**Faculdade de Engenharia da Universidade do Porto**

# Business Models for Energy Community Developers and Assets Investors

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# Abstract

Energy community developers play a vital role in the successful deployment and scalability of energy communities, especially by addressing significant challenges such as high initial investment costs and the complexities of regulatory and licensing frameworks. These developers typically operate under business models that not only ensure financial viability and profit maximization but also create compelling value propositions for prospective community members. By providing clear and tangible benefits—such as reduced energy bills, enhanced self-sufficiency, and improved sustainability—developers can foster member engagement and participation, which are crucial for the long-term success of the energy community.

This work examines strategies for designing and operating an energy management system (EMS) specifically tailored to the requirements of energy community developers. The focus is on a business model in which the developer takes on full responsibility for the installation, ownership, and management of distributed energy resources (DERs), including photovoltaic (PV) systems and battery storage units. These assets are deployed both within the developer's infrastructure and at the locations of energy community members willing to host them. The EMS aims to optimize the local production and consumption of renewable energy, enabling the sale of energy within the community for self-consumption purposes. The proposed strategies seek to ensure economic efficiency for the developer while maximizing the overall energy self-consumption ratio, reducing reliance on external supply, and encouraging the active participation of community members in the energy transition.

**Key words:** Business Models, Energy Communities, Energy Management Systems, Optimization.

# United Nations Sustainable Development Goals (SDGs)

| SGD | Target | Contribution of the Dissertation | Performance Indicators and Metrics |
|---|---|---|---|
| **SDG 7** – Affordable and Clean Energy | **7.2 -** Increase renewable energy share. | Promotes local solar generation and self-consumption through energy communities. | Share of renewable energy in total consumption; reduction in grid dependence. |
| **SDG 9** – Industry, Innovation, and Infrastructure | **9.4 -** Improve sustainability of infrastructures. | Development of an Energy Management System (EMS) using MILP and integration of batteries and EVs (V2G). | Energy efficiency improvement (%); reduction of peak demand. |
| **SDG 11** – Sustainable Cities and Communities | **11.6 -** Reduce urban environmental impact. | Encourages local clean energy use and community-level decarbonization. | $CO_2$ reduction (kg/year); number of participating households. |
| **SDG 12** – Responsible Consumption and Production | **12.2 -** Improve resource efficiency. | Optimizes renewable generation, storage, and consumption to minimize waste. | Collective self-consumption ratio; local energy balance. |
| **SDG 13** – Climate Action | **13.2 -** Integrate climate policies and planning. | Supports EU renewable directives and contributes to energy transition and decarbonization. | Reduction in GHG emissions; share of renewable capacity installed. |

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*“A new idea must not be judged by its immediate results.”*

*Nikolas Tesla*

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# Abbreviations

| | |
|---|---|
| EC | Energy Community |
| REC | Renewable Energy Community |
| RES | Renewable Energy Source |
| EU | European Union |
| UN | United Nations |
| INESC TEC | Intituto de Engenharia de Sistemas e Computadores, Tecnologia e Ciência |
| CPES | Centro de Sistemas e Energia |
| EMS | Energy Management System |
| DER | Distributed Energy Resources |
| MILP | Mixed-Integer Linear Programming |
| H | Host Member |
| NH | Non-host Member |
| CSC | Collective self-consumption |
| DSO | Distribution System Operator |
| SDR | Supply and Demand Ratio |
| CSDR | Compensated Supply and Demand Ratio |

# Nomenclature

## Indices and sets

| | |
|---|---|
| $t \in T$ | Set of time intervals/slots over the operation period. |
| N | Set of CPES of the community. |
| $n, m \in N$ | Set of CPES of the community members. |
| $N_c \in N$ | Set of CPES of the community members that are consuming. |
| K | Number of iterations. |
| $ev \in EV$ | Set of EVs within each CPE's meter. |

## Parameters

| | | |
|---|---|---|
| $\Delta t$ | Optimization step. | h |
| $\hat{\lambda}_{n,t}^{buy}$ | Supply energy tariff of $n$ at $t$. | €/kWh |
| $\hat{\lambda}_{t}^{sell}$ | Feed-in energy tariff at $t$. | €/kWh |
| $\hat{\lambda}_{n,m,t}^{lem}$ | Energy tariff developer to m (different for host and non-host) | €/kWh |
| $\hat{\lambda}_{m,n,t}^{lem}$ | Energy tariff m to developer | €/kWh |
| $\hat{E}_{n,t}^{C}$ | CPE $n/m$ load profile at $t$. | kWh |
| $\hat{E}_{n,t}^{G}$ | CPE $n/m$ behind-the-meter generation at $t$. | kWh |
| $\hat{P}_{n}^{CPE,max}$ | Maximum allowed power flow through the CPE of $n$. | kW |
| $\hat{E}_{n,s}^{B,N}$ | Nominal capacity of battery $s$ of $n$. | kWh |
| $\widehat{SOC}_{n,s}^{B,min}$ | Minimum state of charge of battery $s$ of $n$. | % |

| | | |
|---|---|---|
| $\widehat{SOC}_{n,s}^{B,max}$ | Maximum state of charge of battery $s$ of $n$. | % |
| $\hat{P}_{n,s}^{B,max}$ | Maximum input and output power of battery $s$ of $n$. | kW |
| $\hat{\eta}_{n,s}^{B,C}$ | Charging efficiency of battery $s$ of $n$. | % |
| $\hat{\eta}_{n,s}^{B,D}$ | Discharging efficiency of battery $s$ of $n$. | % |
| $\hat{C}_{n}^{ind}$ | Energy bill of m from stage 1. | € |
| $\hat{\lambda}_{n,m,t}^{grid}$ | Access tariff for self-consumption applicable between $m$ and $n$, at $t$. Since it is based on $\hat{\lambda}_{t}^{grid}$, it is not an individual tariff between two members but rather a value that is equal to $\hat{\lambda}_{t}^{grid}$ in case the members are physically separated by the public grid or equal to 0 €/kWh if they are not. In fact, it can be a different value if there are members on multiple voltage levels, which is rarely the case. | €/kWh |
| $\hat{\lambda}_{n,s}^{deg}$ | Estimated degradation cost of battery $s$ of $n$, applicable to all discharged energy. | €/kWh |
| $\widehat{M}$ | A very big number (e.g., 1E6). | - |
| $\widehat{m}$ | A very small number (e.g., 1E-4) | - |
| $\widehat{E}_{n,ev,t}^{Trip}$ | Vehicle $ev$ at CPE $n$ energy consumption in period $t$. | kWh |
| $\widehat{E}_{n,ev}^{EV,MinCharge}$ | Minimum stored energy to be guaranteed for vehicle $ev$ at meter $n$. | kWh |
| $\widehat{E}_{n,ev}^{EV,BatCapacity}$ | The battery energy capacity of vehicle $ev$ at CPE $n$. | kWh |
| $\widehat{\eta}_{n,ev}^{EV,C}$ | Charging efficiency of vehicle $ev$ at CPE $n$. | % |
| $\widehat{\eta}_{n,ev}^{EV,D}$ | Discharging efficiency of vehicle $ev$ at CPE $n$. | % |
| $\widehat{P}_{n,ev}^{EV,ChargeLimit}$ | Maximum power charge of vehicle $ev$ at CPE $n$. | kW |
| $\widehat{P}_{n,ev}^{EV,DischargeLimit}$ | Maximum power discharge of vehicle $ev$ at CPE $n$. | kW |
| $\widehat{X}_{n,ev,t}^{EV}$ | Whether a vehicle $ev$ at CPE $n$ is plugged-in or not (if plugged-in = 1 else = 0). | - |
| $\widehat{\lambda}_{n,ev}^{deg}$ | Estimated degradation cost of battery ev of $n$ applicable to all discharged energy | €/kWh |

| | | |
|---|---|---|
| $\widehat{E}_{n,ev,t}^{MinUnplug}$ | Required energy in *ev* when unplugging. | kWh |
| $\widehat{SOC}_{n,ev}^{EV,min}$ | Minimum state of charge of the ev battery of n. | % |
| $\widehat{SOC}_{n,ev}^{EV,max}$ | Maximum state of charge of the ev battery of n. | % |
| $\widehat{\mu}$ | Penalty factor (value= Double of max value of $\widehat{\lambda}_t^{buy}$ ). Discomfort cost | €/kWh |

# Variables

| | | |
|---|---|---|
| $E_{n,s,t}^{B}$ | Energy stored by battery *s* of *n*, at *t*. | kWh |
| $SOC_{n,s,t}^{B}$ | SOC of battery *s* of *n*, at *t*. | % |
| $E_{n,s,t}^{B,C}$ | Energy charged by battery *s* of n at *t*. | kWh |
| $E_{n,s,t}^{B,D}$ | Energy discharged by battery *s* of *n* at *t*. | kWh |
| $\delta_{n,s,t}^{B,C}$ | Auxiliary binary variable to impede *s* of *n* from simultaneously charging and discharging at *t*. | kWh |
| $E_{n,t}^{SUP}$ | Energy supplied to *n* from its retailer, at *t*. | kWh |
| $E_{n,t}^{SUR}$ | Energy surplus sold by *n* to its retailer, at *t*. | kWh |
| $\delta_{n,t}^{SUP}$ | Auxiliary binary variable to impede *n* from simultaneously buying and selling to the retailer at *t*. | kWh |
| $E_{n,m,t}^{PUR}/E_{m,n,t}^{PUR}$ | Energy bought locally by *n/m*, from *m/n*, at *t*. | kWh |
| $E_{n,m,t}^{SALE}/E_{m,n,t}^{SALE}$ | Energy sold locally by *n/m*, to *m/n*, at *t*. | kWh |
| $E_{n,t}^{CMET}$ | Net consumption at meter *n*, at *t*. | kWh |
| $E_{n,m,t}^{SLC}$ | Energy self-consumed by *n* allocated from *m*, at *t* (in theory, g.t.e. that value). | kWh |
| $E_{n,t}^{CMET,+}$ | Consumption at meter *n/m*, at *t* (in theory, g.t.e. that value). | kWh |
| $E_{n,t}^{CMET,c}$ | Consumption at meter *n*, at *t*. | kWh |

| | | |
|---|---|---|
| $E_{n,t}^{CMET,g}$ | Generation at meter *n*, at *t*. | kWh |
| $E_{n,m,t}^{ALC+}$ | Consumed energy bought locally by *n* from *m* at *t* (in theory, g.t.e. that value). | kWh |
| $\delta_{t}^{p,exc}$ $\delta_{t}^{p,def}$ | Auxiliary binary variable for imposing proportional coefficients | [0,1] |
| $E_{t}^{AVAIL}$ | Available energy: minimum value of generated and consumed energy | kWh |
| $\hat{C}_{n,t}^{pr,k-1}$ | Coefficient of proportionality (is fixed for k-1: k=iteration) | - |
| $\delta_{n,t}^{LEM\_PUR}$ | Auxiliary binary variable to impede *n* from simultaneously buying and selling from the local market at *t*. | [0,1] |
| $\delta_{n,t}^{R\_PUR}$ | Auxiliary binary variable to impede *n* from simultaneously buying from the local market and selling to the retailer at *t*. | [0,1] |
| $E_{n,ev,t}^{EV,Stored}$ | Energy stored in vehicle *ev* at CPE *n* at the end of period *t* | kWh |
| $E_{n,ev,t}^{EV,Charge}$ | Energy charge of vehicle *ev* at CPE *n* in period $t$. | kWh |
| $E_{n,ev,t}^{EV,Discharge}$ | Energy discharge of vehicle *ev* at CPE *n* in period $t$. | kWh |
| $SOC_{n,t}^{EV}$ | SOC of EV battery of n at $t$. | % |
| $E_{n,ev,t}^{defEV}$ | Slack Variable. (It allows the minimum stored energy constraint in the EV to be more flexible.) | kWh |

# Chapter 1

# Introduction

This chapter provides a structured overview of the motivation for this work, the key objectives it aims to achieve, a review of related projects and prior studies in energy communities and related optimization, and an outline of the dissertation's organization.

## 1.1. Context and Motivation

Energy communities (ECs) are increasingly recognized as a relevant driver for advancing the energy transition towards more sustainable, decentralized, and citizen-focused systems. By facilitating local renewable energy generation—typically through photovoltaic (PV) installations—and enabling shared ownership or collective management, ECs empower consumers to actively engage in energy markets [1]. They also contribute to reducing greenhouse gas emissions, enhancing energy independence, and fostering social cohesion [2].

The real-world implementation of ECs continues to face significant challenges. Among the most obstacles are the high upfront capital requirements, the technical complexities associated with integrating Distributed Energy Resources (DERs), the bureaucracies and inefficiencies of the licensing processes, and uncertainties in regulatory frameworks [3]. These issues underscore the necessity for supportive frameworks and professionalized models that simplify the process for potential members, all while upholding the fundamental values of inclusivity and fairness.

Third-party developers -external entities responsible for planning, financing, and operating energy infrastructure- have emerged as a promising solution to address various barriers in the sector [4]. These challenges include limited public funding, complex regulations, high investment risks, and insufficient technical and institutional capacity within governments agencies. By mobilizing private capital, providing specialized expertise, and implementing more agile and innovative management models, outsourced developers accelerate and enhance the feasibility of strategic energy projects. Furthermore, the developers can facilitate the deployment of energy shares by taking advantage of economies of scale, regulatory expertise, and technical knowledge. For example, [2] illustrated how third-party ownership models in California's photovoltaic sector significantly reduced entry costs and boosted adoption rates. Similarly, [5] demonstrates that such models can prove economically viable in competitive pricing environments, particularly when complemented by cost-reflective tariffs and equitable allocation mechanisms.

## 1.2. Research Problem

The growing adoption of distributed renewable energy resources, such as photovoltaic systems and battery storage, is driving a significant shift towards more decentralized and participatory energy models [1], [2]. Renewable Energy Communities (RECs) and collective self-consumption schemes offer promising frameworks for encouraging the local generation and fostering citizen engagement. However, effectively managing these configurations presents various challenges from both technical and economic perspective [2], [5].

One of the primary difficulties is the design of energy management systems (EMS) that can coordinate production, storage, and consumption among multiple community members while ensuring that operations remain both technically feasible and financially advantageous [6]. In business models involving third-party developers, this complexity is further heightened. The developer must ensure that each participant achieves at least the same economic performance as they would under individual self-consumption, despite sharing infrastructure and engaging in internal energy exchanges as it is essential to attract participants to the business model in the energy community [7].

Most optimization studies on energy sharing target household-level or cooperative ownership scenarios, often **neglecting hierarchical developer objectives and fairness guarantees**, which are essential in third-party-led schemes [8]. Additionally, the integration of electric vehicles (EVs) and other cross sector resources as a source for additional flexibility adds another layer of complexity, introducing operational constraints [1].

Accordingly, there is a need for a **comprehensive optimization framework** that can:

- Model collective self-consumption (CSC) configurations.
- Implement flexible allocation and pricing strategies among community members.
- Guarantee that no participant incurs higher costs compared to operating individually.

- Integrate other flexibility sources from cross-sector assets (such as EV charging and vehicle-to-grid (V2G) capabilities in a unified EMS [9]).

This work addresses these challenges by developing a Mixed-Integer Linear Programming (MILP) formulation and a bilevel heuristic optimization approach, providing a structured and adaptable solution for managing collective energy communities in several scenarios [6].

## 1.3. Proposed Goals

This dissertation seeks to enhance the design and operation of energy communities led by third-party developers by proposing a customized energy management system. The objectives are carefully structured to promote both the economic sustainability of the developer and the active engagement of community members. The proposed energy management system aims to balance profitability with fairness through clearly defined modeling and optimization processes.

### 1.3.1. General goal

The main goal is to design and validate an EMS framework that enables an energy community developer to manage distributed energy resources efficiently, maximizing its profit while guaranteeing measurable economic benefits to the community members.

### 1.3.2. Specific goals

To achieve the general objective, the following specific goals are defined:

1. **Energy Flow Modeling**: Represent and simulate the technical and financial flows between the developer and community members, considering constraints and tariff structures.
2. **Design of Allocation Strategies**: Develop multiple methods for energy allocation based on consumption profiles, pricing structures, and members classification (hosts vs. non-hosts).
3. **Optimization Formulation**: Construct a MILP model that captures the developer's decision process of the energy community, including energy dispatch, storage management, internal and fairness energy trading.
4. **Heuristic Approximation to Bilevel Optimization**: Implement an iterative heuristic algorithm to approximate a bilevel optimization model that reflects the structure of decision between the developer and community members. The traditional multi-objective formulations may favor developer profitability while failing to guarantee that no member pays more than they would under individual operation. The proposed heuristic strategy progressively minimizes the cost for each member during the iterations.
5. **Scenario-Based Validation**: Evaluate the EMS performance under different operational conditions, assessing trade-offs among the developer and better cost savings for the member.

## 1.4. Research Relevance and Contribution

This work introduces an innovative framework that integrates commercial and technical decision-making in an environment where the developer plays a central role. Its primary contribution lies in the detailed modeling of an EMS tailored for a third-party developer business model—a configuration that, while increasingly common in practice, remains underexplored in academic research. It is important to note that it does not address investment decision processes, such as asset sizing or economic evaluation of DER installations.

By introducing a hybrid algorithm that combines MILP techniques with an iterative allocation process, this study offers a practical tool to maximize the developer's benefit while ensuring that community members are not economically disadvantaged.

In addition, the research adopts a progressive modeling approach that enables a precise evaluation of incremental improvements:

- An initial EMS formulation was developed using a multi-objective function to maximize the developer's benefits while minimizing the members' costs using an iterative fixed-point algorithm and proportional-to-consumption energy sharing.
- Then, alternative allocation coefficients, such as price-weighted proportional-to-consumption and an ad-hoc decision tree were tested to improve the EMS behavior.
- Since the behavior of community members was not well represented with the multi-objective function (as members' assets were dispatched to benefit the REC developer), the model was restructured to use a heuristic approach to the bilevel model for a better representation of the members' behavior.
- Finally, the system was enhanced by integrating EVs into flexible consumption and storage resources, including vehicle-to-grid (V2G) capabilities, thereby increasing the available flexibility.

## 1.5. Document Structure

This thesis is structured as follows:

- **Chapter 1 – Introduction:** Presents the motivation, the goals, and the improvement of the model.
- **Chapter 2 – State of the Art**: Reviews key concepts related to energy communities, applicable business models, investment and pricing strategies, and EMS optimization techniques.
- **Chapter 3 – Proposed Business Model**: Describes the developer's role, types of community members, energy, and revenue flows.
- **Chapter 4 – Optimization Problem Formulation:** Details the mathematical models developed to support the proposed business model. The Collective Self-Consumption (CSC) formulation using a multi-objective function is introduced, incorporating internal energy

sharing, allocation strategies, benefit guarantee constraints, and integrating electric vehicles (EVs) as flexible storage and consumption assets.

- **Chapter 5 Assessment of Energy Sharing and Allocation Strategies Based on Case Studies:** Explores the iterative fixed-point algorithm to allow different allocation coefficients, such as price allocation, proportional, and price-weighted to the consumption, and the decision tree method.
- **Chapter 6 – Heuristic Approximation to a Bilevel Model for Energy Sharing in RECs:** Compares the performance of using the multi-objective function with an iterative heuristic bilevel model, also described in this chapter, that represents better the behavior of the CSC members.
- **Chapter 7 – Conclusions and Future Work:** Summarizes key findings, outlines research limitations, and suggests directions for further study, including scaling the model to larger communities and validating it through real-world pilot implementations.

# Chapter 2

# State of the Art

This chapter offers a comprehensive literature review covering the theoretical foundations, business strategies, and optimization techniques applicable to energy communities. The discussion establishes the background against which the proposed modeling and methodological contributions have been developed.

## 2.1. Renewable Energy Communities

RECs have emerged as a transformative approach to democratizing energy generation and consumption. By leveraging local renewable energy sources-such as photovoltaic systems, small-scale wind turbines, and battery storage- RECs enable end consumers to produce, share, and optimize their energy use within a defined geographic or virtual boundary [7].

A recent case study in Portugal by [10] explores a business model where a third party facilitates access to solar energy through fixed tariffs and no upfront investment. In this model, members may act as hosts-offering their premises for equipment installation-or as passive consumers. The study highlights that while such a structure effectively reduces market barriers and shields members from price volatility, it can also limit the development of a genuine sense of community. This occurs because interactions remain transactional and centralized, with limited opportunities for shared decision-making or ownership.

The European Union’s **Clean Energy for All Europeans Package** formally established the legal recognition of RECs, outlining rights and responsibilities for participants [11]. Under this framework, RECs can own or lease distributed energy resources, participate in energy markets, and engage in **CSC** schemes. In a CSC configuration, multiple users share the electricity produced by shared installations, with surplus energy either allocated among members or sold to the grid. This concept aims to:

- **Empower local actors**, giving citizens more control over their energy supply and costs.
- **Improve self-sufficiency**, reducing dependence on centralized infrastructure.

- **Foster decarbonization**, accelerating the integration of renewable sources [5].
- **Promote social innovation**, building new forms of cooperation.

Depending on regulatory frameworks, CSC can be implemented within a single building, across several adjacent buildings, or through virtual aggregation of meters [12]. Allocation of shared energy can follow **static rules**—such as proportional distribution based on installed capacity or contracted shares—or **dynamic mechanisms** that adapt to real-time consumption and production profiles [13].

However, despite the regulatory progress and technological feasibility, several barriers persist implementing RECs. The work in [14] highlights that, from the consumer’s perspective, major obstacles include a lack of awareness, uncertainty about economic benefits, and trust in centralized actors. Moreover, insufficient communication, limited technical knowledge and bureaucratic obstacles, such as regulatory fragmentation, prevent citizens from confidently engaging in REC initiatives.

Reference [15], in a comparative review of community energy models in the UK, Germany, and the USA, identifies structural and institutional challenges that significantly shape the success of RECs. While local empowerment, economic resilience, and environmental gains are widely recognized, issues like bureaucracy, funding access, and inconsistent political support remain prevalent. These findings reinforce the need for supportive governance and consistent long-term policy frameworks.

The design of energy communities involves technical considerations (e.g., metering, control systems) and legal, economic, and social aspects [16]. Ensuring transparency in cost allocation, defining equitable benefit distribution, and maintaining trust among participants are critical success factors [17]. Additionally, integrating **flexible assets**—such as storage systems and electric vehicles—introduces further opportunities to optimize local energy use while providing ancillary services to the grid [18].

The growing adoption of RECs reflects a broader paradigm shift towards **distributed energy systems**, where communities are active stakeholders rather than passive consumers [19]. This evolution demands sophisticated energy management and optimization approaches capable of coordinating diverse assets, balancing individual and collective interests, and ensuring compliance with evolving regulations.

Moreover, RECs are increasingly recognized as **a strategic tool to address energy poverty and promote social equity** [20]. As [21] emphasize, RECs empower citizens to become renewable energy producers and serve as mechanisms to reduce structural inequalities by providing vulnerable households access to affordable clean energy. Through shared infrastructures, simplified access to subsidies, and inclusive governance models, RECs foster environmental and social benefits within communities.

## 2.2. Business Models for Energy Communities

The development of RECs and collective self-consumption schemes has driven **innovative business models** that combine technological solutions with novel contractual arrangements. These models seek to align the incentives of all participants—end-users, developers, and grid operators—while ensuring regulatory compliance and financial sustainability [1], [7].

A prominent configuration involves a **third-party developer** or aggregator who designs, finances, and operates DERs on behalf of the community [22]. In this approach, the developer retains ownership of assets such as photovoltaic installations and battery storage throughout the contract term. Community members can host the infrastructure on their premises or participate as consumers purchasing locally generated electricity. Differentiated pricing schemes are commonly applied, typically offering:

- **Lower tariffs for host members**, those who allow installations of the developer assets (such as PVs or batteries), compensating them for using their rooftops or facilities.
- **Slightly higher tariffs for non-host members**, who participate in the community as consumers but do not host any developer assets.

These arrangements enable the **pooling of investments and operational costs**, facilitating economies of scale and reducing barriers to entry for individual participants [12], [23]. As [24] identify, the innovative business models are key enablers for integrating prosumers into energy systems. However, they also identify several barriers, including regulatory complexity, cultural resistance, and technical knowledge gaps, which can limit adoption despite potential economic gains.

Furthermore, [25] offers a critical analysis of regulatory and financial instruments used in Italy to support energy communities. Their work highlights the importance of a participatory energy transition and underscores that effective governance frameworks should promote economic and technical viability and foster social engagement. They advocate for public policies that actively incentivize citizen participation, particularly in contexts where bottom-up community leadership remains underdeveloped.

Developers often recover their investments through:

- The sale of energy to community members (local supply contracts).
- Revenues from exporting surplus electricity to the grid or an aggregator [8].
- Incentives or subsidies apply to renewable generation.

In parallel, **peer-to-peer (P2P) trading models** have emerged, allowing participants to directly exchange energy using platforms that track transactions and automate settlement processes [27]. While conceptually similar to local energy sales, P2P models differ in that pricing and trading are decentralized or negotiated among users. However, the practical deployment of P2P schemes often faces regulatory and metering challenges, especially in multi-tenant buildings or networks without advanced submetering capabilities [4].

The choice of business model is strongly influenced by:

- **Regulatory frameworks**, that define eligibility criteria, metering requirements, and tariff structures [1], [28].
- **Technical configurations**, including storage integration, and energy management capabilities [9].
- **Social acceptance**, as trust and transparency, is critical for community engagement [7], [23].

## 2.3. Energy Management Systems and Optimization

The effective operation of RECs and CSC schemes relies on **EMS** capable of calculating local energy surpluses and deficits, managing battery charging and discharging schedules, assigning internally produced energy to community members and to the grid [29], [30]. EMS platforms are responsible for acquiring real-time data, forecasting consumption and generation profiles, and determining optimal scheduling decisions.

A wide range of optimization approaches has been explored in the literature to support EMS design and operation. Among these, **MILP** formulations have become prominent due to their capacity to model complex constraints—such as battery dynamics, power flow limits, and allocation rules—while maintaining computational tractability [4], [9]. MILP models can capture both continuous decisions (e.g., energy quantities) and discrete operational states (e.g., on/off, buy/sell), enabling representation of realistic system behaviors.

**Bilevel optimization frameworks** have been proposed in contexts where multiple objectives coexist, such as minimizing community-wide costs while ensuring individual benefit guarantees [23]. Bilevel models hierarchically structure the problem into two levels: the upper-level optimization defines global decisions (e.g., total allocation of shared resources). In contrast, lower-level optimization verifies compliance with individual constraints or behavior, or fairness criteria.

Other contributions have investigated **heuristic and metaheuristic approaches**, including genetic algorithms, particle swarm optimization, and multi-agent systems [6]. These techniques are particularly suitable for larger-scale problems with non-linearities and uncertainty, although they often lack the guarantee of finding globally optimal solutions.

In recent years, attention has also focused on integrating **flexible assets**—such as electric vehicles (EVs) and controllable loads—into EMS optimization [9]. Introducing these assets increases the potential for self-consumption and grid services and adds significant complexity to forecasting and scheduling.

Despite advances in modeling techniques, significant challenges remain in developing EMS solutions that can:

- Efficiently balance community-wide objectives and individual member interests.
- Operate under evolving regulatory frameworks and pricing schemes.
- Scale to larger networks while ensuring computational efficiency [7], [12].

This dissertation builds upon these research directions by proposing a flexible MILP-based EMS capable of representing collective self-consumption scenarios using an iterative algorithm, integrating advanced allocation strategies, and performing a bilevel optimization approach to guarantee economic benefit for the developer and all the community members.

# Chapter 3

# Proposed Business Model

The business model (BM) was developed in an INESC Tec project with a consultancy firm and is described in Figure 3.1. It is based on a third-party developer that deploys and operates DERs within an EC. This developer model diverges from traditional cooperative ECs by introducing a centralized actor that manages assets, handles energy trading, and coordinates community interactions, all while pursuing economic sustainability for both the developer and the community members.

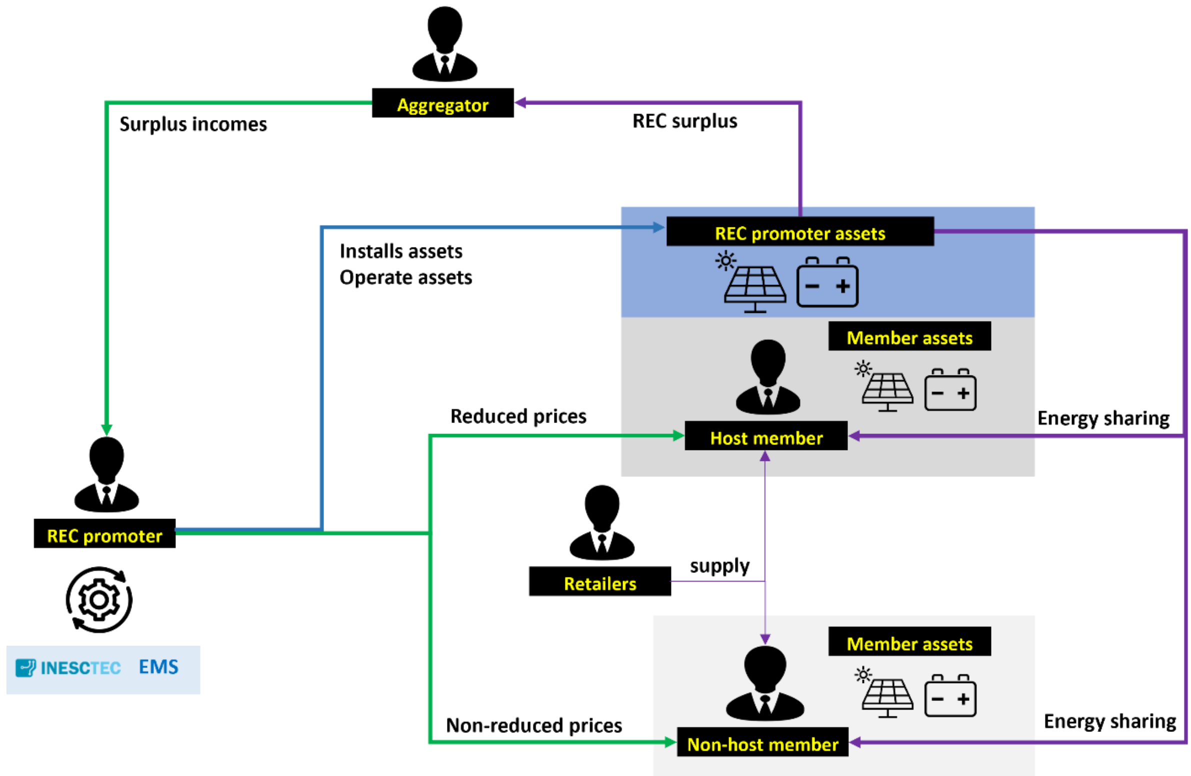


Figure 3.1: Business Model.

In this business model, **REC developers** establish a **CSC** arrangement and deploy DERs across selected community members. The installed assets, which may include **batteries and solar PV systems,** remain under the developer's ownership throughout the contract [31].

All community members sign long-term contracts with the REC developer to purchase locally generated energy. As provided in Section 3.2, members who host DERs on their premises benefit from lower tariffs as compensation for providing installation space and the non-host members pay higher tariffs for access to the same local renewable energy. Importantly, these local tariffs are always **lower than the retail purchase price of electricity**, ensuring that all members have benefit from participating in the community.

The REC developer is **remunerated only through energy sales** to CSC members. Investment costs for asset installation are not considered in this framework but should be considered by the REC developer while designing the REC and sizing its investments. All energy metering and settlement processes require **submetering**, ensuring accurate accounting of local energy transactions.

In the event of **energy surpluses** following local sharing, the excess energy is sold to the **EGAC aggregator**, and the resulting revenue is treated as a **benefit for the REC developer**. It is also assumed that each developer asset is associated with a unique **CPE (Energy Delivery Point)** which corresponds to a DSO smart meter.

The allocation of energy among community members depends on the selected sharing strategy (e.g., proportional, price-weighted, or decision-tree-based). These strategies are incorporated into an **iterative fixed-point algorithm**, in which energy allocation coefficients are updated across successive iterations based on members' consumption, pricing, and contractual conditions. Among the tested methods, the decision-tree strategy includes a redistribution step to reallocate excess energy from what was initially allocated.

Additionally, **non-Developer members** may own and operate their **behind-the-meter assets**, such as solar panels or batteries, which are not managed by REC developers. Also, the REC developer may operate assets and EVs **not hosted on any CSC member site**, further contributing to the local energy ecosystem.

## 3.1. Role and definition of EC Developer

In this framework, the EC developer is a private or institutional entity responsible for financing, installing, owning, and operating energy infrastructure, including photovoltaic systems and batteries. The developer's primary objective is to optimize internal energy flows and maximize its profit by selling energy to EC members and the final surplus to the REC aggregator [1], [2].

Unlike in member-owned ECs, where participants share governance and operational responsibilities, the developer acts as a service provider, managing technical complexity, ensuring regulatory compliance, and bearing investment risk. This model facilitates access to renewable energy so that users lacking capital or technical expertise can participate directly [23].

Typically, assets installed by the developer in members' premises remain under the developer's ownership during the contractual period. The ownership of these assets could be transferred to the host members after a pre-defined time specified in the contract. This arrangement ensures long-term engagement while providing financial and operational benefits to both parties.

Therefore, while third-party-driven models offer scalability, professionalization, and financial relief, they must be carefully designed to balance efficiency with community values. Strategies to promote transparency, long-term member benefits, and inclusive governance should be incorporated to enhance trust and engagement.

## 3.2. Member Typologies and Pricing (Host and Non-Host)

Members of the EC are categorized into two main typologies based on their level of infrastructure involvement:

- **Host members**: These users allow the developer to install DERs (e.g., solar panels or battery systems) on their premises. Although the developer owns and manages the assets during the operational phase, it is often agreed that ownership may be transferred to the host after a predefined contractual period.
- **Non-host members**: These participants do not host assets but benefit from the local energy produced by the community. Typically, they pay higher tariffs than hosts due to the absence of infrastructure contribution.

Energy prices within the community are differentiated by member typology. A typical pricing structure includes:

- Lower tariffs for host members to compensate for the use of their premises.
- Higher tariffs for non-host members reflect their passive role in infrastructure deployment.

## 3.3. Profitability vs. Fairness Trade-offs

One of the most critical challenges in this model is the trade-off between developer profitability and reasonably fair treatment of community members. While it is economically optimal for the developer to prioritize energy sales to members who pay higher tariffs (typically non-hosts), but it is unjust to host members, who not only contribute spaces for DER installations but also need the energy produced to reduce their consumption if it is necessary to buy from the grid.

To address this, the EMS must incorporate constraints or multi-objective criteria that ensure:

- No member incurs higher costs than they would without community participation.
- Hosts receive tangible benefits from participation.
- Profitability targets for the developer are still met.

These trade-offs are explored and quantified in later chapters through simulation and optimization. Solutions tested are proportional, price, price-weighted, and decision tree allocation coefficients for the energy sharing within the optimization framework [4].

# Chapter 4

# Optimization Problem Formulation

This chapter presents the mathematical formulation of the EMS developed as a business model of an EC third-party developer business model. The formulation aims to balance two primary goals: maximizing the economic return for the EC developer and ensuring tangible benefits for all participating members. It also adopts a MILP approach to represent the optimization problem, incorporating system constraints, allocation decisions, and fairness guarantees considering only photovoltaic generation and battery storage.

The optimization process is solved using an iterative fixed-point algorithm because the allocation of locally generated energy depends on consumption, prices, and the members' conditions. At each iteration, the allocation coefficients are updated based on the MILP results, and the problem is solved again until convergence is achieved.

## 4.1. Collective Self-Consumption (CSC) Formulation

This section describes the constraints of the **CSC** formulation, which extends the individual self-consumption model to a member configuration with developer assets, differentiated pricing, and internal energy exchanges.

The primary goal of the optimization problem is to minimize the total cost incurred by the EC developer, which is equivalent to maximizing its net profit. This includes revenues from internal energy sales and costs or penalties associated with energy purchases from the grid, and battery degradation.

At the same time, a key constraint ensures that no community member is worse off by participating in the EC than they would be individually. This is implemented through a three-stage modeling approach borrowed from prior studies on fair benefit sharing in ECs [12].

### 4.1.1. Mathematical Formulation

The multi-objective function of the optimization model is designed to **minimize the total operation cost of the energy community** while balancing the objectives of the developer and the members.

Specifically, equation (4.1) aggregates the perspectives of both the developer and the community members:

- The costs of purchasing energy from the external grid.
- The revenues from selling surplus energy to the grid or aggregator.
- The costs and revenues of internal energy transactions between the developer and community members.
- The degradation costs are associated with battery cycling and electric vehicle charging/discharging (when included).

The first part of the equation represents the minimization of the developer's cost, and the second part, introduced after the factor $m$ , corresponds to minimizing the members' cost. It means that it balances the profitability of the developer and the economic advantage of the members.

The primary goal of this function is to **identify the most cost-efficient scheduling of local generation, storage usage, and energy exchanges**, while respecting all technical constraints (e.g., power limits, state of charge) and fairness requirements (ensuring no member pays more than in individual operation).

$$
\begin{aligned}
min \sum_{t} \Bigg( \Bigg( & \sum_{n \in P} \left( E_{n,t}^{SUP} \cdot \lambda_{n,t}^{buy} - E_{n,t}^{SUR} \cdot \lambda_{n,t}^{sell} \right) + \sum_{n,m \in P} \left( E_{n,m,t}^{SLC} \cdot \hat{\lambda}_{n,m,t}^{grid} \right) \\
& + \sum_{n \in P} \sum_{s \in S_n} E_{n,s,t}^{B,D} \cdot \hat{\lambda}_{n,s}^{deg} + \sum_{n \in P} \sum_{ev \in EV_n} \left( E_{n,ev,t}^{EV,Discharge} \cdot \hat{\lambda}_{n,ev}^{deg} + \hat{\mu} \cdot E_{n,ev,t}^{defEV} \right) \\
& - \sum_{n \in P} \sum_{m \notin P} \left( E_{n,m,t}^{SALE} \cdot \lambda_{n,m,t}^{lem} \right) \Bigg) \\
& + m \Bigg( \sum_{n \notin P} \left( E_{n,t}^{SUP} \cdot \lambda_{n,t}^{buy} - E_{n,t}^{SUR} \cdot \lambda_{n,t}^{sell} \right) + \sum_{n,m \notin P} \left( E_{n,m,t}^{SLC} \cdot \hat{\lambda}_{n,m,t}^{grid} \right) \\
& + \sum_{n \notin P} \sum_{m \in P} \left( E_{n,m,t}^{PUR} \cdot \lambda_{n,m,t}^{lem} \right) \\
& + \sum_{n \notin P} \sum_{s \in S_n} E_{n,s,t}^{B,D} \cdot \hat{\lambda}_{n,s}^{deg} \\
& + \sum_{n \notin P} \sum_{ev \in EV_n} \left( E_{n,ev,t}^{EV,Discharge} \cdot \hat{\lambda}_{n,ev}^{deg} + \hat{\mu} \cdot E_{n,ev,t}^{defEV} \right) \Bigg) \Bigg)
\end{aligned} \tag{4.1}
$$

This formulation is subject to:

- **Energy balance constraints** at each CPE (internal and external).
- **Battery charge/discharge behavior** respecting maximum power and SOC bounds.
- **No simultaneous buying and selling** by the same meter.
- **Community-level energy allocation limits**, based on different types of coefficients.
- **Electric vehicles** with charging and discharging flows.
- **Benefit guarantee** for members: total cost when participating in the EC must not exceed individual operation cost $\hat{C}_n^{ind}$ (computed separately).

### 4.1.2. System Constraints

This section focuses on the limitations that need to be considered to ensure that the CSC system operates. It begins by identifying and describing the limitations of each constraint.

#### 4.1.2.1. Equilibrium and Net Consumption Constraints

These **equilibrium and net consumption constraints** define the relationships between energy imported, exported, consumed, and exchanged within the community.

Equation (4.2) enforces the reciprocity of local transactions by requiring that any quantity of energy purchased by meter $n$ from another CPE $m$ must match the amount sold by CPE $m$ to CPE $n$.

$$E_{n,m,t}^{PUR} = E_{m,n,t}^{SALE} \tag{4.2}$$

This ensures consistency in bilateral trade and prevents discrepancies in energy accounting.

Equation (4.3) defines the **net consumption** of each meter as the balance between its nominal consumption, local generation, and the battery's charge/discharge and electric vehicle contributions.

$$E_{n,t}^{CMET} = \hat{E}_{n,t}^{C} - \hat{E}_{n,t}^{G} + \sum_{s \in S_n} \left(E_{n,s,t}^{B,C} - E_{n,s,t}^{B,D}\right) + \sum_{\text{ev} \in EV_n} \left(E_{n,ev,t}^{EV,Charge} - E_{n,ev,t}^{EV,Discharge}\right) \tag{4.3}$$

This formulation captures the practical energy requirement after accounting for on-site generation and storage operations.

Equation (4.4) further decomposes net consumption into the **balance of external supply and surplus exports** and the net result of local energy exchanges with other community members.

$$E_{n,t}^{CMET} = E_{n,t}^{SUP} - E_{n,t}^{SUR} + \sum_{m \neq n \in N} \left(E_{n,m,t}^{PUR} - E_{n,m,t}^{SALE}\right) \tag{4.4}$$

This equation guarantees that all energy flows are reconciled, including imports from the grid, internal transactions, and surplus injections.

Finally, constraint (4.5) imposes a technical limit on each meter's **power flow capacity** at the connection point (CPE).

$$-\hat{P}_{n}^{CPE,max} \leq \frac{E_{n,t}^{CMET}}{\Delta t} \leq \hat{P}_{n}^{CPE,max} \tag{4.5}$$

This restriction ensures that neither import nor export exceeds the contractual or physical capacity of the grid connection.

To enable the distinction between periods of net consumption and net generation, equation (4.6) describes how the model decomposes the variable $E_{n,t}^{CMET}$ into two components.

$$E_{n,t}^{CMET} = E_{n,t}^{CMET,c} - E_{n,t}^{CMET,g} \tag{4.6}$$

This formulation allows the optimization process to detect whether each CPE effectively acts as a net consumer or a net generator at each time step.

#### 4.1.2.2. Battery Constraints

To accurately model the dynamics of battery energy storage systems (BESS) within each CPE, the optimization problem incorporates several constraints governing the evolution of stored energy, the state of charge (SOC), and the allowable charging and discharging power. These battery operation constraints ensure that the EMS respects the storage systems' physical capabilities and operational safety.

- **State of Energy Update Constraint:** Equation (4.7) defines how the stored energy in the battery $s$ of meter $n$ evolves, accounting for charging and discharging efficiencies.

$$E_{n,s,t}^{B} = E_{n,s,t-1}^{B} + \left( E_{n,s,t}^{B,C} \cdot \hat{\eta}_{n,s}^{B,C} - \frac{E_{n,s,t}^{B,D}}{\hat{\eta}_{n,s}^{B,D}} \right) \tag{4.7}$$

- **State of Charge Limits:** Constraint (4.8) ensures that the SOC remains within safe operational thresholds.

$$\widehat{SOC}_{n,s}^{B,min} \leq SOC_{n,s,t}^{B} = \frac{E_{n,s,t}^{B}}{\hat{E}_{n,s}^{B,N}} \cdot 100\% \leq \widehat{SOC}_{n,s}^{B,max} \tag{4.8}$$

- **Power Constraints:** Constraints (4.9) define the limits on charging and discharging power in each timestep, ensuring that the battery does not exceed its rated capacity and that charging and discharging do not co-occur.

$$\begin{aligned} \frac{E_{n,s,t}^{B,C}}{\Delta t} &\leq \hat{P}_{n,s}^{B,max} \cdot \left(\delta_{n,s,t}^{B,C}\right) \\ \frac{E_{n,s,t}^{B,D}}{\Delta t} &\leq \hat{P}_{n,s}^{B,max} \cdot \left(1 - \delta_{n,s,t}^{B,C}\right) \end{aligned} \tag{4.9}$$

### 4.1.2.3. Individual Benefit Guarantee Constraint

Constraint (4.10) ensures that each member's energy cost within the community does not exceed the individual reference cost ($\hat{C}_n^{ind}$) that would be incurred under individual operation. This condition guarantees that no participant is financially penalized by joining the energy community.

$$\sum_{t \in T} \left( \begin{array}{c} E_{n,t}^{SUP} \cdot \hat{\lambda}_{n,t}^{buy} - E_{n,t}^{SUR} \cdot \hat{\lambda}_{n,t}^{sell} + \sum_{s \in S} E_{n,s,t}^{B,D} \cdot \hat{\lambda}_{n,s}^{deg} + \\ \sum_{m \neq n \in N} \left( E_{n,m,t}^{PUR} \cdot \lambda_{m,n,t}^{lem} + E_{n,m,t}^{SLC} \cdot \hat{\lambda}_{n,m,t}^{grid} \right) \end{array} \right) \leq \hat{C}_n^{ind} + \hat{m} \tag{4.10}$$

### 4.1.2.4. Simultaneity Prevention Constraints

To maintain logical consistency in energy transactions, the model includes a set of constraints designed to **prevent simultaneous mutually exclusive operations** within the same time interval. These restrictions ensure that CPEs cannot engage in contradictory activities, such as buying and selling energy to the grid or reporting both net consumption and net generation simultaneously.

Constraint (4.11) enforces the prevention of simultaneous supply and surplus exports.

$$\begin{gathered} E_{n,t}^{SUP} \leq \hat{M} \cdot \left( \delta_{n,t}^{SUP} \right) + \hat{m} \\ E_{n,t}^{SUR} \leq \widehat{M} \cdot (1 - \delta_{n,t}^{SUP}) + \hat{m} \end{gathered} \tag{4.11}$$

Constraint (4.12) prevents CPEs from simultaneously **purchasing and selling energy** from the local market.

$$\begin{gathered} \sum_{m} E_{n,m,t}^{PUR} \leq \hat{M} \cdot \left( \delta_{n,t}^{LEM\_PUR} \right) + \hat{m} \\ \sum_{m} E_{n,m,t}^{SALE} \leq \widehat{M} \cdot (1 - \delta_{n,t}^{LEM\_PUR}) + \hat{m} \end{gathered} \tag{4.12}$$

Constraint (4.13) prevents CPEs from simultaneously **purchasing energy** from the local market and **selling energy** to the retailer.

$$\begin{gathered} \sum_{m} E_{n,m,t}^{PUR} \leq \hat{M} \cdot \left( \delta_{n,t}^{R\_PUR} \right) + \hat{m} \\ E_{n,t}^{SUR} \leq \hat{M} \cdot \left( 1 - \delta_{n,t}^{R\_PUR} \right) + \hat{m} \end{gathered} \tag{4.13}$$

Constraint (4.14) prevents CPEs from simultaneously **purchasing energy** from the retailer market and **selling energy** to the local energy market.

$$\sum_{m} E_{n,m,t}^{SALE} \leq \widehat{M} \cdot (\delta_{n,t}^{R\_SALE}) + \widehat{m}$$
$$E_{n,t}^{SUP} \leq \widehat{M} \cdot \left(1 - \delta_{n,t}^{R\_SALE}\right) + \widehat{m} \tag{4.14}$$

Constraint (4.15) ensures that a CPE does not report both net consumption and net generation simultaneously.

$$E_{n,t}^{CMET,c} \leq \widehat{M} \cdot \left(\delta_{n,t}^{CMET,c}\right) + \widehat{m}$$
$$E_{n,t}^{CMET,g} \leq \widehat{M} \cdot (1 - \delta_{n,t}^{CMET,c}) + \widehat{m} \tag{4.15}$$

These binary variables ($\delta$) activate or deactivate specific flows, ensuring that the EMS produces operationally coherent schedules consistent with market rules.

#### 4.1.2.5. Scenario Detection Constraints

To distinguish between periods of **surplus** and **deficit** in the community's aggregated energy balance, the model includes a set of constraints that detect the active scenario at each time step and activate the corresponding logic for energy allocation. These **scenario detection constraints** rely on binary variables ($\delta_t^{p,exc}$ and $\delta_t^{p,def}$), identifying whether surplus or deficit conditions apply.

Constraint (4.16) defines the upper bound of available energy in surplus scenarios based on net consumption components, ensuring that it cannot exceed the aggregated consumption of the community.

$$E_t^{AVAIL} \leq \sum_{n \in N} E_{n,t}^{CMET,c} + \widehat{m} \tag{4.16}$$

Similarly, constraint (4.17) defines the upper bound in deficit conditions, limiting the available energy to the aggregated generation of all members.

$$E_t^{AVAIL} \leq \sum_{n \in N} E_{n,t}^{CMET,g} + \widehat{m} \tag{4.17}$$

Constraints (4.18) and (4.19) introduce binary variables combined with a big-M ($M$) formulation to enforce the activation depending on the scenario.

First, constraint (4.18) enforces surplus detection.

$$E_t^{AVAIL} \geq \sum_{n \in N} E_{n,t}^{CMET,c} - M\left(1 - \delta_t^{p,exc}\right) - \widehat{m} \tag{4.18}$$

Then, constraint (4.19) enforces deficit detection.

$$E_t^{AVAIL} \geq \sum_{n \in N} E_{n,t}^{CMET,g} - M\left(1 - \delta_t^{p,def}\right) - \widehat{m} \tag{4.19}$$

Finally, Equation (4.20) guarantees that only one scenario is active at each time $t$.

$$\delta_t^{p,exc} + \delta_t^{p,def} = 1 \tag{4.20}$$

This mechanism ensures the unambiguous identification of system conditions and enables the EMS to correctly select the appropriate allocation logic and pricing rules for each time interval.

#### 4.1.2.6. Available Energy and Allocation Constraints

The model includes a set of constraints governing how available energy is distributed among members to ensure that energy allocations respect both the calculated availability and the internal trading rules. These **available energy and allocation constraints** define upper bounds for purchases, link allocation variables to system states, and prevent infeasible assignments.

Constraint (4.21) defines an auxiliary variable $E_{n,m,t}^{ALC+}$ that captures the net amount of energy effectively purchased from each peer.

$$E_{n,m,t}^{ALC+} \geq E_{n,m,t}^{PUR} - E_{n,m,t}^{SALE} \tag{4.21}$$

Constraint (4.22) ensures that the local grid charges apply to the relevant transactions.

$$E_{n,m,t}^{SLC} \geq E_{n,m,t}^{ALC+} \tag{4.22}$$

Constraint (4.23) enforces that the total energy purchased by each CPE does not exceed the available energy proportionally allocated according to the allocation coefficient $\hat{C}_{n,t}^{pr,k}$.

$$\sum_{m} E_{n,m,t}^{PUR} \leq E_t^{AVAIL} \cdot \hat{C}_{n,t}^{pr,k} \tag{4.23}$$

#### 4.1.2.7. Electric Vehicle Constraints

The integration of EVs introduces new constraints governing battery dynamics, power limits, and minimum energy requirements before unplugging. Additionally, the **energy balance equation is modified to include EV charging and discharging flows**, ensuring that all energy sources and sinks are consistently tracked.

- **EV State of Energy Update:** Equation (4.24) defines the update of stored energy in the EV battery, accounting for charging, discharging, and consumption during trips.

$$E_{n,ev,t}^{EV,Stored} = E_{n,ev,t-1}^{EV,Stored} + \hat{\eta}_{n,ev}^{EV,C} \cdot E_{n,ev,t}^{EV,Charge} - \frac{1}{\hat{\eta}_{n,ev}^{EV,D}} E_{n,ev,t}^{EV,Discharge} - \hat{E}_{n,ev,t}^{Trip} \tag{4.24}$$

- **EV Charging and Discharging Power Limits:** Constraint (4.25) limits the charging and discharging power of the EV, considering the connection status.

$$\begin{aligned} E_{n,ev,t}^{EV,Charge} &\leq \hat{P}_{n,ev}^{EV,ChargeLimit} \cdot \hat{X}_{n,ev,t}^{EV} \cdot \triangle t \\ E_{n,ev,t}^{EV,Discharge} &\leq \hat{P}_{n,ev}^{EV,DischargeLimit} \cdot \hat{X}_{n,ev,t}^{EV} \cdot \triangle t \end{aligned} \tag{4.25}$$

- **EV State of Charge Limits:** Constraint (4.26) enforces the allowed range of state of charge (SOC) as a percentage of nominal battery capacity.

$$\widehat{SOC}_{n,ev}^{EV,min} \leq SOC_{n,ev,t}^{EV} = \frac{E_{n,ev,t}^{EV,Stored}}{\hat{E}_{n,ev}^{EV,BatCapacity}} \cdot 100\% \leq \widehat{SOC}_{n,ev}^{EV,max} \tag{4.26}$$

- **Minimum Stored Energy Before Unplugging:** Finally, constraint (4.27) ensures that the battery maintains a minimum stored energy before unplugging, accounting for possible deficits.

$$E_{n,ev,t-1}^{EV,Stored} \geq \hat{E}_{n,ev,t}^{MinUnplug} - E_{n,ev,t}^{defEV} \tag{4.27}$$

Additionally, the EMS allows **V2G** operations, enabling EVs to supply energy to the local grid or other members during periods of high demand. This increases the flexibility and self-consumption potential of the community while introducing new decision layers in the optimization process.

## 4.2. Guaranteeing Member Benefits

An essential requirement of the proposed energy management system (EMS) is to ensure that **no community member incurs higher costs by participating in the collective self-consumption arrangement than they would under individual operation**. This principle, referred to as a *benefit guarantee*, underpins the economic fairness of the model and supports member engagement and trust.

To operate this guarantee, the optimization process follows a **two-stage approach**:

- **Stage 1 - Baseline Cost Calculation:** For each member $n$, the EMS determines the reference cost $\hat{C}_n^{ind}$ representing the total energy cost if the member operates independently, purchasing and selling energy exclusively from and to the external grid. This baseline is computed by solving the MILP problem without internal energy allocation.

- **Stage 2 – Community Optimization:** The EMS performs the complete optimization, including local energy exchanges, DER operation, and allocation strategies. A **condition is imposed** to ensure that the total cost incurred by each member does not exceed their baseline cost:

$$C_n^{ind\_after} \leq \hat{C}_n^{ind\_before}$$

where $C_n^{ind\_before}$ the individual reference cost calculated assuming no participation in the community and $C_n^{ind\_after}$ the cost while being part of the community.

This condition guarantees that all participants **receive a tangible economic benefit** (or, at least, are not financially disadvantaged) by joining the energy community. It also ensures that the optimization process does not disproportionately favor the developer's profitability at the expense of individual members.

Combined with the bilevel heuristic approach described in Section 6.3, this mechanism allows the EMS to first identify better performance to the global solution and then iteratively adjust allocation and scheduling until all benefit guarantees are respected.

# Chapter 5

# Assessment of Energy Sharing and Allocation Strategies Based on Case Studies

This chapter presents and demonstrates several allocation methods determining how the developer distributes available energy to host and non-host members. These methods are implemented within the iterative fixed-point algorithm explained in Section 5.5 and each strategy affects cost savings, developer profit, and member engagement differently.

## 5.1. Proportional Method

The proportional-to-consumption allocation ($\hat{C}_{n,t}^{prop}$) method distributes available energy among community members based on relative consumption. In each time step $t$, the allocation coefficient for member $n$ is defined as in equation (5.1).

$$\hat{C}_{n,t}^{prop} = \frac{E_{n,t}^{CMET}}{\sum_{n \notin P} E_{n,t}^{CMET}} \tag{5.1}$$

This strategy does not consider the typology of members when distributing the energy available. However, since host and non-host members are subject to different local tariffs, the resulting economic benefit can still vary by type. This constraint tends to favor members with higher loads, only benefiting host members when they are the large consumers.

## 5.2. Price-Weighted Method

The price-weighted allocation ($\hat{C}_{n,t}^{\lambda prop}$) method introduces price sensitivity into the proportional-to-consumption allocation rule. Members paying higher local energy tariffs are given proportionally more energy. The allocation coefficient becomes equation (5.2).

$$\hat{C}_{n,t}^{\lambda prop} = \frac{\hat{\lambda}_{P,n,t}^{lem} \times E_{n,t}^{CMET}}{\sum_{n \notin P} \hat{\lambda}_{P,n,t}^{lem} \times E_{n,t}^{CMET}} \tag{5.2}$$

Where $\hat{\lambda}_{P,n,t}^{lem}$ is the local energy selling price of the developer to member $n$. In most cases, this method maximizes the developer revenue since more energy is allocated to those paying more per kWh. However, a key limitation is that the method does not guarantee that the locally generated energy will be fully absorbed within the community. In other words, if there is surplus energy not used by any member, it still penalizes members who need energy to supply the remaining consumption because the surplus is redirected to the grid, reducing their engagement incentive.

## 5.3. Price Method

A price allocation ($\hat{C}_{n,t}^{\lambda}$) method divides the available energy between host (H) and non-host (NH) members based on the relative prices they pay for local energy. Rather than allocating energy based on consumption or fixed group proportions, this method weights group-level allocations according to pricing incentives.

At each time step $t$, the allocation weights ($\hat{C}_{n,t}^{\lambda}$) for the NH and H groups are defined as in equation (5.3).

$$\hat{C}_{n,t}^{\lambda} = \left\{ \begin{array}{c} \alpha_{NH,t} = \dfrac{\hat{\lambda}_{P,NH,t}^{lem}}{\hat{\lambda}_{P,NH,t}^{lem} + \hat{\lambda}_{P,H,t}^{lem}} \\ \alpha_{H,t} = \left(1 - \alpha_{NH,t}\right) \end{array} \right\} \tag{5.3}$$

Where $\hat{\lambda}_{P,NH,t}^{lem}$ is the local energy price charged by the developer to non-host members at time $t$ and $\hat{\lambda}_{P,H,t}^{lem}$ is the local energy price for host members. Once the energy is allocated between the NH and H groups using these ratios, the energy is further distributed within each group proportionally to the members' consumption.

This method ensures that groups paying higher prices (usually non-hosts) receive a larger portion of the energy. It thus prioritizes profitability for the developer while maintaining a price-sensitive allocation framework. However, suppose non-host members consume significantly less than hosts. In that case, this method may leave excess energy unallocated or lead to imbalanced cost benefits, an issue mitigated in dynamic strategies like the decision-tree approach (Section 5.4) [1].

## 5.4. Decision Tree Method

The decision-tree allocation ($\hat{C}_{n,t}^{tree,k}$) method is proposed to dynamically select the most beneficial method for the developer, depending on the current energy balance and member demand patterns. Figure 5.1 shows step-by-step.

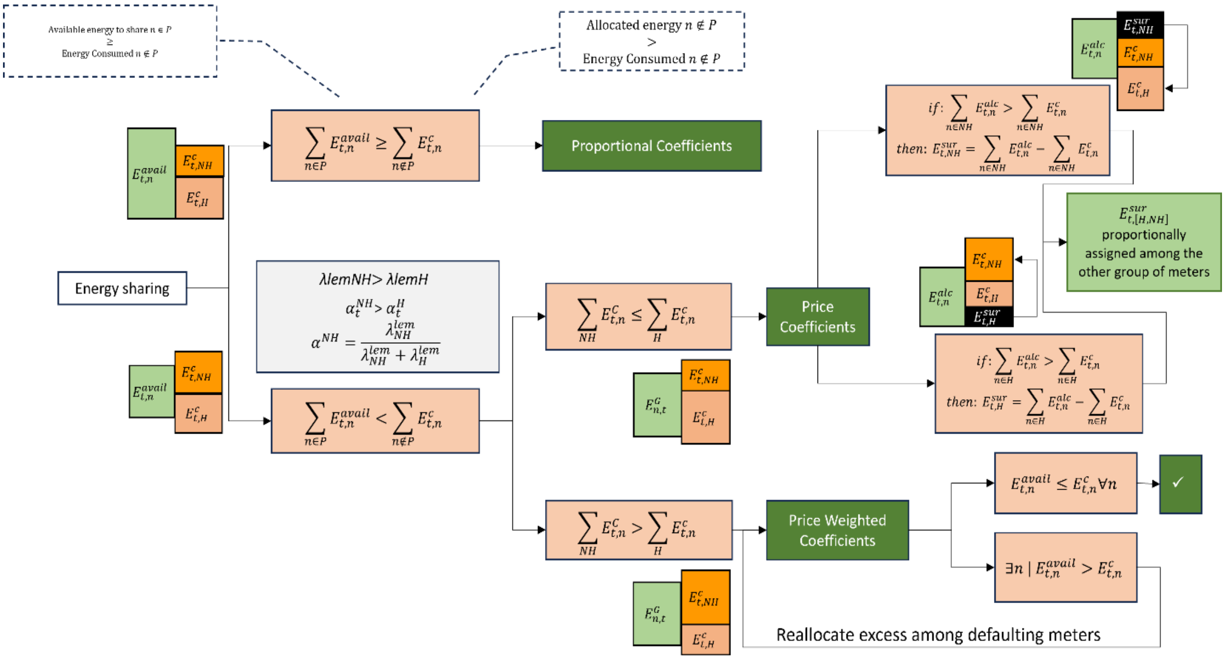


Figure 5.1: Energy allocation algorithm.

The structure works as follows:

- **Step 1**: If local production exceeds total community consumption, use proportional allocation (5.1).
- **Step 2**: If there is a deficit:
    - Compare consumption of hosts vs. non-hosts.
    - If hosts consume more, apply the pricing method (5.3).
    - If non-hosts consume more, apply the price-weighted method (5.2).
- **Step 3**: If any group receives more energy than it can consume, the surplus is redistributed within the other group using proportional logic.

This strategy acts as a hybrid model, combining rules from all prior methods to adaptively select the allocation mechanism that maximizes developer profit and preserves fairness energy share among the members, i.e., the remaining energy available is reallocated to the members who did not have the full energy supply demanded.

## 5.5. Iterative Fixed-Point Algorithm

Several energy allocation strategies, especially those involving dynamic coefficients based on consumption or pricing, introduce recursive dependencies into the EMS optimization problem. In these cases, allocation coefficients used as energy sharing inputs depend on the outcomes of the EMS (such as net consumption and grid exchanges). This creates a circular dependency, which, if embedded directly into the MILP formulation, would lead to a nonlinear and non-convex problem structure.

To address this, a fixed-point iterative algorithm is employed. This approach decouples the allocation logic from the MILP structure, solving the optimization problem in successive stages while updating allocation coefficients at each iteration. Figure 5.2 shows the energy sharing process among meters in an iteration.

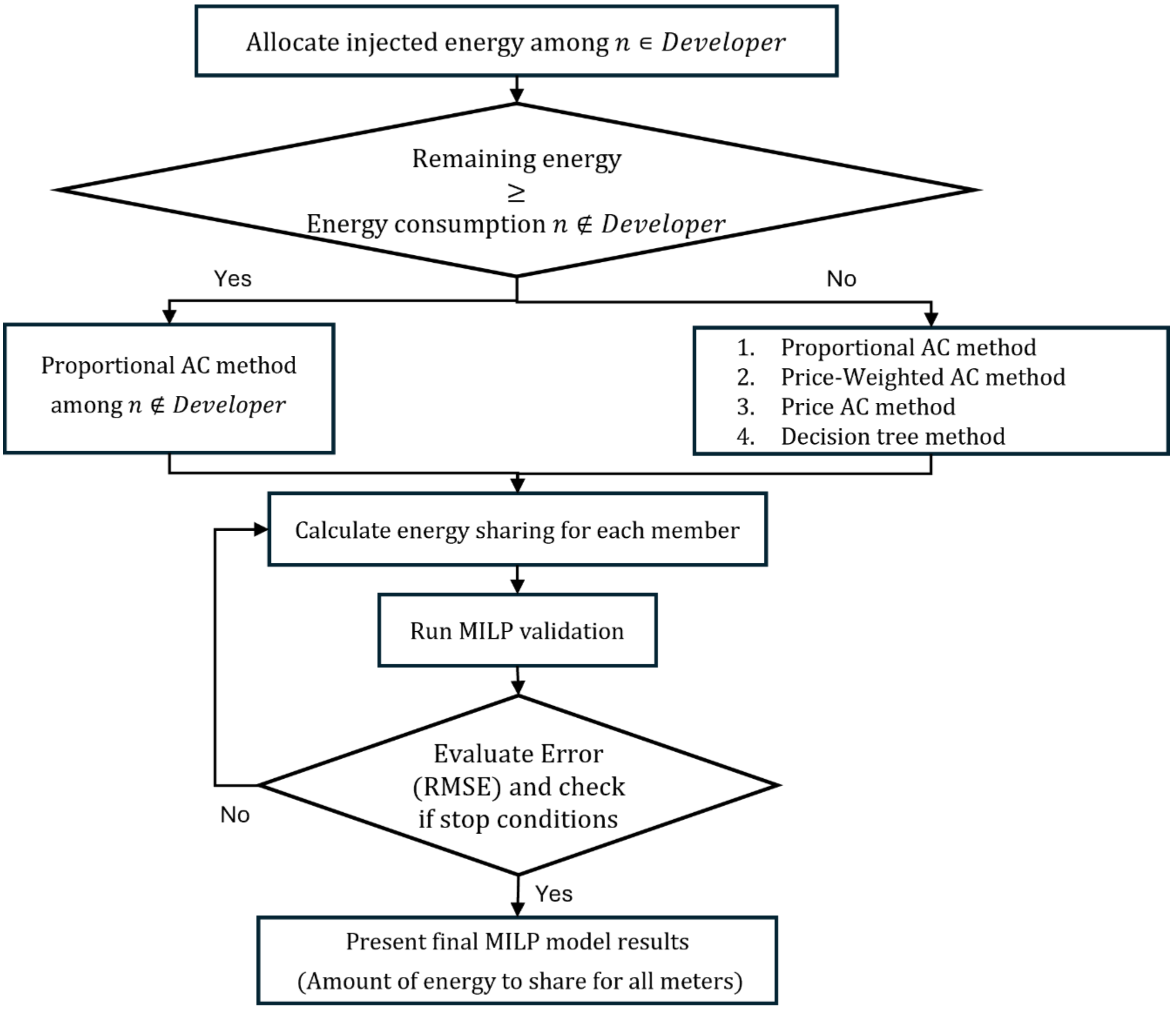


Figure 5.2: Fixed-point algorithm iterative.

The algorithm proceeds as follows:

- **Initialization**: A first set of allocation coefficients $\hat{C}_{n,t}^{,(0)}$ is chosen based on a predefined rule (e.g., proportional to consumption).
- **Optimization**: The MILP model is solved using $\hat{C}_{n,t}^{,k}$ as fixed inputs. The outputs include energy flows, battery schedules, and member-level consumption and costs.
- **Update**: Based on the new results, updated allocation coefficients $\hat{C}_{n,t}^{k+1}$ are calculated using the selected allocation strategy (e.g., price-weighted or decision-tree-based).
- **Convergence Check**: Equation (5.4) is the Root Mean Square Error (RMSE) metric computed to assess the difference between iterations until convergence is achieved.

$$RMSE_k = \sqrt{\sum\nolimits_n \left(\hat{C}_{n,t}^{,k} - \hat{C}_{n,t}^{k-1}\right)^2 + \left(\frac{OF_{n,t}^k - OF_{n,t}^{k-1}}{OF_{n,t}^{k-1}}\right)^2} \tag{5.4}$$

Where $OF_{n,t}^k$ is the objective function of iteration $k$.

- **Repeat**: If $RMSE_k <$ tolerance (around $10^{-3}$), convergence is achieved. Otherwise, step 2 is repeated.

This iterative process enables the model to integrate sophisticated allocation dynamics into a MILP-compatible structure, ensuring both feasibility and optimality.

## 5.6. System Description and Community Configuration

Figure 5.3 shows the energy community (EC) in the simulation that comprises four residential members, configured to reflect realistic heterogeneity in behavior and participation level:

- **MH1 (host member)**: Equipped with a photovoltaic system provided by the developer.
- **MH2 (host member)**: Equipped with a battery system provided by the developer.
- **MNH1 and MNH2 (non-host members)**: Consumers without infrastructure contribution.

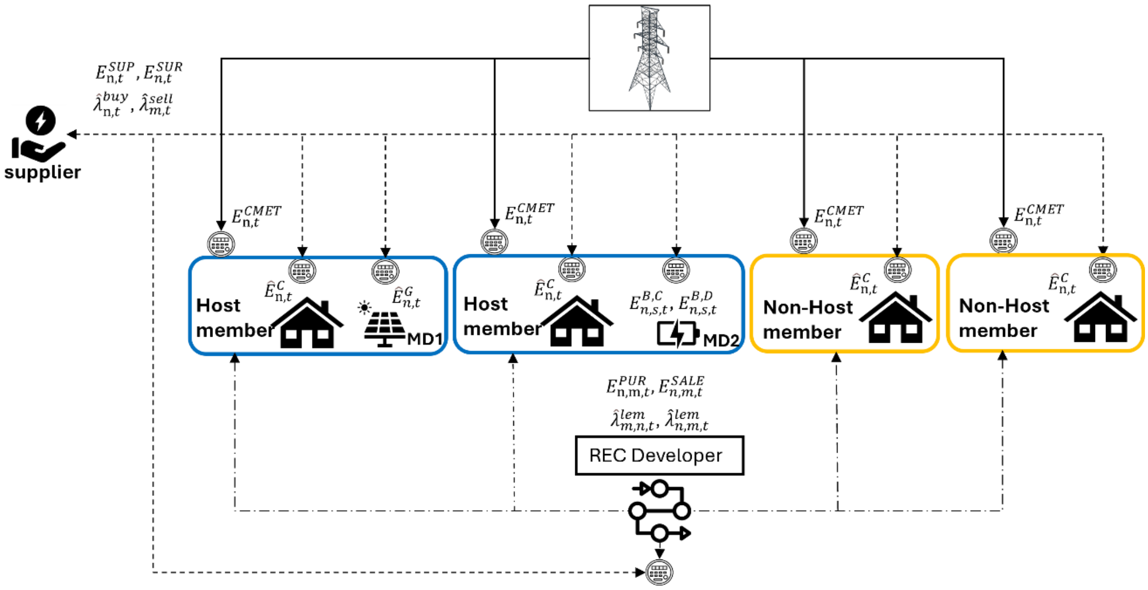


Figure 5.3: Structural Architecture of the REC considering the Developer’s Assets.

The **third-party developer** manages the EMS, DER assets (generation and storage), and all local trading processes. Smart metering infrastructure is assumed to be available, enabling hourly monitoring of generation, consumption, storage operation, and local energy exchanges.

**Key Parameters:**

**Battery size**: $\hat{E}^{B,N}_{n,s}$ with 250 kWh capacity, $\hat{P}^{B,max}_{n,s}$ with 100 kW power, $\hat{\eta}^{B,C}_{n,s}$ and $\hat{\eta}^{B,D}_{n,s}$ with 90% efficiency and $\hat{\lambda}^{deg}_{n,s}$ with 0.0176 €/kWh.

**PV production**: The total energy generation varies by scenario during the day according to Figure 5.5 and Figure 5.6, specified in the dark blue line. It is also assumed that all the energy generated is used.

**Tariffs**: Figure 5.4 shows the price values vary hourly reflecting retail and local trading conditions, encouraging economically rational behavior for both developers and members.

- Retail buy price ($\hat{\lambda}^{buy}_{n,t}$): 0.077-0.165 €/kWh (hourly)
- Retail sell price ($\hat{\lambda}^{sell}_{n,t}$): 0.035-0.074 €/kWh

- Local energy price for **host members**: 0.056-0.120 €/kWh
- Local energy price for **non-host members**: 0.066-0.142 €/kWh
- Internal sharing tariff ($\hat{\lambda}_{n,t}^{grid}$): 0.008-0.017 €/kWh.

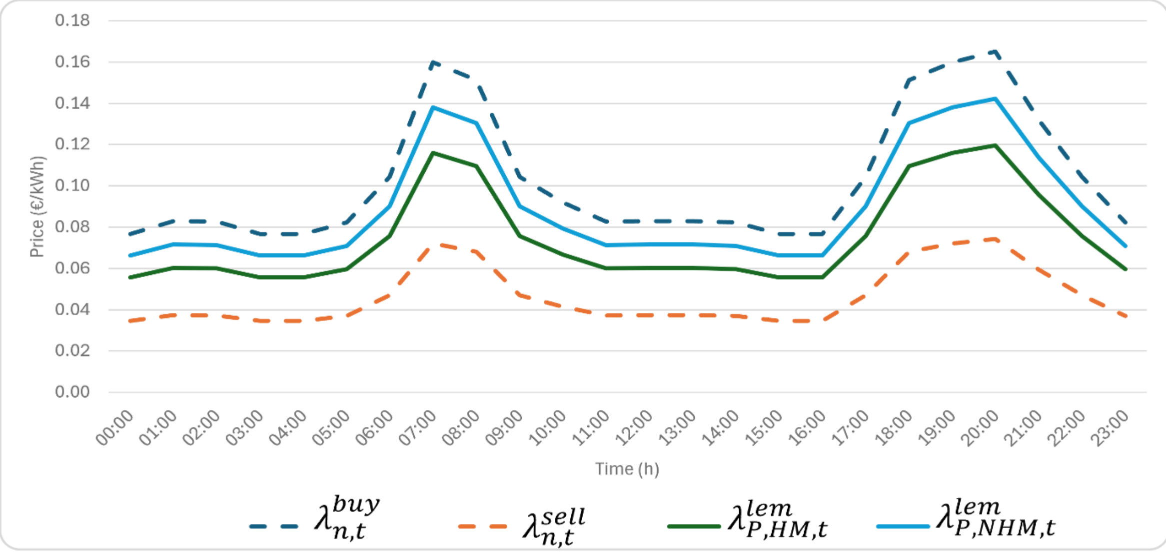


Figure 5.4: Price values estimate during the day.

### 5.6.1. Scenario - Energy Deficit

In this scenario, two cases are analyzed in subsections 5.6.1.1 and 5.6.1.2 considering the distribution of energy consumption within of the community. In both cases, PV panels in insufficient to meet the total demand of the community.

#### 5.6.1.1. Subcase 1

For this subcase, condition (5.5)(5.5) indicates that the total energy consumption of non-host members is lower than the host-members. As shown in Figure 5.5, PV generation reaches its peak at 12 p.m., producing 22 kWh. However, community consumption follows different profiles: non-host members exhibit a relatively constant demand between 5 and 10 kWh while host members present higher consumption energy from 10 a.m. to 8 p.m. This mismatch confirms that PV generation alone is insufficient to meet the demand of all community members.

$$\sum_{n \in NH} E_{n,t}^{C} < \sum_{n \in H} E_{n,t}^{C} \tag{5.5}$$

Under these conditions, it becomes necessary to rely on battery storage or external grid purchases during periods when there is insufficient generation to meet the total demand.

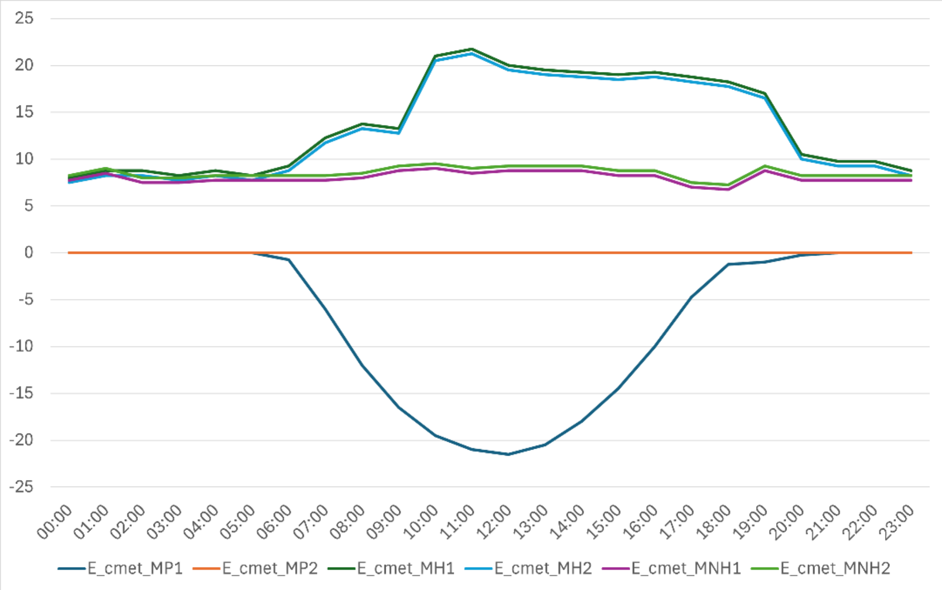


Figure 5.5: CPEs initial liquid consumption for subcase 1.

#### 5.6.1.2. Subcase 2

Similar to Subcase 1, Subcase 2 considers the situation shown by condition (5.6), in which the consumption of non-host members exceeds that of host members. Figure 5.6 is also comparable to Figure 5.5 and reflects this change by illustrating a higher consumption for non-host members relative to host members.

$$\sum_{n \in NH} E_{n,t}^{C} > \sum_{n \in H} E_{n,t}^{C} \tag{5.6}$$

All the allocation methods are also tested to observe whether they favor hosts due to higher demand or penalize them due to the tariffs.

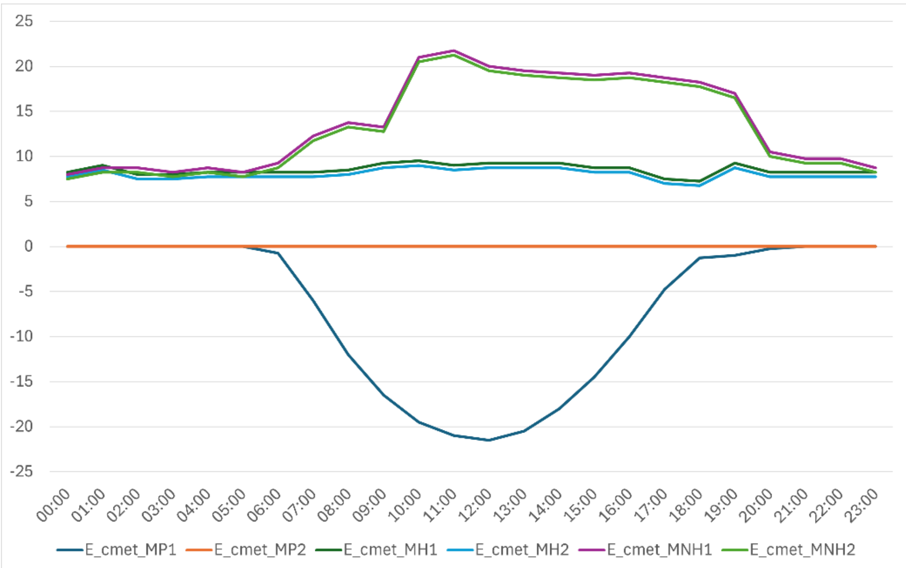


Figure 5.6: CPEs initial liquid consumption for subcase 2.

### 5.6.2. Comparative Analysis of Allocation Strategies

Table 5.1 shows that this scenario has different types of allocation test strategies. Due to the interdependence between energy allocation coefficients and the dispatch of flexible resources, the problem requires the use of a fixed-point iterative algorithm. Initially, the coefficients are defined based on consumption and generation data. Then, after dispatching the flexible resources, all these data are updated, and the coefficients are recalculated. This iterative process continues until convergence is reached, which typically occurs within 3 to 4 iterations.

Table 5.1: Results of different allocation types.

| Case study | Coeff. | Cost MP$_1$(€) | Cost MP$_2$(€) | Cost EC Developer | Cost MNH$_1$ (€) | Cost MNH$_2$ (€) | Cost MH$_1$(€) | Cost MH$_2$(€) | $\widehat{C}^{ind}_{MNH1}$ | $\widehat{C}^{ind}_{MNH2}$ | $\widehat{C}^{ind}_{MH1}$ | $\widehat{C}^{ind}_{MH2}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | $\widehat{C}^{prop,k}_{n,t}$ | -6.71 | -8.13 | -14.84 | 19.30 | 20.24 | 30.94 | 30.94 | 19.56 | 20.52 | 32.92 | 32.92 |
| $E^{c}_{t,NH}$ | $\widehat{C}^{\lambda prop,k}_{n,t}$ | -6.85 | -7.99 | -14.84 | 19.30 | 20.23 | 31.22 | 31.24 | 19.56 | 20.52 | 32.92 | 32.92 |
| $E^{c}_{t,H}$ | $\widehat{C}^{\lambda}_{n,t}$ | -8.38 | -6.72 | -15.11 | 19.26 | 20.20 | 31.44 | 31.44 | 19.56 | 20.52 | 32.92 | 32.92 |
| | $\widehat{C}^{tree,k}_{n,t}$ | -8.42 | -6.69 | -15.11 | 19.26 | 20.20 | 31.44 | 31.44 | 19.56 | 20.52 | 32.92 | 32.92 |
| 2 | $\widehat{C}^{prop,k}_{n,t}$ | -9.58 | -6.77 | -16.33 | 32.43 | 32.43 | 18.44 | 19.32 | 32.92 | 32.92 | 19.56 | 20.52 |
| $E^{c}_{t,NH}$ | $\widehat{C}^{\lambda prop,k}_{n,t}$ | -9.90 | -6.44 | -16.34 | 32.42 | 32.42 | 18.61 | 19.51 | 32.92 | 32.92 | 19.56 | 20.52 |
| $E^{c}_{t,H}$ | $\widehat{C}^{\lambda}_{n,t}$ | -8.45 | -7.41 | -15.86 | 32.51 | 32.51 | 18.43 | 19.31 | 32.92 | 32.92 | 19.56 | 20.52 |
| | $\widehat{C}^{tree,k}_{n,t}$ | -9.62 | -6.75 | -16.38 | 32.42 | 32.42 | 18.51 | 19.40 | 32.92 | 32.92 | 19.56 | 20.52 |

According to Table 5.1, it shows that this scenario has different types of allocation test strategies. Due to the interdependence between energy allocation coefficients and the dispatch of flexible resources, the problem requires the use of a fixed-point iterative algorithm. Initially, the coefficients are defined based on consumption and generation data. Then, after dispatching the flexible resources, all these data are updated, and the coefficients are recalculated. This iterative process continues until convergence is reached, which typically occurs within 3 to 4 iterations.

Also, Table 5.1 ensures that:

The **proportional allocation** method ensures straightforward energy distribution based on consumption, but results in higher costs for the non-host member. While more responsive to energy cost signals, **the price** and **price-weighted methods** often resulted in marginal imbalances in the treatment of host and non-host members, particularly when the developer's assets dominated the energy flows.

The **decision-tree strategy** demonstrated consistently better performance. By applying rule-based logic that dynamically accounted for member type (host/non-host), energy availability, and historical consumption behavior, this approach was delivered:

- **Greater cost savings** for the members.
- Improved satisfaction with individual benefit guarantees.
- **Sustained better profitability** for the developer.

Finally, the decision-tree allocation strategy will be adopted as the default mechanism in the following case studies. Its flexibility, fairness, and performance make it the most suitable approach for the better operation of energy communities managed by developers.

# Chapter 6

# Heuristic Approximation to a Bilevel Model for Energy Sharing in RECs

This chapter introduces a heuristic bilevel optimization approach designed to address the limitations identified in the initial multi-objective EMS formulation. In earlier implementations, the EMS prioritized the developer's profit to such an extent that community members experienced little to no economic improvement compared to their operation outside the community when centralized assets such as stationary batteries, members' behaviors and incentives were not accurately reflected, resulting in unfair benefit distribution.

A heuristic approximation to a bilevel model was developed to explicitly incorporate individual member constraints into the optimization process to overcome this issue. The proposed approach suits global system optimization with individual cost guarantees, ensuring that no participant incurs higher costs while being part of the community when the developer installs assets.

## 6.1. Case Study using Multi-Objective Function

To evaluate the practical implications of energy sharing strategies in RECs, Figure 6.1 and Figure 6.2 presents a case study involving a simplified community composed of host and non-host members. The aim is to assess whether a traditional centralized multi-objective optimization model can maximize the developer profits. Optimization is carried out using a multi-objective function that prioritizes the developer benefit. The key parameters are the same as mentioned in Section 5.6.

Figure 6.1 demonstrates the community considering only the developer's photovoltaic panel in the host member and an EV in the non-host member. In this scenario, the developer owns and coordinates the energy flow of photovoltaic generation.

The left section of the diagram (outlined in blue) includes the host members—community participants who agree to host DER infrastructure such as PV systems and batteries on their premises. The right section (outlined in yellow) represents the non-host members with one electrical vehicle, who do not provide physical space for any developer assets but still participate in the community by consuming energy generated and managed by the developer.

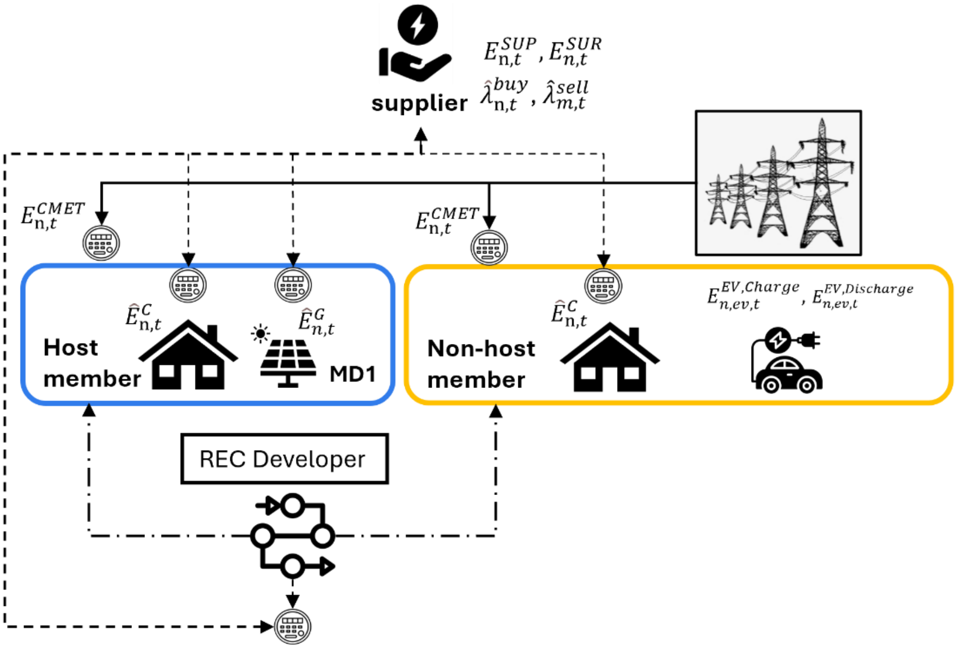


Figure 6.1: Structural Architecture of the REC not considering the Developer’s Battery.

Table 6.1 shows the individual cost was higher before members joined the community. Joining the community benefited the members and helped the developer by allowing their assets to be installed. The non-host member received a smaller benefit because it did not own the developer's assets as expected.

Table 6.1: Results not considering the Developer's Battery.

| Case study | OF | Cost $MP_1$(€) | Cost EC Developer | Cost MH (€) | Cost MNH(€) | $\hat{C}^{ind}_{MP_1}$ | $\hat{C}^{ind}_{MH}$ | $\hat{C}^{ind}_{MNH}$ |
|---|---|---|---|---|---|---|---|---|
| **Without Promoter Battery** | -12.64 | -12.64 | -12.64 | 18.40 | 21.57 | -7.13 | 19.56 | 21.79 |

Figure 6.2 demonstrates the community considering photovoltaic generation, and the developer includes a battery in the host member, while there is still an EV in the non-host member:

- **MH1 (host member)**: Equipped with the developer’s photovoltaic system and battery.
- **MNH1 (non-host members)**: Consumers with EV.

The **Key Parameters** and **Tariffs** are the same as the case study in Figure 5.3.

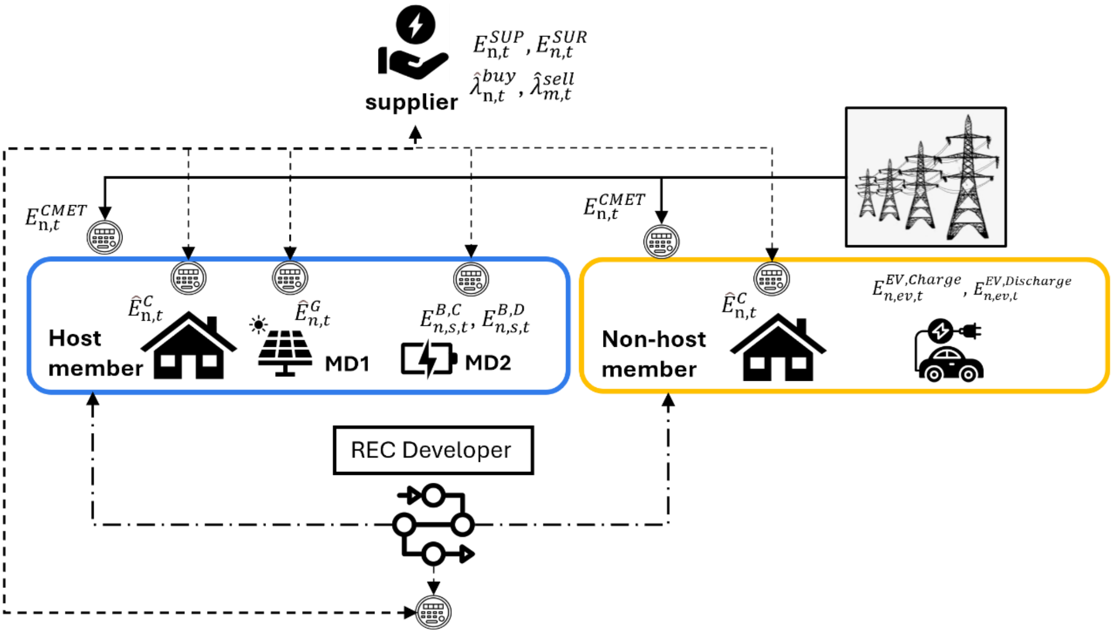


Figure 6.2: Structural Architecture of the REC considering the Developer's Battery.

Table 6.2 shows that, despite the objective function being better, after the insertion of the developer battery, the individual cost of the non-host member increased compared to when there was no developer battery in the case of Figure 6.1. In contrast, before the insertion, it was more beneficial.

Table 6.2: Results considering the Developer's Battery.

| Case study | OF | Cost MP$_1$(€) | Cost MP$_2$(€) | Cost EC Developer | Cost MH (€) | Cost MNH(€) | $\hat{C}^{ind}_{MP_1}$ | $\hat{C}^{ind}_{MP_2}$ | $\hat{C}^{ind}_{MH}$ | $\hat{C}^{ind}_{MNH}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **With Promoter Battery** | -14.10 | -9.40 | -4.70 | -14.10 | 18.26 | 21.79 | -7.13 | 0.0 | 19.56 | 21.79 |

However, this case study demonstrates in Table 6.2 that the model fails to reduce the cost of the non-host member after installing the developer battery in the host member. This motivates the need for a heuristic approach to the bilevel formulation, introduced in the Section 6.3, which addresses these limitations by explicitly embedding member-level constraints into the optimization process.

## 6.2. Bilevel Optimization and Heuristic Strategies

Bilevel optimization has gained significant attention in recent decades due to its ability to model hierarchical decision-making systems involving two interacting agents with conflicting objectives. This structure is especially relevant in RECs, where developers and community members make decisions at different levels. The theoretical basis and solution strategies for bilevel problems are well documented in the literature.

**Bilevel Optimization: Structure and Applications**

According to ([20],[21]), a bilevel programming problem consists of two nested optimization problems: the upper-level (leader) problem and the lower-level (follower) problem. The leader makes decisions first, anticipating the follower's rational reaction, which is modeled as an optimization problem parameterized by the leader's decision variables.

This hierarchical structure is formally expressed as:

- Bilevel programming has been applied across various domains such as:
- Transportation systems: toll optimization and congestion management.
- Environmental planning: hazardous material routing and sustainability policies.
- Energy markets: tariff design, generation planning, and subsidy allocation.
- Principal-agent models in economics and engineering systems.

However, solving bilevel programs is inherently tricky. Even simple linear bilevel problems are NP-hard, and non-convex or mixed-integer variants introduce significant computational challenges.

**Relevance to Energy Sharing in RECs**

The complexity of modeling fair and efficient energy sharing in RECs—with multiple DERs, varying member preferences, and a profit-seeking developer—makes using heuristic and bilevel formulations particularly suitable. Traditional MILP approaches may either fail to capture the individual incentives of members or over-optimize developer benefit at the expense of fairness. Metaheuristics and bilevel approximations enable the modeling of these multi-agent systems in a tractable and behaviorally realistic manner.

## 6.3. Integration of the Heuristic Approach to the Bilevel Model in the Iterative Process

The model considered in this work must simultaneously account for two layers of decision-making: the economic optimization performed by the developer and the need to guarantee that community members (excluding the developer) do not incur higher costs compared to operating independently. This level structure naturally leads to a **bilevel model optimization**.

However, solving such models is computationally intractable for large-scale MILP problems due to their nested nature and non-convexity. To address this, Figure 6.3 shows a **heuristic approximation of the bilevel structure** employed within a **fixed-point iterative framework**.

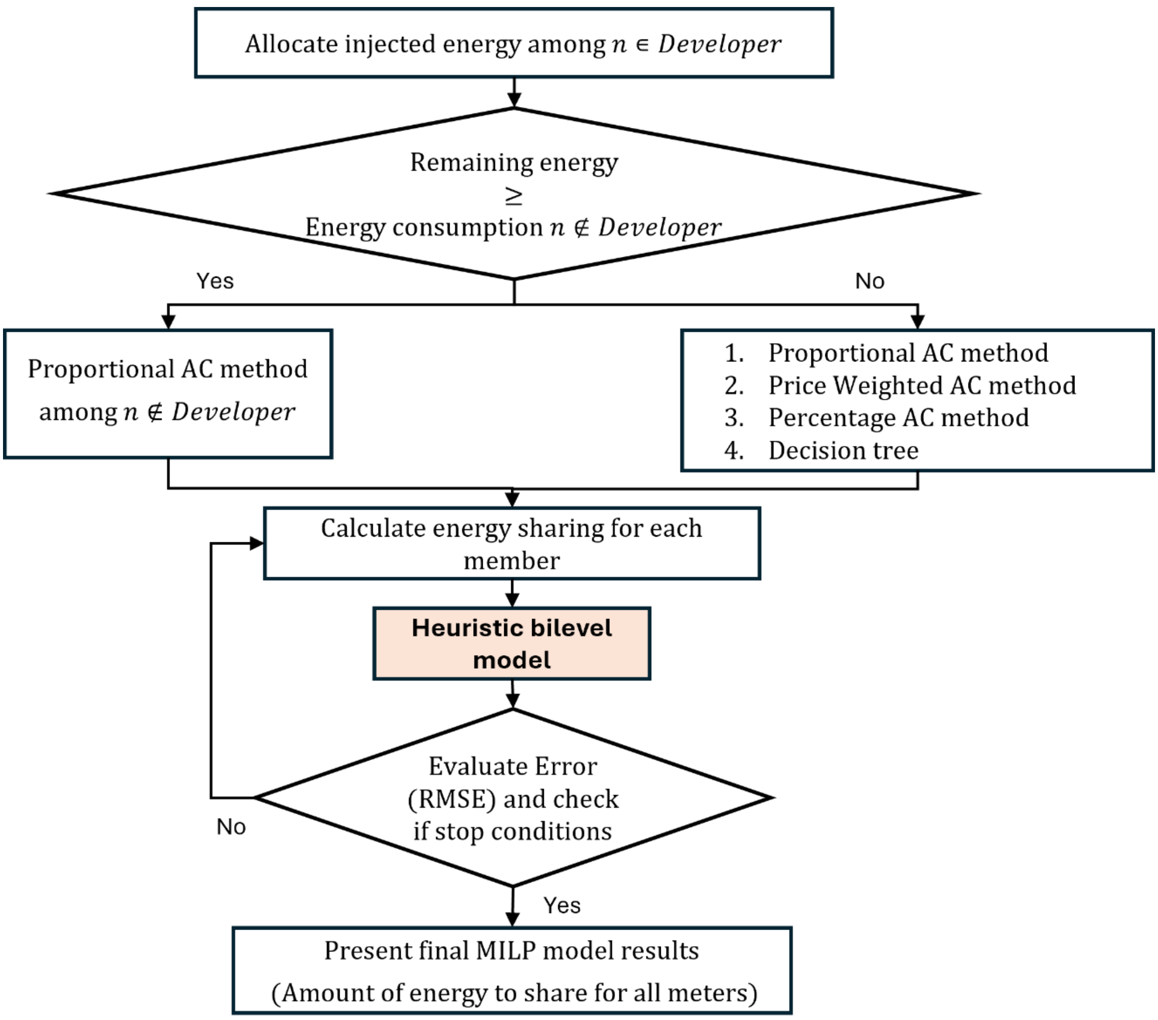


Figure 6.3: Fixed point iterative algorithm with heuristic approach to the bilevel model.

**Step 1 - Coefficient Initialization**

Like Figure 5.2, in the first iteration, the EMS computes the initial allocation coefficients (e.g., proportional, price-weighted, or decision tree-based) that determine how members' locally generated energy is distributed.

**Step 2 - Developer-Centered Optimization with Fairness Constraint**

A new constraint (6.1) is proposed that iteratively operates during the MILP resolution process. This constraint progressively tightens the bound from the right-hand side by gradually decreasing the value of individual cost ($\hat{C}_n^{ind}$) in small steps (e.g., 0.01). The process continues until the solution becomes infeasible, and at this point, the algorithm retains the last feasible value immediately preceding infeasibility.

$$\sum_{n\in N}\sum_{t\in T}\left(\begin{array}{c} E^{SUP}_{n,t}\hat{\lambda}^{buy}_{n,t} - E^{SUR}_{n,t}\hat{\lambda}^{sell}_{n,t} + \sum_{s\in S_n} E^{B,D}_{n,s,t}\cdot\hat{\lambda}^{deg}_{n,s} + \\ \sum_{ev\in EV_n}\left(E^{EV,Discharge}_{n,ev,t}\cdot\hat{\lambda}^{deg}_{n,ev} + \hat{\mu}\cdot E^{defEV}_{n,ev,t}\right) \\ \sum_{m\neq n\in N}\left(E^{PUR}_{n,m,t}\cdot\lambda^{lem}_{m,n,t} - E^{SALE}_{n,m,t}\cdot\lambda^{lem}_{m,n,t} + E^{SLC}_{n,m,t}\cdot\hat{\lambda}^{grid}_{n,m,t}\right)\end{array}\right) \le \sum_{n\in N}\hat{C}^{ind}_n\cdot(1-j\cdot 0.01) \qquad (6.1)$$

Figure 6.4 presents the workflow of **the heuristic approach to the bilevel model**, showing how the MILP problem is solved with this incremental constraint to ensure that no member incurs higher costs than in individual operation.

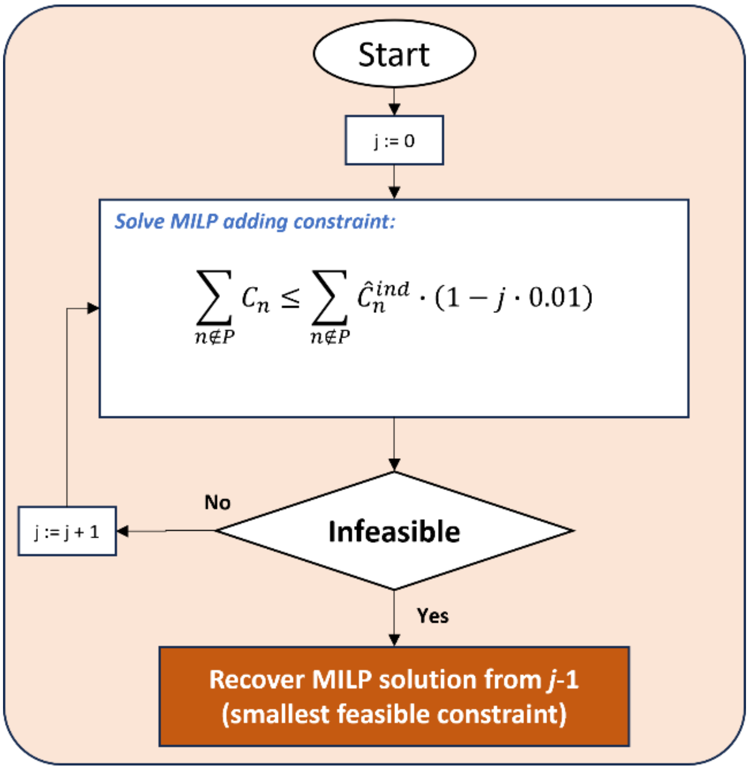


Figure 6.4: Heuristic approach to the bilevel model.

**Step 3 - Feasibility Recovery and Best Solution Storage**

As the constraint tightens, the EMS monitors feasibility. When infeasibility is detected, the algorithm restores the last feasible solution (i.e., corresponding to $j-1$) from memory. This solution represents the best trade-off between developer profitability and member cost fairness for that iteration.

**Step 4 - Convergence Check and Iteration**

Once the best feasible solution is recovered, the EMS compares the current allocation with the previous iteration using a convergence metric (e.g., RMSE error of allocation vectors). If the stopping criteria are not satisfied (e.g., RMSE above threshold), the algorithm enters a new outer iteration:

- Allocation coefficients are recalculated based on the updated solution.

- The bilevel heuristic (Steps 2–3) is executed again using the new coefficients.

This iterative loop continues until convergence is achieved.

## 6.4. Validating Bilevel Model of Study Case 6.2

To evaluate the effectiveness of the proposed **bilevel heuristic approximation**, the study case presented in Section 6.2 is reviewed. The objective is to compare the economic outcomes for the community developer and the members when operating under the multi-objective problem versus the improved bilevel approach.

Table 6.3 presents the outcomes of **the heuristic approach to the bilevel model**, alongside the results of the multi-objective problem corresponding to the community illustrated in Figure 6.2. The bilevel model achieves better cost savings by more accurately capturing the behavior of community members. Moreover, the developer realizes a positive financial return, indicating that equity and profitability are not mutually exclusive within this coordinated framework.

Table 6.3: Cost comparison between Multi-Objective Function and Heuristic Bilevel Approach for Study Case of Figure 6.2.

| Case study | OF | Cost $MP_1$(€) | Cost $MP_2$(€) | Cost EC Developer | Cost MH (€) | Cost MNH(€) | $\widehat{C}^{ind}_{MP_1}$ | $\widehat{C}^{ind}_{MP_2}$ | $\widehat{C}^{ind}_{MH}$ | $\widehat{C}^{ind}_{MNH}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Multi-Objective** | -14.10 | -9.40 | -4.70 | -14.10 | 18.26 | 21.79 | -7.13 | 0.0 | 19.56 | 21.79 |
| **Heuristic Bilevel Approach** | -8.31 | -11.81 | 3.50 | -8.31 | 16.50 | 21.14 | -7.13 | 0.0 | 19.56 | 21.79 |

Finally, the results validate that implementing the developer assets in host members achieves a better performance for all the members. This confirms the advantage of embedding bilevel logic into the iterative optimization framework proposed in Section 6.3.

## 6.5. Scenario including Host Battery

Figure 6.5 illustrates the structural configuration of the proposed REC, similar to that shown in Figure 6.2, but with the addition of a battery owned by the host member. This architecture allows for analyzing battery behavior when the host owns it. The key parameters remain unchanged, and the host member's battery has the exact specifications as the developer's battery.

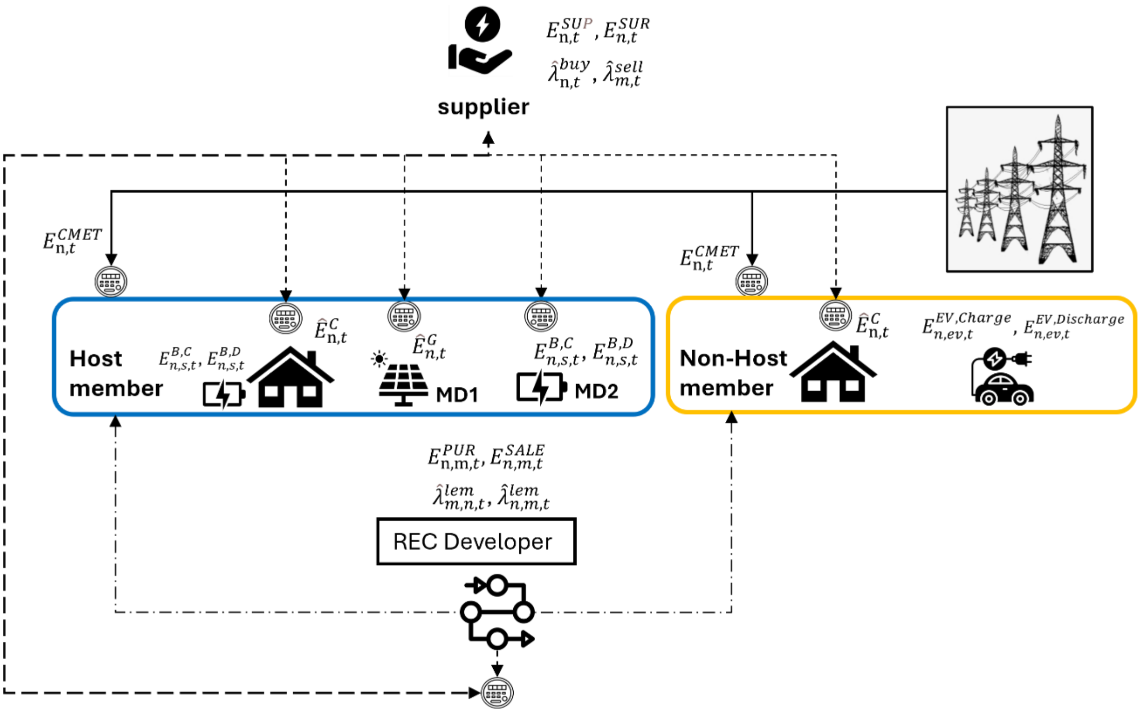


Figure 6.5: Structural Architecture of the REC considering the Developer's and Host's batteries.

Table 6.4 compares the case study with a multi-objective function and a heuristic bilevel approach. Despite the decrease in the objective function, it is valid to affirm that the members' costs before implementing the heuristic approach to the bilevel model are lower.

Table 6.4: Cost comparison between Multi-Objective Function and Heuristic Bilevel Approach for Study Case of Figure 6.5.

| Case study | OF | Cost $MP_1$(€) | Cost $MP_2$(€) | Cost EC Developer | Cost MH (€) | Cost MNH(€) | $\hat{C}^{ind}_{MP_1}$ | $\hat{C}^{ind}_{MP_2}$ | $\hat{C}^{ind}_{MH}$ | $\hat{C}^{ind}_{MNH}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| **Multi-Objective** | -14.29 | -11.22 | -2.19 | -13.41 | 16.88 | 21.79 | -7.13 | 0.0 | 17.65 | 21.79 |
| **Heuristic Bilevel Approach** | -9.49 | -12.51 | 3.02 | -9.49 | 15.90 | 21.17 | -7.13 | 0.0 | 17.65 | 21.79 |

This case is designed to analyze the behavior of an individually owned battery and to assess whether the bi-level heuristic approach effectively manages such a resource compared to the multi-objective model. Based on Table 6.4, although the overall objective function slightly decreases, the individual costs for the members are lower after implementing the bi-level heuristic model compared to the multi-objective approach. Therefore, this approximation strategy not only continues to maximize the developer's benefit but also demonstrates strong performance in managing the individual interests of each member.

# Chapter 7

# Conclusions and Future Work

This chapter summarizes the main contributions of this dissertation and outlines potential directions for future research. It reviewed the proposed business model and energy management framework for renewable energy communities operated by third-party developers, highlighting the design and implementation of a heuristic bilevel optimization strategy to ensure profitability and fairness. In addition, this chapter identifies key areas for further development, including scaling to more complex community scenarios, integrating real-time pricing and uncertainty, and testing the model in real-world environments to validate its practical applicability.

## 7.1. Conclusions

This dissertation proposed a comprehensive business model and optimization framework for Renewable Energy Communities (RECs) managed by third-party developers. The model accounts for differentiated member roles—**host** and **non-host**—while incorporating dynamic pricing structures and coordinated management of Distributed Energy Resources (DERs), including photovoltaic panels, battery storage systems, and electric vehicles.

The key contributions of this work are as follows:

- **Development of an Energy Management System (EMS)** based on a multi-objective optimization function that simultaneously maximizes the developer's profit and ensures that no community member incurs higher costs than they would in an individual consumption scenario.
- **Promoting fairness in energy allocation** by integrating mechanisms that guarantee equitable distribution of community-generated resources among members with different roles.
- **Implementing and evaluating multiple energy allocation strategies**, notably a dynamic decision-tree method capable of adapting to varying system states to optimize performance and equity.

- **Application of a fixed-point iterative algorithm** to solve the underlying optimization problem with interdependent variables, enabling convergence and computational efficiency.
- **Identifying of limitations in the centralized multi-objective approach**, particularly when introducing DERs like batteries or EVs. It was observed that member behavior was not adequately represented in these scenarios. To address this, a **heuristic bilevel model** was integrated into the EMS, allowing for a more accurate behavioral representation and effective cost minimization at the community sharing contract (CSC) level.

## 7.2. Future Work

Building on the findings and developments of this dissertation, several avenues for future research and practical implementation are proposed:

- **Development of an integrated energy solution for B2B energy communities**, focusing on service-sector and industrial customers. This solution would encompass the full cycle of REC management—operation, optimization, and maintenance—and involve the creation of an intelligent digital platform capable of optimizing energy flows and costs. The platform would account for heterogeneous consumption and generation profiles, storage systems, and interaction with the public grid, offering **flexible, scalable, and replicable** architecture for broader deployment.
- **Extension of the simulation horizon** to multi-day or multi-week periods, allowing for the incorporation of temporal variability in both energy demand and renewable generation. This would improve the robustness of the EMS under realistic operating conditions and support more comprehensive planning strategies.
- **Scaling of the model to larger communities**, including adding more members and exploring **clustering strategies** or **decentralized EMS architectures**. These approaches may enhance local autonomy while maintaining coordination through hierarchical or distributed optimization frameworks.
- **Integration of real-time pricing mechanisms and uncertainty modeling**, using forecast-based control or stochastic optimization techniques. This would enable the EMS to better respond to market volatility and operational risks.
- **Exploration of regulatory and contractual frameworks**, particularly those involving **asset ownership transfer**, **tariff design**, and **benefit-sharing mechanisms**. These aspects are critical for ensuring the long-term viability and fairness of REC business models.
- **Implementation of a pilot project**, applying the proposed model to a real-world community using actual consumption and production data. This would allow for empirical validation of the model and provide insights into **user behavior, engagement levels**, and practical constraints in deployment.

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