SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

EXECUTIVE SUMMARY OF THE THESIS

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 – INGEGNERIA ENERGETICA

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1. Introduction

The transition to a low-carbon energy system is not limited to replacing fossil-based generation with renewable technologies. It also changes the way energy is produced, consumed, governed and shared. Renewable Energy Communities (RECs) are part of this transformation because they combine decentralised renewable generation with collective participation, local ownership and benefit distribution. The European framework defines RECs as legal entities based on open and voluntary participation, whose primary purpose is to deliver environmental, economic or social benefits to members and to the local area rather than financial profits alone [1].

In Italy, RECs operate through a virtual energy-sharing model. Electricity is not physically transferred from one member to another through a private network; instead, the electricity injected by the REC's renewable plants and the electricity withdrawn by eligible members are compared ex post on an hourly basis. The corresponding shared energy is remunerated through network-charge valorisation and a premium tariff, and the economic value is subsequently allocated according to the internal rules of the community [2], [3]. This model makes the technical and economic performance of a REC measurable, but it does not by itself explain how households decide to enter, remain in or leave the community.

Most quantitative REC studies focus on techno-economic optimisation, energy management, investment sizing, self-consumption and benefit allocation. These approaches are essential for evaluating energy and economic feasibility, but they usually treat the membership of the community as fixed or externally imposed. This is a relevant limitation when the research question concerns the evolution of a REC as a collective process. Participation is voluntary and may depend on individual motivations, local exposure, perceived benefits, trust and the behaviour of nearby households. Agent-Based Modelling (ABM) is appropriate for this type of problem because it represents heterogeneous agents, repeated decision-making and system-level outcomes that emerge from individual interactions [4], [5].

The thesis develops an ABM to analyse a REC as a socio-technical system, linking energy flows, incentives and household participation over time. The model is applied to CER.ca.MI, a solidarity-based REC operating in Milan. The work has four related aims: to represent the Italian virtual energy-sharing mechanism at household level; to test how behavioural and spatial assumptions affect REC growth; to examine the effect of different shares of environmentally oriented households on long-term membership; and to assess how the electrification of heating and cooling modifies aggregated community electricity demand up to 2040.

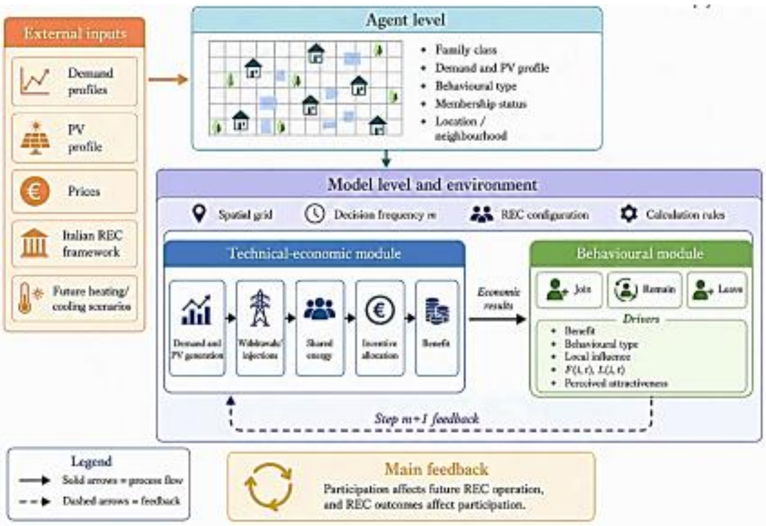

Figure 1: Conceptual structure of the Agent-Based Model and feedback between REC operation and household participation.

2. Methodology

2.1. Model

The developed model follows a bottom-up architecture. Each agent is assigned a spatial location, a household class, an hourly baseline electricity-demand profile, potential household photovoltaic (PV) ownership, and a behavioural type. The behavioural population is divided into environmentalist and non-environmentalist agents. This distinction is not intended to reproduce an observed distribution of environmental attitudes in Milan, it is a scenario assumption used to explore how different predispositions to participate influence the evolution of the REC.

As illustrated in Figure 1, the model has three connected dimensions: technical, economic and social.

The technical module calculates household consumption, PV generation, grid withdrawals, grid injections and virtually shared energy. The economic module calculates individual bills, the total REC incentive and its allocation among active members. The behavioural module updates membership at a predefined decision frequency. These dimensions form a feedback loop: the current membership determines which households participate in shared-energy calculations; the resulting benefits affect future participation decisions; and membership changes alter the community's subsequent energy and economic outcomes. For each agent and hour, PV generation depends on installed capacity and the hourly production profile per installed kilowatt. Consumption and generation are compared to calculate grid withdrawal and injection. For active REC members, hourly withdrawals and injections are aggregated; shared energy is then computed consistently with the Italian virtual model. The total incentive is allocated through a sharing index. Two allocation rules are implemented. The balanced 50/50 rule rewards both consumption and production contributions, whereas the producer-only 20 rule allocates a limit part of the incentives and only to prosumers, representing a different community business model. Once individual incentives have been allocated, the model calculates each member's benefit as the difference between the reference bill without REC participation and the bill after incentive allocation.

The behavioural module updates membership at the end of each decision period, which is monthly in the scenario simulations. Existing members may remain or leave the REC depending on their realised benefit, their baseline retention probability and local social pressure. Environmentalist agents are assumed to tolerate negative benefits for a longer period than non-environmentalist agents. Non-members can join according to a probability that combines a baseline predisposition and a perceived economic-attractiveness term, named social envy. The final joining rule retained after sensitivity analysis is shown in Eq. (1):

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

The two spatial factors capture different mechanisms. $F_{i,t}$ measures the normalised, distance-weighted presence of REC members in the local context of household i. It therefore represents local penetration: a household's predisposition to join becomes effective only to the extent that the REC is meaningfully represented in its neighbourhood. $L_{i,t}$ follows a noisy-OR logic and represents the probability that at least one nearby REC member makes the community visible. It therefore acts as a signal-transmission mechanism through which economic attractiveness can become perceptible. Separating F and L allows the model to distinguish local diffusion from local visibility rather than treating neighbourhood influence as a single additive term.

2.2. Future demand construction

The multi-year extension does not change the structure of the ABM. Instead, it changes the demand assigned to individual agents. Starting from 2026, the baseline electricity profile of each household is augmented by the demand associated with the heating and cooling technologies assigned over time. Households are first associated with a building category defined by apartment type and construction period. Annual technology targets determine how many additional households receive electrified or partially electrified heating systems and dedicated cooling systems. Once assigned, the corresponding hourly profile is added to the baseline demand.

3. Case Study

The developed model was applied to the area served by one of the primary substations in Milan, associated with CER.ca.MI. The simulated population comprises 81’143 household agents, derived from the 2011 Milan Census and distributed across five household-size classes. Thirty households are introduced as initial REC members at the beginning of the 2025 reference year.

Each household receives a randomly selected hourly electricity-demand profile consistent with its household-size class. Individual PV ownership is assigned probabilistically; when present, installed capacity is randomly drawn between 0 and 10 kW. The REC also includes a 998 kW community PV plant, modelled separately from household systems. Electricity purchase prices are derived from 2025 PUN data, transformed into monthly F1, F2 and F3 values to reproduce the time-of-use structure of household retail prices, while the selling price corresponds to the northern Italian zonal market price.

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.

4. Results

4.1. Sensitivity Analysis

The sensitivity analysis does not claim to estimate the true behavioural parameters of the local population. Its purpose is to identify which assumptions dominate the simulated dynamics, to avoid automatic and implausible diffusion, and to select a transparent behavioural formulation for the multi-year scenarios.

The 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 $L_{i,t}$.

The number of active REC members at the end of the 2025 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. 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.

The first stage examined an earlier additive joining rule in which base join, neighbourhood pressure and social envy directly entered the probability of joining. The preliminary base case produced 32,383 active members at the end of 2025, revealing that a moderate individual joining probability can generate a large inflow when repeatedly applied to a population of more than 81,000 non-members.

One-at-a-time variations confirmed that base join was the most influential direct behavioural parameter: changing it by ±0.03 altered final membership by −14.0% and +11.6%, respectively. The direct neighbourhood-influence term had a smaller effect (−4.6% to +4.65%), while the social-envy parameters had negligible effects over their tested ranges. PV-adoption probability had the largest indirect effect, between −35.2% and +35.0%, because it changes household generation, the incentive available to the REC and the economic signal used in subsequent decisions.

The same screening showed that reducing retention alone could not compensate for an excessive initial inflow. Even a reduction of 0.50 in baseline retention still produced 12’232 end-of-year members. Joint tests of lower joining and retention values produced communities closer to the intended scale—901, 1’010 and 1’135 members for selected combinations—but they also made clear that the original additive structure did not adequately distinguish local presence from local signal activation. This motivated the revised spatial formulation based on F and L.

The second stage compared three assignments of the spatial factors to the two joining components: F-F, F-L and L-L. Simulations were performed with progressively wider spatial radii, a residual distance weight of η = 0.01, and both incentive-allocation rules. Table 1 reports the mean number of final members at the intermediate radius of 50 cells, selected because the main change in the F-L response occurred between radii 10 and 50, while larger radii produced only limited additional differences.

Factor assignment	Balanced_50_50	Producer_only_20
F-F	13.39	11.57
F-L	4’061.86	16.15
L-L	28’046	27’418

Table 1: Comparison of mean final REC members for the two incentive-allocation rules at the selected spatial radius R = 50 cells.

The F-F configuration was too conservative under both allocation rules, because normalised local penetration constrained both individual predisposition and perceived economic attractiveness when the REC was initially small. The L-L configuration was too expansive and produced implausibly large communities that were weakly sensitive to the allocation rule. The F-L configuration provided the most balanced mechanism: individual predisposition required a meaningful local REC presence, while economic attractiveness could be transmitted through the visibility generated by nearby members. The model therefore retained F-L, R = 50 cells, η = 0.01 and the balanced_50_50 allocation rule for the long-term scenario analysis. Figure 2 illustrates the response of the three configurations to spatial radius under the balanced allocation rule.

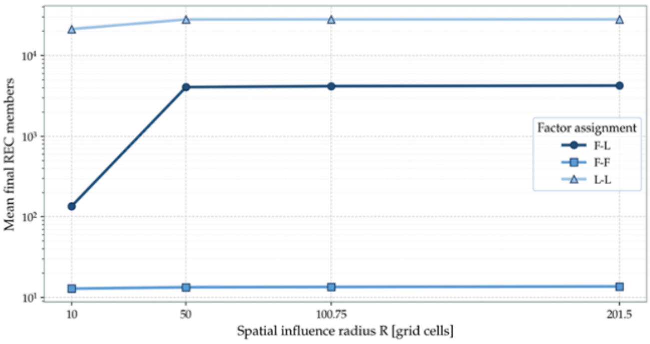

Figure 2: Mean final REC membership by factor assignment and spatial influence radius under the balanced_50_50 allocation rule.

4.2. Future Scenarios

The future analysis covers the period 2026–2040. It retains the final behavioural and spatial settings selected through the sensitivity analysis and varies only the composition of the household population: the share of environmentalist agents ranges from 10% to 90%, while the complementary share is non-environmentalist. The 50%–50% configuration is used as the base scenario. Each scenario is evaluated through 100 stochastic simulations. The scenario assumptions for technology diffusion are based on Pozzi’s PhD thesis, while the heating and cooling profiles differentiated by apartment type and construction period are taken from Bellusci’s master thesis [5], [6].

The 2025 value is treated as a pre-electrification baseline. It is not interpreted as an observed decomposition of electricity use for heating and cooling, because the baseline profiles do not separately identify those end uses. Future demand is therefore analysed from 2026 onward and compared with the 2025 baseline of 205.23 GWh. Future electricity purchase and selling prices are selected from a set of 100 long-term day-ahead-market scenarios, while building-stock composition and annual technology targets remain the same across behavioural scenarios.

Two main results were analysed, REC membership evolution and the aggregate electricity demand.

The long-term membership results show a clear and persistent relationship between behavioural composition and REC size. All scenarios exhibit an initial diffusion phase followed by a dynamic long-term regime in which membership fluctuates seasonally around an average level. The duration of the diffusion phase differs across scenarios: communities with a lower environmentalist share approach their long-term level within 2025, whereas the scenarios with 80% or 90% environmentalist agents continue to expand until 2027. In the 50%–50% base scenario, the mean community reaches 90% of its December 2040 membership by May 2026, as shown in Figure 3.

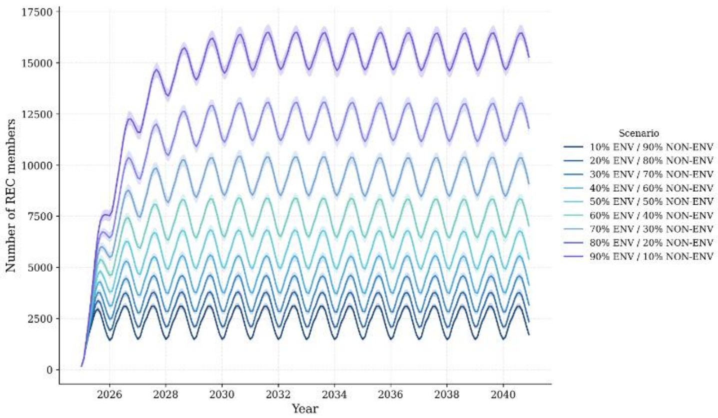

Figure 3: Monthly REC membership trajectories across the nine behavioural-composition scenarios. Lines represent mean outcomes; shaded areas indicate P05–P95 simulation bands.

The 50%–50% base case reaches 5,412 members, equivalent to 6.67% of the potential household population, while the highest environmentalist share reaches 18.85%. The response is nonlinear: increasing the environmentalist share from 10% to 20% adds about 633 members, while increasing it from 80% to 90% adds about 3,476. This happens because a larger environmentalist share changes several agent characteristics at once: base join, retention and PV-adoption probabilities.

Aggregate electricity demand follows a substantially different logic from REC membership. Across the nine behavioural scenarios, the maximum difference in annual mean demand is only 0.027%, observed in 2038. This is because the building-stock composition and heating/cooling technology targets are identical across scenarios, and technology assignment is independent of REC membership. Participation therefore affects the size of the community but does not materially change the underlying demand trajectory. The demand results can consequently be represented by the 50%–50% base scenario without loss of relevant information.

As shown in Figure 4, the annual demand increases from 205.23 GWh in the pre-electrification baseline to 279.79 GWh in 2026, 294.68 GWh in 2030, 319.10 GWh in 2035 and 323.53 GWh in 2040. The corresponding increases relative to 2025 are 36.3%, 43.6%, 55.5% and 57.6%. Most of the growth occurs before 2035, as electrified heating and cooling technologies diffuse towards their scenario targets. Heating is responsible for 64.6% of the additional annual demand in 2040, while cooling accounts for 35.4%.

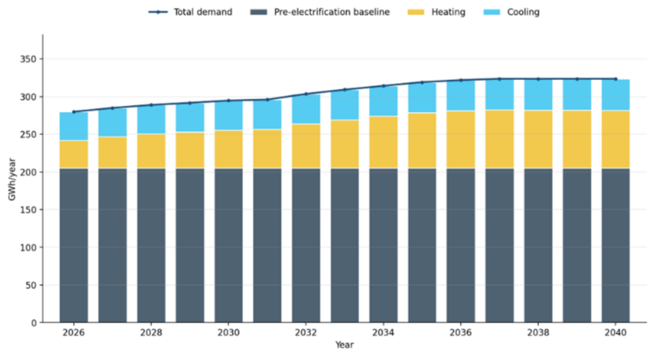

Figure 4: Evolution and decomposition of mean annual aggregate electricity demand in the base scenario

The annual decomposition does not fully capture how the demand profile changes within the year. Heating increases winter loads, whereas cooling generates the most pronounced hourly peaks. On the selected winter day, peak demand rises from 51.28 MWh/h in 2026 to 78.48 MWh/h in 2040. In the latter year, heating contributes 65.30 MWh/h to that peak. The selected summer day has the highest hourly demand in every year: its maximum rises from 139.79 MWh/h in 2026 to 150.12 MWh/h in 2040, with cooling contributing 112.17 MWh/h at the 2040 peak. The selected spring day remains unchanged because no heating or cooling load is activated.

Heating therefore dominates the cumulative annual increase, while cooling is more relevant for the highest short-term demand conditions.

5. Conclusions and Limitations

The thesis analyses a REC as a socio-technical system in which energy flows, economic incentives and household behaviour interact over time. The ABM does not seek a single optimal configuration; instead, it explains how a technically feasible REC can grow or remain limited depending on individual predispositions, local social exposure, perceived benefits and retention. The sensitivity analysis was central to this purpose. It showed that an additive joining rule can be dominated by baseline joining propensity when applied to a large population, and that retention alone cannot correct an excessive inflow. The final F-L formulation provides a more interpretable mechanism by requiring a meaningful local presence of the REC before individual predisposition becomes effective, while allowing economic attractiveness to be transmitted through visible nearby members. The future scenarios identify two distinct transition processes. Electrification changes the local electricity system by increasing annual demand and reshaping hourly and seasonal profiles. Participation, however, follows a separate social process: it depends strongly on the behavioural composition of the population and does not automatically rise because local demand becomes larger. In the 50%–50% scenario, aggregate electricity demand is 57.6% higher in 2040 than in the pre-electrification baseline, whereas only 6.67% of potential households are REC members. This result suggests that policies supporting electrification and policies supporting REC participation are related but not interchangeable.

For REC planning, the findings indicate that renewable generation and economic incentives should be accompanied by mechanisms that make the community visible, accessible and trustworthy at local level. Benefit-allocation rules matter because they influence the household-level economic signal, but the model also shows that monetary incentives alone do not guarantee diffusion. Communication, local promotion, community intermediaries and governance arrangements able to sustain participation are likely to be important complements to technical and financial design.

The results should be interpreted within the exploratory scope of the study. First, the behavioural parameters are theory-informed assumptions and are not calibrated against longitudinal evidence on CER.ca.MI membership or individual joining and exit decisions. Second, household behaviour is represented through two broad agent types and probabilistic rules, which simplify the roles of income, tenure, roof availability, investment capacity, prior experience with energy technologies, trust in institutions and administrative burden. Third, social influence is represented primarily through spatial proximity; actual communication networks, municipal initiatives, public meetings and information campaigns are not explicitly modelled. Finally, the long-term scenarios focus on heating and cooling electrification and simplify other sources of change, including additional PV and storage investment, demand response, regulatory evolution, grid constraints and potential changes in incentive schemes.

Future work could use surveys and observed REC data to calibrate behavioural rules, introduce richer socio-economic and building characteristics, integrate empirical social networks or external-awareness channels, and expand the technical module to include storage, demand response and network constraints. These developments would improve the model's usefulness as a decision-support tool while preserving its main contribution: linking household-level decisions with the collective evolution of a Renewable Energy Community.

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