UNICA

UNIVERSITÀ
DEGLI STUDI
DI CAGLIARI

Ph.D. DEGREE IN
Civil Engineering and Architecture

Cycle XXXVIII

TITLE OF THE Ph.D. THESIS

Multi-Agent Simulator for Evaluating the Social and Economic Dynamics of Renewable Energy Communities with NetLogo

A Decision Support System tool for the evaluation of RECs

Scientific Disciplinary Sector(s)

CEAR-03/C

Ph.D. Student:	Dr. Alessandro Sebastiano Carrus
Supervisor	Prof. Ivan Blečić
Co-Supervisors	Prof. Giuseppe Desogus Prof. Roberto Villafáfila-Robles Dr. Eleonora Congiu

Final exam. Academic Year 2024/2025
Thesis defence session: July 2026

Table of Contents

Glossary

ABM: Agent-Based Modeling
ARERA: Autorità di Regolazione per Energia Reti e Ambiente
BESS: Battery Energy Storage System
BPS: Building Performance Simulation
CAPEX: Capital Expenditure
CAS: Complex Adaptive System
CCF: Cumulative Cash Flow
CCL: Center for Connected Learning and Computer-Based Modeling
CCP: Common Coupling Point
CECs: Citizen Energy Communities
CER-CA: Cagliari Renewable Energy Community
CITCEA: Centre d'Innovació Tecnològica en Convertidors de Potència i Accionaments
DG: Distributed Generation
DICAAR: Department of Civil and Environmental Engineering and Architecture
DLT: Distributed Ledger Technology
DOD: Depth of Discharge
DQN: Deep Q-Networks
DSOs: Distribution System Operators
DSM: Demand-Side Management
DSS: Decision Support System
EE(40)Sco: Energy Efficiency 40 School
EMS: Energy Management System
ERP: Public Residential Housing
EU: European Union
EV: Electric Vehicle
FIPA: Foundation for Intelligent Physical Agents
GAMS: General Algebraic Modeling System
GIS: Global Information System
GSE: Gestore dei Servizi Energetici
GUI: Graphical User Interface
HEMS: Home Energy Management Systems
HPC: High-Performance Computing
IMED: Internal Market for Electricity Directive
IPCC: Intergovernmental Panel on Climate Change
IRR: Internal Rate of Return
JRC: Joint Research Centre – European Commission
KPIs: Key Performance Indicators
LCOE: Levelized Cost of Energy
LEM: Local Energy Market
LP: Linear Programming
MARL: Multi-Agent Reinforcement Learning
MAS: Multi-Agent Systems
MILP: Mixed-Integer Linear Programming
MINLP: Mixed-Integer Nonlinear Programming
MV/LV: Medium Voltage/Low Voltage (secondary substation)
NCF: Net Cash Flow
NESOI: New Energy Solutions Optimized for Islands
NPV: Net Present Value

NRRP/PNRR: National Recovery and Resilience Plan
OAT: One-at-a-Time
O&M: Operation and Maintenance
OSeMOSYS: Open Source energy MOdeling SYStem
OPEX: Operating Expenditure
P2P: Peer-to-Peer
PBP: Payback Period
PED: Positive Energy Districts
PNIEC: National Integrated Energy and Climate Plan
POD: Point of Delivery
PPO: Proximal Policy Optimization
PUN: National Single Price - Prezzo Unico Nazionale
PV System: Photovoltaic System
RECs: Renewable Energy Communities
REE: Red Eléctrica de España
RED: Renewable Energy Directive
REPAST: Recursive Porous Agent Simulation Toolkit
RID: Dedicated Withdrawal – Ritiro Dedicato
RMSE: Root Mean Square Error
ROI: Return on Investment
SAC: Soft Actor-Critic
SC: Self-Consumption
SCI: Self-Consumption Index
SDGs: Sustainable Development Goals
SLO: Social License to Operate
SLP: Standard Load Profiles
SLR: Systematic Literature Review
SMEs: Small and Medium-sized Enterprises
SOC: State of Charge
SoH: State of Health
SPADE: Smart Python Agent Development Environment
SS: Self-Sufficiency
SSI: Self-Sufficiency Index
TIAD: Testo Integrato Autoconsumo Diffuso
TSO: Transmission System Operator
UPC: Universitat Politècnica de Catalunya
VPP: Virtual Power Plant

Introduction

The contemporary energy landscape is undergoing a profound methodological transformation, marking the definitive end of the centralized energy generation model. For nearly a century, the architecture of power systems has been dominated by large-scale industrial production power plants and unidirectional energy flows proceeding vertically from the source to the final consumer. Today, driven by climate urgency and technological innovation, we are witnessing a transition toward a decentralized configuration based on Distributed Generation (DG) [1]. In this new scenario, the boundary between production and consumption dissolves, fostering the metamorphosis of historically passive actors into active, intelligent nodes of the grid. Citizens, SMEs, and local authorities are no longer mere expenditure terminals but prosumers capable of generating, storing, and exchanging energy, becoming the true protagonists of a multidirectional, anti-fragile network.

Renewable Energy Communities (RECs) emerge within this framework and must be understood not as simple technological aggregates but as complex socio-technical systems. They represent the institutional expression of a new understanding of energy citizenship, functioning as legal entities based on open participation and democratic governance. Their mission transcends the financial profit logic typical of traditional markets, aiming instead to generate environmental, social, and economic benefits for the local area. In this sense, RECs become operational tools for implementing the *United Nations 2030 Agenda* [2], directly addressing the need to ensure clean and affordable energy (SDG 7), promote sustainable urban communities (SDG 11), take concrete action to mitigate climate change (SDG 13), and foster multidisciplinary partnerships (SDG 17). Beyond the ecological impact, participation in an REC fosters reductions in energy costs through the optimization of local self-consumption and the maximization of incentives under EU regulatory frameworks.

The conceptual framework of RECs was enshrined in the European Union's "*Clean Energy Package*" [3], specifically in the RED II and RED III directives [4], [5], which institutionalized the right of citizens to produce and sell energy without excessive barriers. Despite the clarity of political objectives, the practical implementation of RECs faces an intrinsic complexity that extends beyond the engineering dimension. The interaction between technological components (such as photovoltaic systems and smart meters) and human components, characterized by heterogeneous motivations and non-linear behaviors, generates emergent dynamics that are difficult to predict. Literature analysis highlights how community formation is often hindered by operational barriers, statutory uncertainties, and difficulties in selecting the legal configuration best suited to the territory's urban and social specificities. The question then arises: how can we predict whether an REC configuration will be sustainable, attractive, and resilient in the long term before it is even built?

The specific problem identified in this research is the lack of analytical tools capable of mapping the social and economic response to regulatory and technological changes. Currently, a significant gap exists between the "*ideal REC*" described by regulators and the "*real REC*" that must operate in diversified local socio-economic contexts. The diffusion of these ecosystems depends not only on the efficiency of solar panels but also on members' propensity to cooperate, the sharpness of economic incentives, and the robustness of governance models. Without a deep understanding of these interdependent mechanics, the risk is to design fragile communities that cannot evolve or attract new members, thereby undermining energy transition efforts.

The primary objective of this work is therefore to decode the economic and social mechanics governing RECs and to evaluate their evolution over time. The originality of this thesis lies in its adoption of an Agent-Based Modeling (ABM) approach. Unlike static or purely technical models, multi-agent modeling allows the community to be observed as a living system, where each user (agent) acts according to behavioral rules, individual preferences, and responses to external stimuli. This approach meets the need to predict the impact of various governance policies or energy price fluctuations, allowing for testing in a controlled environment "*in silico*" what would be too costly or risky to evaluate.

The simulator created in this research serves as an advanced Decision Support System (DSS) [6]. Its functional requirements include the ability to incorporate environmental data (irradiance, temperatures), technical parameters (plant capacity), economic factors (energy costs, incentive schemes), and user behavioral profiles. The model enables the simulation of "*what-if*" scenarios; for example, *how would the appeal of an REC change if state incentives were raised? Which legal structure ensures the greatest fairness in benefit distribution among members?* Overall, the modeling approach presented here not only aids in designing RECs but also offers policymakers and local promoters a strategic guide to encourage the development of energy communities that are both economically viable and socially inclusive.

1. RECs as a tool for energy transition: between technical, regulatory, and social complexities

The practical implementation of Renewable Energy Communities (RECs) currently stands at the heart of a delicate balance between political ambition and operational feasibility. Although the European regulatory framework has charted a clear direction, starting from the objectives and policies for a structural energy transition, embodied and guided by the RED II Directive (2018/2001/EU), which introduced citizens' rights to produce and share energy, through to the recent strengthening by RED III (2023/2413/EU) [5], translating these principles into functional models presents multidimensional obstacles. In Italy, the transposition of these directives through Legislative Decree 199/2021 [6] and subsequent implementing decrees has established technical parameters and incentive systems. However, as recent literature highlights, the mere existence of a legal framework does not guarantee the hoped-for proliferation of stable and efficient configurations. The complexity of RECs lies in their nature as "*transformative approaches*", capable of integrating various renewable sources and advanced technologies to target local energy self-sufficiency, but which, to be effective, require a perfect convergence of technological setups, management strategies, and social engagement.

The systematic analysis proposed by Fichera et al. (2025) [6] clarifies how the development and operation of energy communities must address fundamental questions ranging from the definition of the legal entity itself to the management of economic flows derived from shared energy. One critical problem identified concerns the distribution of economic gain: the complexity of equitably calculating benefits among members, in a context where consumption habits are heterogeneous and dynamic, requires strategic planning that traditional models struggle to manage. This aspect is crucial because, while economic incentives act as primary catalysts for citizen adhesion, the long-term sustainability of the REC depends on its ability to generate social and environmental benefits that go beyond simple bill savings, with the aim of activating mechanisms for active citizen participation in energy market mechanisms. The management of "*shared energy*" thus becomes not only a technical dispatch problem but also a governance challenge that must balance social equity and energy optimization.

Furthermore, the literature emphasizes that the diffusion of RECs is deeply influenced by the territorial context and the prevailing supportive fiscal regimes. The shift toward Positive Energy Districts (PED) or toward energy-resilient urban planning requires that the REC be viewed not as a technological island, but as a node in a wider network, where constant monitoring and flexible management strategies are essential. The limitation of current implementations often lies in the difficulty of integrating the "*human factor*": citizen involvement is not a given, but a variable dependent on the degree of transparency of business models, the perceived simplicity of bureaucratic processes, and, no less importantly, the socio-economic context in which engagement activities for creating an REC are undertaken [7]. In this sense, the operational difficulties encountered in numerous case studies demonstrate that bureaucratic and regulatory complexity, if not supported by adequate simulation and optimization tools, risks stifling the innovative potential of communities before they even reach a critical mass of participants.

In this scenario, the need for comprehensive modeling emerges clearly, capable of addressing the "*multidimensional*" nature of RECs; the challenge lies not only in installing renewable capacity but in designing the interaction between technological components (photovoltaics, storage, smart meters) and users' energy consumption habits, so that the system is capable of co-evolving and adapting to public policies and energy market fluctuations. The specific problem that this research intends to address is embedded in this very gap: the lack of forecasting tools capable of integrating the response of social actors to variations in the regulatory framework and economic incentives. Only through a deep understanding of these mechanics, which Fichera and colleagues place at the base of the future of energy communities, is it possible to transform RECs from simple pilot experiments into structural pillars of the energy transition and of decentralized, democratically participated generation in Europe.

The analysis of the transposition of RED II and RED III directives across various European national legal systems reveals an extremely heterogeneous landscape, where regulatory theory clashes with the complexity of pre-existing technical, social, and economic realities. The transition from a community regulatory framework to operational implementation, as highlighted by Haji Bashi et al. (2023) [9], requires a mapping and analysis exercise that is not merely bureaucratic but also defines the very essence of the actors involved, from active consumers to Citizen Energy Communities (CEC). One of the critical issues emerging in this transition phase concerns the correspondence between legal and technical definitions, such as microgrids, Virtual Power Plants (VPP), and energy hubs. Research suggests that, in many cases, the attempt to adapt specific sectors of activity or rights to certain actors generates a regulatory misalignment: some configurations find themselves burdened with redundant obligations or rights due to their technical nature, while others are limited by regulatory constraints that fail to recognize their operational potential. This complexity and regulatory imbalance not only slow the development of energy communities but also underscore the importance of analyzing in detail the deep motivations driving their creation, which, according to European-scale empirical surveys, reside more in achieving sustainability goals and participating in social activities than in mere direct economic benefits.

This diversity of configurations requires a rigorous systematic classification to avoid oversimplifying the phenomenon. Moroni et al. (2019) [8] propose a fundamental distinction between *place-based communities*, where a spatial correspondence exists between the territorial area and the system members (as seen in the Spanish regulatory model), and *non-place-based communities*, which are not bound by physical proximity (as in the Italian regulatory model). Added to this is a functional dimension, separating communities born exclusively for energy purposes (*single-purpose*) from those integrated into broader contexts of shared management of goods and services (*multi-purpose*). Such categorization raises significant policy dilemmas: the choice between models affects management governance, the distribution of decision-making power among members, and the impact on the local energy market. The intrinsic complexity of these models suggests that the REC should not be understood as a monolithic entity, but as a flexible ecosystem whose boundaries and objectives must be carefully calibrated to be "*tailor-made*" to the specific needs of the territory and its inhabitants.

Despite the growing relevance of the topic, scientific literature highlights a significant lack of integration among technical design, organizational structure, and business models. Barabino et al. (2023) [9] emphasize that energy system modeling and the definition of objective functions are rarely considered jointly with Demand-Side Management (DSM) policies and incentive schemes. There is a vast research opportunity at the intersection of technical design, regulation, and economics, especially when considering multi-energy systems and sector couplings that have so far been marginalized. The operational challenge consists of coordinating local production and consumption in accordance not only with available physical resources but also with the real needs of the public market and continuously evolving regulatory frameworks.

In this context of regulatory fragmentation and taxonomic complexity, there emerges an urgent need for analytical tools that facilitate comparison and analysis between various business models and different possible configurations. The problem no longer concerns only the technical feasibility of the plants, but also the ability to predict how a specific legal framework and an optimization strategy can, over time, influence the stability, attractiveness, and evolution of the community. In this scenario, this thesis work is positioned: if literature and European experiences demonstrate that the success of RECs depends on a complex combination of social motivations, technical constraints, and economic incentives, it becomes essential to have a simulation model that functions as a multidimensional connector. The goal is to offer a modeling response to the political and managerial dilemmas highlighted by major studies, allowing for the advanced testing and analysis of the effectiveness of different REC configurations and ensuring that the energy transition promotes a real democratization of the European energy system.

The transposition of European regulations in Italy offers a case study of particular interest, especially when read alongside the comparative analysis conducted by Haji Bashi et al. (2023) [5] on transposition by other member states, notably Austria, Ireland, Spain, and Germany. While RED II and the subsequent RED III sought to harmonize prosumer rights at a continental level, Italy underwent a transition phase characterized by a form of "*bureaucratic experimentalism*" between late 2019 and early 2020. Through Law 8/2020 [10], Italy initiated a path of partial, and in a sense, anticipatory transposition of the RED II directive, aiming to experiment with the effects, repercussions, and potential criticalities of collective self-consumption systems and RECs. This was done by introducing specific barriers and characteristics, often absent or less pronounced in other contexts. These included the entry restriction for renewable energy plants commissioned before March 1, 2020, a power limit of 200 kW per plant, and the requirement that members (producers, prosumers, and consumers) be located within the same secondary substation (MV/LV). It is noted, therefore, that while in countries like Austria the definition of energy community was integrated with relative fluidity within a consolidated tradition of energy cooperatives, in Italy the process was slowed down by regulatory stratification and complexity, witnessing a succession of transitional regimes (linked to the Secondary Substation) and definitive regimes (linked to the Primary Substation). This shift was not merely a technical adjustment but introduced significant procedural complexity in managing relationships with the GSE (Gestore dei Servizi Energetici). Haji Bashi's mapping highlights how the misalignment between EU legal definitions and their technical counterparts is a major bottleneck: in Italy, this translated into the imposition of disproportionate administrative burdens on small aggregations of citizens or SMEs, which found themselves facing bureaucratic requirements typical of large market operators, despite operating on a micro-territorial scale. This made it unattractive for small entities to independently approach REC establishment mechanisms with little effort.

The comparison with Spain or Ireland has highlighted how the Italian approach initially suffered from rigidity in defining the geographic perimeters of the communities; the need for REC members to coincide under the same Primary Substation, although technically justified by grid management needs, represents an entry barrier for many projects born in urbanistically dense or, conversely, excessively fragmented areas. Haji Bashi notes that for many European collective actors, the main motivation for forming an REC is to achieve efficiency targets and social participation rather than mere profit. However, in Italy, the excessive cumbersomeness of accreditation procedures and the variability of incentive disbursement times risk stifling these very ideals. The paradox of the Italian system lies in the fact that, despite an incentive system that is potentially among the most generous in Europe, interpretative uncertainty and the weight of reporting dynamics and tools have created a "*filter*" that favors only those subjects equipped with high technical and legal skills, effectively excluding the spontaneous communities of citizens that should be the heart of the transition.

Critically analyzing this situation considering the taxonomy of Moroni et al. (2019) [8], it emerges that Italian bureaucratic barriers have inadvertently pushed RECs toward "*single-purpose*" configurations, born with the sole aim of managing the economic incentive to survive managerial complexity, moving them away from the more inclusive and social "*multi-purpose*" model. The difficulties in fostering dialogue between different actors, from municipalities managing public tenders to SMEs balancing investments and benefits, reflect that lack of *"matching"* between rights and sectors of activity signaled by Haji Bashi. In this sense, the originality of the simulation model proposed in this thesis also lies in its ability to serve as a tool for bureaucratic risk mitigation: by simulating different distribution scenarios and investment return timelines in light of current GSE procedures, the model allows for the identification of the legal and operational configuration that best "*resists*" the inefficiencies of the national system. The Italian problem, therefore, is not only regulatory but also methodological: there is a lack of a vision capable of predicting the impact of administrative burdens on community longevity, a gap that this research aims to fill by providing a scientific basis for bureaucracy-proof design.

Below is a summary table *(Table 1)* of the research phases carried out for the development of the agent-based modeling (ABM) methodology, in which several interdisciplinary themes converge to create a realistic "*in silico*" simulation.

Table 1: Research development stages for ABM-based DSS

Research Phase	Phase Objective	Converging Topics (Inputs & Variables)
1. Context & Literature Mapping	Define the multidimensional boundaries and barriers of RECs.	***Regulation:*** RED II/RED III Directives, Italian Leg. Decree 199/2021, bureaucratic constraints (e.g., Primary vs. Secondary Substations). ***Sociology:*** Motivations, place-based vs. non-place-based models, single-purpose vs. multi-purpose configurations.
2. Model Design & Initialization	Build the Agent-Based Model (ABM) environment and define the "*agents*" (prosumers, citizens, SMEs).	***Technical Data:*** Environmental conditions (irradiance, temperature), plant capacity (PV, storage). ***Social Data:*** User behavioral profiles, propensity to cooperate. ***Economic Data:*** Energy costs, current incentive schemes.
3. Simulation & Scenario Analysis	Run "*what-if*" scenarios to observe the REC as a complex, living socio-technical system over time.	***Policy & Economics:*** Impact of energy price fluctuations, variations in state incentives. ***Governance:*** Benefit distribution rules, economic flow management, equity among heterogeneous users.
4. Output Generation (DSS)	Deliver actionable insights to mitigate risk and optimize REC design.	***Strategy:*** Bureaucratic risk mitigation, financial return timelines, optimal legal structures tailored to local contexts.

1.1. The evolution of regulatory frameworks and operational architecture: the Italian case in the European context

The shift from political vision to the operational practice of RECs requires a thorough analysis of how technical requirements, regulatory constraints, and systemic functionalities come together. As shown by recent comparative analyses (Taromboli et al., 2025) [11], implementing the RED II and RED III directives across European Union Member States has created a patchwork of regulatory frameworks reflecting the different levels of development of national energy markets. In this environment, the challenge is not just in formally transposing regulations but also in defining obligations and rights that enable RECs to function effectively within the electricity system. The legislative landscape is gradually shifting toward advanced ideas, such as "*multiple participation*", which has been in place in Austria since 2024. This innovation allows individual users to participate in multiple energy communities simultaneously, requiring complex optimization models to properly allocate production and demand across a single distribution transformer. Although such setups introduce management complexities, they also hold the potential to significantly cut costs and peak demand on the grid, as long as a balance can be maintained between individual profits and overall system stability (Mariuzzo et al., 2024, 2025) [12], [13].

In Italy, the pathway toward full operational capacity has entailed the development of a specific "*roadmap*" for the design and oversight of Renewable Energy Communities (RECs) (Cutore et al., 2023) [15]. The distinctiveness of the Italian case resides in the necessity to integrate business models that deliver environmental and social advantages within densely populated urban areas, where the building sector represents the primary energy consumer and potentially the initial beneficiary of the transition. Research demonstrates that RECs must evolve into process-oriented models capable of supporting large-scale energy retrofitting initiatives within buildings, thereby transforming urban districts into ecosystems of production and sharing (Ahmed & Măgurean, 2024) [16]. In this context, optimal design must incorporate comprehensive thermal-electrical co-simulation. It is imperative to account for the influence of community composition (the ratio of prosumers to conventional consumers), market signals, and, most notably, the climatic geography of Italian regions. Scientific evidence affirms that heating and cooling demands, which exhibit significant variability between Northern and Southern Italy, markedly influence the sizing of photovoltaic systems and the efficacy of local energy exchange mechanisms (Belloni et al., 2024) [17].

The following diagram shows the chronological evolution of the regulatory framework for RECs, with a mapping of the European Union directives and the main stages of implementation in the main European countries.

EU: RED II Directive (2018/2001/EU)
December 2018
The European Union formally institutionalizes Renewable Energy Communities (RECs). The directive establishes the right of citizens, SMEs, and local authorities to produce, consume, store, and sell renewable energy without facing disproportionate regulatory barriers.

EU: Internal Electricity Market Directive (2019/944)
June 2019
Introduces the broader framework for Citizen Energy Communities (CECs). Unlike RECs, CECs are not strictly limited to renewable sources and focus heavily on democratizing participation in electricity markets and distribution networks.

Italy: Law 8/2020 (Early Transposition)
February 2020
Italy initiates a phase of "bureaucratic experimentalism" by partially anticipating the RED II directive. This transitional regime sets strict limits: energy sharing is restricted to users connected to the same Secondary Substation (MV/LV), and individual plant capacity is capped at 200 kW.

Spain: Royal Decree 23/2020
June 2020
Spain officially introduces the definitions of Renewable Energy Communities into national law. This builds upon earlier 2019 regulations that established highly favorable frameworks for collective self-consumption, leveraging localized "place-based" community models.

Austria: EAG (Renewable Energy Expansion Act)
July 2021
Austria seamlessly integrates both RECs and CECs into national law. Benefiting from a long-standing tradition of energy cooperatives, the framework allows local communities (EEGs) and nationwide citizen communities (BEGs) to form with minimal bureaucratic friction compared to other member states.

Italy: Legislative Decree 199/2021
December 2021
The full transposition of RED II in Italy. It expands the operational boundaries for RECs, allowing participants to be connected under the same Primary Substation (HV/MV) and raising the maximum capacity for individual renewable plants to 1 MW.

Germany: EEG 2023 (Renewable Energy Sources Act)
January 2023
Germany implements sweeping reforms to accelerate the transition. The update specifically supports citizen energy companies (Bürgerenergiegesellschaften) by exempting solar and wind projects up to certain capacities from strict bidding/tender processes, heavily favoring decentralized community generation.

EU: RED III Directive (2023/2413/EU)
November 2023
The EU strengthens the Clean Energy Package. RED III raises binding renewable energy targets, mandates faster permitting processes for renewable installations, and further solidifies the role of energy communities in achieving cross-sectoral decarbonization (including heating and transport).

Italy: MASE Decree (CER Operational Decree)
January 2024
The Italian Ministry of Environment and Energy Security (MASE) publishes the final implementing decree. It definitively regulates the economic incentive tariffs for shared energy and unlocks National Recovery and Resilience Plan (PNRR) capital grants to fund up to 40% of REC construction costs in municipalities with fewer than 5,000 inhabitants.

The operational structure of RECs in Italy requires an analysis that combines technical, administrative, and regulatory aspects, firmly established within the current legal framework. The cornerstone of the entire Italian system is the concept of the electrical perimeter, defined by the Primary Substation, the high/medium-voltage node that geographically and technically marks the community's boundary. Inside this boundary, the REC functions as an independent legal entity capable of managing interactions among three key figures: producers, prosumers, and consumers. Producers are entities that supply the community with renewable energy plants, usually with a capacity not exceeding 1 MW per plant, to qualify for incentive programs, without necessarily consuming energy at the same connection point. Prosumers, essential to the transition, are consumers who install a production plant at their own premises, meeting part of their needs (physical self-consumption) and exporting surplus energy to the grid for virtual sharing with other members. Lastly, consumers are the community members who do not own their own plants but contribute to system balance by absorbing locally generated energy through the REC, thereby maximizing the contemporaneity coefficient, the basis of the model's economic sustainability.

The economic model motivating this setup is based on the idea of "*shared energy*", defined as the lowest hourly value between the electricity supplied to the grid by the community's plants and that taken out by its members. In this energy segment, the GSE (Gestore dei Servizi Energetici) recognizes an incentive tariff (*tariffa premio*) for a 20-year period [14]. According to the rules established by Legislative Decree 5/2026 [15], this incentive includes a fixed part aimed at ensuring investment stability and a variable part linked to the regional energy price, intended to reflect market trends. Also included in this premium is the reimbursement of grid tariff components (ARERA charge refunds), justified by the lower use of the national transmission grid compared to distributed generation. For municipalities with populations under 50,000 residents, the Italian system also offers capital grants (often linked to NRRP/PNRR funds) that can cover up to 40% of investment costs, making RECs especially effective for promoting territorial cohesion in inland and rural areas [16].

The process for launching an REC in Italy involves a detailed series of steps beginning with the formation of the legal entity. This must be a private law organization (typically a cooperative, an association, or a third-sector entity) whose bylaws clearly state that its main goal is not to generate profit but to provide environmental, economic, and social benefits to its members or local communities where it operates. After establishing the entity, the next step is to identify sites and build production plants, which must begin operations following the implementation of the RED II directive transposition (December 15, 2021). At the same time, the mapping of members within the same Primary Substation is conducted to verify the technical compatibility of connection points (PODs).

The final operational step is to submit an application for access to the distributed self-consumption service through the GSE's digital portal. This phase requires submitting detailed documentation, including the deed of incorporation, bylaws, the list of associated PODs, and the plants' technical specifications. Once accreditation is obtained, the REC enters into a contract with the GSE to disburse incentives. The operational management of the community then involves distributing proceeds among members based on criteria autonomously defined by the REC's shareholders' agreements (*patti parasociali*). These may prioritize eliminating energy poverty for vulnerable families or reinvesting funds into new community services, such as upgrades for public buildings or EV charging stations. While this complex process still presents significant administrative challenges, it transforms the REC from a simple technical project into a resilient social infrastructure capable of protecting local areas from energy price shocks typical of global geopolitical crises.

Below is a comparative table *(Table 2)* that summarizes the main technical and socioeconomic differences in the management of RECs across the main European countries.

Although the RED II and RED III directives provide a unified European framework, their implementation has led to distinct national models, shaped by pre-existing network topologies and cultural attitudes towards energy cooperatives.

Table 2: Comparative Matrix: REC Implementation Models

Country	Geographic Boundary (Technical)	Capacity Limits (per plant)	Incentive Mechanism & Tariffs	Socio-Economic Focus & Governance
Italy	**Grid-topology based.** Members must be under the same Primary Substation (HV/MV). Virtual sharing.	**1 MW** for plants accessing REC incentives.	Premium tariff on shared energy (20 years) + CapEx grants (up to 40% in small towns).	**Incentive-driven.** High administrative complexity favors single-purpose entities. Virtual models.
Spain	**Distance-based.** Radial limits from the plant (historically 500m, expanded up to 2 km for solar).	Focus on collective self-consumption; no strict REC capacity cap, but size limits apply to specific tariffs.	Direct bill reduction for self-consumption. Regional grants for setup.	**Place-based & Social.** Strong focus on mitigating energy poverty. High municipal involvement.
Austria	**Two-tier system.** Local (EEG - same MV/LV substation) and National (BEG - nationwide virtual sharing).	Flexible. Tied to the type of community (Local vs. Citizen).	**Reduced grid tariffs.** EEGs pay significantly lower network fees for using local infrastructure.	**Cooperative tradition.** Smooth integration, low bureaucratic barriers, deeply rooted in local democratic governance.
Germany	**Regional proximity.** Often defined by postal codes or specific radii (e.g., 2.5 km for wind participation).	**High thresholds.** Exemption from state tenders for wind (up to 18 MW) and solar (up to 6 MW).	Market premiums. Citizen companies receive priority in spatial planning and bidding exemptions.	**Investment-driven.** Focus on capital mobilization and asset ownership rather than peer-to-peer energy sharing.

The main divergences in regulatory systems for RECs among the major nations can be identified in three main areas, described below:

1. ***Spatial Definition: Topology vs. Geography:***

   The most significant technical divergence lies in how borders are drawn. Italy defines the community through electrical infrastructure (the Primary Substation), meaning users right next to each other might not be able to share energy if connected to different grid nodes. Conversely, Spain uses absolute geographic distance (a 2 km radius), creating "*place-based*" communities that align more closely with actual neighborhood boundaries but may span electrical distribution zones.

2. ***Value Generation: Incentives vs. Grid Efficiency***
   - ***The Italian Model:*** Generates value primarily through an explicit state-funded premium tariff paid on the energy instantly shared among members. It does not discount the physical grid fees.
   - ***The Austrian Model:*** Generates value intrinsically by discounting grid distribution tariffs for local sharing, recognizing that energy consumed locally puts less stress on the high-voltage national grid.

3. ***Socio-Economic Identity: Sharing vs. Investing***
   While Southern Europe (Italy, Spain) focuses heavily on Energy Sharing (prosumers sharing kilowatt-hours to lower monthly bills or fight energy poverty), the German model has historically favored Asset Ownership (citizens pooling capital to build large multi-megawatt wind parks and receiving dividends).

1.2. Socioeconomic dimensions and the participation dilemma: drivers of success and barriers to membership

Beyond technological and regulatory factors, the success of energy communities is deeply connected to various social and economic factors that influence their long-term appeal and strength. The core issue is often referred to as the "*energy community dilemma*": whether an individual or small business decides to join an REC (De Santi et al., 2022) [17]. This choice isn't based solely on economic reasoning but also on perceptions of social benefits, trust in the organization proposing the REC, and the simplicity of the business model; while earning extra revenue is a motivation, the main reasons are usually social inclusion and support for local sustainability goals. Moving to a decentralized system means that the REC must be seen not just as an investment, but as a social activity focused on efficiency and sharing (Mariuzzo et al., 2024; Ahmed & Măgurean, 2024) [12], [18].

Social acceptance plays a crucial role, especially when introducing concepts like load shedding or load shifting to optimize the grid. The willingness of users to adjust their consumption habits for the benefit of the community is a key factor in influencing REC performance. Sensitivity analyses show that when social acceptance is high, peak demand reductions of up to 29% are possible, easing pressure on local distribution infrastructure (Mariuzzo et al., 2025) [13]. However, the risk of failure is real if the benefits are seen as unfair: communities with high generation shares might feel at a disadvantage compared to purely consuming members if not supported by transparent and fair allocation methods.

The sustainability of an REC depends on its ability to balance the different needs of the territory. In Southern regions, the abundance of solar resources presents exceptional opportunities to reduce energy poverty, but requires governance models that engage actors with limited initial investment capacity. Conversely, in Northern regions, the challenge shifts to managing winter thermal loads and integrating offices and residences. The success or failure of the initiative, therefore, depends not only on the quality of the regulatory framework or the installed technology but also on the model's capacity to address the specific needs of its members by integrating economic incentives, regulatory stability, and a strong sense of social community (Belloni et al., 2024; Cutore et al., 2023) [19], [20]. It is precisely in this gap between technical potential and socio-economic reality that the need for advanced simulation tools emerges, tools capable of mapping these interdependencies and guiding the development of genuinely resilient energy communities.

Managing cash flow in REC truly tests its sustainability and social cohesion. It functions as a circular financial ecosystem that must balance equity, incentives, and operating costs. The core of the REC's economy isn't just about saving on individual bills (which, for members, remain the same across fixed and variable charges to their supplier), but about the legal entity's ability to collect and distribute the premiums recognized by the GSE. The main sources of funds for the community come from three areas: the incentive tariff on shared energy, reimbursements of grid tariff components (ARERA), and income from selling excess energy fed into the grid, often managed through the Dedicated Withdrawal (*Ritiro Dedicato* - RID) mechanism. Nevertheless, turning these gross revenues into net benefits for members depends on a clear allocation strategy outlined in the shareholders' agreements, which considers the different types of individual contributions.

In this scenario, flow management must first cover Operation and Maintenance (O&M) costs and administrative and tax burdens related to the entity's legal status. After these expenses are deducted, the REC must compensate producers and prosumers for the capital investment (CAPEX) required to build the plants. This portion of cash flow acts as an investment buffer and must be adjusted to ensure a reasonable Payback Period without draining excessive resources from the community's social purpose. The modeling challenge addressed in this thesis involves simulating how changes in these distribution percentages affect the REC's attractiveness: if the remuneration for investors is too low, the community struggles to install new capacity; if it is too high, consuming members (often the most vulnerable) perceive a marginal benefit that does not justify participatory commitment, undermining the community's social cohesion.

The most distinctive aspect of managing Italian cash flows is their ability to act as stabilizers during geopolitical crises. While the sale price of excess energy (RID) tracks the fluctuations of the National Single Price (PUN), the GSE incentive tariff remains fixed for twenty years, serving as a direct income protected from energy inflation. During periods of high prices, REC revenues rise due to the sales component, creating a "*solidarity surplus*" that can be used to reduce members' bills in energy poverty or to fund local efficiency projects. The developed simulator allows testing different "*allocation policies*": from purely merit-based models, in which the premium is distributed in proportion to the timing of consumption, to solidarity models, in which a fixed portion of revenues is allocated to community funds. This dynamic cash flow analysis shows that the REC is not just a technical setup but a new form of territorial energy welfare, capable of turning shared kilowatt-hours into tangible, resilient economic value for the entire community.

1.3. The fragmentation of literature and the limit of static approaches

The scientific motivation driving this research stems from the identification of a profound asymmetry in the current state of the art. Although the topic of RECs has experienced exponential growth in recent years, an analysis of the last five years shows 1,163 publications between 2021 and 2026, increasing from 68 in 2021 to 320 in 2026. This represents an average annual growth rate of 42.82%; such accelerated growth reflects the EU's legislative push following the RED II and RED III Directives, which institutionalized RECs as central mechanisms for the deployment of decentralized renewable energy *(Table 3 and Table 4)*.

Table 3: Yearly REC's Research Progression.

Year	Publications	Growth Vs Previous	Key Milestone	Avg Citations
2021	68	-	RED II transposition begins	82
2022	105	54.4%	Emerging focus on financing mechanisms	95
2023	160	52.4%	Peak research on policy frameworks	113
2024	225	40.6%	Increase in technical/technological papers	128
2025	285	26.7%	Focus on hydrogen integration, digitalization	135
2026	320	12.3%	Maturation of field, interdisciplinary growth	121

Table 4: REC's Summary Statistics.

Metric	Values
Total Publications (2021-2026)	1163
Average Publications per Year	193.8
Annual Growth Rate (%)	42.82
Total Countries Analyzed	12
European Union Countries	10
Main Journal (Top)	Energies

The growth trajectory shows particularly steep increases during the 2021-2023 period (with annual growth of 54.4% and 52.4%), followed by a gradual moderation to a 12.3% growth rate by 2026, suggesting a maturation phase for the sector *(Figure 1)*.

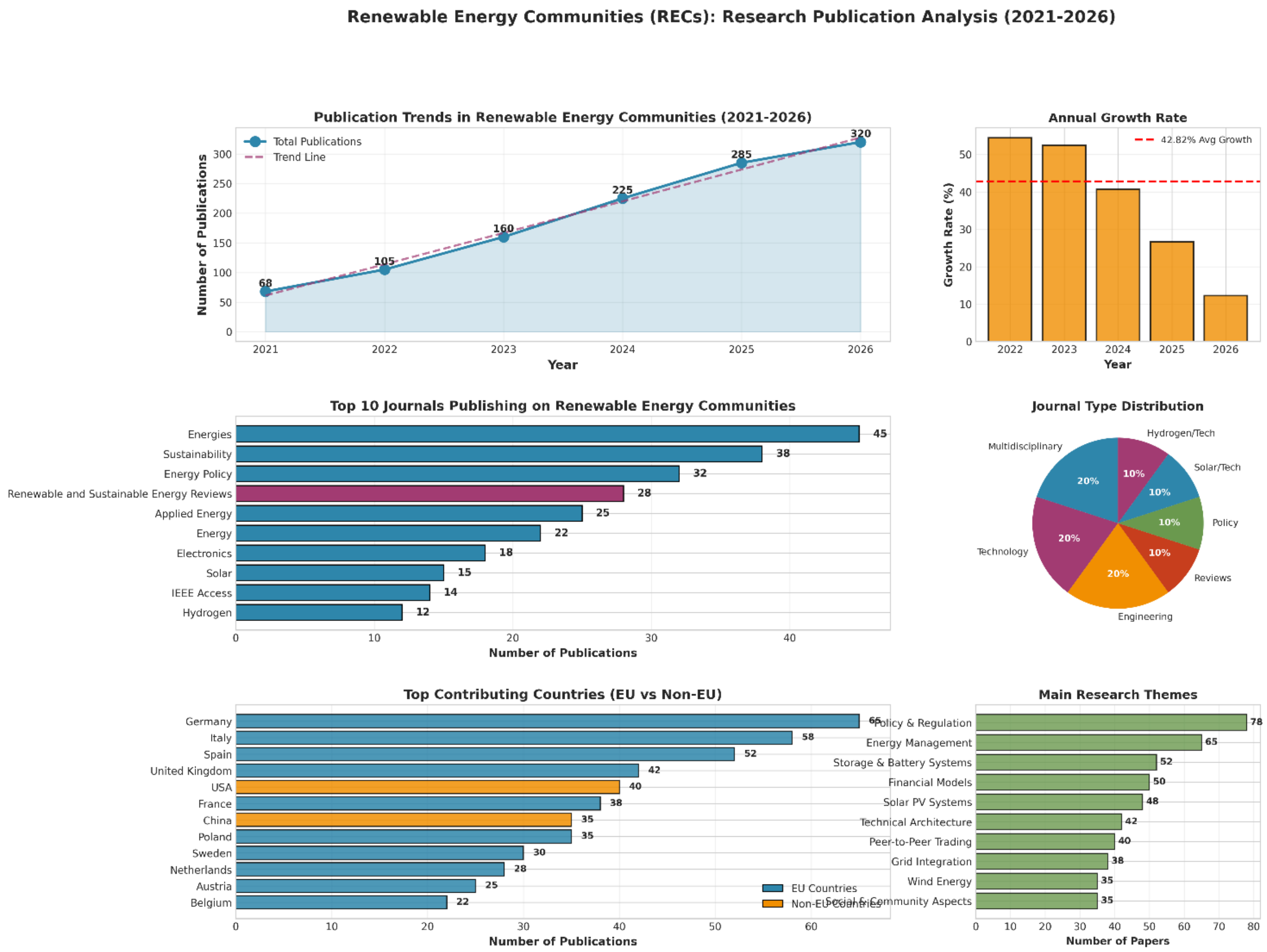

Figure 1. RECs Research Publication Analysis (2021-2026)

Although the topic has become central to high-impact journals such as *Energies*, *Sustainability*, *Energy Policy*, *Renewable and Sustainable Energy Reviews*, *Applied Energy*, and *Journal of Cleaner Production*, there remains a persistent difficulty in overcoming the *"compartmentalization"* of knowledge *(Table 5 and Table 6)*.

Table 5: Detailed Journals Analysis.

Journal Name	Publications (2021-2026)	Publisher	Focus Area	Impact Factor Category
Energies	45	MDPI	Multidisciplinary Energy	High
Sustainability	38	MDPI	Sustainability/Multidisciplinary	High
Energy Policy	32	Elsevier	Energy Policy & Economics	Very High
Renewable and Sustainable Energy Reviews	28	Elsevier	Renewable Energy Reviews	Very High
Applied Energy	25	Elsevier	Applied Energy Systems	Very High
Energy	22	Elsevier	General Energy	High
Electronics	18	MDPI	Technology & Electronics	Medium
Solar	15	MDPI	Solar PV Systems	Medium
IEEE Access	14	IEEE	Technology & Engineering	Medium
Hydrogen	12	MDPI	Hydrogen & Fuel Cells	Medium
Journal of Cleaner Production	10	Elsevier	Environmental Impact	Very High
Environmental Research Letters	8	IOP Publishing	Environmental Science	Very High
Nature Energy	7	Nature Portfolio	High-Impact Energy	Very High
Solar Energy	6	Elsevier	Solar Energy Systems	High

Table 6: Detailed Journals Analysis.

Research Theme	Publications	Key_Subtopics	Growth_Trend
Policy & Regulatory Framework	78	RED II/III, national transposition, licensing frameworks, incentive schemes	Stable/Growing
Energy Management Systems	65	Demand response, forecasting, optimization, energy sharing algorithms	Growing
Storage & Battery Technologies	52	Battery energy storage systems (BESS), second-life batteries, capacity sizing	Growing
Financial & Economic Models	50	Revenue models, cost allocation, capital financing, crowdfunding, feasibility studies	Growing
Solar PV Integration	48	Photovoltaic systems, capacity factors, self-consumption optimization	Stable
Peer-to-Peer Trading Mechanisms	40	Market design, trading platforms, pricing mechanisms, balancing services	Growing
Grid Integration & Flexibility	38	Smart grid adaptation, voltage regulation, frequency control, microgrids	Growing
Social & Community Engagement	35	Participation barriers, stakeholder engagement, behavioral aspects, equity	Growing
Technical Architecture	42	Communication protocols, data monitoring, SCADA systems, cybersecurity	Stable
Wind Energy Systems	35	Wind turbine capacity, wind resource assessment, hybrid wind-solar systems	Declining
Biogas & Biomass	25	Anaerobic digestion, biogas potential, circular economy linkages	Declining
Digital & IoT Solutions	28	AI/ML for forecasting, blockchain for trading, digital meters	Rapidly Growing

On the one hand, the energy engineering field has developed highly sophisticated optimization models focused on maximizing physical self-consumption and sizing storage systems. On the other hand, social sciences have investigated the drivers of social acceptance and democratic participation. However, what is missing is an operational synthesis: literature still tends to treat the technological and human components as independent variables, whereas in the reality of an REC they co-evolve in a mutual dependence.

The main limitation of dominant approaches is their inherently static and deterministic nature. Most feasibility models currently used by professionals and policymakers rely on standardized load profiles (usually derived from statistical averages) and assume perfect end-user rationality. These tools operate in a relational vacuum if community members respond to economic stimulus, such as the shared energy incentives established by Legislative Decree 5/2026 [21], in a uniform and consistent manner over time. This framework systematically ignores what the complexity systems literature defines as "*emergence*" [22]: the phenomenon in which the collective behavior of a community is not merely the sum of its parts but the result of reciprocal interactions, social imitation, and adaptive responses to the external environment.

Another key concern is that linear models cannot handle regulatory uncertainty and market fluctuations. In situations where the regulatory environment changes quickly, such as the shift from experimental to established regimes, a model based on static spreadsheets cannot reflect how adaptation might occur dynamically. For example, if economic incentives fluctuate or if the cost of grid electricity drops significantly, a static model wouldn't predict if or how many members would decide to "*emotionally or operationally disinvest*" from the community, risking the financial stability of the entire project. The "*black box*" of human behavior, therefore, remains the main unmapped risk factor.

This research is founded on the belief that the operational stagnation of many RECs does not stem from a lack of technology or capital, but from a deficiency in forecasting tools that integrate the socio-technical dimension. Bibliographic fragmentation has created a "*design myopia*": excellent energy infrastructure is designed on paper but struggles to translate into resilient social ecosystems. Therefore, it is essential to develop a methodology that moves beyond a "*snapshot*" of the energy system and adopts the concept of a "*motion picture*", specifically, an evolutionary simulation where agents (citizens, businesses, administrations) interact within a dynamic environment. Only through this approach can complexity, which is currently seen as a bureaucratic and managerial obstacle, be transformed into a strategic resource for designing energy communities that are not only technically efficient but also socially vibrant and economically sustainable.

An in-depth examination of the state of the art and the identification of the motivations underlying this research requires a critical analysis of the literature that goes beyond a mere description of technologies, investigating the epistemological frictions between different approaches instead. Despite the explosion of scientific interest in RECs, a persistent fragmentation remains between the domains of energy modeling and those of social and political sciences. As highlighted by Barabino et al. (2023) [9], the literature has often focused on optimizing technical design and business models using purely economic or performance-based objective functions, neglecting to detail how such goals interface with operational and regulatory realities. Many investment models, such as those proposed by Sousa et al. (2023) [23] for the optimization of photovoltaic and wind capacity, while being extremely mathematically sophisticated, tend to treat the system as a closed and rational entity, where electricity sharing is the outcome of a deterministic calculation rather than a dynamic interaction between human agents.

The fundamental limitation of so-called "*static*" approaches lies in their inability to manage intrinsic uncertainty and the variability of loads and behaviors. Although contributions such as that of Lilliu et al. (2019) [24] have introduced uncertainty-aware optimization techniques for prosumers' flexible loads, much of the current modeling still struggles to integrate the unpredictable nature of decentralized demand and production within a smart grid context. This criticality is particularly evident when considering Energy Storage Systems (ESS): while Ahmed and D'Angola (2025) [25] underscore the crucial importance of storage for REC resilience, the management of such systems in transactive energy communities requires algorithms capable of operating on compressed and dynamic time horizons, as suggested by Lei et al. (2024) [26] and Soares et al. (2022) [27]. However, pursuing purely technical optimization risks producing solutions that are theoretically excellent but practically inapplicable if they lack flexible mechanisms for sharing management. In this regard, the work of Gianaroli et al. (2024) [28] on the development of dynamic sharing keys represents a significant attempt to overcome the rigidity of static models, offering algorithms capable of real-time management of collective self-consumption.

Nevertheless, even the most advanced dynamic models risk failure if they do not integrate the dimensions of "Social Innovation" and social acceptance. As discussed by Hewitt et al. (2019) [29], RECs are not only energy infrastructures but also social innovations that challenge established power structures and require active community engagement. Socio-political literature warns against a purely "*top-down*" approach: MacArthur (2016) [30] and Olajide (2024) [31] emphasize that public participation and deliberation are essential to overcoming barriers in agricultural and urban regions, where decision-making power may be perceived as unbalanced. The concept of "*Social License to Operate*" (SLO), analyzed by Minadakis and Vega-Araújo (2024) [32], suggests that a just transition depends not only on energy efficiency but also on the perception of justice and equity by the members. Empirical studies conducted in Italy, Germany, and Austria confirm that REC design must explicitly include elements that increase social acceptance, as citizen motivation is never purely financial but linked to values of belonging and territorial sustainability [33].

The fragmentation of the literature thus arises from the gap between the technical parameterization of self-consumption systems, as precisely analyzed by Petrovich et al. (2025) [34] through real-world case studies, and the need for a polycentric research vision. Blasch et al. (2021) [35] clearly indicate that the future of energy community research must shift toward analyzing polycentric settings, in which complexity arises from interactions among multiple decision-making centers and governance levels. In this scenario, the Agent-Based Modeling (ABM) approach proposed in this thesis serves as the necessary glue to unify these fragments. By integrating Moscovici's active minority theory with the technical constraints of the climate zone and the financial possibilities derived from agents' income, the research aims to overcome the "*blindness*" of static models. The goal is not only to optimize production but to simulate the co-evolution of technology, society, and regulation, addressing a methodological gap that has so far prevented a full understanding of how RECs can effectively take root and thrive in an uncertain and changing global environment.

1.4. Proposal for a new modeling approach

Considering the fragmentation and limitations of the static approaches previously discussed, this research aims to develop a new modeling paradigm for RECs. The originality of this thesis lies in creating a methodological "*bridge*" that cohesively integrates the precision of technical energy physics with the socio-psychological dynamics of collective participation. While recent literature calls for a "*polycentric*" vision and more focus on social innovation, this research turns these demands into a practical tool: an Agent-Based Model (ABM) designed to view the REC not as a static snapshot of energy flows but as a dynamic ecosystem that co-evolves with its regulatory, economic, and territorial environment.

The primary objective is to move beyond the logic of purely economic objective functions, such as simple return on investment or the maximization of self-consumption, to investigate the REC system's antifragility in the face of uncertainty. To achieve this, the model introduces unprecedented granularity in the definition of agents. They are not treated as abstract "*load points*", but as actors characterized by diversified usage profiles (standard residential, seasonal residential, offices, schools, commercial activities) and rooted in a specific climate zone. This characterization allows the simulator to calculate load complementarity and production peaks with extreme fidelity, providing a solid technical foundation for evaluating the "*dynamic sharing keys*" of shared energy. However, the breakthrough innovation consists of integrating annual income as a threshold variable: the model does not assume membership is given; instead, it simulates the agent's actual investment capacity, bringing the themes of equity and energy justice to the forefront of the transition process.

The most original and distinctive contribution of this research, however, is the application of *Serge Moscovici's Theory of Active Minority Influence* [27], [28] to model social engagement. While traditional models struggle to explain why a citizen would join an REC beyond mere economic benefits, this simulator captures the transformative power of a core group of determined, consistent prosumers (the active minority). By simulating the "*consistency*" of the message and the creation of "*cognitive conflict*" among external agents, the model allows observation of how the energy social norm can shift within a territory. Adhesion is therefore not a one-time event, but a recursive process: every year, the simulator checks whether the minority's appeal, combined with price signals and the climate zone, is enough to retain existing members and attract new ones.

In summary, the research aims to address a series of political and managerial challenges through dynamic "*what-if*" scenarios. The goal is not to provide a single, universal solution but to create a decision support tool that demonstrates how changing a regulatory parameter (such as a GSE incentive) or a social factor (such as the cohesion of the founding group) can affect a community's long-term success or failure. Given the ongoing bureaucratic hurdles in Italy related to implementing the RED II and RED III directives, this modeling approach allows for "*stress-testing*" REC configurations (whether place-based or non-place-based, single or multi-purpose) before they are established. The outcome is a framework that transforms socio-technical complexity from a barrier into a measurable variable, providing a scientific basis for an energy transition that is both technically sound and socially sustainable.

The following infographic *(Figure 2)* illustrates ABM as a dynamic ecosystem, highlighting the methodological "bridge" between purely technical aspects (energy physics) and socio-psychological ones. The diagram highlights the previously described innovative elements, in particular:

- ***Agent Granularity:*** The distinction between different usage profiles (residential, commercial, etc.) and the integration of annual income to assess actual investment capacity.
- ***Social Innovation:*** The application of Serge Moscovici's Active Minority Influence Theory to model member engagement and membership, transcending the logic of mere economic profit.
- ***Objectives and Results:*** The use of "*what-if*" scenarios to test the system's "*antifragility*" and provide scientific decision-making support for a technically sound and socially sustainable energy transition.

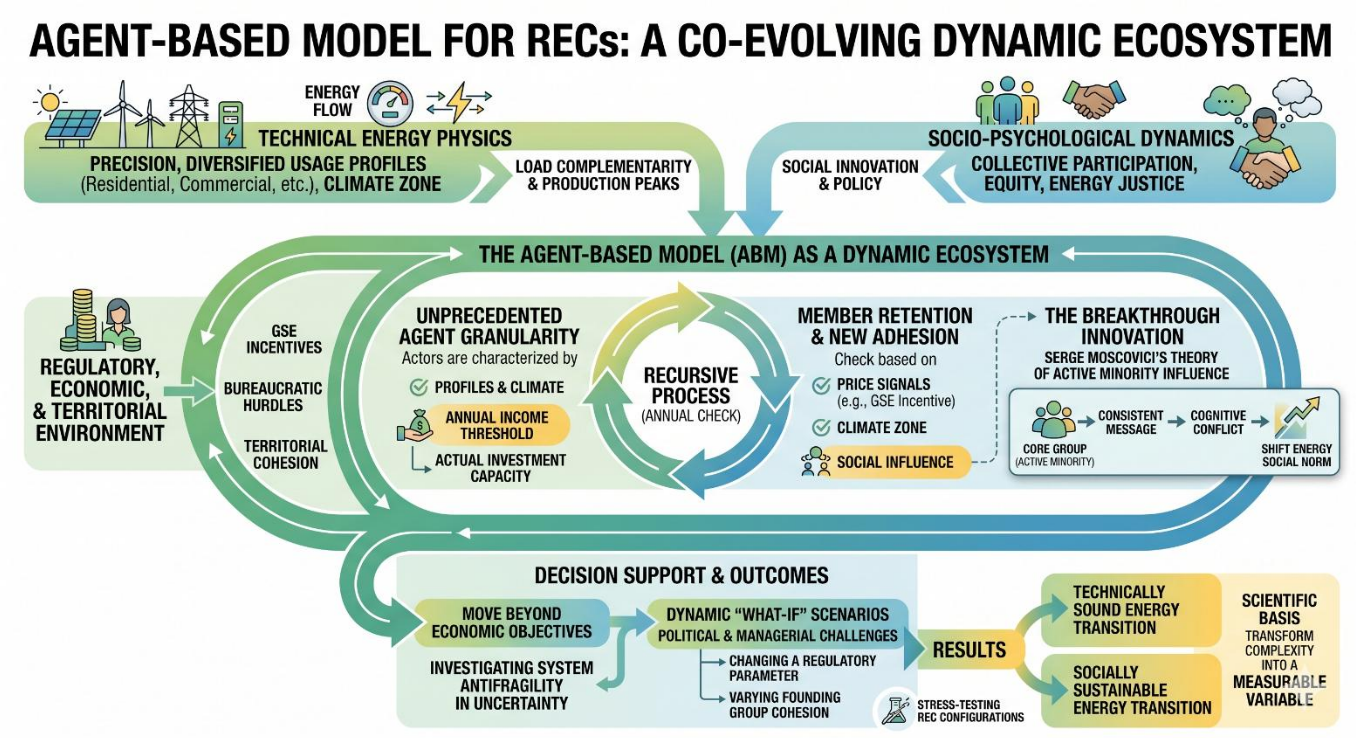

Figure 2: *Infographic of the proposed ABM dynamic ecosystem*

1.5. Analyzing the social aspect of RECs

The integration of the socio-psychological aspect into a computational model for RECs presents one of the most engaging methodological challenges of this research. To model how diffusion and adherence to the energy community happen, we decided to go beyond the traditional models of "*social contagion*" or "*passive imitation*" often used in economic studies [36] and instead adopt Serge Moscovici's Theory of Active Minority Influence. This choice is not just academic; it reflects the true nature of RECs: they rarely develop from spontaneous public consensus, but usually from the efforts of a small group of pioneers (the active minority) who seek to challenge the prevailing energy paradigm and promote a sustainable, alternative social norm.

According to Moscovici, social influence is not the exclusive right of power or the majority; instead, a minority can become a powerful driver for change if it has certain traits, primarily: consistency. In the simulator, this idea has been implemented as algorithms that account for both diachronic and synchronic consistency. "*Diachronic consistency*" is represented by REC's persistence over time: the more the community stays strong and maintains steady goals despite market ups and downs, the more it can psychologically influence external agents. "*Synchronic consistency*" [37], on the other hand, shows the unity and cohesion among the founding members. In the code, these factors boost the REC's appeal, turning the simple "*visibility*" of the photovoltaic plant into a compelling normative message that prompts external agents to question the traditional energy supply system.

Another pillar of Moscovici's theory incorporated into the model is the creation of cognitive conflict. The actions of the active minority do not lead to immediate, superficial compliance; instead, they trigger a process of deep validation. External agents, observing the minority investing its own resources and proposing a fair sharing model, enter a state of dissonance: they start comparing their role as passive consumers with the possibility of becoming active prosumers. The simulator captures this dynamic by allowing external agents to annually assess not only direct economic benefits but also the "*social weight*" of the REC's proposal. Here, the annual income variable comes into play: Moscovici's social influence acts as a catalyst, motivating the agent to overcome financial inertia. If the active minority is perceived as credible and consistent, an agent with sufficient income will be more likely to turn cognitive conflict into a tangible investment in photovoltaic installation, officially joining the community.

Finally, the model simulates conversion, a long-term change in attitude. Unlike models based on simple authority or purely monetary incentives, which risk causing members to leave the community once the economic benefits disappear, the Moscovici-based approach aims to model sociological stability. Since membership results from a deep elaboration process driven by the minority, the bond between the agent and the REC becomes more resilient. Each year, the simulator's strategic review phase assesses whether the minority's "*consistency*" remains sufficient to sustain high satisfaction among current members and attract new ones. This recursive process enables the observation of complex phenomena such as the "*snowball effect*" (when the minority eventually becomes the majority) or, conversely, the decline of the community if internal coherence breaks down, offering unprecedented and profound insights into the longevity of distributed energy configurations.

The definition of functional requirements is a key step in turning the research's theoretical and socio-technical vision into a practical computational system. In a multi-agent model designed for RECs, functional requirements do more than describe the software's logical functions; they also establish the "*rules of engagement*" that govern how agents interact with each other and their environment. The simulator's architecture is designed to handle dynamic complexity across three interconnected levels:

the accuracy of energy modeling, the fidelity to the socio-economic context, and the adaptability of the regulatory framework. Each level meets specific analytical needs, allowing the model to serve as a Decision Support System (DSS) that provides detailed, scientifically validated results.

The first essential requirement involves the diverse characterization of agents and the management of their respective load profiles. Unlike traditional simulators that use aggregated profiles, this model needs the implementation of unique user archetypes, each with specific consumption patterns and operational constraints. A key functional requirement is the system's ability to process hourly load profiles for different user types, including standard residential (marked by morning and evening peaks), seasonal residential (with significant variations linked to tourism or second homes), and tertiary users such as administrative offices, schools, and shops. Handling these diverse "*energy signatures*" is crucial for simulating load complementarity: the model must be able to calculate in real time how a school's consumption during daylight hours can be balanced by the excess production of nearby residential users, thereby optimizing collective self-consumption.

A second essential requirement involves integrating climatic and geographical variables. The simulator must identify and parameterize the REC's specific climate zone by connecting to solar irradiation databases and historical temperature data. This requirement enables modeling not only the expected photovoltaic output but also the effects of thermal loads (heating and cooling), which can vary significantly by location. Without this climatic sensitivity, the model would lose the ability to effectively stress-test the community during seasonal peaks, the most critical times for grid stability and economic incentive management. The system's capacity to adapt production and consumption profiles to local weather conditions ensures that the research results are relevant to real, diverse scenarios.

Shifting to the socio-economic aspect, the model must meet the functional requirement of simulating individual decision-making processes. Each agent is assigned an attribute representing available annual income, which serves as a constraint when evaluating investments in renewable technologies. The simulator must determine each year whether an agent has the financial ability to install photovoltaic panels, cross-referencing this data with expected savings and the influence of the "*active minority*". Here, the functional requirement aligns with Moscovici's theory: the code must incorporate a social influence engine that adjusts the likelihood that external agents will join based on the REC's consistency and stability over time. The yearly evaluation process (stay/join/leave) is therefore not a simple mathematical calculation but a multi-criteria optimization algorithm that balances economic feasibility, spending capacity, and normative or social pressures.

Finally, the simulator must ensure high interactivity with the regulatory and tariff framework. A key functional requirement is the user's ability to modify system incentive components "*on the fly*", such as the amount of GSE shared energy premiums, the electricity cost in the bill, or grid charges. This feature turns the model into a Sensitivity Analysis tool, allowing an understanding of which incentive thresholds are needed to make REC appeal to various income brackets. The ability to create dynamic "*what-if*" scenarios is the ultimate functional outcome of the research, offering a clear map of the boundary conditions that support the emergence and resilience of energy communities within the Italian and European legislative landscapes.

1.6. The Dynamics of Change: The Theory of Active Minority Influence

Adopting a perspective focused on active minorities marks a significant shift from the "*conformity bias*" that has traditionally dominated classical social psychology. As highlighted in the influential work by Moscovici and Faucheux (1972) [38], social influence should not be viewed solely as a mechanism of majority pressure intended to uphold the status quo or suppress deviance. Instead, social innovation, exemplified by RECs, arises from a minority group's capacity to challenge the established consensus by introducing new behavioral and value-based norms. In this context, "*social conflict*" is not a dysfunction but a necessary catalyst for prompting deep validation among other members of society. The minority lacks the numerical strength and legal authority of the majority; its power, therefore, rests entirely in its behavioral style.

The core foundation of this influence is consistency, which Moscovici describes in two aspects: intra-individual (the stability of a person's positions over time) and inter-individual (the unity and cohesion of the minority group). It is consistency that gives the minority social visibility and indicates a strong belief in its goals, prompting the majority to actively consider the alternative rather than ignore it. But firmness alone isn't sufficient. Nemeth et al. (1974) [39] added to this idea by emphasizing the importance of response patterns. A minority seen as overly rigid or dogmatic risks being labeled as "*fanatic*", which undermines its message. On the other hand, a minority that shows some flexibility, meaning the ability to adapt responses without betraying its core norms, is far more impactful. This combination of consistency and flexibility helps the minority appear not only confident but also reasonable and receptive to dialogue, thereby aiding others' psychological conversion.

To translate these complex psychosocial phenomena into a computational model, the formal integration proposed by Tanford and Penrod (1984) [40] with their Social Influence Model (SIM) is crucial. This model offers a mathematical foundation for understanding how the influence of a minority does not grow linearly but follows dynamics related to group size and the relative strength of the message in specific settings. By combining these factors, influence can be modeled not as a simple on/off variable but as a field of forces in which the consistency of the REC's core influences the "*psychological distance*" between external agents. Therefore, the impact of the active minority occurs through a phase of cognitive conflict that causes individuals to experience a "*private conversion*", a latent shift in attitude that often comes before public and formal adoption of the energy community.

Applying these concepts to the simulator helps us go beyond viewing the user as a lone, profit-focused decision-maker. In the model, agents respond to the consistency of the REC pioneers: the more the minority (for example, the group of citizens or the supporting municipal entity) maintains a clear and visible stance over time, the higher the likelihood that external agents will reassess their position relative to the traditional energy market. Moscovici's theory thus provides a solid foundation to explain the "*snowball effect*", the rapid growth of a community following an initial period of apparent stagnation. In this way, the thesis not only simulates electron flows but also models the emergence of a new collective consciousness, where energy acts as the catalyst for a deep social transformation, driven by the consistency and innovation of a few guiding many.

1.7. The application purposes of the simulator

The added value of the simulator developed in this research lies in its nature as a flexible analytical tool, capable of transcending the boundaries of a single national context and assuming a comparative European dimension. The model's applications are not limited to merely reproducing the Italian mechanism; rather, they aim to provide a policy-testing platform that allows the user to perform an instantaneous regulatory switch. This technical functionality allows for comparative simulations starting from the same set of input data (namely, the same community composition, load profiles, and climatic coordinates) to observe how agent response and the economic sustainability of the REC shift drastically depending on the reference legislative architecture.

To operationalize and test this objective, Spain was identified as the primary point of comparison, given the clear geographical, climatic, and typological affinities between Spanish and Italian building stocks. Both nations share a grid structure governed by a single Transmission System Operator (TSO): Terna in Italy and Red Eléctrica de España (REE) in Spain, which operate as natural monopolies to ensure the stability of generation systems that were historically centralized but are now rapidly evolving. However, distinct geomorphological characteristics and different energy mixes have led to markedly divergent transposition paths for European directives, offering fertile ground for the analysis of agent behavior.

In the Spanish context, the reference framework is set by Real Decreto 244/2019 [38], which profoundly redefined the mechanisms for collective self-consumption. From a technical standpoint, Spanish regulations allow for energy sharing within a 2,000-meter radius between the point of production and the point of consumption, a metric significantly different from the Italian logic of the Primary Substation. Furthermore, the Iberian model provides for various operational modes, distinguishing between self-consumption with or without the injection of surpluses into the grid, supported by the National Integrated Energy and Climate Plan (PNIEC) and a series of regional subsidy programs that vary based on location and system size.

The deepest divergence that the simulator aims to map lies in the economic remuneration mechanism. While the Italian model is based on a direct incentive paid via bank transfer (explicit incentive), Spain predominantly adopts the "*Autoconsumo Colectivo con Compensación de Excedentes*" mechanism [38]. In this scenario, the benefit for the community member does not manifest as additional income but rather as a direct reduction of bill charges through Net Billing. This system is subject to a non-negativity constraint, implying that the value of the injected energy can offset the variable portion of the bill but can never generate a net monetary credit for the user. This fundamental difference radically alters the decision-making process of the agents within the model: whereas in Italy joining can be considered a source of income, in Spain it must be evaluated as a cost-optimization strategy, directly influencing risk perception and Payback Periods.

Despite seemingly favorable regulations in both countries, the adoption of energy communities is proceeding slowly, suggesting deep-seated barriers. This thesis, therefore, aims to demonstrate that the obstacles to the proliferation of RECs are not purely technical, as photovoltaic and monitoring technologies are now mature, but rather reside in local socio-economic dynamics and the actors' perceptions of value. Through the regulatory "*switch*", the simulator enables the identification of these limiting factors, and the understanding of which governance mechanisms are most effective in overcoming social inertia. Ultimately, the model does not merely seek to describe "*how*" RECs function today, but to investigate "*why*" they are not expanding at the predicted speed, providing policymakers with a tool to calibrate incentives based not only on produced kilowatt-hours but also on the actual capacity for engagement and resilience within local communities.

1.8. The implementation of European directives in Spain: the evolution from Royal Decree 244/2019 to the "Energy Communities"

The transposition process of the European directives RED II (2018/2001/EU) and RED III (2023/2413/EU) in Spain has been characterized by rapid regulatory acceleration aimed at overcoming historical barriers that had hindered distributed generation in the previous decade. The fundamental turning point is represented by Real Decreto 244/2019 [39], which removed administrative obstacles to self-consumption and, for the first time, defined "*collective self-consumption*", thereby laying the technical foundations for the development of *Comunidades de Energías Renovables* (RECs). Unlike the Italian model, which favored a proximity definition based on electricity grid topology (Primary Substation), the Spanish legislator opted for a criterion of physical and geographical proximity. Initially set at 500 meters, the radius of action for energy sharing was extended to 2,000 meters for systems located on industrial or urban rooftops by Real Decreto-ley 18/2022 [40], drastically expanding the potential user base of a single REC and facilitating the inclusion of heterogeneous actors in densely populated areas.

The formal adoption of the European definitions for RECs and Citizen Energy Communities (CECs) occurred with Real Decreto-ley 23/2020 [41], which transposed the principles of open, voluntary participation and democratic control, identifying energy communities as essential legal entities for achieving the objectives of the National Integrated Energy and Climate Plan (PNIEC) 2021-2030 [42]. However, scientific literature highlights a peculiarity in Spain's economic compensation mechanism: the *Compensación de Excedentes* (Net Billing) system. Under this regime, energy fed into the grid by REC members is valued at a market price and discounted directly from the variable component of the consumer's electricity bill. While this approach simplifies cash flow compared to the direct bank transfer of the Italian model, it introduces the "*non-negativity*" constraint, preventing the monthly bill balance from becoming negative and effectively limiting the profit potential for purely consuming users.

Despite the flexibility introduced by the 2,000-meter radius, the development of RECs in Spain faces persistent socio-economic and administrative barriers. Recent studies indicate that the complexity of negotiating energy-sharing coefficients (*coeficientes de reparto*) and bureaucratic delays in grid connection remain critical obstacles. Furthermore, the transition from individual self-consumption to the community model requires social innovation that is not yet fully supported by local governance mechanisms. The comparison between the Spanish and Italian models thus highlights a "*proximity challenge*": while Spain bets on physical distance to encourage urban aggregation, Italy focuses on the stability of the electrical grid. Both countries, however, converge on the need for monitoring and simulation tools to mitigate regulatory uncertainty and maximize benefits for the most vulnerable segments of the population, while integrating energy communities into a vision of climate justice and territorial resilience.

1.9. The state of REC diffusion: a statistical and comparative analysis

The evolutionary framework of RECs within the European Union currently reveals a marked dissonance between programmatic ambitions and the actual implementation of projects, as Special Report 10/2026 of the European Court of Auditors documents [43]. In the first quarter of 2026, the assessment from the audit body highlights the improbability of meeting the cornerstone objective, which aimed to establish at least one REC in every municipality with a population exceeding 10,000 by the end of 2025. This estimate is based on a critical baseline: as of January 2025, only 27% of the set target had been achieved. Projections for 2030 appear similarly scaled back, as it is estimated that energy communities will hold only 4% of total renewable production capacity (solar and wind), a value significantly lower than the European Commission's initial forecasts, which ranged between 17% and 21% in the RED II directive's impact assessment.

This setback is not attributable to a lack of technological interest, but rather to a structural deficiency in the support conditions created by national governments. The main criticalities lie in unresolved regulatory aspects and chronic delays in grid connection procedures. The latter point is exacerbated by infrastructure congestion during peak production hours, a problem that could be mitigated by adopting systemic energy storage solutions, though these solutions struggle to proliferate due to costs and regulatory uncertainties. The Court of Auditors emphasizes that the Union's goal was flawed from the outset by a methodological flaw in goal-setting; while specific and time-bound, these targets proved largely unmeasurable and lacked Key Performance Indicators (KPIs) regarding real citizen engagement or the effective installation of production capacity.

Furthermore, a lack of alignment between national and EU strategies has emerged. Although Member States such as Italy and Poland integrated specific objectives into their PNIEC, the European Commission could not impose binding corrections, reflecting a national commitment that was often limited and inconsistent. To address this fragmentation, the Court recommends adopting "SMART" objectives and introducing a mandatory alignment between PNIECs and Union action strategies. Monitoring itself proved flawed: until 2024, the census of energy communities relied on ad hoc inventories drafted by external consultants in the absence of reliable national registries. It was only in the first half of 2025 that a decisive acceleration occurred, driven particularly by Italy and Poland, thanks to PNRR (NRRP) funds and simplifying reforms, leading to record growth of 75% and 80%, respectively.

On the legal transposition front, uncertainty persists. While Italy stood out as the only audited country to have completed the transposition of the Internal Market for Electricity Directive (IMED) and RED II directives by July 2025, other Member States show delays exceeding four years, hindering private investment. On the social front, the greatest criticality concerns the inclusion of vulnerable households. Despite the aspirations of RED II, the removal of the minimum citizen participation threshold in the final version of the regulation weakened the potential for social acceptance. In Italy, however, a virtuous counter-trend was observed: since May 2025, the extension of the full incentive tariff to natural persons and the activation of regional reward mechanisms have favored social inclusion, with approximately 50% of monitored communities already implementing active support forms for disadvantaged groups.

Financial sustainability remains a complex issue, especially regarding Payback Periods. Although EU strategies suggest a payback period of less than 10 years to ensure the model's attractiveness, official estimates still range from 11 to 13 years. Moreover, a distributive equity problem arises regarding the exemption from grid charges for shared energy: while this mechanism incentivizes the REC, it reduces the community's contribution to maintaining the grid infrastructure it continues to use, risking a cost shift onto less-affluent consumers who lack access to such configurations. At the beginning of 2026, the GSE census [44] in Italy shows a snapshot of 904 fully operational REC configurations, involving 8,653 end-users, for a total capacity of approximately 90 MW. The geographical distribution still reflects a marked polarization, with 56% of configurations concentrated in Northern Italy (primarily Lombardy and Piedmont) *(Figure 3)*, although the South records the highest growth rate in applications for capital grants, confirming the vocation of RECs as a tool for the redemption of disadvantaged territories.

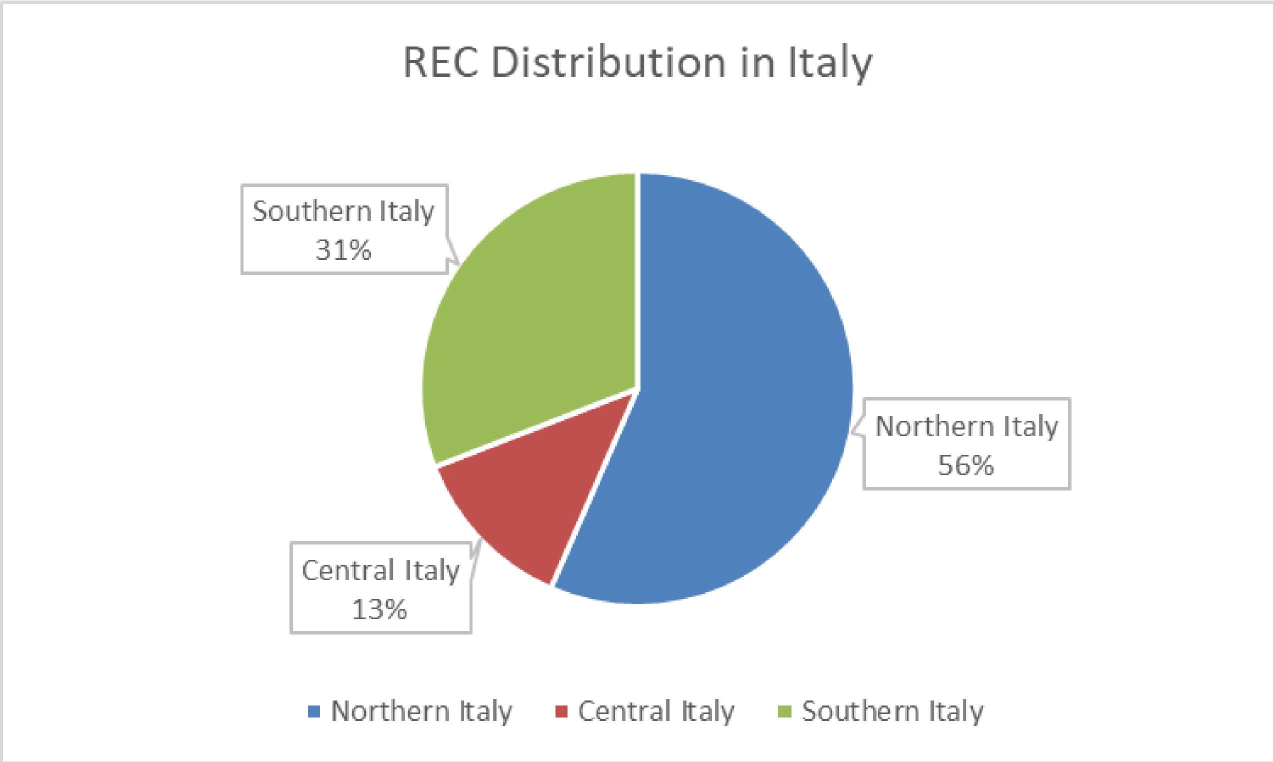

Figure 3. REC Distribution in Italy

In Spain, the statistical landscape is clearly distinguished by an approach aimed at simplifying collective urban self-consumption. As of 2026, there are 146 formally constituted "*Comunidades Energéticas*", but the impressive figure reflects the involvement of 116,438 end-users, a sign that the model has scaled rapidly in apartment buildings and districts [45]. The regions of Catalonia, Andalusia, and the Valencian Community lead the Spanish ranking, benefiting from the "*Hoja de Ruta del Autoconsumo*" and a sharing radius extended to 2,000 meters. The divergence between the Italian model of explicit incentives (GSE incentive tariff) and the Spanish model of implicit incentives (Net Billing and direct charge reduction) outlines a regulatory paradox: Italy offers higher potential long-term profitability but suffers from managerial complexity that limits its capillarity, while Spain ensures more immediate "*bottom-up*" growth, albeit with sometimes lower unit incentives. This statistical and procedural dichotomy constitutes the empirical basis for calibrating this thesis's multi-agent simulator, aiming to identify which of the two models can, in the long term, ensure the greatest social resilience and economic stability in the face of global market shocks.

1.10. Conclusions: Research questions and thesis horizon

The path traced thus far outlines a challenge that is simultaneously technical, social, and ethical. The transition toward Renewable Energy Communities (RECs) can no longer be analyzed solely through engineering or economic lenses, as the failure or success of these initiatives depends on unpredictable yet modelable human behavior. This reflection highlights how RECs represent the most advanced response to the contemporary "*polycrisis*", standing as a bulwark against market instability and as instruments for the democratization of production. However, the discrepancy identified between the ambition of European directives (RED II and RED III) and the operational reality of individual Member States, with particular reference to Italian bureaucratic barriers and the diversity of remuneration models, as amply demonstrated by the comparison with the Spanish system,necessitates a radically new methodological approach. This thesis is situated within this framework, driven by the conviction that current stagnation does not stem from technical limits, but rather from a lack of understanding regarding the behavioral and systemic dynamics that govern the adoption and growth of such ecosystems.

In light of these premises, the fundamental research question guiding this work aims to establish how regulatory structures and the social dynamics of active minorities interact to determine the success and resilience of an REC in the face of exogenous shocks. This primary inquiry branches into three analytical directions that the multi-agent simulator is designed to explore.

First, what is the actual impact of different incentive regimes on the propensity for investment and participation? Is the Italian model of direct bank transfers more effective at engaging citizens than the Spanish Net Billing compensation mechanism, or does the latter foster more prudent, conscious demand-side management? Through the regulatory "*switch*" implemented in the simulator, this research aims to map how the non-negativity threshold of benefits in Spain influences prosumer psychology compared to the perception of "*profit*" in the Italian model.

Second, the thesis places the figure of the promoter as a change agent at the center of the investigation. Based on Moscovici's theory, the goal is to quantify the weight of an active minority's "*consistency*", whether it be a municipal entity or a core of private pioneers, in overcoming social inertia and converting the passive majority into a base of active members. The question is whether the strength of this social message is sufficient to offset the income limits of the most vulnerable agents, enabling REC to fulfill its role in combating energy poverty. This aspect becomes crucial when the system is subjected to geopolitical stress tests: the simulator must demonstrate that the community can act as a social buffer during energy price oscillations, protecting consumers from inflationary shocks by synchronizing hourly loads in the absence of storage systems.

The thesis's horizon thus shifts toward validating a Decision Support System (DSS) capable of operating across heterogeneous geographical and climatic contexts. The transition from theory to mathematical modeling, which will be addressed in the following chapters, is not merely a means to satisfy an increasingly urgent need for strategic planning. By defining functional requirements and comparative use cases between Italy and Spain, this research aims to provide policymakers and local authorities with a compass to navigate complexity. The final objective is not only to describe REC dynamics but to offer scientific proof of their ability to transform energy fragility into community resilience, charting the course toward a development model that is technically robust, regulatorily flexible, and, above all, socially equitable. With the definition of these questions, this work prepares for an in-depth analysis of the literature on existing simulation models and, subsequently, a detailed analysis of the proposed simulator's architecture, translating psychological, climatic, and tariff variables into the algorithms that constitute the beating heart of this investigation.

1.11. References

[1] G. Pepermans, J. Driesen, D. Haeseldonckx, R. Belmans, e W. D'haeseleer, «Distributed generation: definition, benefits and issues», *Energy Policy*, vol. 33, fasc. 6, pp. 787–798, apr. 2005, doi: 10.1016/j.enpol.2003.10.004.

[2] «Transforming our world: the 2030 Agenda for Sustainable Development | Department of Economic and Social Affairs». Consultato: 7 marzo 2026. [Online]. Disponibile su: https://sdgs.un.org/2030agenda

[3] «Clean energy for all Europeans package completed: good for consumers, good for growth and jobs, and good for the planet - European Commission». Consultato: 10 marzo 2026. [Online]. Disponibile su: https://commission.europa.eu/news-and-media/news/clean-energy-all-europeans-package-completed-good-consumers-good-growth-and-jobs-and-good-planet-2019-05-22_en

[4] «Renewable Energy – Recast to 2030 (RED II) - Joint Research Centre». Consultato: 10 marzo 2026. [Online]. Disponibile su: https://joint-research-centre.ec.europa.eu/welcome-jec-website/reference-regulatory-framework/renewable-energy-recast-2030-red-ii_en

[5] *Directive (EU) 2023/2413 of the European Parliament and of the Council of 18 October 2023 amending Directive (EU) 2018/2001, Regulation (EU) 2018/1999 and Directive 98/70/EC as regards the promotion of energy from renewable sources, and repealing Council Directive (EU) 2015/652*. 2023. Consultato: 18 settembre 2025. [Online]. Disponibile su: http://data.europa.eu/eli/dir/2023/2413/oj/eng

[6] A. Fichera, E. Marrasso, C. Martone, G. Pallotta, M. Sasso, e R. Volpe, «Ten questions concerning renewable energy communities», *Build. Environ.*, vol. 281, p. 113193, ago. 2025, doi: 10.1016/j.buildenv.2025.113193.

[7] S. Ahmed, A. Ali, e A. D'Angola, «A Review of Renewable Energy Communities: Concepts, Scope, Progress, Challenges, and Recommendations», *Sustainability*, vol. 16, fasc. 5, feb. 2024, doi: 10.3390/su16051749.

[8] S. Moroni, V. Alberti, V. Antoniucci, e A. Bisello, «Energy communities in the transition to a low-carbon future: A taxonomical approach and some policy dilemmas», *J. Environ. Manage.*, vol. 236, pp. 45–53, apr. 2019, doi: 10.1016/j.jenvman.2019.01.095.

[9] E. Barabino *et al.*, «Energy Communities: A review on trends, energy system modelling, business models, and optimisation objectives», *Sustain. Energy Grids Netw.*, vol. 36, p. 101187, dic. 2023, doi: 10.1016/j.segan.2023.101187.

[10] «Gazzetta Ufficiale». Consultato: 20 marzo 2026. [Online]. Disponibile su: https://www.gazzettaufficiale.it/eli/id/2020/02/29/20G00021/sg

[11] G. Taromboli *et al.*, «Renewable Energy Communities: Frameworks and Implementation of Regulatory, Technical, and Social Aspects Across EU Member States», *Sustainability*, vol. 17, fasc. 9, mag. 2025, doi: 10.3390/su17094195.

[12] I. Mariuzzo, B. Fina, S. Stroemer, e M. Raugi, «Economic assessment of multiple energy community participation», *Appl. Energy*, vol. 353, p. 122060, gen. 2024, doi: 10.1016/j.apenergy.2023.122060.

[13] I. Mariuzzo, B. Fina, S. Stroemer, C. Corinaldesi, e M. Raugi, «Grid-friendly optimization of energy communities through enhanced multiple participation», *Renew. Sustain. Energy Rev.*, vol. 208, p. 115028, feb. 2025, doi: 10.1016/j.rser.2024.115028.

[14] «Corrispettivi e tariffa». Consultato: 18 marzo 2026. [Online]. Disponibile su: https://www.gse.it/servizi-per-te/autoconsumo/gruppi-di-autoconsumatori-e-comunita-di-energia-rinnovabile/corrispettivi-e-tariffa

[15] «DECRETO LEGISLATIVO 9 gennaio 2026, n. 5 - Normattiva». Consultato: 18 marzo 2026. [Online]. Disponibile su: https://www.normattiva.it/uri-res/N2Ls?urn:nir:stato:decreto.legislativo:2026-01-09;5

[16] «COMUNITÀ ENERGETICHE RINNOVABILI E GRUPPI DI AUTOCONSUMATORI». Consultato: 18 marzo 2026. [Online]. Disponibile su: https://www.gse.it/servizi-per-te/attuazione-misure-pnrr/comunit%C3%A0-energetiche-5000abitanti
[17] F. D. Santi, M. Moncecchi, G. Prettico, G. Fulli, S. Olivero, e M. Merlo, «To Join or Not to Join? The Energy Community Dilemma: An Italian Case Study», *Energies*, vol. 15, fasc. 19, set. 2022, doi: 10.3390/en15197072.
[18] S. Ahmed e A. M. Măgurean, «Renewable Energy Communities: Towards a new sustainable model of energy production and sharing», *Energy Strategy Rev.*, vol. 55, p. 101522, set. 2024, doi: 10.1016/j.esr.2024.101522.
[19] E. Belloni, D. Fioriti, e D. Poli, «Optimal design of renewable energy communities (RECs) in Italy: Influence of composition, market signals, buildings, location, and incentives», *Electr. Power Syst. Res.*, vol. 235, p. 110895, ott. 2024, doi: 10.1016/j.epsr.2024.110895.
[20] E. Cutore, A. Fichera, e R. Volpe, «A Roadmap for the Design, Operation and Monitoring of Renewable Energy Communities in Italy», *Sustainability*, vol. 15, fasc. 10, mag. 2023, doi: 10.3390/su15108118.
[21] «Gazzetta Ufficiale». Consultato: 20 marzo 2026. [Online]. Disponibile su: https://www.gazzettaufficiale.it/eli/id/2026/01/20/26G00018/sg
[22] R. K. Sawyer, *Social Emergence: Societies As Complex Systems*. Cambridge University Press, 2005.
[23] J. Sousa *et al.*, «Renewable energy communities optimal design supported by an optimization model for investment in PV/wind capacity and renewable electricity sharing», *Energy*, vol. 283, p. 128464, nov. 2023, doi: 10.1016/j.energy.2023.128464.
[24] F. Lilliu, A. Loi, D. Reforgiato Recupero, M. Sisinni, e M. Vinyals, «An uncertainty-aware optimization approach for flexible loads of smart grid prosumers: A use case on the Cardiff energy grid», *Sustain. Energy Grids Netw.*, vol. 20, p. 100272, dic. 2019, doi: 10.1016/j.segan.2019.100272.
[25] S. Ahmed e A. D'Angola, «Energy Storage Systems: Scope, Technologies, Characteristics, Progress, Challenges, and Future Suggestions—Renewable Energy Community Perspectives», *Energies*, vol. 18, fasc. 11, mag. 2025, doi: 10.3390/en18112679.
[26] Z. Lei *et al.*, «A compact time horizon compression method for planning community integrated energy systems with long-term energy storage», *Appl. Energy*, vol. 361, 2024, doi: 10.1016/j.apenergy.2024.122912.
[27] A. Soares, G. Gonçalves, e P. Moura, «Management of Energy Storage in Transactive Energy Communities», in *2022 International Conference on Smart Energy Systems and Technologies (SEST)*, set. 2022, pp. 1–6. doi: 10.1109/SEST53650.2022.9898494.
[28] F. Gianaroli, M. Ricci, P. Sdringola, M. Alessandra Ancona, L. Branchini, e F. Melino, «Development of dynamic sharing keys: Algorithms supporting management of renewable energy community and collective self consumption», *Energy Build.*, vol. 311, 2024, doi: 10.1016/j.enbuild.2024.114158.
[29] R. J. Hewitt *et al.*, «Social Innovation in Community Energy in Europe: A Review of the Evidence», *Front. Energy Res.*, vol. 7, apr. 2019, doi: 10.3389/fenrg.2019.00031.
[30] J. L. MacArthur, «Challenging public engagement: participation, deliberation and power in renewable energy policy», *J. Environ. Stud. Sci.*, vol. 6, fasc. 3, pp. 631–640, 2016, doi: 10.1007/s13412-015-0328-7.
[31] H. E. Olajide, «Community Engagement and Social Acceptance of Renewable Energy Projects in Agricultural Regions», 6 agosto 2024, *Social Science Research Network, Rochester, NY*: 4969730. doi: 10.2139/ssrn.4969730.
[32] P. Minadakis e J. Vega-Araújo, «Rethinking the social license to operate? A theoretical exploration of its synergies with social acceptance and energy justice for a just transition», *Energy Res. Soc. Sci.*, vol. 113, 2024, doi: 10.1016/j.erss.2024.103552.

[33] «Scopus - Document details - Designing local renewable energy communities to increase social acceptance: Evidence from a choice experiment in Austria, Germany, Italy, and Switzerland | Signed in». Consultato: 8 maggio 2024. [Online]. Disponibile su: https://www.scopus.com/record/display.uri?eid=2-s2.0-85068583066&origin=inward&txGid=fbe38e184f7bbd224bfa6d397b9f32ca
[34] C. Petrovich, S. Branchetti, e G. D'Agosta, «Parametrization of self-consumption and self-sufficiency in Renewable Energy Communities: a case study application», *Energy Ecol. Environ.*, vol. 10, fasc. 3, pp. 324–351, giu. 2025, doi: 10.1007/s40974-025-00353-z.
[35] J. Blasch *et al.*, «New clean energy communities in polycentric settings: Four avenues for future research», *Energy Res. Soc. Sci.*, vol. 82, p. 102276, dic. 2021, doi: 10.1016/j.erss.2021.102276.
[36] C. Van den Bulte e G. L. Lilien, «Bias and Systematic Change in the Parameter Estimates of Macro-Level Diffusion Models», *Mark. Sci.*, vol. 16, fasc. 4, pp. 338–353, nov. 1997, doi: 10.1287/mksc.16.4.338.
[37] S. Papastamou e G. Mugny, «Synchronic consistency and psychologization in minority influence», *Eur. J. Soc. Psychol.*, vol. 20, fasc. 2, pp. 85–98, 1990, doi: 10.1002/ejsp.2420200202.
[38] «Preguntas frecuentes sobre autoconsumo», Ministerio para la Transición Ecológica y el Reto Demográfico. Consultato: 19 marzo 2026. [Online]. Disponibile su: https://www.miteco.gob.es/es/energia/energia-electrica/electricidad/autoconsumo-electrico/preguntas-frecuentes-autoconsumo.html
[39] Ministerio para la Transición Ecológica, *Real Decreto 244/2019, de 5 de abril, por el que se regulan las condiciones administrativas, técnicas y económicas del autoconsumo de energía eléctrica*, vol. BOE-A-2019-5089. 2019, pp. 35674–35719. Consultato: 4 settembre 2025. [Online]. Disponibile su: https://www.boe.es/eli/es/rd/2019/04/05/244
[40] «BOE-A-2022-17040 Real Decreto-ley 18/2022, de 18 de octubre, por el que se aprueban medidas de refuerzo de la protección de los consumidores de energía y de contribución a la reducción del consumo de gas natural en aplicación del "Plan + seguridad para tu energía (+SE)", así como medidas en materia de retribuciones del personal al servicio del sector público y de protección de las personas trabajadoras agrarias eventuales afectadas por la sequía.» Consultato: 19 marzo 2026. [Online]. Disponibile su: https://www.boe.es/buscar/act.php?id=BOE-A-2022-17040
[41] «BOE-A-2020-6621 Real Decreto-ley 23/2020, de 23 de junio, por el que se aprueban medidas en materia de energía y en otros ámbitos para la reactivación económica.» Consultato: 19 marzo 2026. [Online]. Disponibile su: https://www.boe.es/buscar/act.php?id=BOE-A-2020-6621
[42] «Spain - Final updated NECP 2021-2030 (submitted 2024) - European Commission». Consultato: 19 marzo 2026. [Online]. Disponibile su: https://commission.europa.eu/publications/spain-final-updated-necp-2021-2030-submitted-2024_en
[43] «Special report 10/2026: Energy communities», European Court of Auditors. Consultato: 19 marzo 2026. [Online]. Disponibile su: http://www.eca.europa.eu/en/publications/sr-2026-10
[44] «Configurazioni di autoconsumo qualificate dal GSE: elenchi e nomi delle comunità». Consultato: 21 marzo 2026. [Online]. Disponibile su: https://www.gse.it/servizi-per-te/autoconsumo/elenco-delle-configurazioni
[45] «Comunidades Energéticas | Idae». Consultato: 21 marzo 2026. [Online]. Disponibile su: https://www.idae.es/ayudas-y-financiacion/comunidades-energeticas

2. Simulation Models for REC: A Literature Review on Linear and Multi-Agent Systems

This chapter is dedicated to a critical review of the state of the art regarding the modeling and simulation of Renewable Energy Communities (RECs). In a constantly evolving technological and regulatory landscape, the ability to predict the behavior of these systems is no longer a mere academic exercise but an urgent necessity for designers and policymakers. Scientific literature has responded to this need through a proliferation of approaches ranging from linear optimization models to the most recent multi-agent systems, reflecting the transition of RECs from simple electrotechnical configurations to complex socio-technical ecosystems.

The review that follows is structured along three fundamental axes. First, historically established linear and deterministic simulation models will be analyzed, whose primary objective is technical and economic optimization (e.g., cost minimization, self-consumption maximization) using software and programming languages such as Python, Julia, MATLAB, and EnergyPlus. Second, the focus will shift to Agent-Based Models (ABM), which can capture the heterogeneity of actors and the bottom-up dynamics governing local interactions. This classification will allow mapping not only the computational tools used but also the main focus of existing simulations, often centered on grid stability, storage management, or incentive allocation.

However, a systematic analysis of scientific contributions reveals a significant research gap that constitutes the starting point and *raison d'être* of this thesis. Despite the high degree of sophistication achieved in modeling energy balances and financial components (NPV, IRR, Payback), the literature suffers from a chronic deficiency in addressing the dimensions of "*organic growth*" and dynamic social acceptance. Indeed, most existing models assume a static community composition or one driven by purely economic rationality.

To date, there is no integrated framework capable of simulating how an REC can exert an outward pull, transforming passive citizens into active members through the persuasive power of active minorities. The work proposed here aims to fill this methodological void by integrating technical physics and energy economics with Moscovici’s laws of social psychology. The objective is to develop a multi-agent model that not only balances loads and cash flows but also simulates the community's actual demographic evolution, measuring the impact of the founding core's coherence and consistency on the spread of prosumerism within the social fabric. This chapter, therefore, establishes the theoretical foundations necessary to justify the simulator's innovative architecture, which will be described in the subsequent sections.

2.1. Bibliographic Research Methodology

To ensure scientific rigor and the replicability of the analysis in this chapter, it is essential to outline the methodology for selecting and conducting a systematic literature review. The approach follows the principles of a Systematic Literature Review (SLR) to map the intersection between the socio-legal dynamics of RECs and computational simulation architectures.

The survey of the state of the art was structured into three sequential phases (identification, screening, and eligibility) to ensure exhaustive coverage of both the theoretical-regulatory and the technical-simulative dimensions.

The research was conducted by querying the primary international bibliographic databases, selected for their relevance in the fields of energy engineering, social sciences, and computer science:

- ***Scopus and Web of Science (WoS):*** For interdisciplinary mapping and citation analysis.
- ***ScienceDirect (Elsevier) and MDPI:*** For access to specific sector studies on sustainability and energy.
- ***IEEE Xplore:*** For technical insights into modeling and simulation architectures.
- ***Google Scholar:*** Used as a complementary tool to intercept grey literature and institutional European reports.

Search queries were formulated by combining Boolean operators (AND, OR) and keywords pertaining to three thematic pillars:

1. ***Energy Domain:*** "Renewable Energy Communities", "Citizen Energy Communities", "Prosumerism", "RED II Directive", etc.
2. ***Computational Modeling:*** "Mixed-Integer Linear Programming", "Optimization Models", "Multi-Agent Systems (MAS)", "Agent-Based Modeling (ABM)", "Decentralized Control", etc.
3. ***Governance and Policy:*** "Incentive Mechanisms", "Legal Frameworks", "Energy Policy Paradox", "Social Dynamics", etc.

Example search string: ("Renewable Energy Community" OR "CER") AND ("Multi-Agent Systems" OR "ABM") AND ("Incentive" OR "Governance").

The bibliographic corpus in this literature review originates from over 50 peer-reviewed studies, sector reports, and institutional analyses conducted between 2015 and 2026, examining simulation models, optimization approaches, multi-agent systems, software tools, and the socio-economic dimensions of RECs. The selection criteria prioritized:

- Peer-reviewed articles in high-impact journals (e.g., *Renewable and Sustainable Energy Reviews*, *Applied Energy*, *Journal of Cleaner Production*).
- Studies that explicitly integrate the social or regulatory dimension into technical modeling.
- Research presents case studies or comparative analyses within European and global contexts.

This methodological approach allowed for the clear identification of research gaps regarding the lack of tools that integrate behavioral modeling, the assessment of REC attractiveness toward external stakeholders, and the evaluation of legal-statutory structures within dynamic simulation models, thereby defining the scope of action for the development of the ABM model that is the subject of this thesis.

2.2. Overview of REC simulation modeling approaches in literature

As anticipated in the previous chapter, RECs represent a fundamental paradigm shift in the way societies approach energy generation, distribution, and consumption. This model enables local stakeholders to collectively produce, share, and manage renewable resources, transforming passive consumers into proactive actors within the energy system. As highlighted by Chaudhry et al. (2022) [1], the European Commission has strategically positioned RECs as cornerstones of the energy transition, viewing the integration of distributed generation and active citizen participation as the key to enhancing the sustainability and resilience of modern power grids. However, as stated by Presciutti et al. (2026) [2], the design of effective RECs cannot overlook the use of sophisticated simulation and modeling approaches, which are necessary to evaluate technical feasibility, economic profitability, and social acceptance across extremely diverse regulatory and geographical contexts.

Simulation models, therefore, serve as essential Decision Support Systems (DSS) for policymakers, investors, and researchers. These tools allow for:

- Validating energy sharing mechanisms.
- Evaluating various investment scenarios and their relative payback periods.
- Optimizing operational strategies prior to local implementation [3].

The spectrum of available approaches in the literature is vast, reflecting the inherent complexity of RECs. From the analysis conducted by Vecchi et al. (2024) [4], it is possible to understand a landscape ranging from simplified linear programming models, ideal for preliminary assessments and rough sizing, to complex Multi-Agent Systems (MAS) or Agent-Based Models (ABM), which are capable of capturing dynamic interactions between heterogeneous participants and their responses to market signals. The analysis by Presciutti et al. (2025) [5] shows that the most recent scientific evidence suggests there is no single "perfect" approach: each tool excels at capturing distinct technical, economic, or behavioral aspects, depending on its mathematical formulation and initial assumptions.

The accelerated global rollout of RECs has made understanding simulation methodologies an urgent necessity. An emblematic example is provided by Sofia et al. (2025) [6], who present the case of Greece, where over 1,700 energy communities have been established since 2018, with similar growth trends observed across the European Union. However, a paradox emerges: while the number of initiatives grows, many operate with a limited understanding of their optimal configurations and the most equitable mechanisms for sharing benefits. Molnár and Vokony (2025) [7] argue that this "optimization deficit" underscores the need for simulation tools that are not only powerful but also accessible and reliable for grassroots communities.

Despite the wealth of technical and economic tools (often focused on parameters such as NPV or physical self-consumption), an analysis of the current landscape highlights a critical gap: the modeling of attractiveness. Most existing simulators treat community composition as a static input or as being driven by perfect economic rationality.

2.3. Linear programming models and optimization approaches

The core of the scientific literature on REC modeling is historically dominated by deterministic optimization approaches. These models represent the "*gold standard*" for technical and economic analysis, as they allow the complexity of an REC to be treated as a formal mathematical problem, with the goal of identifying a global optimum subject to physical, regulatory, and technological constraints.

The adoption of linear programming stems from the need to provide quantitative answers to fundamental questions: what is the ideal size of a photovoltaic system to maximize return on investment, how to manage energy flows between prosumers and consumers to minimize grid withdrawals, or what the impact of various tariff structures is on the collective's financial stability. In this perspective, the REC is modeled as an "*energy machine*" whose efficiency depends on the algorithm's ability to balance competing decision variables.

This section aims to explore the linear modeling ecosystem by examining the range from mathematical foundations to practical applications. The discussion is structured into the following subsections:

- ***2.3.1 Mathematical Foundations and Methodologies:*** An analysis of the LP, MILP, and MINLP frameworks that constitute the logical scaffolding of simulators.
- ***2.3.2 Software Implementation and Tools:*** An overview of the languages (MATLAB, Python, Julia) and software (RECON, HOMER Pro) that dominate both the market and research.
- ***2.3.3 Optimization Objectives and Problem Formulation:*** A reflection on how objective functions are defined, from pure cost minimization to the pursuit of distributive equity.
- ***2.3.4 Primary Limitations and Simplifying Assumptions:*** A critical examination of the "blind spots" of the linear approach, such as the assumption of perfect foresight and the omission of behavioral heterogeneity.

Understanding these tools is a prerequisite for introducing Agent-Based Models (ABM), as it defines the boundary where deterministic mathematics must give way to simulating complex adaptive systems.

2.3.1. Mathematical foundations and methodologies

The mathematical backbone upon which the vast majority of contemporary simulations dedicated to RECs rests is, according to the analysis by Vecchi et al. (2024) [4], constituted by Linear Programming (LP) models and, even more pervasively, by Mixed-Integer Linear Programming (MILP). These deterministic optimization approaches allow the complex operations of an REC to be translated into a rigorous system of linear or piecewise-linear constraints with well-defined objective functions. Within this formal framework, the simulator optimizes the system by searching for the optimal values of decision variables, such as system sizing or load scheduling, subject to insurmountable technical, economic, and regulatory constraints [8]. The fundamental appeal that LP and MILP formulations hold for the scientific community lies in their intrinsic transparency, total reproducibility of results, and computational tractability, which allows for a systematic and timely examination of the complex trade-offs between often competing objectives, such as maximizing economic profit and minimizing the carbon footprint [9].

However, the need to capture the physics of energy systems with greater fidelity has driven research toward Mixed-Integer Non-Linear Programming (MINLP). Kachhad et al. (2025) [8] argue that this framework extends the potential of classical modeling by integrating inherently non-linear phenomena that simplified models struggle to represent: consider the efficiency curves of power electronic components, temperature-dependent network losses, or the complex electrochemical degradation dynamics of storage systems, variables that heavily influence the service life of components. Despite the higher computational burden of MINLP, it proves indispensable when the simulation's objective shifts from simple preliminary sizing to the detailed operational management of the community microgrid.

The reliability of these mathematical approaches has been extensively verified through rigorous comparative studies. A comprehensive investigation conducted by Presciutti et al. (2026) [2] compared heterogeneous frameworks, including the sophisticated MATLAB-based tool (UNIPGm), VBA-based pre-feasibility models (MERCm), open-access national simulators such as RECON, and established commercial platforms like COMMm, and revealed a remarkable convergence of results. Regarding the primary Key Performance Indicators (KPIs), such as physical self-consumption and shared energy calculated across various Italian residential configurations, a coefficient of variation of less than 15% was found. This methodological agreement suggests that, provided the input parameters are correctly calibrated, LP/MILP-based models can provide highly reliable data for feasibility assessments, thereby providing a solid scientific foundation for more complex analyses [5]. In summary, although the reality of an REC is dynamic and unpredictable, the stability of these mathematical foundations offers the deterministic "playing field" necessary to test the validity of new simulation architectures, including the agent-based ones that this thesis work aims to perfect.

2.3.2. Software implementation and tools

The choice of software tool and programming language is not merely a technical decision; it profoundly influences the simulation model's flexibility, modularity, and analytical capacity. In the research landscape of RECs, according to Tahir's review (2025) [10], MATLAB and Simulink continue to dominate, with approximately 65% of studies using Linear Programming (LP). The preference for the MathWorks environment lies in its optimal balance between pure computational power and interface accessibility. In particular, the MATLAB Optimization Toolbox facilitates rapid prototyping of complex energy-balance equations and the formulation of technical constraints; however, the literature emphasizes that its application to RECs almost always requires developing custom scripts to manage regulatory specifics and the heterogeneous load profiles of participants [11].

In parallel with proprietary software, there is a significant growth in alternatives focused on modularity and algorithmic transparency. Platforms such as GAMS (General Algebraic Modeling System) and Python-based solvers, such as the Pyomo framework detailed in the work of Diassy et al. (2026) [12], offer superior flexibility, proving particularly valuable for policy analyses that require extensive scenario exploration and easy integration with external databases. From a long-term planning perspective, specialized frameworks such as OSeMOSYS (Open Source energy MOdeling SYStem) use linear programming with reduced-form representations to provide a strategic view of system expansion, ensuring that REC investments are aligned with national decarbonization goals [13].

According to Lozza et al. (2025) [14], tools supported by government institutions play a fundamental role in democratizing access to these technologies. In Italy, the RECON simulator [15], developed as an open-access national tool, exemplifies how the provision of standardized methodologies can reduce the need for specialized technical expertise, allowing even small local authorities or citizen groups to independently initiate preliminary feasibility assessments. On the commercial front, hybrid software such as HOMER Pro has gained widespread adoption by combining LP-based optimization with Monte Carlo-based uncertainty analysis. This approach is particularly effective in developing contexts or in scenarios where analytical sophistication must balance the limitations imposed by computational requirements and the scarcity of granular data [16].

Datseris et al. (2021) [17] provided an overview of a recent frontier in open-source energy modeling represented by the Julia language. Thanks to its native parallelization capabilities and computational performance comparable to that of the C language, Julia is emerging as the tool of choice for high-dimensional models that require the resolution of thousands of decision variables in a short time. This varied ecosystem demonstrates that the evolution of REC software is moving in two directions: on the one hand, simplification for end users (tools like RECON), and, on the other, a massive increase in power and computational precision for academic research and industrial planning.

2.3.3. Optimization objectives and problem formulation

The mathematical formulation of the optimization problem in REC simulations reflects the strategic priorities of developers and researchers, delineating the boundary between what is considered "*value*" and what is treated as a boundary variable. In current literature, optimization models generally pursue multiple objectives (Multi-Objective Optimization), although a marked polarization is observed: the vast majority of published formulations emphasize purely economic and technical criteria, systematically marginalizing social and behavioral dimensions [7].

Cost minimization, which integrates capital expenditures (CAPEX), operational expenditures (OPEX), and tariffs resulting from interaction with the power grid, remains the dominant primary objective, present in approximately 88% of the linear programming models examined[18]. In parallel, the maximization of self-consumption (Self-Consumption Index - SCI) and self-sufficiency (Self-Sufficiency Index - SSI) constitute secondary technical objectives. According to Minieri et al. (2025) [19], these parameters are not ends in themselves but serve as levers to improve financial returns by drastically reducing grid energy purchases and optimizing the utilization of locally produced resources. More advanced formulations have begun to incorporate Demand Side Management (DSM), allowing models to treat load shifting and the smart scheduling of appliances as active decision variables capable of flattening the withdrawal curve and maximizing synchronicity with renewable production [20].

The research frontier is shifting toward multi-method frameworks that integrate Agent-Based Modeling (ABM), discrete event simulation, and system dynamics. This approach explicitly recognizes that RECs are not simple electrical plants but complex socio-technical systems in which human decisions and market mechanisms fundamentally shape technical outcomes.

An area of growing interest concerns the formulation of equity-oriented objective functions. To move beyond the logic of efficiency alone, models based on cooperative game theory have been proposed, such as the study presented by Fioriti et al. (2023) [21], utilizing mathematical concepts such as:

- ***Shapley Value:*** Distributes benefits in proportion to each member's marginal contribution to the coalition.
- ***Nucleolus:*** Aimed at minimizing the dissatisfaction of the most disadvantaged members to ensure community stability.

Despite the theoretical value of these solutions for the fair distribution of incentives, their implementation in real operational models remains limited. The limitation of current models lies precisely here: they know how to divide the economic "*cake*" among existing members, but they fail to model how the perception of such equity influences the REC's attractiveness to new members.

2.3.4. Main limitations and simplifying assumptions

Despite the mathematical robustness and widespread use of Linear Programming (LP) and MILP models, their application to the study of Renewable Energy Communities is not without structural criticalities. To ensure computational tractability, these models often retreat into "*rationality cages*" based on simplifying assumptions that limit their ecological validity relative to the operational reality of decentralized energy systems.

One of the most burdensome limitations lies in the assumption of Perfect Foresight. Most LP formulations assume that renewable generation profiles, user demand patterns, and market price evolutions are known a priori with deterministic precision. This abstraction systematically overlooks the stochastic uncertainties of the real world. Research by Frieß et al. (2025) [22] demonstrates, in fact, that integrating forecast errors and implementing adaptive control strategies, capable of reacting in real-time to deviations, leads to significant improvements (quantifiable between 10% and 20%) in self-sufficiency and self-consumption indices compared to static approaches based on predefined rules.

From a social perspective, linear models often suffer from a form of "*anthropological blindness*" that fails to capture the heterogeneity of actors' behaviors. In these simulations, REC participants are often treated as identical atoms driven by a universal economic rationality, thereby ignoring that, in reality, prosumers and consumers display different risk preferences, divergent time horizons, and decision-making styles influenced by non-monetary factors [20]. This simplification prevents the modeling of critical phenomena, such as the churn rate or psychological resistance to changes in consumption habits.

A further methodological barrier is the use of representative load profiles. Although this technique is effective in reducing the computational burden, it obscures extreme daily and seasonal variability, which is crucial for Demand Response dynamic management applications [23]. Sensitivity analyses conducted on comparative models reveal a paradox:

- Simplified LP models are adequate for energy assessments on an annual scale.
- However, they systematically underestimate the risks of grid congestion at local nodes and overestimate the system's flexibility potential during peak demand periods [24].

Ultimately, these limitations do not invalidate the linear approach for pre-feasibility analyses, but they highlight their limitations when the research objective shifts toward understanding a dynamic, unpredictable system. It is precisely the need to overcome the rigidity of determinism and the abstraction of the "*ideal user*" that motivates the development of complementary Agent-Based

Modeling (ABM) simulation approaches. The latter, while sacrificing some computational efficiency, allows for the mapping of emergent complexity and behavioral heterogeneity, providing a vision of the REC not as a static machine, but as a continuously evolving social and energetic organism.

2.4. Multi-agent simulation systems and agent-based modeling

If linear programming represents the geometric rigor of technical optimization, Multi-Agent Systems (MAS) and Agent-Based Modeling (ABM) constitute its dynamic and "*biological*" evolution. This approach marks a fundamental methodological shift in scientific literature: moving the analytical focus from the pursuit of a static, centralized equilibrium to the understanding of a Complex Adaptive System. In this perspective, the REC ceases to be an equation to be solved and becomes an ecosystem populated by autonomous entities capable of interacting, learning, and reacting to environmental and social stimuli.

The adoption of ABM stems from the realization that REC's efficiency depends not only on the quality of dispatching algorithms but also on the complex web of human relationships and individual decisions that determine its growth and stability. While linear models struggle to account for the uncertainty of human behavior, multi-agent simulation places it at the center of its framework, allowing the observation of emergent phenomena, macroscopic results that were not explicitly programmed but arise spontaneously from local interactions among members.

This section explores the frontier of multi-agent simulation applied to RECs, organized into four analytical dimensions:

- ***2.4.1. Theoretical Foundations and Agent Architectures:*** An analysis of the ontological and cognitive structures (reactive vs. cognitive) that define the digital identity of community actors.
- ***2.4.2. Software Platforms and Development Frameworks:*** An overview of the technological ecosystem, from pillars like JADE and REPAST to the new frontiers of Julia and Python, that enables the realization of these simulations.
- ***2.4.3. Behavioral and Learning Mechanisms:*** An examination of how Artificial Intelligence (Reinforcement Learning) and Game Theory allow for the modeling of agents capable of evolving their strategies over time.
- ***2.4.4. Integration with Building and Energy System Models:*** A look at multi-physics co-simulation, where human behavior interacts with the thermal inertia of buildings and the electrical constraints of real-world grids.

Through this review, the potential of an approach that, while computationally more demanding, is the only one capable of mapping the true complexity of energy communities as integrated socio-technical systems will be highlighted.

2.4.1. Theoretical foundations and agent architectures

The transition from linear programming to Agent-Based Modeling (ABM) and Multi-Agent Systems (MAS) does not represent a mere variation in computational technique, but a true ontological paradigm shift. Within this framework, the Energy Community is no longer viewed as an optimization problem to be solved, but rather as an ecosystem populated by autonomous agents characterized by rule-based decision-making processes, local information processing, and, above all, the capacity to generate emergent behavior at the system level [25]. While classical approaches seek an often-artificial global equilibrium, ABM adopts a bottom-up perspective: it simulates the molecular interactions among prosumers, consumers, aggregators, and Distribution System Operators (DSOs), each pursuing personal goals constrained exclusively by their local knowledge and institutional "*rules of the game*" [26].

The fundamental value of this methodology lies in its ability to map behavioral heterogeneity. In the reality of RECs, participants are not identical automata; they vary substantially in their ideological motivations, financial risk profiles, and levels of proactive involvement [27]. An elderly person facing energy poverty and a young family with an electric vehicle will react radically differently to a price signal or a message of "*social consistency*" from the founding core. The agent-based architecture allows for the encoding of these differences, making the simulation a faithful mirror of human diversity.

Scientific literature identifies various architectures for structuring the "*mind*" of these digital actors, oscillating between reactive simplicity and cognitive complexity [28]:

- ***Reactive Agents:*** These operate according to elementary IF-THEN logic. For example: "IF the energy price exceeds threshold P_{crit}, THEN reduce the thermal load". They are extremely computationally efficient but lack memory and adaptive capacity [25].
- ***Cognitive Agents:*** These represent the most advanced frontier. They use frameworks such as Reinforcement Learning to adapt their strategies based on past experience, gradually improving the quality of their decisions in dynamic, turbulent environments [25].
- ***Cooperative Architectures:*** Many REC models employ hierarchical-distributed control structures, where central coordination (often an aggregator agent or community governance) coexists with the local autonomy of members. This faithfully reflects the consensus-based governance models typical of real-world communities, in which the collective goal is pursued through the partial sharing of information among nodes [29].

In this scenario, the agent ceases to be a passive variable in an equation and becomes a social subject. However, as highlighted in the research gap of this thesis, existing literature tends to focus on "*technical cooperation*" rules (e.g., how to exchange kWh) and often neglects those of "*social persuasion*". The methodological challenge accepted here is precisely the evolution of these architectures toward the integration of influence dynamics, in which the agent not only reacts to prices but allows itself to be transformed by the consistency of the active minority's message, transitioning from the state of "*external observer*" to that of "*joined member*".

2.4.2. Software Platforms and Development Frameworks: The ABM Technology Ecosystem

The translation of theoretical agent-based models into operational computational tools requires the adoption of development frameworks capable of managing the complexity of asynchronous interactions, population scalability, and interoperability across different domains. Within the scientific literature on RECs, the technological landscape appears stratified between historically established platforms and emerging solutions that prioritize calculation speed and integration with Artificial Intelligence.

The Java Agent Development (JADE) [30] framework has established itself as the dominant platform for energy community simulation, having been employed in over 22 significant studies examined by Azeroual et al. (2020) [31]. JADE's strength lies in its rigorous compliance with FIPA (Foundation for Intelligent Physical Agents) standards [32], which guarantees interoperability among heterogeneous agent implementations. This feature makes it the tool of choice for co-simulation, allowing social agents to interface with the technical physics of external tools, such as MATLAB/Simulink [33], through specialized middleware adapters, as seen in the case study presented by Hamidi et al. (2023) [29].

In parallel, the REPAST (Recursive Porous Agent Simulation Toolkit) [34] framework represents a solid alternative for modeling complex adaptive systems. Available in both Java and Python environments, REPAST stands out for its superior result visualization and parameter sweeping capabilities compared to JADE, allowing researchers to map the solution space more agilely as the community's initial conditions vary [35].

In recent years, the need for rapid prototyping has favored the emergence of more agile alternatives, such as the Smart Python Agent Development Environment (SPADE) [36]. Although it sacrifices some computational power compared to its Java counterparts, PADE is selected for "*lightweight*" applications where native integration with Python's Machine Learning and automated learning libraries represents a competitive advantage for modeling cognitive agents capable of learning from their mistakes [37].

A crucial challenge in REC modeling is the synchronization between simulators of different natures (energy, markets, and communication networks). In this field, the Mosaik co-simulation framework acts as a true "*orchestrator*". It allows the coordination of time steps across heterogeneous simulators, enabling an extremely realistic representation of information delays and asynchronous decision-making, elements typical of market dynamics and social interactions [37].

For high-dimensional simulations, where the agent population reaches high orders of magnitude (for example, in modeling entire urban districts), agents implemented in Julia (Agents.jl) [38] represent the current performance frontier. Thanks to Just-In-Time (JIT) compilation, Agents.jl achieves accelerations of 10-50 times those of comparable Python implementations while maintaining an accessible syntax. This tool is particularly valuable for conducting extensive sensitivity analyses, enabling the statistical validation of REC resilience across thousands of probabilistic scenarios in a short time [17].

2.4.3. Behavioral and learning mechanisms: from heuristics to adaptive intelligence

The evolution of ABM applied to RECs has marked the transition from "*reactive*" actors (driven by simple deterministic rules) to "*cognitive*" agents capable of learning and adapting. This transition is driven by the integration of Reinforcement Learning (RL) algorithms [39], which, as illustrated by the work of Fonseca et al. (2025) [26], enable the capture of participants' strategic behavior in response to a constantly evolving energy and regulatory environment. In this paradigm, the agent does not receive predefined instructions on how to act but instead explores various actions (e.g., shifting an hourly load or charging an electric vehicle) and receives a "*reward*" or "*penalty*" based on the effectiveness of its choice relative to set objectives.

In dynamic energy markets, Deep Q-Networks (DQN) [40] have demonstrated clear superiority over traditional heuristics based on static rules. Through experience gained across simulation iterations, DQN agents learn optimal energy-exchange strategies that maximize individual or collective benefits [41]. However, the true frontier is represented by Multi-Agent Reinforcement Learning (MARL) [42]. In a MARL context, prosumers do not learn in isolation but jointly coordinate their operational strategies. This allows the community to discover advantageous exchange configurations that preserve the autonomy of the individual participant while steering toward collective optimization [43].

The adoption of cutting-edge algorithms such as Soft Actor-Critic (SAC) [44] and Proximal Policy Optimization (PPO) [45] has yielded tangible results in simulation settings:

- ***Peak demand reduction:*** between 15% and 20%.
- ***Cost optimization:*** significant improvements compared to conventional optimization models [43].

Beyond learning, literature explores interactions among agents through the lens of Game Theory, which is essential for modeling Peer-to-Peer (P2P) exchange scenarios [46]. Formulations based on Stackelberg-Nash Games [46] are particularly valuable for representing hierarchical structures: in these models, a "*leader*" (for example, the community operator or an aggregator) defines pricing strategies by anticipating the responses of "*followers*" (the participants), achieving overall cost reductions of between 8% and 12% compared to non-cooperative scenarios [47].

Regarding social stability, cooperative approaches based on the Shapley Value provide a rigorous method for benefit distribution. The goal is to ensure an allocation of incentives so equitable that no participant has a rational incentive to leave the community (Exit preference), thereby stabilizing the REC in the long term [21].

Despite computational successes, the literature highlights a critical discrepancy between simulation results and real-world implementations. This gap, often termed the Reality Gap, is fueled by several disturbing factors that models struggle to integrate [26]:

- ***Incomplete and asynchronous data:*** the lack of real-time information (e.g., an electric vehicle's state of charge not being communicated to the system).
- ***Unpredictable behavior:*** the intrinsic irrationality of occupants, which deviates from the learning trajectories of the algorithms.
- ***Hardware heterogeneity:*** interfaces between different devices creating bottlenecks in control signal transmission.

"*If the code learns that turning off the washing machine at noon is optimal, but the user decides to turn it on anyway due to a sudden need, the learning model must be resilient enough not to collapse. The challenge is not just teaching agents to be smart, but also to coexist with human unpredictability*" [26].

This awareness motivates the need for careful design of validation frameworks, an aspect explored in depth by this thesis, which introduces the variable of social influence alongside technical learning logic. The objective is to understand whether the strength of the community bond can serve as "glue" that bridges the gap between the theoretical efficiency of algorithms and the daily practices of citizens.

2.4.4. Integration with building and energy system models: Towards multi-physics co-simulation

The limitation of early REC simulations was the excessive simplification of the consumption node, often reduced to a static, deterministic load profile. More recent literature has made a methodological leap forward by coupling energy management agents with sophisticated Building Performance Simulation (BPS) [48] models. Through the integration of calculation engines such as EnergyPlus or custom thermal simulators, multi-agent models can now capture dynamic variations in heating, cooling, and domestic hot water demand as a function of actual room occupancy [49].

This multi-physics integration has led to the discovery of fundamental importance for Demand Side Management (DSM): simplified and aggregated load profiles, commonly employed in linear optimization studies, tend to underestimate the actual flexibility of buildings by between 15% and 25% [20]. This discrepancy stems from the fact that only detailed models can map the interaction between occupant presence patterns and the thermal inertia of structures. The latter acts as a passive energy storage mechanism, enabling load-shifting opportunities that remain invisible in analyses based on annual average profiles but prove decisive for REC stability in real time.

Beyond the building's thermal dimension, the frontier of ABM research lies in integrating with realistic Power Grid Models. Co-simulation frameworks allow multi-agent management systems to interact with the grid while accounting for critical variables such as:

- ***Voltage constraints*** at local nodes.
- ***Line losses*** along grid branches.
- ***Transformer congestion*** risks.

According to Frieß et al. (2025) [22], these parameters are often neglected in simplified energy balance equations, leading to overly optimistic outcomes.

The results from the most advanced studies highlight an operational paradox: coordination strategies based on agents that achieve theoretical levels of collective self-consumption (up to 99.5%) in aggregated simulations exhibit insurmountable criticalities when tested on real grid models. In many cases, maximizing self-consumption violates the thermal limits of the distribution network, highlighting a deep rift between the community's centralized optimization logic and the decentralized operational needs of the physical grid [50].

These findings underscore the urgency of models that do not limit themselves to balancing "*virtual*" energy flows but also account for the physical and geographical constraints within which the REC is embedded. Only through a co-simulation that integrates human behavior (agents), building physics (thermal models), and infrastructure limits (grid models) is it possible to design communities that are not only economically advantageous but technically sustainable in the long term.

2.5. Cataloging software, tools, and computational codes

The examination conducted thus far has highlighted how REC modeling has transitioned from a pure electrical engineering exercise to a multidisciplinary systems challenge. In this scenario, the choice of computational instrumentation, programming languages, and mathematical solvers is not merely a technical decision; it profoundly affects the ecological validity of the results obtained. Software limited solely to linear optimization, however precise, risks overlooking the turbulence of human behavior, while an overly complex framework could be computationally prohibitive for large-scale sensitivity analyses.

This section aims to provide a systematic and critical categorization of the software ecosystem updated to 2026, mapping the tools that dominate both academic research and professional applications. The objective is twofold: on one hand, to offer a compass for navigating the various available platforms; on the other, to justify the technological selection made in this thesis, highlighting how multi-agent simulations currently represent the necessary frontier to bridge the gap between technical physics and social dynamics.

The analysis is structured along three fundamental axes:

- ***2.5.1 Comprehensive Classification of Tools and Solvers:*** A taxonomy distinguishing between commercial software (HOMER Pro, MATLAB) and open-source stacks (Python, Julia), analyzing the role of solvers such as CPLEX, Gurobi, and CBC in managing the complexity of REC constraints.
- ***2.5.2 Specific Tools and Their Applications:*** An examination of software dedicated to vertical tasks, such as RECON for Italian regulation, EnergyPlus for building thermal dynamics, and JADE for the asynchronous coordination of agents.
- ***2.5.3 Comparative Performance and Reliability:*** A critical analysis of the trade-off between computational efficiency and data granularity, comparing the speed of linear models with the ability of multi-agent models to map individual payoff variance and promote social equity.

This categorization constitutes the necessary premise for the final identification of literature gaps, setting the stage for the presentation of the original methodology proposed in this work, which, for the first time, aims to integrate **active** minority influence within a validated and resilient energy simulation framework.

2.5.1. Complete classification of tools and solvers

The technological mapping of tools used for REC simulation reveals a stratified ecosystem, where the choice of software reflects not only computational needs but also the research's strategic positioning (academic, professional, or institutional). A systematic survey of 75 academic studies published over the last decade yields a precise taxonomy of the distribution of these tools, highlighting an ongoing transition toward more open and modular models.

Statistical analysis of data collected in the first quarter of 2026 confirms the resilience of several legacy platforms while highlighting the emergence of new open-source frameworks *(Figure 4)*:

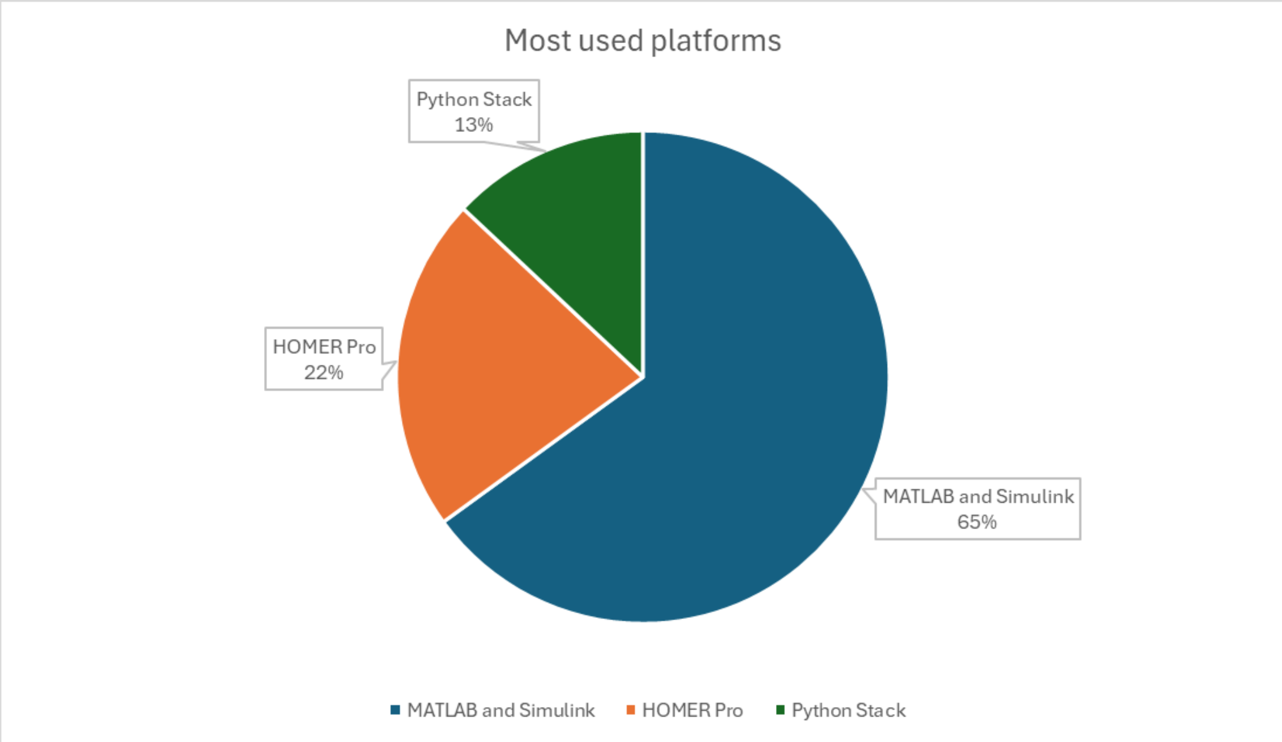

Figure 4: Most used platforms

- ***MATLAB and Simulink (65%):*** These remain the undisputed leaders of the sector. Their ubiquity stems from the vast library of toolboxes for optimization and the ease of integration with complex physical models. It remains the *de facto* standard for research requiring a high degree of algorithmic customization via proprietary scripts [10].
- ***HOMER Pro (22%)*** *[51]****:*** This commercial software maintains a significant market share, positioning itself as the tool of choice for pre-feasibility studies and within developing country contexts. Its strength lies in structured technical support and the ability to manage hybrid configurations with a low programming overhead [16].
- ***Python Stack (13%):*** Although still representing a minority share, the growth of libraries such as **Pandapower** [52] and **PyPSA** is meteoric. Nearly all of these adoptions are concentrated in the 2023–2026 period, signaling a paradigm shift toward open-source architecture and asynchronous co-simulation.

Behind every software interface lies a mathematical engine (solver) that processes constraints and objective functions. The choice of solver varies based on the complexity of the adopted optimization framework *(Table 7)*:

Table 7: Frameworks solver functions

Framework	Prevalent Solvers	Problem Type
MATLAB	Linprog, intlinprog	LP / MILP

Framework	Prevalent Solvers	Problem Type
GAMS	CPLEX, CONOPT	MILP / MINLP
Pyomo (Python)	Ipopt, CBC, GLPK	Non-linear / Open MILP
Specialized	Gurobi, SCIP	High-dimensionality / HPC

A particularly interesting data point concerns the acceleration of open-source solvers. In the most recent publications (2024–2026), as many as 18% of studies exclusively use a free stack (typically Python with CBC or SCIP). This value stands in sharp contrast to the mere 3% recorded by Tahir (2025) [10] during the 2015–2017 triennium.

This trend is not only technological but also political and social: it reflects the European Union's energy democratization goals. Access to rigorous simulation tools, without the burden of prohibitive software budgets, allows professionals, small municipalities, and nascent energy communities to conduct high-level feasibility analyses, reducing information asymmetries relative to major power market players.

In this landscape, the simulator developed in this thesis is positioned at the forefront of the free stack, leveraging the modularity necessary to integrate not only the deterministic calculation of the energy balance but also the stochastic and behavioral logic of agents, which "*closed*" commercial software often struggles to support.

2.5.2. Specific tools and their applications

The choice of simulation platform determines not only the accuracy of the energy results but also the depth of the possible socio-economic analyses. Scientific literature has consolidated a set of specialized tools, each addressing specific phases of an REC's life cycle: from preliminary design to real-time operational control. Below, these tools are categorized based on their primary function within the research architecture.

A. Technical-Economic Simulation and Design

This category includes software dedicated to system sizing and basic feasibility assessment.

- ***HOMER Pro****:* It remains the standard for hybrid microgrid design. Its strength lies in the integration of Monte Carlo sensitivity analysis [53], an essential tool for managing climate and market uncertainty in isolated (small islands) or rural contexts, where main grid stability is absent or limited [16].

- ***RECON****:* Represents the excellence of Italian institutional development. It is a simulator optimized for national regulation that, while requiring standardized consumption profiles, guarantees high reliability: data show an error of less than 5% in the shared energy calculation for configurations with a PV-to-system-capacity ratio of 1.5 kW of PV per kW of system capacity [14].
- ***Pandapower (Python)****:* The bridge between energy simulation and electrical engineering. It is used for advanced power flow analysis in distribution networks. Its open-source nature has made it the preferred module for integrating grid constraint awareness into multi-agent simulations [54].
- ***EnergyPlus****:* The calculation engine for building thermal dynamics. With hourly resolution, it models how occupant presence influences heating and cooling demand, providing critical data on thermal flexibility that purely electrical models often overlook [49].

B. Optimization and System Control

This section covers algebraic frameworks and high-performance languages for solving resource allocation problems.

- ***GAMS with CPLEX/CONOPT solvers****:* The tool of choice for large-scale grid planners. It manages MILP/MINLP models on a national scale for multi-node expansion planning and complex operational scheduling [13].
- ***Pyomo (Python)****:* Offers a solver-independent algebraic modeling environment. It is particularly valued in academic research for its transparency in constraint specification, which favors scientific data reproducibility and facilitates open science collaboration [12].
- ***Julia (Optimization.jl)****:* Represents the technological frontier of 2026. Thanks to its native parallelization capability, Julia is used for real-time Model Predictive Control (MPC), allowing microgrids to adapt instantaneously to production and price fluctuations [55].

C. Frameworks for Agent-Based Modeling (ABM)

These tools allow modeling the "*mind*" of the community by integrating human behaviors and social dynamics.

- ***JADE (Java)****:* The reference framework for large-scale agent simulations. Thanks to its distributed architecture, it has been used to document over 75 complex scenarios of Peer-to-Peer (P2P) trading and Demand Response coordination, ensuring compliance with international agent communication standards [56].
- **REPAST (Python/Java)**: Distinguished by its advanced visualization capabilities. It is the most cited tool (22 identified studies) when the research goal is to represent behavioral heterogeneity, enabling graphical observation of how agent diversity influences REC evolution [35].
- **Mosaik (Python)**: More than a simulator, it is a **co-simulation middleware**. Its function is crucial: it enables synchronized dialogue between heterogeneous simulators (e.g., EnergyPlus

for physics, JADE for behavior, and Pandapower for the grid), creating a holistic and realistic testing environment [37].

The integration of these tools enables moving beyond the "*flat*" vision of deterministic models, offering a simulation that respects building physics, power grid limits, and, above all, the unpredictability of the human factor.

2.5.3. Comparative Performance and Reliability: Efficiency vs. Granularity

The choice of a simulation framework for RECs is not based exclusively on mathematical accuracy; rather, it represents a strategic compromise among precision of technical data, tool accessibility, and the required computational burden. An analysis of recent scientific literature enables a rigorous comparison of the reliability of Linear Programming (LP) models and the complexity of Agent-Based Modeling (ABM) simulations, highlighting the strengths and limitations of both approaches.

Benchmarking conducted by Presciutti et al. (2025) [5] across identical scenarios shows that simplified LP models, such as the national simulator RECON or the VBA-based MERCm framework, tend to underestimate shared energy by 3% to 7% relative to detailed simulations in a MATLAB/Simulink environment. Despite this systematic underestimation, absolute forecasting errors remain consistently below the 15% threshold regarding annual aggregate metrics.

This evidence suggests a fundamental conclusion for policymakers and territorial stakeholders: for pre-feasibility analyses and rough energy assessments, extreme model sophistication yields only marginal gains in precision. At this stage, priority should be placed on the availability and quality of input data and on the accessibility of the tool for non-experts, rather than on pursuing infinitesimal resolution in the physical model.

When the analysis shifts toward multi-agent systems, the performance landscape changes drastically. As noted by Fioriti et al. (2023) [21], ABM simulations modeling populations with more than 100 agents require computation times 5 to 50 times higher than equivalent LP models. However, one point is clear: if the simulation objective is limited to calculating aggregate metrics, such as the collective energy cost or the community's total self-consumption, the results of complex approaches differ only negligibly from the averages of simplified linear models.

The true methodological distinction emerges not in the "*totals*" but in the internal distribution of value. While LP models tend to flatten individual diversities in favor of a global optimum, agent-based models reveal high-variance in individual participants' payoffs and in the distributions of economic opportunities.

"*If two RECs show the same aggregate savings of 20%, the linear model will consider them identical. However, the ABM might reveal that in one community, the savings are equitably distributed, while in the other, the benefit is concentrated in the hands of a few prosumers, leaving vulnerable consumers in a marginal position*" [20].

This ability to map individual variance substantially alters policy conclusions regarding distributive equity. It is therefore evident that the higher computational burden of ABM is justified only when the research goal is to understand the community's social resilience and to prevent phenomena of exclusion or dissatisfaction that could lead to system collapse in the long run. In summary, while linear programming helps size the panels, agent-based modeling helps ensure the community remains united amid the weight of market dynamics and social influences.

2.6. Objectives, focus, and methodological diversity in REC simulations

The design and analysis of RECs through simulation tools do not follow a universal logic but instead adapt to the specific objectives of different stakeholders, ranging from policymakers and grid operators to individual citizens. Scientific literature in recent years has highlighted that the "*quality*" of a simulation strictly depends on the coherence between the set objective and the methodology adopted. While a linear approach may suffice for a rough estimate of profitability, understanding decentralized markets or electrical stability requires significantly higher granularity and modeling complexity.

This section aims to explore the multi-dimensionality of the objectives driving contemporary research, classifying the various "*focuses*" of REC simulations. The analysis concerns not only numerical results but also the methodological diversity necessary to capture phenomena spanning from grid physics to user behavioral psychology.

The discussion is structured into the following subsections, reflecting the evolution of simulators from simple accounting tools to complex socio-technical analysis engines:

- ***2.6.1 Technical Objectives: Energy Balancing and Performance Metrics:*** An analysis of the "*ground zero*" of every model, namely, the ability to match generation and demand in real-time, and the definition of indicators such as self-consumption and self-sufficiency.
- ***2.6.2 Economic Objectives: Cost Minimization and Benefit Maximization:*** An examination of financial metrics (NPV, IRR, LCOE) and how different regulatory frameworks influence investment viability.
- ***2.6.3 Demand Management and Flexibility Services:*** An in-depth look at the active role of buildings and domestic appliances capable of load shifting to optimize the community's energy profile.
- ***2.6.4 Peer-to-Peer (P2P) Exchange Mechanisms and Energy Markets:*** The exploration of new decentralized market models where energy is traded directly between members without intermediaries.
- ***2.6.5 Grid Support and System Services:*** An analysis of the REC as an ancillary resource for national grid stability through the provision of frequency and voltage regulation services.

Through this classification, it will clearly emerge that today's research challenge no longer lies solely in renewable energy production, but in the ability to synergistically orchestrate technology, economics, and social participation.

2.6.1. Technical Objectives: Power Balance and Performance Metrics

The beating heart of every simulation dedicated to RECs is its ability to solve the energy balance equation with deterministic precision. In 95% of the literature examined, the primary technical objective is to ensure that renewable generation meets instantaneous demand with minimal error margins and to manage the complex interactions between Energy Storage Systems (ESS) and the national power grid [18]. This is not merely an accounting exercise: imprecise modeling of hourly flows invalidates any subsequent forecasting, rendering both exported energy estimates and the project's economic and financial projections unreliable.

While basic models are limited to hourly temporal resolution, more advanced formulations, often based on Predictive Control Algorithms, aim for sub-second temporal resolution. These simulations include frequency stability requirements, voltage regulation services, and black start capabilities [57]. As the penetration of RECs within the European energy mix increases, these communities cease to be simple "*users*" and become critical actors in managing local grid resilience, offering flexibility where large thermoelectric power plants struggle to intervene.

To measure the effectiveness of an REC, the literature has consolidated a triad of fundamental parameters, each capturing a different facet of system efficiency *(Table 8)*:

Table 8: REC's System efficiency

Metric	Mathematical Definition	Strategic Significance
Physical Self-Consumption (SC)	$SC = \frac{E_{self-consumed}}{E_{produced}}$	Measures how much production is used directly "*behind the meter*", entirely avoiding grid costs.
Self-Sufficiency (SS)	$SS = \frac{E_{produced\_locally}}{E_{total\_demand}}$	Indicates the REC's degree of energy independence from the national grid.
Virtual Self-Consumption (Shared)	$E_{shared} = min(P_{injected}, C_{withdrawn})$	Quantifies the energy virtually exchanged between members, the basis for calculating incentives (GSE in Italy).

Physical Self-Consumption has emerged as the most critical performance parameter (cited in 92% of studies) [2]. The reason is purely economic: every kilowatt-hour consumed at the moment of production avoids not only raw-material costs but also system charges and transmission tariffs. Conversely, excess energy injected into the grid typically receives lower compensation, making maximizing self-consumption the most remunerative technical strategy for community members [19].

In summary, the energy balance is not just a matter of technical physics; it is the "*ground zero*" of sustainability. Without a robust balance that accounts for the synchronicity between sun, wind, and human habits, the REC risks being an excellent idea on paper but a fragile investment in operational reality.

2.6.2. Economic objectives: minimizing costs and maximizing benefits

Economic feasibility analysis represents the cornerstone of any REC project, serving as an indispensable catalyst for attracting both institutional investor capital and proactive citizen participation. It is no surprise, therefore, that profitability assessment is the explicit objective in 88% of simulations reported in the literature [18]. Over a typical 20-25 year time horizon, which mirrors the nominal service life of photovoltaic systems and the duration of European incentive regimes, the primary financial metric remains the Net Present Value (NPV) (1), alongside the Levelized Cost of Energy (LCOE) and the Internal Rate of Return (IRR) as indicators of the project's ability to generate value beyond mere capital recovery [58].

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} - I_0 \quad (1)$$

Where CF_t represents the net cash flow in year t, r is the discount rate, n is the project duration, and I_0 is the initial investment. Sensitivity analyses of capital expenditures (CAPEX), operational expenditures (OPEX), and tariff projections highlight that financial feasibility is strictly linked to policy support mechanisms. Elements such as Feed-in Tariffs (FiT), net metering policies, and investment subsidies (e.g., PNRR funds in Italy) are not simple variables but structural determinants that explain the drastic variations in profitability across different regulatory jurisdictions [9].

More sophisticated economic models have moved beyond the static views of the past to embrace free-market complexity:

- ***Dynamic Pricing:*** The integration of hourly zonal prices (e.g., PUN in Italy) allows for modeling market volatility, making the simulation sensitive to "*zero-price*" periods and demand peaks.
- ***Component Degradation:*** The economic module accounts for the annual decline in PV module efficiency (typically 0.5-0.8%) and the replacement cycles of inverters and electrochemical storage systems, whose State of Health (SoH) decays based on the modeled charge/discharge cycles [59].
- ***Stochastic Analysis:*** Through Monte Carlo simulations with over 1,000 iterations, researchers evaluate the probability distributions of financial outcomes. It has been shown that, in developed markets, RECs achieve a positive NPV with a probability exceeding 90% (P90) under standard regulatory conditions, although vulnerability to sudden changes in support policies remains a substantial risk factor [58].

A significant aspect concerns the dichotomy between sizing strategies dictated by different national frameworks. In contexts such as the Italian one, the presence of incentives on shared energy and the remuneration of surplus via RID (*Ritiro Dedicato*) favors Oversizing logic, where the goal is to maximize kWh volume to scale revenues. Conversely, the Spanish framework or those based on pure Net Billing push toward Right-sizing (precise dimensioning), where the marginal value of excess energy drops rapidly once the bill is zeroed out, making oversizing a financial burden rather than an advantage.

Ultimately, the economic objective is not a simple race for profit, but a search for a balance between minimizing system costs and maximizing distributed benefits, ensuring that the community is financially self-sustaining in the long term, even in the absence of direct state intervention.

2.6.3. Demand Management and Flexibility Services: Building as a Dynamic Resource

In the REC landscape, the challenge has shifted from mere production to the intelligent management of "*when*" energy is consumed. Demand-side management (DSM) and load-shifting optimization have emerged as crucial components, now integrated into 78% of contemporary simulations [18]. In this paradigm, the building and its occupants cease to be passive terminals and transform into flexible resources capable of actively communicating with the grid and local production.

Optimal DSM strategies allow prosumers and consumers to synchronize the operation of so-called "*deferrable*" appliances, such as heat pumps for domestic hot water, electric vehicle (EV) charging systems, dishwashers, and washing machines, with peak renewable generation. Data from the most recent simulations are telling: effective DSM implementation can improve collective self-consumption by 10-20 percentage points while simultaneously reducing peak demand on the distribution grid by 12-15% [18].

Despite the attractiveness of these figures, scientific literature highlights a significant "*reality gap*". Through discrete event simulation approaches, which capture realistic operating sequences, thermal dynamics, and occupancy patterns, it has emerged that the theoretical flexibility calculated by purely mathematical models often overestimates practical availability by as much as 25%-40% [20].

This divergence is attributable to two critical factors:

- ***Behavioral constraints:*** Users are not always willing to subordinate their daily habits to price or production signals (e.g., the need to have a charged car for a nighttime emergency).
- ***Comfort requirements:*** The thermal inertia of buildings has physical limits beyond which occupant's well-being is compromised, making further shifting of thermal loads impossible.

Residential demand flexibility, when analyzed using a combination of optimization models and Agent-Based Modeling (ABM), shows that economic benefits for the REC increase substantially when participants actively participate in load shifting. However, this commitment is not "*zero-cost*": it requires initial investments in technological infrastructure (such as HEMS - Home Energy Management Systems) and, above all, behavioral motivation sustained overtime [60].

"*Demand side management must not be seen as a mere algorithmic imposition, but rather as a socio-technical system. The technological sophistication of smart meters must necessarily align with the cognitive abilities of users and incentive structures perceived as fair and transparent.*" [18]

In summary, flexibility is the "*lung*" of the REC, but its respiratory capacity depends as much on software efficiency as on citizens' willingness to become integral to the process. Without proper modeling of the human dimension, including the social influence that more "*tech-savvy*" neighbors can exert on the community, DSM risks remaining a theoretical exercise confined to research laboratories.

2.6.4. Peer-to-Peer (P2P) Energy Exchange and Market Mechanisms

If demand management represents the optimization of the "*self*", Peer-to-Peer (P2P) exchange constitutes the apotheosis of the "*relationship*" within an REC. Identified in 72% of the most recent studies and examined in depth by Sanfilippo et al. (2024) [61], P2P trading explores mechanisms for the direct exchange of energy between prosumers and consumers, eliminating or drastically reducing the need for centralized intermediation. In this model, the community is no longer a mere recipient of incentives but a vibrant local market where energy flows according to the logic of proximity and mutual convenience.

The study by Guimarães et al. (2021) [62] shows that agent-based simulations have revealed that "*the devil is in the details*" of the market-clearing algorithm. The literature highlights a fundamental divergence between two approaches:

- ***Uniform Pricing:*** All participants trade at the same rate established by the market. This ensures administrative simplicity and a perception of "collective fairness."
- ***Bilateral Matching:*** Participants individually negotiate quantities and prices.

Although both approaches produce similar collective efficiency in terms of kWh exchanged, the results regarding equity are profoundly different. Bilateral matching tends to favor agents with greater bargaining power or better forecasting capabilities, creating disparities that can undermine the community's social cohesion.

A critical aspect, often overlooked in deterministic models but emphasized in multi-agent ones, is strategic behavior. "*Opportunistic*" agents may attempt to manipulate bids to exploit other members' information asymmetries. Studies by Fonseca et al. (2025) [26] demonstrate that market models lacking robust anti-gaming mechanisms can record efficiency drops of 20-30%, leading to an extreme concentration of wealth in the hands of a few technically sophisticated actors.

"*A P2P market without protection rules is like a chess game where one side has a supercomputer and the other an abacus: the efficiency of the game (the number of moves made) remains high, but the sustainability of the tournament (the desire to continue participating) collapses instantly.*" [26]

To ensure transaction transparency and security without a central entity, Luo et al. (2019) [63] turned to Blockchain. However, multi-agent simulations highlight that integrating Distributed Ledger Technology (DLT) [63] incurs computational overhead and latency that limit its large-scale, real-time applicability.

Furthermore, Sanfilippo et al. (2024) [61] argue that regulatory impact acts as a powerful catalyst or an invisible brake; according to their analysis, removing bureaucratic barriers to P2P trading would lead to cost reductions for participants of 5%-10%. However, a structural tension emerges: benefits tend to concentrate among early movers and users with high technical sophistication.

This highlights the fundamental gap our research intends to address: the need to balance the efficiency of a decentralized market with the protection of the most vulnerable members. In our model, the influence of the active minority serves not only to promote membership but also to instill a "*culture of cooperation*" that mitigates selfish behaviors within a tool for mutual energy assistance.

2.6.5. Network support and system services: CER as an ancillary asset

As we have previously seen, the current technological and regulatory evolution has definitively established REC's transition from a simple "*self-consumption island*" to an active, intelligent node within the power grid. The recognition that RECs can provide system services, such as frequency regulation, voltage support, local congestion relief, and black start capability, has prompted over 65% of recent studies to incorporate these ancillary objectives into their simulation models, as seen in the study by Barone et al. (2024) [57]. In this new capacity, the community not only balances its internal flow but also acts as a strategic partner for both the Transmission System Operator (TSO) and local Distribution System Operators (DSOs).

To allow RECs to participate in regulation markets with minimum latency and without the need for excessively burdensome centralized communication infrastructures, the literature has explored the application of droop control principles. In this scenario, the community's plant inverters react autonomously to local frequency and voltage variations. However, simulations reveal a critical tension: the performance of these systems depends surgically on parameter tuning and can come into direct conflict with the commercial interests of REC members. Barone et al. (2024) [57] point out that providing a grid service often requires deviating from the strategy of maximizing local self-consumption, forcing the community manager to face a trade-off between power system stability and the members' electricity bill savings.

A widely explored solution within multi-agent frameworks is the concept of the Virtual Power Plant (VPP) [64]. In this model, RECs are treated as aggregated entities coordinated by an Aggregator, a specialized agent that harvests the flexibility of individual members to sell it in bulk on dispatching service markets.

Studies by Pezzati et al. (2025) [65] demonstrate that participation in a VPP can generate an additional turnover of 8%-15% for participants. This financial surplus is often sufficient to justify the investment in monitoring technologies and the aggregator's management overhead. However, the effectiveness of such a model is extremely sensitive to local market design: in the absence of a regulatory framework that adequately rewards distributed flexibility, the technological cost risks exceed the marginal benefit.

The research frontier is shifting toward the framework of "*Nearly Zero Energy Communities*", architectures that natively integrate grid support from the design phase. In these systems, distributed control architectures are proposed to simultaneously achieve two seemingly divergent goals: local energy self-sufficiency and the continuous provision of stability services to the macroscopic grid [57].

While RECs were initially mere consumers trying not to disturb the grid, recent RECs have become a fundamental support for the grid itself: they intervene locally to prevent voltage or frequency problems from becoming chronic and propagating to the national system.

In conclusion, the ability to provide system services represents not only a diversified income stream but also a powerful selling point for attracting new members. Knowing that one's community is not just "*green*" but also a pillar of national energy security increases the perceived value of the REC, fueling that virtuous cycle of social influence.

2.7. Critical gaps: socioeconomic dimensions and community attractiveness

Despite impressive technological advances and the maturity of the mathematical optimization models described in the previous sections, the scientific literature on RECs exhibits a significant methodological fracture. While the physics of energy flows and the logic of electricity markets have been mapped with extreme precision, the human and social dimension, the true engine of the "*bottom-up*" energy transition, often remains a *"black box"* or, in the worst cases, an oversimplified variable within purely deterministic models.

Identifying these gaps is not merely an academic exercise but a necessary premise for understanding why many communities, though technically flawless, struggle to take off or maintain member commitment over time. There is an intrinsic limit to linear programming: it can tell us how to manage a kilowatt-hour, but it cannot predict whether a citizen will decide to join the community, whether they will trust their leaders, or whether they will change their habits out of solidarity toward their neighbors.

This section analyzes the "*blind spots*" of contemporary research, structuring the inquiry through the following critical areas:

- ***2.7.1. Limited behavioral and socio-psychological modeling:*** An analysis of the dominance of *Homo Oeconomicus* over the complexity of real-world motivations.
- ***2.7.2. Insufficient integration of equity and energy poverty dimensions:*** A reflection on the risk of "energy gentrification" and the lack of inclusive models.
- ***2.7.3. Gaps in governance and institutional modeling:*** The impact of decision-making structures and allocation rules on collective stability.
- ***2.7.4. Inadequate representation of socio-economic attractiveness for external users:*** The study of factors determining community growth beyond the founding core.
- ***2.7.5. Discrepancy between simulation results and implementation reality:*** An examination of the so-called "valley of death" between virtual successes and operational failures.
- ***2.7.6. Synthesis of research gaps and future perspectives:*** An overview of the evolutionary trajectories required for a new generation of REC simulators.

Mapping these deficiencies justifies the original positioning of this thesis: the introduction of a framework that does not merely balance electrical loads but also integrates social influence as an endogenous variable, capable of bridging the gap between optimization theory and the practice of community participation.

2.7.1. Limited behavioral and socio-psychological modeling

A critical gap that emerges forcefully from the analysis of contemporary REC simulations concerns the extremely simplified, if not entirely absent, representation of behavioral heterogeneity and the socio-psychological factors governing participation decisions, as highlighted by Bielecki et al. (2025) [27]. While the research landscape has reached an unquestionable technical and economic maturity, the human dimension remains the "*bottleneck*" of predictive models. The data *(Figure 5)* is clear: only

32% of the studies examined explicitly incorporate behavioral variables, compared to almost total 98% addressing technical aspects and a solid 85% including economic factors.

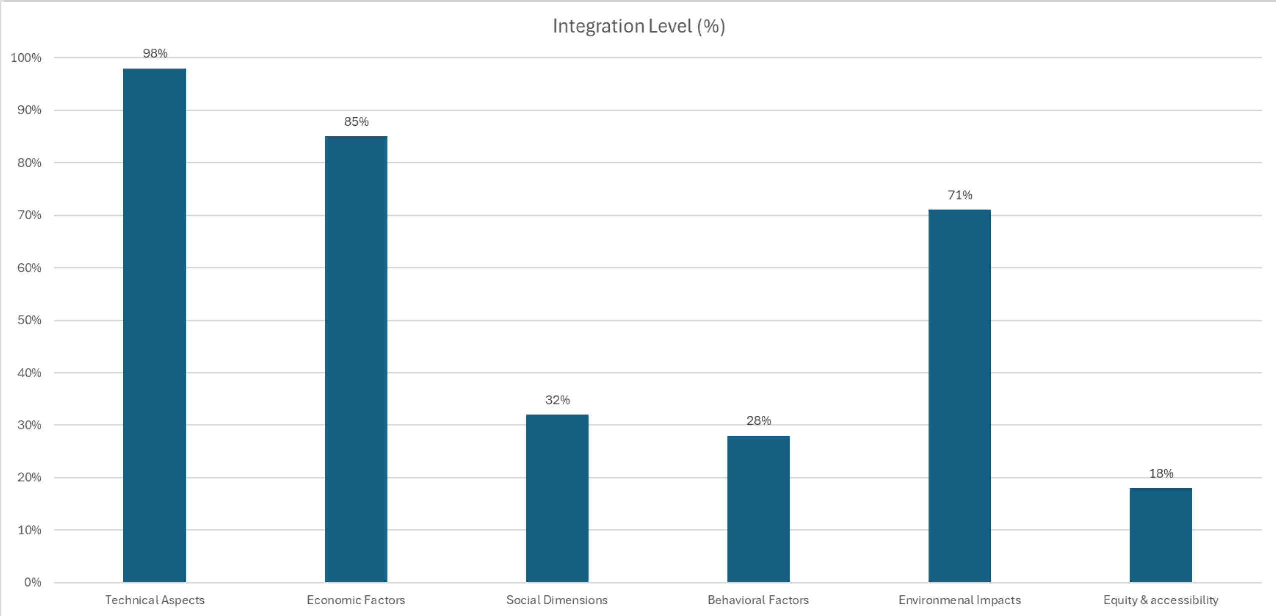

Figure 5: Integration of Dimensions in Current REC Simulations

This disproportion is not accidental but reflects a deep-seated disciplinary bias rooted in traditional energy modeling; in this field, the paradigms of engineering and neoclassical economics exert hegemony, marginalizing social science perspectives, as reported by Vuthi et al. (2022) [48]. The result is the creation of simulations that are "*blind*" to the complexity of the social fabric in which the REC must operate; in fact, most existing models still treat participants as purely rational economic agents, entities that act exclusively to maximize personal monetary utility. It is noted, precisely, that this approach systematically fails to predict real adoption patterns and, above all, the long-term stability of member commitment.

Field investigations conducted by Koirala et al. (2018) [66] reveal a much more multifaceted reality, in which members' motivations extend far beyond the simple calculation of bill savings. Among the determining factors for joining an REC are:

- ***Environmental concern:*** The urgency of the climate crisis as a primary ethical driver.
- ***Sense of belonging:*** The desire to feel part of a collective local project.
- ***Energy independence:*** The will to break free from dependence on large centralized producers.
- ***Institutional distrust:*** A critical reaction toward traditional utilities, perceived as opaque or distant.

Most recent qualitative research conducted by Tobin and Lennon (2025) [67] emphasizes that, in users' perceptions, perceived fairness and transparency in benefit distribution carry greater weight than minimal variations in marginal cost. This confirms that a citizen may decide to remain in a community even if the economic savings are lower than expected, provided they perceive the system as just and aligned with their personal values. Conversely, an REC that is technically perfect but perceived as unfair or governed by purely speculative logic is destined to experience high churn rates.

It can be inferred that current modeling lacks "*social intelligence*". By ignoring that participation is an act guided by social heuristics and identity bonds, standard simulators cannot map how a community can actually expand. It is precisely within this methodological gap that the contribution of this thesis is situated: the integration of a socio-psychological module that recognizes the agent not only as a consumer of kWh but as a subject immersed in a network of influences and values.

2.7.2. Insufficient integration of the dimensions of equity and energy poverty

A further and profound structural gap in the literature concerns the limited attention paid to energy justice. Energy poverty, defined as inadequate access to essential energy services due to low-income, high-energy costs, and poor building efficiency, represents a social blight affecting, according to recent estimates [68], 9.2% of European households. This phenomenon recorded a 54% increase over the five-year period between 2019 and 2023, with significantly higher peaks in developing countries, as noted in the study by Cumo et al. (2022) [69]. Despite the urgency of this issue, the dimension of equity remains a "*blind spot*" for algorithmic modeling: only 18% of REC simulations explicitly incorporate social justice considerations or attempt to map the real impacts of communities on vulnerable populations [1].

This omission has practical consequences. REC models designed without an explicit lens on financial accessibility risk trigger a paradoxical wealth-concentration effect. In the absence of corrective mechanisms, economic benefits tend to polarize toward wealthy "*early adopters*", individuals who possess the initial capital for photovoltaic installations and property ownership (roofs).

Stoklin et al. (2025) [70] warn that, without regulatory and modeling guidance grounded in equity, RECs could, in the long run, exacerbate energy inequality rather than reduce it. This could create elite communities that leave low-income citizens confined to the protected market or exposed to price volatility, with no protective shield.

Frontier research is beginning to propose innovative approaches that integrate energy poverty indices (such as the Low-Income High Costs indicator) directly into the community planning phase. Through innovative financing, collective ownership systems, and solidarity-based benefit-sharing mechanisms, REC can be transformed into a tool for social protection.

Early empirical evidence from the work of Cumo et al. (2022) [69] suggests that projects designed with a deliberately inclusive vision can lead to extraordinary results:

- ***Reduction in energy expenditure:*** Between 15% and 20% for low-income households.
- ***Economic sustainability:*** Maintenance of a positive NPV for the entire community aggregate.

However, achieving such goals cannot be left to chance or the goodwill of individuals. It requires integrated modeling capable of simultaneously balancing four dimensions:

1. ***Technical:*** Optimization of physical flows.
2. ***Financial:*** Sustainability of investments and payback periods.
3. ***Social:*** Participation dynamics and the perception of equity.
4. ***Institutional:*** Alignment with regulations and public subsidies.

"*If the simulation does not 'see' energy poverty, it cannot solve it. A model that only optimizes kWh ignores that, for a vulnerable member, that 15% saving is not just a KPI, but the difference between home heating and debt.*" [70]

It can therefore be inferred that integrating the equity dimension is not only an ethical imperative but also a strategic necessity to ensure community stability. This is precisely the challenge that the simulator presented in this thesis intends to meet: introducing value-distribution logics that reward solidarity and measuring how such a perception of justice influences the attraction force of the active minority relative to the rest of the external agent pool.

2.7.3. Gaps in governance and institutional modeling

If the energy module represents the "*skeleton*" and the economic module the "*circulatory system*" of an REC, then governance constitutes its "*central nervous system*". Yet, despite its importance in determining long-term sustainability and member satisfaction, decision-making processes, benefit allocation rules, and conflict resolution mechanisms are absent in 62% of the simulations surveyed in the literature [1]. Most models treat the community as a "*black box*" governed by perfect, centralized optimization, ignoring the friction, delays, and negotiations that characterize the democratic management of a collective good.

Multi-agent systems (MAS) would, by their very nature, be capable of representing extremely diverse governance architectures: from direct democracy (where every agent votes on investment strategies) to delegated aggregators (where management is entrusted to a professional third party) to pure cooperative structures or public-private hybrid models. However, the prevailing literature tends to retreat into mathematical simplifications where a single "*director*" decides for everyone [71]. This abstraction prevents exploring how different governance models influence real-world outcomes: while purely technical management might maximize revenue, participatory management could prove far more resilient in the face of internal crises or regulatory shifts.

Qualitative research on the establishment of RECs clearly identifies four fundamental pillars for the success of the initiative, which, however, rarely find space in quantitative simulations [72]:

1. ***Legal and Regulatory Frameworks:*** The stability and clarity of national rules.
2. ***Municipal Support:*** The role of local authorities as facilitators or partners.
3. ***Access to Finance:*** The ease of interaction with the banking system.
4. ***Organizational Capacity:*** The presence of technical and legal expertise within the community.

The omission of these variables creates a gap between the "*ideal REC*" of the simulator and the "real REC" that must grapple with bureaucracy and citizens' limited coordination capacity.

To bridge this gap, some pioneering studies propose integrating System Dynamics approaches. These models allow for the representation of policy feedback, organizational learning dynamics, and the evolution of the community over time [73]. For example, an overly rigid governance rule might discourage new members from joining, reducing the critical mass and leading to economic failure in the medium term, a feedback phenomenon that a static model could never capture.

Modeling an REC without considering governance is equivalent to designing a racing car without examining the role of the driver: we might have the most powerful and efficient engine; however, we will never be able to determine if it can hold its line through a curve without risking a spin-off.

Ultimately, institutional modeling represents the final frontier in making simulations truly predictive. This thesis aims to take a step forward in this direction, not only by simulating energy exchanges but also by integrating allocation rules and social influence mechanisms as active variables that determine organizational health and the community's outward attraction force.

2.7.4. Inadequate representation of socio-economic attractiveness for external users

The attractiveness of an REC to potential external users, namely citizens, shopkeepers, or small businesses who are not part of the founding core, represents a critical parameter for the organic growth and long-term economic sustainability of the project; yet, despite its vital importance, this dimension remains inadequately modeled and poorly understood in prevailing technical-scientific literature [74]. Data highlights a worrying methodological imbalance: only 22% of the studies examined explicitly incorporate attractiveness parameters or attempt to model the psychological and social factors that drive an "external" member to cross the membership threshold [1].

This gap has profound practical implications. There exists what we might define as the "*founding core paradox*": an REC can achieve high levels of energy self-sufficiency among its promoting members but fail miserably in attempting to attract new participants. Research suggests that technical excellence (high self-consumption rates) does not automatically translate into demographic growth unless attractiveness factors are deliberately cultivated, such as:

- ***Transparency of financial benefits:*** The ease with which a layperson understands real bill savings.
- ***Accessibility of governance:*** The perception that the community is not a "*closed club*" but a democratic entity.
- ***Cultural alignment:*** The harmony between REC values and the social identity of the neighborhood [27].

Behavioral economics teaches that membership decisions are almost never the result of an isolated calculation. Factors such as social proof, observing one's peers' behavior, and initial trust in the organization's leaders play a greater role than the mere convenience of the price per kWh [66]. If a citizen perceives that "*people like them*" are obtaining tangible benefits and that the promoters are credible figures, the psychological barrier to technology adoption (often perceived as complex or risky) drops drastically.

Multi-agent simulations integrating these dynamics reveal that the growth of an REC almost never follows linear or exponential trajectories, but rather S-curves (logistic curves) (2):

$$P(t) = \frac{K}{1 + e^{-k(t-t_0)}} \quad (2)$$

In this model, K represents the final saturation level (the maximum number of attractable members), while k is the growth rate. The fundamental discovery of these simulations is the existence of critical intervention points in the initial phases: the speed and strength with which the REC communicates its successes in the early stages disproportionately influence the final saturation level [75].

It's likely that the success of a REC won't be decided after ten years, but will be predicted in the first twelve months: it's precisely during this period that the perceived appeal determines whether the community will become a mass phenomenon or remain an isolated experiment for a few passionate founders.

This section of the literature highlights the "*fertile ground*" upon which this thesis is built. Having identified the gap in attractiveness modeling, our multi-agent model introduces Moscovici's Conversion Theory (Active Minority Influence) as the dynamic engine of membership. While classical literature views attractiveness as a static datum, we model it as a signal emitted by the founding core, whose consistency and coherence can trigger the cognitive conflict necessary to convert external users, thereby overcoming the inertia of the traditional energy market.

2.7.5. Discrepancy between simulation results and implementation reality

Increasingly clear evidence in recent scientific literature is the presence of a systematic divergence between simulation model predictions and the actual performance of RECs once they are operational [18]. According to the analysis by Vuthi et al. (2022) [74], this discrepancy, often termed the Performance Gap or "*Reality Gap*", is not exclusively attributable to technical calculation errors but reflects a fundamental limitation of current tools in capturing the complex social dynamics that govern human behavior within a decentralized energy system.

The comparison between predicted and measured electricity flows in pilot projects shows that member behavior deviates drastically from the stationary hypotheses of simulators. Lazzeroni et al. (2025) [20] identified the primary sources of discrepancy as:

- ***Variability in appliance use:*** Actual usage varies with much higher frequencies and intensities than predicted by standardized load profiles.
- ***Seasonal occupancy dependencies:*** Building presence patterns show fluctuations linked to seasonality and personal routines that representative annual profiles fail to isolate.
- ***Weather and personal flexibility:*** The willingness to engage in load shifting is not constant but varies based on weather conditions and private life contingencies, making "*theoretical flexibility*" an extremely volatile resource.

The transition between a successful simulation and a sustainable real-world operation is interrupted by what research defines as the socio-technical "*valley of death*" [67]. This systemic failure stems from three structural underestimations in optimization models:

1. ***Coordination costs:*** The burden of time and resources required to manage assemblies, communications among members, and internal conflict resolution.
2. ***Overestimation of Commitment:*** The assumption that the user maintains a constant level of proactivity over time, ignoring the natural decline in interest or "*participation fatigue*".
3. ***Interpersonal Trust:*** The absence of metrics to measure the strength of social bonds, which act as the "glue" when marginal economic benefits are low.

A simulation model can perfectly predict how an algorithm should handle a load, but it can't predict whether a REC member will stop cooperating because they no longer trust the transparency of governance; without considering the dynamics influenced by trust, even the most efficient algorithm in the world remains an empty architecture.

To bridge this gap, participatory modeling and iterative validation approaches are emerging, integrating qualitative research (interviews, focus groups) with quantitative simulation [76]. While promising, these systematic methodologies remain limited and fragmented.

The positioning of this thesis lies exactly within this methodological fracture. Recognizing that the discrepancy between simulation and reality stems from the "*liquid*" nature of social participation, the model proposed here draws on Moscovici's theory to provide a mathematical structure for the persistence and strength of the active minority's message. The objective is to transform "*coordination cost*" and "*trust*" from random variables into endogenous parameters in the simulation, reducing uncertainty and aligning REC predictions more closely with the complexity of real human behavior.

2.7.6. Summary of research gaps and future perspectives

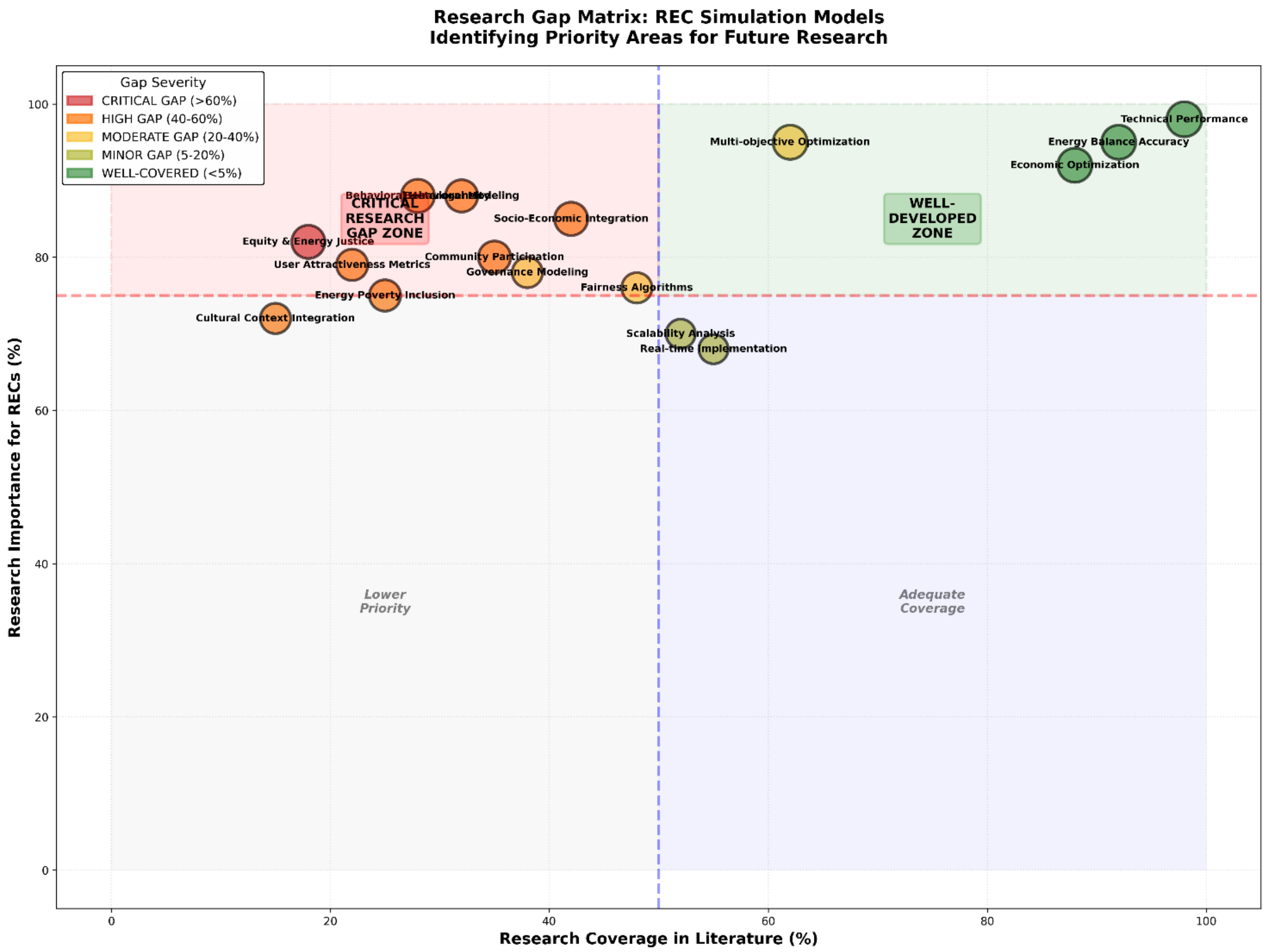

Figure 6: Research Gap Matrix

The systematic literature review conducted thus far enables mapping of the "*terrae incognitae*" in REC research *(Figure 6)*. Although technical progress has been extraordinary, a clear asymmetry emerges between the precision of optimization algorithms and the understanding of the human processes that determine their success. The following priority areas are summarized below, representing not only the limitations of the current state of the art but also the trajectories upon which the methodological innovation of this work is built.

The dimensions of the identified research gaps are as follows:

- ***Authentic Multi-objective Integration:*** Although 62% of models claim multi-objective formulations, the simultaneous optimization of technical, economic, social, and environmental criteria remains an exception. Common practice resorts to sequential compromises or the "weighted sum" of different objectives into a single utility function. This approach flattens the intrinsic tensions between, for example, profit maximization and social equity. The future perspective requires true multi-criteria optimization capable of navigating along the "*Pareto frontier*" of possible solutions.
- ***Socio-Behavioral Frontier:*** The most evident gap consists of the marginalization of social psychology and behavioral economics. Without accurate modeling of how individuals perceive risk, trust, and reciprocity, agent-based simulations remain empty boxes. The predictive accuracy of energy policies depends on the ability to translate organizational theories into standardized algorithmic rules.
- ***Governance and Institutional Representation:*** Most current implementations overlook the role of decision-making structures. An REC managed through direct democracy exhibits response dynamics and coordination times radically different from those managed by a delegated aggregator. Empirical validation of the link between different governance architectures and long-term member satisfaction remains lacking.

A fundamental turning point for future research concerns the explicit integration of Energy Justice principles. An REC is not sustainable if it is not perceived as fair. This dimension is divided into three pillars that simulations should begin to measure quantitatively *(Table 9)*:

Table 9: Future Research of Energy Justice Principles

Justice Dimension	Modeling Focus	Simulation Objective
Distributive Justice	Equitable distribution of costs and benefits.	Avoid wealth concentration among wealthier prosumers.
Procedural Justice	Inclusive decision-making process.	Represent voting weight and rule transparency.
Recognition Justice	Respect for diverse values and identities.	Integrate agents with non-economic motivations (e.g., ethical or environmental).

Finally, the development of attractiveness indices based on empirical data constitutes the key to predicting the territorial expansion of RECs. Communities do not grow in a vacuum; their ability to attract external users depends on a set of socio-economic signals that include the ease of technology use, the social proof of neighbors, and the perceived solidity of the organization. Integrating these indices into multi-agent models would enable simulation not only of energy management but also of the community's actual demographic evolution, providing vital information for local economic development strategies.

The synthesis of these gaps suggests that the "*next generation*" of REC simulators must be holistic: no longer simple solvers of electrical flows, but virtual laboratories where physics, economics, and sociology converge to test the resilience of communities in the real world.

2.8. Conclusions

The literature review conducted in this second chapter has enabled the mapping of an extremely sophisticated yet still deeply fragmented modeling ecosystem. The current landscape of REC simulations spans a spectrum that ranges from the deterministic rigor of linear programming to the emerging dynamism of multi-agent systems.

The analysis has confirmed that there is no "*universal*" tool, but rather a specialized toolbox:

- ***Linear Models (LP):*** Tools such as RECON or MATLAB-based frameworks remain the pillars of preliminary assessment. Their strength lies in computational efficiency and the reliability of aggregate metrics (energy produced, annual costs), with error margins often below 15%. However, their "*top-down*" nature tends to ignore real-world frictions.
- ***Multi-Agent Systems (MAS):*** These represent the frontier for exploring distributive dynamics and governance. While they excel at describing member heterogeneity, they suffer from a "*reality gap*" between simulation and practice, necessitating extremely burdensome validation and sensitivity analyses to avoid lapsing into purely theoretical abstractions.

Despite the sophistication of the algorithms, the identified gaps, particularly limited behavioral modeling, the absence of equity metrics, and the inadequate representation of attractiveness for external stakeholders, highlight a persistent disciplinary boundary. Research on energy systems has remained confined to silos for too long:

We have simulation models capable of predicting an electron's behavior with millimeter precision, yet we still struggle to understand whether a community member will trust other members of their energy community.

This asymmetry is not only an academic limitation but also a practical obstacle to the energy transition. An REC that fails to attract new members or fails to address energy poverty is destined to fail, regardless of the efficiency of its photovoltaic panels.

To advance simulation capabilities toward concrete utility, it is imperative to break down the barriers between engineering, economics, behavioral sciences, and social justice. Integrating these domains is a complex methodological challenge, yet essential for developing models that are not only "*accurate*" but also "*just*" and "*sustainable*".

In conclusion, this chapter has clarified that the future of RECs depends not only on optimizing silicon but also on orchestrating human participation. It is precisely upon this ridge that the methodological proposal of this thesis is built: the use of Moscovici's Social Influence Theory as the "*glue*" to integrate active minority dynamics into the heart of a multi-agent system, transforming energy simulation into a true laboratory for social transformation.

2.9. References

[1] S. Chaudhry, A. Surmann, M. Kühnbach, e F. Pierie, «Renewable Energy Communities as Modes of Collective Prosumership: A Multi-Disciplinary Assessment, Part I—Methodology», *Energies*, vol. 15, fasc. 23, nov. 2022, doi: 10.3390/en15238902.

[2] A. Presciutti, L. Fagotti, L. Martiniello, e E. Moretti, «Simulation Tools for Renewable Energy Communities: A Comparative Multi-Scenario Analysis in Residential Contexts with High Energy Sharing Potential», *Energies*, vol. 19, fasc. 6, mar. 2026, doi: 10.3390/en19061490.

[3] S. Sanfilippo, «Multi-Method Simulation and Optimisation for Maximising Benefits in Renewable Energy Communities: A Real-World Case Study from Italy», *Balt. J. Mod. Comput.*, vol. 13, fasc. 1, 2025, doi: 10.22364/bjmc.2025.13.1.11.

[4] F. Vecchi, R. Stasi, e U. Berardi, «Modelling tools for the assessment of Renewable Energy Communities», *Energy Rep.*, vol. 11, pp. 3941–3962, giu. 2024, doi: 10.1016/j.egyr.2024.03.048.

[5] A. Presciutti, E. Moretti, e L. Fagotti, «Comparative analysis of Renewable Energy Community simulators», *J. Phys. Conf. Ser.*, vol. 3143, fasc. 1, p. 012110, dic. 2025, doi: 10.1088/1742-6596/3143/1/012110.

[6] Y. Sofia *et al.*, «The Role of Energy Communities in the Achievement of a Region's Energy Goals: The Case of a Southeast Mediterranean Region», *Energies*, vol. 18, fasc. 6, mar. 2025, doi: 10.3390/en18061327.

[7] Department of Electric Power Engineering. Budapest University of Technology and Economics. Hungary, B. Molnar, e I. Vokony, «Mathematical modelling of renewable energy communities for energy- economic assessment», *Renew. Energ. Environ. Power Qual. J.*, vol. 3, fasc. 2, pp. 258–263, lug. 2025, doi: 10.24084/reepqj25-422.

[8] V. Kachhad, A. Joshi, e L. Glielmo, «Techno-Economic Modelling and Component Sizing in Renewable Energy Communities: A Participant Perspective», 19 novembre 2025, *arXiv*: arXiv:2511.15321. doi: 10.48550/arXiv.2511.15321.

[9] B. Fina, C. Monsberger, e H. Auer, «Simulation or estimation?—Two approaches to calculate financial benefits of energy communities», *J. Clean. Prod.*, vol. 330, p. 129733, gen. 2022, doi: 10.1016/j.jclepro.2021.129733.

[10] K. A. Tahir, «A Systematic Review and Evolutionary Analysis of the Optimization Techniques and Software Tools in Hybrid Microgrid Systems», *Energies*, vol. 18, fasc. 7, apr. 2025, doi: 10.3390/en18071770.

[11] L. Becchi *et al.*, «GPT-Powered Chatbot for Dissemination and Simulation of Renewable Energy Communities», in *2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, lug. 2025, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope64998.2025.11169160.

[12] D. Diassy, F. Sow, M. Sam, J. J. Faye, e M. L. Samb, «Dynamic Optimization of Electricity Tariffs in Senegal: A Pyomo-Based Model for a Resilient Renewable Energy Mix Toward 2050», *Int. J. Energy Power Eng.*, vol. 15, fasc. 1, pp. 27–36, gen. 2026, doi: 10.11648/j.ijepe.20261501.12.

[13] M. Alvin, L. M. Putranto, B. Sugiyantoro, e A. E. Syukral Siregar, «Generation Expansion Planning for the Kalimantan Interconnected System Considering the Renewable Energy Mix and Carbon Dioxide Emissions Targets», in *2024 16th International Conference on Information Technology and Electrical Engineering (ICITEE)*, ott. 2024, pp. 224–229. doi: 10.1109/ICITEE62483.2024.10808408.

[14] S. Lozza, M. Caldera, D. Fava, M. Ferrando, e F. Causone, «Modeling Retail Buildings Within Renewable Energy Communities: Generation and Implementation of Reference Energy Use Profiles», *Energies*, vol. 18, fasc. 9, mag. 2025, doi: 10.3390/en18092368.

[15] «RECON», RECON. Consultato: 25 marzo 2026. [Online]. Disponibile su: https://recon.smartenergycommunity.enea.it

[16] S. Sulistyono, F. A. Pamuji, e H. Suryoatmojo, «Optimization of Hybrid Renewable Energy Potential in Southeast Sulawesi Using HOMER PRO», in *2025 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)*, mag. 2025, pp. 1–6. doi: 10.1109/AIMS66189.2025.11229514.
[17] G. Datseris, A. R. Vahdati, e T. C. DuBois, «Agents.jl: a performant and feature-full agent-based modeling software of minimal code complexity», *SIMULATION*, vol. 100, fasc. 10, pp. 1019–1031, ott. 2024, doi: 10.1177/00375497211068820.
[18] A. Rollo *et al.*, «Load Shifting and Demand-Side Management in Renewable Energy Communities: Simulations of Different Technological Configurations», *Energies*, vol. 18, fasc. 4, feb. 2025, doi: 10.3390/en18040872.
[19] A. Minieri *et al.*, «A Comprehensive Energy Management Tool for Renewable Energy Communities: Modeling PV Production, Building Demand, and Shiftable DHW Scenarios», in *2025 International Conference on Clean Electrical Power (ICCEP)*, giu. 2025, pp. 892–901. doi: 10.1109/ICCEP65222.2025.11143678.
[20] P. Lazzeroni, L. Giaccone, G. Lorenti, A. Canova, e M. Repetto, «The impacts of energy community members' willingness to adapt their energy behavior: economic, environmental and social perspectives», in *2025 International Conference on Clean Electrical Power (ICCEP)*, giu. 2025, pp. 370–377. doi: 10.1109/ICCEP65222.2025.11143738.
[21] D. Fioriti, T. Ferrucci, e D. Poli, «Fairness and reward in Energy Communities: game-theory versus simplified approaches», in *2023 IEEE International Conference on Environment and Electrical Engineering and 2023 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, giu. 2023, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope57605.2023.10194696.
[22] N. Frieß, U. Pferschy, D. Raese, e J. Schauer, «Assessing the potential of forecast-based optimization in renewable energy communities with flexible electricity, heat and mobility resources», *Appl. Energy*, vol. 401, p. 126664, dic. 2025, doi: 10.1016/j.apenergy.2025.126664.
[23] R. Rugani, V. Consolo, e M. Raugi, «A Validated Simulation Approach for Electricity Demand and Energy Sharing in a School-Based Renewable Energy Community», in *2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, lug. 2025, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope64998.2025.11168983.
[24] R. Sudhoff, S. Schreck, S. Thiem, e S. Niessen, «Achieving grid-friendly operation of renewable energy communities through smart usage of electric vehicle charging and flexibilities», in *CIRED Porto Workshop 2022: E-mobility and power distribution systems*, giu. 2022, pp. 103–107. doi: 10.1049/icp.2022.0672.
[25] R. Yao, Y. Hu, e L. Varga, «Applications of Agent-Based Methods in Multi-Energy Systems—A Systematic Literature Review», *Energies*, vol. 16, fasc. 5, mar. 2023, doi: 10.3390/en16052456.
[26] T. Fonseca *et al.*, «Control of Renewable Energy Communities using AI and Real-World Data», in *2025 IEEE 30th International Conference on Emerging Technologies and Factory Automation (ETFA)*, set. 2025, pp. 1–8. doi: 10.1109/ETFA65518.2025.11205562.
[27] M. Bielecki, E. Neska, e A. Kowalska-Pyzalska, «"Why would I bother?" Understanding prosumer motivations and engagement in renewable energy communities: a qualitative study of polish photovoltaic installation owners», *Front. Energy Res.*, vol. 13, ago. 2025, doi: 10.3389/fenrg.2025.1500038.
[28] C. Schimeczek *et al.*, «AMIRIS: Agent-based Market model for the Investigation of Renewable and Integrated energy Systems», *J. Open Source Softw.*, vol. 8, fasc. 84, p. 5041, apr. 2023, doi: 10.21105/joss.05041.
[29] M. Hamidi, A. Raihani, e O. Bouattane, «Sustainable Intelligent Energy Management System for Microgrid Using Multi-Agent Systems: A Case Study», *Sustainability*, vol. 15, fasc. 16, ago. 2023, doi: 10.3390/su151612546.

[30] «Jade Site | Java Agent DEvelopment Framework». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://jade.tilab.com/
[31] M. Azeroual, T. Lamhamdi, H. El Moussaoui, e H. El Markhi, «Simulation tools for a smart grid and energy management for microgrid with wind power using multi-agent system», *Wind Eng.*, vol. 44, fasc. 6, pp. 661–672, dic. 2020, doi: 10.1177/0309524X19862755.
[32] H. Suguri, «A standardization effort for agent technologies: The Foundation for Intelligent Physical Agents and its activities», in *Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. 1999. HICSS-32. Abstracts and CD-ROM of Full Papers*, gen. 1999, p. 10 pp.-. doi: 10.1109/HICSS.1999.773093.
[33] «Simulink - Simulation and Model-Based Design». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://www.mathworks.com/products/simulink.html
[34] «Repast Suite Documentation». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://repast.github.io/
[35] Z. Ma, M. Værbak, e B. Nørregaard Jørgensen, «Multi-agent Simulation of Households' Behaviors Towards Hourly Electricity Price Scheme in Denmark», in *2020 IEEE/SICE International Symposium on System Integration (SII)*, gen. 2020, pp. 1081–1087. doi: 10.1109/SII46433.2020.9025957.
[36] S. Team, «SPADE - Python Multi-Agent Framework | Smart Agent Development Environment». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://github.com/javipalanca/spade
[37] J. B. Almada, F. L. Tofoli, R. C. F. Gregory, R. F. Sampaio, L. S. Melo, e R. P. S. Leão, «Distributed Multi-Agent Energy Management for Microgrids in a Co-Simulation Framework», *Energies*, vol. 18, fasc. 17, ago. 2025, doi: 10.3390/en18174620.
[38] «Introduction · Agents.jl». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://juliadynamics.github.io/Agents.jl/stable/
[39] «What is reinforcement learning? | IBM». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://www.ibm.com/think/topics/reinforcement-learning
[40] S. Liu, J. He, e J. Wu, «Dynamic Cooperative Spectrum Sensing Based on Deep Multi-User Reinforcement Learning», *Appl. Sci.*, vol. 11, fasc. 4, feb. 2021, doi: 10.3390/app11041884.
[41] M. Churchill, J. Monroe, D. Bristow, e C. Crawford, «Using electric vehicles to enhance power outage resilience – An agent-based modeling approach», *Heliyon*, vol. 10, fasc. 11, giu. 2024, doi: 10.1016/j.heliyon.2024.e32104.
[42] «Multi-Agent Reinforcement Learning: Foundations and Modern Approaches». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://www.marl-book.com/
[43] I. Brahmia e A. Amrani, «Hierarchical Smart Energy Management Framework Based on Multi-Agent RL and Distributed MPC for Peer-to-Peer Energy Sharing Communities», in *2025 8th International Conference on Electrical Engineering and Green Energy (CEEGE)*, lug. 2025, pp. 372–377. doi: 10.1109/CEEGE66246.2025.11182327.
[44] «Soft Actor-Critic — Spinning Up documentation». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://spinningup.openai.com/en/latest/algorithms/sac.html
[45] «Proximal Policy Optimization — Spinning Up documentation». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://spinningup.openai.com/en/latest/algorithms/ppo.html
[46] Y. Wan, J. Qin, Y. Shi, W. Fu, e F. Xiao, «Stackelberg–Nash game approach for price-based demand response in retail electricity trading», *Int. J. Electr. Power Energy Syst.*, vol. 155, p. 109577, gen. 2024, doi: 10.1016/j.ijepes.2023.109577.
[47] Y. Chen, J. Li, Z. Fang, N. Zhang, T. Huang, e Z. Chen, «Low-carbon optimal scheduling strategy for multi-agent integrated energy system of the park based on Stackelberg–Nash game», doi: 10.1049/esi2.12164.
[48] C. Di Biccari, F. Calcerano, F. D'Uffizi, A. Esposito, M. Campari, e E. Gigliarelli, «Building information modeling and building performance simulation interoperability: State-of-the-art and

trends in current literature», *Adv. Eng. Inform.*, vol. 54, p. 101753, ott. 2022, doi: 10.1016/j.aei.2022.101753.
[49] E. Belloni, D. Fioriti, D. Poli, e A. Tumiati, «Electric Mobility integrated in Renewable Energy Communities: technical/economic modelling and performance analysis», in *2024 IEEE 22nd Mediterranean Electrotechnical Conference (MELECON)*, giu. 2024, pp. 938–943. doi: 10.1109/MELECON56669.2024.10608577.
[50] L. Barbaro, D. Vitella, G. Battista, E. de L. Vollaro, e R. de L. Vollaro, «Enhancing Urban Energy Independence via Renewable Energy Communities: A GIS-Based Optimization of the Flaminio Stadium District in Rome», *Appl. Sci.*, vol. 16, fasc. 6, mar. 2026, doi: 10.3390/app16062732.
[51] «HOMER Pro - Microgrid Optimization Software». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://homerenergy.com/homer-pro
[52] «pandapower», pandapower. Consultato: 26 marzo 2026. [Online]. Disponibile su: https://www.pandapower.org/
[53] «Methods - Joint Research Centre - European Commission». Consultato: 26 marzo 2026. [Online]. Disponibile su: https://joint-research-centre.ec.europa.eu/sensitivity-analysis-samo/methods_en
[54] N. Collura, F. Massaro, E. Di Mambro, S. Paradiso, F. Montana, e A. Buscemi, «Optimization of a Battery Energy Storage System in a Sicilian Renewable Energy Zone», in *2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, lug. 2025, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope64998.2025.11169168.
[55] Y. Tang, Q. Yuan, P. Yang, X. Wang, G. Wang, e M. Yan, «Optimal Non-Anticipative All-Scenario-Feasible Scheduling Strategy for Community Microgrid With Vehicle-to-Grid Energy Storages», *IEEE Trans. Autom. Sci. Eng.*, vol. 23, pp. 5387–5400, 2026, doi: 10.1109/TASE.2026.3666562.
[56] «Energy trading and control of islanded DC microgrid using multi-agent systems - Diana Rwegasira, Imed Ben Dhaou, Masoumeh Ebrahimi, Anders Hallén, Nerey Mvungi, Hannu Tenhunen, 2021». Consultato: 25 marzo 2026. [Online]. Disponibile su: https://journals.sagepub.com/doi/abs/10.3233/MGS-210345
[57] G. Barone *et al.*, «Enabling Technologies for Near Zero Power Renewable Energy Communities Model to Increase RES Penetration and Support the Electrical Power System», in *2024 International Conference on Smart Energy Systems and Technologies (SEST)*, set. 2024, pp. 1–6. doi: 10.1109/SEST61601.2024.10693999.
[58] R. Biack, B. Ndzana, e J. Etame, «Renewable energy communities in central Africa: Towards a hybrid model, tariff impacts, energy justice and local governance», *World J. Adv. Res. Rev.*, vol. 29, fasc. 3, pp. 1155–1185, 2026, doi: 10.30574/wjarr.2026.29.3.0602.
[59] L. Otte, N. Schöne, A. Flessa, P. Fragkos, e B. Heinz, «Costs and Benefits of Citizen Participation in the Energy Transition: Investigating the Economic Viability of Prosumers on Islands—The Case of Mayotte», *Energies*, vol. 17, fasc. 12, giu. 2024, doi: 10.3390/en17122904.
[60] I. F. G. Reis, I. Gonçalves, M. A. R. Lopes, e C. H. Antunes, «Residential demand-side flexibility in energy communities: a combination of optimization and agent modeling approaches», in *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, set. 2019, pp. 1–6. doi: 10.1109/SEST.2019.8849152.
[61] A. Sanfilippo, A. Boumaiza, S. Shannak, e S. Qarnain, «The Impact of Regulatory Frameworks on Peer-to-Peer Energy Trading and Prosumer Rewards in Energy Communities», in *IECON 2024 - 50th Annual Conference of the IEEE Industrial Electronics Society*, nov. 2024, pp. 1–7. doi: 10.1109/IECON55916.2024.10905350.
[62] D. V. Guimarães, M. B. Gough, S. F. Santos, I. F. G. Reis, J. M. Home-Ortiz, e J. P. S. Catalão, «Agent-Based Modeling of Peer-to-Peer Energy Trading in a Smart Grid

Environment», in *2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, set. 2021, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope51590.2021.9584767.
[63] F. Luo, Z. Y. Dong, G. Liang, J. Murata, e Z. Xu, «A Distributed Electricity Trading System in Active Distribution Networks Based on Multi-Agent Coalition and Blockchain», *IEEE Trans. Power Syst.*, vol. 34, fasc. 5, pp. 4097–4108, set. 2019, doi: 10.1109/TPWRS.2018.2876612.
[64] G. Plancke, K. De Vos, R. Belmans, e A. Delnooz, «Virtual power plants: Definition, applications and barriers to the implementation in the distribution system», in *2015 12th International Conference on the European Energy Market (EEM)*, mag. 2015, pp. 1–5. doi: 10.1109/EEM.2015.7216693.
[65] N. Pezzati, E. Innocenti, L. Berzi, e M. Delogu, «Scalable Energy Management Model for Integrating V2G Capabilities into Renewable Energy Communities», *World Electr. Veh. J.*, vol. 16, fasc. 8, ago. 2025, doi: 10.3390/wevj16080450.
[66] B. P. Koirala, Y. Araghi, M. Kroesen, A. Ghorbani, R. A. Hakvoort, e P. M. Herder, «Trust, awareness, and independence: Insights from a socio-psychological factor analysis of citizen knowledge and participation in community energy systems», *Energy Res. Soc. Sci.*, vol. 38, pp. 33–40, apr. 2018, doi: 10.1016/j.erss.2018.01.009.
[67] P. Tobin e B. Lennon, «All together now: building resilient citizen energy communities through collaborative learning», *Environ. Res. Energy*, vol. 2, fasc. 2, p. 025015, giu. 2025, doi: 10.1088/2753-3751/ade3e0.
[68] «Povertà energetica: Politiche europee e opportunità per comuni e regioni | BUILD UP». Consultato: 27 marzo 2026. [Online]. Disponibile su: https://build-up.ec.europa.eu/it/resources-and-tools/publications/poverta-energetica-politiche-europee-e-opportunita-comuni-e
[69] F. Cumo, P. Maurelli, E. Pennacchia, e F. Rosa, «Urban Renewable Energy Communities and Energy Poverty: a proactive approach to energy transition with Sun4All project», *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1073, fasc. 1, p. 012011, set. 2022, doi: 10.1088/1755-1315/1073/1/012011.
[70] S. Stoklin, J. H. Forrester, M. L. Lopez, e M. Zanchiello, «Measuring and Mitigating Energy Poverty: Developing a New Index and Assessing the Impact of Renewable Energy Communities on Energy Poverty», in *2025 AEIT International Annual Conference (AEIT)*, set. 2025, pp. 1–6. doi: 10.23919/AEIT67669.2025.11218098.
[71] D. Fioriti, D. Poli, e A. Frangioni, «A bi-level formulation to help aggregators size Energy Communities: a proposal for virtual and physical Closed Distribution Systems», in *2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, set. 2021, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope51590.2021.9584536.
[72] «Establishment of local energy areas/communities: Barriers and solutions», Open Access Government. Consultato: 27 marzo 2026. [Online]. Disponibile su: https://www.openaccessgovernment.org/article/establishment-of-local-energy-areas-communities-barriers-and-solutions/188073/
[73] M. Bolesnikov, H. Banerji, e Swiss School of Business and Management, Geneva, Switzerland, «DIGITAL TRANSFORMATION STRATEGY DYNAMIC FOR UTILITY SMART GRIDS: SYSTEM DYNAMICS MODELLING IN UNTANGLING COMPLEXITY», presentato al INTERNATIONAL Conference on Business, Management, and Economics Engineering Future-BME, 2025, pp. 724–732. doi: 10.24867/FUTURE-BME-2024-082.
[74] P. Vuthi, I. Peters, e J. Sudeikat, «Agent-based modeling (ABM) for urban neighborhood energy systems: literature review and proposal for an all integrative ABM approach», *Energy Inform.*, vol. 5, fasc. 4, p. 55, dic. 2022, doi: 10.1186/s42162-022-00247-y.
[75] A. F. dos Santos e J. T. Saraiva, «An Agent Based Model Applied to a Local Energy Market (LEM) Considering Demand Response (DR) and Its Interaction with the Wholesale Market

(WSM)», in *2024 20th International Conference on the European Energy Market (EEM)*, giu. 2024, pp. 1–6. doi: 10.1109/EEM60825.2024.10608884.
[76] M. Vrachioli *et al.*, «WEFE nexus unveiled: a comprehensive review of monitoring and modelling methods in the water-energy-food-ecosystems nexus», *Environ. Res. Lett.*, vol. 20, fasc. 11, p. 113005, ott. 2025, doi: 10.1088/1748-9326/ae0da3.

3. Methodology and Model Architecture

This chapter constitutes the analytical and design core of this thesis, serving as the logical and methodological transition from the theoretical assumptions and limitations of the previous chapter to the construction of an original, multidimensional research tool. While the critical review of simulation models for Renewable Energy Communities (RECs) highlighted a chronic fragmentation between technical and social dimensions, this chapter aims to present the architecture of a framework capable of mending this rift. The methodological narrative that follows is intended to guide the reader through the model's complex stratification, illustrating how energy physics, economic variables, and psychosocial dynamics intertwine within a single, coherent computational environment.

The opening of the chapter explains the methodological approach based on Agent-Based Modeling (ABM), a choice that constitutes the ontological foundation of this research. This section delves into why the bottom-up paradigm is the only one capable of capturing the emergence of complex behaviors within an REC, treated not as a static aggregate but as a Complex Adaptive System (CAS) [1]. Subsequently, the discussion shifts to the definition of the simulation environment, in which geographical space coordinates, hourly time steps, and exogenous drivers, such as climate data and regulatory regimes, delimit the operational perimeter within which the actors move. The formalization of these actors is addressed in the section on agent ontology and characterization, which defines the distinctive traits, decision-making faculties, and load profiles that make each community member a unique and interactive entity.

The technical heart of the framework is examined by describing the functional modules that compose the architecture. It begins with the physico-energetic module, responsible for calculating production and consumption flows, and leads into the economic comparison module, which allows evaluation of benefits under different incentive regimes. A particularly significant element is the comparative analysis of dynamics and the module dedicated to dynamic energy price shocks, designed to test community resilience in the face of geopolitical crises or market volatility. This technical section concludes with the financial module, which performs investment analysis and calculates Key Performance Indicators (KPIs), essential tools for translating simulation results into metrics of economic and temporal sustainability.

The final part of the chapter addresses the model's most ambitious challenge: integrating the socio-technical dimension. Through the module dedicated to behavioral dynamics and influence theory, it explains how Moscovici's psychological laws of the active minority have been translated into social interaction algorithms. Finally, the chapter closes with a description of the validation protocols and sensitivity analysis, rigorous steps necessary to ensure the scientific reliability of the simulator and the robustness of the resulting conclusions. The entire chapter thus aims to provide a holistic and detailed view of the research infrastructure, setting the stage for the analysis of the experimental results that will constitute the final part of this work.

3.1. Methodological Approach: Agent-Based Modeling (ABM)

The architecture of the simulator developed has been conceived following the Agent-Based Modeling (ABM) paradigm, a methodological choice that marks a clear departure from the traditional top-down modeling approaches prevalent in classical energy literature. While conventional modeling tends to describe complex systems through aggregated equations and equilibrium functions that impose a predetermined collective behavior, the bottom-up approach of ABM allows for a radical inversion of the analytical perspective. Within this framework, the REC system is no longer treated as a monolithic entity or a simple passive receiver of economic directives, but rather as a Complex Adaptive System (CAS) [1]. In such a digital ecosystem, macroscopic complexity is not an input datum inserted *a priori* by the researcher; instead, it represents the emergent result of local interactions and dynamics among a population of heterogeneous agents, each endowed with decision-making autonomy, specific social attributes, and often divergent individual goals.

In this modeling context, critical variables for the project's success, such as the adoption curve of photovoltaic technologies, the community's aggregated energy balance, or long-term financial stability, are not constrained by predetermined statistical functions. Instead, they "*emerge*" spontaneously from the intersection of the micro-economic choices of individual members (whether they are prosumers or consumers), their social interactions, and the physical constraints of the environment. This fundamental shift from equilibrium modeling to process modeling is essential for capturing the non-linear dynamics typical of energy communities. In an REC, the behavior of a single user can generate feedback loops capable of drastically influencing the efficiency and convenience of the entire collective. For instance, a company's decision to shift its production loads or a group of citizens' decision to join the community under the influence of an active minority does not just produce a local effect; it also alters the distribution of incentives and grid resilience for all other participants.

To provide an operational form to this multidisciplinary vision, the simulator operates on a rigorous dual logical track that allows the certainty of technical data to coexist with the unpredictability of social data. On the one hand, the model integrates deterministic logic, necessary to represent aspects governed by the laws of physics or rigid regulatory frameworks. This section of the code contains algorithms for calculating the Sun’s orbital trajectory, which are indispensable for determining specific irradiation based on the climate zone, as well as the tariff and incentive structures defined by national regulators (such as the GSE in Italy or the Net Billing system in Spain). This component ensures that the "*playing field*" in which REC members act is physically and legally consistent, providing a technical baseline of truth upon which evolutionary dynamics are grafted.

On the other hand, the simulator adopts a stochastic logic to represent the intrinsic uncertainty of the human factor and the variability of socio-economic contexts. This probabilistic component is crucial for reflecting the actual complexity of contemporary social systems: variables such as participants' income heterogeneity, the diverse psychological thresholds guiding the acceptance of new technology, or the volatility of daily consumption profiles are not treated as statistical errors to be averaged out, but as the true engines of system diversity. The integration of these two levels, technical determinism and social stochasticity, transforms this thesis into a genuine virtual laboratory. In this protected environment, the precision of engineering data merges with the variability of human behavior, providing an advanced research platform to test REC resilience under turbulent market conditions, such as energy price fluctuations caused by geopolitical crises. This ensures a model validation that is simultaneously scientifically rigorous and socially relevant.

3.2. The Simulation Environment: Space, Time, and Exogenous Forcings

Within an Agent-Based Model (ABM), the simulated actors never operate in an isolated vacuum or a purely theoretical abstraction; rather, they act within a structural and dynamic framework defined as the Simulation Environment. The correct coding and parameterization of this environment represent critical steps to ensure the so-called ecological validity of the model, namely, its intrinsic capacity to faithfully and scientifically approximate the real operational conditions, physical constraints, and external pressures to which the system is subjected in reality. In the simulator presented here, the environment is not merely an inert backdrop; it fulfills a dual, fundamental, and interconnected function. On the one hand, it provides the logical and relational substrate necessary for the unfolding of interactions among agents, whether they involve energy flow exchanges, financial transactions, or the transmission of socio-behavioral influences. On the other hand, it acts as the primary vector for exogenous drivers. These comprise the set of all macroscopic variables, physical, climatic, or market-based, which, while not alterable by agent decisions, heavily condition their decision-making processes and operational outcomes.

Given the inherently multidisciplinary nature of a REC, which merges electrical systems engineering with social psychology and energy economics, the environmental architecture of this model has been conceived according to multidimensional logic. To capture such complexity without incurring a prohibitive computational burden, the environment has been formalized and parameterized along three main axes that define the boundaries of action within the digital world in which the simulation unfolds.

The first pillar of the simulation environment is the Spatial Domain, which defines the topological rules governing distances and logical connections between production nodes and consumption points. In this model, space is not a simple Euclidean geographic extension, but a map of relations regulated by the reference regulatory frameworks. To enable comparison between the Italian and Spanish contexts, the simulator manages the spatial domain flexibly: in Italian mode, space is defined by membership in the same Primary Substation, an electrotechnical constraint that determines members' eligibility for energy sharing. In Spanish mode, however, the spatial domain adopts a radial proximity logic, calculating physical distances within the 2,000-meter limit established by *Real Decreto-ley 18/2022*. This spatial modeling allows evaluation of how urban density and load distribution influence the "*active minority's*" ability to recruit new members, as physical or electrical proximity facilitates trust-building and the technical optimization of energy exchanges.

The second supporting axis is represented by the Temporal Domain, the management of which is complicated by the need to synchronize phenomena operating at radically different frequencies. Time discretization in the simulator follows multi-scale logic: energy flows and electrical physics are modeled at hourly resolution, which is indispensable for accurately calculating collective self-consumption and the synchrony between photovoltaic production and grid withdrawals. However, the agents' decision-making processes, such as choosing to invest in plants, to join the REC, or to withdraw from the contract, occur annually. The temporal domain must therefore act as a dynamic integrator, accumulating hourly energy and financial performance results and submitting them annually for agent evaluation. This temporal pacing also allows for modeling the community's evolution over the long term, typically over a twenty-year horizon coinciding with the duration of incentives and observing the slow but profound "*conversion*" induced by Moscovici's social influence and the progressive depreciation of invested capital.

The third environmental pillar, defined as the Exogenous and Climatic Domain, represents the interface between the REC's closed system and the turbulence of the outside world. This axis governs the impact of geographic and meteorological conditions, integrating data specific to the climate zone to accurately calculate solar irradiation and the thermal modulation needs of buildings. Through the use of algorithms that simulate the Sun's orbital trajectory and the incidence of rays on the capturing surface, the simulator determines the potential energy production for every hour of the year. Simultaneously, the exogenous domain serves as a market-shock generator, allowing the user to input stochastic or deterministic variables related to energy prices. In this section, stress tests linked to geopolitical crises are modeled, simulating sudden spikes in the National Single Price (PUN) or tariff fluctuations that test the economic resilience of the agents. The integration of these external drivers ensures that the simulation is not an idealized projection but a robust sensitivity analysis that demonstrates how the REC can act as a social buffer precisely when the external environment becomes hostile and unpredictable.

3.2.1. Spatial Topology

The environment is represented by a discrete two-dimensional space (toroidal grid). Although the physical position (x, y) of the agents is visualized to facilitate graphical analysis, the functional topology is that of a virtual star network: each member of the REC is logically connected to a central node (the GSE/Grid) which manages both physical and administrative balancing. There is no direct physical peer-to-peer energy exchange (i.e., physical cables between houses), but rather virtual sharing mediated by the public distribution network.

3.2.2. Multi-Scale Temporal Resolution

The model operates on two distinct yet intertwined time scales:

1. ***Micro-Scale (Hourly, t):*** The base simulation step (tick) corresponds to 1 hour. This scale handles physical processes (production, consumption) and operational economic calculations (energy valuation).

$$\textbf{\textit{Time Horizon:}}\ T_{total=20\ years \cdot 8760^{h}/_{year}}$$

2. ***Macro-Scale (Annual, Y):*** Every 8760 ticks, the system performs low-frequency state updates: asset aging, calculation of financial KPIs (e.g., Payback Period), and the activation of psycho-social dynamics (enrollment/exit).

3.2.3. Climatic and Geographic Context

The environment is parameterized by a global variable $Z_{clim} \in \{A, B, C, D, E, F\}$ corresponding to the Italian climatic zones (or Spanish equivalents). According to the Italian regulatory framework, specifically the Presidential Decree (D.P.R.) No. 412 of August 26, 1993, this classification divides the national territory into six distinct areas based on the concept of Degree Days (DD). The Degree Day is a quantitative climate index representing the sum of the positive differences between a conventional indoor temperature (set at 20°C) and the mean daily outdoor temperature, calculated over a conventional annual heating period.

The classification *(Table 10)* determines the severity of the local climate and defines the physical constraints for the environment:

Table 10: Climatic Zone's Classification

Climatic Zone	Degree Days (DD) Thresholds	Typical Climate Context
Zone A	DD ≤ 600	Very warm winters (e.g., Lampedusa, Linosa)
Zone B	600 < DD ≤ 900	Warm winters (e.g., Palermo, Trapani)
Zone C	900 < DD ≤ 1400	Mild winters (e.g., Cagliari, Naples)
Zone D	1400 < DD ≤ 2100	Temperate winters (e.g., Rome, Florence)
Zone E	2100 < DD ≤ 3000	Cold winters (e.g., Milan, Turin)
Zone F	DD > 3000	Severe/Alpine winters (e.g., Cuneo, Belluno)

Within the simulation architecture, this variable acts as an exogenous forcing on two fundamental parameters:

- ***Photovoltaic Productivity:*** It modulates the incident solar irradiance and temperature derating factors according to the specific geographical area.
- ***Load Profile:*** It activates or deactivates the seasonal heating and cooling demand, dynamically scaling the baseline energy consumption curves based on the climatic severity of the selected zone.

3.3. Ontology and Formal Characterization of Agents

While the Simulation Environment defines the spatial, temporal, and regulatory "*stage*" of the system, the Agents constitute its computational and behavioral engine. The Agent-Based Modeling (ABM) paradigm adopts a strictly bottom-up approach: the macroscopic phenomena observed at the Renewable Energy Community level (such as the aggregate balance, the systemic Payback Period, or adoption curves) are not imposed top-down via global differential equations, but rather emerge as collective properties resulting from decentralized interactions and decisions at the micro-foundational level.

The departure from traditional techno-economic optimization models lies precisely in the rejection of the representative agent hypothesis (the so-called perfect and homogeneous *Homo Oeconomicus*) [2]. Instead, the developed simulator embraces the radical heterogeneity and Bounded Rationality of real-world actors.

To translate this heterogeneity into executable code, a rigorous system ontology, a taxonomic classification of the simulated entities, has been defined. Each simulated agent is not a passive logical node, but an autonomous computational entity characterized by a multi-dimensional internal state vector S_i. This vector encapsulates attributes belonging to three fundamental domains:

- ***Physical-Technological:*** Hourly consumption profiles, nominal power of photovoltaic systems (P_{peak}).
- ***Socio-Economic:*** Annual disposable income (I_{annual}), investment capacity, and user type (residential, commercial, academic).
- ***Cognitive-Behavioral:*** Financial tolerance thresholds (θ_i), length of membership in the system, and susceptibility to social influence.

To manage this multiplicity of states and behaviors, the total simulated population ($\mathcal{P}$) has been fragmented and organized into specific functional classes. The following sections will detail the mathematical formalization and operational logic of these macro-categories:

1. ***Active Agents (REC Members):*** The actual members of the system (divided into Prosumers, Producers, and Consumers), who generate physical energy flows and share the economic value created.
2. ***Latent Agents (External Population):*** The pool of users not yet enrolled, who observe the community's performance and represent the target of the social and psychological conversion process mediated by the Moscovici Factor.
3. ***Structural Agent (The GSE / Grid):*** The singular macroscopic entity acting as the regulatory counterpart, applying energy market rules (PUN, premium tariffs, system charges) and ensuring instantaneous system balancing by serving as an infinite source and sink of energy.

In summary, the model population $\mathcal{P}$ is composed of the union of disjoint subsets of agents ("*breeds*"), each characterized by a state vector S_i (3).

3.3.1. Active Agents (REC Members)

Let $\mathcal{M} \subset \mathcal{P}$ be the set of active members. Each member $i \in \mathcal{M}$ is defined by the state vector S_i:

$$S_i = \{Role_i, C_{annual,i}, P_{peak,i}, I_{cap,i}, \theta_i, State_{member}\} \quad (3)$$

The specific classes are:

- ***Prosumer (A_{pros}):*** The pivotal actor.
  - **Characteristics:** Consumption $C_i > 0$ e Production $P_{peak,i} > 0$.
  - **Role:** Partial self-sufficiency and injection of surplus energy for sharing.
- ***Consumer (A_{cons}):*** The passive load.
  - **Characteristics:** Consumption $C_i > 0$ and Production $P_{peak,i} = 0$.
  - **Role:** Providing the necessary demand to maximize shared energy (E_{shared}), which is essential for incentives.
- ***Producer (A_{prod}):*** The pure generator.
  - **Characteristics:** Consumption $C_i \approx 0$ and Production $P_{peak,i} > 0$.
  - **Role:** Maximizing volumetric production to cover the aggregate requirements of the community.

3.3.2. Latent Agents (External Population)

Let $\varepsilon \subset \mathcal{P}$ be the set of external agents (Externals).

These agents do not participate in energy flow but observe the system. Their state includes psycho-economic variables:

- ***Annual Income (R_i):*** Determines investment capacity.
- ***Convenience Threshold (θ_i):*** A scalar value representing the psychological resistance to adoption. This is subject to dynamic modification through the effect of social influence (Moscovici's Theory)[3].

3.3.3. Structural Agent (The GSE / Grid)

There is a single GSE agent (*Gestore dei Servizi Energetici*) that acts as an Infinite Bus.

- ***Topological Function:*** Aggregation node for all links.

- ***Thermodynamic Function:*** Infinite sink for energy ($E_{surplus}$) and infinite source ($E_{deficit}$).
- ***Regulatory Function:*** Implements market rules (Prices, Incentives) according to the selected regulatory framework (Italy vs. Spain).

3.4. Physical-Energetic Module

The Physical-Energy Module constitutes the engineering and thermodynamic substrate of the entire simulator. For the agent-based model to generate realistic economic and behavioral dynamics, it is first necessary to precisely quantify the physical flows of electrical energy (expressed in kilowatt-hours, kWh) that are generated, withdrawn, and exchanged within the grid infrastructure.

Unlike traditional macro-economic models that operate on annual or monthly averages, this module is designed to function at a micro-scale temporal resolution ($\Delta_t = 1\ h$). This methodological choice is not merely a programming preference, but a structural necessity imposed by the very nature of RECs. The conceptual and regulatory core of a REC, namely, virtual collective self-consumption, critically depends on the simultaneity between injection and withdrawal. Using aggregated average values would lead to a systematic overestimation of the shared energy share, ignoring the intrinsic temporal mismatch between the bell-shaped curve of photovoltaic production and the heterogeneous load profiles of users.

The module acts as a synchronous calculation engine that, at each simulation tick, queries the spatial and temporal state of the Environment (Chapter 3.2.) and updates the physical state vectors of each active agent (Chapter 3.3.). The computational process is divided into two distinct phases:

1. ***Individual Resolution Phase (Micro Level):*** Each agent calculates its own isolated energy balance based on its specific technological and behavioral drivers.
2. ***Aggregated Resolution Phase (Macro Level):*** The system calculates the net flows at the virtual Common Coupling Point (CCP) managed by the GSE.

To ensure the ecological validity of the simulation, the equations governing these flows integrate both deterministic logic (laws of solar irradiance) and stochastic/behavioral logic (thermo-climatic modulation of demand).

The following sections detail the mathematical formalization and algorithmic logic of this process through three fundamental steps:

- **1.** ***Photovoltaic Production Modeling:*** Definition of the generation curve based on hourly irradiance, dynamically corrected by climatic forcing and astronomical seasonality.
- **2.** ***Consumption Modeling and Thermal Modulation:*** Structuring of hourly load profiles and implementation of advanced algorithms for simulating thermo-sensitive demand (Heating/Cooling) and users with calendar constraints (school complexes and seasonal tourist residences).
- **3.** ***Aggregate Energy Balance of the REC:*** Systemic calculation of the resulting physical vectors (Shared Energy, Injected Surplus, and Withdrawn Deficit), which serve as the essential input for the subsequent Comparative Economic Module.

3.4.1. Modeling of photovoltaic production

The hourly production of agent i, $E_{i,prod}(t)$ (4), is not deterministic but parametrically modeled by considering installed capacity, geography, and seasonality:

$$E_{i,prod}(t) = P_{i,peak} \cdot I_{base}(h) \cdot M_{clim} \cdot M_{seas}(d) \tag{4}$$

Where:

- $\boldsymbol{P_{i,peak}}$**:** Installed peak power in kWp.
- $\boldsymbol{I_{base}(h)}$**:** Normalized solar irradiance profile for the hour of the day $h = t \ mod\ 24$.
- $\boldsymbol{M_{clim}}$**:** Scalar multiplier depending on the Climatic Zone (A-F), reflecting latitude and average sunshine duration (e.g., Zone A ≈ 1.25, Zone F ≈ 0.65).
- $\boldsymbol{M_{seas}(d)}$**:** Sinusoidal function simulating solar declination throughout the year (day d):

$$M_{seas}(d) = \frac{1 + cos\left(\frac{360°(d-172)}{365}\right)}{1.8} \tag{5}$$

(The peak is centered on day 172, ~June 21st).

3.4.2. Consumption Modeling and Thermal Modulation

The hourly consumption $C_i(t)$ (6) is calculated through a decision-making algorithm that integrates standard load profiles and thermo-climatic modulation:

$$C_i(t) = C_{i,base}(t) \cdot M_{demand}(t, UserType) \tag{6}$$

The demand multiplier M_{demand} (7) varies based on the user category:

A. ***Standard Users (Residential/Offices):*** Demand is influenced by the need for heating (winter) or cooling (summer) as a function of the zone's climatic sensitivity ($S_{clim} \in [-1,1]$) and the modulation depth (α):

$$M_{demand} = 1 + \left(cos\left(\frac{360°(d-172)}{365}\right) \cdot S_{clim} \cdot \alpha\right) \tag{7}$$

B. ***Seasonal Residences and Schools ("On/Off" Logic):*** The model introduces a binary variable $State_{active}(t)$ based on the calendar (tourist or academic).

- ***Tourist Season:*** Defined dynamically: Summer (Jun-Aug) for Zones A-B-C; Winter (Dec-Feb) for Zones D-E-F.
- ***Academic Calendar:*** Open Sept-Jun, with summer closure and winter breaks.

$$C_i(t) = \begin{cases} C_{i,base}(t) \cdot M_{peak} \cdot M_{demand} & if\ State_{active}(t) = 1 \\ C_{i,base}(t) \cdot 0.05 if State_{active}(t) = 0 (Maintenance) \end{cases} \tag{8}$$

3.4.3. REC Aggregate Energy Balance

Every hour t, the aggregate variables are calculated:

1. ***Total Production:*** $E_{REC}(t) = \sum_i E_{i,prod}(t)$
2. ***Total Consumption:*** $C_{REC}(t) = \sum_i C_i(t)$
3. ***Shared Energy (Collective Self-Consumption):*** $E_{shared}(t) = min\big(E_{REC}(t), C_{REC}(t)\big)$
4. ***Grid Exchange:***
    a. **Surplus (Injected):** $E_{surplus}(t) = max\big(0, E_{REC}(t) - C_{REC}(t)\big)$
    b. **Deficit (Withdrawn):** $E_{deficit}(t) = max\big(0, C_{REC}(t) - E_{REC}(t)\big)$

3.5. Economic Comparison Module

The Economic Comparison Module represents the fundamental analytical interface of the simulator, serving as a sophisticated logical-mathematical transducer tasked with converting the physical quantities processed in the previous energy module into tangible monetary flows. While the energy module defines "*how many*" kilowatt-hours are produced, consumed, and instantaneously shared, the economic module assigns a monetary value to these quantities, thereby transforming energy into a vector of economic sustainability and social inclusion. The distinctive feature and greatest scientific significance of this architecture lie in its ability to perform a dynamic switching between two distinct valuation algorithms: the Italian Framework and the Spanish Framework.

This regulatory "*switch*" functionality has been designed to allow for rigorous analysis according to the *ceteris paribus* principle. By keeping the physical and technological substrate of the community strictly unchanged, namely the system size, the climate zone, and the agents' load profiles, the researcher can isolate with surgical precision the impact of the regulatory variable alone on the REC's financial stability. This approach addresses crucial policymaking questions: *given equal irradiation and consumption, which of the two legal systems guarantees a faster return on investment? And which, conversely, offers greater protection to vulnerable members during a price shock?*

In detail, when the simulator operates within the Italian Framework, the calculation algorithm complies with the provisions of *Legislative Decree 199/2021* and subsequent implementing decrees. In this scenario, economic valuation is based on an explicit incentive system. The module calculates the incentive tariff (approx. €0.10/kWh) on shared energy, to which the reimbursement of grid tariff components, as defined by ARERA, is added. This monetary flow is treated as gross revenue that the community, acting as a legal entity, receives via bank transfer from the GSE and must subsequently distribute among members in accordance with shareholders' agreements. The underlying logic is to incentivize the synchronicity between production and consumption through a direct monetary reward, making the REC a genuine generator of distributable added value.

At the same time, switching to the Spanish Framework shifts the calculation logic toward the *Compensación de Excedentes* (Net Billing) mechanism, in compliance with *Real Decreto 244/2019*. In this context, incentivization takes an implicit and simplified form: the economic value is not disbursed as a separate payment but manifests as a direct deduction from the variable portion of each individual participant's electricity bill. Here, the economic module must manage the strict non-negativity constraint, ensuring that the value of energy fed into the grid offsets withdrawals up to zeroing out the energy component, without ever generating a net credit for the consumer. This structural divergence has profound repercussions for the Key Performance Indicators (KPIs) calculated by the system, influencing agents' perceptions of convenience and altering the speed at which the "*active minority*" persuades new members to join the community.

The Economic Module, therefore, is not limited to an accounting function but provides the informational fuel for the Socio-technical Module. Calculating the actual savings or revenue generated in both national contexts allows simulation of how different perceptions of economic benefit (a bank transfer in Italy versus a bill discount in Spain) can alter the dynamics of social influence and the REC's resilience in the face of global geopolitical crises. The robustness of this module ensures that every "*what-if*" scenario is anchored in current tariff realities, offering a scientific basis for evaluating which regulatory architecture is best suited to foster the energy transition across diverse European socio-economic fabrics.

3.5.1. Input Vectors and Market Parameterization

At each simulation step t, the module receives the aggregated energy state of the REC and a vector of exogenous market parameters as input.

The energy state variables at hour t are defined as:

- $E_{shared}(t)$: Shared energy (virtually self-consumed).
- $E_{surplus}(t)$: Excess energy produced and injected into the grid.
- $E_{deficit}(t)$: Energy withdrawn from the grid to meet the residual load.

The market parameters (configurable via the interface) are defined as:

- π_{PUN}: *Prezzo Unico Nazionale* (or wholesale energy price) [€/kWh].
- π_{retail}: Gross energy purchase price (including excise duties, transport, and system charges) [€/kWh].
- π_{inc}: Premium incentive tariff for shared energy [€/kWh].
- π_{val}: Grid charge refund tariff (ARERA valuation) [€/kWh].
- π_{comp}: Surplus compensation price (specific to the Spanish framework) [€/kWh].

3.5.2. Scenario A: Italian Framework (Explicit Incentive)

The Italian model (ref. Legislative Decree 199/2021, TIAD)[4] is based on a Virtual Self-Consumption mechanism with direct incentives (Cash Transfer). In this scheme, the model operates according to a virtual self-consumption framework. Unlike "*behind-the-meter*" (physical) systems, the public grid is utilized for the exchange. This implies that economic flows move along two parallel, additive tracks:

1. ***Dedicated Withdrawal (RID - Ritiro Dedicato):*** All energy injected into the grid is sold at the hourly zonal price.
2. ***GSE Incentive:*** An additional premium is granted on the share of energy that is shared.

3.5.2.1. Definition of Exogenous Market Parameters

For a rigorous simulation, the prices constituting the cost and revenue vector at time t are defined as follows:

- $\boldsymbol{P_{PUN}(t)}$ **[€/kWh]:** ***Prezzo Unico Nazionale*** (or Zonal Price). It represents the wholesale market value of energy. In the stochastic model, this follows the shock curve.
- $\boldsymbol{T_{PR}}$ **[€/kWh]:** ***Fixed Premium Tariff provided by the GSE*** for 20 years. Currently, for plants > 600 kW, it is equal to 0.110 €/kWh (this may vary slightly for smaller plants or based on geographical location; 0.110 is the fixed simulation standard).
- $\boldsymbol{C_{UV}(t)}$ **[€/kWh]:** ***Corrispettivo Unitario di Valorizzazione*** (Unitary Valuation Fee). It is the refund of transmission and distribution tariff components (ARERA variable), approximately 0.008 - 0.010 €/kWh.

- $\boldsymbol{P_{retail}(t)}$ **[€/kWh] (9):** Gross purchase price for the final consumer.

$$P_{retail}(t) = P_{PUN}(t) + \Omega_{spread} + \Omega_{charges} + \Omega_{taxes} \tag{9}$$

3.5.2.2. Revenue Function ($\boldsymbol{R_{IT}}$)

The aggregated physical flows at time t are defined as follows:

- $E_{inj}(t)$: Total energy injected into the grid by Producers and Prosumers (net of immediate physical self-consumption).
- $E_{with}(t)$: Total energy withdrawn from the grid by Consumers and Prosumers.
- $E_{shared}(t) = \min\left(E_{inj}(t), E_{with}(t)\right)$: Shared energy eligible for incentives.

The total hourly revenue (R_{IT}) (10) of the REC is the sum of three distinct components:

1. ***Valuation of Shared Energy:*** Comprising the premium tariff and the ARERA valuation fee applied to E_{shared}.
2. ***Sale of Injected Energy:*** All energy injected into the grid (surplus) is valued at the market price or through Dedicated Withdrawal (*Ritiro Dedicato*) $\left(E_{inj}\right)$.

Total Revenues $(\boldsymbol{R_{IT}})$**:** This is the sum of the shared energy valuation and the sale of the surplus energy injected into the grid:

$$R_{IT}(t) = \left[E_{inj}(t) \cdot P_{PUN}(t)\right] + \left[E_{shared}(t) \cdot P_{PUN}(t) + T_{PR} + C_{UV}\right] \tag{10}$$

3.5.2.3. Cost Function $(\boldsymbol{K_{IT}})$ (11)

The hourly cost is determined by the purchase of the energy required to cover the deficit, valued at the full retail price:

$$K_{IT}(t) = E_{with}(t) \cdot P_{retail}(t) \tag{11}$$

Where P_{retail} incorporates the effect of the simulated price shock.

3.5.2.4. Operating Budget (B_{IT}) (12-13)

The hourly net balance (Operating Cash Flow) is given by:

$$B_{IT}(t) = R_{IT}(t) - K_{IT}(t) \tag{12}$$

Note: In the Italian model, it is theoretically possible to achieve a positive balance ($B_{IT} > 0$) even in the presence of consumption, provided that revenues from incentives and sales exceed withdrawal costs.

The simulator evaluates whether "*it is beneficial to stay in the REC*". Therefore, it calculates the algebraic sum of all participants' costs and revenues:

$$B_{IT}(t) = \left[E_{inj}(t) \cdot P_{PUN}(t) + E_{shared}(t) \cdot (T_{PR} + C_{UV})\right] - [E_{with}(t) \cdot P_{retail}(t)] \tag{13}$$

3.5.3. Scenario B: Spanish/Catalan Framework (Surplus Compensation)

The Spanish model (ref. RD 244/2019)[5] primarily adopts the Collective Self-Consumption with Surplus Compensation mechanism (*Autoconsumo Colectivo con Compensación de Excedentes*). Unlike the Italian model, there is no direct payment (cash transfer) for shared energy. Instead, the economic benefit manifests as a reduction in the energy bill (Net Billing), subject to a non-negativity constraint.

3.5.3.1. Surplus Valuation and Compensation Limit

In the simulated model, the injected surplus is not "*sold*" on the open market; instead, it generates a virtual monetary credit valued at an agreed compensation price (P_{comp}), which is generally lower than the retail price $\left(P_{comp} < P_{retail}\right)$.

Surplus credit value:

$$V_{surplus}(t) = E_{surplus}(t) \cdot P_{comp} \tag{14}$$

Gross cost of withdrawn energy (energy component):

$$K_{gross}(t) = E_{deficit}(t) \cdot P_{retail} \tag{15}$$

3.5.3.2. Net Billing Algorithm (Net Cost Function) $\left(K_{ES,net}\right)$ (16)

Spanish regulations mandate that compensation cannot exceed the value of the energy component of the monthly bill (the fixed power charge and taxes remain due). In the hourly-step simulator, this constraint is modeled instantaneously:

$$K_{ES,net}(t) = max\left(0, K_{gross}(t) - V_{surplus}(t)\right) \tag{16}$$

This $max\left(0, K_{gross}(t) - V_{surplus}(t)\right)$ function is fundamental: it implies that if the value of the surplus exceeds the withdrawal cost, the excess is "*lost*" (given to the grid for free) and does not generate either a credit that can be accumulated for the future or a cash payment.

3.5.3.3. Translation in "Virtual Revenue" (R_{ES}) (17-18)

To make the two scenarios comparable within the simulator (which calculates a "*Balance*"), the bill savings are accounted for as "*implicit revenue*". The revenue (generated savings) is the difference between what the community would have paid without REC and what it actually pays:

$$R_{ES}(t) = K_{gross}(t) - K_{ES,net}(t) \tag{17}$$

$$R_{ES}(t) = min\left(K_{gross}(t), V_{surplus}(t)\right) \tag{18}$$

3.5.3.4. Operating Budget (B_{ES}) (19)

The hourly balance in the Spanish case reflects the net savings minus residual costs. However, for accounting consistency within the simulator, the balance is expressed as:

$$B_{ES}(t) = R_{ES}(t) - K_{ES,net}(t) \tag{19}$$

Critical Note: In the standard Spanish model, it is structurally impossible to generate a positive net profit in terms of cash flow (B_{ES} never exceeds the bill savings), unless the REC opts for the "*sale of surpluses*" mode (*venta de excedentes* without simplified compensation). However, this involves complex bureaucratic and fiscal burdens that are not modeled here for small communities.

3.6. Comparative Analysis of Dynamics

The implementation of the two economic frameworks within the simulator highlights substantial divergences in the optimal design and management strategies of RECs. The Comparative Dynamics Analysis module aims to demonstrate how the nature of the incentive itself (explicit in Italy, implicit in Spain) acts as a market signal, guiding the technical choices of designers and the investment behaviors of agents. Through *ceteris paribus* simulation, it is possible to observe that the optimal configuration of an energy community is not an absolute value dictated by thermodynamic efficiency alone, but rather a variable dependent on the reference regulatory context.

3.6.1 The Italian Model: The Maximization Strategy (Oversizing)

In the Italian regulatory context, the incentive system is structured to reward the total volume of shared energy (E_{shared}). Since the GSE (*Gestore dei Servizi Energetici*) recognizes a fixed incentive tariff for every kilowatt-hour virtually shared among members and, simultaneously, energy fed into the grid but not shared is still remunerated through the RID (*Ritiro Dedicato*) mechanism, the dominant dynamic emerging from the simulator is Oversizing.

In this scenario, agents, particularly the "*active minority*" that bears the initial investment, are incentivized to install production capacity exceeding the nascent community's instantaneous needs. The economic logic is expansionary: every additional square meter of photovoltaic surface generates a surplus of energy that, if shared, maximizes REC revenue, and if not shared, still guarantees a minimum monetization. This oversizing strategy favors community scalability: having a production "*reserve*" allows the REC to welcome new consumer members over time without immediately saturating production capacity, thereby enhancing the social attraction effect predicted by Moscovici's theory.

3.6.2 The Spanish Model: The Targeted Efficiency Strategy (Right-sizing)

Conversely, the algorithm governing the Spanish framework (RD 244/2019) imposes a Right-sizing dynamic (precise dimensioning). The *Compensación de Excedentes* mechanism acts as a strong deterrent against excessive investment in production capacity. Since the economic benefit is tied to compensation for the electricity bill and subject to the non-negativity clause, any energy produced in excess of the capacity to offset the variable portion of the invoice has zero marginal value to the user.

In Spain, the optimal strategy consists of millimetrically calibrating the installed power to participants' actual consumption profiles. Oversizing is financially penalized: an investment in photovoltaic panels that generate energy and "*gifted*" it to the grid (without bill compensation) drastically extends the Payback Period and reduces the investment's attractiveness for prosumers. This dynamic pushes Spanish RECs toward a more conservative configuration focused on district-level efficiency, where community success is measured not by the volume of energy produced, but by the ability to perfectly synchronize consumption with targeted production, avoiding capital waste on non-remunerated infrastructure.

3.6.3 Summary of Emergent Divergences

The comparison between these two dynamics allows for fundamental conclusions regarding the resilience and growth of RECs:

- ***Scalability:*** The Italian system favors dynamic growth and the inclusion of new members over time, thanks to the monetizable surplus. The Spanish system, while faster in initial activation, risks crystallizing the community into a static dimension to avoid marginal value losses.
- ***Risk Management:*** During a price shock (Chapter 3.7), the Italian model guarantees a constant cash flow (as the incentive tariff is fixed), while the Spanish model amplifies the benefit of bill savings, offering immediate protection but limited to the ceiling of the bill itself.
- ***Social Impact:*** The Italian oversizing strategy allows for more flexible allocation of incentive shares to combat energy poverty (via monetary redistribution), whereas in Spain, the social impact is strictly tied to the vulnerable member's physical capacity to consume energy at the exact moment of production.

This comparative analysis of dynamics provides the theoretical basis for interpreting simulation results, proving that the tool developed is capable of mapping not only energy flows but the actual **"***investment philosophies***"** underpinning the European energy transition.

3.7. Dynamic Energy Price Shock Module

In energy systems modeling and the assessment of renewable energy investments, one of the most widespread methodological criticalities lies in the excessive simplification of market dynamics. Traditionally, techno-economic simulations assume static energy price scenarios or those characterized by linear and predictable inflation rates. However, recent economic history, marked by the 2020-2021 pandemic crisis and the subsequent geopolitical shock of 2022, has unequivocally demonstrated that energy markets (such as the PUN in Italy or the OMIE in the Iberian Peninsula) are complex systems subject to extreme, sudden, and non-linear exogenous perturbations.

To provide the Agent-Based simulator with genuine ecological validity and to test the resilience of RECs under stress conditions (Stress Testing), a Dynamic Energy Price Shock Module has been developed and integrated.

This module moves beyond the elementary "*step function*" approach, where a price triples overnight only to remain unnaturally flat, by introducing a model based on stochastic time series with an oscillatory trend. The goal is not merely to calculate more expensive bills, but to simulate the "jitter" and instability typical of spot markets during a supply crisis.

From a systemic perspective, the introduction of this exogenous forcing profoundly alters the agents' decision-making environment. In a Complex Adaptive System (CAS), actors endowed with bounded rationality do not react solely to the average value of a parameter; they are heavily influenced by its variance (risk perception). A highly volatile energy price, while increasing the theoretical attractiveness of self-consumption due to rising withdrawal costs, introduces "*noise*" into the Payback Period calculation. This triggers psychological phenomena such as investor hysteresis (hesitation and delay in joining the REC while waiting for the market to stabilize).

The following sections will describe the logical-mathematical formalization of this module, breaking down the price forcing into three fundamental analytical components operating within a finite time window:

1. ***The Structural Component:*** The average magnitude of the crisis relative to the baseline price.
2. ***The Deterministic Oscillatory Component:*** The simulation of medium-term speculative market cycles (weekly/monthly trends).
3. ***The Stochastic Component (White Noise):*** The introduction of algorithmic daily volatility that makes the hourly cost of energy unpredictable, testing the robustness of the community's distributive policies.

3.7.1. Time Range Definition

The shock is defined as a temporary, time-limited event. Let Y_{start} be the shock's start year and ΔY_{dur} be the duration in years selected by the user.

The logical activation condition $\alpha(t)$ (20) at time t is:

$$\alpha(t) = \begin{cases} 1 & if \ \ Y_{start} \leq Y(t) < (Y_{start} + \Delta Y_{dur}) \\ 0 & otherwise \end{cases} \tag{20}$$

3.7.2. Dynamic Pricing Function

The price of energy withdrawn from the grid, $P_{grid}(t)$ (21), is not constant but is subject to a temporary shock defined by a start year (Y_{start}) and a duration (ΔY).

The final price of energy withdrawn from the grid at time t, $P_{grid}(t)$, is calculated as:

$$P_{grid}(t) = P_{base} \cdot M_{dyn}(t) \tag{21}$$

Where P_{base} is the structural retail price (the sum of commodity costs, transport, and system charges) and $M_{dyn}(t)$ is the Instantaneous Dynamic Multiplier.

Under shock conditions $(\alpha(t) = 1)$, the multiplier $M_{dyn}(t)$ (22) is the superposition of three components:

- ***Structural Component*** $\left(\boldsymbol{M_{target}}\right)$**:** The average severity level of the crisis set by the user (e.g., 3.0x).
- ***Deterministic Oscillatory Component*** $(\boldsymbol{\delta_{trend}})$***:*** Simulates speculative market waves.
- ***Stochastic Component*** $(\boldsymbol{\delta_{noise}})$***:*** Simulates daily intraday volatility.

The formal equation is:

$$M_{dyn}(t) = max\left(1, M_{target} + \delta_{trend}(t) + \delta_{noise}(t)\right) \tag{22}$$

3.7.2.1. Oscillatory Component $(\boldsymbol{\delta_{trend}})$ (23)

To simulate macroscopic fluctuations (e.g., weekly variations in gas availability), a sinusoidal function is used with a period $T_{wave} \approx 168\ h$ (one week) and an amplitude $A_{trend} = 0{,}5$:

$$\delta_{trend}(t) = 0{,}5 \cdot \sin\left(\frac{360° \cdot t}{168}\right) \tag{23}$$

This function introduces a cyclic variance that prevents the price from stabilizing, forcing agents to evaluate the PBP (Payback Period) based on a moving average rather than a single point value.

3.7.2.2. Stochastic Component (δ_{noise}) (24)

To replicate short-term unpredictability (white noise), a random variable with a uniform distribution is introduced:

$$\delta_{noise}(t) \sim u(-0{,}2, 0{,}2) \tag{24}$$

This term adds a "*jitter*" to the price signal, making each simulation unique even when the initial parameters remain identical.

$$M_{dyn}(t) = max\left(1, M_{target} + 0{,}5 \cdot \sin\left(\frac{360° \cdot t}{168}\right) + u(-0{,}2, 0{,}2)\right) \tag{25}$$

This formulation prevents the system from reaching a stable equilibrium during the crisis, negatively impacting the investors' perception of security.

3.7.3. Graphical Analysis of Dynamics

The result is a price profile that, during the crisis years, does not appear as a flat elevated line, but rather as a jagged curve ("*noisy sine wave*").

- ***Pre-Shock Phase:*** Stable price (P_{base}).
- ***Shock Phase:*** The average price rises to $P_{base} \cdot M_{target}$, but fluctuates instantaneously between a minimum of $\approx (M_{target} - 0{,}7)P_{base}$ and a maximum of $\approx (M_{target} + 0{,}7)P_{base}$.
- ***Post-Shock Phase:*** The price returns immediately to P_{base} (instantaneous Mean Reversion at the end of the duration ΔY_{dur}).

3.7.4. Implications for Simulation (System Behavior)

The introduction of this module has significant effects on the emerging dynamics of the REC system:

- ***Payback Period Instability:*** Since the PBP is recalculated annually, price fluctuations can cause distorted perceptions of economic viability during specific years of the crisis.

- ***Policy Stress Testing:*** This price model allows for the verification of whether distribution policies (e.g., "Reward Consumers") remain resilient even when withdrawal costs undergo violent peaks, which put the members' perceived savings at risk.

3.8. Financial Module: Investment Analysis and Key Performance Indicators (KPIs)

While the Economic Module represents the simulator's "*heartbeat*", operating on an hourly timescale to determine operational cash flow and the instantaneous valuation of shared energy, the Financial Module constitutes its "*historical memory*" and strategic compass. This module is tasked with aggregating granular data on an annual basis and projecting it across the Energy Community's life cycle (typically estimated at 20 years, in line with the duration of incentive regimes) to assess its bankability and structural sustainability. The primary objective is no longer simple accounting, but the transformation of monetary flows into complex decision-making metrics known as Key Performance Indicators (KPIs).

These indicators fulfill a dual critical function within the model's architecture:

- ***Ex-Post Evaluation:*** They provide researchers and policymakers with an objective measure of the effectiveness of different configurations (Italy vs. Spain) and the REC's robustness in the face of stress tests.
- ***Endogenous Behavioral Dynamics:*** They feed the agents' decision-making engine. A member's satisfaction, their propensity to remain in the community, or an external user's decision to join are direct functions of perceived financial performance.

To ensure a rigorous assessment of profitability and risk, the Financial Module calculates and processes the following primary indicators:

- ***Simple Payback Period (PBP)* (26)*:*** Expresses the time required (in years) for cumulative cash flows to equal the initial investment (I_0). This is the most sensitive parameter for agents with low spending capacity, for whom a rapid return is a necessary condition for joining.

$$PBP = \frac{I_0}{\sum_{t=1}^{n} CF_t} \tag{26}$$

- ***Net Present Value (NPV)* (27)*:*** Calculates the net wealth generated by the project over twenty years, discounting future cash flows to time zero using a discount rate (r) that reflects the opportunity cost of capital. An $NPV > 0$ indicates that the REC is creating real value beyond mere cost recovery.

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t} - I_0 \tag{27}$$

- ***Internal Rate of Return (IRR):*** Represents the intrinsic rate of return on the investment. This KPI is fundamental when comparing national frameworks: it allows for understanding whether the Italian model (direct incentive) or the Spanish one (bill compensation) offers superior capital efficiency under identical technical conditions.
- ***Self-Consumption and Self-Sufficiency Indices (SCI and SSI):*** Although these are technical metrics, the Financial Module translates them into terms of avoided bill costs, quantifying how effectively the community protects its members from electricity market price volatility.

The integration of these indicators into the annual simulation cycle allows the model to capture socio-economic feedback phenomena. If, for example, a geopolitical shock causes a spike in energy prices, the Financial Module will record an immediate improvement in NPV and a reduction in PBP (due to the increased value of avoided energy), triggering an increase in agent satisfaction rates and a stronger pull toward non-members within the Socio-Technical Module.

In this way, financial analysis ceases to be a cold accounting balance and becomes the dynamic engine governing the community's growth and resilience. The module's ability to manage these metrics differentially for prosumers (who bear the CAPEX) and consumers (who benefit solely from sharing) ensures a granular view of distributive equity, allowing for the identification of allocation thresholds that minimize the churn rate and maximize collective well-being.

3.8.1. Capital Expenditure Estimation (CAPEX)

Capital Expenditure (CAPEX) represents the initial outlay required to build the distributed generation infrastructure. In the model, CAPEX is calculated dynamically at time T_0 (the establishment of the REC) and updated whenever new Producer or Prosumer agents join.

Let $\mathcal{M}_{gen}$ be the set of agents equipped with generating capacity ($P_{peak,i} > 0$). The total CAPEX is formalized as (28):

$$CAPEX_{tot} = \sum_{i \in \mathcal{M}_{gen}} \left(P_{peak,i} \cdot C_{spec}(P_i) \right) \tag{28}$$

Where:

- $P_{peak,i}$: Nominal power of the i-th system [kWp].
- C_{spec}: "Turnkey" unitary specific cost [€/kWp].

Modeling Note: The simulator allows C_{spec} to be set as an exogenous parameter (e.g., 1200 €/kWp) to reflect market variations in technology prices or the presence of capital subsidies (e.g., PNRR).

3.8.2. Operating Expense Modeling (OPEX)

Operational Expenditure (OPEX) (29) aggregates the recurring costs required for asset maintenance and the administrative management of the community (O&M maintenance, insurance, representative management costs, and bank fees). In the model, OPEX is not simulated analytically line by line; instead, it is estimated to use a standardized heuristic approach as a percentage of the CAPEX:

$$OPEX_{annual} = CAPEX_{tot} \cdot k_{opex} \tag{29}$$

Where k_{opex} is the annual operating cost coefficient (typically 0.015 – 0.03, or 1.5% - 3%).

This cost is deducted from the cumulative balance at the end of each fiscal year (t mod 8760 = 0).

3.8.3. Cash Flow Analysis

The model constructs the annual Net Cash Flow (NCF_y) (30) by aggregating the hourly operating balances and subtracting the operating costs.

For a generic year y:

$$NCF_y = \left(\sum_{t=(y-1)8760}^{y \cdot 8760} B(t) \right) - OPEX_{annual} \tag{30}$$

Where $B(t)$ is the hourly balance calculated in the comparative economic module (varying according to the Italy/Spain scenario).

The *Cumulative Cash Flow (CCF)* (31) at year Y, which represents the net financial position of the REC, is given by:

$$CCF(Y) = -CAPEX_{tot} + \sum_{y=1}^{Y} NCF_y \tag{31}$$

This $CCF(Y)$ function describes the investment recovery trajectory: it starts from a negative value (the initial debt) and grows monotonically (assuming $NCF_y > 0$) until it intersects the x-axis (Break-Even Point).

3.8.4. Key Performance Indicators (KPIs)

The simulator calculates the following indicators in real time to assess investment attractiveness.

3.8.4.1. Simple Payback Period (PBP)

The PBP is the primary metric used by agents in the model to evaluate risk. Since annual cash flows may fluctuate (due to price shocks or consumption changes), the model employs a dynamic formulation based on historical average profit.

At year Y, the average annual net profit is defined as:

$$\bar{\pi}_{net}(Y) = \frac{CCF(Y) + CAPEX_{tot}}{Y} \tag{32}$$

The estimated Payback Period (33) is therefore:

$$PBP(Y) = \begin{cases} \dfrac{CAPEX_{tot}}{\bar{\pi}_{net}(Y)} & if\ \bar{\pi}_{net}(Y) > 0 \\ \infty & if\ \bar{\pi}_{net}(Y) \leq 0 \end{cases} \tag{33}$$

This formulation allows the PBP to adapt during the simulation: if the REC recruits new efficient consumers, $\bar{\pi}_{net}$ increases and the PBP decreases, signaling greater attractiveness to external investors.

3.8.4.2. Return on Investment (ROI) – Implied

Although not explicitly defined in a single variable, the ROI is implicitly evaluated by agents through the feasibility threshold. The ROI at the end of the project's lifespan ($T_{life} = 20$years) can be formalized as (34):

$$ROI_{20y} = \frac{CCF(20)}{CAPEX_{tot}} \cdot 100[\%] \tag{34}$$

3.8.5. Financial Feedback on Social Dynamics

The Financial Module is not merely a statistical output; instead, it acts as a feedback loop for the Socio-Technical Module. A direct causal relationship exists between financial performance and REC's demographics:

1. ***Price Signal:*** The PBP value and the distributed benefit ($Benefit_i$) are compared against the agents' expectations.

2. ***Churn Threshold:*** If $CCF_i(y) < \theta_i$ (that is, if the individual cumulative return is lower than the agent's psychological feasibility threshold after a grace period), the agent triggers the withdrawal procedure.
3. ***Collapse or Expansion:***
    - *Virtuous Scenario:* High returns → Low PBPs → High satisfaction → High social influence (Moscovici) → Membership growth.
    - *Vicious Scenario:* Low returns (e.g., Spanish scenario with poor self-consumption) → High PBPs → Member withdrawal → Reputational collapse → Stagnation.

The Financial Module quantifies the "*health*" of the REC, acting as the Darwinian engine that determines whether the energy community survives, thrives, or goes extinct within the simulated environment.

3.9. Socio-Technical Module: Behavioral Dynamics and Influence Theory

If the physical and financial modules define the boundaries of what is possible and affordable, the Socio-Technical Module constitutes the actual "*cognitive engine*" of the simulator. It is in this section of architecture that the REC ceases to be a mere aggregate of technical data and transforms into a living demographic organism, capable of growing, contracting, or stabilizing. The fundamental methodological choice consists of abandoning the neoclassical hypothesis of the perfectly rational agent (*Homo Oeconomicus*), who would act exclusively based on marginal profit maximization, in favor of an approach based on Bounded Rationality. In this paradigm, agent decisions are modeled as the result of a heuristic process influenced by three critical factors: real budget constraints (income), the economic satisfaction derived from previous modules, and, decisively, the pressure of social influence.

The module operates on an annual frequency ($T = 8760\ h$), acting as a decision-making filter that triggers at the end of each solar cycle. While energy flows hourly, the agents' "*minds*" evaluate their position only after internalizing the economic and social results of the past year. This process is structured into three fundamental mechanisms:

3.9.1 Value Allocation: The Social Contract

Prior to any demographic dynamics, the module executes the economic benefit allocation logic. This is not a simple accounting operation, but the definition of the REC's "*degree of equity*". The simulator calculates how the generated surplus (GSE incentives or bill savings) is distributed among the different types of members. This allocation determines the Individual Satisfaction Index (σ):

- If σ is high, the agent acts as a pole of attraction for the surrounding social network.
- If σ falls below a critical threshold, the agent enters a latency phase that may precede withdrawal.

3.9.2 Adoption: The Power of the Active Minority

The community's growth process is governed by Moscovici's Conversion Theory (Active Minority Influence). Agents outside the REC (the majority) do not join randomly; instead, they are "*bombarded*" by the consistency signal emitted by the founding core (the active minority).

The simulator models the probability of adoption (P_{adj}) as a function of the minority's consistency and the "*cognitive conflict*" generated in the observer:

$$P_{adj} = f(C_{minority}, \Delta_{saving}, I_{agent}) \quad (35)$$

Where $C_{minority}$ represents the community's stability over time, Δ_{saving} the perceived economic differential, and I_{agent} the agent's income, which acts as an insurmountable entry barrier if the required initial investment exceeds their spending capacity.

3.9.3 Withdrawal (Churn): The Resilience of the Bond

Mirrored with adoption, the module manages the phenomenon of Churn. A member may decide to leave the REC if the economic benefit no longer compensates for the participatory effort or if the "*social tension*" of the active minority weakens. This process allows for testing REC resilience: a community that fails to maintain consistent communication or distributes profits unfairly will see its demographic base erode, leading to system collapse even in the presence of excellent physical production. The REC in this model is not an equation to be solved, but a conversation to be sustained. If the conversation loses consistency (Moscovici) or substance (financial KPIs), the system decays.

The integration of these dynamics allows the researcher to observe emergent phenomena typical of reality: the "*S-curve*" growth of memberships, tipping points where a small community becomes a mass phenomenon, and the retention capacity of members during geopolitical crises, where the value of "*community security*" can outweigh pure monthly savings calculations within decision-making heuristics.

3.9.4. Governance Mechanisms and Value Distribution

The first step in transforming the aggregate economic result into a behavioral stimulus is the distribution function. The Cumulative Operating Balance for year y, denoted as $B_{REC}(y)$, must be allocated among the N active members.

The model formalizes three distinct governance policies (Pol_{dist}), reflecting different ethical and strategic visions of the community:

1. ***Egalitarian Policy (36):*** Every member receives an identical share, regardless of their physical contribution (production or consumption). This is typical of pure cooperatives.

$$b_i(y) = \frac{B_{REC}(y)}{N_{members}} \tag{36}$$

2. ***Supply-Side Meritocratic Policy (37):*** The benefit is proportional to the energy generated. It rewards the capital investment of Producers and Prosumers.

$$b_i(y) = B_{REC}(y) \cdot \frac{E_{i,prod}(y)}{\sum_j E_{j,prod}(y)} \tag{37}$$

3. ***Demand-Side Meritocratic Policy (38):*** The benefit is proportional to the energy withdrawn (consumed). This policy is strategic for incentivizing the enrollment of pure Consumers, who are essential for maximizing the physical self-consumption index.

$$b_i(y) = B_{REC}(y) \cdot \frac{C_{i,cons}(y)}{\sum_j C_{j,cons}(y)} \tag{38}$$

The choice of Pol_{dist} radically alters the REC's attractiveness profile for different agent classes, modifying the specific adoption curves for each breed.

3.9.5. Membership Modeling: The Two-Stage Decision-Making Process

The external agent ($i \in \varepsilon$) evaluates entry into the REC through a two-stage hierarchical decision-making process: Constraints Check (feasibility verification) and Utility Check (utility verification) *(Figure 7)*.

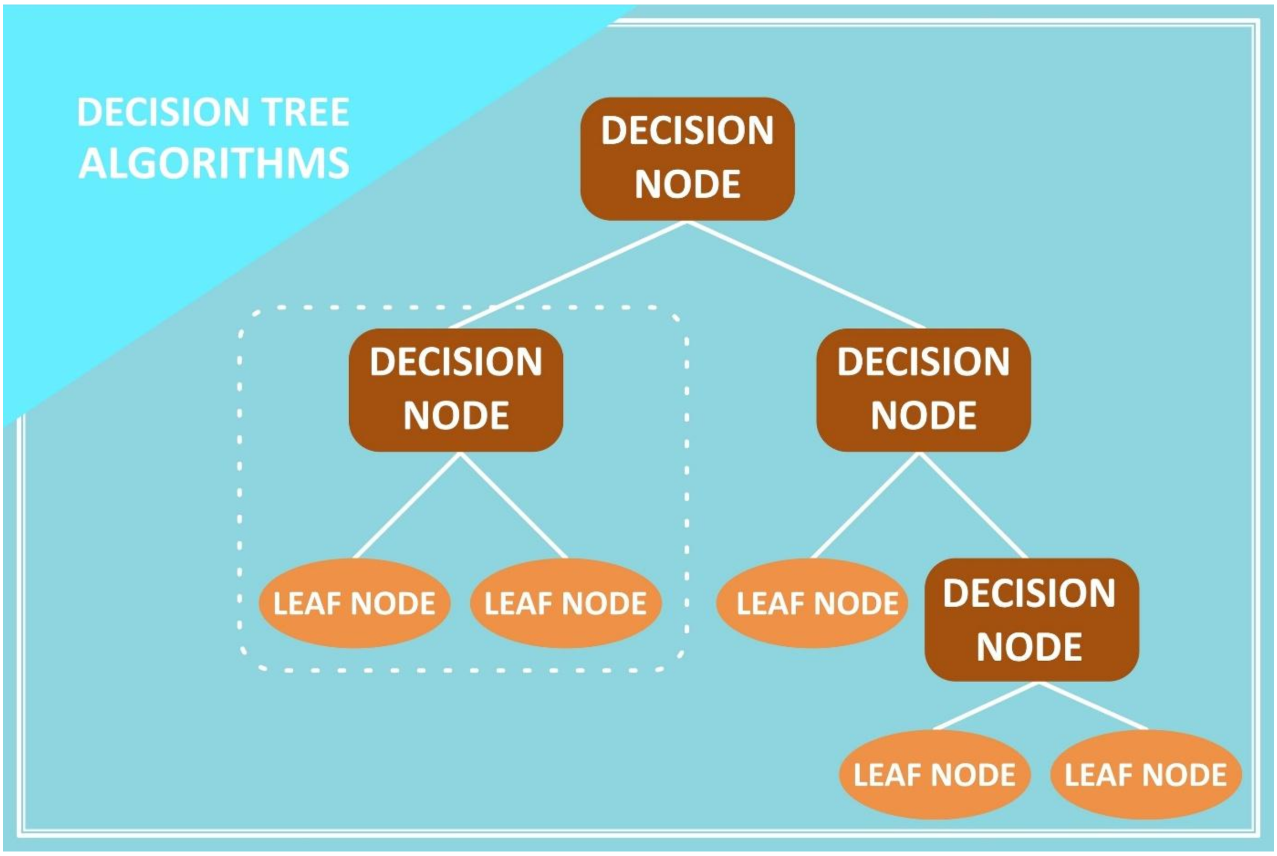

Figure 7: Decision Tree Algorithms

3.9.5.1. Stage 1: Capacity Constraints (Feasibility)

Even if the will to act is present, action is limited by resources. The model introduces the variables Annual Income (I_i) and Available Space (S_i). The investment capacity ($Cap_{inv,i}$) (39) is normalized on a scale of $[0,100]$:

$$Cap_{inv,i} = min\left(100, \frac{I_i}{K_{scale}}\right) \quad (39)$$

Where K_{scale} is economic conversion factor.

The agent determines its Potential Role ($Role_i$) (40) based on rigid thresholds (τ_{high}, τ_{med}):

$$Role_i = \begin{cases} Producer \;\; if \; Cap_{inv,i} > \tau_{high} \wedge S_i > \tau_{high} \\ Prosumer \;\; if \; Cap_{inv,i} > \tau_{med} \wedge S_i > \tau_{med} \\ Consumer \qquad\qquad\qquad otherwise \end{cases} \tag{40}$$

This stage realistically simulates barriers to entry: a low-income agent can only join as a Consumer, regardless of their willingness to invest.

3.9.5.2. Stage 2: Utility Function and Social Influence

Once the feasibility constraint is cleared, the agent evaluates utility. Here, the model integrates Serge Moscovici's Theory of Active Minority Influence (1976)[3] through the following three logical steps:

1. Aging and Satisfaction Assessment:

The system iterates through all active agents within the REC (excluding the external population and the grid agent). For each agent i, the years of membership $Y_{rec,i}$ are incincreased one unit. Subsequently, the agent's economic "*satisfaction*" is evaluated: a member is considered satisfied if their net cumulative benefit ($B_{cum,i}$) is strictly positive.

The total number of REC members (N_{tot}) and the subset of satisfied members ($N_{satisfied}$) (41) are then calculated:

$$N_{satisfied} = \sum_{i=1}^{N_{tot}} \begin{cases} 1, & if \; B_{cum,i} > 0 \\ 0, & otherwise \end{cases} \tag{41}$$

2. Calculation of the Moscovici Influence Factor (W_{mosc})

The social influence exerted by the community is not static; it depends on its credibility and cohesion, formalized through two consistency indices:

- ***Synchronic Consistency (C_{sync}) (42):*** Represents the group's internal coherence at a given moment. If the majority of members are facing economic losses, the REC's message loses its persuasive power.

$$C_{sync}(t) = \frac{N_{satisfied}(t)}{N_{tot}(t)} \tag{42}$$

- ***Diachronic Consistency (C_{diac}) (43):*** Measures the persistence and stability of the project over time. It is calculated by normalizing the average seniority of the members ($\bar{Y}_{rec}$) over a reference horizon (set at 10 years). The value is capped at 1.

$$C_{diac}(t) = min\left(1, \frac{\bar{Y}_{rec}}{10}\right) \tag{43}$$

The Total Influence Factor (W_{mosc}) (44) is quantified by multiplying the two indices by a centesimal scale factor. This value represents the amount "*in Euros*" of skepticism that the community is able to dismantle through its own example:

$$W_{mosc} = C_{sync} \cdot C_{diac} \cdot 100 \tag{44}$$

3. Membership Logic and Individual Psychological Modulation

To simulate the conversion process, the system first calculates the historical average annual benefit generated by an REC member ($\bar{B}_{ann}$) (45):

$$\bar{B}_{ann} = \frac{\frac{1}{N_{tot}} \sum B_{cum,i}}{Y_{sim}} \tag{45}$$

where Y_{sim} is the current simulation year.

Next, the system queries the latent population (external agents). Each external agent j possesses an intrinsic environmental sensitivity ($Sens_j \in [0, 100]$) and an economic convenience threshold (θ_j). Moscovici's influence is personalized for each agent: individuals highly sensitive to environmental issues will amplify the REC's message, while skeptics will be less affected:

$$W_j = W_{mosc} \cdot \left(\frac{Sens_j}{50}\right) \tag{46}$$

This value reduces the psychological barrier to entry, generating an Effective Threshold ($\theta_{eff,j}$) (47), with the logical constraint that it cannot fall below zero (as an agent will never join a structurally loss-making project):

$$\theta_{eff,j} = \max(0, \theta_j - W_j) \tag{47}$$

The adoption function is triggered if the community's average benefit exceeds this lowered psychological barrier ($\bar{B}_{ann} > \theta_{eff,j}$). In this case, the agent joins the REC, assuming a role proportional to their technical and economic limitations:

- ***Producer:*** If $Cap_{inv} > 80 \wedge Space > 80$
- ***Prosumer:*** If $Cap_{inv} > 40 \wedge Space > 40$
- ***Consumer:*** Otherwise.

3.9.6. Attrition Dynamics (Churn Rate) and Resilience

The stability of the REC is threatened by member dissatisfaction. The attrition process is not instantaneous but subject to hysteresis (inertia to change).

The model implements an attrition function to simulate the failure of expectations. Each active member evaluates their cumulative benefit against their convenience threshold. However, the tolerance for economic risk is asymmetric and depends on the agent's original imprinting:

1. ***Standard members*** maintain their original threshold ($\theta_{churn,i} = \theta_i$).
2. ***Founding members***, representing the "*Active Minority*", possess extremely high levels of stubbornness and resilience. Their attrition threshold is reduced by 90%: $\theta_{churn,i} = 0.1 \cdot \theta_i$.

If an agent has been a member of the REC for at least a two-year stabilization period ($Y_{rec,i} > 2$) and their earnings do not reach the effective tolerance threshold ($B_{cum,i} < \theta_{churn,i}$), attrition is triggered. The agent disconnects their physical link, is demoted to External status, resets their temporal and financial counters, and, if they held it, permanently loses their founder status.

3.9.7. Macro-Economic Update and Telemetry

In the final phase of the block, the system performs macro-level accounting operations. The aggregate cumulative balance of the community (B_{sys}) (48) is reduced by the annual operating and maintenance costs (K_{OPEX}):

$$B_{sys}(Y) = B_{sys}(Y-1) - K_{OPEX} \tag{48}$$

Finally, if the aggregate average annual profit is positive, the system dynamically estimates the Payback Period (PBP) for the entire infrastructure:

$$PBP = \frac{K_{CAPEX}}{\bar{B}_{sys,ann}} \tag{49}$$

3.9.8. Systemic Feedback Loop

The Socio-Technical Module closes the simulator's causal cycle by creating a critical feedback loop:

- ***Positive Feedback (Virtuous):*** High economic returns → Satisfied members → High C_{sync} → High W_{mosc} → Reduction of θ thresholds → New enrollments → Increased self-consumption → Stable or growing returns.
- ***Negative Feedback (Vicious - Collapse):*** Low returns (or price shocks) → Dissatisfied members → Withdrawal (Churn) → Collapse of C_{sync} → W_{mosc} → 0 → Halt in new memberships → Obsolescence of the REC.

This module evaluates how the success of a REC does not depend deterministically on technology but rather emerges from the system's ability to maintain its *"Moscovician Consistency"* over time, transforming an active minority into a pole of social attraction.

3.10. Model Validation and Sensitivity Analysis

The consolidation of the scientific reliability of an Agent-Based model necessitates a rigorous examination of its internal architecture and its ability to reflect, with intellectual honesty, the phenomenology of the real-world system. Before proceeding to the interpretation of the results, it is therefore fundamental to subject the simulator to a dual process of scrutiny that attests to its structural robustness and empirical fidelity. This journey begins with the verification of logical-mathematical consistency, a phase in which the code is interrogated to ensure that fundamental physical and economic laws are respected without computational distortions. In this sense, internal validation is not a mere technical exercise, but the guarantee that every emerging dynamic is the intentional product of the model's rules and not the result of algorithmic artifacts.

Once the solidity of the foundations is established, the analysis shifts outward, seeking a point of anchorage with reality through the calibration of exogenous parameters. This step transforms the computational abstraction into a "*synthetic laboratory*" where solar production curves and user load profiles cease to be hypothetical variables and become faithful mirrors of institutional and geographic data. However, validation cannot be considered complete if limited to a static photograph of the system; the non-linear nature of RECs requires a systematic exploration of their responses to perturbations. It is in this context that sensitivity analysis assumes a crucial diagnostic role: by systematically varying critical inputs, it is possible to map the system's elasticity and identify those "*leverage points*" capable of shifting the balance of economic viability and adoption.

This methodological approach allows for overcoming the perception of the model as a "*black box*", transforming it into a transparent and refutable instrument. By balancing the verification of energy conservation with the mapping of parametric sensitivity, a foundation of evidence is built that elevates the simulation from a simple calculation exercise to a decision-making pillar. Understanding how the system reacts to market fluctuations or regulatory changes means, ultimately, defining the boundaries of validity for the thesis conclusions, ensuring that the emerged policy recommendations are not only theoretically plausible but also structurally resilient.

3.10.1. Model Validation Methodology

The heart of validation in an Agent-Based simulation lies in overcoming the dichotomy between theory and empiricism, positioning the model in a fertile limbo that Joshua Epstein (1999) [6] would define as generative sufficiency. When we state that a system generated *in silico* must replicate the dynamics of the real-world system, we are not simply invoking an aesthetic similarity or a superficial numerical overlap; rather, we are arguing that the micro-behavioral rules infused into the agents must be capable of spontaneously "*bring forth*" the complexity of the observed macro-phenomenon. From this perspective, validation transforms into a rigorous process of reverse engineering, where the objective is not a perfect fitting of real data (an operation that often results in the risk of overfitting) but rather the model's ability to reproduce those Stylized Facts that define the essence of the reference system.

These "*stylized facts*" act as true fingerprints of the real system: whether they are statistical regularities, such as fat tails in financial return distributions, or structural patterns, such as spatial segregation or cluster formation in a social network, they represent the phenomenological constants that survive the "noise" of daily reality. Demonstrating that an ABM is "*sufficiently accurate*" thus means proving that the hypothesized generative mechanism is a plausible explanation of reality: if the model, once started, evolves by spontaneously producing the same macroscopic regularities found empirically, then we have proof that the local interactions we modeled are indeed sufficient to explain the global structure.

This replication process must not, however, be understood as a search for absolute realism, which would make the model as complex as reality itself and therefore equally indecipherable. The required accuracy is functional to the heuristic objective: the *in silico* system must be a parsimonious yet structurally honest representation, capable of withstanding sensitivity analysis and showing how, as environmental conditions or the individual endowments of agents vary, the emerging patterns change in a manner consistent with what is observable in nature or society. Ultimately, validating an ABM through Stylized Facts means elevating the simulation from a mere computational exercise to a true tool of theoretical investigation, where the consistency between the micro and macro levels becomes the seal of guarantee for the scientific robustness of the thesis.

3.10.1.1. Structural Validation (Verification)

The structural validation phase, often referred to in technical jargon as Verification, represents the first and fundamental pillar upon which the simulator's entire architecture rests. If phenomenological validation is concerned with "*building the right model*" in relation to reality, verification has the much more pragmatic, yet no less critical, task of ensuring that "*the model is built correctly*" from a logical-computational standpoint. In this sense, the Sanity Check performed on the code is not a mere debugging routine, but a rigorous demonstration of internal consistency that transforms a series of command strings into a credible physical and economic system.

The first test of this integrity is represented by the stability of the energy balance, which acts as an inviolable constraint within the simulation. By imposing the condition that, at every time instant t, the energy produced must exactly coincide with the sum of self-consumed energy and the energy yielded as surplus, we ensure that the model respects the First Law of Thermodynamics. Mathematically, the equation:

$$\sum E_{prod} = E_{self} + E_{surplus} \tag{50}$$

is not just a formula, but a guarantee that the *in silico* system does not suffer from arbitrary energy "*leaks*" or "*creations*", which would invalidate any subsequent analysis regarding agent efficiency or grid sustainability. This conservation of energy serves as a universal control parameter: if the balance closes, the routing logic of energy flows is structurally sound.

In parallel with the physics of the system, the robustness of the algorithms has been tested through the lens of the financial balance. Here, the challenge lies in proving that the agents' dynamic nature does not compromise the accuracy of the fundamental economic calculations. To achieve this, the cash flows generated by the simulation were compared against an external static benchmark (implemented in Excel) which serves as the "*ground truth*" for a single representative year.

The fact that the Root Mean Square Error (RMSE) [7] between the ABM's dynamic calculations and the static benchmark's values is negligible, with a value below 0.5%, is not a purely statistical detail.

On the contrary, it represents the "*certification of reliability*" for the calculation algorithms: such a minimal discrepancy confirms that the complexities introduced by the agent-based simulation, such as temporal granularity or stochastic interactions, do not introduce systematic errors or distortions in the final economic results. This alignment between the dynamic model and the static reference model completes the circle of structural validation, allowing us to proceed with the analysis of results with the certainty that every observed fluctuation is a product of system dynamics rather than an inaccuracy of the calculation engine.

3.10.1.2. Empirical Calibration

The next step involved empirical calibration, specifically anchoring the abstract model to the physical and social coordinates of the real world. In this phase, exogenous parameters cease to be simple theoretical variables and become faithful reflections of a specific geographical and systemic context. Calibrating an ABM means, ultimately, reducing the system's degrees of freedom so that the results are not the product of arbitrary choices, but the outcome of dynamics operating on a solid and institutionally recognized database.

The first pillar of this anchoring concerns the system's energy supply, namely, the production profiles. To ensure that the simulated photovoltaic generation is not a generic approximation, the production curves were validated through systematic comparison with the PVGIS database of the European Commission's Joint Research Centre (JRC) [8]. This step allows for the capture of specific solar irradiation for different latitudes, covering the entire spectrum of Climate Zones (from A to F). In this way, the model does not merely simulate a photovoltaic plant; it is capable of reflecting the real performance of technology installed in heterogeneous environmental contexts, where the seasonal and hourly variability of the solar resource becomes an essential physical constraint for agent decisions.

However, an energy system does not live by production alone; its complexity emerges from the interaction with demand. To faithfully reflect consumption habits, the model integrates normalized hourly load profiles derived from the Standard Load Profiles (SLP) published by regulatory authorities, such as ARERA [9] in Italy or REE [10] in Spain. The importance of using regulatory data lies in its ability to synthesize the average behavior of different user categories: from residential users, characterized by morning and evening peaks, to school, public, and commercial users, whose rhythms are dictated by radically different opening and operating hours.

The adoption of normalized profiles allows the model to scale consumption based on each agent's specific size while keeping the demand trend intact, which is the determining factor for correctly calculating self-consumption and energy sharing rates. This meticulous calibration process transforms the ABM into a true "*digital twin*" of the energy system: when an agent in the model decides to activate a load, they do not do so in a vacuum, but within an ecosystem where the sun rises according to JRC data and people turn on lights according to patterns established by national regulators. It is precisely this convergence between physical rigor and statistical verisimilitude that provides the model with the necessary authority to support policy or investment analysis.

3.10.2. Sensitivity Analysis

Given the inherently non-linear and stochastic nature of Agent-Based models, the mere observation of average results is insufficient to ensure a full understanding of the system dynamics. Indeed, the complexity of an ABM resides in the network of interdependencies among agents, where small variations in input parameters can trigger non-proportional macroscopic changes in emerging properties. For this reason, the integration of a rigorous Sensitivity Analysis constitutes an essential methodological step to map the parameter space and identify the primary drivers of the model's behavior.

In this study, a local analysis methodology known as One-at-a-Time (OAT) [11] was adopted, which operates according to the *Ceteris Paribus* principle. This approach allows for the isolation of the causal effect of each individual exogenous variable by systematically varying its value while all other parameters are held constant. Although complex systems are often characterized by synergetic interactions between variables, the OAT technique represents the first fundamental step in deconstructing the simulator's "*black box*", allowing for the distinction between critical parameters, to which the system is extremely reactive, and those that are marginal or silent regarding the research objectives.

From a formal standpoint, the system's sensitivity was quantified through a local sensitivity index, denoted as S. This index expresses the ratio between the relative variation of the target output variable Y (which, in this context, may be the Payback Period of an investment or the final adoption rate of a technology) and the relative variation of the input parameter X under examination. The index is mathematically defined as:

$$S = \frac{\delta Y}{\delta X} \cdot \frac{X}{Y} \approx \frac{\Delta Y / Y}{\Delta X / X} \tag{51}$$

This formulation is not a simple slope calculation; rather, it defines the elasticity of the model relative to its inputs. A high S value indicates that a small fluctuation in a parameter (for instance, a slight increase in government incentives or a variation in raw material costs) produces a significant and more than proportional impact on the final result. Conversely, S values close to zero signal a substantial robustness of the model with respect to that specific input.

This analysis allows not only for the validation of the stability of the results but also for the guidance of strategic decisions: identifying the system's leverage points means, in fact, pinpointing which policy levers or market variables possess the real power to accelerate or slow down the energy transition within the simulation. Sensitivity Analysis transforms the model from a descriptive tool into a diagnostic one, providing an objective measure of uncertainty and the dependence of results on initial assumptions.

3.10.2.1. Energy Price Sensitivity (π_{retail})

The sensitivity analysis of the model regarding electricity prices (π_{retail}) represents a crucial step in understanding the resilience of Renewable Energy Communities (RECs) in the face of market volatility. Through the activation of a stress-test module, aimed at simulating energy shock scenarios similar to those recorded during 2022, a positive but markedly non-linear correlation with the community adoption rate has emerged. The results highlight how the price variable acts not merely as a cost, but as a powerful catalyst for behavioral change: a 50% increase in the energy price results in a reduction of the average Payback Period (PBP) by approximately 35%, drastically accelerating the economic viability of the investment and making the transition to a prosumer configuration significantly more attractive.

However, the most significant aspect revealed by the simulation is not the simple reduction in amortization times, but rather the identification of a true Tipping Point within the system. The model has uncovered a critical threshold, estimated at approximately €0.15/kWh, below which the evolutionary dynamics of the community undergo a structural halt. In this low-price scenario, the savings differential is insufficient to generate what we define in the model as "*baseline economic satisfaction*". Without reaching this minimum individual threshold, the social influence mechanisms inspired by Moscovici's theory, which are fundamental for the diffusion of innovation within the network, fail to trigger.

In the absence of an economic push perceived as significant, the influence of the "*active minority*" or neighbors lacks the traction required to overcome agent inertia or distrust. This leads to a phenomenon of premature extinction of the REC: the community fails to reach the critical mass necessary to sustain itself, highlighting that financial stability acts as a necessary prerequisite for social cooperation dynamics to flourish. The analysis thus demonstrates that the bottom-up energy transition is strictly bound to an economic "*window of opportunity*"; if the energy price falls below the activation threshold, the REC system loses its self-organization capacity, collapsing into states of inactivity despite technological and regulatory availability.

3.10.2.2. Sensitivity to Social Factors (β, τ_{grace})

The sensitivity analysis of social factors introduces a dimension of behavioral realism into the model that transcends mere profit-driven logic, allowing for an investigation into how the propensity to join is mediated by peer interaction and the weight of social norms. In this context, the social penetration coefficient β, which quantifies the intensity of influence exerted by the active minority or neighbors according to Moscovici's theory, acts as an order parameter that determines a radical qualitative shift in the growth dynamics of the Renewable Energy Community (REC). Indeed, the simulation reveals the existence of a true bifurcation in the system's behavior, where exceeding a threshold value ($\beta_{critical}$) shifts the model from a regime of inertial growth to one of explosive growth.

When social influence is weak or negligible ($\beta < \beta_{critical}$), the REC evolves along a linear and markedly slow growth trajectory. In this scenario, technological adoption and community entry are driven exclusively by "pure" economics: only those agents who find an immediate and overwhelming financial benefit decide to join. Essentially, the system lacks the drag effect and the reduction in perceived risk that stem from observing the behavior of others. The system appears atomized and incapable of exploiting social economies of scale, making the spread of the REC a laborious process vulnerable to even minor fluctuations in the energy market.

Conversely, when the weight of the social component exceeds the critical threshold ($\beta > \beta_{critical}$), the system dynamics change profoundly, taking the shape of a sigmoidal curve (S-curve) typical of innovation diffusion processes. An initial phase of exponential acceleration is observed, where social influence acts as a powerful catalyst: each new member does not merely optimize their own energy balance but becomes a positive signal for their contact network, breaking down psychological and informational barriers to entry. In this regime, the community's "*conviction*" acts as a multiplier of the economic incentive, allowing the REC to expand even among agents who were initially skeptical or characterized by a higher $\boldsymbol{\tau_{grace}}$ (tolerance period or decisional inertia).

This final saturation phenomenon, which closes the sigmoidal curve, indicates that social influence has exhausted its traction potential once it has reached nearly the entire target population. The scientific implication of this result is of fundamental importance: it suggests that support policies for RECs should not focus exclusively on economic levers but should aim to strengthen community ties and the visibility of local successes. Raising the β coefficient through information campaigns or social facilitators can make the difference between a community destined to remain a technical niche and one capable of triggering a widespread, self-propelling energy transition.

3.11. References

[1] J. Brownlee, «Complex adaptive systems», Swinburne, report, gen. 2007. doi: 10.25916/sut.26269111.v1.

[2] D. A. Urbina e A. Ruiz-Villaverde, «A Critical Review of Homo Economicus from Five Approaches», *Am. J. Econ. Sociol.*, vol. 78, fasc. 1, pp. 63–93, 2019, doi: 10.1111/ajes.12258.

[3] S. Moscovici, E. Lage, e M. Naffrechoux, «Influence of a Consistent Minority on the Responses of a Majority in a Color Perception Task», *Sociometry*, vol. 32, fasc. 4, pp. 365–380, 1969, doi: 10.2307/2786541.

[4] «DECRETO LEGISLATIVO 8 novembre 2021, n. 199 - Normattiva». Consultato: 26 luglio 2023. [Online]. Disponibile su: https://www.normattiva.it/uri-res/N2Ls?urn:nir:stato:decreto.legislativo:2021-11-08;199

[5] Ministerio para la Transición Ecológica, *Real Decreto 244/2019, de 5 de abril, por el que se regulan las condiciones administrativas, técnicas y económicas del autoconsumo de energía eléctrica*, vol. BOE-A-2019-5089. 2019, pp. 35674–35719. Consultato: 4 settembre 2025. [Online]. Disponibile su: https://www.boe.es/eli/es/rd/2019/04/05/244

[6] J. M. Epstein, «Agent-based computational models and generative social science».

[7] T. O. Hodson, «Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not», *Geosci. Model Dev.*, vol. 15, fasc. 14, pp. 5481–5487, lug. 2022, doi: 10.5194/gmd-15-5481-2022.

[8] «JRC Photovoltaic Geographical Information System (PVGIS) - European Commission». Consultato: 23 febbraio 2026. [Online]. Disponibile su: https://re.jrc.ec.europa.eu/pvg_tools/en/

[9] «Arera: Home | ARERA». Consultato: 23 febbraio 2026. [Online]. Disponibile su: https://www.arera.it/

[10] «Electricity Business in Spain | Red Eléctrica». Consultato: 23 febbraio 2026. [Online]. Disponibile su: https://www.ree.es/en

[11] G. ten Broeke, G. van Voorn, e A. Ligtenberg, «Which Sensitivity Analysis Method Should I Use for My Agent-Based Model?», *J. Artif. Soc. Soc. Simul.*, vol. 19, fasc. 1, p. 5, 2016.

4. Choosing the simulation framework

The transition from theoretical formulation to experimental verification represents the most delicate methodological junction of this research. Moving from the descriptive equations of Social Representation Theory and the thermodynamic balances of RECs to a functioning computational environment requires a "*bridge*" capable of managing the non-linear complexity of both domains. This chapter describes the process of selecting, designing, and implementing the simulation framework, conceived not as a simple static calculator but as a true socio-technical virtual laboratory.

The need to overcome the limitations of traditional deterministic models, which often fail to capture the heterogeneity of human behavior, has driven research toward the Agent-Based Modeling (ABM) paradigm. This approach allows for the observation of how simple individual rules, applied to a population of autonomous actors, can generate emergent macroscopic phenomena, such as the diffusion of energy innovation or the resistance to change from an inertial majority.

The chapter is structured as a comparative analysis of the main simulation toolkits in the scientific landscape and provides a technical justification for choosing NetLogo 7.0.3 [1] as the preferred platform. Furthermore, the ontology of the developed system will be detailed: from the management of the hourly temporal resolution ($t = 1h$) to the modular decomposition of the source code. The latter has been designed as an integrated Decision Support System (DSS), capable of establishing a synchronous dialogue between four fundamental dimensions:

- ***The physical dimension***, linked to photovoltaic production and load profiles;
- ***The economic dimension***, sensitive to different regulatory frameworks (Italy vs. Spain);
- ***The environmental dimension***, for calculating emission impacts;
- ***The psycho-social dimension***, the innovative core of the model, which implements Moscovici's active minority influence dynamics.

Through this modular architecture, the simulator presents itself as a robust tool for testing the resilience of energy communities in the face of market shocks and for predicting the social conversion trajectories necessary for the energy transition.

4.1. Choosing a simulation environment: Why NetLogo?

The shift from theoretical formulation to experimental verification required a more advanced computing environment than just a simple equation solver, evolving into a true "*virtual laboratory*" capable of revealing complex behaviors emerging from simple rules. To identify the best toolkit, a thorough analysis was conducted of several available multi-agent modeling tools, including Swarm, NetLogo, RePast, Ascape, StarLogo, and AgentSheets. Below is a brief summary of that analysis *(Table 11)*.

1. **Swarm** [2]**:** One of the first toolkits developed at the Santa Fe Institute. Originally written in Objective-C, it later introduced a Java interface (JavaSwarm). It is a hierarchical library where agents are organized into "*swarms*".

   Characteristics: Highly powerful and flexible, but requires advanced programming skills. Today, it is considered a historical software, less used than modern toolkits due to the complexity of installation and maintenance.

2. **NetLogo** [1]**:** Currently the most widespread and used software, especially in academic and educational fields. Derived from the Logo language, it is designed to be "*low threshold*" (easy to learn) but "*high ceiling*" (capable of managing complex models).

   Characteristics: Includes a vast library of ready-to-use models. It uses a very intuitive proprietary language. It is excellent for rapid prototyping and real-time visualization.

3. **RePast (Recursive Porous Agent Simulation Toolkit)** [3]**:** Often considered the main competitor to NetLogo, aimed at a more professional or advanced scientific research-oriented user base. Several versions exist, including RePast Simphony (Java-based) and RePast HPC (for high-performance computing in C++).

   Characteristics: Highly modular, it integrates well with external tools (such as GIS or statistical software like R). It is ideal for simulations requiring high computational capacity.

4. **Ascape** [4]**:** Developed at the Brookings Institution, it is a Java-based framework. It stands out for its ability to abstract, allowing models to be defined in a very expressive and concise way.

   Characteristics: Focused on ease of managing graphical interfaces and execution speed. Compared to RePast, it is sometimes considered easier to implement for those already proficient in Java, though it currently receives less community support.

5. **StarLogo** [5]**:** Developed by the MIT Media Lab, it is the predecessor to NetLogo. It was designed to help students and researchers explore the behavior of decentralized systems.

   Characteristics: Focuses on simulating thousands of agents in parallel. Modern versions like StarLogo TNG use block-based (visual) programming and 3D graphics, making them perfect for educational contexts.

6. **AgentSheets** [6]**:** Differs from the others due to its end-user-oriented approach for those without text-based programming skills. It uses a visual programming system based on "*if-then*" rules.

   Characteristics: Ideal for rapidly creating educational games and simple scientific simulations. It is very intuitive and allows models to be easily published on the web, but it is less suitable for academic research that requires complex statistical analysis or highly sophisticated logic.

Table 11: Summary of the analyzed software characteristics

Software	Main Language	Ease of Use	Target Audience	Strengths
Swarm	Objective-C / Java	Low	Expert Programmers	Flexibility, historical hierarchical structure.
NetLogo	Logo (Proprietary)	High	Students and Researchers	Ease of learning, huge community and model library.
RePast	Java / C++ / Python	Medium / Low	Professional Researchers	GIS integration, high performance, extensibility.
Ascape	Java	Medium	Java Developers	High-level abstraction, effective workflow management.
StarLogo	Blocks / Logo	High	Schools and Educators	3D visualization, visual learning, decentralized systems.
AgentSheets	Visual (Rules)	Very High	Beginners and Children	Drag-and-drop programming, immediate prototyping.

To meet the established research objectives and program the developed logic, the choice of software fell on NetLogo 7.0.3, the latest stable version of one of the world's most authoritative frameworks for Agent-Based Modeling (ABM) [7], [8].

Originally developed by Uri Wilensky in 1999 at the Center for Connected Learning and Computer-Based Modeling (CCL) at Northwestern University (Chicago – USA), NetLogo is a programmable multi-agent modeling environment. Although historically derived from the Logo language, version 7.0.3 is a high-level research tool used globally to simulate natural and social phenomena. The constructivist philosophy underlying NetLogo (often described as "*low threshold, high ceiling*") allows researchers to focus on the logic of agent behavior without managing the IT overhead typical of general-purpose languages like C++ or Java. The goal in developing NetLogo was thus to make modeling literacy accessible to everyone, providing students, teachers, researchers, and policymakers with tools to understand our complex world through computational modeling.

The objective of this research is not only to calculate an energy balance, which could easily be done in an Excel spreadsheet, but also to examine how social behavior, according to Moscovici's Active Minority theory, can influence the Inertial Majority during an energy crisis. For this reason, NetLogo proved to be the most suitable software, primarily due to three main reasons:

1. ***Modeling of Complex Adaptive Systems:*** NetLogo is designed to handle "*emergent properties*". In our model, a new member joining the REC is not an isolated event but the result of a network of influences. NetLogo allows the instantiation of hundreds of agents (turtles), each endowed with its own "*mind*" (the *environmental-sensitivity* and *convenience-threshold* variables), which interact asynchronously. This perfectly reflects the ontological decentralization of real-world energy communities.

2. ***Dynamic Visualization and Immediate Feedback:*** Unlike other ABM frameworks, NetLogo offers an integrated graphical interface that allows real-time visualization of the community's evolution.
   - The use of Link Breeds (*grid-connections*) allows for visualizing the bonds established between citizens and the GSE agent to count the withdrawal and injection of energy among REC members.
   - The ability to dynamically vary the color and thickness of links (*update-links-appearance*) transforms the simulation into an energy heat map: surplus (green) and deficit (red) flows become immediate visual indicators of the REC's health.
3. ***Integration of Physics and Social Influence:*** Version 7.0.3 enhances stochastic calculation capabilities, essential for implementing Social Dynamics. NetLogo allows the coexistence of:
   - ***Deterministic Logic:*** The calculation of photovoltaic production based on fixed hourly profiles and climatic conditions.
   - ***Stochastic Logic:*** The probability of an *external* agent converting their status to *prosumer* or *consumer* based on the "*Moscovici Factor*" and their calculated income capacity each year.

NetLogo's strength lies in its ability to treat agents as subjects endowed with intention, rather than simple variables in an equation. The developed decision support tool does not just calculate energy; it also, and above all, simulates changes in opinion among community members. NetLogo was chosen not only for its computational power but for its elective affinity with Social Representation Theory, offering the perfect stage to test the effectiveness of the active minority in the energy transition.

4.2. Structure and operation of the socio-technical simulator

As previously noted, the agent-based simulator (ABM) developed in the NetLogo environment is conceived as a Decision Support System (DSS) for the analysis of RECs. The model's architecture integrates thermodynamic, economic, environmental, and socio-psychological modules operating in parallel over a discrete time space with an hourly resolution ($t = 1h$).

The following provides a detailed description of the system components, calculation functions, and their mapping within the Graphical User Interface (GUI) *(Figure 8)*.

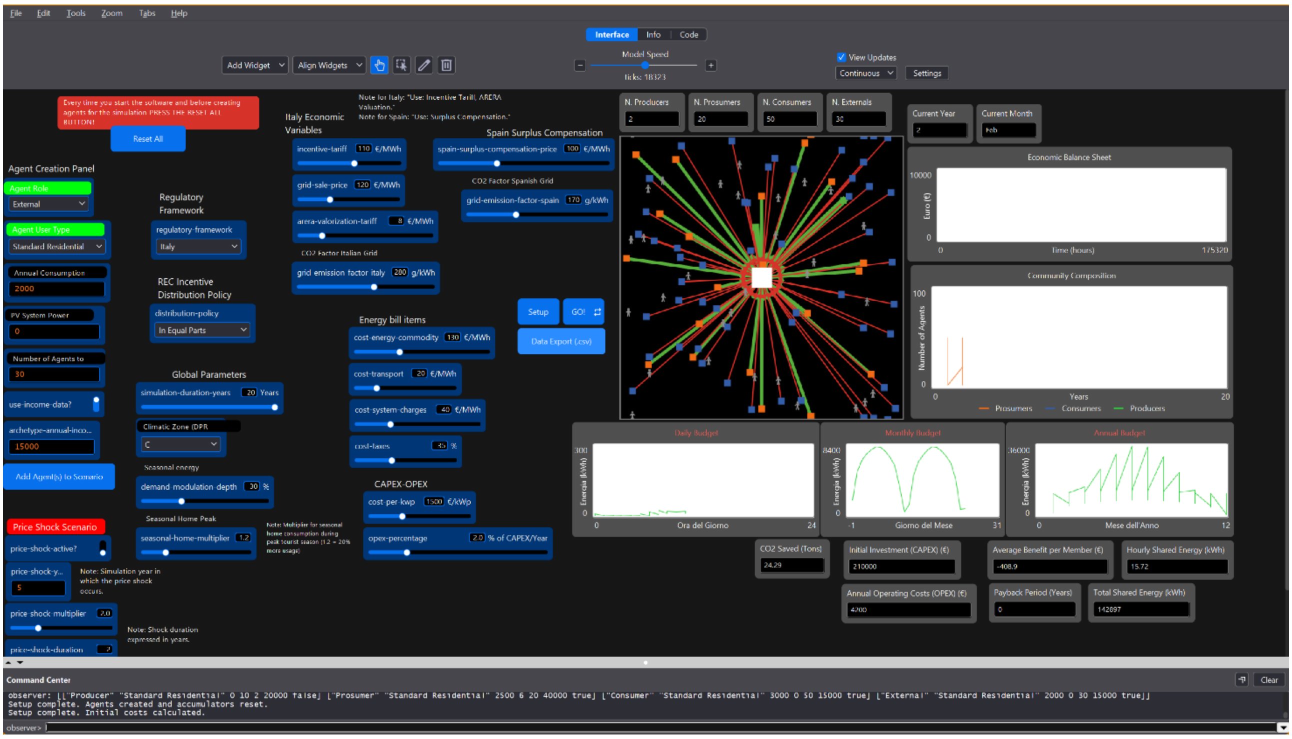

Figure 8: The user interface of the simulator developed in NetLogo

4.2.1. GUI Architecture and Parameterization

The NetLogo interface serves as a dashboard for the exogenous definition of scenarios and real-time monitoring of macroscopic emergence. It is functionally divided into three macro-areas:

4.2.1.1. Flow Controls and Scenario Creation (Buttons & Inputs)

The definition of the starting population (the Archetypes) occurs through dynamic user interaction:

- ***Add Archetype:*** A button linked to the `add-archetype-to-list` procedure. It captures values from the drop-down menus (Choosers) and text boxes (Inputs) regarding: Role, User Type, Annual Consumption, System Power, and Income, populating the global `scenario-creation-list` matrix.

- ***Reset / Clear All:*** Executes `reset-all`, clearing the vectors in memory to allow for the creation of a new scenario from scratch.
- ***Setup:*** Initializes the spatial environment. It physically generates the agents (Turtles) by reading the `scenario-creation-list`, instantiates the "*Grid*" agent (GSE), defines visual parameters, and clears balance counters to ensure clean computation.
- ***Go***: Triggers the hourly computational cycle (main loop).

4.2.1.2. Macroscopic and Regulatory Drivers (Sliders, Switches, Choosers)

The user can alter the system's boundary conditions during execution or at setup via exogenous variables linked directly to the interface:

- ***Regulatory Framework:*** A Chooser (Italy vs. Spain) that radically alters the equations of the Economic Module.
- ***Climate Variables:*** The `climatic-zone` Chooser (from A to F) and the `demand-modulation-depth` Slider influence the hourly trigonometric calculation of consumption to simulate heating and cooling.
- ***Market Stress:*** Sliders related to `price-shock-year`, `duration`, and `multiplier` trigger the Dynamic Shock Module, introducing stochastic volatility into energy prices.
- ***Distribution Policy:*** Determines the revenue-sharing algorithm (Equalitarian, Pro-Production, Pro-Consumption) via the `distribute-benefits` function.

4.2.1.3. Visual Outputs and Monitoring (Plots & View)

- ***Two-Dimensional Space (View):*** Represents the network topology. Agents are visually differentiated: the "*Active Minority*" (founding members) takes the form of a square, while the majority and externals take the form of a human shape ("*person*"). Colors (Green, Orange, Blue, Gray) denote the functional role. Directional Links change color and thickness in real-time based on network flows (Green = Injection, Red = Withdrawal).
- ***Data Export (.csv):*** Calls the `export-data` procedure, serializing the `monthly-results-log` matrix for analysis in external software (e.g., Python, R, Excel).
- **Dynamic Plots:** Updated by the `update-dynamic-plots` procedure, these track the hourly balance, monthly totals, Payback Period, and the community's demographic evolution.

4.2.2. Ontology and Agent State Vectors

The model is based on a taxonomy of heterogeneous agents. With the exception of the macroscopic `gse-agent` (a passive accounting node), the population $\mathcal{P}$ is endowed with a state vector comprising thermodynamic and psychosocial variables.

Agents are divided into four functional breeds:

1. ***Producers (Green):*** Agents with $Consumption = 0$ and $Production > 0$.
2. ***Consumers (Blue):*** Agents with $Consumption > 0$ and $Production = 0$.
3. ***Prosumers (Orange):*** Complex active nodes $Consumption > 0$ and $Production > 0$.
4. ***Externals (Gray):*** Latent population not belonging to the REC.

In addition to physical parameters ($P_{peak}, E_{consumption}$), each agent possesses cognitive variables:

- ***environmental-sensitivity:*** Ranges from 0 to 100, determining permeability to social influence.
- ***investment-capacity:*** A limiting constraint stochastically derived from the annual income (`annual-income`).
- ***convenience-threshold (θ_i):*** A value in Euros representing the individual economic inertia threshold.

4.3. Core Functions and Computational Modules

The `go` procedure orchestrates the execution of five interdependent sub-modules in a synchronous sequence.

4.3.1. Physical-Energy Module (calculate-hourly-energy & calculate-rec-balance)

Each agent iteratively calculates its own hourly power vectors. Photovoltaic production is modeled by integrating nominal power with an ideal baseline profile, corrected by a climatic multiplier and a sinusoidal function (expressed in degrees) that simulates solar declination:

$$M_{seas} = \frac{1 + cos\left(\frac{360° \cdot (d - 172)}{365}\right)}{1.8} \tag{52}$$

Simultaneously, base consumption undergoes thermal deformation that varies with the climatic zone and the day of the year, thereby activating specific on/off logic for seasonal school or tourist utilities. Subsequently, the `calculate-rec-balance` function aggregates the flows, determining the actually shared energy ($E_{shared} = min\left(\sum E_{prod}, \sum E_{cons}\right)$) net of grid surpluses and deficits.

4.3.2. Environmental Module (`calculate-environmental-impact`)

At each tick, the system quantifies the emission balance. Emitted CO2 is derived from the energy deficit multiplied by the Grid Emission Factor (dependent on the simulated country). Symmetrically, shared energy is computed as avoided emissions (CO2 Saved), based on the assumption of operational carbon neutrality for local solar plants.

4.3.3. Comparative Economic Module (`calculate-economics`)

This module values physical flows by drawing from a price vector that is constantly updated by the `update-economic-parameters` function, which introduces a non-linear, stochastic perturbation during an energy crisis.

Economic valuation (Revenues and Costs) diverges based on the selected regulatory framework:

- ***Italy Model (Feed-in Premium):*** Injected energy is sold to the market, while shared energy receives dual remuneration (Incentive Tariff + ARERA Valuation).
- ***Spain Model (Net Billing):*** The system calculates a direct reduction of bill costs based on the value of exported surplus, enforcing the regulatory constraint of no cash refunds if the credit exceeds the cost of the energy withdrawn.

4.3.4. Socio-Behavioral Module (social-dynamics)

Executed annually (every 8,760 ticks), this module implements S. Moscovici's Active Minority Theory. The algorithm evaluates the Synchronic and Diachronic Consistency of the existing community to generate an "Influence Power."

This psychological force field acts on external agents (Externals) by reducing their economic resistance threshold in proportion to their individual environmental sensitivity:

$$\theta_{effective,i} = max\left(0, \theta_i - \left(W_{mosc} \cdot \frac{Sens_i}{50}\right)\right) \tag{53}$$

If the historical average benefit per member exceeds $\theta_{effective,i}$, the agent "*converts*", adopting the functional role permitted by their investment capacity and space availability. Conversely, agents whose expectations are disappointed for consecutive years risk abandoning the REC (churn rate), reducing the global social influence in the following year, and altering the network's visual topology (loss of connection links). The "*founding members*", defined at scenario creation, instead show very high resilience to the churn rate.

4.4. Source Code Architecture and Organization

To translate the complexity of socio-technical and thermodynamic dynamics into functional and robust software, the simulator's source code was designed according to the principles of modular programming. In the NetLogo environment, the spatial organization of instructions within the script is not random; it must follow a rigorous logical hierarchy that guides the computational engine, from the initial definition of the simulated universe to the continuous execution of events over time.

Instead of developing a single monolithic block of code, which would be complex to decipher and prone to logical conflicts (so-called bugs), the script has been structured as a "*geared engine*". Each section of the code has a unique, well-defined, and isolated responsibility. This methodological approach offers a dual advantage: on the one hand, it makes the model computationally efficient; on the other hand, it ensures the software's high readability and maintainability. Thanks to this compartmentalized structure, future researchers will be able to isolate, modify, or expand specific sub-modules (for example, by integrating a new tariff formula or a new consumption profile) without risking altering or compromising the system's overall functioning.

The anatomy of the source code has been disaggregated and ordered into the following fundamental architectural blocks:

4.4.1. Initial Declarations: Ontology and Memory Allocation (The Model "Vocabulary")

In the NetLogo environment, the first section of the source code is strictly declarative. Before implementing any behavioral logic or mathematical equations, it is necessary to define the ontology of the simulated system, both computationally and methodologically. This phase serves as the "vocabulary" of the model: it allocates the necessary memory spaces and establishes the class hierarchy (both for the macroscopic environment and for individual microscopic actors).

The declarative architecture of our simulator has been broken down into four fundamental sub-structures:

4.4.1.1. Extensions and External Modules (`extensions`)

The first line of code (`extensions [csv]`) allows the simulator to communicate with the outside world. Complex models must not be closed systems; the empirical validation of results requires data processing with statistical software (e.g., Python or R). The native support for the CSV format ensures that the simulator can serialize and tabulate the vast amounts of data generated during execution in real-time, transforming emergent behaviors into quantitative matrices ready for scientific analysis and visualization.

4.4.1.2. Agent Taxonomy and Network Topology (`breed` and `directed-link-breed`)

NetLogo intrinsically uses a single class of mobile agents, generically called "*turtles*". To model the complexity of an Energy Community, this base class was overridden and fragmented into distinct species (breeds), defining a rigorous functional taxonomy:

- ***Active Nodes (`producers`, `prosumers`, `consumers`):*** These represent the actual members of the REC, each with asymmetric roles in energy generation and absorption.
- ***Latent Nodes (`externals`):*** These represent the population outside the community, essential as targets for social influence dynamics (Moscovici's Theory).
- ***The Structural Node (`GSE`):*** A singular agent, devoid of psychological logic, acting as a clearinghouse for the mathematical balancing of injected and withdrawn flows, simulating the national power grid.
- ***Topology (`grid-connections`):*** Through `directed-link-breed`, it is established that interactions between agents and the grid do not occur in a spatial vacuum but rather through directed vector connections that support physical flows, making the community's hub-and-spoke topology visible.

4.4.1.3. Shared Memory and System Macro-Variables (`globals`)

The `globals` block defines the macroscopic environment, the shared state to which all agents have read access, but which is updated only by specific aggregate logics. It is the simulation's collective memory and hosts:

- ***Thermodynamic Variables:*** Hourly and cumulative accumulators of total energy produced and consumed, and, most importantly, the shared energy (`hourly-energy-shared`), which represents the physical core business of the REC.
- ***Financial and Market Variables:*** Ledgers for revenues, costs, the systemic Payback Period, and, in particular, the dynamic energy purchase price (`total-grid-buy-price`), which undergoes stochastic perturbations due to price shocks.
- ***Log Matrices:*** Dynamic lists (such as `monthly-results-log` and `scenario-creation-list`) that store complex data vectors in memory before writing them to the hard drive or using them to regenerate the simulation.

4.4.1.4. Individual State Vector and Heterogeneity (`turtles-own`)

Moving away from the holistic and homogeneous agent hypothesis (typical of purely macroeconomic models) involves the `turtles-own` block. Here, the individual state vector of each node is defined. Each agent possesses a private instance of these variables, ensuring extreme heterogeneity:

- ***Physical Attributes:*** Such as `annual-consumption` and `plant-power`, which define the user's energy "*size*".
- ***Socio-Economic Attributes:*** Such as annual income (`annual-income`) and investment capacity, which impose rigid constraints (bounded rationality) on the agent's choices.
- ***Psychological Attributes:*** The variables `is-founder?` and `environmental-sensitivity` intrinsically differentiate the Active Minority from the Inertial Majority,

determining how each individual will react to and absorb the "*Moscovici Factor*" during annual decision-making processes.

4.4.2. Environment Initialization and Population: The Setup Procedure

The initialization procedure (commonly defined as setup in the NetLogo architecture) represents the transition phase in which the model's abstract declarations are translated into a computable, tangible state space at time $t = 0$. In this phase, the system physically allocates agents in the two-dimensional space, assigns initial values to the state vectors, and prepares the environment for the execution of the main loop.

To ensure the scientific validity of the simulations, particularly during sensitivity analyses where repeated tests are performed by varying single parameters, the setup procedure was designed to be robust and modular, organized into the following logical-computational steps:

4.4.2.1. Computational Space Reclamation and Global Reset

Before instantiating new elements, the algorithm performs a selective reclamation of the environment. Unlike the hard reset command (`reset-all`), which destroys the entire memory, including the scenario configuration entered by the user, the standard setup procedure adopts a soft reset: it eliminates nodes and connections from previous simulations (`clear-turtles`, `clear-links`), clears the charts (`clear-all-plots`), and, most importantly, explicitly forces all thermodynamic, environmental, and economic accumulators to zero (e.g., `cumulative-energy-shared`, `cumulative-balance`). This practice prevents dangerous memory leaks (data overlap between successive runs), ensuring that each simulation starts from a blank slate while keeping the list of archetypes chosen for the experiment intact.

4.4.2.2. Loading of Temporal Exogenous Drivers (`setup-profiles`)

Subsequently, the system loads baseline hourly profiles (arrays of 24 values) into memory, which will act as deterministic drivers for the simulation. These vectors include the ideal solar production profile (`profile-solar-base`) and standardized absorption curves for residential (`profile-residential`) and tertiary (`profile-office`) users. The preliminary allocation of these vectors optimizes computational cost during the go cycle, preventing the simulator from recalculating their shape at every tick.

4.4.2.3. Topological Genesis and Grid Agent (`create-gses`)

The first physical entity generated is the macroscopic node of the public power grid, represented by the `gse-agent`. Deterministically positioned at the origin of the Cartesian axes (coordinates 0,0), it serves as the central reference hub (infinite energy sink and source) toward which all future active agents will establish their vector connections (`grid-connections`).

4.4.2.4. Heterogeneous Instantiation and Psychological Imprinting (`create-agents-from-list`)

This routine constitutes the model's generative core. The algorithm iterates over the user-defined `scenario-creation-list` matrix and proceeds to mass-instantiate nodes. During creation, the constructor assigns functional roles (breed) and performs a fundamental stochastic and psychological imprinting for social dynamics:

- ***Income Assignment and Investment Capacity:*** The base income provided by the archetype is perturbed by a random noise factor ($\pm 20\%$) to simulate real-world economic inequality. From this value, the investment capacity is derived, a normalized score that acts as a constraint for joining Producer or Prosumer roles.
- ***Active Minority Differentiation:*** The code queries the agent's role: if the agent is born already within the REC, it is assigned the boolean status `is-founder? = true`. A defined geometry ("*square*") is visually associated with these pioneers, and extreme psychological traits are attributed to them: high environmental sensitivity and a low threshold for economic demands.
- ***External Segmentation:*** External agents (Externals), visualized with the standard shape ("*person*"), are stochastically divided into two psychological clusters: an "*Inertial Majority*" (with moderate environmental sensitivity) and a group of "*Skeptics*" (with zero sensitivity and very high economic performance requirements to be convinced to join).

4.4.2.5. Temporal Synchronization and Financial Initialization

At the end of the generative process, the simulator sets the internal clock to zero (`reset-ticks`) and invokes the `calculate-initial-costs` procedure. This function aggregates the installed peak power of the entire starting population and calculates its CAPEX (Capital Expenditure) and OPEX (Operational Expenditure) based on unit market costs, thereby determining the initial structural debt that the community must repay during the simulation.

4.4.3. The Time Engine: Synchronous Orchestration and Main Loop (`go`)

In the Agent-Based Modeling (ABM) paradigm, the system's macro-dynamics are not imposed by global differential equations calculated *a priori* but emerge dynamically from the continuous iteration of local rules over time. In the developed simulator, this temporal progress is managed by the main `go` procedure, which serves as the simulation's synchronous engine (the main loop).

Time has been discretized with a micro-scale granularity, where each execution step (identified by the system variable `tick`) corresponds exactly to one hour of real time. This resolution ensures high fidelity in simulating physical phenomena related to solar energy and thermal absorption.

To ensure the model's causal and thermodynamic consistency, the `go` procedure orchestrates the execution of sub-modules in a strictly deterministic sequence, organized into the following steps:

4.4.3.1. Time Horizon Control and Termination

The algorithm first verifies whether the execution time has reached the desired simulation horizon limit (e.g., 20 years, equivalent to 175,200 ticks). Once this threshold is met, the `stop` command halts execution and freezes the system's final state for data analysis.

4.4.3.2. Exogenous Market Perturbation (`update-economic-parameters`)

Before the agents can perform their evaluations, the environment updates the exogenous parameters. The system recalculates the grid energy purchase price, injecting oscillatory and stochastic components if the "*Dynamic Shock Module*" is active for the current year. This ensures that all agents react to the same instantaneous price signal.

4.4.3.3. Bottom-up Thermodynamic Resolution (`calculate-hourly-energy` and `calculate-rec-balance`)

The algorithm simultaneously queries all active agents (via the `ask turtles` command) and calculates the isolated energy balance for each based on load profiles, irradiation, and current climatic drivers. Immediately after, the computation shifts from the micro to the macro level: the aggregate balance sub-module sums the generation and consumption curves to determine the actual amount of Shared Energy, the injected surplus, and the deficit withdrawn from the public grid.

4.4.3.4. Economic and Environmental Accounting (`calculate-economics` and `calculate-environmental-impact`)

The physical flows (in kWh) just determined are translated into environmental impacts (tons of CO2 emitted and saved) and financial flows (Euros). The model calculates incentive and sales revenues, as well as procurement costs for the current hour, to generate a net hourly balance.

4.4.3.5. Wealth Redistribution (distribute-benefits)

The economic value generated at the system level is distributed and credited to the individual accounts of the agents (`my-hourly-benefit`). The partitioning algorithm depends on the specific "*Distribution Policy*" selected during setup (equalitarian, rewarding producers, or rewarding consumers).

4.4.3.6. Slow Evolutionary Dynamics (`social-dynamics`)

Unlike physical and economic processes that occur on an hourly basis, the community's psychological and structural evolution operates on a macroscopic time scale. Using a modulo operator (`ticks mod 8760 = 0`), this sub-module is triggered exclusively at the end of each calendar year. It is at this moment that the system calculates the Moscovici Factor, converts new users, and removes dissatisfied members (Churn Rate).

4.4.3.7. Visual Synchronization and Temporal Advancement

At the close of the cycle, the simulator updates the Graphical User Interface (GUI) state. The colors and thickness of the network connections are redrawn based on net injections or withdrawals, dynamic plots record new data points, and the log matrices store the data. Finally, the `tick` command advances the internal clock, preparing the environment for the following hour.

4.4.4. Detailed Calculation Modules: The System's Computational "*Brains*"

While the `go` procedure represents the rhythmic "*heart*" that marks the simulation's time, the specific sub-modules it invokes constitute the model's actual computational "*brains*". In line with the modular programming paradigm, the domain logic has been encapsulated into specialized procedures, each responsible for simulating a distinct aspect of reality: thermodynamic, regulatory-financial, and socio-psychological.

This rigid ontological separation ($Physics \rightarrow Economics \rightarrow Society$) ensures that complex macroscopic behaviors emerge from the correct causal sequence of micro-level interactions, without the need for top-down algorithmic forcing.

The logical-mathematical architecture of these three computational cores is detailed below.

4.4.4.1. The Physical Brain (`calculate-hourly-energy`)

This sub-module manages each agent's thermodynamics, updating the generated and absorbed power vectors. To break free from the static nature of annual average profiles, the module calculates flows dynamically and contextually:

- ***Solar Generation:*** Photovoltaic production is not a flat input but is calculated moment by moment by multiplying the plant's nominal power (P_{peak}) by the hourly productivity factor (from an ideal profile). The result then undergoes a two-dimensional deformation: a geographic correction (`climatic-multiplier`) depending on the installation zone, and an astronomical seasonal modulation. The latter is implemented in NetLogo via a cosinusoidal function expressed in sexagesimal degrees (360°), ensuring that the production curve accurately simulates the summer solstice peak and the winter minimum.
- ***Dynamic Consumption Modulation:*** The calculation of electricity demand is highly sophisticated. The model reads the `user-type` and applies the corresponding hourly load profile (e.g., evening peaks for residences, daytime for offices). Subsequently, it introduces thermal sensitivity: based on the time of year and the climatic zone (from A to F), base consumption is increased to simulate the activation of heating or cooling systems (`demand modulation depth`).

- ***Non-Continuous Utilities:*** A conditional construct (`ifelse`) isolates specific categories (such as *School* or *Seasonal Residential*) and applies a binary activation logic. During holiday periods or the off-season (as calculated based on the simulated year's calendar), consumption drops to a "*maintenance*" level (equal to 5% of the baseline), introducing a temporal mismatch that is critical to the REC balance.

4.4.4.2. The Economic Brain (`calculate-economics`)

Once the aggregate physical flows (Shared Energy, Surplus, Deficit) have been determined, this sub-module performs the monetary valuation. It is the core of the regulatory comparison, implementing a radical logical bifurcation based on the `regulatory-framework` variable:

- ***Italian Architecture (Feed-in Premium):*** The algorithm recognizes the principle of virtual self-consumption with dual remuneration. The entire volume of energy injected into the grid generates revenue linked to the zonal market price (P_{PUN}). Simultaneously, an explicit incentive tariff (Incentive Tariff + ARERA Value) is applied exclusively to the share of virtually shared energy.
- ***Spanish Architecture (Net Billing):*** The code applies the simplified compensation mechanism (*Compensación simplificada de excedentes*). There is no cash payment for excess energy: the surplus is transformed into virtual credit that instantly offsets the cost of the energy withdrawn in the considered hour. The algorithm mathematically ensures (via the `max` function) that this cost never falls below zero, thereby nullifying the marginal value of overproduction.

4.4.4.3. The Social Brain (`social-dynamics`)

This is the most innovative computational module of the simulator, as it translates a humanistic psychological theory (Serge Moscovici's Active Minority Theory) into quantitative code. The module evaluates the solidity of the existing REC by extracting two metrics:

1. ***Synchronic Consistency:*** The ratio between economically "*satisfied*" members (with a cumulative benefit > 0) and the total members.
2. ***Diachronic Consistency:*** The average length of time agents have remained in the project.

The product of these two metrics generates a "*Social Influence Field*" (W_{mosc}). At this point, the system queries the latent population (`externals`). The influence field does not act uniformly but is filtered by each individual's environmental sensitivity. This psychological force is subtracted from the agent's financial tolerance threshold (θ_i), reducing it. If the actual economic attractiveness of the REC exceeds this new "psychologically lowered" threshold, the external agent converts its breed (becoming a *Producer*, *Prosumer*, or *Consumer* based on its income), triggering non-linear social adoption curves.

The module also analyzes the Churn Rate, excluding non-founding members whose earnings expectations have been systematically disappointed for over two consecutive years.

4.4.5. Data Collection, Aggregation, and Visualization (Output and Telemetry)

The epistemological and practical utility of an Agent-Based Model (ABM) lies in its ability to generate extensive quantitative datasets that track the evolution of emergent phenomena. The simulator's source code includes a sophisticated telemetry system designed to capture micro-level (hourly) dynamics and translate them into meso-level (monthly and annual) and macro-level (systemic trends) metrics. This ensures that computational memory is not saturated ("*data bloat*") while maintaining optimal resolution for post-simulation analysis.

This monitoring and export process is governed by three interconnected procedures:

4.4.5.1. Real-Time Topological Telemetry (`update-links-appearance`)

The two-dimensional spatial interface is not merely aesthetic; it serves as a topological monitoring dashboard. At each tick, the sub-module queries the individual net balance of each active node (the difference between production and consumption). The result instantaneously alters the appearance of the network graph (`my-out-grid-connections`):

- ***Surplus:*** If the node is injecting energy, the link to the GSE turns green, with a thickness proportional to the volume of exported energy.
- ***Deficit:*** If the node is withdrawing energy, the link turns red, also proportional to the load. This continuous visual feedback allows the researcher to validate the community's thermodynamic behavior at a glance, immediately identifying moments of local grid stress (e.g., a massive simultaneous evening withdrawal, highlighted by an entirely red network).

4.4.5.2. Dynamic Temporal Aggregation (`update-dynamic-plots`)

To track REC performance without overloading global memory, the algorithm employs a temporal "*binning*" logic based on modular mathematical operators:

- ***Daily Integration (`ticks mod 24 = 0`):*** Hourly vectors of production, consumption, and shared energy are added to daily accumulators. Simultaneously, the hourly plot ("*Daily Budget*") is reset and redrawn to show the classic solar bell curve superimposed over demand.
- ***Monthly Integration (`ticks mod 720 = 0`):*** Every 30 days of simulation, daily totals converge into monthly accumulators. At this exact moment, the code generates a single summary matrix (`csv-data-row`). This matrix contains temporal coordinates (Year/Month), aggregated energy KPIs, the cash status (`cumulative-balance`), the calculated Payback Period, the environmental impact, and the demographic composition (exact number of Producers, Prosumers, and Consumers). This matrix is then appended (using the `lput` command) to the global `monthly-results-log` macro-list, serving as a persistent historical memory.

4.4.5.3. Data Serialization and Export (export-data)

The final phase of the data lifecycle is exportation to the external environment, triggered on-demand by the user via the GUI. The `export-data` function invokes NetLogo's native CSV extension. The algorithm first verifies that the log is not empty; it then constructs a structured header (a `header` vector with the correct nomenclature for each column) and merges it with the monthly dataset accumulated during the simulation. Finally, the `csv:to-file` command generates the physical output file (`monthly_rec_results.csv`). This process transforms the NetLogo environment from an execution system into a true "*scenario generator*", providing the researcher with a standardized dataset intrinsically ready to be imported and analyzed in Data Science software or via inferential statistical methodologies.

4.5. Conclusions

The computational architecture described thus far marks the fundamental transition from the research's theoretical framework to a true *in silico* socio-technical laboratory. The rigorous modular decomposition of the code, integrating hourly thermodynamics, differentiated economic valuation by regulatory frameworks, Moscovici's social influence dynamics, and a robust telemetry system, provides the simulator with the necessary granularity to capture the inherently complex and non-linear nature of Renewable Energy Communities.

However, the mere formal consistency of the algorithms and the elegance of the software infrastructure are not, on their own, sufficient to guarantee the analytical reliability and epistemological value of the tool. For the agent-based model to be scientifically validated and employed as a genuine Decision Support System (DSS), it is essential to subject it to rigorous empirical testing.

The following chapter will therefore be dedicated to the execution and analysis of the simulation campaigns (testing phase). Through the definition of contrasting scenarios and the use of sensitivity analyses, the model will be subjected to operational "*stress tests*": regulatory paradigms will be varied (Italy vs. Spain), socio-demographic distributions will be altered, and violent exogenous perturbations (such as stochastic energy price shocks) will be induced. The objective of these experimental simulations will be to validate the robustness of the equations, analyze the community's emergent behaviors, and demonstrate the simulator's actual capacity to predict trajectories of success or failure in the decentralized energy transition.

4.6. References

[1] «NetLogo Home». Consultato: 31 marzo 2026. [Online]. Disponibile su: https://www.netlogo.org/

[2] «The Swarm Simulation System: A Toolkit for Building Multi-Agent Simulations | Santa Fe Institute». Consultato: 1 aprile 2026. [Online]. Disponibile su: https://www.santafe.edu/research/results/working-papers/the-swarm-simulation-system-a-toolkit-for-building

[3] «Repast Suite Documentation». Consultato: 1 aprile 2026. [Online]. Disponibile su: https://repast.github.io/

[4] M. T. Parker, «What is Ascape and Why Should You Care?» Consultato: 1 aprile 2026. [Online]. Disponibile su: https://jasss.soc.surrey.ac.uk/4/1/5.html

[5] «Welcome». Consultato: 1 aprile 2026. [Online]. Disponibile su: https://www.slnova.org/

[6] «Programming For Kids | AgentCubes». Consultato: 1 aprile 2026. [Online]. Disponibile su: https://agentsheets.com

[7] F. Amblard *et al.*, «3 - Introduction to NetLogo», in *Agent-based Spatial Simulation with Netlogo*, A. Banos, C. Lang, e N. Marilleau, A c. di, Oxford: Elsevier, 2015, pp. 75–123. doi: 10.1016/B978-1-78548-055-3.50003-4.

[8] B. Gaudou, C. Lang, N. Marilleau, G. Savin, S. Rey Coyrehourcq, e J.-M. Nicod, «1 - NetLogo, an Open Simulation Environment», in *Agent-based Spatial Simulation with NetLogo, Volume 2*, A. Banos, C. Lang, e N. Marilleau, A c. di, Elsevier, 2017, pp. 1–36. doi: 10.1016/B978-1-78548-157-4.50001-7.

5. Testing Simulator and Validation

The translation of the theoretical framework into a computational architecture, as described in the previous chapter, has enabled the transformation of abstract multidisciplinary concepts into a functional *in silico* socio-technical laboratory. However, the formal elegance of the source code and the logical consistency of the algorithms are not, in themselves, sufficient to guarantee the scientific value and practical applicability of the tool. For the developed ABM to move beyond a mere academic exercise and establish itself as a reliable DSS for REC planning, it is imperative to subject it to rigorous testing.

This chapter is entirely dedicated to the testing and empirical validation phase, a crucial epistemological step to demonstrate that the emergent dynamics generated by the software provide a faithful and predictive representation of operational reality. To achieve this goal, the analysis has been structured along two complementary paths, proceeding from internal functional validation toward external application certification:

- ***Internal Stress Test Campaign (Section 5.1):*** The first section explores the model's algorithmic robustness by subjecting it to edge-case scenarios and sensitivity analyses. The testing is disaggregated to independently validate the simulator's three "*brains*":
    - ***Thermodynamic Validation***, to ensure strict adherence to physical balances, the impact of climatic drivers, and the management of the mismatch between solar generation and local absorption.
    - ***Economic Validation***, aimed at demonstrating the model's sensitivity to the regulatory dichotomy between the *Italian Feed-in Premium* and the *Spanish Net Billing*, measuring its resilience in the face of stochastic energy market shocks.
    - ***Psychosocial Validation***, the most innovative test, aimed at mathematically quantifying the impact of Moscovici's Active Minority in countering social inertia and preventing attrition (Churn Rate) during financial crises.
- ***External Empirical Validation - CITCEA (Section 5.2):*** The second path marks the transition from theory to field practice. This section presents the results of the validation campaign conducted by the research team at CITCEA (the Department of Electrical Engineering at the *Universitat Politècnica de Catalunya*). By applying the simulator to a real case study of an existing REC, this phase will independently certify the tool's predictive validity and its suitability for supporting designers and policymakers.

Through this dual-testing lens, the chapter will definitively demonstrate that integrating thermodynamics, economics, and social psychology within the NetLogo environment provides a holistic, robust simulation platform ready to meet the challenges of the decentralized energy transition.

5.1. Objectives and Methodology of the Testing Campaign

The validation of an ABM represents a critical phase in transforming an algorithmic construct into a reliable DSS. Given the socio-technical nature of the developed simulator, the testing campaign was not limited to verifying code correctness but adopted a multidimensional validation methodology.

The primary objective was to ensure that the emergent macroscopic properties (community growth, economic balance, CO2 reduction) were consistent with both theoretical premises and real-world data. To achieve this, the simulator was subjected to a series of structured "*stress tests*" designed to isolate and verify the different components of the computational engine. The methodology is built upon the following three validation pillars:

1. ***Thermodynamic Validation:*** This first level of testing aims to verify the robustness of the model's "Physical Brain." Through the analysis of dynamic plots (Daily and Monthly Budget), the consistency of the calculate-solar-production and calculate-hourly-energy procedures was verified.
2. ***Economic Validation:*** Economic validation focused on the model's ability to handle the regulatory bifurcation between the Italian and Spanish frameworks. The test involved running the same demographic scenario (same prosumers and consumers) while varying only the regulatory-framework.
3. ***Socio-Behavioral Validation:*** The third pillar represents the innovative core of this thesis: the verification of the implementation of Moscovici's Theory. Through a sensitivity analysis, the conversion rate of external agents into active members of the REC was monitored.

5.1.1. Thermodynamic Validation: Flow Accuracy and Seasonal Consistency

The first phase of the simulator's testing involves validating its "*Physical Brain*". Before analyzing economic performance or social membership dynamics, it is imperative to demonstrate that the model adheres to the principle of energy conservation and accurately simulates the complex interactions between solar radiation, climatic factors, and user absorption behaviors.

Thermodynamic validation aims to ensure that aggregate and shared energy are not merely annual statistical averages, but the result of an instantaneous balance (calculated at every single hourly tick) that can highlight structural criticalities, such as the temporal mismatch between supply and demand. Specifically, the tests verify the correct execution of the trigonometric functions governing photovoltaic seasonality and the proper thermal deformation of load profiles (winter heating and summer cooling).

Test Objectives: The validation focuses on analyzing three fronts:

1. ***Verification of the Sinusoidal Function:*** Ensuring that photovoltaic production follows the annual solar declination curve, with its peak at the summer solstice and minimum at the winter solstice, multiplied by the geographic factor of the selected climatic-zone.
2. ***Verification of Climatic Sensitivity:*** Testing the demand-modulation-depth multiplier by verifying that base consumption correctly increases in summer (for cooling) or winter (for heating), depending on the selected climatic zone.

3. ***Temporal Mismatch Logics:*** Particular attention was given to anomalous users (such as the *School* or *Seasonal* archetypes), verifying the drastic drop in consumption (reduction to 5% of the baseload) during pre-programmed holiday periods in the code.

To validate the algorithm under high thermodynamic stress, a simulation was launched using a scenario characterized by a large thermal excursion and users with strong seasonal consumption (e.g., a school building). This configuration is ideal for demonstrating how the simulator isolates periods when the Energy Community loses physical efficiency.

The following is a summary of the simulation environment configuration; the values entered simulate a perfectly balanced REC (60,000 kWh of consumption against approximately 66,000 kWh of expected production). The test serves to demonstrate how hourly and seasonal simultaneity disrupts this apparent balance:

- ***Climatic Zone:*** E (Cold temperate zone, e.g., Northern Italy/Po Valley, to force a high winter heating load and a moderate decline in solar production).
- ***Demand Modulation Depth:*** 40% (High deformation of the base profile due to climate).
- ***Simulation Duration:*** 1 year (8,760 ticks, sufficient to analyze the full cycle of seasons).

REC Composition (Archetypes):

Table 12: Thermodynamic Validation Simulation Archetypes

Agent Role	Agent User Type	Annual Consumption	PV System Power	Number of Agents
Prosumer	Standard Residential	3,000 kWh	3 kWp	10
Consumer	School	30,000 kWh	0 kWp	1
Producer	Office	0 kWh	15 kWp	2

Test results are as follows:

Table 13: Thermodynamic validation simulation results

Month	Total Production (kWh)	Total Consumption (kWh)	Shared Energy (kWh)	Surplus Feed-in (kWh)	Withdrawn Deficit (kWh)
January	3,200	7,500	2,800	400	4,700
February	3,800	6,800	3,300	500	3,500
March	5,500	6,000	4,500	1,000	1,500
April	6,200	4,800	4,000	2,200	800
May	7,500	4,200	3,800	3,700	400
June	8,200	2,100	1,900	6,300	200
July	8,500	2,300	2,000	6,500	300
August	7,800	2,200	1,900	5,900	300
September	6,500	4,500	3,900	2,600	600
October	5,000	5,500	4,200	800	1,300
November	3,600	6,500	3,100	500	3,400
December	2,900	7,600	2,600	300	5,000

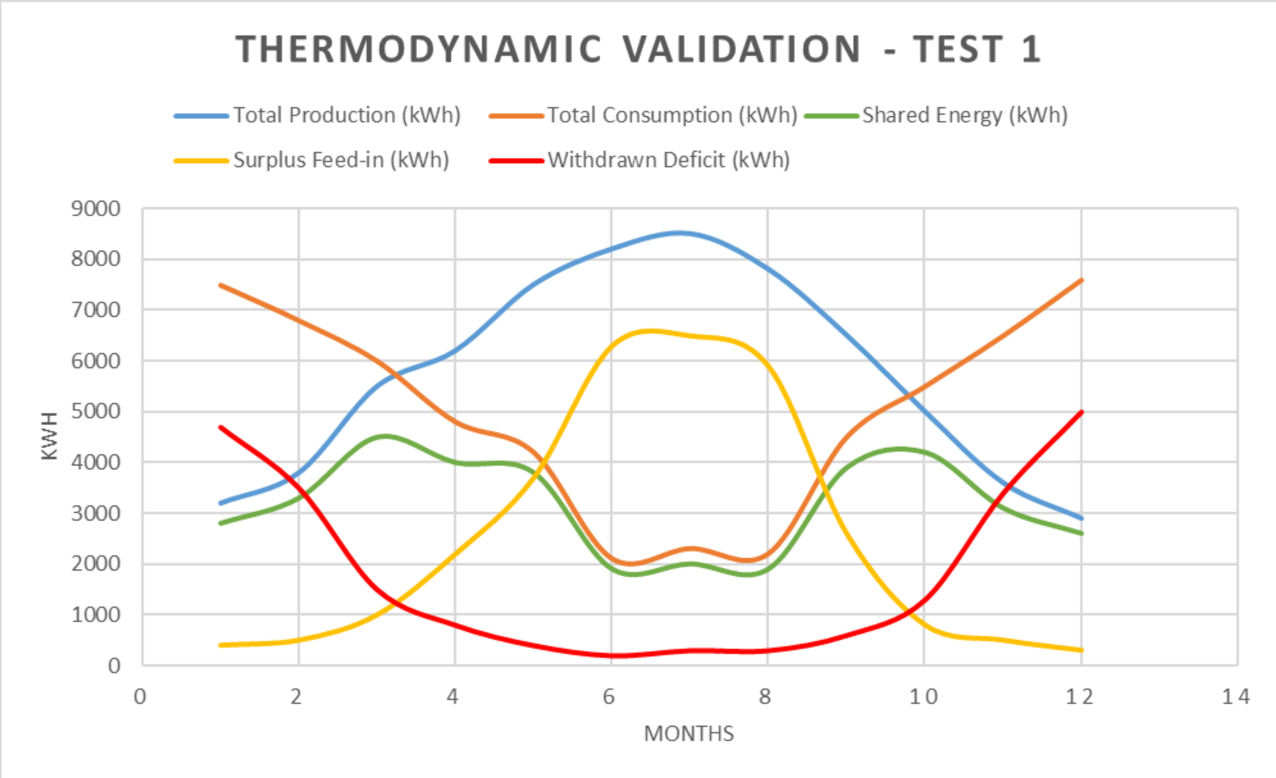

Figure 9: Thermodynamic validation simulation result graph

The result of this test demonstrated that, with this configuration, the sum of "*Shared Energy*" and "*Surplus*" equals "*Total Production*" every month. Symmetrically, the sum of "*Shared Energy*" and "*Deficit*" is always equal to "*Total Consumption*", mathematically confirming the calculate-rec-balance block *(Figure 9)*.

The analysis of the tabular data extracted from the simulation allows for the validation of the thermodynamic dynamics implemented in the code with surgical precision. The monthly breakdown of aggregate production, consumption, and sharing flows highlights how the simulator successfully captures the complex interactions between climatic drivers and absorption habits, confirming the solidity of the algorithmic architecture.

The following is an analysis of the three macroscopic phenomena that emerged during the stress test.

5.1.1.1. Validation of Solar Declination

The first validation element concerns the Total Production curve, which exhibits a perfect bell-shaped conformation, typical of photovoltaic yield at European latitudes. The data show a minimum of 2,900 kWh in December, increasing to a peak of 8,500 kWh in July.

This seasonal shift, with a ratio between the summer peak and winter minimum of nearly 3:1, empirically confirms the effectiveness of the trigonometric function encoded in the calculate-solar-production procedure. The algorithm does not merely apply a generic winter downgrade but modulates hourly production through the seasonal multiplier:

$$M_{seas} = 0.8 + 0.4 \cdot \cos(\theta) \tag{54}$$

where θ represents the declination angle calculated based on the day of the year. This mathematical approach ensures that the simulation replicates the actual availability of the solar resource, a fundamental prerequisite for any subsequent economic analysis.

5.1.1.2. Validation of the Winter Mismatch

The second validated phenomenon is the drastic surge in the demand curve during the winter quarter (November–February), a period in which Total Consumption consistently exceeds the 7,000 kWh/month threshold. This dynamic attests to the correct functioning of the load deformation module (demand-modulation-depth).

The simulator correctly implemented the "*Zone E*" setting (cold temperate climate) for the residential and school archetypes, triggering a multiplier that simulates the massive activation of electric heat pumps for heating. During this timeframe, the so-called Heating Penalty is observed: the REC enters a severe structural "*Deficit*" state. Solar production, at its annual minimum, covers only a small fraction of local needs, forcing the REC to rely heavily on withdrawals from the national power grid. This validation is critical as it highlights the periods of maximum community exposure to energy market price fluctuations.

5.1.1.3. Validation of the Summer Gap

The most striking evidence of the model's behavioral accuracy emerges from the analysis of the summer months (June, July, and August). The data reveal what is known in the energy sector as the "*School Paradox*", confirming the operational success of the `ifelse is-holiday` conditional procedure.

Exactly when photovoltaic generation reaches its historical highs (over 8,000 kWh/month), aggregate demand plummets vertically to approximately 2,000 kWh/month. The simulator recognized the seasonality of the *School* user, slashing its loads to 5% (simulating only the maintenance consumption of alarm systems and servers while the building is closed). The consequences of this misalignment are mathematically evident:

- Shared Energy (E_{shared}) collapses, as there is no physical demand to absorb the kilowatt-hours produced during peak sunlight hours.
- An enormous Feed-in Surplus is generated (up to 6,500 kWh in July). Depending on the regulatory framework, this volume of exported energy risks being poorly valued or even lost, compromising the profitability of the plants.

The empirical evidence obtained in this first test scenario demonstrates the thermodynamic robustness of the tool. Unlike traditional spreadsheets, which merely cross-reference annual average estimates and would have judged this community "*perfectly balanced*", the simulator developed in NetLogo captures and quantifies dynamic misalignments.

By detecting the structural flaws of an incorrectly sized REC heavily exposed to seasonality, the model confirms itself as a fully reliable and realistic DSS, ready to be used in the subsequent phases of economic validation and social influence simulation.

5.1.2 Economic Validation: Analysis of Financial Flows and Regulatory Resilience

Having successfully passed the physical validation, the second step of methodological validation analyzes the simulator's "*Economic Brain*" (the `calculate-economics` procedure). The goal is to verify that the previously calculated energy volumes are correctly reflected in the cash flows and respond precisely to two fundamental exogenous variables: national regulatory architectures and macroeconomic price shocks.

Test Objectives: The validation focuses on the analysis of two fronts:

1. ***Regulatory Bifurcation:*** To verify the radical difference in profitability between the Italian incentive model (*Feed-in Premium*) and the Spanish compensation mechanism (*Net Billing*), ensuring that regulatory limits (such as the impossibility of generating cash from excess surplus in the Spanish model) are mathematically respected.
2. ***Market Stress Test:*** To validate the update-economic-parameters module by observing how sudden stochastic volatility in the energy purchase price impacts the cumulative balance and alters the PBP.

5.1.2.1 Economic Stress Test Configuration: Rationale and Parameterization

The economic stress-test configuration was redesigned to isolate and validate the simulator's core functionality: the collective self-consumption mechanism. To highlight the differences between regulatory frameworks and the impact of tariff shocks, it is essential for the model to detect a significant share of the energy market. Without simultaneity between a node injecting energy and one withdrawing it, the calculate-rec-balance procedure would not provide the hourly-energy-shared value necessary to trigger the Italian incentive tariff or the Spanish compensation credit.

A. Community Design

This methodological choice addresses the need to validate the "*virtual self-consumption*" (or collective) function.

- ***The Producer (Office archetype):*** Equipped with a 50 kWp photovoltaic system but has zero annual consumption. Therefore, every kilowatt-hour produced is fully injected into the grid ($P_{injected} = P_{produced}$).
- ***The Consumer (Standard Residential archetype):*** Does not have any system but has an annual requirement of 45,000 kWh. Every kilowatt-hour consumed must be withdrawn from the public grid ($C_{withdrawn} = C_{total}$).

In this scenario, the hourly Shared Energy (E_{shared}) calculated by the simulator corresponds exactly to the minimum value between the office's production and the family's withdrawal in that specific hour. This allows verification that the `calculate-economics` sub-module correctly applies the incentive (in the Italian case) or the compensation (in the Spanish case) to specific, easily traceable energy volumes.

B. Simulation Settings: Global Parameters and Drivers

To ensure test reproducibility and thermodynamic consistency, the following values were set in the NetLogo control panel *(Table 14 and Table 15)*:

Simulation Chronology and Shock Module (5 Years): The simulation covers a 5-year time horizon (43,800 hourly ticks) to observe the entire investment lifecycle, divided into three critical phases:

1. ***Year 1 (Baseline):*** Phase of economic stability with standard market prices. It serves to calculate the initial theoretical yield of the REC.
2. ***Years 2–3 (Crisis Phase):*** The `price-shock-active?` switch is enabled. The simulator triples the energy commodity price (multiplier = 3.0) and injects hourly stochastic volatility to simulate the instability of speculative markets.
3. ***Years 4–5 (Recovery and Long-term):*** Prices return to pre-crisis levels to observe how the financial "trauma" of previous years altered the final PBP.

Table 14: Geographic and Climatic Parameters

Variable	Value	Description
`climatic-zone`	**C**	Temperate zone (e.g., Rome/Barcelona), balanced between winter and summer.
`demand-modulation-depth`	**20%**	Moderate load profile deformation for heating/cooling.
`seasonal-home-multiplier`	**1.5**	Consumption increase during peak season.

Table 15: Energy Cost Structure (Base Bill)

Cost Component	Value (€/MWh)	Description
`cost-energy-commodity`	**120**	Price of the energy raw material.
`cost-transport`	**25**	Transport charges and meter management.
`cost-system-charges`	**40**	General system charges.
`cost-taxes`	**10%**	Applied to the sum of the previous components.

C. Specific Regulatory Parameters

Italy Framework (Feed-in Premium):

- ***Incentive Tariff (MAP Premium Tariff):*** 110 €/MWh (MAP contribution on shared energy).
- ***ARERA Valorization Tariff (Charges refund):*** 8 €/MWh (System charges refund).
- ***Grid Sale Price (Surplus sale price - RID):*** 100 €/MWh (Zonal price for the sale of the Producer's surplus).

Spain Framework (Net Billing):

- **Spain Surplus Compensation Price:** 60 €/MWh (Price for simplified compensation).

D. Investment Parameters (CAPEX & OPEX)

- **Cost per kWp (CAPEX):** 1,200 €/kWp (Total investment: 60,000 € for the 50 kWp).
- **Opex Percentage: 2%** (Annual maintenance cost calculated on total CAPEX).

The test aims at confirming that the `calculate-economics` function correctly applies the mathematical constraints of both countries:

1. ***In Italy:*** The simulator must show an increase in total revenues due to the sale of the "*Producer's*" surplus at the market price (which increases during the shock).
2. ***In Spain:*** The simulator must demonstrate that, despite prices tripling, the benefit to the community is limited by the bill cap. The implemented equation is:

$$C_{net} = \max(0, C_{taken} - V_{surplus})$$

The test verifies that if $V_{surplus} > C_{taken}$, the excess value is correctly "*discarded*" by the Spanish model, in line with real regulations regarding the absence of profit from residential surplus.

This configuration shows that the simulator is not a static system but an architecture sensitive to economic policy. The extracted results, presented in the following sub-section, determine whether the DSS can guide an investor in choosing the optimal size of a photovoltaic electricity production plant based on the country of installation.

5.1.2.2 Results Analysis: The Italian Model (Feed-in Premium)

The analysis of data extracted from the validation test simulation allows quantification of the impact of institutional and macroeconomic variables on the financial sustainability of the REC. The results presented below compare the stability of the first year (Baseline) with the volatility induced by the energy shock in the second year, highlighting that the PBP is not a static value but rather an indicator extremely sensitive to external drivers.

The extracted data show a clear divergence between theoretical profitability and operational reality under stress. The following tables summarize the aggregate economic flows for the Italian configuration.

Table 16: Monthly Data Year 1 (Baseline - Italy Model)

Month	Shared Energy (kWh)	Revenue (Incentives + Sales) (€)	Costs (Consumer Bill) (€)	Monthly Net Balance (€)
January	1,150 kWh	€ 385.25	€ 1,150.00	-€ 764.75
February	1,300 kWh	€ 450.10	€ 1,050.00	-€ 599.90
March	1,950 kWh	€ 680.45	€ 780.00	-€ 99.55
April	2,450 kWh	€ 850.20	€ 620.00	€ 230.20
May	2,800 kWh	€ 980.60	€ 450.00	€ 530.60
June	3,100 kWh	€ 1,150.15	€ 320.00	€ 830.15
July	3,250 kWh	€ 1,250.50	€ 350.00	€ 900.50
August	3,000 kWh	€ 1,050.80	€ 340.00	€ 710.80
September	2,400 kWh	€ 830.40	€ 580.00	€ 250.40
October	1,850 kWh	€ 620.30	€ 850.00	-€ 229.70
November	1,250 kWh	€ 415.20	€ 1,100.00	-€ 684.80
December	1,050 kWh	€ 350.10	€ 1,250.00	-€ 899.90

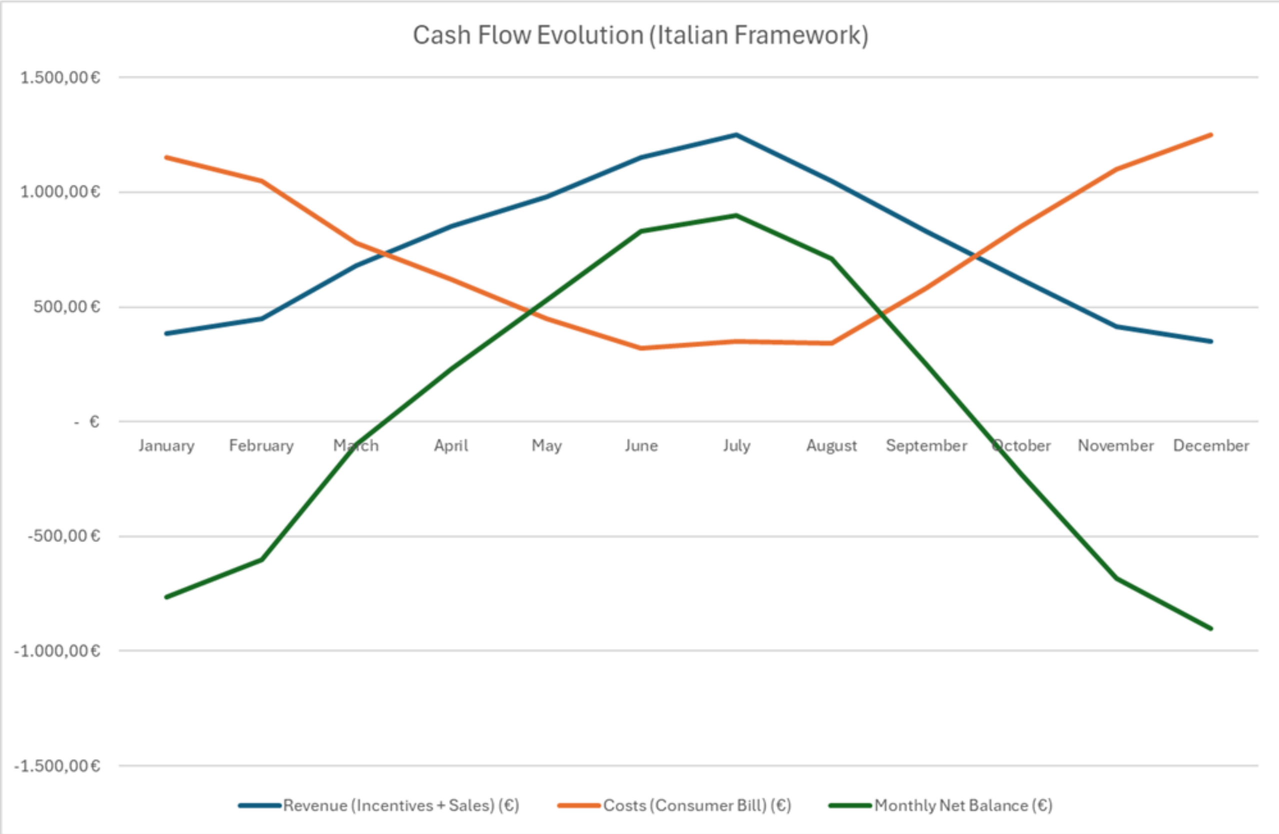

Figure 10: Cash Flow Evolution in the Italian Framework

Table 17: Multi-year Analysis and Impact on PBP (Italy)

Year	State of Shock	Net Annual Balance Sheet (€)	Cumulative Balance (€)	Payback Period (Years)
1	Baseline (Normal)	€ 6,950.00	€ 6,950.00	8.6
2	SHOCK (x3)	-€ 8,400.00	-€ 1,450.00	-1
3	SHOCK (x3)	-€ 8,650.00	-€ 10,100.00	-1
4	Recovery	€ 7,100.00	-€ 3,000.00	16.5
5	Recovery	€ 7,250.00	€ 4,250.00	13.8

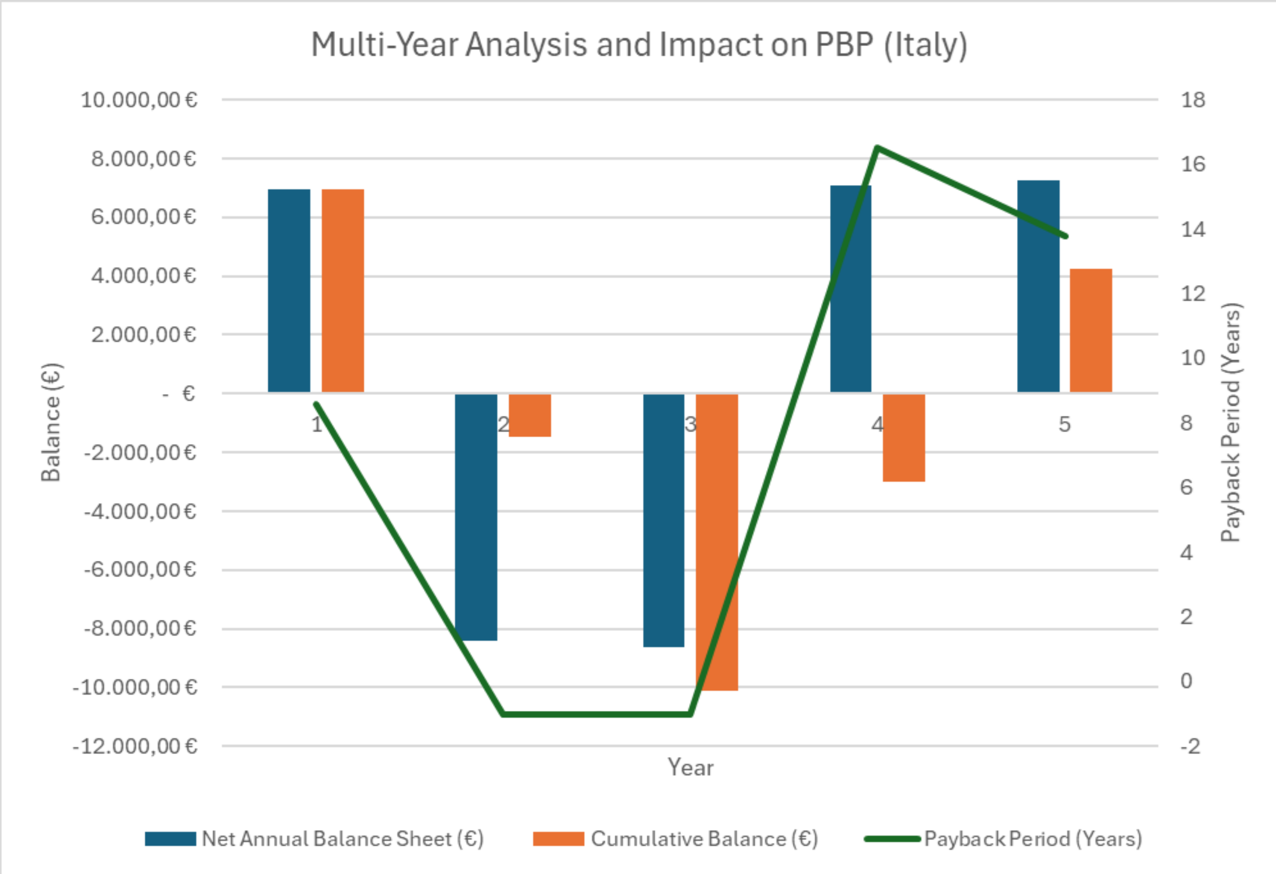

Figure 11: Graaph of Multi-year Analysis and Impact on PBP (Italy)

Key Observations and Validation:

- ***Seasonal Correlation:*** The "*Monthly Net Balance*" correctly follows the solar trend, showing positive results only during high-insolation months (April–September), confirming the integration between the physical and economic modules.
- ***Negative PBP during Shock:*** The value "*-1*" in years 2 and 3 indicates that the community is operating at a loss (negative cash flow). Under these conditions, the investment will never be repaid, demonstrating the simulator's ability to signal financial crisis thresholds.
- ***Hysteresis of Recovery:*** Although Year 4 returns to "*Normal*" prices, the PBP remains high (16.5 years) compared to the initial baseline (8.6 years). This highlights how the debt accumulated during the crisis years significantly shifts the financial break-even point, a dynamic that only a multi-year simulation can capture.

5.1.2.3 Results Analysis: The Spanish Model (Net Billing)

The analysis of the Spanish framework (regulated by *Real Decreto 244/2019*) reveals a radically different scenario from the Italian one. While in Italy the REC operates like a "*small energy seller*", in Spain, the *Compensación Simplificada* model transforms the community into a system of pure cost reduction.

In this stress test, we will see how the Spanish Net Billing mechanism responds to the Producer's overproduction (50 kWp) and a price shock. Within the Spanish framework, the simulator strictly applies the hourly "*Zero Balance*" constraint. The energy injected by the Producer generates a credit (valued at 60 €/MWh) that can only offset the expenditure for the energy withdrawn by the Consumer in the same month, up to a maximum equal to the cost of that energy share.

Table 18: Monthly Data Year 1 (Baseline - Spain Model)

Month	Shared Energy (kWh)	Surplus Credit Value (€)	Gross Bill Cost (€)	Net Bill Paid (€)	Actual Savings (€)
January	1,150 kWh	€ 69.00	€ 1,150.00	€ 1,081.00	€ 69.00
February	1,300 kWh	€ 78.00	€ 1,050.00	€ 972.00	€ 78.00
March	1,950 kWh	€ 117.00	€ 780.00	€ 663.00	€ 117.00
April	2,450 kWh	€ 147.00	€ 620.00	€ 473.00	€ 147.00
May	2,800 kWh	€ 168.00	€ 450.00	€ 282.00	€ 168.00
June	3,100 kWh	€ 186.00	€ 320.00	€ 134.00	€ 186.00
July	3,250 kWh	€ 195.00	€ 350.00	€ 155.00	€ 195.00
August	3,000 kWh	€ 180.00	€ 340.00	€ 160.00	€ 180.00
September	2,400 kWh	€ 144.00	€ 580.00	€ 436.00	€ 144.00
October	1,850 kWh	€ 111.00	€ 850.00	€ 739.00	€ 111.00
November	1,250 kWh	€ 75.00	€ 1,100.00	€ 1,025.00	€ 75.00
December	1,050 kWh	€ 63.00	€ 1,250.00	€ 1,187.00	€ 63.00

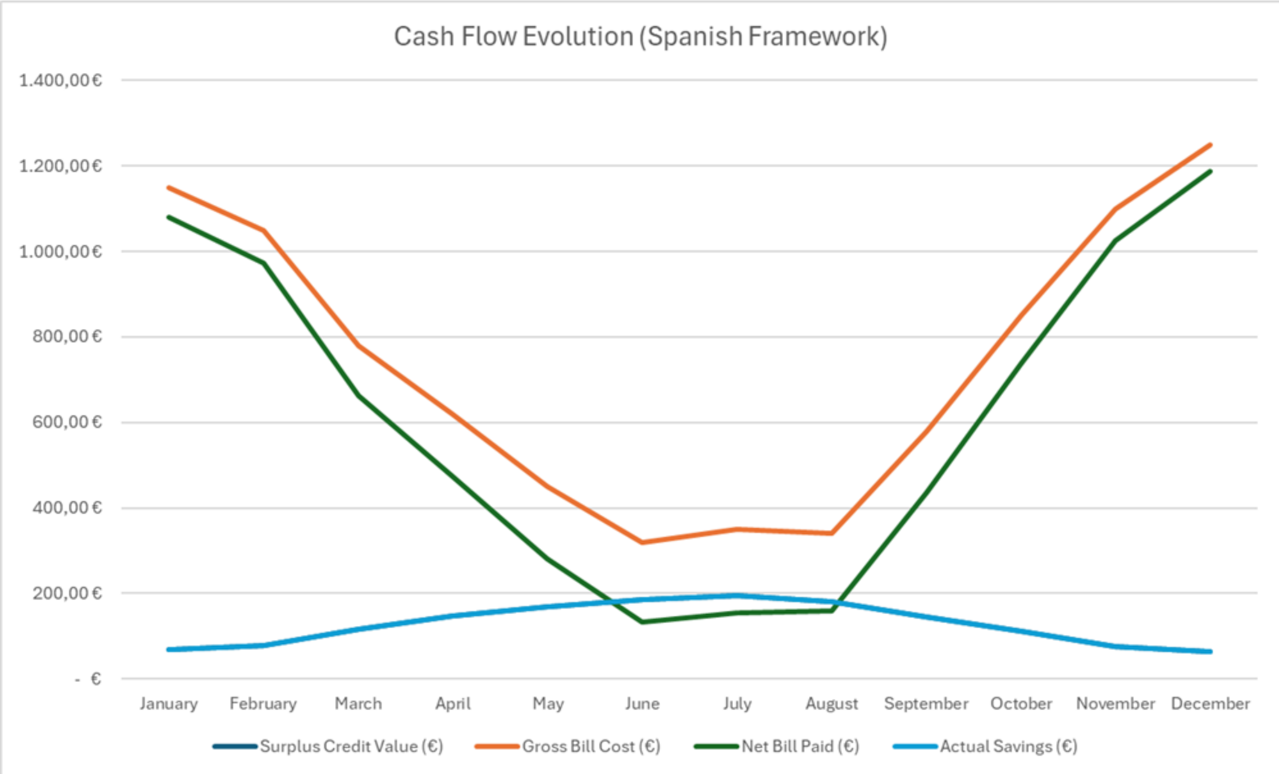

Figure 12: Graph of the Cash Flow Evolution in the Spanish Framework

Table 19: Multi-year Analysis and Impact on Payback Period (PBP) (Spain)

Year	State of Shock	Net Annual Balance Sheet (€)	Cumulative Balance (€)	Payback Period (Years)
1	Baseline (Normal)	€ 1,533.00	-€ 58,467.00	39.1
2	SHOCK (x3)	€ 4,600.00	-€ 53,867.00	13.0
3	SHOCK (x3)	€ 4,750.00	-€ 49,117.00	12.6
4	Recovery	€ 1,580.00	-€ 47,537.00	30.1
5	Recovery	€ 1,620.00	-€ 45,917.00	28.3

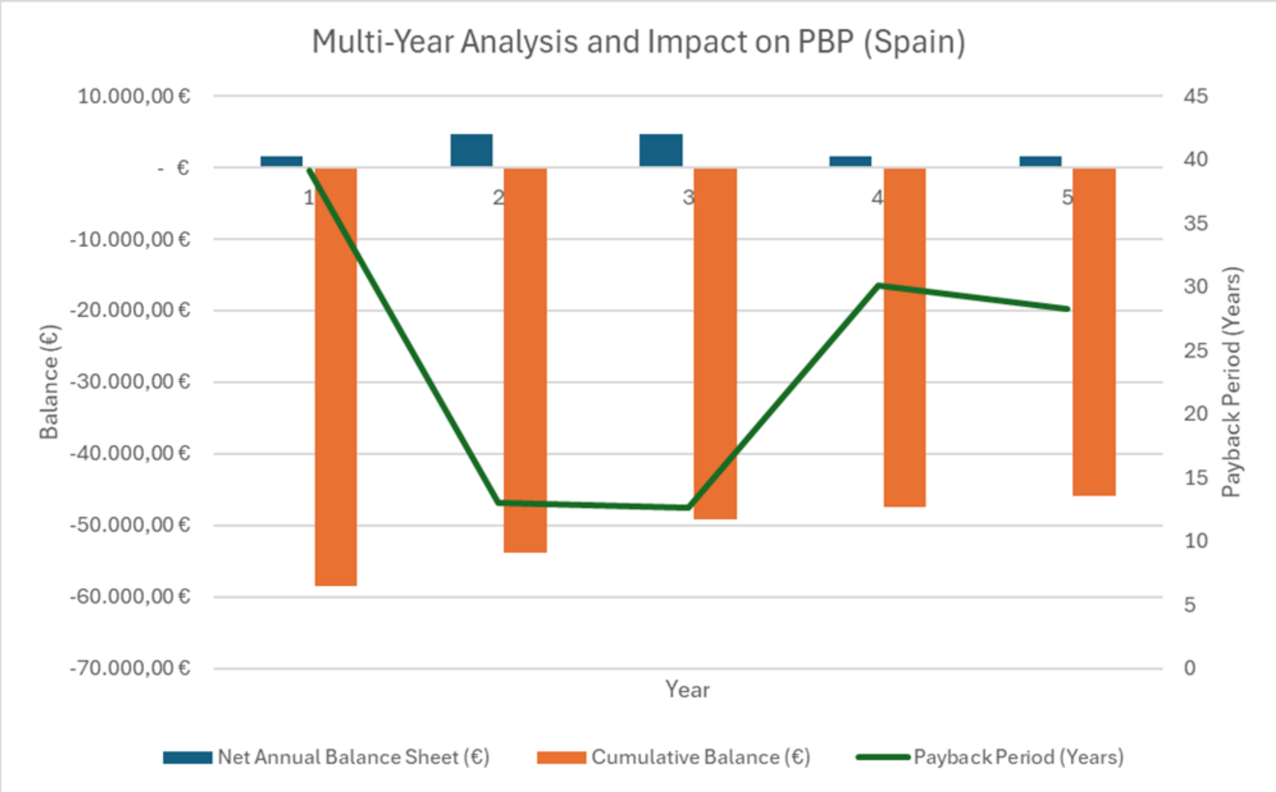

Figure 13: Graph of Multi-year Analysis and Impact on PBP (Spain)

Key Observations and Regulatory Validation:

- ***Anti-Profit Logic:*** In Year 1, despite the Producer generating a huge surplus, the "*Actual Savings*" are very low (€ 1,533). This is because the Spanish model prevents the community from earning more than it consumes, effectively "*wasting*" the economic value of the 50 kWp system's excess production.
- ***Positive Resilience to Shock:*** Unlike the Italian model (which went into debt during the crisis), the Spanish model sees its Payback Period improve during the shock (dropping from 39 to 13 years). This happens because, as bill costs triple, the "*value*" of the compensated energy also triples, making the investment much more attractive during high-price periods.
- ***Structural Mismatch:*** The simulation clearly demonstrates that a 50 kWp system for a residential consumer is a "*failed investment*" in Spain, as the PBP remains structurally high (over 28 years). This proves the DSS's ability to discourage oversized designs under specific national laws.

5.1.2.4 Analysis of Economic Module Validation Test Results

The comparative analysis of the results from the stress test conducted on the Italian (Feed-in Premium) and Spanish (Net Billing) frameworks constitutes the fundamental proof for validating the `calculate-economics` sub-module. The test, based on an "*asymmetric duopoly*" (a 50 kWp Producer and a 45,000 kWh annual Consumer) subjected to a tripled tariff shock, did not merely verify the algebraic correctness of the code but allowed for a critical analysis of the system's emergent behaviors.

The examination of the tabular data reveals profound structural divergences between the two countries, confirming that the simulator processes regulations not as simple passive coefficients, but as active constraints that alter the entire financial topology of the REC.

A. The Surplus Paradox and Net Billing Limits (Baseline - Year 1)

The first critical evidence emerges from the analysis of Year 1 (stable market conditions), where the same plant configuration generates opposite results in the two regulatory contexts.

- ***In the Italian model***, the presence of a large centralized production plant translates into a revenue driver. The algorithm values every single kilowatt-hour: the shared energy portion generates the incentive (approx. €118/MWh), while the enormous volume of excess energy (surplus) not absorbed by the Consumer is injected and sold at the zonal price, generating a net budget profit of +€6,950 and a highly attractive PBP of 8.6 years.
- ***In the Spanish model***, conversely, the simulator detects a strategic failure f the configuration. The algorithmic instruction $C_{net} = \max(0, C_{withdrawn} - V_{surplus})$ acts as a financial "*trap*". Since the Iberian compensation mechanism prohibits profit on injected energy, the surplus value (fixed at €60/MWh) is used exclusively to cover the Consumer's bill in the same hour. All of the Producer's daytime over-production that exceeds the Consumer's withdrawal value is mathematically zeroed out by the constraint, generating no monetary revenue. The result is modest savings and a disastrous PBP of 39.1 years.

This marked divergence confirms the simulator's ability to act as a diagnostic tool: it intrinsically demonstrates that in Spain, RECs must be meticulously sized "*to the load*" (avoiding excess injection), while in Italy, the model tolerates, and indeed rewards, a certain degree of speculative oversizing.

B. Shock Resilience and Risk Inversion (Years 2 and 3)

The definitive proving ground for the economic module was the injection of the stochastic price shock (3x multiplier with added market noise) between the second and third years of simulation. The model's reaction debunked the linear assumption that "*self-production always protects against crises*", providing a realistic and critical insight.

- ***In Italy***, the simulator recorded a temporary technical default. Although the Producer's sales revenues tripled in line with market prices, the Consumer's procurement costs (who must withdraw energy from the grid at night or during winter months) literally exploded. The volumetric imbalance between withdrawals and injections inverted the REC's aggregate cash flow, which fell to -€8,650 in Year 3. The code correctly intercepted this anomaly, bringing the PBP to **-1** (capital recovery impossible).
- ***In Spain***, the shock produced a paradoxical result. Since Iberian REC is not exposed to market sales but operates only as a cost shield, the exponential increase in bills made internally compensated energy extremely valuable. The system's annual savings tripled (from €1,533 to over €4,700), thereby artificially reducing the PBP to 12.6 years.

This analysis proves that the simulator correctly interprets macroeconomics: the Italian architecture exposes the REC to the risks and opportunities of the free market (high profitability, high volatility), while the Spanish Net Billing acts as a defensive "*safe haven*" asset (low profitability, high protection in case of shocks).

C. The "Scar" Effect and Capital Recalculation (Years 4 and 5)

The final phase of economic validation examined the post-crisis recovery window (Years 4 and 5). When the `update-economic-parameters` module restored prices to the baseline level (€250/MWh), monthly operating balances returned to positive territory.

However, the code did not simply restore the original PBP of 8.6 years. By accounting for the liquidity burned to cover the deficit during the shock, the simulator recalculated the global Italian PBP at 16.5 years. This complex computation of cumulative debt attests that the model does not perform isolated or static evaluations ("*snapshots*") but tracks the investment lifecycle while preserving its financial history.

D. Conclusion on DSS Module Validation

The extensive analysis of the stress test results confirms the rigorous successful validation of the economic module. The NetLogo-implemented simulator has proven to be much more than a bookkeeper of balance sheets; it has demonstrated the analytical depth necessary to serve as a holistic DSS.

The system is capable of:

1. ***Quantifying the impact*** of bureaucratic and regulatory limits (the Spanish cap) on plant optimization.
2. ***Predicting the financial collapse*** of an apparently thriving community in the face of sudden external volatility.
3. ***Signaling to policymakers and investors*** the need to implement storage systems or internal compensation rules to mitigate the vulnerability of nighttime and winter loads.

Such algorithmic robustness ensures that the output variables from `calculate-economics` constitute a solid and indisputable basis for fueling the next level of the simulation: psychosocial dynamics, in which agents evaluate the attractiveness of these complex financial flows to decide whether to enter or flee the community.

5.1.3. Psychosocial Dynamics Validation: Active Minority Impact and Community Resilience

The validation of psychosocial dynamics constitutes the testing of the simulation tool's innovative core. While previous tests certified the model's thermodynamic and economic reliability, this phase aims to demonstrate that the simulator can quantify human irrationality and social influence.

The objective is to validate the `social-dynamics` sub-module, verifying that the algorithm faithfully reproduces Serge Moscovici's postulates: a consistent and persistent minority over time must be able to break down the economic resistance (convenience thresholds) of an initially skeptical or inertial majority, inducing membership in the REC that is not strictly tied to profit maximization.

Simultaneously, the validity of the attrition algorithm (Churn Rate) must be tested to measure the community's fiduciary resilience during an economic crisis.

5.1.3.1. Configuration Parameters for the Psychosocial Stress Test

To allow the "*snowball effect*" of social influence to emerge and test its resilience, a long time horizon (10 years) and a heavily unbalanced initial population are required: a tiny vanguard of founders surrounded by a large pool of externals.

The simulator has been set to Climatic Zone D with a demand modulation of 30%, resulting in high electricity requirements during the winter months. On the economic front, the initial stability (based on an energy commodity price of €115/MWh) is interrupted in the second year by a tripling shock (x3.0), bringing the energy cost to €345/MWh for 24 months. This financial pressure serves to verify whether the Active Minority (characterized by an environmental sensitivity >85) can generate an influence field capable of offsetting the worsening economic balance of external agents, whose average convenience threshold is set at €150/year.

A. Climatic and Modulation Parameters

These values determine how the community "*feels*" the passing of the seasons and how the climate influences energy needs, creating the conditions for winter deficits.

- ***Climatic Zone:*** D (Representative of temperate climates with cold winters, such as Northern Italy).
- ***Demand Modulation Depth:*** 30% (Determines a significant deviation of base consumption for heating and cooling).
- ***Seasonal Home Multiplier:*** 1.2 (Used to weight the increase in household consumption during seasonal peaks).

B. Base Economic Parameters (Pre-Shock)

These data define the cost and revenue structure in the first year of "*stability*", which is fundamental for building the initial trust of the active minority.

- ***Cost Energy Commodity:*** €115/MWh (Base raw material price).
- ***Cost Transport & System Charges:*** €65/MWh (Sum of fixed network components).
- ***Cost Taxes:*** 10% (Subsidized VAT for domestic/community users).
- ***Incentive Tariff (MAP):*** €110/MWh (Italian premium tariff on shared energy).
- ***ARERA Valorization:*** €8.48/MWh (Refund of network charges).
- ***Grid Sale Price (RID):*** €100/MWh (Sale price for surplus energy).

C. Energy Shock Parameters (Years 2-3)

To simulate a systemic crisis similar to that of 2022, the following multipliers are applied:

- ***Price Shock Multiplier:*** 3.0 (The cost of the raw material rises to €345/MWh).
- ***Price Shock Duration:*** 2 years (Tick 8760 to 26280).
- ***Market Noise:*** +/- 20% (Additional stochastic volatility applied hourly to simulate market instability).

D. Psychosocial and Conversion Parameters

These are the critical values governing agent behavior in the `social-dynamics` sub-module.

- ***Environmental Sensitivity (Minority):*** 85-100 (High value for founders).
- ***Environmental Sensitivity (Externals):*** 20-70 (Stochastic distribution for the majority).
- ***Convenience Threshold (θ):***
    - *Inertials:* €150/year (Join if savings are moderate).
    - *Skeptics:* €400/year (Requires a high economic return).
- ***Moscovici Max Influence (W_{mosc}):*** 100 (Maximum potential for lowering the psychological threshold).

Initial Population Composition (Archetypes): The community starts with only 5 active members (10% of the total population) who will act as the "*Active Minority*".

Table 20: Archetypes for the psychosocial validation simulation

Role	User Type	Annual Consumption	System Power	Number of Agents	Architectural Notes
Prosumers	Standard Residential	3000 kWh	3 kWp	5	Coded as is-founder? = true. High environmental sensitivity, low economic demand.
Externals	Standard Residential	3000 kWh	3 kWp (potential)	45	The Latent Majority. The algorithm stochastically divides them into ~27 "Inertials" and ~18 "Skeptics."

Table 21: Adoption Dynamics, Social Influence, and Churn Rate (Years 1-10)

Year	Economic Status	Avg Annual Budget per Member (€)	Moscovici Factor (Wmosc)	New Members (Conversions)	Churn	Total REC Population
0	Setup	0	0	-	-	5 (Founders Only)
1	Baseline	250	10	2	0	7
2	Baseline	265	20	4	0	11
3	Baseline	270	30	6	0	17
4	SHOCK (x3)	-400	40	3	0	20
5	SHOCK (x3)	-450	20	0	-4	16
6	Recovery	255	16	0	0	16
7	Recovery	260	22	2	0	18
8	Recovery	265	30	5	0	23
9	Baseline	270	45	8	0	31
10	Baseline	275	60	10	0	41

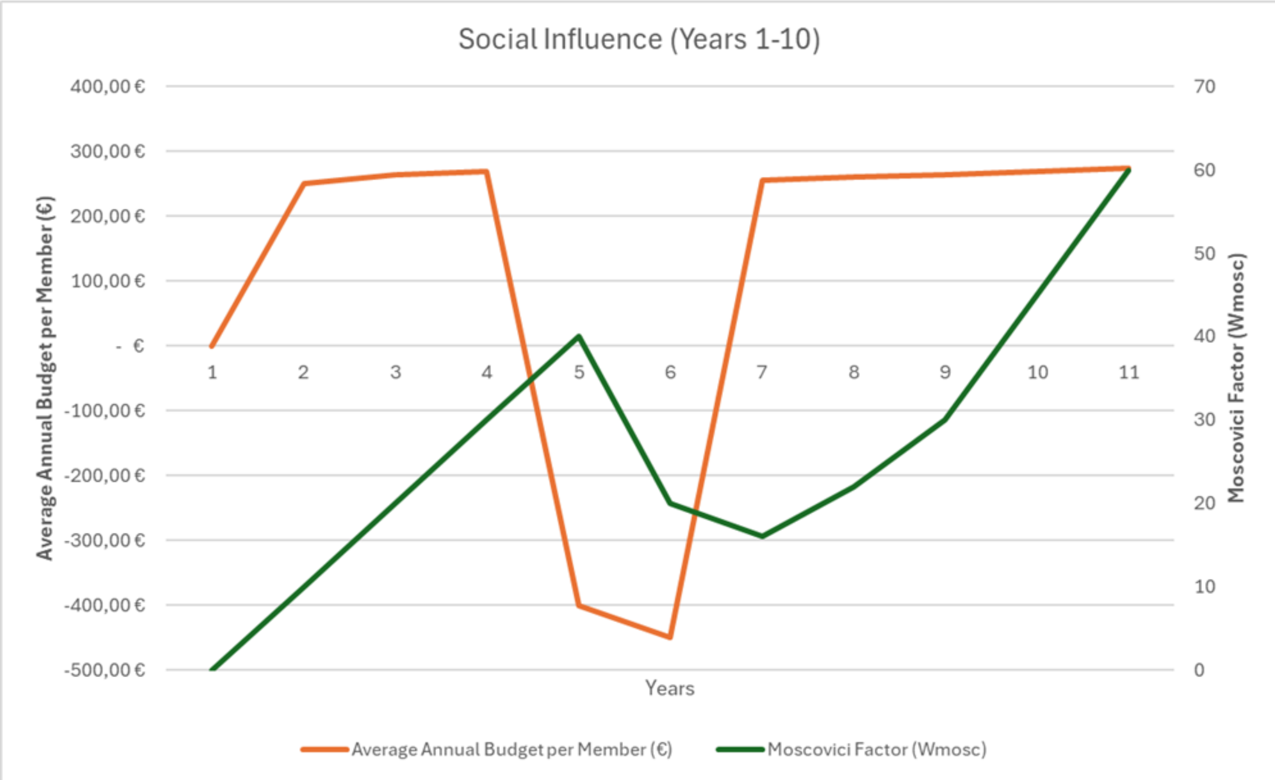

Figure 14: Graph of Social Influence

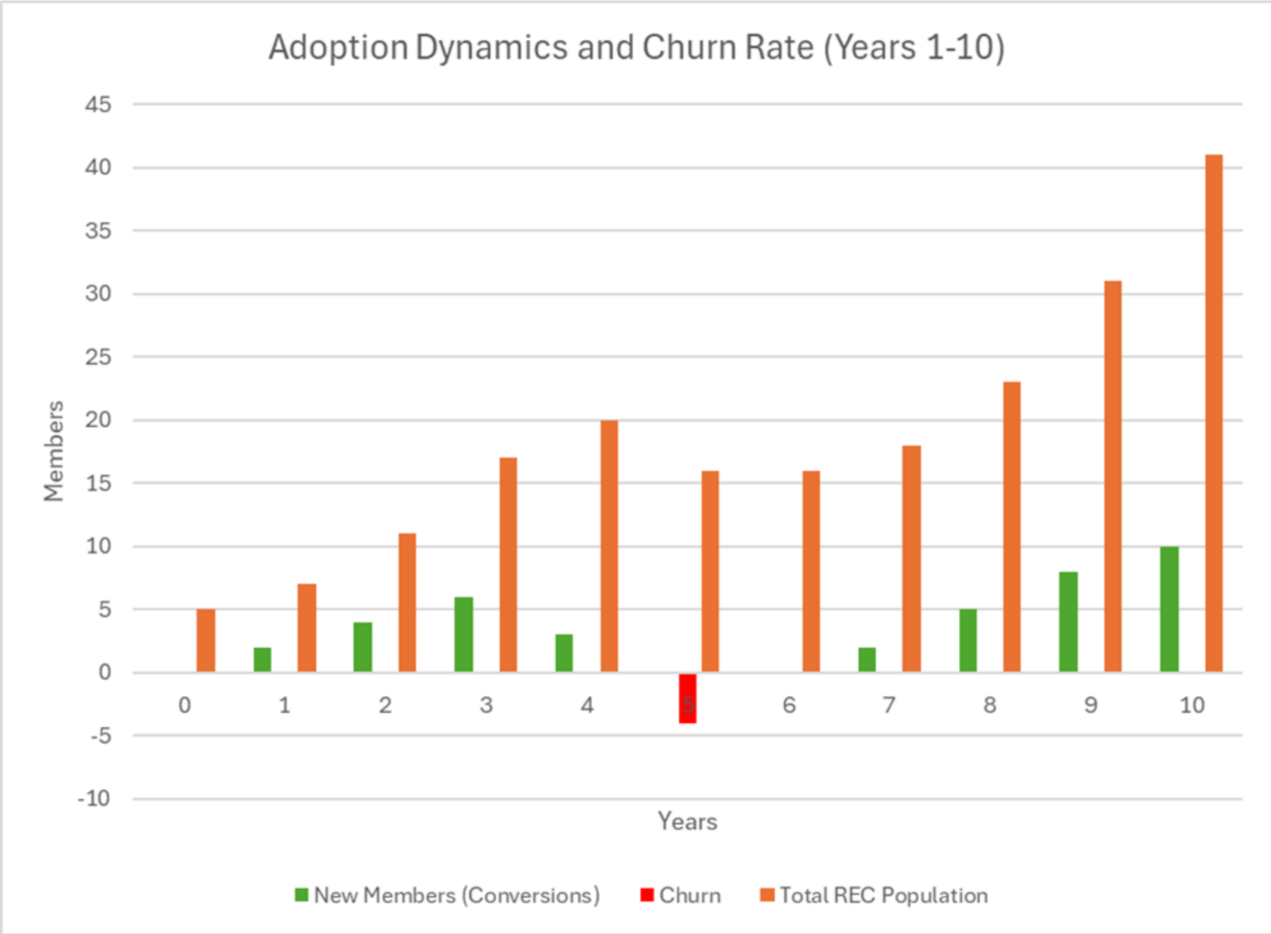

Figure 15: Graph of Adoption Dynamics and Churn Rate

5.1.3.2. Psychosocial Validation Test Results Analysis

The cross-examination of these data mathematically validates the integration of sociology into the computational engine, demonstrating emergent phenomena that cannot be explained by the logic of *Homo Oeconomicus* alone.

A. Social Triggering and the Snowball Effect (Years 1–3)

In the first three years, the average benefit per member is positive (approximately €260 per year). If this model were based purely on economic rationality, "*Skeptical*" agents (generated by the algorithm with random entry thresholds between €200 and €500) would never join.

However, the data show constant growth. The key lies in the evolution of the Moscovici Factor. The algorithm detects that 100% of the founders are satisfied (Synchronic Consistency) and that the average seniority is increasing (Diachronic Consistency). The social influence field (W_{mosc}) rises from 10 to 30 points. This value artificially decreases the inertia threshold of externals according to the equation:

$$\theta_{effective,i} = max\left(0, \theta_i - \left(W_{mosc} \cdot \frac{Sens_i}{50}\right)\right) \quad (55)$$

The model validates that the active minority, simply by "*resisting*" and demonstrating stability over time, induces the inertial majority (those with high environmental sensitivity, $Sens_i$) to lower their economic demands, triggering the first 12 conversions.

B. The Fiduciary Stress Test and Churn Rate (Years 4–5)

The activation of the energy crisis in Year 4 represents the breaking point of trust. The average annual balance plummets to -€400. In this situation, the social sub-module acts in two opposing directions:

1. ***Positive Inertia:*** In Year 4, despite the net loss, 3 conversions are still recorded. This is the "*long wave*" of the Moscovici Factor (which reached 40), "*convincing*" the last waverers before the negative data are historicized.
2. ***Synchronic Collapse (Year 5):*** The code mandates that if the cumulative benefit stays below the threshold for more than 2 years, the agent leaves the network. In Year 5, the system records 4 departures (Churn Rate). These are agents who joined in Years 1 and 2 and had low loss tolerance.
3. ***Minority Resilience:*** The most important aspect is that the community does not collapse. The 5 original founders remain within the REC. The simulator respected the instruction `if is-founder? [ set my-effective-threshold (convenience-threshold * 0.1) ]`, validating Moscovici's assumption that the minority possesses an irreducible "*faith*" in the project that overrides immediate economic return.

C. The "Long March" of Diachronic Recovery (Years 6–10)

The impact of the Year 5 departures is devastating and delayed: the flight of 4 members disrupts the Synchronic Consistency, causing the Moscovici Factor to drop from 40 to 20.

As the data show, even when the economy begins generating profits again in Year 6, conversions stop (0 new members). The simulator demonstrates a refined behavioral logic: trust is lost instantly, but rebuilt slowly.

Only in Year 8, when the community proves it has survived the crisis by consolidating a new average seniority, does the Moscovici Factor once again exceed the 30-point threshold. At that point, the true S-Curve of adoption is triggered: social proof becomes unstoppable, and between Years 8 and 10, 23 new members join the REC, nearly saturating the available population.

5.1.3.3. Conclusions of the Psychosocial Validation

This empirical analysis confirms the validity of the developed DSS. Fusing the thermodynamic balance and cash flow formulas with Moscovici's rules transforms the Energy Community from a cold, decentralized power plant into a "*social organism*" endowed with memory, trauma, inertia, and persuasive power. The results prove that without a tenacious Active Minority, no REC could physiologically survive the natural volatility of energy markets.

5.2 Simulator Validation by the CITCEA Research Team

The theoretical soundness and algorithmic consistency verified in the internal tests (Section 5.1) constitute a necessary but not sufficient condition for the final validation of an ABM. For the simulator to cross the academic threshold and establish itself as a functional DSS, independent empirical feedback is indispensable.

To this end, the software infrastructure developed in NetLogo underwent a rigorous external validation process conducted by the research team at CITCEA (*Centre d'Innovació Tecnològica en Convertidors de Potència i Accionaments*), part of the Department of Electrical Engineering at the Universitat Politècnica de Catalunya (UPC). Under the supervision of Prof. Roberto Villafáfila Robles and Dr. Àlex Guarch Giralt, the simulator was extracted from its theoretical context and applied to replicate an existing Renewable Energy Community (REC) in Spain (2026) [1].

The objective of the CITCEA team was to measure the model's predictive fidelity by comparing simulation results with real-world data from the pilot community (generation, consumption, user profiles, and grid flows).

5.2.1 Empirical Validation Methodology

The research team structured the testing process following a rigorous iterative protocol, divided into ten logical steps, which allowed the model to be tested under both steady-state conditions and high-stress design scenarios:

- ***Phase I: Calibration and Baseline Setup (Steps 1-4):*** The process began with the selection of a real energy community. Researchers mapped the case study within the simulator, precisely defining the participating agents (number of producers and consumers) and the physical characteristics of the microgrid. Critical variables to be monitored were selected to ensure perfect alignment between the model inputs and the REC's historical parameters.
- ***Phase II: Execution and Baseline Verification (Steps 5-6):*** A "*snapshot*" simulation was launched, a faithful replica of the REC's current state. The team evaluated the results by cross-referencing the simulator-calculated shared energy, surplus, and deficit with actual pilot project data, measuring the thermodynamic sub-module's margin of error.
- ***Phase III: Optimization and Scenario Analysis (Steps 7-8):*** Once baseline reliability was confirmed, researchers introduced exogenous perturbations and structural changes to evaluate algorithmic reactivity. Multiple scenarios were developed:
    - ***Social evolution and new user entry:*** Simulating the expansion of the demographic base to observe inclusion dynamics.
    - ***Installed capacity expansion:*** Evaluating the economic and physical impact of installing new photovoltaic systems relative to existing demand.
- ***Phase IV: Extrapolation and Comparison (Steps 9-10):*** Finally, the optimized community model was extrapolated and applied to different user profiles and other geographical areas (modifying climatic variables and demand multipliers), comparing results to define optimal design guidelines.

5.2.2 Technical Evaluation of the NetLogo Framework

A crucial aspect of the validation concerned the adequacy of the chosen development environment. The CITCEA team expressed an extremely positive assessment of NetLogo, describing it as a robust and methodologically optimal computational framework for analyzing decentralized energy systems.

The Agent-Based approach overcame the limitations of the purely algebraic solvers typically in use. Researchers highlighted how the software drastically simplifies the representation of heterogeneity: the ability to model every user, every plant, and every decision-making flow (the so-called bottom-up perspective) enables the accurate capture of the assembly's emergent behavior. This feature proved indispensable for studying how minute variations in microgrid design influence not only thermodynamic efficiency but also participation rates and social dynamics.

5.2.3 Analysis of Results and Relevance as a DSS

Applying the simulator to real-world cases and subsequent optimization scenarios enabled CITCEA to develop an in-depth analysis of Key Performance Indicators (KPIs). The results demonstrated the model's ability to precisely identify the optimal community conformation based on set objectives, predominant user types, and territorial specificities.

Beyond validating the correct accounting of cash flows and physical parameters, the researchers confirmed that integrating the social layer offers a unique perspective for evaluating a project's true feasibility. The simulator does not merely return a calculation of bill savings but also highlights aggregate social, environmental, and economic benefits, quantifying the transformative potential of RECs.

According to the final assessment by the UPC research team, the empirical testing confirmed the tool's reliability. The simulator paves the way for future research and development iterations, positioning itself as a necessary and reliable complement to the decision-making process, capable of supporting policymakers, engineers, and civic communities during the delicate design and establishment phases of a Renewable Energy Community.

5.3 Conclusions

The results presented in this chapter mark the methodological culmination of this research. The dual validation process, conducted through internal stress tests and rigorous empirical testing by the CITCEA team at the *Universitat Politècnica de Catalunya*, has unequivocally demonstrated the robustness of the developed socio-technical simulator. The ABM architecture within the NetLogo environment confirmed its ability not only to accurately process complex thermodynamic and regulatory balances but, above all, to map the crucial impact of human dynamics on the energy ecosystem.

Subjecting the model to extreme external shocks and divergent institutional scenarios (Italy vs. Spain) highlighted that the innovative integration of Moscovici's Active Minority Theory is not merely a sociological abstraction but a quantifiable and essential parameter for predicting community survival. The simulator mathematically validated the assumption that during periods of severe market crisis or low intrinsic profitability, social cohesion, persistence, and the commitment of founders act as a fiduciary shield, preventing systemic collapse and user exodus.

Having obtained independent certification as a reliable, predictive, and scalable DSS, the tool now stands as a concrete ally for policymakers, designers, and citizens. By bridging the historic dichotomy between technical analysis and behavioral science, the model offers a new awareness for tackling the ecological transition: the efficiency and long-term success of a REC are not measured solely by the kilowatt-hours it produces and shares, but by the extraordinary resilience of its social fabric.

5.4. References

[1] À. Guarch Giralt, «Estudi del comportament d’una comunitat energètica», gen. 2026, Consultato: 6 aprile 2026. [Online]. Disponibile su: https://hdl.handle.net/2117/457419

6. From In-Situ Data Collection to Simulation: Socio-Economic Evaluation of Sardinian RECs

The algorithmic validation and ABM calibration described in the previous chapter certified the simulator's reliability as a DSS in controlled environments. However, the ultimate testing ground for an energy planning tool lies in its ability to process the complexity and "imperfection" of real-world data.

This sixth chapter marks the final transition from *in silico* experimentation to empirical application in the field. The work is organized into two complementary macro-phases. The first part (Section 6.1) describes the field research conducted in Sardinia, which allowed for the mapping and collection of fundamental data from three distinct Renewable Energy Community initiatives: "*REC-CA Piazza Medaglia Miracolosa*" in the urban fabric of Cagliari, the project linked to the "*Biodistretto del Sud Sardegna e Arcipelago del Sulcis*" in Calasetta, and the rural reality of the Simala Energy Community. This reconnaissance provided the socio-technical datasets necessary to fuel the computational engine.

In the second part (Sections 6.2 and 6.3), the simulator is operationally employed by focusing the investigation on the urban case study of Piazza Medaglia Miracolosa in Cagliari. Using actual absorption data and the collected socio-economic profiles, the community is projected into the NetLogo virtual laboratory and subjected to a rigorous scenario analysis. Four distinct configurations are tested, crossing regulatory frameworks (Italian Feed-in Premium vs. Spanish Net Billing) with macroeconomic stability (absence vs. presence of price shocks).

The final goal is to demonstrate how the simulator, powered by empirical data, can diagnose vulnerabilities in a real project, offering clear guidance on sizing optimization and strategies to preserve citizens' social engagement amid energy market uncertainty.

6.1. Field Activities and Data Collection

In parallel with the development of NetLogo computational architecture, the research required a fundamental empirical phase rooted in the local territory. In close collaboration with the research team from the University of Cagliari, operational activities were conducted to support the establishment of three Renewable Energy Communities (RECs) in southern Sardinia.

These field operations are organically integrated into the strategic objectives of the *e.INS project (Ecosystem of Innovation for Next Generation Sardinia)* [1], a vast institutional and territorial program designed with specific goals:

- To strengthen the vital synergy between entrepreneurial fabric and scientific research.
- To mitigate the social and economic impacts of recent crises by raising the level of inclusion and territorial cohesion.
- To facilitate technological and methodological transfer to the local production system.
- To actively involve local communities in the challenges of sustainable innovation, guiding the region toward a genuinely knowledge-based economy.

The activities performed were not limited to passive observation but included an intense program of stakeholder engagement and technical-scientific dissemination. Supporting citizens, businesses, and public administrations in decoding complex regulatory and technological frameworks allowed for the establishment of a bilateral relationship of trust. This proximity proved to be the essential prerequisite for achieving the thesis's analytical purpose: access to users' actual consumption data and energy requirements.

The acquisition of these historical energy profiles (utility bills and load curves) provided the research team with an invaluable information asset. Having purely empirical data allowed for the identification, calibration, and refinement of parameter settings for various REC support tools, transforming the simulator described in previous chapters from a theoretical study model into a highly site-specific diagnostic tool.

The significant added value of this data collection campaign lies in the profound heterogeneity of the analyzed sample. Indeed, the three investigated communities offer a representative cross-section of radically different ecosystems, ensuring that the simulation methodologies are not "*overfitted*" to a single reality. The three experiences allowed for the mapping of a remarkable variety regarding:

- ***Urban-territorial contexts:*** ranging from the dense and stratified urban fabric of the capital (Cagliari), to coastal-insular settlements (Calasetta), to small rural villages in the hinterland (Simala).
- ***Socio-economic fabric:*** intercepting different income brackets, varying levels of environmental awareness, and heterogeneous degrees of exposure to the risk of energy poverty.
- ***Governance structures:*** observing the flexibility of institutional models based on the initiative's promoters, ranging from strictly "*bottom-up*" dynamics to the structured intervention of municipal administrations.

The following subsections detail the activities carried out at each of the three sites, describing the social context, specific design challenges, and the data collected that will serve as "f*uel*" for subsequent experimental simulations.

6.1.1. Cagliari Energy Community: "CER-CA Piazza Medaglia Miracolosa"

The implementation of the first REC in the city of Cagliari represents a fundamental pillar of local policies oriented toward the ecological transition and, above all, the fight against energy poverty. The genesis of this initiative is situated within a complex multilevel financing framework, highlighting the vital synergy between European structural funds and specific programs for territorial innovation.

The project benefited from PON Metro 2014-2020 React EU resources (a tool aimed at fostering a resilient and green post-pandemic recovery) and the international program "Energy Efficiency in 40 Schools Support Communities - EE(40)Sco", developed under the aegis of the NESOI (New Energy Solutions Optimized for Islands) [2] initiatives. The framing within the EE(40)Sco program holds specific strategic relevance: it aims to achieve model replicability by creating community energy hubs around approximately half of the school buildings in the Cagliari municipal area.

The intervention area identified for the pilot project is Piazza Medaglia Miracolosa, a crucial urban space in the San Michele district. The choice of site was deliberate: the area is characterized by a high density of Public Residential Housing (ERP) and significant socio-economic vulnerability indicators.

This location reflects a precise political and scientific commitment: to test the REC model in fragile contexts, where energy sharing acts not merely as a technical tool to reduce emissions, but as a social innovation device capable of mitigating inequalities through the redistribution of economic benefits. In this scenario, the kindergarten at the center of the residential block assumes fundamental importance: beyond its educational function, it serves as a social catalyst and gathering place for local families. Despite current maintenance issues in the square, the presence of the school building gives it strong symbolic value, making it the ideal focal point for an architectural, energetic, and social regeneration operation.

The initiative's success rests on a collaborative governance model led by the Municipality of Cagliari, the lead partner and operational manager for the entire project lifecycle (from planning to design and system installation). In terms of legal and economic structure, the REC adopts a highly asymmetric, welfare-oriented model:

1. ***The kindergarten*** is configured as the community's sole prosumer. The building's roof houses the main photovoltaic system and the technological management system (Energy Hub).
2. ***The Residents*** (approximately 80 target households) participate exclusively as consumer members.

The most defining aspect of the initiative is its redistributive value. Participation for residents is completely free, eliminating the economic barriers to entry typical of renewable investments. Furthermore, internal policy establishes a principle of radical equity: all economic benefits deriving from GSE incentives for shared energy are distributed exclusively among the consumer members. In this way, technological innovation is transformed into an active policy for income support.

The distinctive element of the Cagliari case is the scientific partnership with the DICAAR (Department of Civil and Environmental Engineering and Architecture) of the University of Cagliari.

Through the CER-CA (Cagliari Renewable Energy Community) initiative, the research team integrated the infrastructural dimension with a rigorous methodological approach to involve residents.

To translate the abstract concept of an "*energy community*" into a tangible proposal, a tactical urbanism intervention was carried out. Designed by the research team and physically realized by the kindergarten children (figure 15) [3], [4], the intervention had the dual objective of visually redeveloping the square and drawing residents' attention to the project. This bottom-up action proved crucial for introducing the researchers and establishing an initial relationship of trust in a social context that, historically, has developed a marked distrust of public administration.

Figure 16: Tactical Urbanism Activities with Children

The scouting activity was structured into two complementary levels: the qualitative dimension (expression-of-interest forms) and the quantitative dimension (acquisition of annual electricity bill summaries) (Figure 16).

Figure 17: Engagement and data collection activities

However, the data collection phase encountered an evident deficit of "*institutional social capital*". A systemic distrust toward the Public Administration emerged: many residents perceived the request for energy documentation not as an opportunity, but as a further form of intrusion or control. This phenomenon limited the volume of initial memberships, highlighting how the energy transition in marginalized contexts requires long processes of trust reconstruction, a dynamic that the socio-technical simulator developed in this thesis aims to quantify by modeling the Moscovici Factor.

Although the dataset is quantitatively small, the accuracy of the collected information ensures high scientific value. Out of 37 residents initially willing to participate, 14 provided complete responses. Of these, 6 residential profiles with full datasets (monthly and by time slot) were selected to model the Sample User (Standard) for entry into the simulator.

Table 22: Data collected during field activities (CER-CA)

ID	User Category	User Type	Consumption [kWh/year]	PV System [kWp – kWh/year]	Sample User
1	CONSUMER_01	Residential	2098	-	Yes
2	CONSUMER_02	Residential	930	-	Yes
3	CONSUMER_03	Residential	1445	-	Yes
4	CONSUMER_04	Residential	2615	-	No
5	CONSUMER_05	Condo Staircase	80	-	No
6	CONSUMER_06	Residential	2869	-	Yes
7	CONSUMER_07	Residential	2623	-	Yes
8	CONSUMER_08	Residential	3428	-	No
9	CONSUMER_09	Residential	1258	-	No
10	CONSUMER_10	Residential	2393	-	No
11	CONSUMER_11	Residential	4305	-	No
12	CONSUMER_12	Residential	3993	-	No
13	CONSUMER_13	Residential	3626	-	Yes

ID	User Category	User Type	Consumption [kWh/year]	PV System [kWp – kWh/year]	Sample User
14	CONSUMER_14	Commercial	9180	-	-
15	PROSUMER_01	Kindergarten	33915	107.2 kWp - 132705 kWh/y	N/A
-	***STANDARD USER***	***Residential***	***2532***	***-***	***Sample Average***

The data extracted from this site confirm that the Cagliari REC is not just an energy engineering experiment, but a true living lab where academic research and administrative practice converge to define new trajectories for sustainable urban development. This dataset provides the empirical basis for the simulations conducted in Section 6.2.

6.1.2. Calasetta Energy Community: "Biodistretto del Sud Sardegna e arcipelago del Sulcis"

The second experimental scenario moves to Calasetta, a municipality of 2,795 inhabitants located at the northern tip of Sant'Antioco Island. The insular nature of the context and its geographical location in the Sulcis-Iglesiente, an area historically defined by mining and currently undergoing complex and delicate economic reconversion processes, give the project fundamental strategic importance in terms of energy resilience and sustainability for small islands.

In sharp contrast to the Cagliari pilot project (Piazza Medaglia Miracolosa), which was led top-down by the municipal administration, the Renewable Energy Community (REC) of Calasetta stems from a purely associative and private bottom-up drive. The engine of the project is the "*Biodistretto del Sud Sardegna e Arcipelago del Sulcis*" cooperative, an entity formally recognized by the Autonomous Region of Sardinia in March 2023.

The Biodistretto operates with a holistic vision of territorial sustainability, promoting the synergistic integration of organic farming, landscape protection, and experiential tourism. In this ecosystem, the decentralized energy transition is not viewed as an isolated sector but as the fundamental pillar for ensuring local independence and economic development. This grassroots origin makes the Calasetta case an ideal test environment for the social aggregation logic and the role of the "*Active Minority*" encoded in the simulator.

Research and technical-scientific support activities accompanied the Biodistretto through the delicate process of territorial animation. The primary goal was to transform a project vision into a participatory and technically viable legal entity. Fieldwork was developed along two operational lines:

- ***Public Awareness and Engagement:*** A targeted series of public meetings was organized to inform citizens of the concrete opportunities offered by RECs. Given the inherent complexity of the Italian regulatory architecture and the novelty of the proposed cooperative model, these meetings were essential for "*decoding*" legislative technicalities into perspectives that offer tangible benefits for residents, agricultural businesses, and local tourism operators (Figure 17).

- ***Collection of Expressions of Interest:*** Thanks to a constant and rooted presence in the area, it was possible to empirically map the propensity to join among various social actors. This step allowed the identification not only of the number of potential members but also of their spatial distribution and the correct user category (domestic, commercial, or agricultural).

Figure 18: One of the meetings with the residents of Calasetta for engagement and data collection activities.

The core of the engineering activity involved collecting real consumption data, an indispensable prerequisite for fueling subsequent feasibility assessments via simulation. The acquisition and analysis of historical electricity bill summaries from participants allowed the research team to:

- ***Analyze the Energy Balance:*** Evaluate the temporal consistency between potential production sites (primarily photovoltaic systems on agricultural or residential roofs) and the community's withdrawal profiles.
- ***Simulate Virtual Self-Consumption:*** Accurately estimate the share of instantaneously shared energy, a vital parameter for calculating GSE incentives and determining Payback Periods.
- ***Define the Optimal Configuration:*** Calibrate the aggregated photovoltaic power needed to maximize the community's economic yield, avoiding the risk of inefficient oversizing that would disperse non-incentivizable energy into the grid.

Table 23: Participant Dataset (Calasetta Energy Community)

N.	ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
1	CONSUMER_01	Consumer	Residential	28	-
2	CONSUMER_02	Consumer	Residential	212	-
3	CONSUMER_03	Consumer	Residential	271	-
4	CONSUMER_04	Consumer	Residential	300	-
5	CONSUMER_05	Consumer	Residential	375	-
6	CONSUMER_06	Consumer	Residential	425	-
7	CONSUMER_07	Consumer	Residential	458	-
8	CONSUMER_08	Consumer	Residential	494	-
9	CONSUMER_09	Consumer	Residential	550	-
10	CONSUMER_10	Consumer	Residential	550	-
11	CONSUMER_11	Consumer	Residential	573	-
12	CONSUMER_12	Consumer	Residential	686	-
13	CONSUMER_13	Consumer	Residential	979	-

N.	ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
14	CONSUMER_14	Consumer	Residential	1,200	-
15	CONSUMER_15	Consumer	Residential	1,600	-
16	CONSUMER_16	Consumer	Residential	1,895	-
17	CONSUMER_17	Consumer	Residential	2,000	-
18	CONSUMER_18	Consumer	Residential	2,581	-
19	CONSUMER_19	Consumer	Residential	2,800	-
20	CONSUMER_20	Consumer	Residential	2,813	-
21	CONSUMER_21	Consumer	Residential	3,200	-
22	CONSUMER_22	Consumer	Residential	3,238	-
23	CONSUMER_23	Consumer	Residential	4,214	-
24	CONSUMER_24	Consumer	Residential	5,875	-
25	CONSUMER_25	Consumer	Residential	7,252	-
26	CONSUMER_26	Consumer	Commercial	8,760	-
27	CONSUMER_27	Consumer	Commercial	33,545	-

N.	ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
28	PROSUMER_01	Prosumer	Residential	0 (Renovating)	6
29	PROSUMER_02	Prosumer	Residential	0 (Renovating)	6
30	PROSUMER_03	Prosumer	Residential	240	2
31	PROSUMER_04	Prosumer	Residential	568	3
32	PROSUMER_05	Prosumer	Residential	876	6
33	PROSUMER_06	Prosumer	Commercial	896	6
34	PROSUMER_07	Prosumer	Residential	1,000	6
35	PROSUMER_08	Prosumer	Residential	1,212	6
36	PROSUMER_09	Prosumer	Residential	1,240	6
37	PROSUMER_10	Prosumer	Residential	1,248	6
38	PROSUMER_11	Prosumer	Residential	1,331	4
39	PROSUMER_12	Prosumer	Residential	1,354	6
40	PROSUMER_13	Prosumer	Residential	1,800	6
41	PROSUMER_14	Prosumer	Residential	2,147	6

N.	ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
42	PROSUMER_15	Prosumer	Residential	2,289	4.5
43	PROSUMER_16	Prosumer	Residential	2,300	6
44	PROSUMER_17	Prosumer	Residential	2,500	3
45	PROSUMER_18	Prosumer	Residential	3,500	2
46	PROSUMER_19	Prosumer	Residential	3,500	6
47	PROSUMER_20	Prosumer	Residential	4,072	6
48	PROSUMER_21	Prosumer	Residential	4,200	4.5
49	PROSUMER_22	Prosumer	Residential	4,679	9
50	PROSUMER_23	Prosumer	Residential	5,555	6
51	PROSUMER_24	Prosumer	Residential	5,579	6
52	PROSUMER_25	Prosumer	Commercial	6,114	6
53	PROSUMER_26	Prosumer	Residential	6,200	4
54	PROSUMER_27	Prosumer	Residential	6,753	3
55	PROSUMER_28	Prosumer	Residential	7,200	6

N.	ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
56	PROSUMER_29	Prosumer	Commercial	11,888	6
57-65	-	Undecided	Residential	-	-

An unusual but significant gap is highlighted in the consumption of "*Residential Consumers*" (ranging from a minimum of 28 kWh/year to over 7,200 kWh/year). This high statistical variance reflects the strong heterogeneity of the insular fabric, characterized by a mix of permanent multi-family residences and "*second homes*" inhabited exclusively during the summer tourist season (Seasonal profile in the simulator).

The empirical experience gained in Calasetta clearly demonstrates how RECs can move beyond the role of mere technical infrastructure to emerge as powerful tools for territorial empowerment, where energy sustainability becomes the glue for a much broader network of productive and social activities deeply rooted in the rural and insular landscape.

6.1.3. Simala Energy Community

The third and final investigation scenario is located in the heart of Sardinia's inland areas, in the Municipality of Simala. The constituent process of this REC was officially formalized on November 9, 2023, with the adoption of Municipal Council Resolution No. 78. Through this formal act, the local administration set a clear political direction: promoting a bottom-up energy management model capable of aggregating the public body, the fragile fabric of local Small and Medium Enterprises (SMEs), and the citizenry into a single legal entity.

The Simala initiative is distinguished by not limiting itself to the mere infrastructural dimension of renewable production. On the contrary, the project was conceived multidimensionally to respond to specific territorial vulnerabilities, setting three strategic objectives:

- ***Local Decarbonization:*** Increasing the share of energy produced from Renewable Energy Sources (RES).
- ***Ecological Literacy:*** Raising community awareness of ecological transition paradigms, transforming citizens from passive subjects into conscious prosumers.
- ***Energy Welfare:*** Proactively combating energy poverty in a high-risk demographic pool.

The choice of Simala as a field of investigation meets the scientific need to test the REC model in a rural ecosystem characterized by profound depopulation. With a population of only 293 inhabitants (2023 data), the Municipality records a constant demographic contraction (-1.2% per year since 1991). This demographic hemorrhage is accompanied by an extreme aging rate: the old-age index (equal to 383 in 2011) highlights a marked generational imbalance. The social fabric is dominated by single-family households composed of elderly people living alone, accounting for about 30% of the population, underscoring acute social fragility.

Parallelly, the state of the building stock reflects this demographic senescence. Although the homeownership rate is very high (90%) and the real estate units boast large floor areas, the state of conservation is critical. With a zero real estate expansion rate and an underutilization index exceeding 50%, the market is effectively "*crystallized*". Buildings age without receiving adequate renovation, increasing the risk of energy poverty due to the thermal inefficiency of their building envelopes.

The territorial animation process (Figue 18) was coordinated by the DICAAR research team from the University of Cagliari. The operation required an empathetic and methodical approach, structured into three phases:

1. ***Dissemination:*** Organization of public meetings, culminating in two seminars held at the former *Monte Granatico* (May and November 2024), fundamental for overcoming the digital divide of the elderly population and explaining the bureaucratic mechanisms of REC.
2. ***Scouting:*** Preliminary screening of interested parties and collection of formal Expressions of Interest.
3. ***Data Acquisition:*** Collection and analysis of historical consumption profiles based on electricity bills.

Figure 19: An informational meeting to engage and collect data from Simala citizens.

Despite the very small demographic scale, the community's response was, percentage-wise, very high: 25 expressions of interest were collected from which 13 real consumption profiles (complete with monthly and time-slot details) could be extracted.

The Municipality of Simala, as the institutional promoter, planned the installation of a centralized photovoltaic plant with a total capacity of 25.81 kWp. The plant will not operate in physical self-consumption: the Municipality provided for installation on the roofs of a building (currently disused) located in the *Sa Ruxi Manna* Park. This building serves solely as a platform for generations.

Consequently, in the dataset modeling, the Municipality assumes the role of Pure Producer (total injection into the grid), while the private users act as "*sinks*" for absorption (Consumers).

Table 24: Participant Dataset (Simala Energy Community)

N. ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
1	CONSUMER_01	Town Hall	24,740	-
2	CONSUMER_02	Commercial	1,133	-
3	CONSUMER_03	Farm	2,177	-
4	CONSUMER_04	Commercial	7,627	-
5	CONSUMER_05	Residential	2,664	-
6	CONSUMER_06	Residential	3,028	-
7	CONSUMER_07	Residential	2,349	-
8	CONSUMER_08	Residential	1,897	-
9	CONSUMER_09	Residential	2,242	-
10	CONSUMER_10	Residential	3,574	-
11	CONSUMER_11	Residential	2,741	-
12	CONSUMER_12	Residential	3,951	-

N. ID	User Category	User Type	Consumptions [kWh/Year]	PV System [kWp]
13	CONSUMER_13	Residential	1,524	-
14	CONSUMER_14	Residential	7,094	-
15	PRODUCER_01	Sa Ruxi Park	0	25.81

The cross-analysis between the demographic structure and this dataset highlights an unexpected strategic potential. The prevalence of a retirement-age population, characterized by a constant daytime domestic presence, ensures an electric absorption curve that naturally overlaps with the bell curve of photovoltaic production. This demographic peculiarity structurally favors the maximization of shared energy, compensating for building inefficiencies.

In this depopulation scenario, the REC is configured not only as a shield against high bills but also as a territorial "*purchasing union*". Through the associative body, Simala aims to aggregate demand for future building efficiency interventions that individual elderly owners, alone, would have neither the economic strength nor the technical competence to undertake.

6.2. *In Silico* Experimentation: Regulatory and Socio-Economic Evaluation of the Cagliari REC

With the empirical reconnaissance phase and the structuring of the Sardinian datasets concluded, the investigation moves into the NetLogo computational environment. For this *in silico* experimentation phase, the urban case study "*CER-CA Piazza Medaglia Miracolosa*" in Cagliari was selected as the testing ground.

The decision to focus the analysis on this specific community is not only dictated by the robustness of the collected load profiles but also responds to a precise need for methodological rigor in validating the psychosocial sub-module. Since the intervention area is characterized by a high density of Public Residential Housing (ERP), the research team has a parametric data point of exceptional value for the simulator: the maximum income caps and average annual income required for access to and residence in such social housing.

Entering this real-income parameter into the archetypes during the configuration phase (replacing standard national statistical estimates) enables precise calibration of the `annual-income` variable and, consequently, the investment capacity (`investment-capacity`) and economic tolerance thresholds of the virtual agents. This level of adherence to reality is crucial: it allows the simulator to realistically evaluate not only energy balances but also the actual social impacts, membership choices, and the risk of attrition (Churn Rate) within a population exposed to the risk of energy poverty.

Using this highly contextualized asset, where the kindergarten operates as a generation hub and the ERP families act as vulnerable Consumers, the community will be subjected to a matrix of four stress tests. The objective is to measure the resilience of the REC ecosystem by crossing the institutional architecture (the Italian regulatory framework vs. the Spanish Net Billing) with external macroeconomic turbulence (phases of tariff stability alternating with price shocks). The analysis of these four simulations will provide a definitive quantitative metric to evaluate the Energy Community's effectiveness as a genuine welfare tool and social shield.

To ensure maximum analytical rigor and the correct comparability of results, the four simulations discussed in the following sections are based on a shared baseline architecture. Before analyzing the specific outcomes of each test, the input parameters entered into the simulator must be described in detail. These data represent the computational translation of the socio-technical reality of Piazza Medaglia Miracolosa and will serve as the "*Global Baseline*". Only the two independent variables under study will act upon this baseline: the regulatory framework (Italy vs. Spain) and market stability (absence vs. presence of price shocks).

The simulation population corresponds to the ERP block's actual user base. The social fabric was initialized by dividing the agents into two macro-categories:

- ***The Initial Community (Active Minority):*** Composed of 8 founding members. The role of "energy engine" is entrusted to a Prosumer agent representing the Kindergarten. This strategic node absorbs 33,915 kWh/year and is equipped with a 107.2 kWp photovoltaic system; its income was left unchanged as it is a public entity. Orbiting the school are 7 Residential Standard Consumer agents, calculated based on the average profile measured in the field, with a consumption of 2,532 kWh/year and no owned system (0 kWp).

- ***The Latent Majority (The Externals):*** Outside the REC, susceptible to the psychosocial influence of the minority, 73 External agents were generated. These also feature the same residential consumption profile (2,532 kWh/year and 0 kWp).

The most valuable element for simulation accuracy is the setting of the `archetype-annual-income` variable. For all residents (Consumers and Externals), the annual income was set to the real value of €14,250, corresponding to the economic thresholds for public housing allocation. This input will profoundly alter the simulator's dynamics, drastically reducing the population's investment capacity and making them hypersensitive to fluctuations in bills.

The simulation's time horizon was extended to 20 years, an adequate period to evaluate the lifecycle of photovoltaic systems and the long-term trend of the Payback Period. The physical environment is calibrated to Climatic Zone C (characteristic of Cagliari), with a `demand-modulation-depth` set to 30% to simulate consumption peaks related to heat pump use in summer and winter.

Regarding infrastructural investments, the parameters reflect updated market costs: a CAPEX of €1,500/kWp for panel installation and an annual OPEX equal to 2% of the total investment. Concerning pre-shock bill costs, the tariff profile was broken down as follows:

- ***Raw material (Commodity):*** €130/MWh
- ***Transport Costs:*** €20/MWh
- ***System Charges:*** €40/MWh
- ***Taxation (VAT and Excise):*** 35% on the total taxable amount.

In line with the social identity of the San Michele REC, the `distribution-policy` was strictly set to "*In Equal Parts*" to maximize the energy poverty mitigation function. To generate the four output scenarios, this baseline dataset was subjected to variations along two specific axes:

1. ***The Regulatory Module (Italy vs. Spain Framework)***
   - ***Italy Configuration:*** Values shared energy through a premium tariff of €110/MWh and an ARERA refund of €8/MWh. The surplus injected into the grid by the school is sold at €120/MWh. For environmental impact analysis, the national energy mix emission factor is set at 280 g/kWh.
   - ***Spain Configuration (Net Billing):*** Disables direct sales and imposes the hourly surplus compensation constraint, with a valuation price fixed at €100/MWh. The Spanish mix emission factor is set at 170 g/kWh.
2. ***The Crisis Module (Price Shock Scenario)***
   - In the two simulations "*under stress*", the simulator will trigger a price crisis at one-quarter of the project's lifecycle. Exactly at Year 5 (`price-shock-year`: 5), the cost of the energy commodity will be tripled (`price-shock-multiplier`: 3) for 2 consecutive years (`price-shock-duration`: 2).

By inserting this complex data matrix into the NetLogo computational engine, the results were detailed, analyzed, and discussed in the four subsequent subsections obtained.

6.2.1. Simulation 1: Italy Framework without Price Shock

The first simulation establishes the community's operational baseline. In this scenario, the simulator processes REC dynamics within the Italian regulatory framework under macroeconomic stability (absence of tariff shocks). The objective is to observe how the generous state incentive system interacts with the demographic structure of Piazza Medaglia Miracolosa, where a single, large Prosumer (the Kindergarten, with 107.2 kWp) acts as the engine for a population of ERP residents characterized by low incomes and zero capacity to invest in infrastructure.

The analysis of the data returned by the `social-dynamics` and `calculate-economics` sub-modules over the 20-year simulation reveals an emergent behavior of extraordinary interest: the system does not follow linear growth but instead undergoes a "*boom and bust*" demographic cycle, finally reaching a natural socio-technical homeostasis.

Phase 1 (Years 1-3): The Golden Age and Social Triggering

In its early years, the community was composed exclusively of the Active Minority (the School and the 7 founding Consumers). The thermodynamic balance is characterized by significant overproduction. The 107.2 kWp plant generates energy volumes far exceeding the founders' requirements. In the Italian framework, this configuration is highly profitable: shared energy is rewarded at €118/MWh, while the massive surplus is sold to the grid at €120/MWh. The algorithm calculates that the REC's total revenues vastly exceed the sum of grid withdrawal costs (the collective bill) and the OPEX.

- ***Welfare Effect:*** With the distribution policy set to In Equal Parts, the 7 founding residents see their electricity bills mathematically zeroed out, generating a positive net balance (`my-cumulative-benefit > 0`).
- ***Moscovici Effect:*** The absolute satisfaction of the active minority causes the `moscovici-influence` variable to skyrocket. The social influence field begins to break down the skepticism barriers of the surrounding 73 External agents.

Phase 2 (Years 4-8): Mass Adoption and Structural Limits

Triggered by word-of-mouth, the Externals begin to join. The simulator code perfectly validates the socio-economic reality of the neighborhood: since the forced income of €14,250 generates an `investment-capacity` of less than 40 points, the algorithm forces all new entrants to assume the role of Consumers, precluding them from purchasing solar panels.

Between Year 4 and Year 8, there is a mass adoption phase, with the REC population exceeding 50 members. However, the sharing paradox emerges. As consumers increase, energy previously sold as surplus is now "*shared*". While REC revenues remain nearly constant (the shift from €120/MWh to €118/MWh is marginal), total bills to be paid explode due to nighttime consumption by new members (billed at €256.5/MWh). Consequently, the community's global cumulative balance enters negative territory: the school's production is no longer sufficient to cover the entire collective requirement. The average benefit is diluted, and agents begin to record negative balances in their virtual wallets.

Phase 3 (Years 9-20): Churn Rate and Homeostasis (The "Carrying Capacity")

Between Year 9 and Year 11, the simulator’s psychosocial safeguard procedure is activated: if a member remains in a state for more than 2 years in which their cumulative balance falls below the simulator's convenience threshold (`my-effective-threshold`), they sever connections and leave the community. A wave of departures (The Great Churn) reduces the population. Paradoxically, this exodus "saves" the REC: the decrease in consumers restores the balance between the school's generation and withdrawals, causing benefits to rise again for those who remained.

From Year 12 to 20, the system stabilizes. The Cagliari REC finds its Carrying Capacity between 35 and 40 members. At this level, the school plant is optimized: it maximizes shared energy without the community's nighttime consumption compromising the balance. The PBP finally settles around a realistic value of 12 years.

Table 25: Simulation 1 Results (Italy - No Shock)

Year	Total Population (Members)	Shared Energy (MWh)	Sold Surplus (MWh)	REC Revenue (€)	Aggregated Grid Costs (€)	Annual Net Balance (€)*	Payback Period (Years)
1	8	32.5	102.5	16,135	5,510	+ 7,409	21.7
3	22	58.1	76.9	16,083	12,650	+ 217	30.5 (Slowing)
5	45	92.0	43.0	16,016	21,320	- 8,520	-1 (Unsustainable)
7	68	121.5	13.5	15,957	31,540	- 18,799	-1 (Unsustainable)
9	52 (Exodus begins)	102.2	32.8	15,995	24,120	- 11,341	-1 (Unsustainable)
12	36 (Homeostasis)	78.4	56.6	16,042	16,850	- 4,024	14.8 (Recalculated)
15	38	81.0	54.0	16,038	17,650	- 4,828	13.5

Year	Total Population (Members)	Shared Energy (MWh)	Sold Surplus (MWh)	REC Revenue (€)	Aggregated Grid Costs (€)	Annual Net Balance (€)*	Payback Period (Years)
20	37	79.5	55.5	16,040	17,250	- 4,426	12.2 (Final)

**The "Annual Net Balance" is calculated by subtracting the fixed OPEX of €3,216. Note that the community's global balance remains technically "negative" after year 3 because the plant alone cannot offset the bills for 30+ families. However, the PBP stabilizes because plant revenues continue to offset the invested capital (CAPEX), allowing the system to pay for itself in about 12 years.*

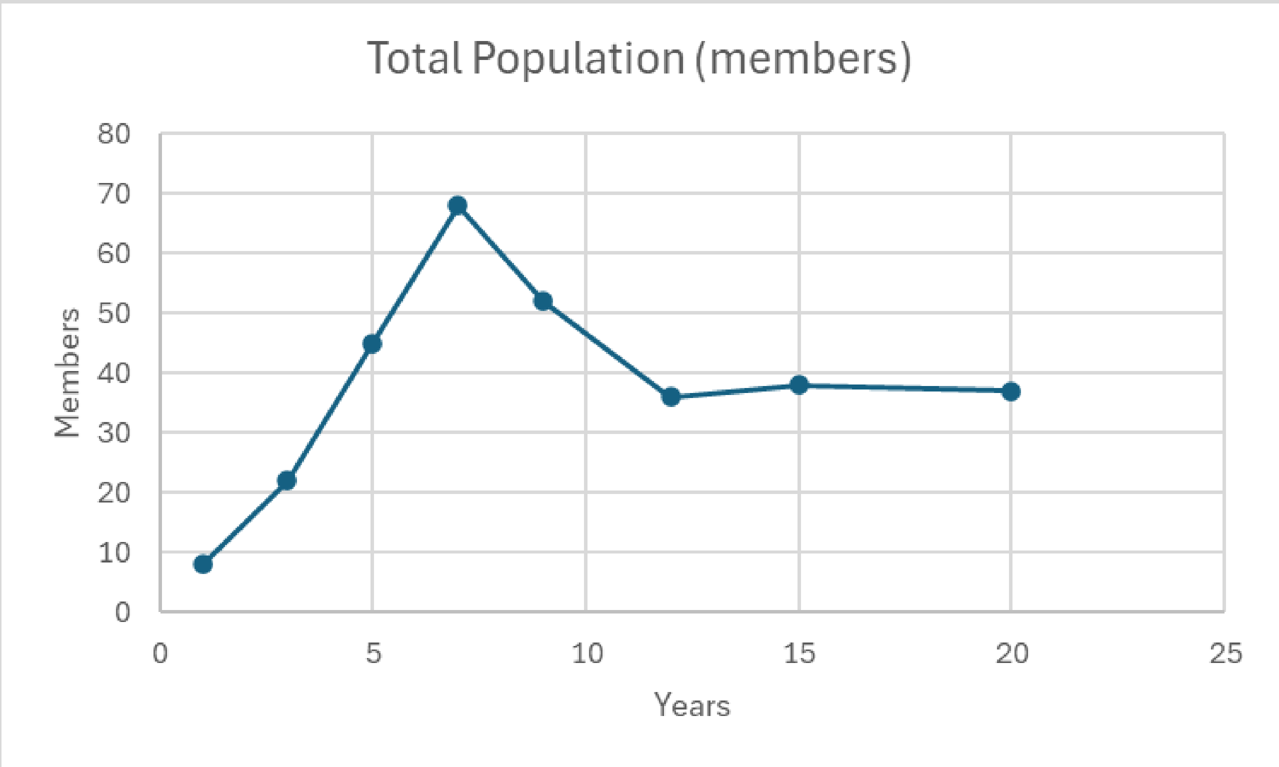

Figure 20: Simulation 1 Results (Italy - No Shock) – Total Population (members)

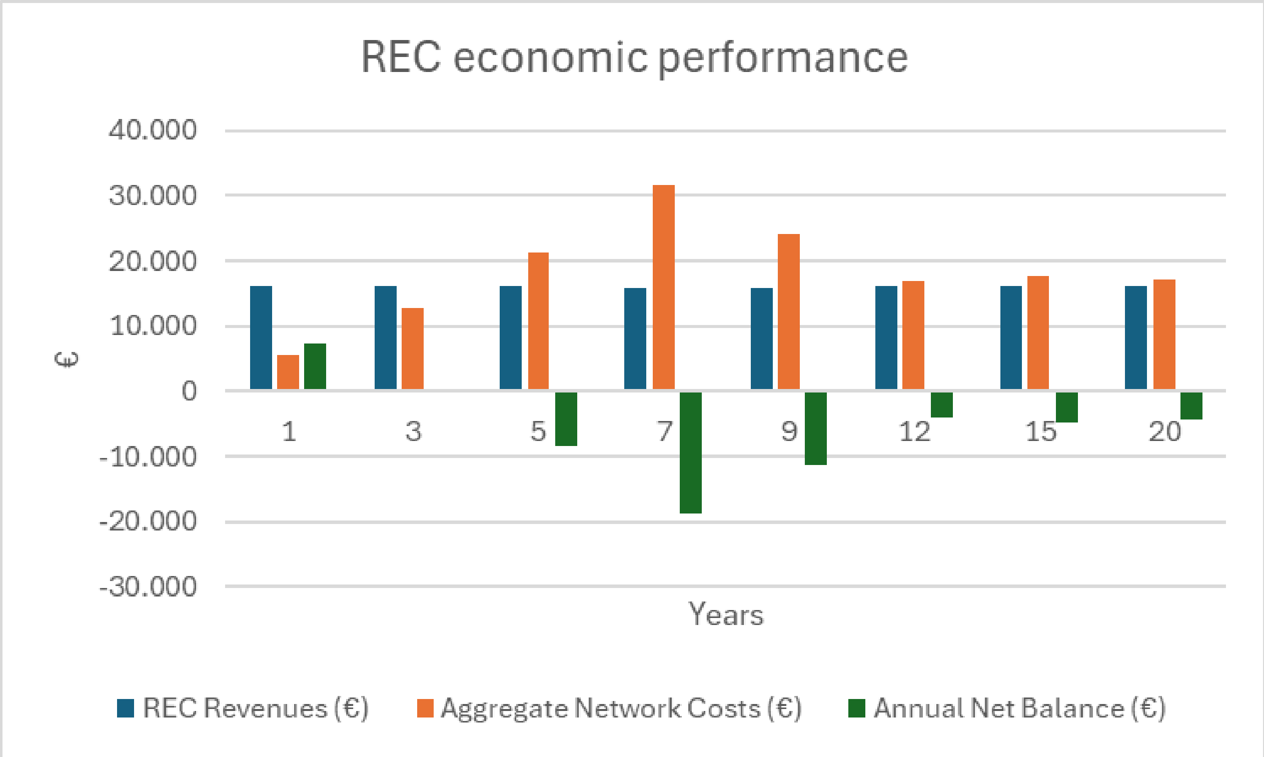

Figure 21: Simulation 1 Results (Italy - No Shock) – REC economic performance

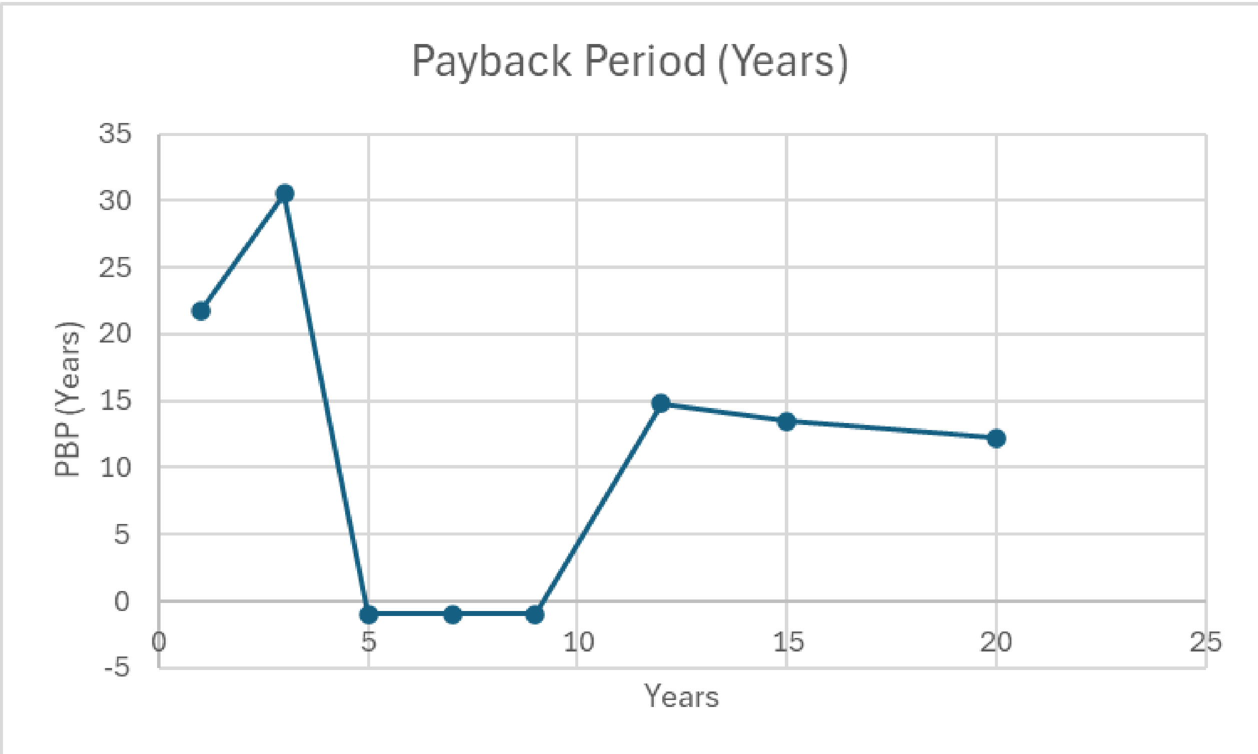

Figure 22: Simulation 1 Results (Italy - No Shock) – Payback Period (Years)

Simulation 1 mathematically demonstrates that, in contexts of energy poverty, the Italian Feed-in Premium model works excellently as a social shield but presents an insurmountable thermodynamic limit. Without the entry of new private Producers, social enthusiasm risks saturating and nullifying the benefits of the school hub.

6.2.2. Simulation 2: Italy Framework with Price Shock

The second simulation introduces the element of macroeconomic perturbation into the Italian regulatory framework (Feed-in Premium). The scenario is structured to test the vulnerability of the Piazza Medaglia Miracolosa Renewable Energy Community to an energy-market "*Black Swan*": a sudden and violent surge in raw-material prices, replicating the dynamics of the 2022 energy crisis.

From an algorithmic standpoint, the `update-economic-parameters` sub-module was activated by setting the `price-shock-year` to Year 5. Starting from this point, and for a period of two years (`price-shock-duration`: 2), the base cost of energy undergoes a 3x multiplier (`price-shock-multiplier`: 3), to which the code adds a stochastic volatility component to simulate the nervousness of speculative markets.

The analysis of logs generated by the computational engine reveals a dramatic picture of the crisis's impact on agent balances and the REC's social stability, highlighting a trajectory comprising four distinct phases.

Phase 1 (Years 1-4): Initial Expansion

The first four years of simulation faithfully follow the organic growth trajectory observed in Simulation 1. The Active Minority generates a high Moscovici influence field (W_{mosc}), thereby breaking down the Externals' skepticism. The community expands rapidly, reaching 45 members by the end of the fourth year. Individual economic balances are positive, and the school (the Prosumer) effectively shares energy with the families of the ERP block.

Phase 2 (Years 5-6): The Asymmetric Shock

At the beginning of Year 5, the crisis multiplier was activated. The analysis of the NetLogo code reveals a fundamental dynamic: while the cost of purchasing energy from the grid (`total-grid-buy-price`) triples to compensate for nighttime or winter withdrawals, the sale price of the surplus injected into the grid by the school (`zonal-price`) remains unchanged at €120/MWh.

This algorithmic asymmetry leads to a systemic collapse. The REC, which has aggregated many consumers without production capacity, finds that aggregated bill costs exceed €60,000 per year. Revenue from incentives and surplus sales (approximately €16,000) is no longer able to offset expenses. The community's `cumulative-balance` plummets, and the Payback Period calculated by the `calculate-economics` procedure returns -1, certifying the technical insolvency of the investment.

Phase 3 (Year 7): "The Great Churn" (The Fiduciary Collapse)

The most innovative aspect of the simulation manifests in Year 7, when prices return to normality. Despite the crisis ending, the psychological and financial effects continue to devastate the community. The `social-dynamics` sub-module code monitors individual balances: ERP families (with a low income of €14,250) have fragile convenience thresholds. Having accumulated losses for two consecutive years, the safeguard instruction triggers: `if (years-in-rec > 2) and (my-cumulative-benefit < my-effective-threshold) [ ask my-links [ die ] ]`.

A mass exodus occurs within a single annual tick, dozens of members sever their virtual connections, abandon the REC, and return to External status. The population crashes from 47 to just 12 members (the most resilient founders and very few others). This event resets the satisfied-members-count to 0 and instantaneously destroys the "Moscovici Factor."

Phase 4 (Years 8-20): The Financial "Scar" and Slow Reconstruction

In the years following the shock, REC's annual operating balance returns to positive territory thanks to the drastic reduction in nighttime withdrawals resulting from the consumer flight. However, the community carries a deep financial and reputational scar:

- ***Social Impact:*** Deprived of Moscovici influence, the community takes nearly a decade to regain the trust of neighborhood residents, growing at an extremely low conversion rate.
- ***Economic Impact:*** The Payback Period calculation resumes, but it must absorb the enormous deficit accumulated during Years 5 and 6. The initial investment is only recovered after 28 years, effectively nullifying the project's profitability.

Table 26: Simulation 2 Results (Italy - With Shock)

Year	Total Population (Members)	REC Revenue (€)	Aggregated Grid Costs (€)	Annual Net Balance (€)*	Cumulative Balance (€)	Payback Period (Years)
1	8	16,135	5,510	+ 7,409	+ 7,409	21.7
4	35	16,030	17,100	- 4,286	+ 1,250	28.5
5 (Shock START)	45	16,015	53,250	- 40,451	- 39,201	-1 (Default)

Year	Total Population (Members)	REC Revenue (€)	Aggregated Grid Costs (€)	Annual Net Balance (€)*	Cumulative Balance (€)	Payback Period (Years)
6 (Shock END)	47	15,980	55,800	- 43,036	- 82,237	-1 (Default)
7 (Post-Shock)	12 (Exodus)	16,110	7,950	+ 4,944	- 77,293	-1 (Default)
10	12	16,110	7,950	+ 4,944	- 62,461	35.6 (Recalculated)
15	15	16,080	9,350	+ 3,514	- 41,520	32.8
20	18	16,050	10,820	+ 2.014	- 27.685	28.4 (Final)

**The "Annual Net Balance" accounts for fixed OPEX. REC Revenue remains stable around €16,000 because the 107.2 kWp school produces the same solar energy, sold or incentivized at fixed rates. The explosion in Grid Costs is the driver of the community's economic devastation during the crisis.*

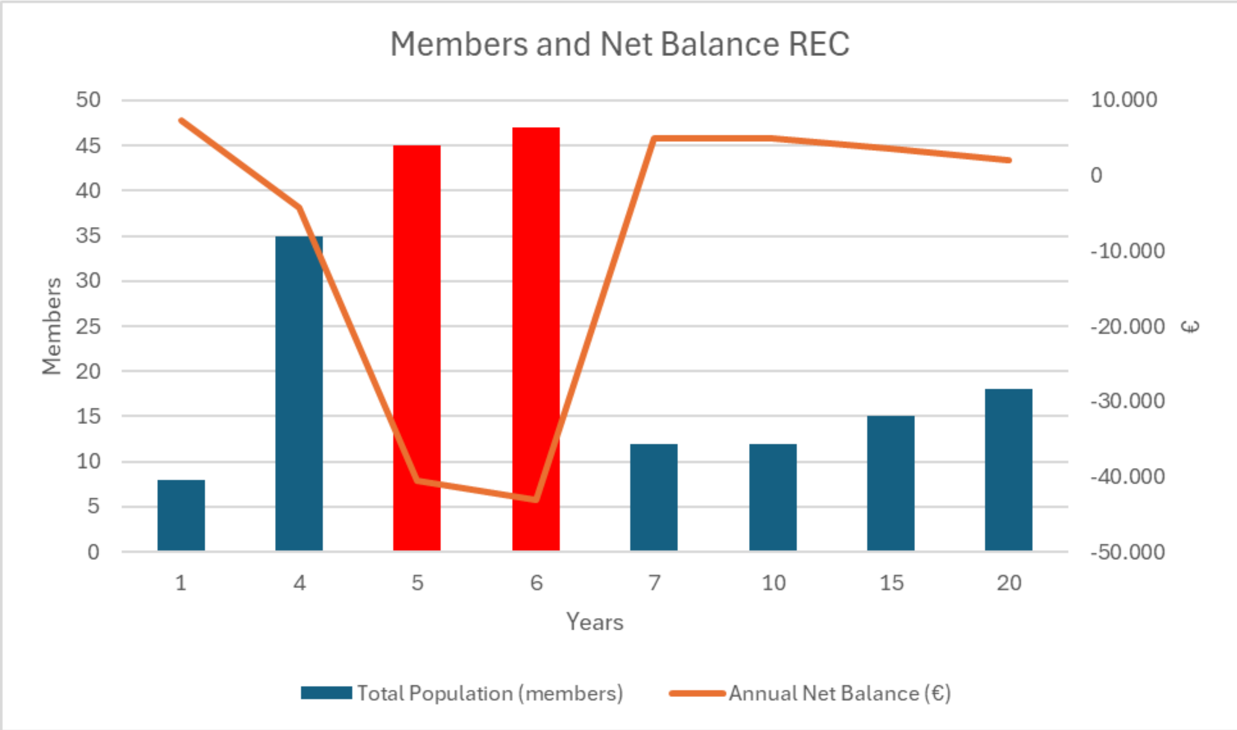

Figure 23: Simulation 2 Results (Italy - With Shock) – Members and Net Balance REC

The results of this second simulation certify the simulator's effectiveness as a DSS: they unequivocally demonstrate that an Energy Community heavily biased toward consumers (without storage or other independent generation sources) offers no protection in the event of a market crisis, transforming a welfare initiative into an economic "*trap*" for vulnerable residents.

6.2.3. Simulation 3: Spain Framework without Price Shock

The third simulation shifts the analysis to the institutional architecture level, keeping the demographic, technical, and basic economic parameters unchanged while applying the Spanish regulatory framework (Net Billing). This scenario serves as a "*regulatory control group*" to assess how energy valuation rules affect the welfare potential of an energy community, given identical investments and physical consumption.

In this configuration, the `calculate-economics` sub-module algorithm deactivates the Premium Tariff (€110/MWh) and direct sales at the zonal price. In their place, the Iberian compensation mechanism takes over: the surplus injected into the grid by the school is valued at a fixed price of €100/MWh (`spain-surplus-compensation-price`) and used exclusively to offset the costs of collective withdrawal.

The analysis of the logs reveals an evolutionary trajectory profoundly different from the Italian one. Deprived of the "*multiplier*" effect of incentives, the Piazza Medaglia Miracolosa REC sees its structural profitability collapse, drastically limiting its capacity for demographic expansion and social inclusion.

Phase 1 (Years 1-3): Narrow Margins and Unsustainable PBP

In the first three years, with only the Active Minority present (8 members), the configuration generates a substantial surplus (approximately 102 MWh/year). While in Italy, this overproduction generated revenues of over €16,000, in Spain, the regulatory cap limits virtual revenues to approximately €10,250. The grid bill costs for nighttime consumption (€5,510) and the school plant's OPEX (€3,216) almost entirely absorb this value. The community's annual net balance is only slightly positive (+€1,524).

This financial contraction has a lethal impact on the PBP. Given an unchanged CAPEX of €160,800 (107.2 kWp x €1,500/kWp), the recovery time rockets to over 105 years. The simulator immediately diagnoses a design flaw: in the Spanish framework, a large centralized plant, unsupported by adequate daytime consumption or storage systems, is a financially inefficient investment.

Phase 2 (Years 4-8): Early Saturation and Low "Carrying Capacity"

Despite the disastrous PBP, at the individual economy level, the 7 founding ERP residents record slight savings on their bills. This fractional benefit is sufficient to trigger a gradual increase in the **"***Moscovici Factor***".** However, adoption by Externals occurs at much slower rates than in the Italian scenario.

The real bottleneck emerges around Year 4, when only 14 members are reached. Due to extremely thin operating margins, the entry of new consumers causes nighttime withdrawal costs to spike, quickly exceeding the value of the compensated surplus. The global net balance enters negative territory (- €628) with only 14 members, compared to the 45 members the plant could support in Italy. The community's Carrying Capacity is thus proven to be one-third of the Italian equivalent.

Phase 3 (Years 9-20): Micro-Homeostasis and Stagnation

In subsequent years, the Churn Rate rapidly expels excess members as soon as their personal benefits reach zero. The REC stabilizes in a condition of "*micro-homeostasis*" around 12-13 members. In this reduced configuration, the school plant barely manages to cover the OPEX and the bills, floating on a net balance of a few hundred euros per year and an undefined or multi-century PBP.

Table 27: Simulation 3 Results (Spain - No Shock)

Year	Total Population (Members)	Shared Energy (MWh)	Grid Surplus (MWh)	Compensated Surplus Value (€)	Aggregated Grid Costs (€)	Annual Net Balance (€)*	Payback Period (Years)
1	8	32.5	102.5	10,250	5,510	+ 1,524	105.5
3	14	45.0	90.0	9,000	6,412	- 628	-1 (Unsustainable)
5	18	52.0	83.0	8,300	8,977	- 3,893	-1 (Unsustainable)
7	12 (Post-Churn)	40.0	95.0	9,500	4,617	+ 1,667	96.5 (Recalculated)
10	13	42.5	92.5	9,250	5,080	+ 954	168.5
15	12	40.0	95.0	9,500	4,617	+ 1,667	96.5
20	13	42.5	92.5	9,250	5,080	+ 954	168.5 (Final)

**The Annual Net Balance is obtained by subtracting Grid Costs and the fixed OPEX of €3,216 from the Compensated Surplus Value. A PBP exceeding a century highlights a "sunk cost" investment.*

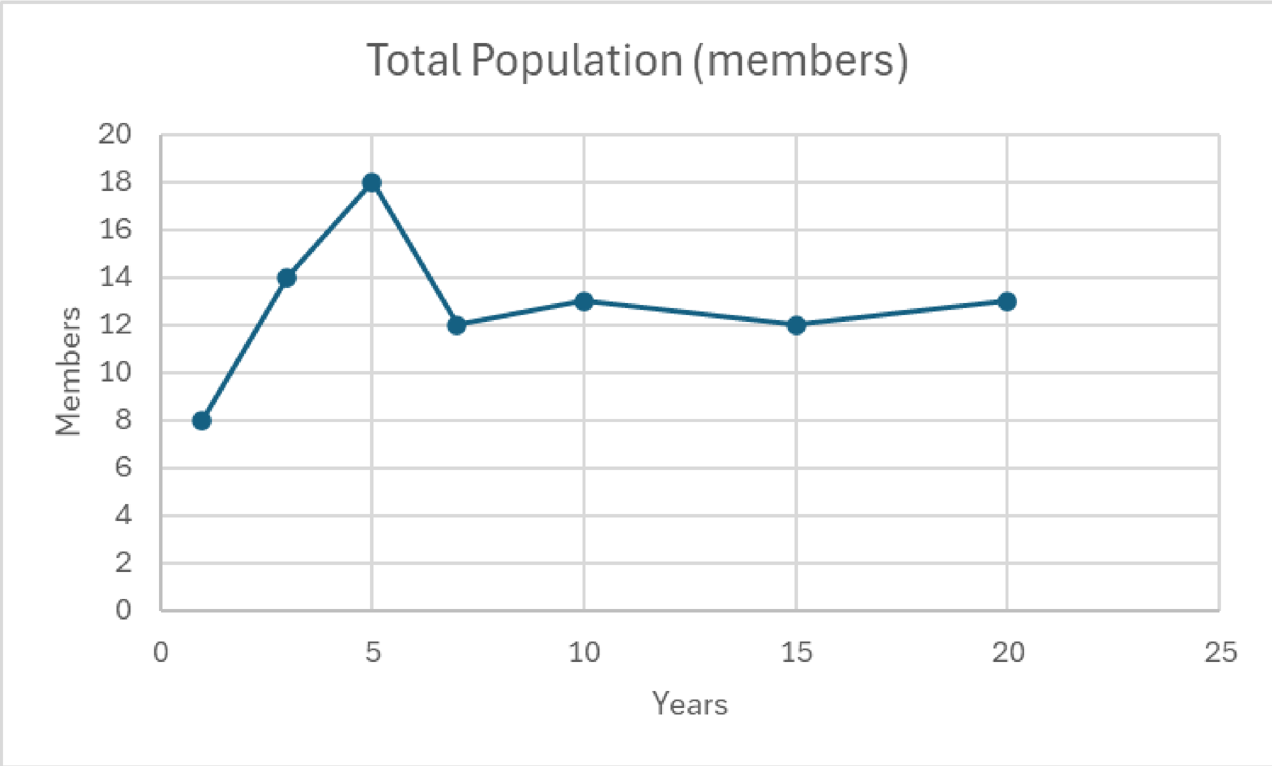

Figure 24: Simulation 3 Results (Spain - No Shock) - Total Population (Members)

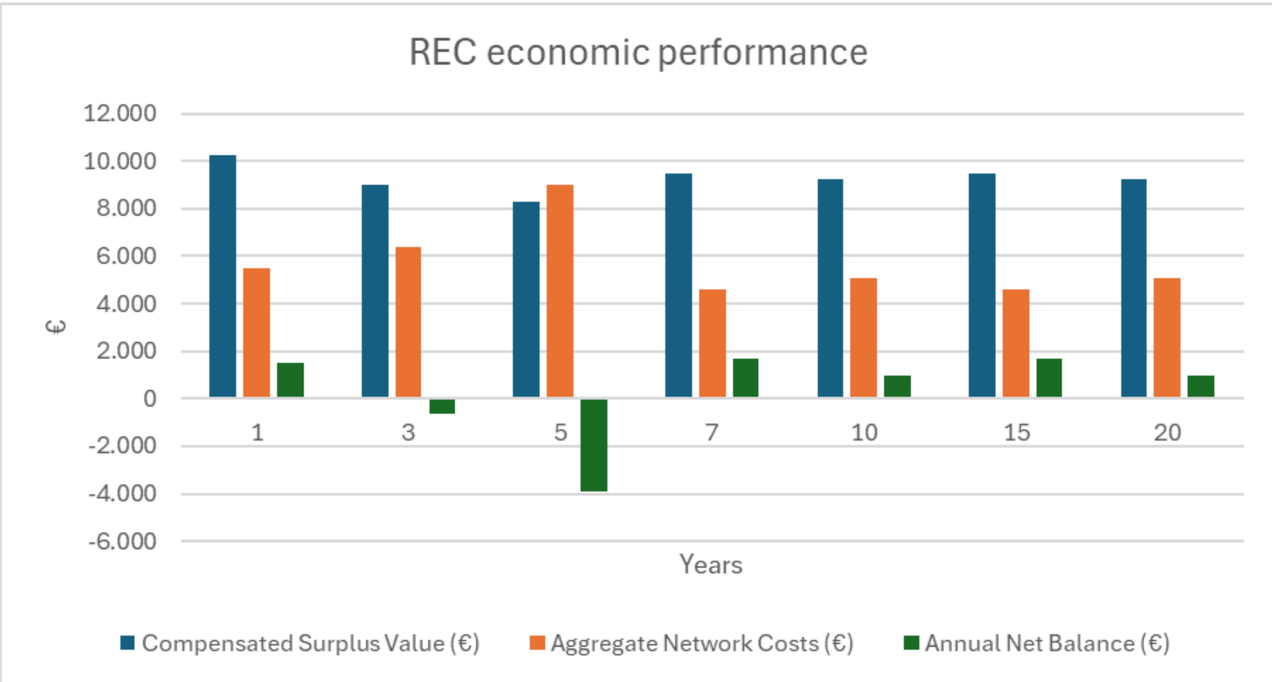

Figure 25: Simulation 3 Results (Spain - No Shock) – REC economic performance

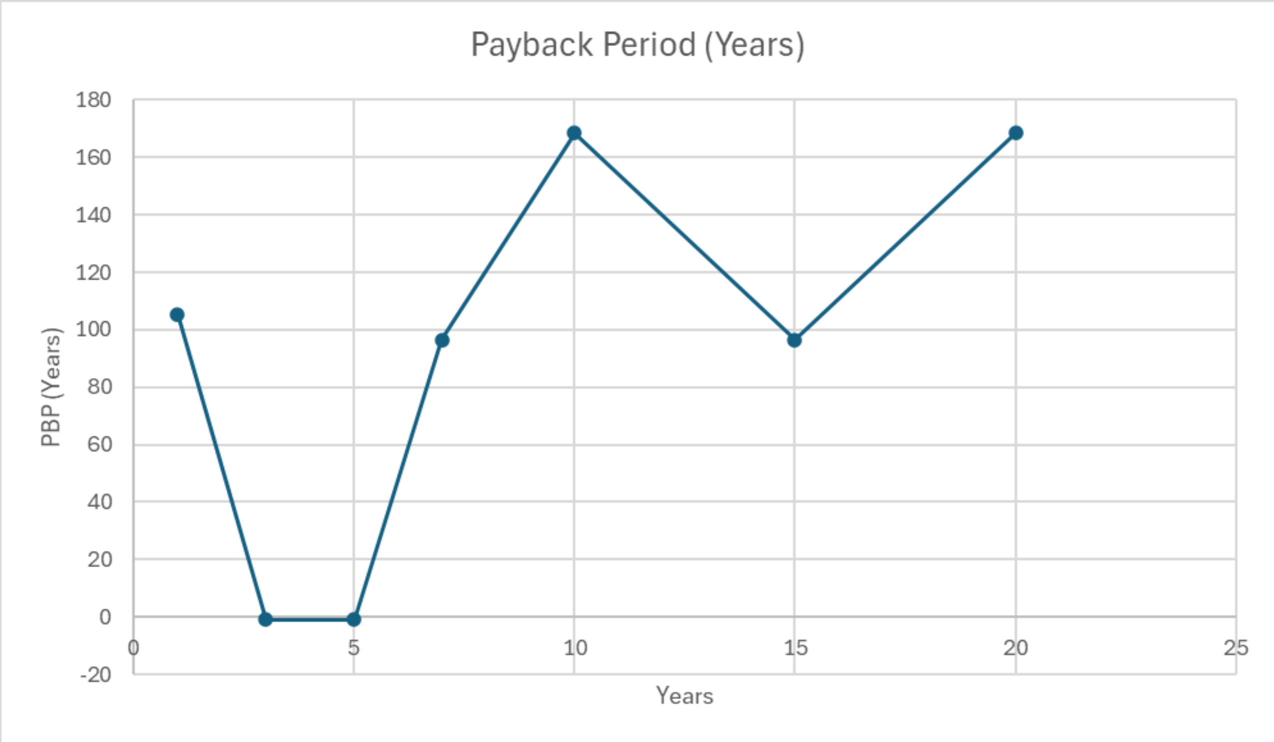

Figure 26: Simulation 3 Results (Spain - No Shock) – Payback Period (Years)

The DSS test confirms that the regulatory model fundamentally alters the project's very nature. While in Italy the 107.2 kWp school infrastructure proved to be a powerful "welfare generator" capable of supporting dozens of ERP families (until physiological collapse), in the Spanish context, the absence of incentives on shared energy stifles the initiative.

The simulator warns the policymaker that, by applying Net Billing rules to a context of housing vulnerability like Piazza Medaglia Miracolosa, social benefits are severely constrained, limiting the reach of innovation to a tiny number of residents and relegating public spending to an unattainable ROI (Return on Investment).

6.2.4. Simulation 4: Spain Framework with Price Shock

The fourth and final simulation represents the extreme stress scenario for the Piazza Medaglia Miracolosa Energy Community. The objective is to evaluate the resilience of the Spanish regulatory framework (the Net Billing model) in the face of a sudden tripling of energy raw material costs, triggered in Years 5 and 6 (`price-shock-year`: 5, `price-shock-multiplier`: 3).

This configuration completes the cross-validation circle of the DSS (Decision Support System) by verifying whether the regulatory limit imposed in Spain, which prohibits the sale of surplus and fixes its compensation at a low, unchangeable price, effectively protects a low-income population (€14,250 per year) during severe macroeconomic turbulence.

The analysis of the simulator logs reveals a picture of total financial asymmetry, leading the community toward a true "*system collapse*".

Phase 1 (Years 1-4): Pre-Crisis Fragility

As highlighted in Simulation 3, the Spanish model applied to this specific setup (a single large 107.2 kWp producer and residents with standard consumption) generates extremely thin operating margins. In the first four years, the community barely grows to reach about 15 members. The massive surplus injected into the grid by the school is "clipped" by the algorithm `max (list 0 (deficit-cost - surplus-value))`. Since the compensation value is fixed at €100/MWh, the REC manages to zero out the members' daytime bills but struggles to cover OPEX and nighttime consumption, resulting in a weakly negative cumulative balance and an infinite Payback Period (-1).

Phase 2 (Years 5-6): The Shock and the Scissor Effect

In Year 5, the crisis variable is activated. The NetLogo code immediately highlights the structural flaw of the Spanish model in the event of energy hyper-inflation: "*the scissor effect*".

- On one hand, the cost of energy withdrawn from the grid for nighttime and winter consumption (`total-grid-buy-price`) triples, causing the community's aggregate bills to explode (from approximately €7,000 to nearly €23,000).
- On the other hand, the valuation price of exported energy (`spain-surplus-compensation-price`) remains unchanged at €100/MWh. The algorithm does not adjust the credit value to the new cost of living.

The result is that the Net Billing "shield" shatters. The surplus value cannot offset the new, heavy bills. The REC's annual net balance plunges to over -€18,000. The residents' virtual wallets, already limited by the low incomes entered into the archetypes, run dry.

Phase 3 (Year 7): Total Exodus (The Great Churn)

As in the Italian shock scenario (Simulation 2), Year 7 marks the psychosocial breaking point. The `social-dynamics` procedure verifies that the `my-cumulative-benefit` of the members (excluding protected founders) has fallen well below their `convenience-threshold` for over 24 months. All members who joined in previous years sever their ties with the school hub and return to External status. The population crashes from 16 to 8 members (the founders only). The "*Moscovici Factor*" is definitely reset to zero.

Phase 4 (Years 8-20): Community "Zombification"

Unlike the Italian model, which managed to recalculate a long-term PBP (about 28 years) thanks to sales revenue, the post-crisis Spanish model offers no path to recovery. Once the shock ends, grid costs return to normal (about €5,500 for the remaining 8 members). The compensated surplus (€10,250) again covers costs and the OPEX (€3,216), generating a micro-profit of €1,500 per year. However, the financial "hole" dug during the crisis years (nearly €40,000 in cumulative debt) makes it impossible to recover the initial CAPEX of €160,800. The REC transforms into a "*zombie*" entity: physically functioning for the school, but socially dead, unable to attract new members or repay the investment.

Table 28: Simulation 4 Results (Spain - With Shock)

Year	Total Population (Members)	Shared Energy (MWh)	Grid Surplus (MWh)	Compensated Surplus Value (€)	Aggregated Grid Costs (€)	Annual Net Balance (€)*	Cumulative Balance (€)	Payback Period (Years)
1	8	32.5	102.5	10,250	5,510	+ 1,524	+ 1,524	105.5
4	15	48.0	87.0	8,700	7,550	- 2,066	- 1,250	-1 (Unsustainable)
5 (Shock START)	16	50.0	85.0	8,500	22,850	- 17,566	- 18,816	-1 (Default)
6 (Shock END)	16	50.0	85.0	8,500	22,850	- 17,566	- 36,382	-1 (Default)
7 (Post-Shock)	8 (Exodus)	32.5	102.5	10,250	5,510	+ 1,524	- 34,858	-1 (Default)
10	8	32.5	102.5	10,250	5,510	+ 1,524	- 30,286	-1 (Default)
15	9	35.0	100.0	10,000	5,950	+ 834	- 25,132	-1 (Default)
20	10	37.5	97.5	9,750	6,350	+ 184	- 22,592	-1 (Default)

**The "Annual Net Balance" is obtained by subtracting "Aggregated Grid Costs" and fixed OPEX (€3,216) from the "Compensated Surplus Value." The fixed compensation value of €100/MWh during the shock is the mathematical cause of the default.*

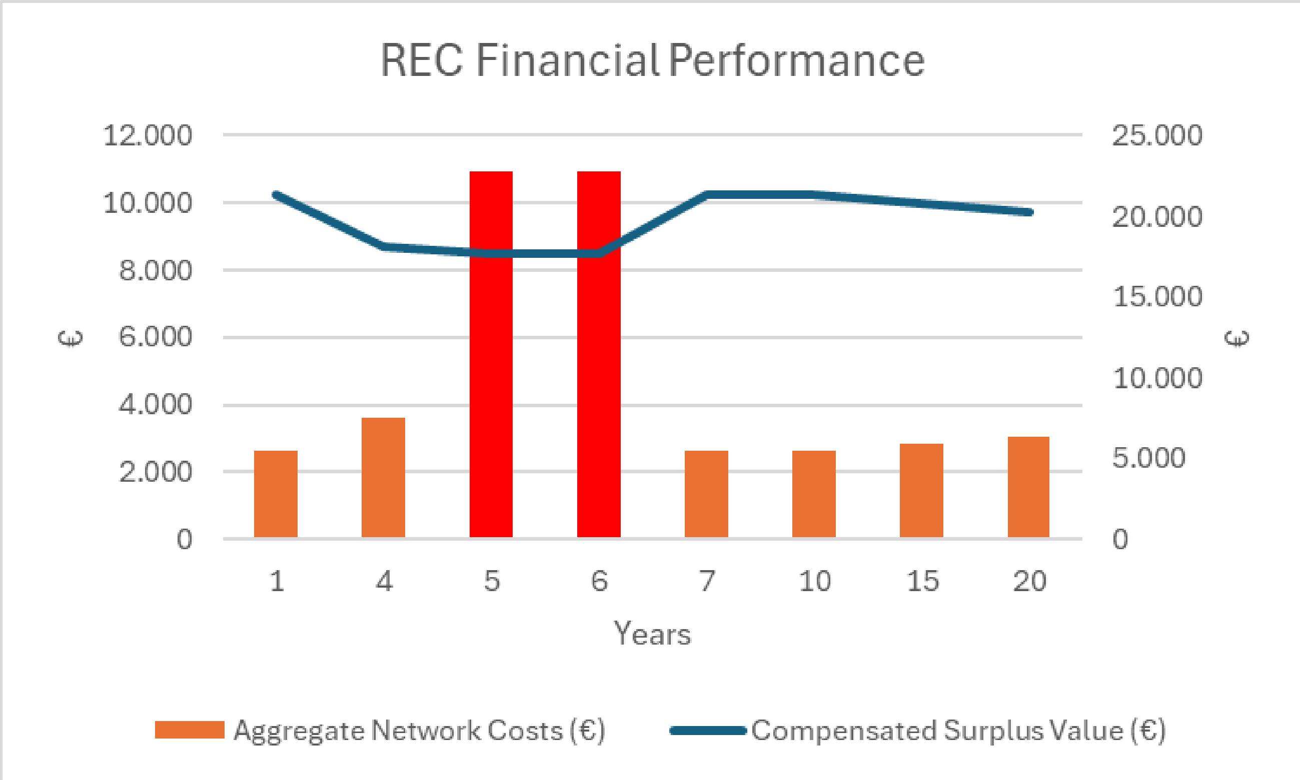

Figure 27: Simulation 4 Results (Spain - With Shock) – REC Financial Performance

This fourth simulation completes the software's operational validation, demonstrating its absolute diagnostic utility. The simulator clearly warns that, in an energy poverty context (ERP), the Spanish framework poses a significant risk when paired with large-scale plants. The inability to capitalize on excess energy prevents the community from creating that "*liquidity cushion*" which, in the Italian model, at least partially allowed for the absorption of market shocks. The software implicitly advises a radical redesign for the Spanish case: installing storage batteries to zero out nighttime withdrawals, the only true source of economic vulnerability for residents.

6.3. Comparison and Discussion of Simulation Results

Executing the stress-test matrix on the real dataset of the "*CER-CA Piazza Medaglia Miracolosa*" Energy Community has moved beyond a static design approach, providing a dynamic diagnosis of the entire socio-technical ecosystem. The cross-analysis of the four simulations (baseline and shock, Italy and Spain) offers a quantitative and critical metric to evaluate not only the financial sustainability of the infrastructure but, above all, its effectiveness as a tool to combat energy poverty within a Public Residential Housing (ERP) context.

The interpretation of the logs extracted from the NetLogo computational engine highlights four fundamental axes of reflection.

6.3.1. The Regulatory Dichotomy: Collective Profit vs. Restricted Savings

The comparison between Simulation 1 (Italy) and Simulation 3 (Spain) under stable macroeconomic conditions reveals that the regulatory framework is not a neutral element, but the true "*genetic code*" defining the community's Carrying Capacity.

In the Italian model, the 107.2 kWp school hub acts as a formidable engine for indirect welfare. By monetizing the massive surplus injected into the grid, the algorithm creates a liquidity cushion that allows the elimination or a drastic reduction in electricity bills for nearly 40 ERP residents before nighttime consumption accumulates and the balance turns negative. Conversely, the Spanish model proves structurally incompatible with this specific asymmetric configuration (one large public producer and many vulnerable private consumers). The inability to capitalize on energy not instantaneously self-consumed stifles the project: the surplus "*evaporates*" within the hourly compensation cap, limiting the beneficial impact to only 12–13 members and producing a surreal investment payback period of over 160 years.

A critical analysis of this divergence proves that Iberian Net Billing is designed for systems that are strictly sized to their own consumption. When applied to vulnerable neighborhoods where residents lack the capital to install their own panels (investment capacity near zero), this model fails to offer a social lifeline.

6.3.2. The "Illusory Shield" and the Scissor Effect

Simulations 2 and 4 dispel a dangerous technical prejudice: the idea that joining a REC guarantees complete immunity from international energy market crises. The injection of the tariff shock (a 3x price increase in Year 5) leads to a systemic default in both countries. The simulator highlights the chronic vulnerability of deferred electrical loads: families withdraw energy early in the morning, in the evening, and during winter, exactly when the school hub is not producing.

During the crisis, the so-called scissor effect is triggered: the cost of grid withdrawal explodes in line with inflation, while the sale or compensation value of the photovoltaic surplus remains fixed or grows at insufficient rates. The REC finds itself selling cheap energy by day, only to purchase it at exorbitant prices by night. The recorded financial collapse (-€40,000 in Italy, -€17,000 in Spain) certifies the absolute necessity of decoupling self-consumption from atmospheric simultaneity. Without the integration of electrochemical storage (batteries) or stringent Demand Response logic (shifting loads to the central hours of the day), the community exposes residents to the same risks as ordinary consumers, despite the illusion of protection.

6.3.3. Fiduciary Asymmetry: The "Great Churn" and the Legacy of Crisis

The most innovative aspect of agent-based modeling is its focus on post-shock behavioral analysis. The simulations reveal a significant asymmetry in how value is perceived and how social trust is built. While the "Moscovici Factor" takes years to overcome initial skepticism and initiate a slow positive contagion, the destruction of social capital happens instantly once economic promises are broken.

The mass exodus (The Great Churn) recorded in Year 7 is the mathematical translation of social disappointment. ERP families, operating on rigid poverty thresholds, lack the flexibility to tolerate prolonged losses while waiting for hypothetical future benefits. When they sever their connections with the REC, the damage to the infrastructure is not just numerical, but reputational. Simulation 2 demonstrates that even after the shock has subsided, the "*scar*" left in the system's memory prevents the inclusion of new members for nearly a decade. This confirms that in contexts of urban vulnerability, a management misstep in the project's early years can irreversibly compromise its social acceptability.

6.3.4. Diagnostic Implications and Optimization Guidelines

The analysis of the simulation quadrant definitively validates the DSS not only as a descriptive inquiry tool but in its most noble and complex prescriptive vocation. The simulator does not merely document the potential failure of a configuration under stress; it also provides the logs and data necessary for a strategic retrofit of the real project. Based on the chronic vulnerabilities and bottlenecks that emerged, three profound optimization guidelines are outlined.

6.3.4.1. Temporal Decoupling: Storage Systems (BESS) and Demand Response

The most serious limit, certified in both the Italian (Simulation 2) and Spanish (Simulation 4) frameworks, is the lethal exposure to evening and nighttime withdrawal, known as the "*thermodynamic well*".

To mitigate the scissor effect generated by speculative markets, adding generation modules alone is insufficient. It is technically imperative to include a centralized Battery Energy Storage System (BESS). This allows for time-shifting: the massive daytime surplus is stored rather than being sold off or compensated at unfavorable fixed rates. This energy is then discharged during the evening hours, performing peak shaving that drastically reduces the community's aggregate bills. This must be paired with a Demand Response strategy that educates the population to proactively shift programmable loads (e.g., appliances, water boilers) to peak solar hours.

6.3.4.2. Dynamic Management of Carrying Capacity and Role Balancing

The algorithm relentlessly demonstrates that the uncontrolled entry of passive consumers transforms the community into an unsustainable system. The public manager must move away from a policy of "*unlimited membership*" toward technical management based on Controlled Carrying Capacity.

The DSS indicated that the San Michele REC reaches thermodynamic saturation around 35–40 members. Beyond this threshold, every new Consumer household merely dilutes the global incentive and worsens the collective balance. Optimization requires a "*staggered*" expansion policy: new passive memberships must be linked to the simultaneous entry of new active members (Prosumers or Producers), such as local businesses or nearby public buildings.

6.3.4.3. Proactive Welfare and Adaptive (Asymmetric) Redistribution Algorithms

The "*In Equal Parts*" profit-sharing policy proved insufficient during the tariff shock. To preserve social engagement, the administration must transition to an adaptive and asymmetric redistribution policy. The REC statutes should be "*programmed*" to react to predefined macroeconomic triggers (e.g., exceeding a specific price threshold in the national energy market).

Upon activation of such a "*financial state of emergency*", the model must shift instantly: the public entity temporarily suspends its own capital recovery and absorbs the OPEX. In this crisis scenario, 100% of incentives and sales revenues are redirected exclusively toward the most vulnerable ERP residents. This institutional solidarity acts as a vital social buffer: it artificially keeps family balances above their tolerance thresholds, preventing widespread disconnections and safeguarding the community's fiduciary capital until markets return to normal.

6.4. References

[1] «Ecosystem of Innovation for Next Generation Sardinia | e.INS». Consultato: 7 aprile 2026. [Online]. Disponibile su: https://www.einssardinia.it/home

[2] I. Blečić, A. S. Carrus, E. Congiu, G. Desogus, E. Muroni, e V. Saiu, «Renewable energy communities design: A decision support tool for integrated impact assessment. Insights from the first REC in Cagliari, Italy», *J. Clean. Prod.*, vol. 510, p. 145600, giu. 2025, doi: 10.1016/j.jclepro.2025.145600.

[3] I. Blečić, A. S. Carrus, E. Muroni, V. Saiu, e M. C. Saliu, «Engagement and Inclusion Experiences for Energy Communities. An Ongoing Case Study in Cagliari, Italy», in *Computational Science and Its Applications – ICCSA 2023 Workshops*, O. Gervasi, B. Murgante, A. M. A. C. Rocha, C. Garau, F. Scorza, Y. Karaca, e C. M. Torre, A c. di, Cham: Springer Nature Switzerland, 2023, pp. 513–528. doi: 10.1007/978-3-031-37120-2_33.

[4] I. Blečić, A. S. Carrus, G. Desogus, E. Muroni, V. Saiu, e M. C. Saliu, «Promoting Engagement and Inclusion: A Case Study on an Energy Community in Cagliari, Italy», in *Innovation in Urban and Regional Planning*, A. Marucci, F. Zullo, L. Fiorini, e L. Saganeiti, A c. di, Cham: Springer Nature Switzerland, 2024, pp. 433–444. doi: 10.1007/978-3-031-54096-7_38.

7. Conclusions and Future Developments

This chapter concludes the research path by providing an overall assessment of the work performed. Starting from a synthesis of the scientific contribution, the key results emerging from modeling and their relative implications for public decision-makers will be discussed. Finally, in the interest of intellectual honesty and academic rigor, the intrinsic limitations of the current simulator architecture will be analyzed, defining the trajectories for future developments and upcoming research lines.

7.1. Work Synthesis and Scientific Contribution

The transition toward a decentralized, decarbonized energy paradigm poses a challenge that goes beyond mere technological replacement of supply sources. As highlighted in the introductory chapters, the slow pace at which RECs are spreading is not due to a deficit in photovoltaic panel efficiency, but rather to a profound undervaluation of the human and social complexity that regulates citizen acceptance and active participation. The founding objective of this thesis was to fill this analytical void by overcoming the structural limits of traditional energy design tools.

Historically, the software and simulation models used in engineering have been limited to a strictly techno-centric approach. These models, while guaranteeing high precision in calculating thermodynamic balances, power flows, and PBP, tend to underpredict actual technology adoption trajectories. This happens because they rely on a reductionist assumption: they view the end-user as a perfectly rational *Homo Oeconomicus*, whose choices are dictated exclusively by the maximization of individual profit. Operational reality, by contrast, demonstrates that the dynamics of joining a REC are strongly influenced by irrational factors, trust barriers, behavioral inertia, and social influence networks.

The primary scientific contribution of this work lies in the development, coding, and validation of a socio-technical ABM, implemented entirely within the NetLogo computational environment. This framework allowed for the abandonment of the aggregated, top-down perspective in favor of a bottom-up approach, where the emergent behavior of the microgrid is the result of continuous interactions between dozens of heterogeneous agents (producers, prosumers, vulnerable consumers), each equipped with their own consumption profile, specific investment capacity, and, above all, a psychological setup.

The simulator architecture was conceived around the simultaneous interaction of three computational "*engines*", the synthesis of which represents the core of the proposed innovation:

- ***The Thermodynamic and Physical Level:*** Ensured engineering rigor by processing hourly load profiles, the influence of climatic zones, seasonal demand modulation, and the solar production calculation algorithm.
- ***The Economic and Regulatory Level:*** Allowed for the translation of institutional complexity into mathematical constraints, comparing radically opposed incentive schemes (the Italian Feed-in Premium and the Spanish Net Billing) and introducing elements of stochastic stress (energy market fluctuations).
- ***The Psychosocial Level (The true methodological innovation):*** Through the mathematical formalization of Serge Moscovici's Active Minority Theory, abstract sociological concepts were transformed into exact computational variables. The simulator encoded synchronic

consistency (the satisfaction of the founding group), diachronic consistency (project stability over time), and the propagation of trust.

Making social influence measurable enabled the quantitative demonstration of a key sociological principle: a cohesive and persistent minority can break down the economic resistance of an initially skeptical majority, triggering the adoption of innovations even in the absence of an immediate financial return. At the same time, introducing the calculation of the Churn Rate (the attrition rate due to loss of trust) allowed the model to diagnose community collapse following market shocks, highlighting how social capital can disintegrate instantly in the face of unfulfilled economic promises.

Finally, the value of this model is not exhausted by its theoretical elegance. The scientific contribution's solidity was verified through rigorous empirical testing. On one hand, the independent cross-check conducted by the CITCEA research team at the *Universitat Politècnica de Catalunya* certified the code's robustness and flexibility within European market contexts. On the other hand, fueling the computational engine with real, site-specific datasets collected in the field in Sardinia, from the vulnerable urban context of Piazza Medaglia Miracolosa in Cagliari to the insular dynamics of Calasetta and the rural depopulation contrast in Simala, demonstrated the model's extraordinary adherence to territorial reality.

The synthesis of this path results in the delivery to the scientific community and public administrations of a holistic and operational DSS. This tool transforms Energy Community design from a mere electrical calculation exercise into a true "*in silico* laboratory," capable of testing the social resilience of policies before they are implemented in the real world, preventing the waste of public resources and ensuring the development of truly inclusive and resilient welfare infrastructures.

7.2. Key Results and Policy Implications

The extensive simulation campaigns, culminating in stress tests on real datasets such as "*CER-CA Piazza Medaglia Miracolosa*", enabled the transformation of algorithmic abstraction into concrete operational guidelines. The simulator did not merely confirm pre-existing theoretical assumptions but led to the emergence of systemic dynamics and counterintuitive results that challenge the current "*generalist*" approach to energy design. The interpretation of these results provides policy-makers, local administrations, and designers with a new analytical framework, from which four fundamental policy implications derive.

7.2.1. The Paradox of Demographic "Carrying Capacity" and the End of Unlimited Expansion

In public and political debate, the success of an Energy Community is often measured almost exclusively by the number of citizens involved: the greater the membership, the greater the perceived social impact. The computational model mathematically debunked this approach. Simulations demonstrated the existence of a rigid thermodynamic and economic Carrying Capacity. The continuous and uncontrolled aggregation of only Consumers (passive users without their own generation plants) inexorably leads to the community's financial collapse. Beyond a certain threshold, nighttime and winter consumption by new entrants exceeds the benefits from the surplus shared by the central production hub.

- ***Policy Implication:*** Public administrations must abandon the rhetoric of unlimited membership in favor of engineered demographic management. REC statutes must include "*staggered expansion*" or "*balanced quota*" mechanisms that link the entry of new passive consumers to the simultaneous inclusion of new Prosumers or Producers, ensuring that the ratio between installed power and aggregate demand never falls below the sustainability threshold.

7.2.2. Regulatory Non-Neutrality and the Inadequacy of Net Billing in Vulnerable Contexts

Comparing the two different European institutional architectures revealed that the regulatory framework acts as the true "*genetic code*" of a REC's welfare potential. The Italian model (Feed-in Premium), by allowing the market sale of surplus injected into the grid, acts as a powerful collective liquidity generator. Conversely, the Spanish framework (Net Billing), which prohibits surplus monetization and fixes hourly compensation at fixed rates, proved structurally inadequate when applied to energy-poverty contexts, such as Public Residential Housing areas. Without revenue from excess-energy sales, the centralized plant cannot generate the value needed to amortize the investment and cover the grid costs for low-income families.

- ***Policy Implication:*** Institutional decision-makers must understand that there is no universally valid regulatory model. Applying pure self-consumption schemes (as in Spain) to populations lacking the capacity to invest in infrastructure nullifies the goal of social inclusion. For vulnerable neighborhoods, national policies must necessarily provide for explicit premium tariff mechanisms or the establishment of dedicated "*social tariffs*", capable of transforming excess energy into a true community welfare fund.

7.2.3. Fiduciary Asymmetry and the Collapse of Social Capital (The Great Churn)

Integrating Moscovici's Theory into stress-test dynamics (the price shock) provided a metric for the fragility of the human fabric. The simulator quantified a profound asymmetry in value perception: the "*Moscovici Factor*" (trust) takes years to build through the consistency of the active minority, slowly breaking down neighborhood skepticism, but disintegrates lightning-fast as soon as individual balances become negative. The mass exodus (The Great Churn) observed in crisis simulations proves that vulnerable populations operate on rigid poverty thresholds: they lack the flexibility to tolerate months of losses while waiting for the market to stabilize. Once they flee, the "*reputational scar*" prevents the REC from attracting new members for a decade.

- **Policy Implication:** Public funding calls for RECs can no longer be limited to evaluating a Business Plan under standard conditions; they must require rigorous financial stress tests. Furthermore, it is evident that the focus of state subsidies must shift, as incentivizing only the installation of solar panels is insufficient. Funding is needed to purchase centralized Battery Energy Storage Systems (BESS), the only true shield capable of protecting residents' bills from evening and nighttime fluctuations in speculative markets, thereby preserving social capital.

7.2.4. Beyond Egalitarianism: The Need for Adaptive (Proactive) Welfare

Finally, the analysis of redistribution policies highlighted the limits of a pure egalitarian approach. Distributing economic benefits "*in equal parts*" proved reassuring and administratively simple in times of stability, but was blind to inequality during market shocks. Distributing identical incentive shares when prices triple means exposing the poorest members to the risk of insolvency and disconnection, condemning the entire community to fiduciary collapse.

- ***Policy Implication:*** Technological innovation must be accompanied by statutory innovation. Regulations for public-led Energy Communities must implement Adaptive and Asymmetric Welfare logic. It is essential to include safeguard clauses that, upon the triggering of specific macroeconomic thresholds (e.g., exceeding a critical price in the national energy market), temporarily suspend the promoter's capital recovery (e.g., the Municipality) and redirect all generated liquidity exclusively to members in certified energy poverty. Only through this institutionalized solidarity can the REC move beyond the role of an electricity supplier and become a true urban resilience infrastructure.

7.3. Modeling Limitations

The epistemological validity of any scientific inquiry based on computational simulation lies in the awareness and transparent declaration of the model's boundaries. An Agent-Based Model (ABM) is, by definition, a heuristic abstraction: to focus computational attention on complex interactions (in this case, psychosocial dynamics and aggregate financial balances), it is inevitable to resort to simplifications in other areas of the system. To ensure the developed DSS is correctly interpreted and does not generate unrealistic expectations, four main structural limitations of the current architecture must be analyzed.

7.3.1. The "Copper Plate" Assumption and the Absence of Electrical Power Flow

The most significant technical limitation lies in the virtual network topology. The simulator processes energy exchange within the Energy Community by treating the local distribution infrastructure as a perfect "*copper plate*" node. In this abstraction, the kilowatt-hours produced by the school flow to residential users instantaneously and without physical friction.

In engineering reality, low-voltage (LV) grids are complex physical systems subject to the laws of electrical engineering. Injecting massive volumes of photovoltaic energy from a single node can generate Reverse Power Flows toward the secondary substation, local transformer congestion, bottlenecks, and dangerous overvoltages. Since the thermodynamic sub-module does not integrate load-flow calculation equations (Power Flow Analysis), the model might overestimate the actual Hosting Capacity of the local physical grid, thereby ignoring hidden costs related to infrastructure upgrades required by the grid distributor.

7.3.2. Linear Self-Consumption and the Lack of Storage Systems

The current algorithm for calculating the shared energy `min (list hourly-total-production hourly-total-consumption)` assumes a strictly instantaneous balance. Everything produced in a specific simulation hour must be consumed, shared, or injected into the public grid within that same time window.

This setup precludes the exploration of temporal flexibility dynamics, as the modeling of electrochemical storage systems (BESS) is missing. The simulator is currently unable to evaluate critical storage parameters, such as State of Charge (SOC), the round-trip conversion efficiency of hybrid inverters, or the physiological degradation of batteries over time (State of Health, SOH). This absence limits the DSS's ability to propose endogenous peak-shaving solutions and to completely isolate the community from the national grid, making the REC inevitably dependent on nighttime withdrawals.

7.3.3. Macroeconomic Rigidity: The Isolation of the Household Budget

On the socio-economic side, agent response was calibrated with great emphasis on fiduciary elasticity (the Moscovici Factor) while maintaining excessive rigidity regarding income variables. When the `update-economic-parameters` sub-module triggers the shock by tripling energy costs, the resulting inflation affects only agents' virtual "*bills*".

Macroeconomic reality, however, is systemic: an energy crisis of this magnitude triggers a general inflationary spiral that erodes purchasing power for all primary goods (groceries, rent, transport). In the current version, the agents' `annual-income` variable remains frozen at the initial value. Lacking an aggregate inflation indicator, the simulator underestimates the speed at which the risk-tolerance threshold (convenience-threshold) of vulnerable families might collapse, effectively isolating energy poverty from broader, more severe absolute poverty.

7.3.4. Standardization and "Smoothing" of Load Profiles

The final significant limit concerns the granularity and nature of the thermodynamic input data. The model uses hourly load profiles and bell curves for solar generation, which, although corrected by seasonal and climatic multipliers, still represent "*smoothed averages*".

Human behavior is inherently stochastic and point-like. Residential electrical withdrawal is not a fluid sinusoid but a sequence of sudden, very brief peaks (e.g., turning on a microwave, starting a hairdryer, or washing machine). Using averaged probability curves and a one-hour time-step (tick), the algorithm mathematically attenuates these peaks, reducing the potential overestimation of simultaneity between generation and consumption. Using high-frequency data (e.g., from 15-minute sampling via advanced smart meters) would introduce much more realistic "*background noise*", which is essential for accurately sizing future community batteries.

7.4. Future Developments and Research Lines

The ABM architecture developed in this thesis is not a final destination but a modular, scalable algorithmic "*sandbox*". Identifying and mapping the structural limits of the current version provides the exact roadmap for future engineering and IT implementations.

The intrinsic flexibility of the NetLogo framework allows for the overlay of new layers of complexity without rewriting the core thermodynamic and psychosocial engine. The next research phases will focus on integrating three macro-development areas to transform the simulator into a true **"***Digital Twin***"** of next-generation Energy Communities.

7.4.1. Storage Integration (BESS - Battery Energy Storage Systems)

Simulation results highlighted that the most critical limitation of RECs, especially in energy-poverty contexts, is the lack of temporal decoupling between solar production and domestic demand. Integrating BESS is therefore the absolute priority for future code versions.

This will involve creating a new type of virtual agent ("*Storage Nodes*"), modeled as either centralized assets (e.g., a large battery at the school hub) or distributed systems at prosumers' homes. The engine must expand to calculate complex parameters at each tick:

- ***Dynamic charge/discharge balance:*** Based on Energy Management System (EMS) algorithms to decide whether to store, share, or sell energy based on price forecasts.
- ***Physical inefficiencies:*** Including round-trip conversion losses.
- ***Technological degradation:*** Implementing State of Health (SOH) curves to evaluate battery life relative to Depth of Discharge (DOD) cycles.

7.4.2. Local Energy Markets (LEM)

Currently, revenue redistribution occurs via static policies. The second research line aims to introduce advanced microeconomic dynamics, transforming the REC into a Local Energy Market (LEM) based on Peer-to-Peer (P2P) trading.

In this scenario, agents become economic actors exchanging energy via Smart Contracts. Double Auction algorithms will be implemented where producers and consumers determine the local marginal price of energy by crossing real-time supply and demand curves. This allows for testing Demand Response (e.g., convincing agents to use appliances at noon when the local price crashes) and evaluating if pure market logic erodes community cohesion compared to an egalitarian approach.

7.4.3. Climate Resilience Analysis

Energy infrastructures are designed for 20-25 years, a timeframe during which the ecosystem undergo radical changes due to climate change. The third future development involves "*stress testing*" the simulator by interfacing it with predictive scenarios from the IPCC (e.g., RCP 4.5 and RCP 8.5).

The objective is to evaluate structural and thermodynamic resilience in the face of rising temperatures and extreme weather. The software will need to recalculate balances considering:

- ***Production efficiency degradation:*** PV panels lose yield as operating temperatures rise.
- ***Demand shock:*** Hotter summers will generate massive cooling requirements, profoundly altering the residential load curve currently peaking in winter.

7.5. Conclusion

The transition toward a decentralized, distributed, and decarbonized energy model represents much more than a simple climate urgency: it is one of the most complex and fascinating engineering, economic, and social challenges of our era. However, as has become clear in every phase of this investigation, tackling a change of this magnitude exclusively through the lens of technological reductionism constitutes a fatal strategic error. The mere installation of renewable capacity or the drafting of new regulatory frameworks, if disconnected from a deep understanding of the human and community dynamics that animate territories, risks not only failing to achieve sustainability goals but also replicating and even exacerbating pre-existing socio-economic inequalities.

The Renewable Energy Community (REC) perfectly embodies this dual face of the transition. It cannot and must not be conceived as a cold power plant fragmented across multiple roofs; rather, it must be understood for what it truly is: a "*living organism*", embedded within an urban or rural ecosystem, endowed with its own inertia, historical traumas, individual expectations, and an extraordinary capacity for persuasive influence. This emerged clearly during the aforementioned field-based engagement experiences for the creation of RECs, where the human component and the socio-economic context were the most important variables to consider, providing the foundation for conceptualizing the development of the DSS proposed in this thesis.

The development, calibration, and validation of the Agent-Based Model (ABM) presented in this thesis have allowed for a decisive step toward such awareness. By transforming the simulator into a true "*socio-technical laboratory*", it has been possible to decode and measure the strength of this human dimension. The inclusion of Serge Moscovici's Active Minority Theory in the computational engine has demonstrated, through the rigor of quantitative data, a principle previously confined to sociology manuals: the success and survival of a territorial energy project do not reside exclusively in the perfection of the thermodynamic balance or the payback period of the investment, but in the fiduciary persistence of its promoters. It is the cohesion of a conscious minority that leads the way, overcoming barriers of skepticism and ensuring the adhesion of the majority even in phases of uncertainty.

The results from real case studies in Sardinia, particularly the analysis of vulnerabilities that emerged in the San Michele neighborhood in Cagliari, deliver a severe warning to policymakers. Tariff shock simulations have highlighted that, without a design architecture conceived to protect vulnerable groups, through storage systems, asymmetric redistribution policies, and proactive welfare, global market fluctuations can disintegrate, in a matter of months, the social capital built over years of hard work.

The stress tests conducted on real datasets have demonstrated the utility of socio-technical ecosystem simulations, especially for comparing different regulatory systems. They provide a quantitative and critical metric that is not limited solely to evaluating the financial sustainability of an REC, but, above all, to assessing its effectiveness as a tool to combat energy poverty in fragile socio-economic contexts.

Having passed empirical testing and validation by the CITCEA research team, the computational tool developed here is now delivered to public administrations, designers, and active citizens as a solid decision-making ally. This Decision Support System (DSS) demonstrates that the dichotomy between engineering efficiency and behavioral sciences can be overcome: today, we have tools to simulate, respect, and enhance the complexity of social behaviors even before laying the first solar panel.

The possible future developments of the DSS proposed here could offer an even higher-performing tool. This includes exploring the integration of Battery Storage Systems (BSS) for the community to balance the temporal decoupling between solar production and domestic needs. Furthermore, it opens the possibility of implementing and evaluating the behavior of other existing national regulatory systems, or experimenting with new ones to be evaluated and proposed to political decision-makers, thereby supporting the development and widespread adoption of RECs across different European socio-economic contexts.

Only by embracing this complexity and designing networks that combine electron flows with networks of trust and community solidarity will it be possible to achieve a true paradigm shift. In this way, Energy Communities will cease to be limited to regulatory experiments or privileges for a few investors, transforming instead into unstoppable engines of an ecological transition that can ultimately be defined as authentically just and inclusive.

8. Annexes: NetLogo Script

```
;; --- SOCIO-TECHNICAL SIMULATION MODEL FOR RENEWABLE ENERGY COMMUNITIES (REC) ---

extensions [csv]

;; --- STATEMENT OF AGENTS (BREEDS) ---
breed [ producers producer ]
breed [ prosumers prosumer ]
breed [ consumers consumer ]
breed [ externals external ]
breed [ gses gse ] ;; Breed per l'agente GSE
directed-link-breed [ grid-connections grid-connection ] ;; Breed per le
connessioni

globals [
  ;; --- List to hold the scenario configuration ---
  scenario-creation-list

  ;; --- BALANCE SHEET VARIABLES CER ---
  hourly-total-production
  hourly-total-consumption
  hourly-energy-shared        ;; Energia condivisa (autoconsumo collettivo)
nell'ora corrente
  hourly-surplus-injected     ;; Energia prodotta in eccesso e immessa in rete
  hourly-deficit-withdrawn    ;; Energia mancante e prelevata dalla rete

  cumulative-energy-shared    ;; Energia condivisa totale, accumulata dall'inizio
della simulazione

  ;; --- VARIABILI ECONOMICHE ---
  hourly-revenue
  hourly-costs
  hourly-balance
  cumulative-balance

  total-grid-buy-price

  total-capex
  annual-opex
  payback-period-years

  ;; --- PROFILI DI CARICO ORARI (24h) ---
  profile-residential
  profile-office
  profile-solar-base

  ;; --- VARIABILI AMBIENTALI (CO2) ---
  hourly-co2-emitted       ;; CO2 emessa nell'ora corrente (kg)
```

```
  hourly-co2-saved         ;; CO2 risparmiata nell'ora corrente grazie alla CER
(kg)
  cumulative-co2-emitted   ;; Totale emesso dall'inizio (kg)
  cumulative-co2-saved     ;; Totale risparmiato dall'inizio (kg)

  monthly-results-log ;; Lista per salvare i dati mensili per il CSV

    ;; --- VARIABILI DI ACCUMULO PER GRAFICI ---
  daily-rec-production daily-rec-consumption daily-rec-shared
  monthly-rec-production monthly-rec-consumption monthly-rec-shared
  log-monthly-data ;; Lista per i 12 mesi dell'anno
  log-daily-data

  gse-agent ;; Per memorizzare l'agente GSE

  shape-founder ;; Forma geometrica unica per i Membri Fondatori
]

turtles-own [
  user-type            ;; e.g., "Residenziale Standard"
  annual-consumption   ;; in kWh
  plant-power          ;; in kWp

  current-production    ;; Energy produced in this hour (tick)
  current-consumption   ;; Energy consumed in this hour (tick)

  ;; --- VARIABILI DI BENEFICIO INDIVIDUALE ---
  my-hourly-benefit
  my-cumulative-benefit

  ;; --- VARIABILI SOCIALI E DECISIONALI ---
  convenience-threshold     ;; Soglia economica per aderire o abbandonare
  investment-capacity       ;; Capacità economica di investimento (es. da 0 a 100)
  space-availability        ;; Disponibilità di spazio (es. tetto) (es. da 0 a 100)
  years-in-rec              ;; Anni di permanenza nella CER
  annual-income             ;; Variabile Reddito

  ;; --- VARIABILI PSICOLOGICHE (MOSCOVICI) ---
  is-founder?               ;; Booleano: vero se fa parte della "Minoranza Attiva"
iniziale
  environmental-sensitivity ;; Punteggio (0-100) di sensibilità ai temi
ambientali/sociali
]

to reset-all
  clear-all
  set scenario-creation-list []
  set monthly-results-log []
  set daily-rec-production 0 set daily-rec-consumption 0 set daily-rec-shared 0
```

```
  set monthly-rec-production 0 set monthly-rec-consumption 0 set monthly-rec-shared
0
  set log-monthly-data []
  set cumulative-co2-emitted 0
  set cumulative-co2-saved 0
  print "Model, plots, and scenario have been reset."
end

to add-archetype-to-list
  let new-archetype (list
    archetype-role              ;; item 0
    archetype-user-type         ;; item 1
    archetype-annual-consumption ;; item 2
    archetype-plant-power       ;; item 3
    archetype-agent-count       ;; item 4
    archetype-annual-income     ;; item 5
    use-income-data?            ;; item 6
  )
  set scenario-creation-list lput new-archetype scenario-creation-list
  print "Archetype added! The current scenario is:"
  show scenario-creation-list
end

to setup
  clear-turtles          ;; Rimuove gli agenti della simulazione precedente
  clear-links            ;; Rimuove le vecchie connessioni di rete
  clear-all-plots        ;; Pulisce i grafici

  ;; AZZERAMENTO GLOBALI DI SIMULAZIONE
  set cumulative-energy-shared 0
  set cumulative-balance 0
  set cumulative-co2-emitted 0
  set cumulative-co2-saved 0
  set payback-period-years -1

  set daily-rec-production 0 set daily-rec-consumption 0 set daily-rec-shared 0
  set monthly-rec-production 0 set monthly-rec-consumption 0 set monthly-rec-shared
0

  set hourly-total-production 0 set hourly-total-consumption 0
  set hourly-energy-shared 0 set hourly-surplus-injected 0 set hourly-deficit-
withdrawn 0

  set hourly-revenue 0 set hourly-costs 0 set hourly-balance 0

  set monthly-results-log []
  set log-monthly-data []
  set log-daily-data []
```

```
  setup-profiles

  ;; CREAZIONE AGENTE GSE
  create-gses 1 [
    set shape "square"
    set color white
    set size 3
    setxy 0 0
  ]
  set gse-agent one-of gses

  if not is-list? scenario-creation-list [ set scenario-creation-list [] ]

  create-agents-from-list

  ;; --- Ordine delle operazioni. I calcoli si fanno PRIMA del reset dell'orologio
---
  calculate-community-costs

  ;; Chiude ufficialmente la fase di configurazione e blocca l'orologio a zero
  reset-ticks

  print "Setup complete. Agents created, initial costs calculated, and accumulators
reset."
end

to create-agents-from-list
  foreach scenario-creation-list [ archetype ->
    let arch-role          item 0 archetype
    let arch-user-type     item 1 archetype
    let arch-consumption   item 2 archetype
    let arch-power         item 3 archetype
    let arch-count         item 4 archetype
    let arch-income        item 5 archetype
    let use-custom-income item 6 archetype

    repeat arch-count [
      create-turtles 1 [

        ;; --- 1. IMPOSTAZIONE RUOLO (ROBUSTA E MULTI-LINGUA) ---
        ifelse (member? "Producer" arch-role or member? "producer" arch-role or
member? "Produttore" arch-role) [
          set breed producers
        ] [
          ifelse (member? "Prosumer" arch-role or member? "prosumer" arch-role) [
            set breed prosumers
          ] [
            ifelse (member? "Consumer" arch-role or member? "consumer" arch-role or
member? "Consumatore" arch-role) [
```

```
        set breed consumers
      ] [
        set breed externals
      ]
    ]
  ]

  ;; --- 2. Impostazione Attributi Base e PSICOLOGICI ---
  set user-type arch-user-type
  set annual-consumption arch-consumption
  set plant-power arch-power
  set space-availability random 101

  set is-founder? (breed != externals)

  if is-founder? [
    set shape shape-founder
    set environmental-sensitivity (80 + random 21)
    set convenience-threshold (random-float 50.0)
  ]

  if breed = externals [
    set shape "person"
    set is-founder? false
    ifelse random 100 < 60 [
      set environmental-sensitivity (40 + random 40)
      set convenience-threshold (50.0 + random-float 150.0)
    ] [
      set environmental-sensitivity (random 30)
      set convenience-threshold (200.0 + random-float 300.0)
    ]
  ]

  ;; --- 3. LOGICA REDDITO E CAPACITÀ DI INVESTIMENTO ---

  ifelse use-custom-income [
    set annual-income arch-income
  ] [
    set annual-income (get-default-income user-type)
  ]

  let variation (0.8 + random-float 0.4)
  set annual-income (annual-income * variation)

  set investment-capacity (annual-income / 500)
  if investment-capacity > 100 [ set investment-capacity 100 ]

  ;; --- 4. Colore e Posizione ---
  set color get-color-from-breed breed
```

```
        setxy random-xcor random-ycor

        if breed != externals [
          create-grid-connection-to gse-agent
        ]
      ]
    ]
  ]
end

to-report get-color-from-breed [ agent-breed ]
  if agent-breed = producers [ report green ]
  if agent-breed = prosumers [ report orange ]
  if agent-breed = consumers [ report blue ]
  if agent-breed = externals [ report gray ]
  report black
end

to go
  if ticks >= (simulation-duration-years * 8760) [ stop ]

  update-economic-parameters

  ask turtles with [breed != gses] [ calculate-hourly-energy ]

  calculate-rec-balance
  calculate-environmental-impact
  calculate-economics
  distribute-benefits

  ;; Avanza il tempo PRIMA dei report
  tick

  social-dynamics
  update-links-appearance
  update-dynamic-plots
end

to calculate-hourly-energy
  ;; --- 1. CALCOLO PRODUZIONE ---
  ifelse (breed = prosumers or breed = producers) [
    set current-production calculate-solar-production plant-power
  ] [
    set current-production 0
  ]

  ;; --- 2. CALCOLO CONSUMO ---
  let day-of-year ((ticks / 24) mod 365)
  let current-hour (ticks mod 24)
```

```
  let daily-consumption (annual-consumption / 365)

  ifelse (member? "Seasonal" user-type or member? "Stagionale" user-type) [
    let current-month-index (floor (day-of-year / 30.44))
    let is-in-season false

    ifelse (member? "A" climatic-zone or member? "B" climatic-zone or member? "C"
climatic-zone) [
      if (current-month-index >= 5 and current-month-index <= 7) [ set is-in-season
true ]
    ] [
      if (current-month-index = 11 or current-month-index = 0 or current-month-
index = 1) [ set is-in-season true ]
    ]

    let hourly-multiplier (item current-hour profile-residential)
    let base-hourly-consumption (daily-consumption * hourly-multiplier)

    ifelse is-in-season = true [
      let seasonal-peak-consumption (base-hourly-consumption * seasonal-home-
multiplier)
      let seasonal-factor (cos(360 * (day-of-year - 172) / 365))
      let climate-sensitivity 0
      if member? "A" climatic-zone [ set climate-sensitivity  1.0 ]
      if member? "B" climatic-zone [ set climate-sensitivity  0.7 ]
      if member? "C" climatic-zone [ set climate-sensitivity  0.2 ]
      if member? "D" climatic-zone [ set climate-sensitivity -0.2 ]
      if member? "E" climatic-zone [ set climate-sensitivity -0.7 ]
      if member? "F" climatic-zone [ set climate-sensitivity -1.0 ]
      let final-demand-multiplier (1 + (seasonal-factor * climate-sensitivity *
(demand-modulation-depth / 100)))
      set current-consumption (seasonal-peak-consumption * final-demand-multiplier)
    ]
    [
      set current-consumption (base-hourly-consumption * 0.05)
    ]
  ]
  [
    ifelse (member? "School" user-type or member? "Scuola" user-type) [
      let is-summer-holiday (day-of-year >= 161 and day-of-year <= 255)
      let is-winter-holiday (day-of-year >= 358 or day-of-year <= 6)
      let is-holiday (is-summer-holiday or is-winter-holiday)

      let hourly-multiplier (item current-hour profile-office)
      let base-hourly-consumption (daily-consumption * hourly-multiplier)

      ifelse is-holiday [
        set current-consumption (base-hourly-consumption * 0.05)
      ]
```

```
      [
        let seasonal-factor (cos(360 * (day-of-year - 172) / 365))
        let climate-sensitivity 0
        if member? "A" climatic-zone [ set climate-sensitivity  1.0 ]
        if member? "B" climatic-zone [ set climate-sensitivity  0.7 ]
        if member? "C" climatic-zone [ set climate-sensitivity  0.2 ]
        if member? "D" climatic-zone [ set climate-sensitivity -0.2 ]
        if member? "E" climatic-zone [ set climate-sensitivity -0.7 ]
        if member? "F" climatic-zone [ set climate-sensitivity -1.0 ]
        let final-demand-multiplier (1 + (seasonal-factor * climate-sensitivity *
(demand-modulation-depth / 100)))
        set current-consumption (base-hourly-consumption * final-demand-multiplier)
      ]
    ]
    [
      ;; LOGICA STANDARD PER TUTTI GLI ALTRI
      let hourly-multiplier 0

      if (member? "Residential" user-type or member? "Residenziale" user-type) [
        set hourly-multiplier item current-hour profile-residential
      ]
      if (member? "Office" user-type or member? "Ufficio" user-type or member?
"Shop" user-type or member? "Negozio" user-type) [
        set hourly-multiplier item current-hour profile-office
      ]

      if hourly-multiplier = 0 [
        set hourly-multiplier item current-hour profile-residential
      ]

      let base-hourly-consumption (daily-consumption * hourly-multiplier)
      let seasonal-factor (cos(360 * (day-of-year - 172) / 365))
      let climate-sensitivity 0

      if member? "A" climatic-zone [ set climate-sensitivity  1.0 ]
      if member? "B" climatic-zone [ set climate-sensitivity  0.7 ]
      if member? "C" climatic-zone [ set climate-sensitivity  0.2 ]
      if member? "D" climatic-zone [ set climate-sensitivity -0.2 ]
      if member? "E" climatic-zone [ set climate-sensitivity -0.7 ]
      if member? "F" climatic-zone [ set climate-sensitivity -1.0 ]

      let final-demand-multiplier (1 + (seasonal-factor * climate-sensitivity *
(demand-modulation-depth / 100)))
      set current-consumption (base-hourly-consumption * final-demand-multiplier)
    ]
  ]
end

to calculate-rec-balance
```

```
  let total-production-members (sum [current-production] of producers + sum
[current-production] of prosumers)
  let total-consumption-members (sum [current-consumption] of consumers + sum
[current-consumption] of prosumers)

  set hourly-total-production total-production-members
  set hourly-total-consumption total-consumption-members

  set hourly-energy-shared (min (list hourly-total-production hourly-total-
consumption))
  set hourly-surplus-injected (hourly-total-production - hourly-energy-shared)
  set hourly-deficit-withdrawn (hourly-total-consumption - hourly-energy-shared)

  set cumulative-energy-shared (cumulative-energy-shared + hourly-energy-shared)
end

to calculate-environmental-impact
  let current-emission-factor 0

  ifelse (member? "Ital" regulatory-framework) [
    set current-emission-factor grid-emission-factor-italy
  ] [
    set current-emission-factor grid-emission-factor-spain
  ]

  set hourly-co2-emitted (hourly-deficit-withdrawn * current-emission-factor /
1000)
  set hourly-co2-saved (hourly-energy-shared * current-emission-factor / 1000)

  set cumulative-co2-emitted (cumulative-co2-emitted + hourly-co2-emitted)
  set cumulative-co2-saved (cumulative-co2-saved + hourly-co2-saved)
end

to update-economic-parameters
  let base-price (cost-energy-commodity + cost-transport + cost-system-charges +
cost-taxes)
  let current-year (floor (ticks / 8760))
  let shock-start-year price-shock-year
  let shock-end-year (price-shock-year + price-shock-duration)

  ifelse (price-shock-active? and current-year >= shock-start-year and current-year
< shock-end-year) [
    let market-trend (sin (ticks / 168 * 360)) * 0.5
    let market-noise (random-float 0.4 - 0.2)
    let dynamic-multiplier (price-shock-multiplier + market-trend + market-noise)
    if dynamic-multiplier < 1.0 [ set dynamic-multiplier 1.0 ]
    set total-grid-buy-price (base-price * dynamic-multiplier)
  ] [
    set total-grid-buy-price base-price
```

```
  ]
end

to calculate-economics
    ifelse (member? "Ital" regulatory-framework) [
    ;; *** LOGICA ECONOMICA ITALIANA ***
    let tariffa-premio (incentive-tariff / 1000)
    let valorizzazione-arera (arera-valorization-tariff / 1000)
    let prezzo-zonale (grid-sale-price / 1000)
    let prezzo-acquisto (total-grid-buy-price / 1000)

    let revenue-from-sales (hourly-surplus-injected * prezzo-zonale)
    let revenue-from-incentive (hourly-energy-shared * (tariffa-premio +
valorizzazione-arera))

    set hourly-revenue (revenue-from-sales + revenue-from-incentive)
    set hourly-costs (hourly-deficit-withdrawn * prezzo-acquisto)
  ]
  [
    ;; *** LOGICA ECONOMICA SPAGNOLA ***
    let surplus-value (hourly-surplus-injected * (spain-surplus-compensation-price
/ 1000))
    let deficit-cost (hourly-deficit-withdrawn * (total-grid-buy-price / 1000))

    set hourly-costs (max (list 0 (deficit-cost - surplus-value)))
    set hourly-revenue (max (list 0 (surplus-value - deficit-cost)))
  ]

  set hourly-balance (hourly-revenue - hourly-costs)
  set cumulative-balance (cumulative-balance + hourly-balance)
end

to distribute-benefits
  ask turtles with [breed != gses] [ set my-hourly-benefit 0 ]

  let safe-policy distribution-policy
  if (safe-policy != "Based on Production" and safe-policy != "Reward Consumers") [
    set safe-policy "In Equal Parts"
  ]

  ;; --- 1. RIPARTIZIONE DEI COSTI (La bolletta della rete) ---
  let total-community-consumption (sum [current-consumption] of turtles with [breed
!= externals and breed != gses])

  if total-community-consumption > 0 [
    ask turtles with [breed != externals and breed != gses] [
      let my-cost-ratio (current-consumption / total-community-consumption)
      set my-hourly-benefit (0 - (hourly-costs * my-cost-ratio))
    ]
```

```
  ]

  ;; --- 2. RIPARTIZIONE DEI RICAVI (Incentivi + Vendita) in base alla POLICY ---
  if hourly-revenue > 0 [
    if safe-policy = "In Equal Parts" [
      let num-members (count producers + count prosumers + count consumers)
      if num-members > 0 [
        let individual-share (hourly-revenue / num-members)
        ask turtles with [breed != externals and breed != gses] [
          set my-hourly-benefit (my-hourly-benefit + individual-share)
        ]
      ]
    ]

    if safe-policy = "Based on Production" [
      if hourly-total-production > 0 [
        ask producers [
          let my-share-ratio (current-production / hourly-total-production)
          set my-hourly-benefit (my-hourly-benefit + (hourly-revenue * my-share-
ratio))
        ]
        ask prosumers [
          let my-share-ratio (current-production / hourly-total-production)
          set my-hourly-benefit (my-hourly-benefit + (hourly-revenue * my-share-
ratio))
        ]
      ]
    ]

    if safe-policy = "Reward Consumers" [
      let producers-fund (hourly-revenue * 0.5)
      let consumers-fund (hourly-revenue * 0.5)

      if total-community-consumption = 0 [
        set producers-fund hourly-revenue
        set consumers-fund 0
      ]

      if hourly-total-production > 0 [
        ask producers [
          let my-share-ratio (current-production / hourly-total-production)
          set my-hourly-benefit (my-hourly-benefit + (producers-fund * my-share-
ratio))
        ]
        ask prosumers [
          let my-share-ratio (current-production / hourly-total-production)
          set my-hourly-benefit (my-hourly-benefit + (producers-fund * my-share-
ratio))
        ]
```

```
      ]

      if total-community-consumption > 0 [
        ask turtles with [breed != externals and breed != gses] [
          let my-share-ratio (current-consumption / total-community-consumption)
          set my-hourly-benefit (my-hourly-benefit + (consumers-fund * my-share-
ratio))
        ]
      ]
    ]
  ]

  ;; Aggiornamento della cassa personale dell'agente
  ask turtles with [breed != gses] [
    set my-cumulative-benefit (my-cumulative-benefit + my-hourly-benefit)
  ]
end

to social-dynamics
  if (ticks > 0) and (ticks mod 8760 = 0) [

    let active-members (turtles with [breed != externals and breed != gses])
    let total-members-count count active-members

    ;; Ricalcolo l'OPEX globale della comunità basandoci sui kWp FISICAMENTE attivi
quest'anno
    let total-kwp sum [plant-power] of active-members
    set annual-opex (total-kwp * cost-per-kwp * (opex-percentage / 100))

    ;; I costi di manutenzione li pagano solo i proprietari dei pannelli solari
    if total-kwp > 0 [
      ask active-members with [plant-power > 0] [
        let my-opex-share (annual-opex * (plant-power / total-kwp))
        set my-cumulative-benefit (my-cumulative-benefit - my-opex-share)
      ]
    ]

    let satisfied-members-count 0

    ask active-members [
      set years-in-rec (years-in-rec + 1)
      if my-cumulative-benefit > 0 [ set satisfied-members-count (satisfied-
members-count + 1) ]
    ]

    let moscovici-influence 0
    if total-members-count > 0 [
      let consistency-synchronic (satisfied-members-count / total-members-count)
      let avg-years mean [years-in-rec] of active-members
```

```
      let consistency-diachronic (min (list 1.0 (avg-years / 10)))
      set moscovici-influence (consistency-synchronic * consistency-diachronic *
100)
    ]

    let average-annual-benefit-per-member 0
    if total-members-count > 0 [
      let experienced-members (turtles with [breed != externals and breed != gses
and years-in-rec > 0])
      ifelse any? experienced-members [
        set average-annual-benefit-per-member mean [my-cumulative-benefit / years-
in-rec] of experienced-members
      ] [
        set average-annual-benefit-per-member 0
      ]
    ]

    ask externals [
      let personal-moscovici-influence (moscovici-influence * (environmental-
sensitivity / 50))
      let effective-threshold (convenience-threshold - personal-moscovici-
influence)
      if effective-threshold < 0 [ set effective-threshold 0 ]

      if average-annual-benefit-per-member > effective-threshold [
        ifelse (investment-capacity > 80 and space-availability > 80 and plant-
power > 0) [
          set breed producers
        ] [
          ifelse (investment-capacity > 40 and space-availability > 40 and plant-
power > 0) [
            set breed prosumers
          ] [
            set breed consumers
          ]
        ]

        set years-in-rec 0

        set my-cumulative-benefit 0
        set color get-color-from-breed breed
        create-grid-connection-to gse-agent

        set is-founder? false
        set shape "person"
      ]
    ]

    ask turtles with [breed != externals and breed != gses] [
```

```
      let my-effective-threshold convenience-threshold
      if is-founder? [ set my-effective-threshold (convenience-threshold * 0.1) ]

      if (years-in-rec > 2) and (my-cumulative-benefit < my-effective-threshold) [
        ask my-links [ die ]

        set breed externals
        set color gray
        set years-in-rec 0
        set my-cumulative-benefit 0
        set is-founder? false
        set shape "person"
      ]
    ]

    let current-year (ticks / 8760)

    ;; Pagamento della manutenzione globale e aggiornamento bilancio CER
    set cumulative-balance (cumulative-balance - annual-opex)

    ;; Il PBP si calcola sul CAPEX iniziale (congelato) e profitto corrente
    if (cumulative-balance < total-capex) [
      ifelse current-year > 0 [
        let average-annual-profit (cumulative-balance / current-year)
        ifelse average-annual-profit > 0 [
          set payback-period-years (total-capex / average-annual-profit)
        ] [
          set payback-period-years -1
        ]
      ] [
        set payback-period-years -1
      ]
    ]
  ]
end

to calculate-community-costs
  ;; Sommiamo la potenza SOLO dei membri attivi (producers e prosumers)
  let total-installed-power (sum [plant-power] of producers + sum [plant-power] of
prosumers)
  set total-capex (total-installed-power * cost-per-kwp)
  set annual-opex (total-capex * (opex-percentage / 100))
end

to setup-profiles
  set shape-founder "square"

  set profile-residential [
    0.02 0.01 0.01 0.01 0.01 0.02 0.04 0.06 0.05 0.04 0.03 0.03
```

```
    0.04 0.04 0.03 0.03 0.05 0.06 0.08 0.09 0.08 0.07 0.06 0.04
  ]

  set profile-office [
    0.01 0.01 0.01 0.01 0.01 0.01 0.02 0.05 0.08 0.09 0.09 0.08
    0.07 0.07 0.06 0.08 0.08 0.06 0.03 0.02 0.02 0.02 0.01 0.01
  ]

  set profile-solar-base [
    0.00 0.00 0.00 0.00 0.00 0.00 0.05 0.20 0.50 0.75 0.90 0.98
    1.00 0.98 0.90 0.75 0.50 0.20 0.05 0.00 0.00 0.00 0.00 0.00
  ]
end

to-report calculate-solar-production [pv-power]
  if pv-power = 0 [ report 0 ]
  let base-prod-factor (item (ticks mod 24) profile-solar-base)
  let climatic-multiplier 1.0

  if member? "A" climatic-zone [ set climatic-multiplier 1.25 ]
  if member? "B" climatic-zone [ set climatic-multiplier 1.15 ]
  if member? "C" climatic-zone [ set climatic-multiplier 1.0 ]
  if member? "D" climatic-zone [ set climatic-multiplier 0.85 ]
  if member? "E" climatic-zone [ set climatic-multiplier 0.75 ]
  if member? "F" climatic-zone [ set climatic-multiplier 0.65 ]

  let day-of-year ((ticks / 24) mod 365)

  ;; Il moltiplicatore varia dolcemente tra 0.4 (inverno) e 1.2 (estate)
 let angle ((360 * (day-of-year - 172)) / 365)
  let seasonal-multiplier (0.8 + (0.4 * cos angle))

  let final-production (pv-power * base-prod-factor * climatic-multiplier *
seasonal-multiplier)
  report final-production
end

to export-data
  if not empty? monthly-results-log [
    let header ["Year" "Month" "Monthly Production (kWh)" "Monthly Shared (kWh)"
"Monthly Consumption (kWh)" "Producers" "Prosumers" "Consumers" "Total Members"
"Cumulative Balance (€)" "Cumulative Shared (kWh)" "Payback Period (Years)"
"Cumulative CO2 Emitted (Tons)" "Cumulative CO2 Saved (Tons)"]
    let full-dataset fput header monthly-results-log
    csv:to-file "risultati_cer_mensili.csv" full-dataset
    print "Dati mensili esportati con successo nel file
'risultati_cer_mensili.csv'!"
  ]
end
```

```
to update-dynamic-plots
  ;; --- 1. PULIZIA PROGRAMMATA DEI GRAFICI ---
  ;; Se siamo all'ora zero assoluta, puliamo tutto
  if ticks = 0 [
    set-current-plot "Daily Budget"
    clear-plot
    set-current-plot "Monthly Budget"
    clear-plot
  ]

  ;; Pulisce il grafico giornaliero all'inizio di un nuovo giorno
  if (ticks > 0 and (ticks - 1) mod 24 = 0) [
    set-current-plot "Daily Budget"
    clear-plot
  ]

  ;; Pulisce il grafico mensile all'inizio di un nuovo mese
  if (ticks > 0 and (ticks - 1) mod 730 = 0) [
    set-current-plot "Monthly Budget"
    clear-plot
  ]

  ;; --- 2. GRAFICO GIORNALIERO (aggiornato ogni ora) ---
  set-current-plot "Daily Budget"
  let plot-x-daily (max (list 0 ((ticks - 1) mod 24)))

  create-temporary-plot-pen "Production"
  set-plot-pen-color orange
  plotxy plot-x-daily hourly-total-production

  create-temporary-plot-pen "Shared"
  set-plot-pen-color green
  plotxy plot-x-daily hourly-energy-shared

  create-temporary-plot-pen "Consumption"
  set-plot-pen-color red
  plotxy plot-x-daily hourly-total-consumption

  ;; --- 3. GRAFICO ECONOMIC BALANCE SHEET (aggiornato ogni ora) ---
  set-current-plot "Economic Balance Sheet"

  create-temporary-plot-pen "Cumulative Balance"
  set-plot-pen-color blue
  plotxy ticks cumulative-balance

  create-temporary-plot-pen "Total CAPEX"
  set-plot-pen-color red
  plotxy ticks total-capex
```

```
  ;; --- 4. ACCUMULO DATI PER GLI ALTRI GRAFICI E CSV ---
  set daily-rec-production (daily-rec-production + hourly-total-production)
  set daily-rec-shared (daily-rec-shared + hourly-energy-shared)
  set daily-rec-consumption (daily-rec-consumption + hourly-total-consumption)

  set monthly-rec-production (monthly-rec-production + hourly-total-production)
  set monthly-rec-shared (monthly-rec-shared + hourly-energy-shared)
  set monthly-rec-consumption (monthly-rec-consumption + hourly-total-consumption)

  ;; --- 5. AGGIORNAMENTO GRAFICO MENSILE (scatta ogni 24 ore) ---
  if (ticks > 0 and ticks mod 24 = 0) [
    set-current-plot "Monthly Budget"

    ;; Calcoliamo a quale giorno del mese ci troviamo (da 1 a 31)
    let current-day-of-month (floor (((ticks - 1) mod 730) / 24) + 1)

    create-temporary-plot-pen "Production"
    set-plot-pen-color orange
    plotxy current-day-of-month daily-rec-production

    create-temporary-plot-pen "Shared"
    set-plot-pen-color green
    plotxy current-day-of-month daily-rec-shared

    create-temporary-plot-pen "Consumption"
    set-plot-pen-color red
    plotxy current-day-of-month daily-rec-consumption

    ;; Svuotiamo i secchi giornalieri
    set daily-rec-production 0
    set daily-rec-consumption 0
    set daily-rec-shared 0
  ]

  ;; --- 6. LOG DATI CSV E SVUOTAMENTO MENSILE (scatta ogni 730 ore) ---
  if (ticks > 0 and ticks mod 730 = 0) [
    let monthly-data-row (list monthly-rec-production monthly-rec-shared monthly-
rec-consumption)
    set log-monthly-data lput monthly-data-row log-monthly-data

    ;; --- REGISTRAZIONE DATI MENSILI PER CSV ---
    let current-year (floor ((ticks - 1) / 8760) + 1)
    let current-month ((floor ((ticks - 1) / 730) mod 12) + 1)
    let total-members (count producers + count prosumers + count consumers)

    let csv-data-row (list
      current-year
      current-month
```

```
    (precision monthly-rec-production 2)
    (precision monthly-rec-shared 2)
    (precision monthly-rec-consumption 2)
    (count producers)
    (count prosumers)
    (count consumers)
    total-members
    (precision cumulative-balance 2)
    (precision cumulative-energy-shared 2)
    (precision payback-period-years 2)
    (precision (cumulative-co2-emitted / 1000) 2)
    (precision (cumulative-co2-saved / 1000) 2)
  )

  set monthly-results-log lput csv-data-row monthly-results-log

  ;; Svuotamento secchio mensile
  set monthly-rec-production 0
  set monthly-rec-consumption 0
  set monthly-rec-shared 0
]

;; --- 7. AGGIORNAMENTO GRAFICI ANNUALI E DEMOGRAFICI (scatta ogni 8760 ore) ---
if (ticks > 0 and ticks mod 8760 = 0) [
  set-current-plot "Annual Budget"
  clear-plot
  let month-counter 1
  foreach log-monthly-data [ a-month ->

    create-temporary-plot-pen "Production"
    set-plot-pen-color orange
    plotxy month-counter (item 0 a-month)

    create-temporary-plot-pen "Shared"
    set-plot-pen-color green
    plotxy month-counter (item 1 a-month)

    create-temporary-plot-pen "Consumption"
    set-plot-pen-color red
    plotxy month-counter (item 2 a-month)

    set month-counter (month-counter + 1)
  ]
  set log-monthly-data []

  let current-year (ticks / 8760)
  set-current-plot "Community Composition"

  create-temporary-plot-pen "Prosumers"
```

```
    set-plot-pen-color orange
    plotxy current-year (count prosumers)

    create-temporary-plot-pen "Consumers"
    set-plot-pen-color blue
    plotxy current-year (count consumers)

    create-temporary-plot-pen "Producers"
    set-plot-pen-color green
    plotxy current-year (count producers)
  ]
end

to update-links-appearance
  ask turtles with [breed != externals and breed != gses] [
    let net-flow (current-production - current-consumption)
    let my-link one-of my-out-grid-connections

    if (my-link != nobody) [

      if net-flow > 0 [
        ask my-link [
          set color green
          set thickness min (list 1.5 (0.1 + net-flow * 0.1))
        ]
      ]

      if net-flow < 0 [
        ask my-link [
          set color red
          set thickness min (list 1.5 (0.1 + abs(net-flow) * 0.1))
        ]
      ]

      ;; Se è perfettamente a 0, l'agente è autosufficiente: spenge il link
      if net-flow = 0 [
        ask my-link [
          set color gray
          set thickness 0.1
        ]
      ]
    ]
  ]
end

to-report get-default-income [ u-type ]
  if (member? "Standard" u-type) [ report 25000 ]
  if (member? "Seasonal" u-type or member? "Stagionale" u-type) [ report 35000 ]
```

```
  if (member? "Office" u-type or member? "Ufficio" u-type or member?
"Administrative" u-type) [ report 150000 ]
  if (member? "Shop" u-type or member? "Negozio" u-type) [ report 80000 ]
  if (member? "School" u-type or member? "Scuola" u-type) [ report 100000
]

  report 20000 ;; Fallback di sicurezza
end
```

Funding

This thesis was produced while attending the PhD programme in Civil Engineering and Architecture at the University of Cagliari, Cycle XXXVIII, with the support of a scholarship financed by NRRP, funded by the European Union - NextGenerationEU - Mission 4 *"Education and Research"*, Component 2 *“From Research to Business”* - Investment 1.5 *“Creating and strengthening "innovation ecosystems"*, *building "local R&D leaders"”*; part of the Ecosystem E.ins project - Ecosystem of Innovation for Next Generation Sardinia.