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Modelling the Socio-Technical Evolution of Renewable Energy Communities: An Agent-Based Analysis of Participation and Electrification through the CER.ca.MI Case Study

TESI MAGISTRALE IN ENERGY ENGINEERING

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Abstract: Renewable Energy Communities are increasingly considered not only as technical tools for renewable electricity sharing, but also as local socio-technical systems that can support citizen participation, social inclusion and a fairer energy transition. For this reason, their analysis should not be limited to energy production, self-consumption or economic performance, but should also consider how households decide to participate and how the community evolves over time.

This work develops an Agent-Based Model applied to the case of CER.ca.MI in Milan, representing households as heterogeneous agents that can join, remain in or leave the community according to technical, economic and behavioural conditions. The model follows the Italian virtual energy-sharing framework and links shared energy, incentives and individual benefits to monthly participation decisions. Results show that REC membership is strongly shaped by behavioural assumptions and by the proportion of environmentally oriented households. Aggregate electricity demand, instead, follows the electrification pathway defined in the scenario and shows very limited dependence on the level of REC participation. This suggests that a growing electricity demand in the local area is not sufficient, by itself, to expand the energy community: participation also requires social visibility, local exposure and stable engagement over time.

Key-words: Renewable Energy Community; Milan; Agent Based Model;

1. Introduction

The transition toward a low-carbon energy system is a fundamental and ongoing structural transformation that aims to reduce greenhouse emissions, limit climate change and decrease the dependence on fossil fuels. However, this does not only involve replacing technologies, hence how energy is produced, but is also a social and institutional process, therefore the way energy is distributed, consumed, governed and paid for.

Renewable energy requires new forms of participation, ownership and local coordination, especially because these technologies are often decentralised and located close to consumers. In this context, the energy transition rises important considerations about energy justice, that states that the benefits and the and costs of the transition should be fairly distributed, vulnerable consumers should not be excluded, and citizens should have the possibility to participate actively in energy decisions rather than remaining passive consumers. The European Union introduced Renewable Energy Communities (RECs) as part of a broader effort to make the energy transition not only faster, but also more inclusive. RECs are defined legal entity based on open and voluntary participation, whose members or shareholders are located in the proximity of renewable energy production plants. Beyond their technical contribution to renewable deployment, RECs may generate wider social impacts, including public acceptance of renewable energy, education and awareness, local value creation, energy democracy, social inclusion, and the mitigation of energy poverty.

In this context the long-term planning of RECs becomes relevant for two main reasons. First, local electricity systems are expected to change significantly in the coming years because the decarbonisation of final energy uses is increasingly linked to electrification. In particular, in the building sector, the diffusion of electric heating technologies, especially heat pumps, and the growing relevance of cooling demand are expected to modify residential electricity demand [1] [2]. This evolution is relevant because heating and cooling electrification modify not only the total annual electricity demand, but also its hourly and seasonal distribution. Heating technologies mainly affect winter electricity demand, while cooling systems increase summer demand and may contribute to higher peak loads. For this reason, the future performance of local energy systems, including Renewable Energy Communities, should not be evaluated only under the electricity demand structure observed in a base year, but also under demand profiles that account for the progressive electrification of residential uses. Second, the planning of RECs cannot be limited only to technical dimension. Consumption profiles, photovoltaic generation, incentives, demand evolution and energy sharing are essential to assess the performance of the community, but they do not fully explain whether households will actually participate. Since RECs are based on voluntary involvement, their development also depends on social and behavioural mechanisms, such as awareness, local interaction, peer influence, perceived benefit and the willingness to remain in the community over time. In this sense, REC planning requires a socio-technical perspective that consider the evolution of both electricity demand and participation.

Despite this context, social dimension is often less represented in quantitative REC analyses, which mainly focus on techno-economic optimisation, energy management, investment planning and benefit allocation, while the active participation of households is often represented in a simplified way or as an external assumption. This creates a gap for analyses that aim to understand how a REC evolves over time, not only as an energy configuration, but also as a community whose size and stability depend on individual decisions and local interactions.

In line with these considerations, this thesis contributes to the analysis of Renewable Energy Communities by developing an Agent-Based Model to describe their evolution over time, with particular attention to the active participation of households. Households are represented as

individual agents characterised by technical, economic, and behavioural attributes, whose decisions are revised according to a predefined frequency. This makes it possible to analyse how energy-related variables and social dynamics jointly influence the growth and stability of the community. The framework is developed within the Italian regulatory context, following the virtual model of energy sharing, and is tested a real Renewable Energy Community, namely CER.ca.MI, operating in Milan. The study is carried out through an exploratory parameter analysis and future scenarios construction up to 2040, combining different behavioural composition with the evolution of the electricity demand due to heating and cooling. By integrating these dimensions, the thesis treats RECs as socio-technical systems rather than purely energy infrastructures, providing a tool to evaluate their potential contribution to a more participatory energy transition.
The rest of this work is organized as follows. Section 2 provides a review of the relevant literature, regarding both the regulatory framework of RECs and the modelling approaches examined. Section 3 details the methodological framework, while Section 4 introduces the inputs and the assumptions employed in the case study, distinguishing between the calibration phase and the future scenario construction one. Section 5 presents the discussion of the results obtained through the sensitivity analysis of the two phases examined, and Section 6 concludes the thesis by summarizing the main findings and identifying possible directions for future research.

2. Literature review

This section provides the background needed to frame the analysis of RECs. It first examines how RECs are defined and regulated at the European and Italian levels; then reviews the main modelling approaches used to study their development, performance and social dynamics.

2.1 Regulatory framework

The development of Renewable Energy Communities (RECs) in European legislation should be seen within the broader context of the evolution of EU energy policy from a centralised, fossil-fuel-based system towards a more decentralised and participatory renewable energy model. Before their formal recognition in EU law, citizen-led renewable initiatives and energy cooperatives already existed in several Member States, but these had developed within fragmented national contexts and in the absence of a common European legal framework. As distributed renewable generation expanded, the EU increasingly recognised the need to regulate new actors, such as prosumers and local energy communities, and to adapt the energy market to more decentralised forms of production and consumption. A key step in this process was the Clean Energy for All Europeans Package, adopted in 2019. This package aimed to integrate decarbonisation, energy efficiency, market reform, innovation, and consumer empowerment within a single policy framework [3] [4]. In practical terms, it marked a change in the role attributed to citizens: consumers were no longer seen only as final users of electricity, but also as actors able to produce, store, share, and sell renewable energy. This shift created the basis for the legal recognition of RECs and for the inclusion of collective energy initiatives within the European energy market.

Within this framework, the RED II Directive formally introduced Renewable Energy Communities and collective self-consumption [3]. Rather than simply defining a new type of organisation, RED II established a set of rights and principles: RECs, according to existing national rules, participate directly in the energy transition producing, selling and distributing energy produced from renewable sources. However, for small or medium-sized enterprises (SMEs), these activities should not constitute their main commercial or professional activity. EU Member States should ensure that RECs have the right to operate as legal entities and to manage and share renewable energy within the community. In any case, the primary objective of a REC should be to provide environmental, economic, or social benefits to the community, its shareholders or members, or the local areas in which it operates, rather than financial profits [5] [3] [6]. The Directive also requires Member States to create enabling frameworks by removing unjustified barriers, simplifying procedures, facilitating access to finance and information, and supporting the participation of low-income and vulnerable households [5] [3] [7]. Therefore, the EU framework is not only a definition, but a regulatory attempt to make community energy practically possible. As a result, the practical development of RECs has varied across Member States, depending on each country's legal system, electricity market structure, administrative capacity and policy priorities. REC models across Europe therefore differ in the organisation of energy sharing, the allocation of economic benefits and the definition of geographical proximity between members and renewable energy plants [4] [8] [9]. This flexibility makes the EU framework both enabling and adaptable, but it also means that the effectiveness of RECs strongly depends on the capacity of each Member State to translate general European principles into clear and workable national rules.

In Italy, Renewable Energy Communities (RECs) were introduced through a gradual transposition of the European framework. The first step was Decree Law No. 162/2019, known as the Milleproroghe Decree, which anticipated part of RED II and opened an experimental phase for collective self-consumption and RECs [10]. This framework allowed the first pilot projects, but under strict limits, including a maximum plant size of 200 kW and the requirement that members and plants were connected to the same secondary substation area [10] [9]. In 2020, ARERA defined the first regulatory rules for the management of shared energy, while the Ministerial Decree of 16 September 2020 introduced an incentive tariff for shared energy, equal to 110 €/MWh for RECs and granted for 20 years [11], [12]. A broader transposition of RED II was later provided by Legislative Decree No. 199/2021, which made REC configurations more scalable by increasing the maximum eligible plant size to 1 MW and expanding the proximity criterion to the primary substation area [13] [9]. The framework was further consolidated through ARERA's Integrated Regulation for Diffuse Self-Consumption (TIAD), approved by Resolution 727/2022/R/eel and later updated in 2024 [12]. The incentive system was then completed by the MASE Decree, Ministerial Decree No. 414 of 7 December 2023, which defines the incentive mechanisms for renewable plants included in configurations for renewable energy sharing, including RECs [14]. The decree introduced a premium tariff on shared energy and a 5 GW ceiling of incentivised capacity, applicable until the limit is reached and, in any case, no later than 31 December 2027 [14].

Italy adopted a virtual model for RECs. This model differs from physical energy-sharing schemes, despite both approaches relying on the public distribution grid, because the electricity bill of each member is not directly reduced by an internal exchange of electricity. Instead, the shared energy is remunerated through monetary incentives, which are distributed a posteriori within the REC according to its statute, internal agreements or benefit-sharing rules [15] [6]. In operational terms, shared energy is determined on an hourly basis as the minimum between the electricity injected into the grid by the REC's renewable plants and the electricity withdrawn by the members located within the same primary substation area [12] [15]. The economic mechanism is managed by the Gestore dei Servizi Energetici (GSE), which calculate the virtually shared energy and recognises the corresponding economic value to the REC. This value is composed by two main elements, as shown in eq. (1): the valorisation of shared energy defined under the TIAD framework and the premium tariff on shared renewable energy [12] [15]. The first component corresponds to the reimbursement of the variable component of the transmission network charges, in a cost-reflective usage of the network ($TRAS_e$) [16]. The second component is a feed-in-premium, called TIP, which is granted for 20 years and varies according to plant size and market conditions, within the range defined by the MASE Decree [14] [15]. Since 2023, the method for setting the TIP level [17] is shown in Tables 1 and 2. The incentive level is tied to the current value of the zonal market price p_z [18] and it varies according to the installed capacity P_n of the REC plants. Additionally, the incentive scheme includes the possibility to correct the TIP according to the community's geographical location. This is done to valorise the energy sharing, that generally comes from PV plants, in the regions of Northern Italy, where the irradiation is generally lower than in the South. [19]

$$Incentive = TRAS_e + TIP + location\ correction \tag{1}$$

P_n	Unit	TIP	CAP	Unit
≤ 200	kW	$80 + max(0.180 - p_z)$	120	€/MWh
$200 - 600$	kW	$70 + max(0.180 - p_z)$	120	€/MWh
≥ 600	kW	$60 + max(0.180 - p_z)$	100	€/MWh

Table 1: Base incentive according to REC size and zonal price

Location	Premium	Unit
North of Italy	+10	€/MWh
Centre of Italy	+4	€/MWh
South of Italy and Islands	+0	€/MWh

Table 2: Correctional coefficient according to REC geographical location

Despite the consolidation of the regulatory framework, the development of RECs in Italy is still emerging. Early initiatives were mainly small-scale photovoltaic projects: by mid-2022, around 20-35 REC and collective self-consumption initiatives had been identified, while by July 2023 there were 57 self-consumption configurations, of which 40 were RECs and only 13 were fully operational [9]. More recent studies report around 221 RECs recorded between 2024 and 2025, mostly in the 10-100 kW range, suggesting a gradual shift from pilot projects towards more structured local energy schemes [20]. In addition, the diffusion of RECs remains geographically uneven: northern regions such as Lombardia, Piemonte, Veneto and Friuli Venezia Giulia host a larger share of initiatives, despite lower solar irradiation than southern regions [20]. This suggests that institutional support, technical capacity, access to funding, regional policies and local governance conditions play a central role in determining where RECs emerge and how they develop [20]. Municipalities and public administrations have often acted as promoters and coordinators, especially where regional tenders or public funding are available, while purely bottom-up citizen-led initiatives remain less common [9] [6].

The literature identifies several barriers that still limit REC consolidation, including regulatory complexity, administrative burdens, difficulties in accessing finance, limited technical knowledge, low citizen awareness, and uncertainty about benefit-sharing mechanisms [6]. RECs are also still weakly integrated into local planning instruments: an analysis of 109 Italian urban planning tools found explicit references to RECs in only seven cases, mostly in central-northern Italy [21]. Collectively, these factors indicate that the development of RECs in Italy cannot be explained solely by regulatory frameworks, financial incentives, and renewable energy potential. Their long-term viability also depends on household awareness, perceived benefits, local coordination and trust. Therefore, the Italian case demonstrates the importance of analysing RECs not only as technical or regulatory configurations, but also as socio-technical systems shaped by participation and sustained local engagement. This perspective is fundamental to the present study, which examines REC evolution by integrating technical and economic operations with the behavioural mechanisms driving citizen participation.

2.2 Modelling approaches

This section reviews the main modelling approaches used to analyse Renewable Energy Communities (RECs), focusing on their ability to represent uncertainty, heterogeneity and social dynamics. As said, RECs are complex socio-technical systems, therefore their performance depends not only on technical and regulatory variables, but also on the behaviour of members over time. Therefore, the modelling approach must be selected according to the objective of the analysis.

Existing studies on RECs have mainly focused on techno-economic optimisation, energy management, peer-to-peer trading, investment planning and benefit allocation. Barabino et al. [22] show that a large part of the literature uses energy system modelling and optimisation to study business models, technical configurations and objective functions. These approaches are usually applied to size photovoltaic systems and storage, maximise self-consumption, minimise costs, allocate shared energy or evaluate the profitability of different regulatory schemes. They are effective when the community is treated as a predefined energy system, but they are less suited to describing how the community forms and evolves socially. The following examples illustrate this tendency. Casalicchio et al. [23] developed a linear bottom-up optimisation model for RECs, which includes investment planning, dispatch optimisation, demand-side management and a fairness index for benefit distribution. De Santi et al. [8] applied a modified Mixed Integer Linear Programming (MILP) approach to an Italian REC case, evaluating optimal generation capacity, net present value and the economic conditions under which new prosumers may be incentivised to join. Barone et al. [24] analysed the role of energy communities in electricity grid balancing through an optimisation-based framework focused on energy management and technical performance. Perger et al. [25] addressed dynamic participation in local energy communities with peer-to-peer trading through a bi-level optimisation model, considering how new participants can be included according to the preferences of existing members. These studies provide relevant tools for technical and economic analysis, but participation is often represented mainly as an optimisation, allocation or profitability issue.

This limitation is important for this thesis, because the objective is not only to assess the energetic or economic performance of a REC, but also to simulate how its membership evolves over time. In particular, broader aspects such as awareness, social acceptance, local influence, trust, willingness to remain in the community and interaction among households need to be represented as dynamic processes. Given this objective, two modelling approaches were considered more closely: Modelling to Generate Alternatives (MGA) and Agent-Based Modelling (ABM). They were selected because they address two different needs relevant to REC modelling. The first concerns the design of the REC under uncertainty. A community can be organised through different combinations of members, technologies, installed capacities, storage options, demand profiles, incentive schemes and benefit-allocation rules. Several of these configurations may lead to similar energy or economic performance, even if they differ in structure. This type of question is addressed by Modelling to Generate Alternatives (MGA), which is used in energy planning to explore alternative near-optimal solutions rather than focusing on a single optimal configuration. The second modelling need concerns instead the evolution of participation. In this case, the main question is not which technical configuration is optimal, but how the community changes as households interact, observe benefits and update their decisions. This requires a representation of heterogeneous actors, local influence, probabilistic behaviour and repeated decision-making. Agent-Based Modelling (ABM) is suitable for this purpose because it represents the system from the bottom up, starting from individual agents and allowing aggregate outcomes to emerge from their interactions.

Agent-Based Modelling (ABM), also referred to as Agent-Based Modelling and Simulation (ABMS), is a computational approach that represents a system as a set of autonomous agents interacting with each other and with their environment [26] [27]. It is commonly used to study complex systems in which aggregate outcomes emerge from individual behaviours and local interactions, such as urban systems, transport, markets, ecological systems, infectious disease transmission and energy transitions [26] [27]. In epidemiology, for example, ABM has been used to simulate how contagious diseases spread through contact networks, mobility patterns and individual behavioural responses. In the energy field, ABM has been applied to technology adoption, electricity markets, demand response, peer-to-peer trading, smart grids and local energy systems [28] [29]. In community energy studies, Fouladvand [30] argues that ABMS is well suited to represent heterogeneous actors, behavioural rules, interaction structures and collective outcomes. At the same time, the review highlights that many existing ABMS applications still focus mainly on economic or market-related mechanisms, while institutional, behavioural and social-learning dimensions remain less developed [30]. Vuthi et al. [28] also show that ABM has been applied to electricity, heating, microgrids, mobility and local energy markets, but that integrated models combining multiple sectors and social dynamics are still limited. Lovati et al. [29], for instance, used ABM to simulate peer-to-peer business models for individual photovoltaic prosumers, showing its usefulness for representing decentralised actors and local market interactions, although mainly from an energy and financial perspective. On the other hand, MGA was also considered because the development of a REC involves uncertain and interdependent choices, such as the number and type of members, photovoltaic capacity, storage, consumption profiles, incentives and future demand. MGA is commonly used in energy planning to move beyond the idea of a single optimal solution. Instead, it generates alternative solutions that remain close to an optimal objective but differ structurally, for example in technology mix, investment level or spatial distribution [31]. DeCarolis [31] introduced MGA in energy futures analysis to expand the range of plausible planning alternatives, while Price and Keppo [32] applied it to energy-environment-economy models to explore uncertainty. Lombardi et al. [33] later analysed its computational trade-offs in energy infrastructure deployment, and Lombardi and Pfenninger [34] showed how MGA can also support stakeholder-oriented energy system design. In principle, MGA could be used to generate alternative REC configurations that reach similar technical or economic performance with different designs. This makes it useful for questions such as which REC configurations are robust under uncertain assumptions, or how much the design can change while maintaining similar performance. It is therefore more appropriate for selecting alternative system designs than for representing decentralised behavioural processes or membership evolution.

The two approaches are not incompatible, but they answer different research questions. MGA can generate technically robust REC designs, while ABM can test whether those designs are socially stable and attractive for households over time. Conversely, ABM can simulate participation trajectories that could later be used as inputs for an optimisation or MGA framework. For this thesis, however, ABM was selected as the main modelling approach because the research question is centred on membership evolution and social dynamics. The model needs to represent households as heterogeneous agents, allow them to interact locally, and update their participation decisions over time according to economic benefits, awareness, peer influence and perceived advantages. A summary of all analysed paper is presented in Table 3.

Table 3: Summary literature review on modelling approaches

Reference	Application / focus	Methodology applied	Treatment of the social dimension
Barabino et al. [22]	Review of energy-community trends, business models, modelling approaches and optimisation objectives.	Literature review of energy system modelling and optimisation approaches.	Discusses business models and objectives, but the reviewed literature is mainly techno-economic; social participation dynamics are not explicitly simulated.
Casalicchio et al. [23]	Investment planning, dispatch optimisation, demand-side management and fair benefit distribution in RECs.	Linear bottom-up optimisation model.	Includes fairness in benefit allocation, but participation is not represented as an evolving behavioural process.
De Santi et al. [8]	Italian REC case study assessing optimal generation capacity, economic performance and conditions for new prosumers to join.	Modified MILP approach.	Considers participation mainly through economic feasibility and prosumer entry conditions; social diffusion and peer influence are not modelled.
Barone et al. [24]	Electricity-grid balancing and smart-grid operation of energy communities.	Optimisation-based energy management framework.	Social participation is not central; the focus is on energy management and grid performance.
Perger et al. [25]	Dynamic participation in local energy communities with peer-to-peer trading.	Bi-level optimisation model.	Includes the entry of new participants according to preferences of existing members, but within an optimisation logic rather than a behavioural diffusion process.
Fouladvand [30]	Systematic review of ABMS applications to community energy systems.	Systematic literature review on ABMS.	Identifies ABM as suitable for heterogeneous actors, behavioural rules and interaction structures; notes that social-learning and institutional dimensions remain underdeveloped.
Vuthi et al. [28]	Urban neighbourhood energy systems, including electricity, heating, microgrids and local energy markets.	Literature review and proposal for an integrative ABM approach.	Recognises heterogeneity and local interactions, but many applications remain focused on technical or market mechanisms.
Lovati et al. [29]	Peer-to-peer business models for individual photovoltaic prosumers in a local electricity market.	Agent-Based Modelling simulation.	Represents decentralised actors and local market interaction, but the focus remains mainly on energy and financial flows rather than REC membership evolution.
DeCarolis [31]	Energy futures analysis and exploration of alternative planning solutions.	Modelling to Generate	Does not address REC participation; social aspects are outside the main modelling scope.

Reference	Application / focus	Methodology applied	Treatment of the social dimension
		Alternatives (MGA).	
Price and Keppo [32]	Exploration of uncertainty in energy-environment-economy models.	MGA applied to scenario and uncertainty analysis.	Uncertainty is treated around model inputs and alternatives, not as household-level social behaviour.
Lombardi et al. [33]	Computational trade-offs in energy infrastructure deployment.	MGA for energy infrastructure planning.	Social participation is not explicitly represented; the focus is on alternative system designs and computational performance.
Lombardi and Pfenninger [34]	Stakeholder-oriented energy system design options.	Human-in-the-loop MGA.	Stakeholder needs are considered in the design process, but household-level participation and social diffusion are not dynamically simulated.
This thesis	Analysis of RECs as an evolving socio-technical system. Application to a real case and future scenarios	Agent-Based Model linking technical-economic REC operation with behavioural joining and retention rules.	Explicitly models social participation: households are heterogeneous agents, decisions to join/remain/leave are updated over time, and local exposure, perceived benefits and behavioural type influence membership.

3. Methodology

3.1 Agent Based Model

Agent-Based Modelling (ABM) is a bottom-up simulation approach used to study systems composed of multiple autonomous entities, called agents. Instead of representing the system only through aggregate equations, ABM starts from the individual components of the system and defines how they behave, interact and evolve over time. The aggregate behaviour of the system is then obtained from the combination of many individual actions and interactions [26] [27]. An ABM can be understood through two main levels: the agent level and the model level. The agent level describes the individual entities included in the simulation, while the model level defines the environment in which they operate, the rules coordinating the simulation, and the collected outputs. At the agent level, each agent represents an autonomous unit of the system, such as a person, household, firm, vehicle, building or institution. Agents are characterised by attributes and internal states, which describe their condition at a given moment. These may include observable characteristics, such as location, income, energy consumption or technology ownership, as well as less directly observable characteristics, such as preferences, memory, risk perception, expectations or willingness to cooperate [26] [27]. Agents can be heterogeneous, meaning that they do not need to have the same characteristics or respond in the same way to external conditions. Each agent follows behavioural rules that determine how it makes decisions. These rules may be simple, for example based on thresholds, or more complex, for example based on probabilities, utility functions,

learning mechanisms or imitation. Agents may react to their own state, to external signals from the environment, or to the behaviour of other agents. This makes ABM suitable for representing systems in which individual decisions are not fully identical or deterministic, but depend on local information, personal characteristics and interaction effects [26] [35].
At the model level, the environment represents the context in which agents are located and within which they act. It defines the external conditions, resources and constraints that influence agents' decisions. Depending on the model, the environment can be spatial, such as a city, a neighbourhood or an energy network, or non-spatial, such as a market, an institutional framework or a social network. It may include physical elements, such as infrastructure, distance and available resources, as well as external variables, such as prices, regulations, weather conditions or information flows. The environment is not necessarily passive: agents can also modify it through their actions. For example, individual decisions can change demand levels, congestion, resource availability or the structure of social interactions. In this sense, the environment works as the link between individual behaviour and system-level conditions.
The model level also includes the scheduler, the time structure and the output collection. The scheduler defines the order in which agents act and how the simulation advances in time. The evolution can be assessed through discrete time steps, such as hours, days, months or years, or through specific events. At each step, agents observe the relevant information, apply their behavioural rules, update their state and interact with other agents or with the environment. After these actions, the model updates aggregate variables and records selected outputs, such as total demand, number of adopters, distribution of agent states or other emerging patterns [26] [27].
From a technical point of view, an ABM is implemented as an iterative simulation. First, it defines the initial population of agents, their attributes, the environment and the global parameters of the model. Then, at each time step, a sequence of operation is repeated: agents perceive information, make decisions, act, and update their state. Their individual actions are aggregated to update system-level variables, which may then influence the agents in the following time step. This creates a feedback loop between micro-level decisions and macro-level outcomes.

3.2 Model structure

The model developed in this thesis is an Agent-Based Model (ABM) designed to simulate the evolution and operation of a Renewable Energy Community (REC) over time. A bottom-up logic is followed: the REC is not represented only as an aggregate energy system, but as a set of individual households whose decisions determine the evolution of the community. This structure is consistent with the general logic of ABM, where the system-level outcome emerges from the behaviour and interaction of autonomous agents [26] [27].

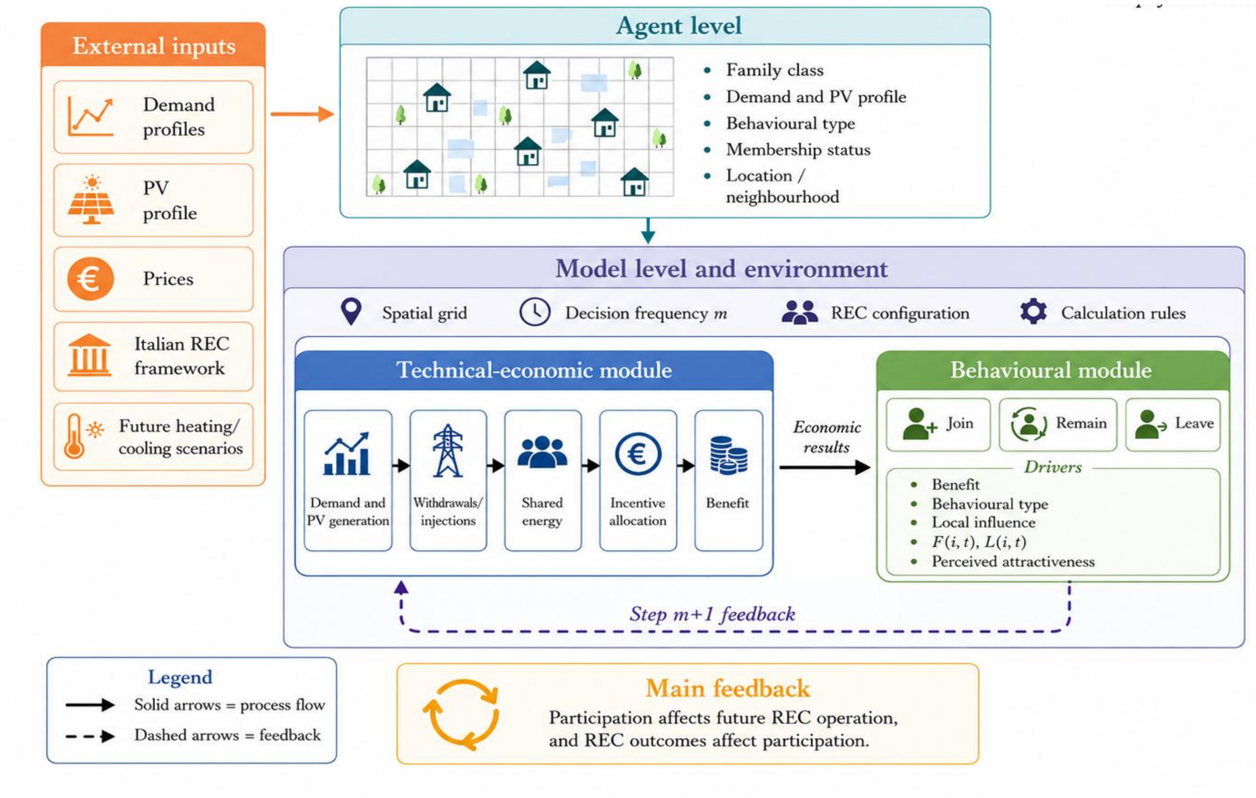


Figure 1: Conceptual structure of the ABM and feedback between REC operation and household participation.

As illustrated in Figure 1, the model has three connected dimensions. The first is the energy dimension, which describes household consumption, photovoltaic (PV) generation, grid withdrawals, grid injections and shared energy. The second is the economic dimension, which calculates the individual electricity bill, the total REC incentive and its allocation among participants. The third is the behavioural dimension, which updates the membership of the REC by simulating whether agents decide to join, remain in or leave the community. The purpose is therefore not only to evaluate the energy and economic performance of the REC, but also to analyse how those results influence participation over time.

The model can be interpreted as a hybrid framework. The technical-economic module calculates the operation of the REC with frequency m, while the behavioural module uses the economic outcome obtained by agents to update their future decisions. In this way, physical functioning of the REC and social evolution are linked: energy sharing generates economic benefits, benefits affect individual behaviour, and individual behaviour changes the size and composition of the REC in the future.

3.2.1 Agent level

At the agent level, each household is represented as an individual agent. Agents are autonomous units with their own technical, economic and behavioural characteristics. Each household is assigned a family class and a behavioural type. For the latter, the model distinguishes between environmentalist and non-environmentalist agents, because the two groups are assumed to differ in their baseline propensity to participate in a REC and in their sensitivity to economic and social signals. In addition, each agent is characterised by a set of states and attributes. These include its current membership status, household class, hourly electricity consumption profile, PV ownership,

installed PV capacity, position on a spatial grid, current individual bill, community bill, allocated incentive and benefit. Dynamic behavioural information is also stored, such as whether the agent has experienced negative benefits in previous decision periods. These variables allow each household to react differently to the same community conditions. The attributes used to initialise and characterise household agents are summarised in Table 4.
The spatial position of the agent is used to define its local neighbourhood. This is important because the model does not assume that all agents are equally influenced by the whole community. Instead, each household is affected by the agents located around it. The local neighbourhood is therefore used to calculate the social pressure that can encourage joining or remaining in the REC.

Table 4: Household-agent attributes used to initialise and characterise the ABM

Attribute group	Household-agent attribute
Household and building characteristics	Household / family class
	Apartment type and construction period
Technical and energy characteristics	Baseline hourly electricity-demand profile
	PV ownership
	Installed PV capacity
	Heating technology assignment
	Cooling technology assignment
Behavioural and social characteristics	Environmental orientation / behavioural type
	Baseline joining propensity
	Baseline retention probability
Spatial characteristics	Grid coordinates / spatial location

3.2.2 Model level and environment

At the model level, the environment represents the context in which agents operate. In this model, the environment is not only a physical space, but also the technical and economic framework of the REC. It contains the spatial grid, the time structure of the simulation, the set of agents, the community configuration, the PV generation logic, the electricity bill calculation, the shared-energy calculation and the incentive-allocation mechanism. In the following, m denotes the frequency update period of the operations.
The environment also coordinates the interaction between individual agents and aggregate REC variables. At the beginning of each period m, the model identifies which agents are active REC members. Only these agents participate in the m-period calculation of community withdrawals, injections, shared energy and incentives. After the energy and economic calculations are completed, each agent receives its m-period outcome and updates its membership decision. In this way, the environment creates a feedback loop between individual decisions and system-level results.
The technical-economic part of the developed model follows the Italian virtual model of energy sharing, as described in Section 2.1. In particular, the implementation is based on the model proposed by Taromboli et al. [19].

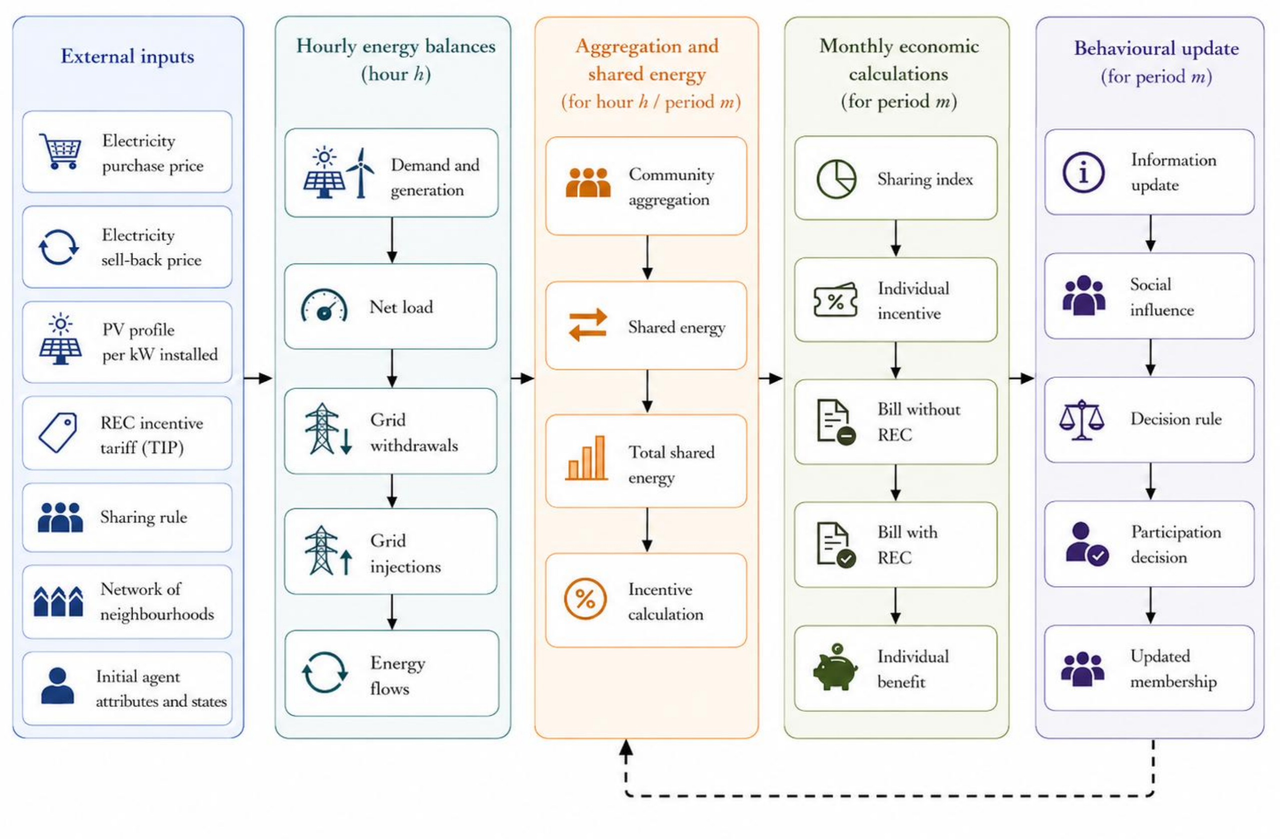


Figure 2: Computational pipeline of the model.

Figure 2 illustrates the computational pipeline underlying the model. The procedure begins by calculating the PV generation of household for each agent i and each hour h according to Eq. (2). Generation depends on the installed PV capacity of the agent and on the hourly production profile of one installed kilowatt:

$$G_{i,h} = \mathrm{PV}_i \cdot g_h^{(1\ \mathrm{kW})} \tag{2}$$

where PV_i is the PV capacity installed by agent i, and $g_h^{(1\ \mathrm{kW})}$ is the hourly PV generation profile for 1 kW of installed capacity.
The model then compares hourly consumption and PV generation. If consumption is higher than generation, the agent withdraws electricity from the grid. If generation is higher than consumption, the surplus is injected into the grid, as defined by Eq. (3) and (4):

$$W_{i,h} = \max(C_{i,h} - G_{i,h}, 0) \tag{3}$$

$$\mathrm{INJ}_{i,h} = \max(G_{i,h} - C_{i,h}, 0) \tag{4}$$

where $C_{i,h}$ is the electricity consumption of agent i, $W_{i,h}$ is the electricity withdrawn from the grid, and $\mathrm{INJ}_{i,h}$ is the electricity injected into the grid.

This individual energy balance is calculated for all households, independently of whether they are members of the REC. According to the computed injection and withdrawal, the m-period individual bill of each household is calculated as in Eq. (5).

$$\mathrm{Bill}_{i,m}^{\mathrm{ind}} = \sum_{h\in m} \left(W_{i,h}\lambda_h^{\mathrm{buy}} - \mathrm{INJ}_{i,h}\lambda_h^{\mathrm{sell}}\right) \tag{5}$$

where λ_h^{buy} is the electricity purchase price and $\lambda_h^{\mathrm{sell}}$ is the selling price for electricity injected into the grid. This quantity is used as the reference bill against which the community benefit is evaluated. Then, the simulation advances over successive m-periods. At the beginning of each period m, the model identifies the set of active REC members, indicated as REC_m. These are the only agents that contribute to the shared energy and incentive calculation during that period. The membership decisions made at the end of the m-period affect the composition of the REC in the following one. For each hour h of the period, the model aggregates the withdrawals and injections of the active households, as defined in Eq. (6) and (7):

$$W_h^{\mathrm{tot}} = \sum_{i\in REC_m} W_{i,h} \tag{6}$$

$$\mathrm{INJ}_h^{\mathrm{house}} = \sum_{i\in REC_m} \mathrm{INJ}_{i,h} \tag{7}$$

If a community plant is present, the total system injection is then given by the sum of household injections and community-plant injection according to Eq. (8):

$$\mathrm{INJ}_h^{\mathrm{sys}} = \mathrm{INJ}_h^{\mathrm{house}} + \mathrm{INJ}_h^{\mathrm{plant}} \tag{8}$$

In line with the Italian virtual REC model, the hourly shared energy is calculated as the minimum between total withdrawal and total injection within the REC [3], as shown in Eq. (9):

$$\mathrm{Shared}_h = \min\left(W_h^{\mathrm{tot}}, \mathrm{INJ}_h^{\mathrm{sys}}\right) \tag{9}$$

Since there is a distinction between energy injected by household PV systems and energy injected by the community plant, the total shared energy is divided proportionally according to the contribution of the two sources. This distinction allows the model to apply different incentive rates to household PV generation and to the community plant, while maintaining the Italian ex-post virtual sharing logic. The monthly incentive is calculated separately for the household component and the community-plant component, since the TIP associated to calculate the incentive is based on the capacity of the plant, as shown in Section 2.1 at Table 1. The total incentive available to the REC is therefore defined by Eq. (10):

$$\mathrm{Inc}_m^{\mathrm{tot}} = \mathrm{Inc}_m^{\mathrm{house}} + \mathrm{Inc}_m^{\mathrm{plant}} \tag{10}$$

Consistently with the Italian virtual model, this incentive is not automatically assigned to individual members through their electricity bills. Instead, it is first recognised at community level and then allocated according to a sharing rule. A sharing index is used to allocate the total incentive among active participants. Two allocation rules are included in the developed model.

- Balanced_50_50 rule. This rule allocates the incentive by considering both consumption and production contributions. For each member i, the sharing index is defined in Eq. (11):

$$\mathrm{SI}_i = 0.5 \cdot \frac{W_{i,m}}{W_{tot}^{\mathrm{sys}}} + 0.5 \cdot \frac{\mathrm{INJ}_{i,m}}{\mathrm{INJ}_{tot}^{\mathrm{sys}}} \tag{11}$$

- Producer_only_20 rule. This rule allocates the incentive only according to production contribution and was considered to test different REC business model, less focused on incentive redistribution and more on community project financing, that may occur under the Italian regulatory framework. For each member i the sharing index is defined in Eq. (12):

$$\mathrm{SI}_i = 0.2 \cdot \frac{\mathrm{INJ}_{i,m}}{\mathrm{INJ}_{tot}^{\mathrm{sys}}} \tag{12}$$

The incentive allocated to each participant is then calculated according to Eq. (13):

$$\mathrm{AllocInc}_i = \mathrm{SI}_i \cdot \mathrm{Inc}_m^{\mathrm{tot}} \tag{13}$$

After the incentive has been allocated, the model re-computes the community bill of each household, as defined in Eq. (14) and (15). For agents that are active members of the REC, the community bill is obtained by subtracting the allocated incentive from the individual bill:

$$\mathrm{Bill}_{i,m}^{\mathrm{com}} = \mathrm{Bill}_{i,m}^{\mathrm{ind}} - \mathrm{AllocInc}_i \tag{14}$$

For agents that are not active members, no REC incentive is assigned, and the community bill is equal to the individual bill:

$$\mathrm{Bill}_{i,m}^{\mathrm{com}} = \mathrm{Bill}_{i,m}^{\mathrm{ind}} \tag{15}$$

The m-period benefit is defined as the difference between the individual bill and the community bill in Eq. (16):

$$\mathrm{Benefit}_{i,m} = \mathrm{Bill}_{i,m}^{\mathrm{ind}} - \mathrm{Bill}_{i,m}^{\mathrm{com}} \tag{16}$$

This formulation links the economic result of the Italian virtual sharing mechanism to the behavioural part of the ABM. In other words, the incentive allocation does not only determine the economic outcome of each member, but also provides the signal that agents use to decide whether to remain in or leave the REC in subsequent periods. At the end of each period m, the model updates the membership status of each agent for the following one. The behavioural rules distinguish between agents that are already members of the REC and agents that are still outside the community: if an agent is already a member, the decision depends first on the sign of the benefit; if the benefit is negative, is assumed that non-environmentalist agents leave the REC immediately, while environmentalist agents tolerate a longer period of negative performance and leave only after three consecutive decision periods of negative benefits. This rule reflects the assumption that environmentalist agents have stronger non-economic motivations and are therefore less reactive to short-term negative outcomes.

If the benefit is non-negative, the agent remains in the REC with a retention probability. The retention probability depends on a baseline tendency to remain in the community and on the local social pressure generated by neighbouring REC members as defined in Eq. (17):

$$\text{retention\_prob}_i = \min\left(1, \text{base\_retention}_i + w_i^{\text{ret}} \cdot \text{pressure}_i\right) \tag{17}$$

where base_ret_i is the agent's baseline retention probability, w_i^{ret} is the weight of neighbourhood influence on retention, and pressure_i measures local exposure to REC members. The neighbourhood pressure is calculated according to Eq. (18) by considering the eight cells surrounding the agent on the spatial grid. It is defined as the ratio between the number of neighbouring REC members and the total number of neighbours:

$$\text{pressure}_i = \frac{N_i^{\text{RECneigh}}}{N_i^{\text{tot neigh}}} \tag{18}$$

This variable ranges from 0 to 1 and represents the intensity of the local social context around each agent. A value close to 0 means that almost none of the agent's neighbours are REC members, while a value close to 1 means that the agent is surrounded by members.
If an agent is not a member of the REC, it can enter the community with a join probability defined in Eq. (19). This probability depends on two components: a baseline propensity to join, and a social-envy component. This structure reflects two different mechanisms. The first term represents the part of the personal predisposition that becomes effective because the agent is exposed to the existence of the REC. The second term represents the part of the general socio-economic attractiveness of the REC that the agent is able to perceive.

$$\text{join\_prob}_i = \min\left(1, F_{i,t} \cdot \text{base\_join}_i + L_{i,t} \cdot \text{social\_envy}_m\right) \tag{19}$$

where join_prob_i is the probability that the agent i joins the REC at time t, base_join_i is the baseline joining probability of the agent, and social_envy_m is *the* m-period attractiveness signal generated by the average incentive observed within the REC. $F_{i,t}$ is the activation factor applied to the personal predisposition to join, and $L_{i,t}$ is the activation factor applied to the perceived socio-economic attractiveness of the REC. The upper bound ensures that the result is a valid probability.
The base join component is an agent-specific parameter, and its value is not the same for all agents, it is differentiated according to the behavioural type of the household: environmentalist end non-environmentalist.
The social-envy component is computed as a saturation function, as shown in Eq. (21), which depends on the average incentive allocated to active members, as shown in Eq. (20). The saturation form ensures that the effect of the perceived benefit increases with the average allocated incentive, but with decreasing marginal impact. This avoids assuming that perceived attractiveness increases linearly without limit. If there are no active members or no allocated incentive in a given time step, social_envy is set equal to zero.

$$\overline{\text{AllocInc}}_m = \frac{1}{N_m^{\text{REC}}} \sum_{i \in REC_m} \text{AllocInc}_i \tag{20}$$

$$\text{social\_envy}_m = \alpha \cdot \frac{\overline{\text{AllocInc}}_m}{\overline{\text{AllocInc}}_m + \text{envy\_scale}} \tag{21}$$

where α controls the maximum contribution of social envy to the joining probability, and envy_scale defines the monetary scale at which the perceived incentive starts to saturate.
Both the components of join probability are activated through the member's REC exposition, $F_{i,t}$ and $L_{i,t}$ are two different ways of representing this exposure. They are both spatial factors, hence related to the weight of the distance between the agent and the CER member. In both cases, the spatial weight is defined through an exponential decay function [36] [37] in Eq. (22):

$$w_{ij} = e^{-\lambda\delta_{ij}} \tag{22}$$

where δ_{ij} is the normalised distance between agents i and j, and λ_F controls how fast influence decreases with distance. [38]The Euclidean distance between the two agents is calculated in Eq. (23):

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{23}$$

If the spatial grid has dimensions L_x and L_y, the maximum theoretical distance is the grid diagonal, defined in Eq. (24):

$$D_{max} = \sqrt{(L_x - 1)^2 + \left(L_y - 1\right)^2} \tag{24}$$

The normalised distance is therefore defined in Eq. (25):

$$\delta_{ij} = \frac{d_{ij}}{D_{max}} \tag{25}$$

This normalisation avoids making the decay parameter directly dependent on the absolute size of the grid. The parameter λ_F can be calibrated by imposing a residual influence η_F at the maximum normalised distance. Since $\delta_{ij} = 1$ at the maximum distance, the condition is given in Eq. (26):

$$e^{-\lambda} = \eta \tag{26}$$

and therefore Eq. (27):

$$\lambda = -\ln(\eta) \tag{27}$$

In the base join component, $F_{i,t}$ is calculated as a distance-weighted exposure to REC members according to Eq. (28):

$$F_{i,t} = \frac{\sum_{j\neq i} w_{ij} c_j(t)}{\sum_{j\neq i} w_{ij}} \tag{28}$$

Where:

- $c_j(t) = 1$ if agent j is a CER member at time t
- $c_j(t) = 0$ if agent j is not a CER member
- w_{ij} is the spatial weight between i and j.

The numerator captures the distance-weighted presence of neighbouring agents who are already REC members, while the denominator captures the overall distance-weighted local population observed by agent i, including both members and non-members. Therefore, $F_{i,t}$ is a normalised exposure factor bounded between 0 and 1. It does not represent the absolute number of nearby REC members; rather, it measures how strongly the REC is represented in the agent's local context relative to all observed agents. If no relevant nearby agent is a REC member, $F_{i,t}$ is close to 0; if most of the spatially influential agents around i are REC members, $F_{i,t}$ approaches 1. The formulation of $F_{i,t}$ is supported by three main ideas. First, innovation adoption can be represented as a diffusion process in which the behaviour of already active nodes influences the behaviour of other nodes in the network [39]. Second, the influence of adopters is not spatially uniform, because peer effects in energy-related decisions tend to decrease with distance [38] [37]. Third, exposure should be measured as a relative local density rather than as a simple count of adopters: a single REC member has a different meaning in a sparse area than in a dense local context [38].
In the social envy component, $L_{i,t}$ measures the probability that at least one nearby REC member will transmit a signal to the agent, this signal is weighted based on spatial distance as defined in Eq. (29):

$$L_{i,t} = 1 - \prod_{j \neq i} \left(1 - w_{ij} c_j(t)\right) \tag{29}$$

Mathematically, the term $c_j(t)$ acts as a boolean trigger. If agent j is actively participating in the REC ($c_j(t)$ = 1), it propagates a distance-decayed signal (w_{ij}) to agent i. Conversely, non-members ($c_j(t)$ = 0) do not generate any active signal. The product $\left(1 - w_{ij} c_j(t)\right)$ thus represents the probability that agent i is not influenced by agent j. Following a noisy-OR logic, the final expression computes the probability that at least one neighbour successfully transmits the REC signal. Therefore, each nearby REC member is treated as a possible independent source of information about the benefits of the community. This formulation is also consistent with Independent Cascade models, where active nodes can influence neighbouring inactive nodes with a certain probability, and several active neighbours can act as independent sources of influence [40] [41] [42]. The noisy-OR formulation is a standard way to combine multiple independent potential causes of the same outcome, because it calculates the probability that at least one cause produces the effect [43] [44].
The main difference between the two factors is that $F_{i,t}$ answers the question: "how strongly is the REC represented in the local context of agent i ?". It is a normalised measure of local REC presence. $L_{i,t}$, instead, answers the question: "is there at least one nearby REC member able to make the REC visible or relevant to agent i ?". It is a measure of local signal activation. The two factors are therefore not interchangeable: $F_{i,t}$captures exposure as local penetration, while $L_{i,t}$ captures exposure as visibility, communication and signal transmission.
For this reason, the model keeps $F_{i,t}$ and $L_{i,t}$ separate in the formulation. Before deciding which spatial factor should be associated with each component of the joining probability, both factors are tested through a sensitivity analysis, which is presented later in the thesis. This allows the final behavioural specification to be supported not only by theoretical reasoning, but also by the observed effect of the two spatial mechanisms on the simulated REC dynamics.
To conclude, the behavioural module therefore combines individual predisposition, local social influence and observed economic attractiveness. By updating membership at the end of each period m, the model creates a dynamic link between the technical-economic performance of the REC and its social evolution. A higher incentive can increase the perceived attractiveness of the community,

a larger number of members can increase neighbourhood pressure, and changes in participation can in turn modify the amount of shared energy and the incentive available in the following period.

3.3 Assumptions behind the behavioural probabilities

Table 5 summarises the main assumptions used to define join probability and retention probability. The last column explicitly indicates how each source supports a specific modelling choice, rather than using the references as generic background literature.

Component	Assumption and model implication	Explicit supporting references
Join probability	Joining is driven by two activated mechanisms: personal predisposition activated by $F_{i,t}$, and perceived socio-economic attractiveness activated by $L_{i,t}$. The final expression combines base join with $F_{i,t}$ and social envy with $L_{i,t}$, while $\min(1,\cdot)$ ensures that the result remains a probability.	Rogers [45] and Guidolin and Manfredi [46] support the multi-stage and multi-channel interpretation of innovation adoption. Caferra et al. [47] and De Simone et al. [48] support the importance of trust, proximity, social interaction and perceived benefits in REC participation.
Retention probability	Remaining in the REC is different from joining because members have already entered the community and directly experienced participation. Retention probability is therefore simpler than join probability and depends on base retention and local influence	Neves et al. [49] and De Simone et al. [48] support the importance of commitment, trust and pro-environmental behaviour for involvement in energy communities. Caferra et al. [47] supports proximity and social capital. Lin et al. [50] supports the idea that continuing as an energy prosumer depends on behavioural reasons and continued willingness.
$\boldsymbol{F_{i,t}}$	Base join should not act fully unless the agent is locally exposed to the existence of the REC. $F_{i,t}$ activates the personal predisposition by measuring the normalised, distance-weighted share of REC members in the agent's local context.	Duanmu and Chai [39] justify modelling adoption as diffusion through a network of active and inactive agents. Barton-Henry et al. [38] support using local density and distance decay in solar adoption. Min [37] and van Casteren et al. [51] support the assumption that peer effects in energy-related decisions are spatially local and decrease with distance.
$\boldsymbol{L_{i,t}}$	Social envy should not be perceived uniformly by all agents. $L_{i,t}$ activates social envy only when nearby REC members make REC benefits visible. Its noisy-OR form represents several nearby members as independent possible sources of a socio-economic signal.	Li et al. [40] and Ye et al. [41] support the Independent Cascade logic of active nodes influencing inactive nodes. Zareie and Sakellariou [42] support behaviour-aware influence processes. Pearl [43] and Cozman [44] justify the noisy-OR structure used to combine multiple independent sources of the same effect.
Social envy	Non-members do not perfectly observe all individual payoffs. Instead, they perceive a general attractiveness signal based on the	Taromboli et al. [19] justify the use of allocated incentives as a behavioural signal in the Italian virtual REC model, where benefits are

Component	Assumption and model implication	Explicit supporting references
	average incentive allocated to active members. The effect is positive but bounded by envy alpha, so higher benefits increase attractiveness with decreasing marginal impact.	recognised ex post. Fehr and Schmidt [52] support the behavioural relevance of relative economic comparison. De Simone et al. [48] and Magni et al. [53] support the role of economic incentives and perceived benefits in REC participation.

Table 5: Assumptions and model implications of behavioural variables

3.4 Sensitivity analysis design

The behavioural assumptions are assessed through an exploratory sensitivity analysis. The number of active REC members at the end of a reference year is used as the main comparison indicator. Starting from an initial number of members and a given population of new potential members, the analysis seeks a final community size in a plausible order of magnitude (approximately 10^3 members), while preserving a non-automatic diffusion process. This analysis is conducted in two stages.

- The first stage screens the preliminary, non-spatial behavioural formulation and identifies the parameters that most affect the simulated inflow and persistence of members.
- The second stage tests the revised spatial joining structure by comparing alternative assignments of the distance-sensitive factors $F_{i,t}$ and $L_{i,t}$.

Both stages are evaluated under the balanced_50_50 and producer_only_20 incentive-allocation rules.

3.4.1 Preliminary behavioural formulation and screening

Before introducing the two distance-sensitive activation factors, joining was represented through an additive formulation combining an individual baseline propensity, local neighbourhood pressure and perceived economic attractiveness. Retention was represented separately by a baseline probability and the same neighbourhood-pressure indicator. In this preliminary specification, pressure is calculated as the share of REC members among the agents located in the eight surrounding grid cells.

The screening varies base join probability, base retention probability, neighbourhood influence on joining and retention, PV adoption probability, and the two social-envy parameters. .The screening assesses all behavioural parameters but gives particular attention to the joining mechanism. Joining is evaluated over the full population of non-members at every entry opportunity, whereas retention affects only agents who have already entered the REC. Consequently, retention can influence community stability but cannot compensate for an excessive initial inflow. In the preliminary formulation, the joining probability of an external agent was defined as in Eq. (30):

$$p_{i,t}^{\text{join}} = \min\{1, b_i^{\text{join}} + w^{\text{join}} \cdot pressure_{i,t} + social\_envy_t\} \quad (30)$$

where the three terms represented, respectively, the individual baseline propensity to join, the local presence of REC members and the perceived economic attractiveness of the community.

3.4.2 Spatial sensitivity design

Building on the definitions provided in Section 3.2.2, the next part of the sensitivity analysis compares the possible associations of $F_{i,t}$ and $L_{i,t}$ with base join and social envy and evaluates how their effects change with the spatial radius. This section focuses on their effect on the simulated REC dynamics and on the choice of their final position in the joining probability. The two factors do not add an independent entry probability; instead, they scale the behavioural component to which they are assigned. A factor equal to zero deactivates the associated component, whereas a value close to one allows it to contribute almost fully. The tested configurations are defined as in Eq. (31), (32) and (33):

$$\mathrm{F-L:}\ \ \mathrm{join_{prob}}_i = \min\left(1, F_{i,t}\cdot \mathrm{base_{join}}_i + L_{i,t}\cdot \mathrm{social_{envy}}_m\right) \tag{31}$$

$$\mathrm{F-F:}\ \ \mathrm{join_{prob}}_i = \min\left(1, F_{i,t}\cdot \mathrm{base_{join}}_i + F_{i,t}\cdot \mathrm{social_{envy}}_m\right) \tag{32}$$

$$\mathrm{L-L:}\ \ \mathrm{join_{prob}}_i = \min\left(1, L_{i,t}\cdot \mathrm{base_{join}}_i + L_{i,t}\cdot \mathrm{social_{envy}}_m\right) \tag{33}$$

The configurations were evaluated over progressively wider spatial radii while maintaining a fixed distance-decay setting. This design separates the activation of the individual propensity to join from the transmission of the economic attractiveness signal. Table 6 summarises the behavioural interpretation of the tested associations.

Behavioural component	When multiplied by F	When multiplied by L	Expected modelling effect
Base join	Only the share of the agent's potential predisposition corresponding to local, distance-weighted REC penetration becomes effective. A meaningful local presence is therefore required.	The predisposition can be activated by at least one sufficiently strong nearby REC signal. A large local share of members is not required.	This association has the strongest effect on community growth because base join applies to every non-member and is generally larger than social envy.
Social envy	The economic attractiveness of the REC is perceived in proportion to its relative local diffusion. Benefits become relevant mainly when membership is widespread in the surrounding context.	The economic attractiveness can be perceived when one or more nearby members make their benefits visible. This represents communication, observation and word-of-mouth.	This association mainly controls how the incentive signal is transmitted and is therefore more sensitive to the allocation rule and the magnitude of household benefits.

Table 6: Behavioural interpretation of multiplying base join and social envy by F or L.

3.5 Future demand construction

The model is implemented also to run for multiple years and this extension does not modify the structure of the ABM, but only the electricity demand assigned to household agents. In future years,

the baseline electricity consumption profile of each household can be increased by adding the electricity demand associated with heating and cooling systems. Each household can therefore receive a different additional load depending on its building characteristics and on the technologies assigned to it over time.
From a methodological point of view, each household is first associated with a building category, defined by the combination of apartment type and construction period. This category is used to link the agent to a specific heating or cooling demand profile. Then, for each year of the simulation, the model reads the penetration targets of the considered technologies and compares them with the number of agents that already have each technology. The difference determines how many additional households receive the corresponding system in that year. Once a technology is assigned, the model adds the related hourly electricity demand profile to the household baseline consumption.
For each household agent i, hour t and year y, the total electricity consumption is defined in Eq. (34):

$$C_{i,t,y}^{tot} = C_{i,t,y}^{base} + C_{i,t,y}^{heating} + C_{i,t,y}^{cooling} \tag{34}$$

where $C_{i,t,y}^{base}$ is the baseline household electricity demand, $C_{i,t,y}^{heating}$ is the additional electricity demand associated with the assigned heating technology, and $C_{i,t,y}^{cooling}$ is the additional demand associated with cooling. If a household is not assigned a heating or cooling system in a given year, the corresponding term is equal to zero.
Once the updated consumption profile has been obtained, the rest of the model operates as in the reference-year simulation: household PV production is compared with total demand, withdrawals and injections are calculated, and the resulting values are used to compute shared energy, incentives, benefits and participation decisions.

4. Case Study

In this chapter, the model described above is applied to real case study, namely to CER.ca.MI, a solidarity-based REC operating in the city of Milan. In particular, the analysis focuses on the area served by the Ponte Nuovo primary substation in Milan, which corresponds to one of the active energy-sharing configurations of the mentioned energy community.
The analysis is carried out in two stages. First, an exploratory parameter analysis is performed over 2025 as reference year. As mentioned, this analysis is intended as an exploratory parameter analysis rather than a formal calibration since observed data on REC membership evolution are not available. Therefore, the objective is to understand how the model reacts to different behavioural assumptions and to identify the parameters that most influence the evolution of community participation. Then, different future scenarios are developed over the period from 2025 to 2040.

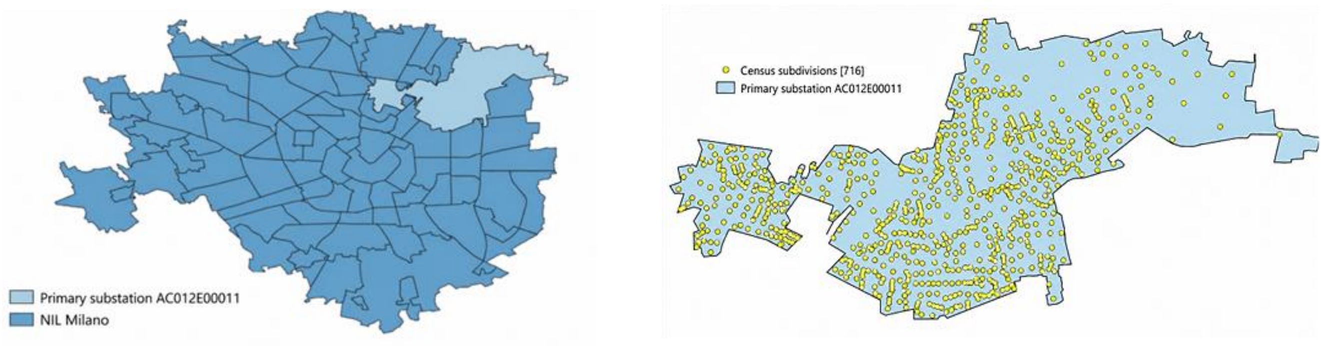
4.1 Exploratory parameter analysis

In this section, the data adopted for the exploratory parameter analysis is described. In particular, four main group of input are needed:

- Demographic structure: necessary to define the physical and social framework of the model, determining the total number of agents, their household sizes, and the initial configuration of the simulated population within the selected area.

- Energy characteristics: necessary inputs to simulate the technical operation of the REC, since they determine the electricity demand of each agent, the potential photovoltaic generation, the energy withdrawn from and injected into the grid, and the electricity bill before the allocation of REC incentives.
- Economic characteristics: required to evaluate the financial performance of the system, providing the market prices, grid tariffs, and system charges needed to compute the economic benefits and the financial attractiveness of the community.
- Behavioural data: essential to define the decision-making rules of the agents, governing their propensity to join, remain in, or leave the REC, as well as their likelihood to adopt individual PV systems based on social and psychological attitudes.

Regarding demographic structure of agent population, the latter is mainly based on the 2011 Census data for the city of Milan [54]. These data were processed using QGIS, which made it possible to identify the census areas included in the selected primary substation perimeter and to extract the corresponding number of households. The total number of households in the selected area was set equal to 81’143 agents, classified into five family classes: one-person households, two-person households, three-person households, four-person households, and households with five or more members [54]. At the same time, maximum values were assigned to each household-size class, so that the simulated population respected the demographic structure observed in the census data. The spatial extent of the case study and the related census subdivisions are shown in Figure 3, while the resulting maximum number of agents by household-size class is reported in Table 7.



(a) Primary substation of CER.ca.MI in the city of Milan

(b) Census subdivisions in the primary substation area considered

Figure 3: Primary substation of CER.ca.MI and census subdivisions.

People class	1	2	3	4	5+	Tot.
Max agents	37644	21992	11715	7666	2106	81143

Table 7: Maximum model agents per people class.

In addition, agents are categorised by behavioural type, separating environmentalist and non-environmentalist households, starting with an equal distribution in the reference case, while alternative distributions will be tested in the scenario analysis. These values do not come directly from the census but are introduced as behavioural assumptions in order to analyse how different levels of environmental orientation can affect REC participation. Finally, based on the adhesion data, 30 households are included as initial CER.ca.MI members at the beginning of 2025.
In terms of energy input, each household agent receives a randomly selected hourly electricity consumption profile derived from empirical datasets provided by Politecnico di Milano, based on previous master's level research. The assignment is performed according to the household-size class of the agent, so that the consumption profile is consistent with the demographic characteristics previously defined. In this way, the model preserves heterogeneity among households while maintaining coherence between family size and electricity demand. In addition to electricity demand, agents may also be assigned an individual photovoltaic system. This assignment is controlled by the predefined parameter, which defines the probability that a household owns a PV system. If an agent is assigned PV, its installed capacity is randomly drawn between 0 and 10 kW. The upper limit of 10 kW is intended to represent a plausible maximum for a residential installation rather than a typical value. With a uniform distribution, the resulting average capacity is approximately 5 kW, which is consistent with the average size of residential PV systems recorded in Lombardy, approximately 5.2 kW in 2024 [55]. The chosen range therefore reproduces the observed order of magnitude of household installations while still allowing for larger systems on dwellings with greater available rooftop area. The hourly profiles of photovoltaic produced were retrieved from Taromboli et al [19]. Besides individual household PV systems, the model also has existing collective renewable generation asset belonging to the REC, in particular, CER.ca.MI already includes a photovoltaic plant with an installed capacity of 998 kW. This plant is treated separately from household-level PV systems, because it is not assigned to a single agent.
Regarding economic data, two main inputs are needed: the electricity purchase price, λ_{buy} and the electricity selling price λ_{sell}. The purchase price was computed as in Eq. (35):

$$\lambda_{buy} = PUN_{new} + grid\ tariff + system\ charges\ [€/kWh] \tag{35}$$

In particular, PUN_{new} was derived from the hourly PUN values for 2025 [18]. Since retailers do not usually transfer the hourly Day Ahead Market (DAM) variability directly to households' electricity offers, the hourly PUN was first grouped according to the Italian time-of-use bands (i.e. F1, F2 and F3). These bands classify electricity consumption hours according to the typical demand pattern during the day and week and are commonly used to differentiate electricity prices over time. For each month, the average PUN was calculated separately for each time-of-use band. This produced a monthly reference value for F1, F2 and F3, which was then reassigned to each hour of the year according to the corresponding time band of that hour. In this way, the final PUN_{new} preserves the monthly variation of the 2025 PUN while representing the time-of-use structure of typical household electricity prices. As for grid tariff and system charges, the values taken were the one provided by ARERA for the year 2025 [16]. The selling price, instead, corresponds to the zonal price [€/kWh] of the NORD Italian market zone [18].
Behavioural parameters cannot be directly derived from the available demographic or energy data, they were selected as theoretically informed assumptions, supported by the literature and then tested through an exploratory parameter analysis. The chosen values are shown in Table 8:

- The base join probability is set higher for environmentalist agents than for non-environmentalists, since REC participation is strongly related to pro-environmental attitudes, community commitment, trust, energy autonomy and perceived social value [49] [48]. However, the non-environmentalist value is not zero, because participation may also be driven by economic convenience, social contact and perceived efficacy [48] [56]. The selected values, shown in Table 8, are kept moderate to avoid making entry almost automatic and to preserve the role of the other behavioural mechanisms.
- The base retention probability is set higher than base join probability because members have already overcome the initial entry barrier and have direct experience of the community [45] [50]. The value is also higher for environmentalists, reflecting stronger commitment and non-economic motivations [49] [48], while non-environmentalists are still assigned a retention probability above their joining probability because continuity, familiarity and local support can encourage persistence.
- The neighbor retention weight is assumed to be mainly driven by the baseline tendency to stay, the neighbourhood effect is included but kept secondary. The same value, is assigned to both behavioural types, allowing local context to reinforce persistence without making it the dominant factor [49] [47] [48].
- The PV adoption probability assigned to environmentalists was anchored to the initial CER.ca.MI configuration, under the simplifying assumption that the 30 initial REC members could be treated as environmentally oriented agents and that the observed availability of PV among them was broadly representative of the adoption propensity of this group in the local population, the value for non-environmentalists was then downward scaled. This is recognised as a strong assumption, since the initial members may not be representative of all environmentally oriented households in Milan. Both probabilities, shown in Table 8, were nevertheless kept relatively low because actual PV ownership also depends on practical constraints not fully represented in the ABM, including roof availability, building ownership, investment capacity and technical suitability.
- Envy alpha is set so that perceived economic attractiveness can influence joining decisions without becoming the dominant driver, consistently with the idea that economic incentives interact with social and psychological factors in REC participation [48] [53].
- Envy scale is set at €50 as this value is consistent with the order of magnitude of the monthly electricity expenditure of a typical Italian household. According to ARERA, the annual electricity expenditure of the reference vulnerable customer amounted to approximately €609 in 2025, corresponding to about €51 per month [57]. The value should not be interpreted as an empirically estimated behavioural threshold, but as a rounded modelling assumption representing an economically perceptible monthly benefit. Its role is to prevent the perceived attractiveness of the REC from increasing linearly without limit and is subsequently tested through the exploratory parameter analysis.

Variable	Values used	Assumptions used to define the value	References
Base join	ENV: 0.15 NON-ENV: 0.05	The baseline probability of joining should not be too high, otherwise REC entry would become almost automatic, and the role of neighbourhood effects and social envy would be hidden. Environmentalists are assigned a higher value because pro-environmental values, community commitment, trust, energy	[56] [48] [49]

		autonomy and positive attitudes are relevant drivers of REC participation. Non-environmentalists are assigned a lower but non-zero value because economic and social motivations can still lead to participation.	
Base retention	ENV: 0.80 NON-ENV: 0.55	Retention should be higher than joining because existing members have already overcome the entry barrier and have direct experience of the REC. Environmentalists are assumed to have stronger intrinsic commitment and are therefore more likely to remain. Non-environmentalists can also remain due to habit, experience and perceived convenience, but their baseline stability is lower.	[48] [49] [50] [47]
Neighbor retention weight	0.06 for both groups	The neighbourhood can reinforce permanence, but remaining in the REC is assumed to depend mainly on baseline stability and direct experience. For this reason, the retention-related neighbourhood effect is lower than the joining-related effect.	[47] [48] [49] [50]
PV adoption probability	ENV: 0.12 NON-ENV: 0.05	Environmentalists are assumed to be more likely to own PV because environmental concern, knowledge, attitudes and subjective norms increase PV adoption intention. The probabilities are kept relatively low because actual PV ownership depends on practical constraints such as roof availability, ownership, investment capacity and technical suitability.	[58] [59] [60] [61]
$\boldsymbol{\alpha}$	0.10	Economic attractiveness is included because incentives and observed benefits can motivate REC participation. However, the social-envy contribution should remain bounded and secondary to other drivers. A value of 0.10 limits its maximum contribution to the joining probability.	[48] [53] [52] [62]
Envy scale	50 €	The scale parameter makes the social-envy effect saturating and avoids transforming monetary benefits directly into probabilities. The value is a modelling assumption and is evaluated later in the exploratory parameter analysis rather than treated as an empirically calibrated threshold.	[53] [62] [16]

Table 8: Summary values assumptions and references

Agent type	People classes	Base join	Base retention	Neighbour influence	Neighbour retention	PV adoption	Envy alpha	Envy scale
Environmentalist	3, 4, 5+	0.15	0.80	0.10	0.05	0.12	0.1	50€
Non-environmentalist	3, 4, 5+	0.05	0.55	0.10	0.05	0.05	0.1	50€

Table 9: Preliminary parameter values used in the first sensitivity tests

4.2 Future scenarios

This section describes the data adopted to extend the analysis from the 2025 reference year to the period 2026–2040. In the CER.ca.MI case study, the future-demand module is built by combining the residential building-stock structure of the area with scenario assumptions on the progressive diffusion of heating and cooling technologies.

The distribution of households by building typology and construction period is based on the Milan census of 2011 [54], and, the apartment types considered in the model are single-family houses, multi-family houses (up to 15 apartments) and multi-apartment blocks., while the construction periods are grouped into four classes: pre-1975, 1976-1990, 1991-2005 and post-2005. For each combination of apartment type and construction period, there is a maximum number of households that can belong to that category, this constraint ensures that the simulated agent population respects the structure of the residential building stock used for the scenario construction.

After the building category is assigned, heating and cooling technologies are progressively introduced over time. For heating, the technologies considered are the electrified or partially electrified systems included in the scenario assumptions, such as air-air heat pumps combined with gas boilers, hybrid air-water heat pump systems combined with gas boilers, and electric air-water heat pumps. Cooling is represented as a dedicated cooling system. The exact set of technologies and their annual diffusion are based on Pozzi PhD Thesis [1], while the hourly energy demand for cooling and heating differentiated by apartment type and period of construction used were computed based on Bellusci Master Thesis [63].

The electricity purchase and selling prices, λ^{buy} and λ^{sell}, are randomly selected from a set of 100 scenarios, providing future DAM prices across the whole 2025-2040 period, estimated based on Taromboli et al. [64].

The scenarios further analysed will be based on the different share of environmentalist and non-environmentalists, after having defined the best value for the model variables through a sensitivity analysis. The analysed configurations are shown in Table 10.

	Base	Config 1	Config 2	Config 3	Config 4	Config 5	Config 6	Config 7	Config 8
Environmentalist	50%	40%	30%	20%	10%	90%	80%	70%	60%
Non-environmentalist	50%	60%	70%	80%	90%	10%	20%	30%	40%

Table 10: Analysed configurations for case study previsions up to 2040.

5. Results and Discussion

5.1 Sensitivity analysis

5.1.1 Preliminary behavioural formulation and screening

The simulations discussed in this subsection were performed on an earlier version of the behavioural module. For the sensitivity analysis, the number of active REC members at the end of the reference year was used as the main key performance indicator (KPI). Starting from 30 existing CER.ca.MI members, the tested parameter combinations were assessed by their ability to produce a plausible REC size, of the order of magnitude of 10^3 members. They therefore precede the final joining rule presented in the methodology chapter. Their purpose was precisely to reveal the limitations of the initial additive formulation and to provide the basis for introducing the two distance-sensitive factors F and L, which are examined in the following subsection. All tests were repeated using both incentive-allocation methods implemented in the model, namely balanced_50_50 and producer_only_20. The differences in final membership and in the qualitative shape of the trajectories were marginal and did not affect the ranking of the parameters or the conclusions of the analysis. The results can therefore be discussed independently of the selected allocation rule.

The preliminary agent-level values used at the beginning of this analysis are reported in Table 9 in the Case study section. The preliminary base case produced an average end-of-year REC membership of 32’383 agents and a cumulative household PV capacity of 34'524.96 kW. The screening results are organised by parameter group. Tables 11-14 report the tested variations together with the resulting end-of-year membership and the corresponding absolute and relative change from the preliminary base case. The results are then discussed parameter by parameter, indicating the value retained for subsequent tests or the reason why the parameter was not retained as an independent element of the preliminary formulation. Where values differed between environmentalist and non-environmentalist agents, the same absolute variation was applied to both groups.

Parameter	Values tested	Change in final members	Relative change	Value retained
Envy scale	50, 100, 150, 200 €	200	- 0,47%	50 €
Envy alpha	0.05, 0.10, 0.15	75	+ 0,17%	0.10

Table 11: Preliminary screening of the Social envy parameters

Parameter varied	− 0.03		−0.02		+0.02		+0.03	
	Final members	Relative change	Final members	Relative change	Final members	Relative change	Final members	Relative change
Base join probability	27’858	−14.0%	29’464	−9.0%	34’969	+8.0%	36’139	+11.6%
Neighbour influence weight	30’907	−4.6%	31’383	−3.1%	33’401	+3.14%	33’890	+4.65%
Neighbour retention weight	31’345	−3.2%	31’653	−2.3%	33’172	+2.4%	33’576	+3.7%
PV adoption probability	22’366	−35.2%	26’284	−23.9%	42’622	+23.4%	46’704	+35.0%

Table 12: Average final REC membership under one-at-a-time parameter variations. Percentages refer to the preliminary base case of 32’383 members

Reduction in base retention	-0.10	-0.15	-0.20	-0.25	-0.30	-0.35	-0.40	-0.50
Average final members	24’922	22’275	20’144	18’343	16’834	15’549	14’472	12’232
Relative change	-23%	-32%	-38%	-43.4%	-48%	-52%	-55.3%	-62.2%

Table 13: Sensitivity of final membership to reductions in base retention probability.

Base join ENV	Base join NON-ENV	Retention adjustment	Average final members
0.12	0.01	-0.50	7’106
0.09	0.01	-0.25	8'644
0.05	0.01	-0.25	5'366
0.03	0.005	-0.25	3'326
0.01	0.0005	-0.35	901
0.01	0.0005	-0.30	1'010
0.01	0.0005	-0.25	1'135
0.0005	0.0001	-0.30	80
0.0005	0.0001	Baseline	307

Table 14: Selected combinations of base join and base retention tested in the preliminary analysis.

Given the results tables, the results of the preliminary screening are the following.

- Social envy parameters: Table 11 shows that varying either envy scale or envy alpha had no material effect on end-of-year membership. The average incentive allocated to members was small relative to the tested monetary scale, and the realised social envy contribution remained of the order of 10^{-3}. Envy scale = 50 € and envy alpha = 0.10 were therefore retained for the subsequent tests.
- Base join probability: Table 12 shows the largest direct behavioural effect: changing the parameter by -0.03 or +0.03 altered final membership by -4’525 and +3’756 members, respectively. This term is applied at every entry opportunity to the full population of non-members and therefore determines the scale of the initial inflow. No final value was selected from this one-at-a-time screening; lower base-join values were subsequently examined jointly with retention in Table 15.
- Neighbour influence on joining: The direct additive neighbourhood term produced a limited response, ranging from -1’476 to +1’507 members in Table 12. This confirms that, in the

preliminary formulation, its contribution remained secondary to the baseline joining propensity. The term was therefore not retained as an independent additive driver of joining.

- Neighbour retention weight: The tested changes affected final membership by between -1'038 and +1'193 members are shown in Table 12. The value of 0.05 for both agent types was retained because local context can reinforce retention without becoming its main driver.
- PV-adoption probability: PV adoption generated the largest indirect effect in Table 12, ranging from -10'017 to +14'321 members. It modifies household generation, the incentive received by the community, and the economic signal that feeds back into participation. The original values, ENV = 0.12 and NON-ENV = 0.05, were retained as technically motivated input assumptions rather than tuned to match membership.
- Base retention probability: Table 13 confirms that lower retention consistently reduces end-of-year membership. However, even the largest reduction -0.50 leaves 12'232 members, which remains above the intended order of magnitude. The baseline retention values were therefore maintained for subsequent tests, while retention reductions were considered only jointly with lower joining probabilities.
- Joint base-join and retention tests: Table 14 identifies combinations that reduce end-of-year membership to the intended order of magnitude, including 901, 1'010 and 1'135 members. These results were used to identify a plausible range rather than to select a statistically calibrated parameter pair. The tested combinations showed that retention cannot compensate for an excessive initial inflow unless base join is reduced substantially.

The small joining values in Table 14 must be interpreted in relation to the size of the potential population, which exceeds 81'000 households. A probability that appears small at the individual level can still generate a large number of entries when it is applied repeatedly to tens of thousands of non-members. For example, a base-join value of 0.10 generated approximately 8,000 entries in the first month, corresponding to about 10% of the total population. This explains why the original moderate values produced an oversized community.

To verify whether lower joining values allowed the endogenous mechanisms to emerge over time, the simulation horizon was extended to three years and a sensitivity analysis on the entry frequency was done, as shown in Table 15. The entry opportunities analysed were every month or every three months. Two contrasting joining settings were considered: a low case ENV = 0.0005 and NON-ENV = 0.0001 and a high case ENV = 0.10 and NON-ENV = 0.005. Each case was tested with the baseline retention values and with a reduction of 0.30.

Entry frequency	Base join ENV / NON-ENV	Retention setting	Final members	Final JP ENV	Final JP NON-ENV
Monthly	0.0005 / 0.0001	Baseline	533	0.016	0.012
Monthly	0.10 / 0.005	Baseline	20'540	0.1267	0.030
Every 3 months	0.0005 / 0.0001	Baseline	44	0.00066	0.000571

Every 3 months	0.10 / 0.005	Baseline	6’211	0.110	0.0478
Monthly	0.0005 / 0.0001	Baseline − 0.30	81	0.0083	0.0045
Monthly	0.10 / 0.005	Baseline − 0.30	8’627	0.110	0.0158
Every 3 months	0.0005 / 0.0001	Baseline − 0.30	7	0.000547	0.000141
Every 3 months	0.10 / 0.005	Baseline − 0.30	1’312	0.104	0.0086

Table 15: Sensitivity analysis on entry frequencies.

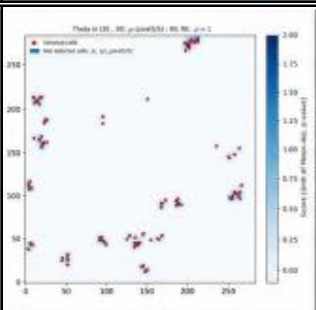
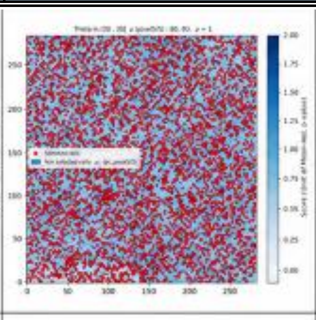
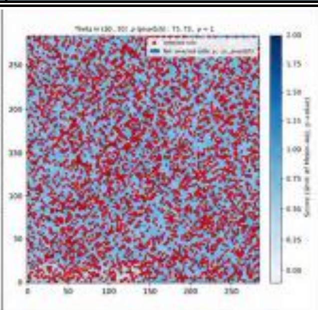
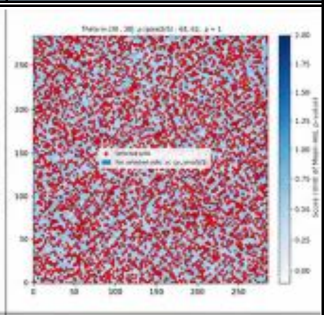
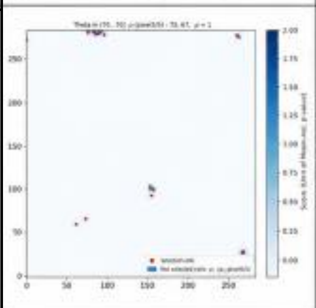
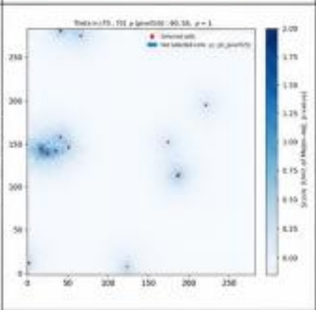
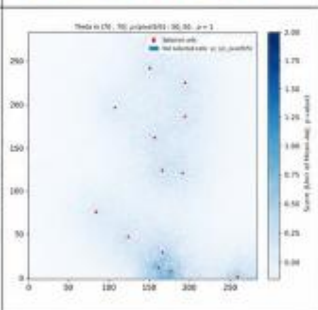
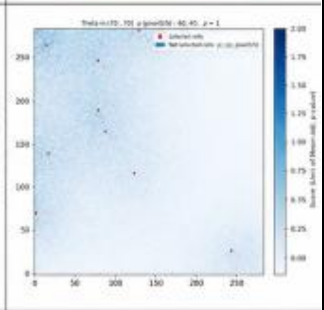
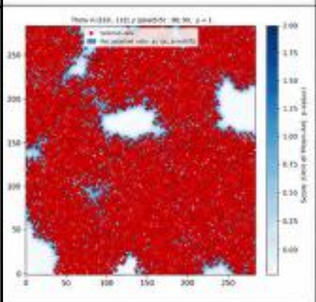
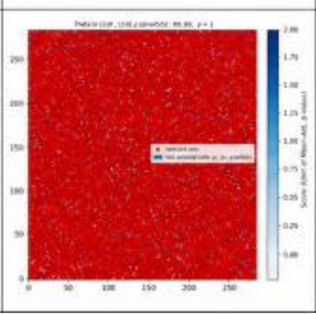
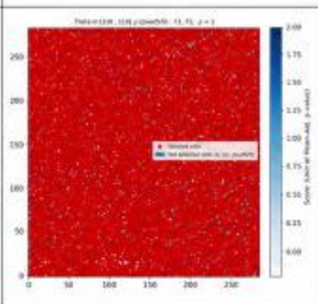
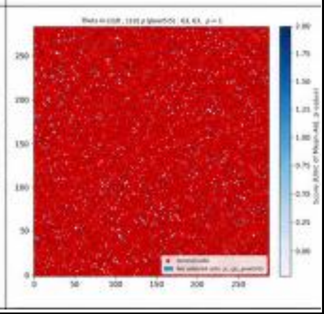
With the high joining setting, membership rose sharply during the first months and then stabilised around a high level. Reducing retention lowered the final number of members, while limiting entry to every three months slowed the expansion, but neither change altered the dominant role of base join. In this range, the additive neighbourhood and social-envy terms remained too small to affect the qualitative dynamics. The low joining setting produced a different behaviour. Growth was slower and less linear, and no clear long-term plateau was reached within the three-year horizon. As the community expanded, the final joining probability became increasingly different from its baseline value, indicating that the state of the REC and its social context could influence subsequent entry decisions. The tests with three-month entry intervals also produced stronger oscillations, because exits occurring between entry opportunities reduced the local presence of members before new agents could join. Taken together, these results explain why the following sensitivity analysis focuses on the joining rule rather than on retention. Retention is relevant for the stability of the community, but it cannot correct an excessive initial inflow. The joining probability acts on the much larger population of non-members and determines both the scale of early growth and the extent to which neighbourhood influence and perceived benefits can become visible.

5.1.2 Spatial sensitivity

The preliminary analysis also revealed a limitation in the mathematical structure of the original formula. Base join, neighbourhood pressure and social envy were added directly despite having very different numerical magnitudes. When base join was high, it dominated the equation; when it was reduced, the two additional terms remained small corrections. Moreover, the original pressure indicator considered only the eight adjacent cells and could not distinguish between two different spatial mechanisms: the relative presence of REC members in an agent’s local context and the activation of a visible signal by one or more nearby members.

For this reason, the joining probability was reformulated so that the spatial mechanisms activate the two behavioural components instead of entering only as an additional term. As mentioned in Section 3.4.2, a sensitivity analysis is also performed to assess the structure of the new join probability.) The simulations used an equally divided population of environmentalist and non-environmentalist agents. The residual spatial weight at the boundary was fixed at eta = 0.01. To test the sensitivity of the model to the spatial scale of interaction, the radius values were defined relative to the maximum Euclidean distance of the spatial grid, whose diagonal is equal to 403 cells. Accordingly, while t R = 201.5 and R = 100.75 correspond respectively to one half and one quarter of the grid diagonal. The

additional values R = 50, approximately one eighth of the diagonal, and R = 10 represent progressively more local interaction ranges.. All other assumptions were kept unchanged. The three factor assignments were simulated using both incentive-allocation rules: balanced_50_50 and producer_only_20. The values reported below are the mean final numbers of REC members.
The three factor assignments were simulated under both incentive-allocation rules, namely balanced_50_50 and producer_only_20. Table 16(a) and (b) provide a spatial representation of the corresponding outcomes under the two incentive-allocation rules. In each panel, the grid represents the full population of household agents considered in the simulation. Red points identify the agents that are REC members at the end of the reference year, whereas the blue gradient represents the base-join probability perceived by each agent. Darker blue shades indicate a stronger perceived local activation of the joining mechanism. Rows correspond to the F-L, F-F and L-L configurations, while columns show the four tested interaction radii. The maps therefore complement the numerical results shown in Table 17(a) and (b), that report the mean final number of REC members for each configuration, while Figure 4(a) and (b) show the corresponding response to the spatial radius. The results are discussed by factor assignment in order to compare the two allocation rules directly.

(a) balanced_50_50 allocation rule				
Factor assignment	**R = 10**	**R = 50**	**R = 100.75**	**R = 201.5**
F-L				
F-F				
L-L				

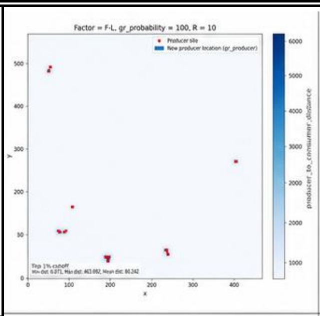
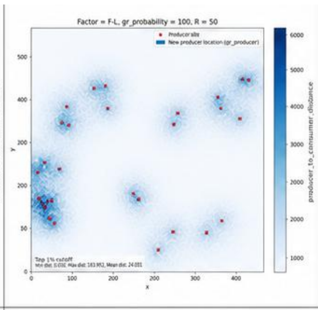
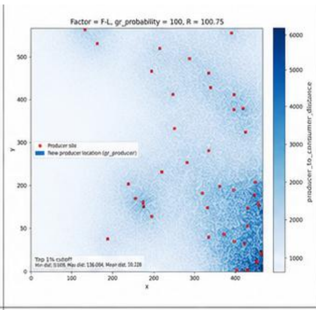
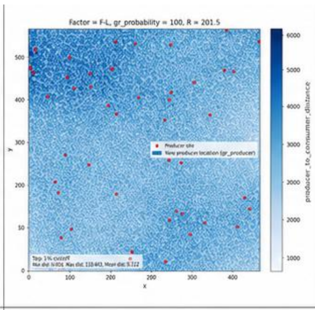
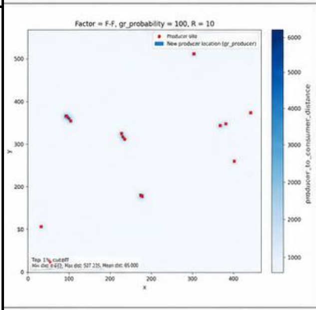
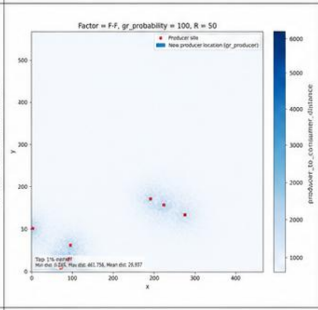
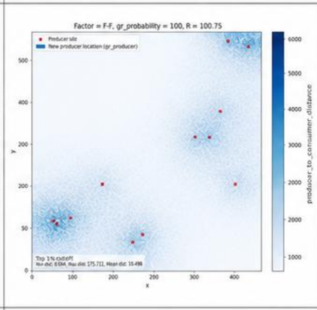
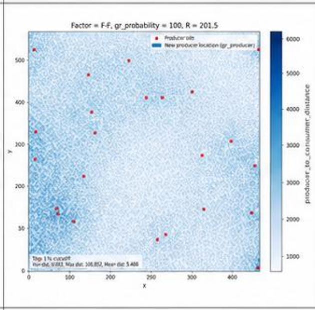
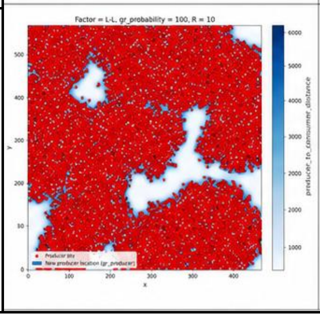
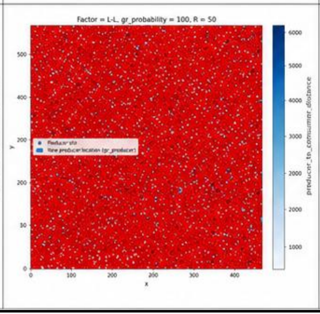
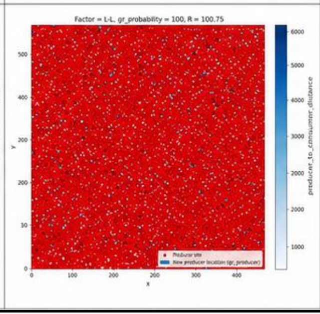
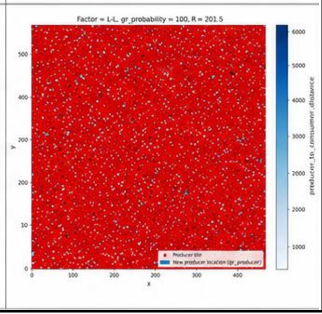
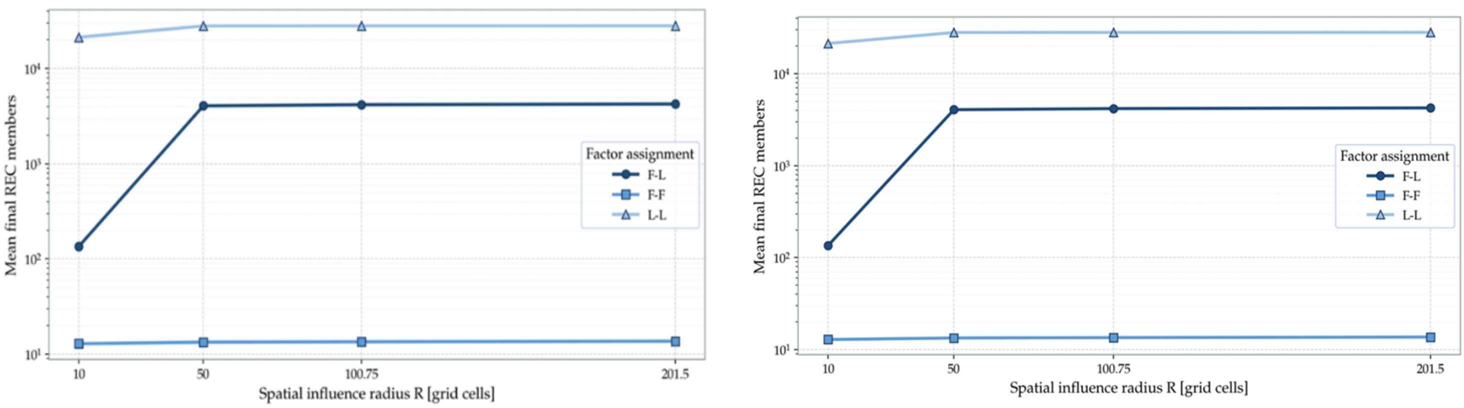
(b) producer_only_20 allocation rule				
Factor assignment	**R = 10**	**R = 50**	**R = 100.75**	**R = 201.5**
F-L				
F-F				
L-L				

Table 16:Spatial distribution of REC members and agent-level base-join probability across factor assignments and interaction radii under (a) the balanced_50_50 allocation rule and (b) the producer_only_20 allocation rule.

(a) balanced_50_50 allocation rule				
Factor assignment	**R = 10**	**R = 50**	**R = 100.75**	**R = 201.5**
F-L	135.50	4’061.86	4’177.00	4’248.00
F-F	12.88	13.39	13.51	13.70
L-L	21’326.00	28’046.00	28’093.00	28’109.00

(b) producer_only_20 allocation rule				
Factor assignment	**R = 10**	**R = 50**	**R = 100.75**	**R = 201.5**
F-L	12.29	16.15	34.17	51.63
F-F	12.00	11.57	11.80	11.73
L-L	20’443.00	27’418.00	27’490.00	27’500.00

Table 17: Mean final REC membership across factor assignments and spatial radii under (a) balanced_50_50 and (b) producer_only_20 allocation rules.



(a) balanced_50_50 (b) producer_only_20

Figure 4: Effect of the spatial radius and factor assignment under (a) balanced_50_50 and (b) producer_only_20 allocation rules.

The results of the sensitivity analysis are the following.

- F-F configuration: F-F was the most conservative configuration under both allocation rules as shown in Table 16 and Figure 4. Final membership remained close to 12-14 agents for every tested radius: 12.88-13.70 under balanced_50_50 and 11.57-12.00 under producer_only_20. The response was therefore almost insensitive to both radius and allocation rule, and the community contracted below its initial membership. This indicates that applying F to both behavioural components does not allow sufficient diffusion from the initial 30 members.
- F-L configuration: F-L was the configuration most strongly affected by the allocation rule. Under balanced_50_50, final membership increased from 135.50 members at R = 10 to 4,061.86 at R = 50, with only limited further increases at larger radii as seen in Table 16(a) and Figure 4(a). Under producer_only_20, the same configuration remained between 12.29 and 51.63 across the tested radii as seen in Table 16(b) and Figure 4(b). The divergence shows that F-L is sensitive to the household-level economic signal: reducing the incentive allocated to household members weakens the social-envy component, so increasing spatial visibility is not sufficient to generate substantial diffusion. The main radius effect under balanced_50_50 was already captured at R = 50.

- L-L configuration: L-L was the most expansive configuration under both allocation rules. Membership rose from 21,326 to 28,046 members between R = 10 and R = 50 under balanced_50_50, and from 20,443 to 27,418 under producer_only_20; larger radii produced negligible additional changes, as shown in Table 16 and Figure 4. The close correspondence between the two allocation rules indicates that this growth regime is only weakly dependent on the household economic signal. The configuration therefore produces rapid saturation and an implausibly large REC.

To provide a direct comparison between the two incentive-allocation rules, Table 18 summarises the final REC membership obtained by the three factor configurations at the intermediate radius (R = 50). This radius was selected because it captures the main change in the F-L response, while further increases in the observation radius produce only marginal variations.

Configuration	Balanced 50/50 at R = 50	Producer-only 20 at R = 50	Interpretation
F-L	4’061.86	16.15	Strongly sensitive to the household economic signal; produces conditional, non-automatic diffusion.
F-F	13.39	11.57	Low under both rules because both components are constrained by normalised local penetration.
L-L	28’046.00	27’418.00	Almost allocation-independent because L activates base join and rapidly saturates.

Table 18: Comparison of the two allocation rules at the intermediate radius R = 50.

As shown in Table 18, the allocation rule changes the magnitude of the F-L outcome without altering the ranking of the spatial configurations. This is consistent with the distinction above: the allocation rule directly changes the household incentive and therefore the social-envy component, but it does not alter the exogenous baseline predisposition. The factor multiplying base join consequently remains the principal determinant of the overall growth regime.
Based on these results, the F-L formulation was retained in the final model, as mentioned in Section 3. This configuration produced the most balanced and interpretable REC growth pattern.
Unlike F-F, it avoided constraining both components under the initially low local penetration of the REC and compared to L-L, it avoided the rapid saturation associated with widespread signal activation. The formulation therefore allows the individual predisposition to join to depend on a meaningful local presence of the REC, while preserving a separate channel through which the economic attractiveness of the community can influence participation. Changes in the incentive-allocation rule can consequently affect membership through the perceived economic component without directly altering the baseline propensity to join. A spatial radius of 50 cells was selected because the simulations showed a substantial increase in diffusion between radii 10 and 50 but only limited additional changes at larger radii. The residual weight was maintained at eta = 0.01 to preserve a strong decay of influence with distance. Finally, the balanced_50_50 allocation rule was adopted because it produced a perceptible but non-dominant household economic signal, whereas producer_only_20 substantially weakened the F-L diffusion mechanism. These choices were

therefore carried forward to the 2025-2040 scenario analysis, while the population composition was varied across the different environmental-orientation scenarios.

5.2 Case study prevision to 2040

The long-term analysis compares nine scenarios in which the share of environmentalist agents ranges from 10% to 90%, while the remaining share is assigned to non-environmentalist agents. The 50%-50% configuration is used as the base case. All behavioural, spatial, technical and economic settings selected through the previous sensitivity analysis are kept unchanged; only the population composition varies. Each scenario is evaluated through 100 stochastic simulations. The lines in the following figures represent the mean outcome, while the shaded areas and table intervals correspond to the empirical 5th-95th percentile range across runs and should therefore be interpreted as simulation uncertainty rather than as statistical confidence intervals.

Base-join activation factor	Social-envy activation factor	Spatial influence radius	Residual spatial weight (eta)	Incentive-allocation rule	Join and retention decisions
$F_{i,t}$	$L_{i,t}$	50 grid cells	0.01	balanced_50_50	Every month
Base join probability	**Base retention probability**	**PV adoption probability**	**Neighbour retention weight**	**envy_alpha**	**envy_scale**
ENV: 0.15 NON-ENV: 0.05	ENV: 0.80 NON-ENV: 0.55	ENV: 0.12 NON-ENV: 0.05	0.05 for both groups	0.10	€ 50

Table 19: Final behavioural and spatial settings used in the future scenario simulations.

5.2.1 REC membership evolution

The membership trajectories reveal two common phases. The first is a diffusion phase, during which the REC expands rapidly from the 30 initial members. The second is a dynamic long-term regime in which the average size of the community becomes broadly stable but continues to fluctuate during the year. The duration of the diffusion phase depends strongly on population composition. Scenarios with a low share of environmentalist agents approach their long-term level within 2025, whereas the configurations with 80% or 90% environmentalist agents continue to grow until 2027. The base scenario reaches 90% of its December 2040 membership in May 2026.

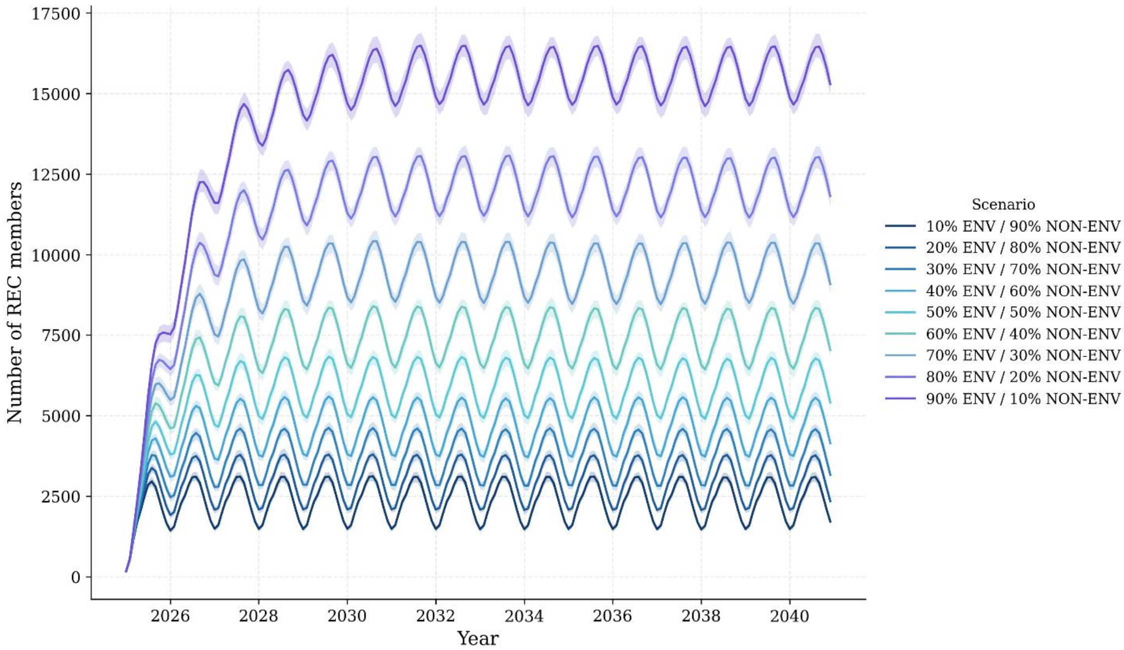


Figure 5: Monthly REC membership trajectories across the nine population-composition scenarios. The shaded areas represent the P05-P95 simulation bands.

The ranking of the scenarios is persistent and becomes increasingly separated over time. In December 2040, mean membership ranges from 1,714 agents in the 10%-90% scenario to 15,292 agents in the 90%-10% scenario, a difference by a factor of approximately 8.9. The base case reaches 5,412 members, corresponding to 6.67% of the potential household population. Even the most favourable behavioural composition does not produce universal participation: the 90%-10% scenario reaches 18.85% of the available households. The results therefore describe a substantial but still selective diffusion process.

The relationship between population composition and final membership is clearly nonlinear. Increasing the environmentalist share from 10% to 20% adds approximately 633 members in December 2040, while the increase from 80% to 90% adds about 3,476. This convex response arises because the scenario change modifies several characteristics simultaneously: environmentalist agents have higher base joining and retention probabilities and a higher PV adoption probability. A larger initial propensity to participate increases membership, which raises the local F factor and exposes more non-members to the REC. The larger community also contains more potential producers and generates a stronger aggregate incentive signal.

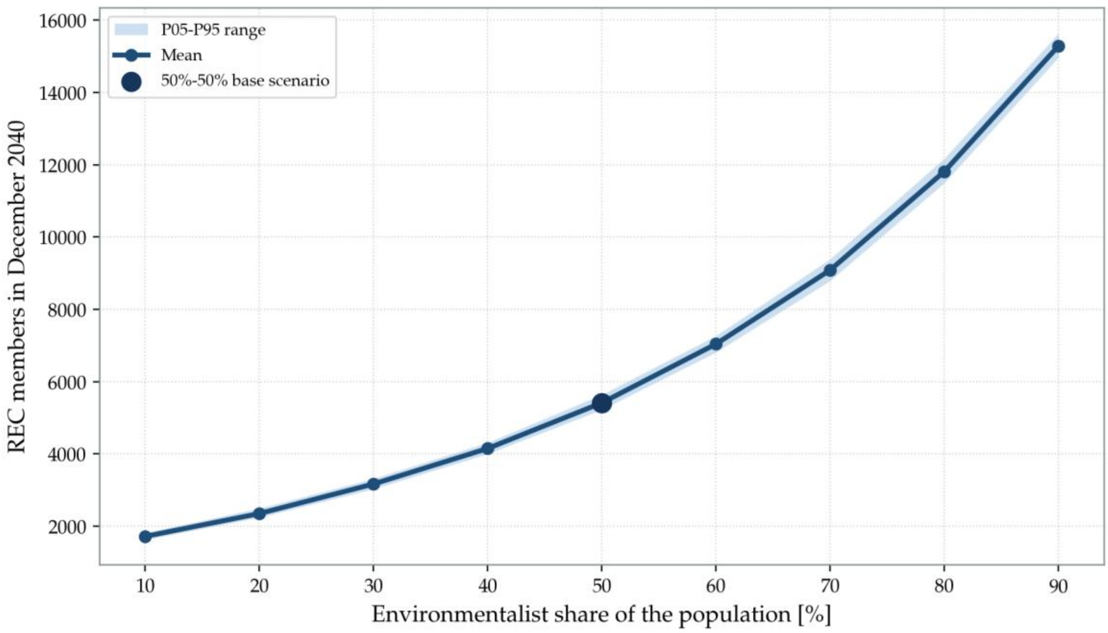


Figure 6: Mean REC membership in December 2040 as a function of the environmentalist share.

The uncertainty analysis supports the robustness of this ranking. In December 2040, the P05-P95 intervals of adjacent population-composition scenarios do not overlap; the smallest separation between two adjacent bands is approximately 426 members. Moreover, relative uncertainty decreases as the community becomes larger: the width of the P05-P95 band corresponds to 11.1% of the mean in the 10%-90% scenario and 4.3% in the 90%-10% scenario. Randomness affects the exact trajectory and final value, but its effect is smaller than the systematic difference created by the behavioural composition.

After the diffusion phase, the REC reaches a dynamic rather than static equilibrium. In the base scenario, the mean number of members in 2040 varies from approximately 4,914 in February to 6,780 in August. The annual amplitude is therefore about 1,866 members. The cycle reflects the interaction between seasonal incentives and monthly behavioural decisions. The average joining probability increases from approximately 0.011 in January to 0.024 in July, when shared energy and household incentives are higher, and then declines during autumn and winter.

The internal behavioural indicators help explain the resulting trajectories. The (L) factor rapidly approaches one during the first year and remains close to saturation afterwards. Once the REC has become locally visible, (L) therefore no longer represents a relevant constraint on the transmission of the economic signal. In the mature phase, changes in the joining probability are mainly driven by seasonal variations in social envy and by the (F) factor, which increases as the relative presence of REC members in the local context grows. This behaviour is consistent with the final joining formulation: (F) regulates the extent to which an agent's baseline predisposition becomes active, while (L) allows the perceived economic attractiveness of the REC to influence non-members once the community is sufficiently visible.

5.2.2 Aggregate electricity demand

Aggregate electricity demand follows a different pattern from REC membership, and it's nearly identical across the nine behavioural scenarios, with a maximum difference in annual mean demand

is only 0.027%, in 2038. This is because electricity demand is determined by the same building-stock composition and by the same annual penetration targets for heating and cooling technologies in all scenarios. These technologies are assigned independently of REC membership: a household may adopt heating or cooling technologies whether or not it joins the community. Consequently, the behavioural composition changes the number of REC members, but not the underlying demand trajectory. For this reason, the demand analysis can be represented through the 50%-50% base scenario without losing relevant information.
The year 2025 is treated here as a pre-electrification baseline, therefore the electricity attributable to the future electrification of heating and cooling is only simulated from 2026 onward. Figure 7 and Table 20 report the annual demand decomposition from 2026, while changes are measured relative to the pre-electrification baseline of 205.23 GWh.

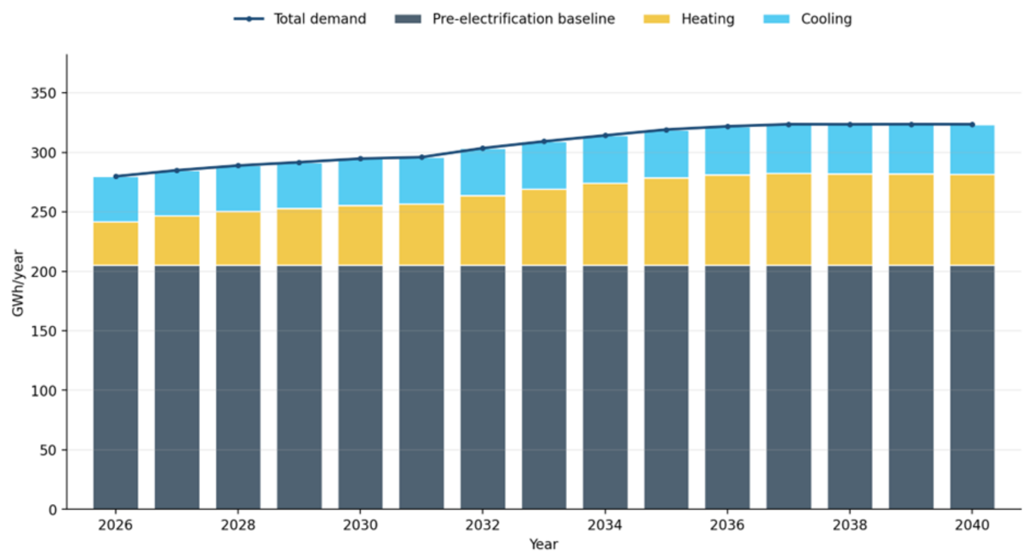


Figure 7: Evolution and decomposition of annual aggregate electricity demand in the base scenario.

Year	Baseline [GWh]	Heating [GWh]	Cooling [GWh]	Total [GWh]	Change from 2025	Heating share	Cooling share
2026	205.23	36.53	38.02	279.79	36.3%	15.6%	11.7%
2030	205.23	50.32	39.12	294.68	43.6%	17.1%	13.3%
2035	205.23	73.37	40.50	319.10	55.5%	23.0%	12.7%
2040	205.23	76.42	41.87	323.53	57.6%	23.6%	12.9%

Table 20: Mean aggregate electricity-demand components in specific years.

As shown in Figure 7 and Table 20, the total annual demand reaches 279.79 GWh in 2026, 294.68 GWh in 2030, 319.10 GWh in 2035 and 323.53 GWh in 2040. Relative to the pre-electrification baseline, this corresponds to increases of 36.3%, 43.6%, 55.5% and 57.6%, respectively.

Most of this increase occurs during the first part of the simulation period: demand grows by 89.45 GWh between the pre-electrification baseline and 2030, by 24.42 GWh between 2030 and 2035, and by only 4.43 GWh between 2035 and 2040. There is a slower growth after 2035 that indicates that the largest effect is produced by the initial diffusion of electrified heating and cooling technologies. As their penetration approaches the long-term scenario targets, annual demand begins to stabilise. By 2040, total annual demand is 118.30 GWh above the pre-electrification baseline. Heating is responsible for 64.6% of this additional annual consumption, while cooling accounts for the remaining 35.4%. Heating is therefore the main contributor to the overall annual increase. However, cooling produces the highest monthly demand peak. This distinction is important because annual energy consumption and peak demand describe different effects: a technology may contribute less electricity over the whole year but still create a more pronounced short-term load on the electricity system.

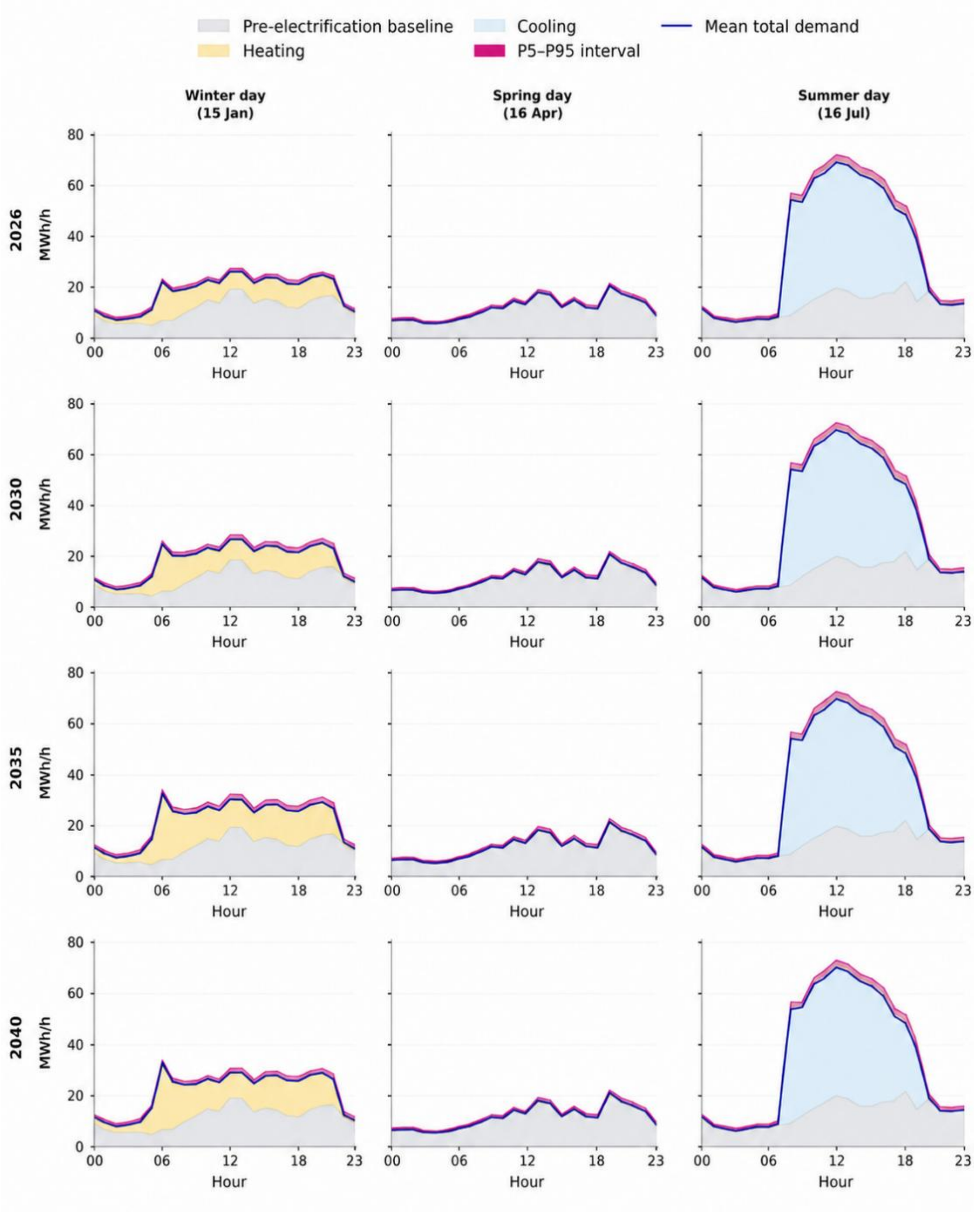


Figure 8: Selected hourly electricity-demand profiles in the 50%-50% base scenario.

Figure 8 complements the annual demand results presented in Figure 7 and Table 20 by showing how electrification modifies the hourly profile of electricity demand on representative winter, spring and summer days. The selected spring day remains unchanged across the four years and coincides with the pre-electrification baseline, as neither heating nor cooling demand is activated. The changes are instead concentrated in winter and summer, when the diffusion of electrified thermal technologies increases both the level and the temporal concentration of demand.

On the winter day, peak demand rises from 51.28 MWh/h in 2026 to 78.48 MWh/h in 2040. The profile also changes shape: the peak occurs in the early afternoon in 2026 and 2030 but shifts to 06:00 in 2035 and 2040 as heating becomes the dominant component of the daily load. In 2040, heating contributes 65.30 MWh/h to the 78.48 MWh/h winter peak. The summer profile exhibits the highest hourly demand in all years. Its maximum increases from 139.79 MWh/h in 2026 to 150.12 MWh/h in 2040 and remains concentrated around midday, when cooling demand reaches 112.17 MWh/h.

The hourly results therefore distinguish the effects of the two electrified end uses more clearly than annual totals alone. Heating accounts for the largest share of additional annual electricity demand, whereas cooling produces the highest instantaneous loads and is therefore more relevant for peak-demand conditions. The P5–P95 interval remains narrow in every panel, indicating that the stochastic allocation of technologies and load profiles generates limited variation in aggregate hourly demand once the building-stock composition and annual technology targets are fixed.

The annual demand profile with monthly granularity across the 2026 – 2040 horizon is shown in Figure 9. For each calendar month, the stacked bars represent the mean contribution of the pre-electrification baseline, heating and cooling across the scenario years, while the shaded envelope shows the minimum–maximum total demand observed for that month across different years. The envelope therefore represents interannual variation associated with the progressive electrification pathway, rather than stochastic uncertainty across simulation runs.

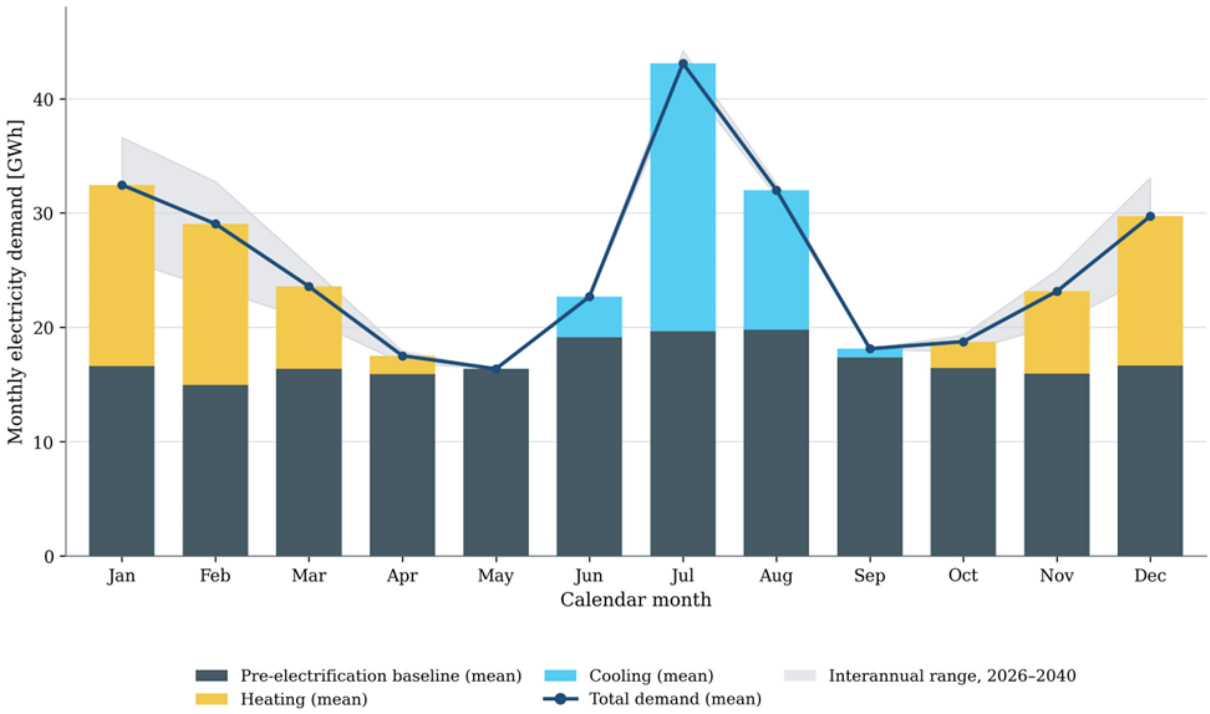


Figure 9: Mean monthly aggregate electricity-demand profile in the simulated CER.ca.MI area over 2026–2040.

The decomposition clarifies the origin of these peaks. The pre-electrification baseline residential demand remains relatively stable throughout the year, whereas heating is concentrated between October and April and cooling between June and September. The highest mean monthly demand occurs in July (43.10 GWh), driven by 23.44 GWh of cooling demand in addition to 19.66 GWh of baseline demand. January is the main winter peak (32.46 GWh), with 15.85 GWh of heating added to 16.61 GWh of baseline demand. The interannual range is widest in heating months: January varies from 26.02 to 36.62 GWh across the scenario horizon, reflecting the progressive diffusion of electrified heating, while the July range is narrower (41.97–44.23 GWh). The two electrified uses therefore reshape the profile in different seasons rather than simply raising all monthly values by the same amount.

Conditional on a given year's scenario targets, run-to-run variation remains limited: in 2040, the difference between the 5th and 95th percentiles of annual total demand is 0.19% of the mean value. Figure 9 should therefore be interpreted as showing temporal variation across the projected electrification path, not high stochastic uncertainty in aggregate demand.

Overall, the scenario analysis highlights two related but distinct transition processes. The first is technical: the electrification of heating and cooling increases electricity demand and makes it more seasonal in every scenario. The second is social: REC participation depends strongly on the behavioural composition of the population. In the 50%-50% base scenario, aggregate electricity demand is 57.6% higher in 2040 than in 2025, while only 6.67% of households are REC members in December 2040. This shows that increasing electricity demand from electrification does not automatically lead to wider participation in local energy communities. Policies supporting electrification and policies promoting REC membership therefore address different, although interconnected, aspects of the energy transition.

5.3 Limitations

Some limitations of the model should be acknowledged, especially because the objective of this work is exploratory rather than predictive. First, the behavioural component is not fully calibrated against longitudinal data, since detailed information on the evolution of REC membership and on individual motivations to join or leave the community is not currently available. For this reason, several behavioural parameters are defined as theory-based assumptions and are assessed through sensitivity analysis rather than estimated from observed participation trajectories.

A second limitation concerns the representation of household decision-making. Agents are divided into two behavioural types and their decisions are modelled through probabilistic rules. This structure makes it possible to analyse participation dynamics in a transparent and computationally manageable way, but it inevitably simplifies real adoption processes. In practice, willingness to participate in a REC may also depend on socio-economic characteristics, income, tenure status, roof availability, previous experience with energy technologies, trust in institutions, administrative effort, perceived risk and personal energy needs.

It's also important to note that the way information and social influence circulate are simplified. Social exposure is represented mainly through spatial proximity, assuming that nearby REC members are more likely to influence non-members. This captures an important local dimension of REC diffusion, but it does not explicitly represent actual communication networks, public meetings, awareness campaigns, municipal initiatives, intermediaries or institutional mediation.

Finally, the long-term scenarios focus mainly on the evolution of electricity demand due to heating and cooling electrification. Other elements that could influence the future development of a REC are simplified, additional PV and storage investments, demand response, changing regulation, grid constraints and possible changes in incentive schemes. These exclusions should be considered when interpreting the 2040 results: the model is useful for exploring how behavioural composition and electrification assumptions interact, but it does not provide a complete techno-economic optimisation of the future REC.
Future developments could address these limitations by calibrating behavioural rules with surveys and observed REC data, adding more detailed socio-economic and building attributes, replacing or complementing the spatial grid with empirical social networks, and introducing an external-awareness component to represent information channels beyond local proximity. These extensions would make the model more suitable as a decision-support tool for REC planning, while preserving its ability to analyse the link between individual behaviour and collective outcomes.

6. Conclusions

This thesis analysed Renewable Energy Communities as socio-technical systems, where technical performance, economic incentives and household behaviour interact over time. Starting from the European and Italian regulatory framework, the work focused on the Italian virtual model of energy sharing and developed an Agent-Based Model to simulate the evolution of a REC. The purpose was not to obtain a fully predictive tool, but to build an exploratory framework able to connect individual decisions with aggregate community outcomes.
The model represents households as heterogeneous agents characterised by demographic, technical, economic and behavioural attributes. The energy and economic module calculate energy flows, electricity bills and energy-sharing incentives, while the behavioural module updates participation through monthly joining and retention decisions. This modelling choice made it possible to connect individual household behaviour with aggregate REC outcomes and to analyse the community as an evolving system rather than as a fixed group of members.
The developed model is tested on a real-life REC as case study, namely CER.ca.MI, a solidarity-based REC operating in the city of Milan. In particular, the analysis is carried out in two phases: first, a sensitivity analysis on parameter values is performed on 2025 data; then, the REC evolution from 2026-2040 is assessed, considering also future changes in household demand profiles due to electrification of consumptions.
From a methodological point of view, the sensitivity analysis played a central role in defining the final behavioural structure. The preliminary formulation showed that the baseline joining probability could dominate the model and generate unrealistic growth when it was applied directly to a large population of potential members. This led to the introduction and testing of two spatial activation factors, F and L. The final F-L formulation was selected because it provided the most balanced interpretation: F activates the individual predisposition to join only when the REC has a meaningful presence in the agent's local context, while L allows the perceived economic attractiveness of the REC to become visible through nearby members.
On the other hand, from an analytical perspective, the long-term scenario analysis highlights that the composition of the population, especially environmental sensibility, has a major effect in driving REC membership. However, the result suggests that the existence of incentives and renewable generation is not sufficient to guarantee widespread involvement: social acceptance, awareness,

trust and local visibility remain essential conditions for REC expansion. Indeed, the long-term scenarios distinguish between two related but separate dimensions of the energy transition: a technical transformation, driven by electrification, and a social transformation, driven by participation. Higher future electricity demand does not automatically lead to stronger REC membership, and policies supporting electrification must be complemented by measures that actively promote community involvement.

The results should be interpreted considering the exploratory nature of the model. Several behavioural parameters were defined as theory-based assumptions rather than calibrated on observed membership trajectories, and household decisions were represented through simplified probabilistic rules. Nevertheless, the model provides a starting point for studying how RECs may evolve when social influence, economic benefits and technical demand changes are considered together.

Overall, the thesis shows that Renewable Energy Communities should be planned not only as local energy infrastructures, but also as collective processes that require governance, information and long-term engagement. The proposed ABM contributes to this perspective by offering a flexible framework to explore how individual behaviour and energy-system conditions jointly shape the growth of a REC. In this perspective, the model can contribute to future analyses aimed at supporting the development of energy communities by combining tecno-economic analysis with social dimension.

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