as total energy injected, withdrawn, or shared, as well as the corresponding revenues and costs.

The total energy demanded, injected and withdrawn by the REC during a given year y, denoted as E_y^D, E_y^I and E_y^W respectively, is obtained by summing the energy values over all periods within that year. This is represented mathematically in equations 7.

$$E_y^D = \int_y e^D(t)\,dt \qquad E_y^I = \int_y e^I(t)\,dt \qquad E_y^W = \int_y e^W(t)\,dt \tag{7}$$

The revenue from selling injected energy and the costs for buying withdrawn energy at the REC level during a specific year y are obtained by integrating the respective instantaneous values over the year. These are expressed in equations 8.

$$R_y = \int_y r(t)\,dt \qquad C_y = \int_y c(t)\,dt \tag{8}$$

The capital expenditures for each PoD, CAPEX_i, is computed individually, taking into account the cost of the PV system per kW, C_{kW}^{PV}, multiplied by the installed PV power in the *i-th* PoD as shown in equation 9.

$$\mathit{CAPEX}_i = C_{kW}^{PV} \times P_i^{PV} \tag{9}$$

The cumulative capital expenditure of the REC is aggregated across all PoDs. The total *CAPEX* represents the sum of the individual capital expenditures of each PoD, as shown in equation 10:

$$\mathit{CAPEX} = \sum_{i=1}^{n} \mathit{CAPEX}_i \tag{10}$$

OPEX_y, represent the yearly costs incurred to maintain and operate the REC, including maintenance, administrative expenses, and other operational fees. The yearly OPEX_y is calculated as a percentage f of the total capital expenditure (*CAPEX*) for each PoD, aggregated across all PoDs, as shown in equation 11.

$$OPEX_y = f \cdot CAPEX \tag{11}$$

The yearly cash-flow, denoted as F_y, represents the net financial balance of the REC during year y, incorporating several factors: operating expenditures $OPEX_y$, the cost of energy purchased C_y, the revenue generated from selling injected energy R_y, and any incentives from the country to the REC I_y. This is given by equation 12:

$$F_y = OPEX_y + C_y - R_y - I_y \tag{12}$$

The term $OPEX_y$ includes the yearly operational costs required to maintain and manage the REC, such as maintenance and administrative expenses. The cost of energy purchased, C_y, accounts for the expenses incurred from withdrawing energy from the grid to satisfy the REC's energy demand. Revenue, R_y, represents the income generated by selling surplus energy injected into the grid, benefiting from market prices or other mechanisms. State incentives, I_y, are financial supports or subsidies provided annually by governmental or local authorities. These incentives are typically tied to renewable energy policies, aiming to encourage the adoption of sustainable practices. They may vary depending on the country or region and are calculated based on the REC's operational characteristics, such as the amount of energy shared or injected into the grid, or compliance with specific regulatory requirements. By incorporating I_y, the cash-flow model reflects both market-based earnings and additional policy-driven benefits.

Finally, the total costs with REC, denoted as T, are calculated as the sum of the initial investment *CAPEX* and the discounted yearly cash flows F_y over the project lifespan Y. This is expressed in equation 13:

$$T = CAPEX + \sum_{y=1}^{Y} F_y \cdot D_y \tag{13}$$

Here, all cash flows are adjusted to their present value using the discount factor D_y, ensuring that the financial evaluation reflects the time value of money over the REC's lifetime. The yearly discount rate, D_y, is used to account for the time value of money in year y, ensuring that cash flows are appropriately adjusted to their present value. The adjusted yearly discount rate is computed as shown in equation 14. d represents the annual discount rate, which reflects the cost of capital.

$$D_y = \frac{1}{(1+d)^y} \tag{14}$$

Now that the model for calculating costs with REC has been established, comparing these costs with those without REC allows for the evaluation of the economic benefit of implementing PV installations and constituting the REC.

The yearly costs without REC, T'_y, are determined by integrating the energy demand $e^D(t)$ multiplied by the price of energy $p^B(t)$, as calculated in equation 15.

$$T'_y = \int_y e^D(t) \cdot p^B(t)\, dt \tag{15}$$

The total costs in the scenario without REC, denoted as T', are obtained by summing the discounted yearly costs T'_y over the entire study duration. The discount factor D_y is applied to adjust each year's costs to their present value. This is expressed in equation 16.

$$T' = \sum_{y=1}^{Y} T'_y \cdot D_y \tag{16}$$

By comparing the costs with REC and the costs without REC, the economic benefit of implementing PV installations and constituting the REC can be evaluated. This comparison highlights the financial advantage provided by reduced operational costs and the potential earnings from energy sharing in the REC scenario.

5 Simulation

The mathematical model defines the energy and financial dynamics of the REC, providing a theoretical support for analysing its performance. This model has been implemented and further developed in the AnyLogic Software Platform (AnyLogic Company, 2024) to create a functional simulation environment. AnyLogic allows for the integration of different simulation paradigms within a single tool, such as Agent-Based, Discrete Event, and System Dynamics. Beyond its modelling capabilities, AnyLogic is also favored for its problem-solving orientation.

The simulation enables the practical application of the model, allowing for detailed analyses of REC behaviour under various scenarios. The tool aims to provide a time-based simulation, allowing for a detailed analysis of the REC's behaviour on an hourly basis. Each PoD has its own PV system and electricity demand, with only the electricity aspect of the REC being considered for simplicity.

The simulation operates with a time period t set to hourly intervals, reflecting the granularity of the input data. This hourly resolution ensures the accurate representation of fluctuations in electricity demand, PV production, and market prices. AnyLogic's flexibility has been utilized to integrate ABM and DES, effectively capturing the interactions within the REC. Each PoD is modelled as an agent, with attributes such as installed PV capacity, hourly electricity demand, and interactions with the REC and the grid.

The model is customisable by the user through an interface and an Excel file, providing flexibility to adjust the REC's structure and the characteristics of each PoD. In the simulation, every PoD is modelled as an agent, with its electricity demand specified hourly for an entire year sourced from an input Excel file. The Excel file is structured across multiple sheets. The first sheet contains information about the PoDs, with each row representing a PoD and providing details such as a unique identifier, year of construction, and available surface area for PV installation. The second sheet contains columns for each consumer, with each column being the electricity demand of the corresponding PoD. This setup offers users flexibility by enabling them to dynamically set the composition of their REC and the electricity demand of each PoD before running the simulation..

During the simulation, the model captures key energy flows, including energy demand, $e_i^D(t)$, energy injected into the grid, $e_i^I(t)$, energy withdrawn from the grid, $e_i^W(t)$, and energy shared within the REC, $\bar{e}_i(t)$, on an hourly basis. They are calculated using AnyLogic's time-based modelling capabilities. Event-driven logic handles updates to external factors, such as changes in market prices or policy incentives, ensuring the simulation remains responsive to dynamic conditions.

When the simulation is executed, the model transfers all input data from the Excel file to its internal datasets and variables. For each PoD, this includes unique characteristics, hourly electricity demand, and hourly PV production for a unitary 1 kW installation. The electricity production of each PoD is calculated based on its installed PV capacity, P_i^{PV}, and the PV production profile, $\phi(t)$, which can either be provided as part of the input data or obtained dynamically via the PVGIS API. If the PVGIS API is used, the profile is based on specific assumptions such as polycrystalline panels, 14% of losses, and historical data from 2005 to 2020, averaged to simulate a generalized year.

The simulation operates for an entire year (8,784 hours to accommodate leap years, or 8,760 hours for non-leap years), providing results that can be extrapolated over the REC's lifetime for comprehensive investment analysis.

Outputs from the simulation include aggregated energy metrics, yearly financial performance indicators, and optimisation results for PV capacities. These outputs are stored in AnyLogic's datasets and visualized through its built-in analytics tools. The model's outputs include yearly energy metrics, such as total energy injected, E_y^I, withdrawn, E_y^W, and shared, $\bar{E}_y$, as well as financial metrics like yearly cash-flow, F_y, cumulative capital expenditure (*CAPEX*), and operating expenditure ($OPEX_y$). Additionally, the model provides insights into the REC's overconsumption, overproduction, and overall energy sharing behaviour.

The simulation results form the basis for optimising the nominal power of each PV system in the REC. By analysing the interplay between incentives, costs, and energy production, the model supports decision-making aimed at maximising financial incentives while minimising operational costs, ensuring the economic and energy efficiency of the REC.

6 Optimisation

For the optimisation, the AnyLogic experiment employs advanced meta-heuristics and the OptQuest solver (OptQuest Website, 2024) to perform optimisation procedures, leveraging AnyLogic's optimisation features. This procedure is specifically designed to handle complex systems with numerous decision variables that present analytical optimisation challenges.

Built on the simulation, the optimisation aims at determining the optimal configuration of installed PV at the PoD level. The optimisation seeks to maximise REC benefits by finding the best combination of installed PV that balances production, demand, and energy sharing within the REC. Key objectives include:

The optimisation problem is mathematically formulated as:

$$\max_{x} \left[T' - T(x) \right] \tag{17}$$

$$with\ \ x = P_i^{PV} \quad \forall i = 1, \ldots, n \tag{18}$$

The optimisation aims to maximise the economic benefit of the REC by minimising the total costs associated with REC operations $T(x)$ relative to the costs in a non-REC scenario T'. This approach provides a decision-support tool for determining the optimal PV capacity at each PoD to balance investment costs, energy flows, and financial incentives while achieving maximum savings.

The optimisation begins with initializing the input data, which includes:

- **Energy-related data**: Hourly electricity demand profiles and hourly PV production per kW at the PoD site.
- **Economic data**: Hourly energy prices, hourly purchasing costs, and other relevant financial parameters.

The input parameters, specifically the range of PV capacities, are also defined. The minimum value is set to zero (representing no installation), and the maximum value corresponds to the highest feasible capacity based on physical constraints.

The optimisation employs advanced meta-heuristics and the OptQuest solver (OptQuest Website, 2024) to perform an optimisation process based on AnyLogic's optimisation feature. The optimisation layer operates atop the simulation iteratively. The objective function, expressed in equation 17, is analogous to the Net Present Value (*NPV*) of the investment, with a notable enhancement: unlike traditional *NPV* calculations that consider only *CAPEX* as the first-year cash flow, the proposed formulation incorporates both revenues and *OPEX* in the first year. This approach reflects the assumption that installations occur at the beginning of the investment period.

The meta-heuristic optimisation layer addresses the complexity of the problem, characterized by a large number of decision variables and interdependencies. The process is visualized in Figure 3, which depicts the flowchart of the optimisation steps. The steps are:

1. **Simulation Execution**: The simulation runs using initialized input parameters and data, calculating the REC Benefits.
2. **Evaluate Stopping Criteria**: The optimisation process assesses whether the predefined stopping criteria—such as reaching the maximum number of iterations, achieving convergence thresholds, or applying a budget constraint to exclude financially unfeasible solutions and ensure alignment with the investor's capacity—have been satisfied. If these conditions are met, the process terminates and determines the optimal sizes for the installed PV panels. Otherwise, it updates the input parameters and continues.
3. **Update Input Parameters**: PV capacities are iteratively adjusted within the defined range to refine the solution and improve the objective function.

4. **Optimal Design Identification**: The solution yielding the maximum REC Benefits is selected, ensuring feasibility and adherence to constraints such as continuous electricity demand coverage and financial limits.

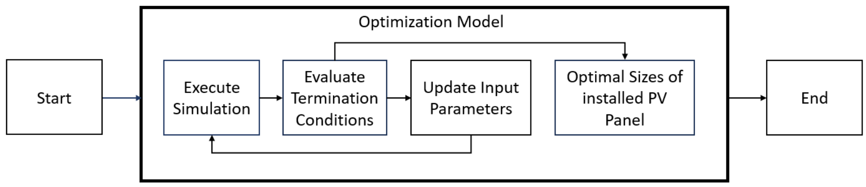

Fig. 3. Flowchart depicting the optimisation process.

This dual-layer optimisation offers flexibility for addressing both economic and operational objectives in REC design. By integrating simulation with meta-heuristic optimisation, the methodology ensures a robust and adaptable solution tailored to the specific characteristics and constraints of REC. The proposed approach is particularly suited for evaluating and optimising REC performance over its lifetime, delivering practical insights for stakeholders and policymakers.

7 Experimental Work

The case study is situated in the Aosta Valley, Italy, a region that benefits from the well-defined national regulations and incentives for renewable shared energy (Gianaroli et al., 2024). Additionally, collaboration with C.E.G. enabled the use of energy smart meter data from multiple locations. The data on PV production have been obtained from the PVGIS website (PVGIS, 2024). The selected coordinates were 45.739° N and 7.426° E, corresponding to the Aosta Valley at an elevation of 528 meters, as provided by the website. The solar radiation database employed PVGIS-SARAH2. The mounting type chosen was Fixed, with optimised slope and azimuth values obtained from the website for the location: Slope: 31 degrees (optimum), Azimuth: -20 degrees (optimum). Furthermore, the PV technology considered was crystalline silicon with a 1 kW system, with system losses set at 14.0% as the default value from the interactive tool. The dataset comprises 8,760 hourly values for the years 2005-2020, with an additional 8,784 values for the leap years (2008, 2012, 2016, and 2020), accounting for the extra day. To obtain an annual average, the hourly values were averaged across all years.

The collected one year of real-measured data consists of electricity power curves from three PoDs located in Northern Italy. The dataset includes the following information: sample date, PoD identification, daily-packed sample values of consumption profiles, and energy measurement type. Data preprocessing has been necessary to convert the raw data format into a tabular dataset. The time resolution from 15 minutes has been converted into hourly averages to align with other data sources, such as market energy prices. Data cleaning involved removing duplicates and filtering the PoDs with the highest number of data points in the studied time frame. The three selected PoDs, shown in Figure 4 have 300 days of real-measured data from June 2023 to June 2024, and represent: a larger consumer, a medium consumer, and a smaller consumer. In cases of missing data due to gaps (less than 1% of the overall dataset), data imputation was performed to create a complete one-year set of energy consumption values. The K-Nearest-Neighbor model has been used as the imputer, one of the standard benchmark methods studied in the literature (Kim et al., 2017).

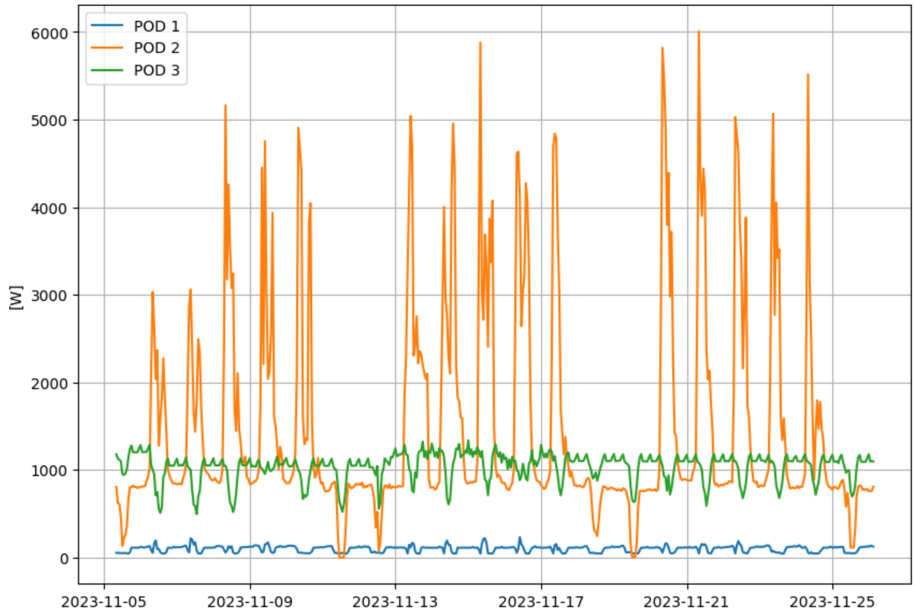

Fig. 4. Exemplary hourly-averaged power profiles.

Table 1. PoD profiles statistics [W].

PoD	min	max	avg	std-dev
1	33	461	96	52
2	0	6477	1067	1005
3	0	2392	1024	334

Since the case study discussed in this paper is located in Italy, the annual incentive is based on the computation of the hourly Italian Premium Tariff (*TIP*) (Gestore dei Servizi Energetici, 2024b) over the course of a year. The financial incentive associated with energy sharing inside the REC is calculated through two main terms, $v_1(t)$ and

$v_2(t)$, in equation 19, which represent different contributions to the total revenue. These terms depend on the energy shared by each PV plant, $\bar{e}_i(t)$, during the period t.

$$I_y = \int_y v_1(t) + v_2(t)\, dt \tag{19}$$

The first term, $v_1(t)$, is calculated using $\mathit{TIP}_i(t)$, as shown in equation 20. For each PoD i, $\mathit{TIP}_i(t)$ reflects a time-dependent incentive parameter that accounts for market prices and other regulatory adjustments. Its calculation is provided in equation 21 and incorporates several factors, including capacity thresholds, market conditions, regional corrections, and governmental contributions.

$$v_1(t) = \sum_{i=1}^{n} \bar{e}_i(t) \times \mathit{TIP}_i(t) \tag{20}$$

$$\mathit{TIP}_i(t) = \left\{\min\left[\mathit{CAP}_i, \mathit{TP}_i + \max(0, 180 - p^B(t))\right] + \mathit{FC}_R\right\} \times (1 - F_i) \tag{21}$$

The parameters CAP_i and TP_i depend on the installed PV capacity of the i-th PoD and are divided into three categories summarized in Table 2.

Table 2. TIP table in €/MWh.

P^{PV} kW	*CAP* €/MWh	*TP* €/MWh
$P < 200$	120	80
$200 \leq P < 600$	110	70
$P \geq 600$	100	60

The parameter CAP_i represents the maximum allowable incentive for the i-th PoD based on its installed PV capacity, as defined in Table 2. TP_i denotes a baseline incentive that is adjusted based on the electricity market price, $p^S(t)$, at time t. If $p^S(t)$ is below 180 €/MWh, an additional incentive proportional to the difference $(180 - p^S(t))$ is added to TP_i. This adjustment ensures that lower market prices do not adversely impact the financial viability of energy sharing within the REC. The term FC_R is a regional correction factor. This factor is set to 10 €/MWh for RECs in Northern regions and 4 €/MWh for those in Central or Southern regions. Finally, the entire expression is scaled by $(1 - F_i)$, where F_i represents the percentage of governmental contribution toward the capital expenditure of the i-th PoD. For simplicity, F_i is assumed to be zero in this analysis, meaning no adjustments are made for governmental contributions.

This formulation ensures that $\mathit{TIP}_i(t)$ dynamically adjusts to market conditions, regional differences, and capacity thresholds, providing a tailored incentive for each PoD in the REC. The energy purchasing price p^B has been set as 282.90 €/MWh, as the average of the gross domestic energy price in 2023 (Autorità di Regolazione per Energia Reti e Ambiente, 2023).

On the other hand, the second term, $v_2(t)$, represents an additional financial incentive associated with energy sharing and is directly linked to the avoidance of transmission losses. It quantifies this benefit, providing a financial acknowledgment of the value created through local energy sharing. This term is calculated using a fixed coefficient, K_{tr}, which applies uniformly to all PoDs, as shown in equation 22. Since K_{tr} is applied uniformly across all PoDs, this term scales proportionally with the total energy shared within the REC, $\bar{e}(t)$, ensuring that larger RECs or those with higher energy-sharing capacities receive greater incentives for avoiding transmission losses.

$$v_2(t) = \sum_{i=1}^{n} \bar{e}_i(t) \times K_{tr} \quad (22)$$

The coefficient K_{tr} is set at a constant rate of 10.57 €/MWh, based on 2023 regulatory values (Gestore dei Servizi Energetici, 2024a). This incentive mechanism is designed to reward RECs for reducing energy transmission distances by sharing energy locally within the community.

No specific requirement for checking whether the investment exceeds a certain budget was included, as the objective was to compare the total costs with and without the REC. This approach was chosen due to the lack of information about the users and their budget. Furthermore, by not setting a maximum acceptable cost, it allowed for the determination of whether the optimal solution provided by the model was the maximum legal capacity of 1MW or an alternative option with lower power levels.

The optimisation has been applied to the specified input data. In this particular case, the selected optimisation engine is Genetic, with the number of iterations set to 10,000. The objective is to find the optimal combination of nominal PV capacity installed on each PoD (ranging from 0 to 1 MW, as per Italian regulations, in increments of 1 kW) to maximise the REC benefits while ensuring continuous electricity coverage for all buildings.

No replacement costs have been factored in, as the lifetime of the PV system is 24 years, while the project's lifespan is considered to be 20 years. d is the discount rate, which has a default value of 7%, while the default percentage value p for OPEX calculation has been assumed equal to 1 [%].

7.1 Results

Three distinct scenarios have been defined, each with a different hourly energy price. Scenario 1 corresponds to 2023, the most recent year for which data is available, with an average hourly energy price of 128 €/MWh over the entire year. Scenario 2 reflects the maximum average hourly energy price over the past six years, which occurred in 2022, at 308 €/MWh. Scenario 3 represents the minimum average hourly energy price over the same period, recorded in 2020, at 38 €/MWh. This approach allows for a comparison under consistent conditions between the most recent year, as well as the highest and lowest price years, to study the benefits of installing a REC under both high and low energy price conditions with the actual incentives regulation.

The hourly energy price data, sourced from the Italian Energy Market Agency (Mercato Elettrico, 2023), correspond to the entire years mentioned earlier and are based on

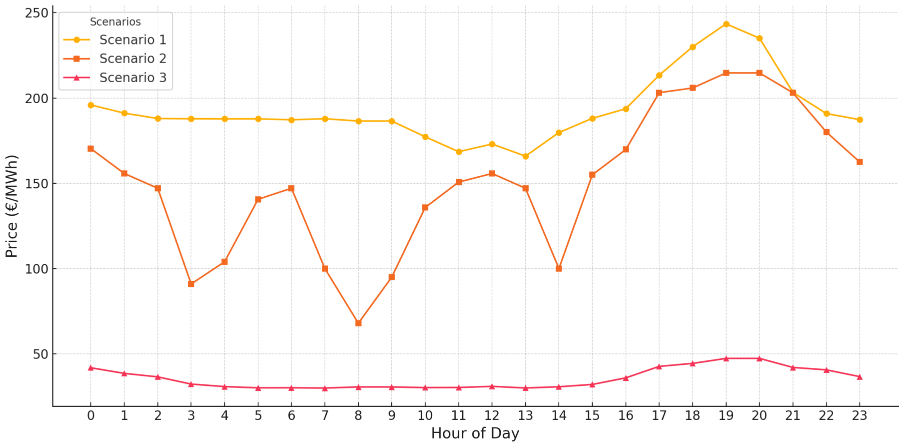

Fig. 5. Hourly Energy Prices in €/MWh for different scenarios.

the North market segment. A sample of this data, representing January 1st, is shown in figure 5.

First, the three scenarios without REC were first executed and the results are provided in Table 3. The analysis confirms that the results are closely aligned across the scenarios since the model has been constructed with identical inputs except for variations in the hourly energy price, which, being the selling price of electricity, does not affect the case without REC. Indeed, no yearly electricity selling is observed in any scenario, as the case without REC does not permit PoDs to sell electricity. Scenario 3 exhibits a slightly higher total cost compared to Scenarios 1 and 2. This difference arises due to 2020 being a leap year, including an additional day (February 29), which marginally increases the yearly buying value and total costs.

Table 3. Comparison of all the scenarios No REC (Yearly).

	Buying [€]	Selling [€]
Scenario 1	5,333	0
Scenario 2	5,333	0
Scenario 3	5,344	0

The Table 4 highlights how variations in average energy prices influence the energy dynamics within the REC. The optimisation results for Scenario 1 converge to a nominal power of 1 kW for Power 1, 7 kW for Power 2, and 4 kW for Power 3. As the average energy price increases, the nominal power of each PoD rises or remains constant across all PoDs. However, the total installed power across the REC increases overall. This increase in installed power results in a reduction in yearly electricity buying, decreasing from 4246 kWh in Scenario 3 to 3765 kWh in Scenario 1 and 3636 kWh in Scenario 2.

Table 4. Comparison of all the scenarios with REC.

Scenario	Nominal Power [kW]			Electricity [kWh]	
	P1	P2	P3	Buying	Shared
Scenario 1	1	7	4	3,765	337
Scenario 2	1	9	5	3,636	284
Scenario 3	0	4	2	4,246	370

Table 5. Comparison of all the scenarios REC Benefits.

	REC Benefit [€]
Scenario 1	7,309
Scenario 2	8,656
Scenario 3	4,179

This aligns with the principle that higher installed power reduces the need to buy energy externally. Conversely, as the average energy price increases, the energy shared within the REC decreases. This is due to greater self-consumption by individual PoDs, leading to less energy available for sharing among them, which in turn reduces the incentives received.

In Table 5 the REC benefits shown. They are highest when the average energy price is maximum, decreasing as energy prices drop, from €8656 in Scenario 2 to €7309 in Scenario 1, and finally to €4179 in Scenario 3. This demonstrates that RECs are more financially advantageous in scenarios where average energy prices are higher.

8 Conclusions and Future Work

This paper presents a multi-method model for simulating and optimising RECs. Developed as part of the PROBONO project, this model represents a significant advancement in the design and management of RECs by enabling detailed performance analysis. Simulation offers detailed insights into electricity demand, production, and energy sharing, alongside evaluating the economic performance of RECs over time. Optimisation identifies the best renewable energy configurations to maximise REC participation benefits while minimising costs.

The model's adaptability and scalability make it suitable for diverse applications, ranging from small to large-scale systems. It allows for adjustments to parameters such as geographical location, PV capacity, and energy prices, ensuring applicability across different regions and regulatory environments. Furthermore, the model's ability to simulate dynamic agent strategies based on national regulations improves decision-making and extends its potential for widespread deployment.

A dedicated tool has been developed to implement the model, allowing users to apply it effectively in diverse contexts and scenarios, bridging the gap between the theoretical framework and practical implementation. Validated through a case study in northern Italy, this tool successfully optimises PV sizes across various energy price scenarios, showcasing the model's applicability and effectiveness in balancing self-consumption and energy sharing within RECs. The study underscores the critical role of strategic planning in REC configurations to maximise both economic and environmental benefits, with higher energy prices further enhancing the financial advantages of REC participation.

Next steps involve expanding the model's use across the PROBONO Living Labs to assess its adaptability in different contexts. Integration of additional technologies, such as heat pumps, wind turbines, biomass, and hydrogen systems, will advance the model towards multi-sector integration. Geographic factors and advanced energy management systems, including district heating and storage solutions, will further enhance its capabilities. Future studies will also explore the interaction between multiple RECs to optimise energy production and consumption on a larger scale, increasing efficiency and resilience.

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