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Optimizing Energy Sharing in Community-Based Virtual Power Plants: A Mixed-Integer Linear Programming Approach for External EV Integration

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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Abstract

The growing penetration of Distributed Energy Resources (DER) such as Photovoltaic (PV), Battery Energy Storage System (BESS), Electric Vehicles (EV) is intensifying local energy exchanges within community settings. While these exchanges can reduce energy costs and grid dependence, existing community frameworks are limited to the management of internal resources neglecting opportunities such as the supply of energy to external users (outside the community). This dissertation proposes a Mixed-Integer Linear Programming (MILP) framework integrating external EVs into a Community-based Virtual Power Plant (cVPP) while preserving internal participants priority and ensuring regulatory consistency. The model optimizes batteries operation, and EV charging and discharging under real market prices. Two model variants are developed, the first only considers internal participants, used to evaluate self-sufficiency and energy costs. The second extends the framework to include external EVs through a State of Charge (SoC) rule, allowing external participants charging from the community when all connected internal EVs exceed a defined SoC threshold. Within this extended model, a pricing mechanism is tested for external participants (when charging from the community without executing vehicle-to-cVPP) and a sensitivity analyses explores the impact of PV availability and price conditions on SoC threshold performance. A simulation with twelve internal participants and four external EVs under real prices validates the approach. External EVs reduce the average internal energy cost from €0.0293/kWh to €0.0278/kWh, while keeping exports during externals charging at 9.13 kWh and maintaining fairness. Overall, the framework provides a transparent and scalable foundation for day-ahead community scheduling with external EV participation.

Keywords

Energy community; Optimization; Community-based Virtual Power Plant; Distributed Energy Resources; Mixed-Integer Linear Programming; External Electric Vehicles

Resumo

O aumento da penetração dos Recursos Energéticos Distribuídos (RED), como sistemas fotovoltaicos (FV), baterias e veículos elétricos (VE), tem intensificado as trocas locais de energia em contextos comunitários. Embora estas trocas reduzam custos energéticos e a dependência da rede, os modelos existentes incluem apenas participantes internos, excluindo externos. Esta dissertação propõe um modelo de Programação Linear Inteira-Mista (PLIM) que integra VEs externos num Centro Virtual de Potência Comunitária (cVPC), preservando a prioridade dos participantes internos e assegurando coerência regulamentar. O modelo otimiza a operação das baterias e o carregamento e descarregamento dos VEs sob preços reais de mercado. Foram desenvolvidas duas variantes, a primeira considera apenas participantes internos, avaliando auto-suficiência e custos energéticos, a segunda inclui VEs externos através de uma regra de limiar do Estado de Carregamento (EdC), permitindo carregamento externo a partir da comunidade apenas quando todos os VEs internos ultrapassam determinado nível de EdC. Nesta segunda variante é testado um mecanismo de preços para participantes externos (quando carregam da comunidade sem descarregar para a cVPC) e realizadas análises de sensibilidade para avaliar o impacto da energia FV e das condições de preço no desempenho do limiar. Uma simulação de 24 horas com 12 participantes internos e 4 VEs externos sob preços reais valida a abordagem. A introdução de VEs externos reduz o custo médio interno de €0.0293/kWh para €0.0278/kWh, limitando exportações a 9.13 kWh e mantendo a equidade. O modelo estabelece uma base transparente e escalável para o planeamento diário de comunidades energéticas com participação externa.

Palavras Chave

Comunidades de Energia; Otimização; Central Virtual de Potência Comunitária; Recursos Energéticos Distribuídos; Programação Linear Inteira Mista; Veículos Elétricos Externos

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Nomenclature

Sets and Indices

$\mathcal{E} \subset \mathcal{N}$ Set of external participants (index i).

$\mathcal{I} \subset \mathcal{N}$ Set of internal participants (index i).

$\mathcal{N}$ Set of community participants/prosumers (index i).

$\mathcal{T}$ Set of time periods (index t).

Parameters and Constants

α Penalty factor applied to SoC relaxation [€/kWh].

Δt period-step duration [h].

δ_i Overload factor applied to the contracted power limit to participant i

$E_i^{EV,\text{arrive}}$ Initial energy level at arrival [kWh].

$E_i^{EV,\text{departure}}$ Required final energy level at departure [kWh].

$\bar{E}_i^{EV}$ Maximum energy capacity of EV battery [kWh].

$\underline{E}_i^{EV}$ Minimum energy capacity of EV battery [kWh].

η Battery discharging efficiency for EV's battery

λ_t^{ext} External purchasing price from community at period t [€/kWh].

λ_t^{buy} Retail buying price at period t [€/kWh].

λ_t^{sell} Purchasing price at period t [€/kWh].

M Big-M constant used for logical linearization.

$\bar{P}_i^{EV}$ Maximum EV charging/discharging power [kW].

$\underline{P}_i^{EV}$ Minimum EV charging/discharging power [kW].

$\bar{P}_i^{\text{EC}}$ Maximum community exchange power for participant i [kW].

$\bar{P}_i^{\text{contracted}}$ Contracted grid power for participant i [kW].

$\bar{P}_i^{\text{grid}}$ Maximum grid exchange power for participant i [kW].

x Internal EV SoC threshold () defining external participation.

γ Battery degradation cost coefficient [€/kWh].

Continuous Variables

$\beta_i^{relaxation}$ Relaxation variable for minor violations of EV SoC targets [kWh].

$E_{i,t}^{EV}$ Energy of EV battery at participant i at period t [kWh].

$P_{i,t}^{\text{batt,ch}}$ Charging power of the stationary battery at participant i [kW].

$P_{i,t}^{\text{batt,dch}}$ Discharging power of the stationary battery at participant i [kW].

$P_{i,t}^{\text{Demand}}$ Local demand of participant i at period t [kW].

$P_{i,t}^{\text{EC}}$ Net internal community exchange (positive import, negative export) at participant i at period t [kW].

$P_{i,t}^{EV,\text{ch}}$ Charging power of EV at participant i at period t [kW].

$P_{i,t}^{EV,\text{dch}}$ Discharging power of EV at participant i at period t [kW].

$P_{i,t}^{\text{grid}}$ Net grid exchange (positive when importing, negative when exporting) at participant i at period t [kW].

$P_{i,t}^{\text{buy grid}}$ Energy imported from the grid at participant i at period t [kW].

$P_{i,t}^{\text{sell grid}}$ Energy exported to the grid at participant i at period t [kW].

$P_{i,t}^{PV}$ Photovoltaic generation of participant i at period t [kW].

$SOC_{i,t}$ State of charge of EV at participant i at period t [%].

Binary Variables

$u_{i,t}^{\text{buy-grid}}$ Binary variable related to grid imports/exports at participant i at period t.

$u_{i,t}^{\text{buy-EC}}$ Binary variable related to imports/exports within the community at participant i at period t.

$u_{i,t}^{\text{ch}}$ Binary variable related to EV charging status at participant i at time t.

$u_{i,t}^{\text{dch}}$ Binary variable related to EV discharging status at participant i at time t.

$z_{i,t}$ 1 if internal EV i has reached SoC $\geq x\%$ at period t, 0 otherwise.

$u_{\text{ext},t}$ 1 if external EVs are allowed to charge from the community at period t, 0 otherwise.

$u_t^{\text{Ext-EV}}$ Alias for $u_{\text{ext},t}$ (same role).

Derived Quantities and Metrics

E_{int}^{used} Total surplus energy utilized by internal EVs [kWh].

E_{ext}^{used} Total surplus energy utilized by external EVs [kWh].

E_{excess}^{sold} Energy sold to the grid during external-charging periods [kWh].

$\tilde{E}_{int}^{used}, \tilde{E}_{ext}^{used}, \tilde{E}_{excess}^{sold}$ Normalized versions of the above (dimensionless).

Score Composite score used to select the optimal threshold x (dimensionless).

Acronyms

BESS	Battery Energy Storage System
cVPP	community-based Virtual Power Plant
DE	Differential Evolution
DER	Distributed Energy Resources
DSO	Distribution System Operator
EMS	Energy Management System
EU	European Union
EV	Electric Vehicle
GA	Genetic Algorithm
ICT	Information and Communication Technology
MILP	Mixed-Integer Linear Programming
P2P	Peer-to-Peer
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Sources
SoC	State of Charge
TSO	Transmission System Operator
VPP	Virtual Power Plant
V2G	Vehicle-to-Grid

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Introduction

Contents

1.1 Motivation

In the last decades, Renewable Energy Sources (RES) have taken a crucial role in the energy sector's development. Particularly in self-consumption, there was a significant increase in the investment of RES in European Union (EU) households over the 15-year period [2]. This valuable development towards the EU target of becoming carbon-neutral by 2050 comes with a challenge: the need for energy systems to be more flexible, efficient, and decentralized.

One promising solution is the emergence of energy communities, which enable collective self consumption, energy sharing, and local trading of surplus energy within a community [3]. These communities empower individuals, households, municipalities and businesses to actively participate in the energy transition while optimizing the use of local RES and reducing dependency on centralized grids. By fostering collaboration and resource sharing, energy communities contribute to grid stability, energy equity, and carbon emission reduction.

The EU's Clean Energy Package recognizes the role of energy communities as key players in achieving its sustainability goals [4]. It promotes frameworks for collective energy management and localized energy markets. However, realizing the potential of energy communities requires addressing several challenges, including designing cost-effective trading mechanisms, ensuring fair allocation of benefits, and managing the interplay between community-level activities and broader market structures.

Within the framework of energy communities, different approaches have emerged, including Peer-to-Peer (P2P) energy communities and community-based Virtual Power Plant (cVPP). While P2P markets focus on direct energy transactions between participants, promoting autonomy and flexibility, Virtual Power Plants (VPPs) aggregate Distributed Energy Resources (DER) to operate as a single entity in the energy market [5]. In this context, community-based energy markets offer a structured approach to enable energy trading and sharing within a defined group, such as a neighborhood or a cooperative. Unlike fully decentralized P2P markets as in [6], community-based markets operate under coordinated governance [7], often mediated by a community manager or aggregator. Both structures share the goals of decentralization, sustainability, and efficient resource utilization, offering complementary strategies to address modern energy challenges.

While significant progress has been made in the development of community-based energy markets, as in [5, 8], existing models are often limited to internal trading among community members. This insular approach may constrain the market's flexibility and its ability to adapt to dynamic energy demands and supplies. In particular, the integration of public charging stations enabling the energy exchange with external peers, such as Electric Vehicle (EV) users outside the community, remains largely unexplored. Allowing these external participants to engage in community activities could enhance market efficiency and provide additional revenue streams for the community.

1.2 Objectives and Contributions

The primary objective of this dissertation is to develop an optimization model for energy communities that includes the participation of external EVs in an energy sharing mechanism. The proposed methodology focuses on minimizing energy costs for community members while maintaining operational fairness, technical feasibility, and sustainable energy use. By integrating external EVs into the energy trading framework, the model seeks to enhance the flexibility and efficiency of cVPP.

To address these goals, the dissertation aims to answer the following research questions:

- How can external EVs be integrated into energy communities without compromising the interests of internal members?
- What constraints are necessary to manage energy flows, grid interactions, and EV operations effectively?
- How can surplus energy utilization be optimized to balance internal priorities and external participation?
- What impact does the inclusion of external EVs have on community-wide energy costs and resource utilization?
- What impact does the implementation of Vehicle-to-Grid (V2G) have when including this in the external EVs participation

The contributions of this work are evaluated using various scenarios, demonstrating the effectiveness of the proposed optimization model in addressing the identified challenges. The main contributions are divided into general contributions and original contributions. General contributions are:

- Development of a base optimization model for cVPPs, focusing on minimizing energy costs while adhering to energy balance and operational constraints.
- Implementation of constraints for energy trading, grid interactions, and EV energy management to ensure technical feasibility and fairness.

Original Contributions are:

- Extension of the optimization model to include external EVs, introducing mechanisms to prioritize internal members while allowing external participation under controlled conditions.
- Design of an iterative adjustment process for surplus energy utilization, dynamically optimizing the participation threshold for external EVs.

- Integration of advanced constraints for EV operations, including State of Charge (SoC) limits, charging rates, and energy flow consistency, ensuring the reliability of EV batteries and community infrastructure.

- Sensitivity analysis to explore the model's adaptability across different scenarios, such as varying numbers of internal and external EVs and diverse energy surplus levels.

- Evaluation of revenue-sharing mechanisms to promote fairness and financial sustainability within energy communities.

This dissertation contributes to advancing the operational and economic efficiency of energy communities by proposing a scalable and flexible model that supports the inclusion of external entities while ensuring sustainability and equity for all participants.

1.3 Thesis Outline

This chapter provides an overview of the document structure, outlining the content and focus of each chapter to guide the reader through the research process and findings.

The report begins with the Introduction, where the research context and motivation are established. This chapter discusses the challenges faced by energy communities, particularly regarding the integration of external EVs, and highlights the potential benefits of addressing these challenges. It also presents the objectives and contributions of the thesis, offering a roadmap for the document structure.

Following this, the State of the Art, Chapter 2, reviews the existing literature and practices related to energy communities and cVPPs. It delves into different energy market structures, such as P2P and community-based models, and examines optimization techniques applied in these contexts. This chapter serves to position the proposed work within the broader research landscape.

Chapter 3 describes the optimization model developed in this thesis. It introduces the base model for minimizing energy costs within energy communities and extends it to incorporate external EVs. The chapter provides a detailed explanation of the objective functions, constraints, and iterative approaches employed to balance resource allocation and prioritize internal participants.

Chapter 4 presents a community-based virtual power plant as the case study. The chapter begins with an overview of the data (community layout, Photovoltaic (PV)/load profiles, pricing and market conditions, and EV/Battery Energy Storage System (BESS) parameters), results for internal participants' operation, and then introduces the Optimal Threshold Method for management of access of external EVs to the community. The impact of the method on dispatch, market trades, charging feasibility, and costs is evaluated, as well as a final robustness sensitivity analysis under different generation profiles and price

scenarios. Outputs are compared with the model based only on internal participants to test economic performance, fairness, and feasibility.

Finally, Chapter 5 summarizes most important findings and proposes future research to be done in further studies.

1.4 Related Projects

This thesis was developed, and is part of, the following research project:

- Horizon Europe EV4EU – Electric Vehicles Management for carbon neutrality in Europe project, funded by the European Union under grant agreement no. 101056765. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or CINEA. Neither the European Union nor the grating authority can be held responsible for them.
- AHEAD - AI-Informed Holistic EVs Integration Approaches for Distribution Grids funded by the European Union under grant agreement no. 101160665.
- ATE- Aliança para a Transição Energética: Project no 56, financed by European Funds, namely "Recovery and Resilience Plan - Component 5: Agendas Mobilizadoras para a Inovação Empresarial", included in the NextGenerationEU funding program.

2

Overview of Energy Communities Governance

Contents

Energy communities have emerged as pivotal players in the energy transition, enabling decentralized energy production, consumption, and trading. These communities allow individuals, households, and businesses to actively exchange energy among them [7, 9] while promoting sustainability and reducing dependency on the main grid. Through collective ownership or shared governance, energy communities foster local engagement and empower members to benefit from renewable energy resources. The European Union's Directive 2019/944 [4] defines *"energy communities as legal entities established to deliver environmental, economic, or social benefits rather than financial profits"*. These communities engage in activities such as renewable energy generation, distribution, storage, and the provision of EV charging infrastructure. By participating in these activities, energy communities play a critical role in advancing sustainability and accelerating the transition to a low-carbon energy system. Such activities are fundamental to the wide concept of VPP. This section provide an overview of the two main types of governance of ECs namelly the cVPPs and the P2Ps market

2.1 Community-Based Virtual Power Plants

Community-based VPPs represent a specific form of energy community that aggregates DER such as solar panels, batteries, and EV to act as an unified participant in the energy market. This integration enables community-based VPP to combine RES and storage systems effectively, providing flexibility and stability within the grid while supporting local energy needs [9]. Community-based VPP prioritize the interests of their members, the primary aim of a citizens energy community is to achieve a balance between maximizing community-wide profits and promoting environmental sustainability, economic growth, or social improvements for its members or the local areas it serves [10]. This model aligns with the structured governance of community-based markets, where a central manager coordinates operations to balance flexibility and efficiency.

Virtual Power Plants improve the functionality of energy communities by:

- Optimizing the use of local renewable resources.
- Enabling dynamic energy trading with external markets.
- Providing grid services such as frequency regulation and demand response [5].
- Promoting local energy independence.

Virtual Power Plants commonly adopt three internal control structures: centralized, distributed, and hybrid (also called comprehensive). These approaches determine how DERs are coordinated and affect system efficiency, scalability, and resilience [1].

2.1.1 Centralized control

A single control center aggregates information and issues dispatch signals to all DERs. The global view enables system-level optimization (costs/revenues, self-consumption, grid services), but requires robust communications and is vulnerable to single points of failure. Advantages include coordinated operation and consistent execution; limitations include IT and infrastructure costs, communication dependence, and reduced autonomy for resource owners [1].

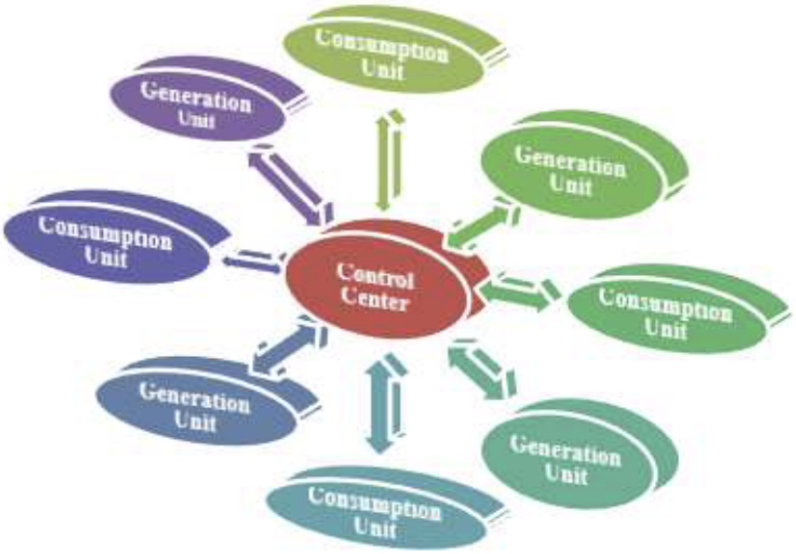

Figure 2.1: Centralized Control from [1]

2.1.2 Distributed control

Control is partitioned across subsystems (for example, by microgrids or asset owners), with local decisions based on partial information and coordination protocols [11]. This increases autonomy and reduces central computational burden, but may yield globally suboptimal outcomes without effective consensus or market mechanisms. It also raises interoperability and cybersecurity requirements for information exchange.

2.1.3 Hybrid (comprehensive) control

A hierarchical architecture combines centralized layers (global objectives and system constraints) with local decision layers (fast response and agent preferences) [12]. This suits larger and heterogeneous VPPs by balancing coordination and flexibility, at the cost of higher orchestration complexity (models, algorithms, communications) and stronger technical governance needs.

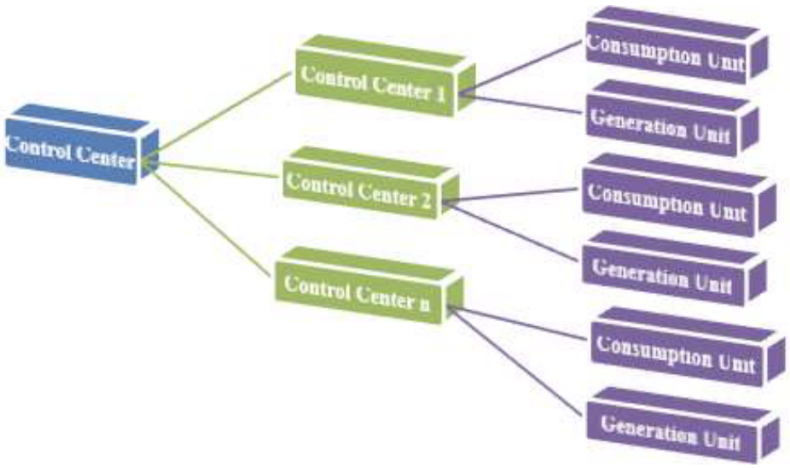

Figure 2.2: Distributed Control from [1]

2.2 Real-world cVPP pilots (EU)

Evidence from European pilots shows that cVPPs are not merely conceptual. The Interreg NWE cVPP project documented three implementations with distinct contexts and governance models: Loenen (Netherlands), Ghent (Belgium), and Tipperary/Community Power (Ireland) [10]. In Loenen, a citizen-led cooperative aggregates rooftop PV, a neighbourhood battery, and flexible loads (e.g., heat pumps and EV charging), coordinating them through a central platform while retaining local Energy Management System (EMS) functions; the emphasis is on local self-sufficiency and reinvestment of benefits. In Ghent, the EnerGent cooperative operates a portfolio of homes with PV and behind-the-meter batteries under a hybrid control arrangement, explicitly linking technical coordination with social goals, including participation of low-income households. In Tipperary, Community Power evolved from a community-owned wind project into a licensed supplier coordinating a geographically distributed portfolio (wind, hydro, planned PV), using a centralised commercial/technical wrapper to interact with wholesale markets and national regulations. Across the three pilots, the cVPP idea is operationalised through Information and Communication Technology (ICT)-enabled aggregation, community governance, and market participation, but is shaped by licensing, Distribution System Operator (DSO)/Transmission System Operator (TSO) rules, and data-access constraints. This empirical evidence grounds the cVPP concept and highlights a technical gap in the quantitative literature: few works formalise day-ahead or intraday Mixed-Integer Linear Programming (MILP) scheduling with explicit internal-priority and fairness rules governing access by external actors (e.g., non-resident EVs) while preserving community objectives [10].

2.3 Optimization Methods in cVPP

In community-based VPPs, optimization typically seeks to minimize total operating cost or maximize community welfare by co-optimizing imports, exports, and internal allocation of DERs. Objective functions often include energy purchases/sales and, in more recent formulations, degradation-related terms for batteries (stationary or onboard EVs) to reflect long-term sustainability of storage assets [13,14]. Feasibility is enforced through constraints for power balance, device limits, and market rules, including prohibition of simultaneous buying and selling at the prosumer level and local market restrictions [15]. Storage and EV participation are bounded by SoC, charge/discharge rates, and availability windows [16–18].

2.3.1 MILP for residential cVPPs: representative model and general patterns

In [19] is presented a MILP framework for a residential renewable energy community that co-optimizes technology investment and operation under realistic tariffs and market signals (including feed-in remuneration). The model is solved on a full-year horizon (8760 hours), capturing seasonal and intraday variability while remaining tractable.

Scope and data - The case study is an Austrian community with nine heterogeneous participants (single-family homes, apartments, and small local entities), distributed rooftop PV and a community battery. Several electricity tariff scenarios are tested (with and without demand rates), PV surplus can be sold to the utility, and internal renewable energy transfer within the community is enabled.

Formulation - The MILP minimizes total annual community energy cost, subject to linear constraints for hourly power balance, storage SoC dynamics and bounds, charge/discharge rate limits, and import/-export limits. Market rules prohibit simultaneous buying and selling at the participant level and clear internal sharing under applicable tariffs; time-varying carbon factors quantify emissions associated with imports.

Results - The annual schedule increases PV self-consumption, reduces grid dependence, and improves both cost and CO_2 outcomes; reported figures include roughly 15% cost reduction and about 34% CO_2 reduction versus a non-coordinated reference, with benefits for all participants.

General patterns in the literature - Community-focused MILP studies commonly: (i) use day-ahead or intraday horizons (15–60 min) or annual horizons with aggregation; (ii) co-optimize imports/exports, internal sharing, BESS operation, and EV charging under availability windows; (iii) enforce linear device and market rules (no simultaneous buy/sell, SoC and rate limits, interconnection caps); (iv) include linear proxies for battery degradation and, in some cases, carbon factors; and (v) retain a linear core that is extendable to uncertainty layers and multi-objective trade-offs [13–18,20,21].

2.3.2 Stochastic and robust extensions on top of MILP

Uncertainty in solar generation, prices, and EV availability motivates stochastic or robust layers built over a MILP core. Two-stage or multi-stage stochastic MILP captures recourse after day-ahead commitments, while distributionally robust formulations hedge against forecast errors without relying on precise probability laws. These approaches preserve the interpretability of MILP while improving reliability of community operations under variability, at the expense of higher model size and solution time [17, 20]. Hybrid market-facing designs also appear, where bidding/imbalance management and intraday re-dispatch are co-optimized with storage flexibility in MILP frameworks [22].

2.3.3 Heuristics and metaheuristics at larger scales

Heuristic and metaheuristic methods (e.g., Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE)) are used when problem size, nonlinearity, or detailed device models challenge exact optimization. They can efficiently explore large search spaces and are flexible with nonconvexities, but they do not guarantee global optimality and may require tuning [23]. In VPP contexts, PSO and related techniques have been applied to day-ahead scheduling and bidding of large portfolios, trading some optimality guarantees for scalability and modeling freedom [24]. For residential community problems with linearizable physics and explicit market rules, MILP remains a common baseline due to transparency, reproducibility, and strong optimality certificates [20, 21].

2.3.4 Multi-objective formulations

Beyond single-cost objectives, cVPP studies increasingly consider simultaneous criteria such as operating cost, peak reduction, reliability, and emissions. These are typically handled via weighted-sum or ε-constraint MILP variants, enabling explicit trade-off analysis without departing from linear structures [20, 25].

2.4 Energy communities' market structures

In comparison to cVPP, there are also decentralized energy markets, known as P2P markets. While in cVPP consumers and prosumers lack the autonomy to choose what they are going to sell or buy, in these decentralized models, "peers" have the freedom to make those choices. Below, two different approaches to decentralized models are presented as well as their advantages and disadvantages together with cVPP in 2.1.

Full P2P market

The full P2P market design aims to meet the energy demand of neighborhood buildings by leveraging RES distributed across multiple locations [26]. However, what sets this market design apart is its decentralized nature.

In this model, there is no central regulatory entity. Instead, it operates through bilateral agreements between consumers, producers, and prosumers. Participants can freely express their preferences, choosing whom to buy energy from - whether different peers or the external grid - without centralized price supervision [7]. This design offers significant autonomy and flexibility for all participants, empowering them to customize their energy transactions based on personal preferences and needs.

P2P Community-based market

A P2P community-based market is a type of consumer-centric electricity market in which a community manager manages trading activities within a community of peers and acts as an intermediary between the community and the rest of the power system [7]. This market design allows a group of prosumers to collaborate in terms of their energy consumption, production, and storage.

Market structures comparison

The table 2.1 summarizes the key characteristics of Full P2P markets, P2P community-based markets, and community-based VPPs.

Energy communities have become fundamental actors in the ongoing energy transition, enabling citizens and local entities to participate actively in energy generation, management, and exchange. Among the various governance and market models, the cVPP and P2P markets represent two main approaches that reflect different degrees of centralization, autonomy, and coordination.

Community-based VPPs illustrate a structured and collective model, where DER such as PV systems, batteries, and EVs are aggregated and managed under a unified framework. This configuration enhances grid stability, optimizes renewable energy utilization, and promotes local self-sufficiency. Optimization techniques, especially MILP, play a crucial role in achieving cost-efficient and sustainable operations, ensuring fair allocation and flexibility within the community. Real-world implementations in Europe (e.g., Loenen, Ghent, and Tipperary) have demonstrated the feasibility of this approach, combining social objectives with advanced digital coordination.

Market Structure	Advantages	Disadvantages
Full P2P	- Increased consumer empowerment and autonomy. - Higher flexibility in energy trading. - Facilitates integration of distributed renewable energy. - Encourages local energy use, reducing grid dependence.	- Higher complexity in market design and coordination. - Regulatory challenges due to decentralized transactions. - Requires advanced infrastructure (smart meters, real-time systems).
P2P Community-Based	- Simplifies market coordination through a central manager. - Supports collective goals such as social equity and local sustainability. - Encourages shared infrastructure investments. - Easier alignment with local regulations.	- Limited autonomy for individual participants compared with full P2P markets. - Risk of unequal cost or benefit distribution.
Community-Based VPP	- Aggregates DER to operate as a single entity in the energy market. - Aims to maximize community-wide welfare (e.g., cost minimization). - Enhances grid services, such as ancillary services. - Optimizes renewable integration and local independence. - Prioritization and fairness rules are enforceable.	- Prosumers have limited autonomy to choose how or to whom to sell surplus. - Requires governance for benefit sharing. - Risk of over-cycling storage if poorly designed.

Table 2.1: Comparison of market structures for Full P2P, P2P community-based, and community-based VPPs.

On the other hand, P2P market models embody a decentralized and consumer-driven paradigm, where peers autonomously negotiate and trade energy, often facilitated by blockchain or smart contract technologies. Full P2P markets maximize individual freedom but face regulatory and coordination challenges, whereas P2P community-based structures balance autonomy with collective management through a community operator.

In summary, both models contribute valuable perspectives to the evolution of energy communities:

- **cVPPs** emphasize coordinated operation, grid services, and shared benefits.
- **P2P markets** promote consumer empowerment, flexibility, and innovation in local energy trading.

The choice between these governance models depends on community objectives, regulatory context, and technological readiness. Together, they demonstrate how decentralized energy ecosystems can strengthen sustainability, resilience, and citizen participation in the low-carbon energy transition.

3

cVPP Optimal Scheduling Methods

Contents

This chapter aims to present the methodology used in this work, beginning with the introduction of the base optimization model. The base model focuses on managing energy communities and their EVs, optimizing energy costs while adhering to operational constraints. Building upon this foundation, an extended model is introduced to explore the inclusion of external EVs users in the cVPP. The chapter details the challenges posed by this integration, such as prioritizing internal members while utilizing surplus energy effectively. To address these challenges, an iterative adjustment process is proposed, refining the model until an optimal solution is achieved. This iterative approach ensures a balance between the efficient use of resources and the equitable participation of external users, all while maintaining the feasibility and functionality of the system.

3.1 Energy Community Model

This section presents the base optimization model used to integrate external EV users into energy communities. The model minimizes the energy costs of participants while adhering to operational constraints that ensure the system's feasibility and functionality. The representation of the energy community simulation can be observed in 3.1

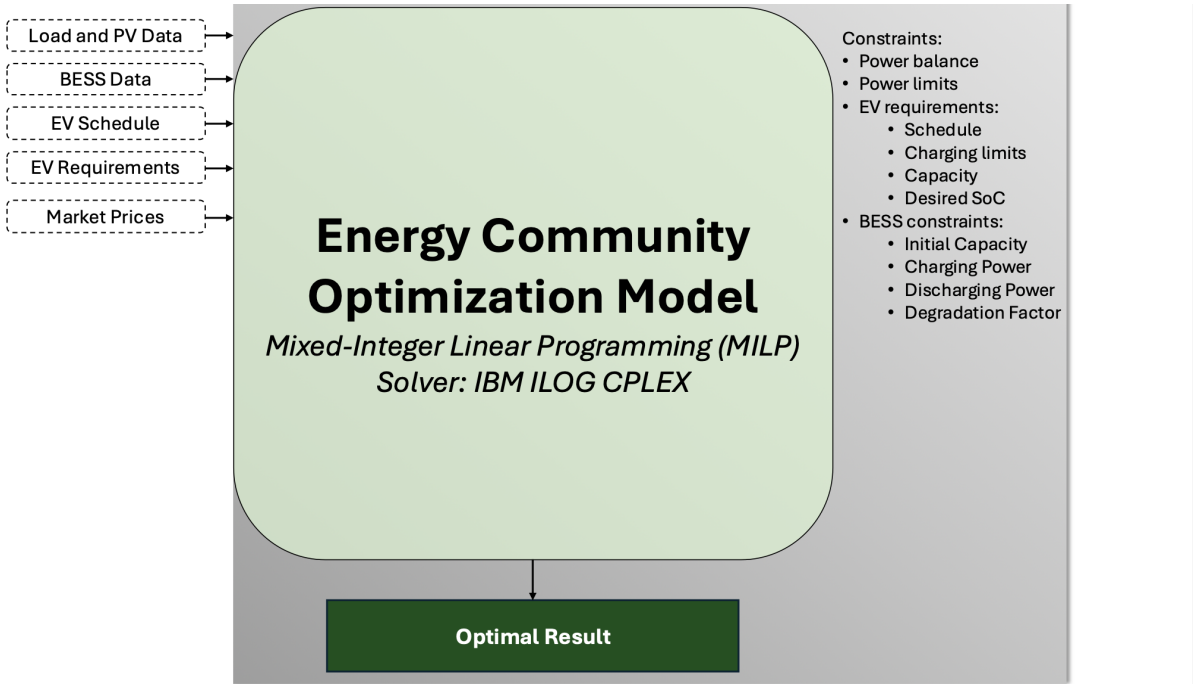

Figure 3.1: Optimization Model

3.1.1 Objective Function

The objective of the function, represented by Equation 3.28, aims to minimize the total cost of energy for all participants $\mathcal{I}$ over a specified time horizon $\mathcal{T}$. The cost includes two main components: the energy purchased from the retailer and the energy sold back to it. Each participant is subject to specific buying and selling prices, indicated by $\lambda_{i,t}^{\text{buy-grid}}$ and $\lambda_{i,t}^{\text{sell-grid}}$, respectively, meaning that each one can have contract with a different retailers. Beyond these tariffed grid transactions, the objective also incorporates two additional terms: (i) a slack α and (ii) a battery degradation estimation. The parameter α [€/kWh] multiplies the slack variable $\beta_i^{relaxation} \geq 0$, which is a relaxation variable introduced to relax EV-related constraints (e.g., required final SoC), in order to have a feasible solution in case of charging infeasibilities. Assigning a high value to penalty ensures that such violations are only used as a last resort. The coefficient γ [€/kWh] represents the cost of BESS degradation per unit of discharged energy, approximating the simulation to the reality. This parameter is applied to the discharging power variable $P_{i,t}^{\text{batt,dch}}$, which denotes the discharging power of the stationary battery of participant i at time t. Finally, it is important to note that only grid transactions are monetized in the objective function, meaning that energy trades within the community do not have an associated cost for participants. This follows the Portuguese regulatory framework (Decreto-Lei n.º 162/2019, de 25 de outubro), under which community members share energy internally but are not allowed to execute priced buy/sell trades inside the community. As such, internal exchanges appear only in the constraints (e.g., balance and clearing), while costs and revenues arise exclusively from imports and exports with the retailer. The sharing coefficients due to internal transactions are defined in the settlement process that is not part of this dissertation

This community-based model was inspired in models [8], [27].

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left[\lambda_t^{\text{buy}} \cdot P_{i,t}^{\text{buy grid}} - \lambda_t^{\text{sell}} \cdot P_{i,t}^{\text{sell grid}} \right] \\ & + \alpha \cdot \sum_{i \in \mathcal{I}} \beta_i^{relaxation} \\ & + \gamma \cdot \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} P_{i,t}^{\text{batt,dch}} \end{aligned} \tag{3.1}$$

This approach aligns with the goals of cost-efficiency in cVPP. Furthermore, it balances economic incentives with environmental considerations, as participants are encouraged to maximize their use of RES. In the objective function $\mathcal{I}$, stands for the group of prosumers within the community and $\mathcal{T}$ is the group of time steps in a day.

3.1.2 Constraints

The optimization model incorporates several constraints to ensure technical feasibility and operational fairness. Each constraint addresses a specific aspect of the energy-sharing mechanisms and is de-

tailed below. These constraints will also be applied to external participants, as it will be presented in 3.2, consequently the set used to represent participants is $\mathcal{N}$, representing both internal and external participants.

Grid exchange constraint

For simplicity in the constraint set, a single signed variable $P_{i,t}^{\text{grid}}$ is used to represent the power exchange with the external grid, while the objective function is formulated in terms of the split variables $P_{i,t}^{\text{buy-grid}}$ and $P_{i,t}^{\text{sell-grid}}$. The binary variable $u_{i,t}^{\text{buy-grid}} \in \{0,1\}$ indicates the direction of exchange. The following constraint establishes the mapping:

$$P_{i,t}^{\text{grid}} = u_{i,t}^{\text{buy-grid}}\, P_{i,t}^{\text{buy-grid}} - \left(1 - u_{i,t}^{\text{buy-grid}}\right) P_{i,t}^{\text{sell-grid}}, \qquad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T}. \tag{3.2}$$

This constraint ensures the correct sign convention for the net grid exchange. When participant i is purchasing energy from the grid at time t, the binary variable $u_{i,t}^{\text{buy-grid}}$ is equal to 1. In this case, $P_{i,t}^{\text{grid}}$ is determined exclusively by $P_{i,t}^{\text{buy-grid}}$, while $P_{i,t}^{\text{sell-grid}}$ is multiplied by zero and therefore inactive, resulting in a positive grid exchange. On the other hand, when the participant is selling energy to the grid, $u_{i,t}^{\text{buy-grid}}$ is equal to 0, so that $1 - u_{i,t}^{\text{buy-grid}}$ activates $P_{i,t}^{\text{sell-grid}}$. In this situation, $P_{i,t}^{\text{grid}}$ becomes negative, reflecting the export of power to the external grid.

Peer Power Balance Constraint

The power balance constraint enforces that, at each time step t, the energy inflows and outflows of every participant $i \in \mathcal{N}$ are equal, similar to the Kirchoff law of currents. This ensures that no energy is unaccounted for and reflects the principle of conservation of energy within the community. On the left-hand side of Equation 3.3, the terms represent the local demans and available generation: $P_{i,t}^{PV}$ is the photovoltaic generation of participant i at time t, $P_{i,t}^{EV,\text{ch}}$ and $P_{i,t}^{EV,\text{dch}}$ denote the charging and discharging power of the electric vehicle battery, and $P_{i,t}^{\text{batt,ch}}$ and $P_{i,t}^{\text{batt,dch}}$ are the charging and discharging power of the stationary battery. The household demand for each participant is represented by $P_{i,t}^{Demand}$.

On the right-hand side, the terms represent energy exchanges: $P_{i,t}^{EC}$ corresponds to the power exchanged internally within the community (positive if consumed, negative if shared), while $P_{i,t}^{\text{grid}}$ denotes the power exchanged with the external grid, defined as positive for purchases and negative for sales.

$$P_{i,t}^{PV} - P_{i,t}^{EV,\text{ch}} + P_{i,t}^{EV,\text{dch}} - P_{i,t}^{\text{batt,ch}} + P_{i,t}^{\text{batt,dch}} - P_{i,t}^{Demand} = P_{i,t}^{EC} + P_{i,t}^{\text{grid}}, \qquad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.3}$$

This formulation ensures that at each time step t, the sum of local generation and storage decisions covers both local consumption and the net exchanges with the community and the main grid.

Community Power Balance Constraint

The community power balance constraint enforces that, at every time step t, the internal trades of energy are balanced. Since the community operates as a closed system, the total amount of energy shared by some participants must be equal to the total amount of energy consumed by others. Equation 3.4 expresses this condition by requiring the sum of all internal exchanges $P_{i,t}^{\text{EC}}$ over the set of participants $\mathcal{N}$ to be equal to zero.

$$\sum_{i \in \mathcal{N}} P_{i,t}^{\text{EC}} = 0, \qquad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.4}$$

This equality guarantees that no energy is artificially created or lost in the process of sharing, ensuring that community-level transactions remain physically consistent.

Contracted Power Limit

The contracted power limit constraint ensures that the total power exchanged by each participant $i \in \mathcal{N}$, both with the external grid and with the internal community, remains within the technical boundaries of its connection point. In practical terms, every household or prosumer has a contracted power capacity $\bar{P}_i^{\text{contracted}}$, which corresponds to the maximum power agreed upon with the distribution system operator. Exceeding this value may lead to penalties, safety issues, or automatic disconnection of the connection point.

To account for short-term flexibility, an overloading factor δ_i is introduced, which represents the admissible percentage above the nominal contracted capacity that can be tolerated without compromising the electrical installation (e.g., inverter ratings or breaker limits). In normal operating conditions, $\delta_i = 1$, meaning that no overloading is allowed and the power limit equals the contracted capacity. In cases where temporary overloading is acceptable, $\delta_i > 1$ allows the participant to momentarily exceed the contracted value up to a safe limit defined by technical parameters.

Equation 3.5 formalizes this condition:

$$P_{i,t}^{\text{grid}} + P_{i,t}^{\text{EC}} \leq \delta_i \cdot \bar{P}_i^{\text{contracted}}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.5}$$

This constraint prevents excessive power exchange through a participant's connection point while still providing controlled flexibility to better integrate renewable generation and storage resources.

Internal Market Transaction Constraints and Conflict Prevention

The internal market of the community must operate under clear rules to remain both physically consistent and economically meaningful. For this reason, a set of constraints is introduced to avoid contradictory

or infeasible decisions regarding energy exchanges. These conditions are implemented through binary variables and power limits, as detailed below.

Equation 3.6 ensures that the power exchanged internally $P_{i,t}^{\text{EC}}$ is limited to a maximum value $\bar{P}^{\text{EC}}$ only when the binary variable $u_{i,t}^{\text{buy-EC}}$ is set to 1. This represents the situation where participant i is receiving energy from the community at time t. If $u_{i,t}^{\text{buy-EC}} = 0$, the constraint forces $P_{i,t}^{\text{EC}}$ to be non-positive, thereby avoiding simultaneous buying and selling.

$$P_{i,t}^{\text{EC}} \leq u_{i,t}^{\text{buy-EC}} \cdot \bar{P}^{\text{EC}}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.6}$$

On the other hand, Equation 3.7 complements this logic by activating the selling condition. When $u_{i,t}^{\text{buy-EC}} = 0$, the participant is allowed to inject energy into the community up to the technical limit $\bar{P}^{\text{EC}}$, represented by a negative value of $P_{i,t}^{\text{EC}}$. This ensures that a participant cannot be a buyer and a seller simultaneously in the internal market.

$$-P_{i,t}^{\text{EC}} \leq (1 - u_{i,t}^{\text{buy-EC}}) \cdot \bar{P}^{\text{EC}}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.7}$$

Equations 3.8 and 3.9 extend this principle to prevent conflicting transactions between the external grid and the internal community. The first condition forbids participants from purchasing from the external grid while simultaneously selling energy to the community, while the second prevents them from purchasing internally and selling externally at the same time. These rules are necessary to avoid infeasible situations, such as arbitrage loops where a participant could artificially profit by buying and selling energy across markets in the same time step.

$$u_{i,t}^{\text{buy-grid}} + (1 - u_{i,t}^{\text{buy-EC}}) \leq 1, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.8}$$

$$u_{i,t}^{\text{buy-EC}} + (1 - u_{i,t}^{\text{buy-grid}}) \leq 1, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.9}$$

Together, these constraints ensure that internal and external exchanges are mutually consistent, preventing dual participation in conflicting roles. They also reflect the regulatory framework of energy communities in Portugal, where participants are not allowed to treat community energy sharing as a conventional buy-and-sell market. Instead, the formulation enforces that community exchanges are strictly matched, while the grid remains the sole external trading partner.

Grid Exchange Limits

The grid exchange limits ensure that participants cannot import and export energy to the external grid simultaneously in a single time step. This condition reflects both the physical impossibility of bidirectional

flows within one interval and the regulatory requirement that grid transactions must be clearly defined. Equation 3.10 enforces that only one operating mode is active at each instant: either importing from the grid or exporting to it, with both directions limited by the admissible grid capacity.

$$\begin{aligned} P_{i,t}^{\text{grid}} &\leq u_{i,t}^{\text{buy-grid}} \cdot \bar{P}^{\text{grid}}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \\ -P_{i,t}^{\text{grid}} &\leq (1 - u_{i,t}^{\text{buy-grid}}) \cdot \bar{P}^{\text{grid}}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \end{aligned} \tag{3.10}$$

By enforcing these limits, the model has logical consistency in grid interactions and preserves the technical feasibility of community–grid exchanges.

The presented model serves as the basis for studying the integration of external EV users into energy communities. By minimizing costs and enforcing constraints, it balances economic efficiency, technical feasibility, and social fairness. The flexibility of the model allows for exploring different market scenarios, providing valuable insights into the dynamics of community-based VPPs.

EVs' Constraints

EVs are modeled with power and energy limits that reflect battery and charger capabilities. The decision variables are the charging and discharging powers $P_{i,t}^{EV,\text{ch}}$ and $P_{i,t}^{EV,\text{dch}}$, and the binary mode indicators $u_{i,t}^{\text{ch}}, u_{i,t}^{\text{dch}} \in \{0,1\}$, which activate charging or discharging at time t for participant i. The parameters are the minimum and maximum admissible charging power $\underline{P}_i^{EV}, \bar{P}_i^{EV}$, the maximum energy capacity $\bar{E}_i^{EV}$, the state of charge $SOC_{i,t} \in [0,1]$, and the time-step duration Δt.

In Equation (3.11), when charging (i.e., $u_{i,t}^{\text{ch}} = 1$), the power must not fall below the technical minimum $\underline{P}_i^{EV}$. On the other hand, when discharging ($u_{i,t}^{\text{dch}} = 1$), power must exceed the same threshold. This avoids inefficient near-zero operation and prevents spurious activation of modes without meaningful energy transfer.

$$P_{i,t}^{EV,\text{ch}} \geq u_{i,t}^{\text{ch}} \cdot \underline{P}_i^{EV}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.11}$$

$$P_{i,t}^{EV,\text{dch}} \geq u_{i,t}^{\text{dch}} \cdot \underline{P}_i^{EV}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.12}$$

In Equation (3.13), charging power is constrained by the physical limit $\bar{P}_i^{EV}$ when the charging mode is active; similarly, Equation (3.14) caps discharging power. These bounds ensure safe operation and respect connector and inverter ratings. The parameter $u_{i,t}^{\text{connected}}$ indicates whether an EV is connected or not to a charging point and equation 3.15 ensures that charging and discharging do not occur at the same time.

$$P_{i,t}^{EV,\text{ch}} \leq u_{i,t}^{\text{ch}} \cdot \bar{P}_i^{EV}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.13}$$

$$P_{i,t}^{EV,\text{dch}} \leq u_{i,t}^{\text{dch}} \cdot \bar{P}_i^{EV}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.14}$$

$$u_{i,t}^{\text{dch}} + u_{i,t}^{\text{ch}} \leq u_{i,t}^{\text{connected}} \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.15}$$

As it is done in [28], Equation (3.16) dynamically adjusts the maximum charging power based on the SoC of the EV battery and the defined time interval Δt in the market. The term $(1 - SOC_{i,t}) \cdot \frac{\bar{E}_i^{EV}}{\Delta t}$ calculates the maximum charging power required to fully charge the battery if the EV is expected to leave in the next time period. This ensures that EVs meet the owner's charging requirements the best way possible while maintaining the stability of the energy system and not using unnecessary amounts of energy.

$$P_{i,t}^{EV,\text{ch}} \leq (1 - SOC_{i,t}) \cdot \frac{\bar{E}_i^{EV}}{\Delta t}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.16}$$

The SoC of each EV battery evolves dynamically at every time step. Equation 3.17 describes this evolution by linking the current energy content $E_{i,t}^{EV}$ to the previous state $E_{i,t-1}^{EV}$, the charging and discharging powers, the round-trip efficiency η, and the time-step duration Δt. The term $\eta \cdot P_{i,t}^{EV,\text{ch}} \cdot \Delta t$ increases the stored energy when the vehicle is charging, while $\frac{P_{i,t}^{EV,\text{dch}}}{\eta} \cdot \Delta t$ reduces it when discharging, accounting for conversion losses. This constraint ensures that the energy balance of the battery is consistent with physical operation, prevents infeasible charging or discharging profiles, and provides a realistic representation of how EVs contribute to community flexibility.

$$E_{i,t}^{EV} = E_{i,t-1}^{EV} + \eta \cdot P_{i,t}^{EV,\text{ch}} \cdot \Delta t - \frac{P_{i,t}^{EV,\text{dch}}}{\eta} \cdot \Delta t, \quad \forall i \in \mathcal{N},\ \forall t > 1 \tag{3.17}$$

The SoC of each EV battery must remain within predefined limits, $[\underline{E}_i^{EV}, \bar{E}_i^{EV}]$. Equation (3.18) protects the battery from overcharging or deep discharging, which could reduce its lifespan or lead to operational issues. By maintaining the SOC within safe bounds, the model ensures the reliability and longevity of EV batteries. It is worth noting that, in a real world scenario, a relaxation of the minimum limit could be required considering the situation when the EV arrives with a SoC lower than the minimum imposed in the formulation. For instance if an EV was connected with an initial SoC lower than the minimum bound the constraint would be infeasible without a relaxation variable.

$$\underline{E}_i^{EV} \leq E_{i,t}^{EV} \leq \bar{E}_i^{EV}, \quad \forall i \in \mathcal{N},\ \forall t \in \mathcal{T} \tag{3.18}$$

The initial and final state of charge of each EV battery are fixed to predefined targets, with a small degree of flexibility at departure to preserve feasibility. Equation 3.19 sets the arrival energy $E_i^{EV,\text{arrival}}$ at the beginning of the charging. At the end of charging, Equation 3.20 enforces the required departure level $E_i^{EV,\text{departure}}$ using a nonnegative slack variable $\beta_i^{relaxation} \geq 0$. This slack captures any shortfall in the final energy (when the exact target cannot be reached due to lack of time). Its presence maintains

model feasibility across adverse conditions, while the objective function penalizes $\beta_i^{relaxation}$ to discourage unmet user needs. The inequality allows the optimizer to exceed the target when beneficial (e.g., surplus PV), but never to fall short without incurring the prescribed penalty.

$$E_{i,start}^{EV} = E_i^{EV,\text{arrival}}, \qquad \forall i \in \mathcal{N} \tag{3.19}$$

$$E_{i,End}^{EV} + \beta_i^{relaxation} \;\geq\; E_i^{EV,\text{departure}}, \quad \beta_i^{relaxation} \geq 0, \qquad \forall i \in \mathcal{N} \tag{3.20}$$

Battery Constraints

Stationary batteries play a complementary role to electric vehicles within the cVPP, providing flexibility, stability, and peak-shaving capabilities. To ensure their safe and efficient operation, a set of technical constraints was introduced to govern the charging/discharging process, energy limits, and SoC evolution over time.

Similarly to the electric vehicle modeling, batteries are represented through power and energy variables that evolve dynamically at each time step. The associated parameters include: $\bar{P}_i^{\text{batt}}$ (maximum charge/discharge power [kW]), $\bar{E}_i^{\text{batt}}$ and $\underline{E}_i^{\text{batt}}$ (maximum and minimum allowable energy levels [kWh]), η (charge/discharge efficiency [%]), and Δt (time-step duration [h]). The binary variables $u_{i,t}^{\text{batt,ch}}$ and $u_{i,t}^{\text{batt,dch}}$ indicate the operational state of the battery, charging or discharging, while $u_{i,t}^{\text{batt}}$ indicates whether a participant has a BESS or not.

The first constraint ensures that a battery cannot charge and discharge simultaneously. This logical rule prevents conflicting energy flows that would violate physical feasibility:

$$u_{i,t}^{\text{batt,ch}} + u_{i,t}^{\text{batt,dch}} \leq u_{i,t}^{\text{batt}}, \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.21}$$

The evolution of the stored energy is described by Equation 3.22, which tracks the variation of the battery's energy level based on charging and discharging power. At each time step, the stored energy $E_{i,t}^{\text{batt}}$ depends on the previous level, the charging and discharging decisions, and the efficiency factor η. The term Δt represents the duration of each time step that multiplied by the charging or discharging power yields the energy stored or injected respectively.

$$E_{i,t}^{\text{batt}} = E_{i,t-1}^{\text{batt}} + \eta \cdot P_{i,t}^{\text{batt,ch}} \cdot \Delta t - \frac{P_{i,t}^{\text{batt,dch}}}{\eta} \cdot \Delta t, \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.22}$$

To ensure minimum and maximum physical limits and and to ensure reliable operation, the energy content is limited within a predefined range defined by $\underline{E}_i^{\text{batt}}$ and $\bar{E}_i^{\text{batt}}$:

$$\underline{E}_i^{\text{batt}} \leq E_{i,t}^{\text{batt}} \leq \bar{E}_i^{\text{batt}}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.23}$$

Equation 3.24 defines the state of charge (SoC) of the battery as the ratio between its current energy level and the maximum capacity, offering a normalized indicator (in [0,1]) of the available energy reserve:

$$SoC_{i,t}^{\text{batt}} = \frac{E_{i,t}^{\text{batt}}}{\bar{E}_{i}^{\text{batt}}}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.24}$$

Finally, Equations 3.25 and 3.26 impose upper bounds on charging and discharging power, ensuring that these rates never exceed the technical capacity of the converter or the rated power of the battery system:

$$P_{i,t}^{\text{batt,ch}} \leq u_{i,t}^{\text{batt,ch}} \cdot \bar{P}_{i}^{\text{batt}}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.25}$$

$$P_{i,t}^{\text{batt,dch}} \leq u_{i,t}^{\text{batt,dch}} \cdot \bar{P}_{i}^{\text{batt}}, \quad \forall i \in \mathcal{I}, t \in \mathcal{T} \tag{3.26}$$

Together, these constraints ensure that stationary batteries contribute effectively to community optimization while respecting technical and operational limits. They enable the model to capture the dynamic interplay between renewable generation, storage flexibility, and market interaction, all while safeguarding battery performance and extending system lifetime.

3.2 Energy Community Model considering External EVs

This section addresses the integration of external EVs into the cVPP framework. External EVs refer to vehicles not primarily associated with the community but allowed to participate in energy sharing under specific conditions. To ensure fairness and preserve the community's primary objective of serving its internal members, a prioritization mechanism is imposed: external EVs may only charge their batteries using energy from the community once all internal EVs have reached at least a threshold SoC, denoted as x%. This rule guarantees that local surplus energy is first made available to core members before being traded with this external participants.

However, the static application of a fixed threshold may lead to inefficiencies. For instance, when internal EVs have not yet reached the required SoC, surplus energy generated by the community (typically from solar PV) may go unused, even if external EVs are available and in need of charging. To address this issue, the model incorporates an iterative process that systematically adjusts the threshold to identify an optimal trade-off between internal EV prioritization and surplus utilization.

The iterative process begins with a high threshold and reduces it in fixed steps across a predefined number of iterations. In each iteration, the optimization model is executed with the current threshold, and key metrics are collected:

- The amount of **surplus energy used by external EVs**: E_{ext}^{used}
- The amount of **surplus energy used by internal EVs**: E_{int}^{used}
- The **amount of surplus energy sold to the grid during external EV charging periods**: E_{excess}^{sold}

After collecting results for all threshold levels, a **composite score** is calculated for each iteration. This score is a weighted sum of the normalized indicators mentioned above:

$$Score = w_1 \cdot \tilde{E}_{ext}^{used} + w_2 \cdot \tilde{E}_{int}^{used} + w_3 \cdot (1 - \tilde{E}_{excess}^{sold}) \tag{3.27}$$

Where:

- $\tilde{E}_{ext}^{used}$, $\tilde{E}_{int}^{used}$, and $\tilde{E}_{excess}^{sold}$ are the normalized values;
- w_1, w_2, and w_3 are the weights assigned to each component;
- The goal is to maximize the score, favoring configurations that boost internal consumption and external participation while minimizing wasted solar energy.

The threshold with the highest composite score is chosen as the optimal one. The final results are obtained and presented the optimal threshold. This iterative process is described in Figure 3.2

In parallel to this priority reasoning, the objective function optimizes the total energy cost for the community on the horizon $\mathcal{T}$. The model accounts for three terms: the net energy transaction cost with the grid, a penalty term for any missing EV energy requests, and the stationary battery degradation cost. This model ensures that the model includes both the economic and the technical features of the operation of a community in an understandable and intuitive way.

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left[\lambda_t^{\text{buy}} \cdot P_{i,t}^{\text{buy grid}} - \lambda_t^{\text{sell}} \cdot P_{i,t}^{\text{sell grid}} \right] + \sum_{i \in \mathcal{E}} \sum_{t \in \mathcal{T}} \left[\lambda_t^{\text{buy}} \cdot P_{i,t}^{\text{buy grid}} - \lambda_t^{\text{sell}} \cdot P_{i,t}^{\text{sell grid}} \right] \\ & + \alpha \cdot \sum_{i \in \mathcal{N}} \beta_i^{relaxation} \\ & + \gamma \cdot \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} P_{i,t}^{\text{batt,dch}} \end{aligned} \tag{3.28}$$

In this formulation:

- λ_t^{buy} and λ_t^{sell} represent, respectively, the grid's buying and selling prices at each time step t [€/kWh];
- $P_{i,t}^{\text{buy grid}}$ and $P_{i,t}^{\text{sell grid}}$ denote the power imported from and exported to the grid by participant i [kW];

- $\beta_i^{relaxation}$ is a slack variable that relaxes the final SoC requirement of each EV when strict feasibility cannot be achieved, penalized through the coefficient α;
- γ is the degradation cost coefficient [€/kWh] associated with the energy discharged from stationary batteries $P_{i,t}^{\text{batt,dch}}$.

Only transactions with the external grid are monetized in this objective function. Energy exchanges within the community are not subject to financial compensation, in accordance with the Portuguese regulatory framework, which defines energy sharing as a non-commercial redistribution process among members. As such, internal energy flows contribute to the community's physical balance but do not affect its total cost.

This formulation therefore ensures consistency with both technical feasibility and regulatory reality. By integrating penalty and degradation terms, the model promotes operational reliability and long-term asset sustainability, while focusing the optimization on real monetary transactions and physical energy balance within the cVPP.

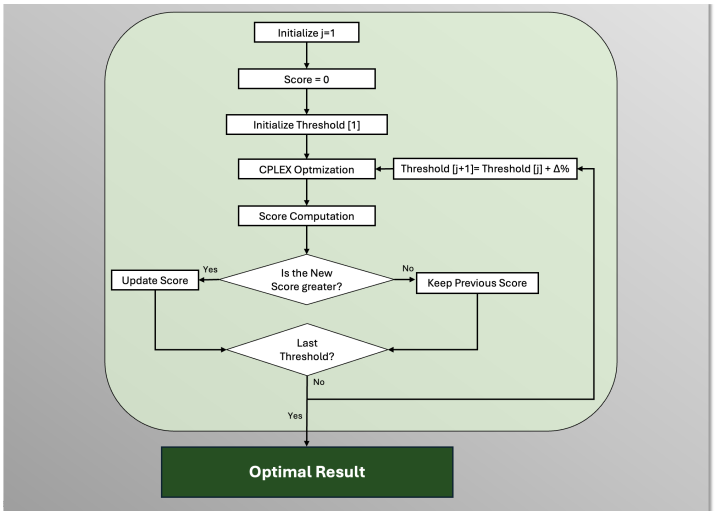

Figure 3.2: Optimization Model Flowchart with external vehicles

3.2.1 External EV's Constraints

The implementation of this method required the introduction of new constraints and variables into the optimization model.

To incorporate the conditional charging requirement, a binary variable $z_{i,t}$ was introduced. This variable indicates whether an internal EV $i \in I$ (where I is the group of internal participants) has reached at least x% of its battery capacity at time t. The following constraints enforce this condition:

$$E_{i,t}^{EV} - \frac{x \cdot \bar{E}_i^{EV}}{100} \geq -M \cdot (1 - z_{i,t}), \quad \forall i \in \mathcal{I},\ \forall t \in \mathcal{T} \tag{3.29}$$

$$E_{i,t}^{EV} - \frac{x \cdot \bar{E}_i^{EV}}{100} \leq M \cdot z_{i,t}, \quad \forall i \in \mathcal{I},\ \forall t \in \mathcal{T} \tag{3.30}$$

Here, M represents a sufficiently large constant, commonly known as a "big-M parameter," which ensures these constraints are always satisfied when $z_{i,t}$ is either 0 or 1. Effectively, $z_{i,t} = 1$ if and only if $E_{i,t}^{EV} \geq \frac{x \cdot \bar{E}_i^{EV}}{100}$.

The participation of external EVs in the VPP is determined by the binary variable $u_{ext}[t]$. Equations (3.31) and (3.32) control the availability of energy derived from the community for external EVs:

$$u_{ext}[t] \leq z_{i,t}, \quad \forall i \in \mathcal{I},\ \forall t \in \mathcal{T} \tag{3.31}$$

$$u_{ext}[t] \geq \sum_{i \in \mathcal{I}} z_{i,t} - |\mathcal{I}| + 1, \quad \forall t \in \mathcal{T} \tag{3.32}$$

where $|I|$ denotes the total number of internal EVs. These constraints ensure that $u_{ext}[t]$ is set to 1 only when all internal EVs have reached the defined threshold of their battery capacity.

To ensure that external EVs can only purchase energy from the community when $u_{ext}[t] = 1$, the following constraint was introduced:

$$P_{i,t}^{EC} \leq u^{Ext-EV} \cdot \bar{P}_{i,t}^{EV,ch}, \quad \forall i \in \mathcal{E},\ \forall t \in \mathcal{T} \tag{3.33}$$

Here, $\bar{P}_{i,t}^{EV,ch}$ represents the upper limit on the power that external EVs can charge from the energy community. This constraint prevents charging energy transactions between external EVs and the community when $u^{Ext-EV} = 0$.

Compensation Mechanism for External EVs

During the simulation process, a situation was identified where the inclusion of external EVs could lead to unfavorable outcomes. Considering that prices between energy community members are not considered in the formulation, this means that the exernal EVs can also be charged without cost when the EC have surplus of energy. This aspect can be compensated by the provision of flexibility using V2G by external EVs

To address this issue and ensure fair participation, a compensation mechanism was designed and incorporated into the model. The rule establishes a conditional access policy for external EVs based on their contribution to the community. When significant discharges occur, defined as injections above a certain ammount of energy sustained for more than one time step, the external EVs are granted free access to community energy, consistent with all previously defined operational constraints. Conversely, when no discharge meeting these criteria is recorded, the external EVs must compensate the community for the energy consumed.

The payment rate applied to non-contributing external EVs is set proportionally to market conditions, ensuring economic fairness while preserving the cooperative character of energy sharing. The unit price λ_t^{ext} is calculated as half the interval between the grid purchase and selling prices at each time step, as expressed in Equation 3.34.

$$\lambda_t^{\text{ext}} = \frac{1}{2}\left(\lambda_t^{\text{buy}} - \lambda_t^{\text{sell}}\right), \quad \forall t \in \mathcal{T} \tag{3.34}$$

This formulation ensures that the rate remains dynamically aligned with external market prices, preventing overpricing relative to grid electricity while maintaining the economic consistency of the community framework. The mechanism thus promotes reciprocity: external participants that contribute flexibility through discharging maintain free access, whereas those that only consume energy compensate the community at a fair, market-based rate.

4

Case Study

Contents

This chapter presents the case study designed to evaluate the proposed optimization framework within a realistic community energy system. The main objective is to assess the model's ability to minimize energy costs while integrating EVs into a cVPP in a coordinated and fair manner.

Section 4.1 begins with the description of the modeled community and main assumptions, including the number of participants, their respective load and PV generation profiles, BESS technical characteristics, market prices and schedules of internal EVs.

The case study evaluates different approaches and scenarios, each designed to explore the trade-offs between internal user protection, external EV participation, cost minimization, and local energy usage. The first scenario (Section 4.2) corresponds to the model that only considers internal participants and serves as a reference to validate the optimization model's feasibility and operational behavior.

Subsequently, Section 4.3 presents the energy community model that considers external EVs, which combines a modified objective function with the threshold rule to manage the participation of external EVs presented in Chapter 3. The section includes the results of the iterative threshold exploration and analyzes the resulting energy flows, EV behavior, market interactions, and overall system performance under the selected configuration.

To assess the robustness of the proposed method, Section 4.4 presents a sensitivity analysis under various conditions. These include reductions and increases in PV generation (e.g., winter vs. summer), as well as alternative market price profiles. In each case, the same methodology is applied and the results are compared with the optimal configuration obtained under baseline conditions.

4.1 General Data Description

4.1.1 Community-based VPP Description

The case study considers a small-scale energy community consisting of twelve residential participants, with photovoltaic systems and different electricity consumption profiles. Both photovoltaic and demand profiles were obtained in the U2DEMO project. Among these, eight participants own EVs and BESS, which are integrated into the cVPP.

Each participant has different daily consumption patterns, reflecting realistic variations in household energy use. The simulation spans a 24-hour period, divided into 96 time steps of 15 minutes each, capturing the dynamics of generation, consumption, EV and BESS operation. The optimizer used throughout the whole study is CPLEX.

4.1.2 PV Generation and Load Profiles

Each participant is characterized by a unique load profile in order to approximate the diversity of consumption patterns in real residential communities. These profiles capture different daily routines and behaviors, reflecting typical household electricity usage in a small neighborhood.

For instance, some participants show clear morning and evening peaks, simulating working families with energy intensive routines before and after office hours (e.g., Participants 1 and 2). Others maintain relatively constant energy consumption throughout the day, representing households with retired residents. Additionally, one participant (e.g., Participant 5) follows a load profile typical of a home-office scenario.

PV systems installed across the community range in generation from 1.25 kW to 12.6 kW, reflecting the variability in rooftop photovoltaic installations often seen in residential neighborhoods. By assigning different PV capacities and generation profiles to each household, the case study ensures a more realistic approximation of a small neighborhood where individual energy production capabilities vary depending on factors such as available roof area, shading, or investment preferences.

PV production profiles were constructed based on real measured data of photovoltaic generation, following typical daily solar radiation patterns observed in residential PV installations. Generation starts after sunrise, peaks around midday, and tapers off toward sunset, reflecting realistic weather and irradiance conditions. These profiles were fixed for all simulations to ensure consistency and result reproducibility, providing a reliable and realistic basis for evaluating energy sharing and optimization strategies within the community.

This diversity in both load and PV generation enables the model to test complex energy-sharing dynamics, balancing localized renewable energy production with individual consumption needs, and assessing the potential for maximizing self-consumption and minimizing reliance on external energy sources.

4.1.3 Pricing and Market Conditions

Given that the objective of the model is to minimize the total energy cost of the VPP, it is essential to incorporate market prices for both grid energy purchases and sales.

For simulation purposes, it is assumed that the VPP operates in the liberalized electricity market, acting as both an energy producer and consumer. In this sense, real hourly prices from the OMIE market over a full 24-hour period were adapted to represent the energy purchasing and selling prices, sourced via the REN Data Hub. To estimate the energy selling price, a typical market assumption was applied: the selling price was set at 90% of the corresponding purchasing price. This approximation reflects common contractual arrangements between prosumers and retailers.

As illustrated in Figure 4.1, electricity prices tend to decrease until midday, where they reach the minimum value. After this, prices start to rise, reaching maximum values at the end of the day, around 19:00. This price profile significantly influences the model's optimization decisions, particularly in relation to energy storage, self-consumption, and grid interaction.

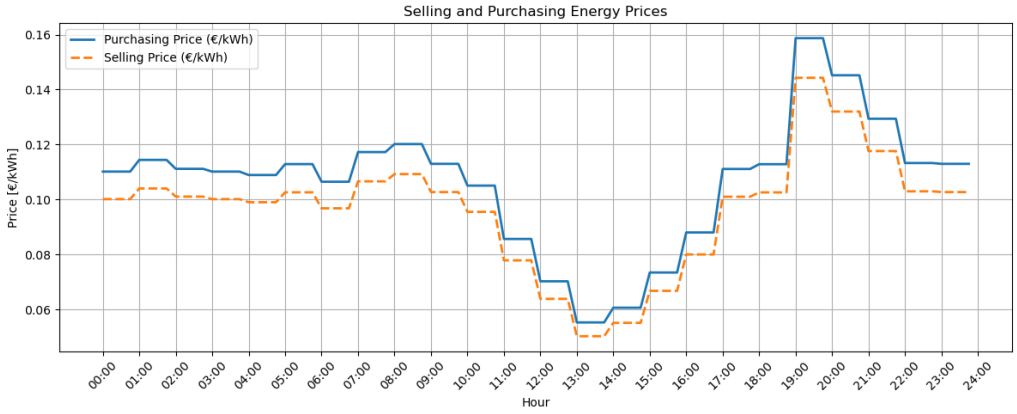

Figure 4.1: OMIE Hourly market prices - 2025/03/04

4.1.4 EVs and BESS parameters

For this simulation, it was considered that eight out of the total participants own an EV. The maximum charging (and discharging) power of the EVs was assumed to range between 3.6kW and 22kW. This range reflects the diversity of EV types and the differences in household electrical installations, such as single-phase or three-phase systems, in order to make the simulation as realistic as possible. The EVs were also assigned with different storage capacities, as shown in table 4.1, these parameters correspond to different types of EVs presented in A.1. An efficiency of $\eta = 97\%$ was assumed for both charging and discharging processes.

User ID	$P_{ch,max}$ (kW)	$P_{ch,min}$ (kW)	E_{max} (kWh)	E_{min} (kWh)	E_{init} (kWh)	$E_{final\ desired}$ (kWh)	Connect (h)	Disconnect (h)
1	11	1.38	58.0	5	10.0	58.0	0	8
2	7.4	1.38	48.1	8	14.4	45.7	18	24
3	11	1.38	75.0	5	10.0	56.3	0	7
4	3.6	1.38	39.0	5	10.0	35.1	6	13
5	11	1.38	64.8	6	15.0	47.0	19	24
6	11	1.38	72.5	10	10.0	72.5	9	17
8	22	1.38	52.0	5	10.0	49.5	9	13
10	11	1.38	66.5	5	19.9	53.7	17	24

Table 4.1: EV scheduling and energy parameters (connected EVs only).

Regarding BESS, it was assumed that not all participants own a battery system. Among those who do, different battery capacities and maximum charging powers were considered.

Batteries with higher capacity were assigned to participants with higher PV generation, and vice-versa, as it can also be observed in the table below.

The battery degradation factor was determined based on the minimum number of cycles a battery can perform while maintaining a state of health above 80%. This degradation factor was computed using an investment cost of 400 €/kWh, meaning that the degradation cost is directly proportional to the battery's capacity, leading to a degradation factor of 0.04€/kWh. This value is consistent with empirical and simulation-based analyses of residential lithium-ion batteries. [29] reports degradation rates corresponding to effective costs between 0.02 and 0.07 €/kWh (assuming prices of BESS between 300-600 €/kWh), depending on the chemistry, temperature, and depth of discharge. Therefore, 0.04 €/kWh was adopted as a conservative estimate for stationary applications. The technical parameters of each BESS is presented below in table 4.2.

User ID	Max Charging Power (kW)	Max Capacity (kWh)	Min Capacity (kWh)	Initial Energy (kWh)
1	2.5	5	0.5	0.5
2	5	10	1.0	10
3	2.5	5	0.5	5
4	2.5	5	0.5	0.5
5	2.5	5	0.5	5
6	2.5	5	1.0	5
7	5	10	1.0	1.5
9	5	15	1.5	15

Table 4.2: BESS Parameters per User

4.2 Energy Community Results

This section presents the results obtained by applying the optimization model described in section 3.1 to the VPP defined in Section 4.1. These simulations were carried out using the CPLEX solver through the Pyomo interface in Python.

Section 4.2.1 analyzes the total energy consumption and generation of the energy community. Section 4.2.2 discusses the operational behavior of EVs and batteries, highlighting charging patterns, SoC evolution, and control decisions. Finally, Section 4.2.3 presents the internal and external market interactions that occurred during the 24-hour simulation, analyzing trading volumes and cost implications.

4.2.1 Community Energy Demand and Supply

The total energy demand of the community includes household consumption, battery charging, and EV charging. Figure 4.2 illustrates the disaggregated demand profile together with community exports over 24 hours. During the early morning hours, demand remains relatively low and stable, predominantly due to household consumption and some overnight EV charging. As the day progresses, EVs and BESS begin to charge during low-price periods, leading to an increase in total demand. This is particularly noticeable from 11:00 to 15:00.

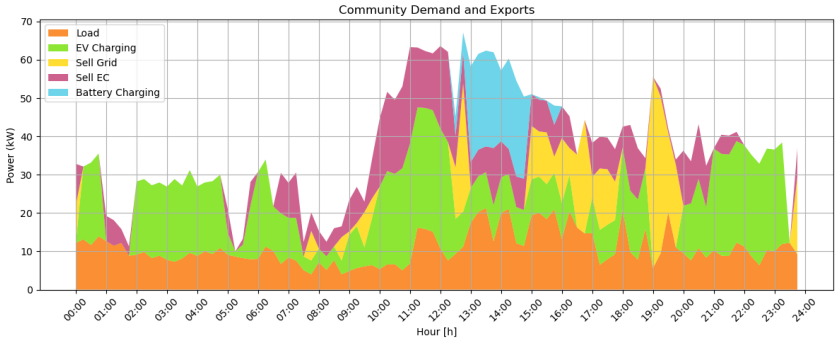

Figure 4.2: Total community demand: household load, EV charging, and battery charging

Simultaneously, Figure 4.3 shows the total generation profile of the community jointly with community imports. This includes PV generation, as well as discharging activities from EVs and batteries. PV generation dominates during daylight hours, peaking between 12:00 and 15:00. Battery and EV discharging tend to complement PV in the evening peak, when household demand is high and market prices rise.

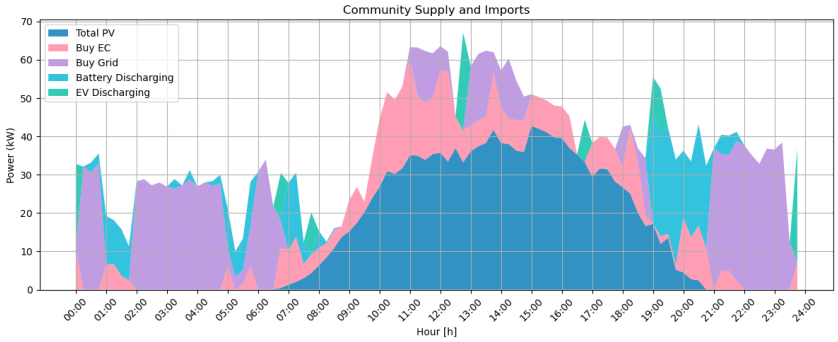

Figure 4.3: Total community generation: PV production, EV discharging, and battery discharging

As expected the generation and demand profiles outlines of Figures 4.3 and 4.2 match, indicating that the optimization, specifically the power balance constraint is working correctly.

4.2.2 EV and Battery Behavior

A key aspect of the model lies in the coordinated scheduling of flexible storage assets: EVs and BESS. These assets are essential to reducing grid dependency and shifting energy consumption away from expensive periods.

Figure B.1(a) shows the evolution of the SoC for EVs and BESS across all participants. A clear distinction can be seen in their operational behavior. Several EVs charge in the early morning hours, however their charging is not continuous. Charging periods occur between 00:00–01:00 and 02:00–05:00, with intentional pauses from 01:00–02:00 and from 05:00–06:00, as well as a shorter pause around

19:00–20:00. These interruptions coincide with temporary increases in market prices relative to other hours, indicating that the optimizer strategically manages charging to avoid costly imports while still ensuring final SoC targets are reached. Three of the EVs also begin charging after 18:00, consistent with user availability windows and aligned with expected evening price drops.

In contrast, stationary batteries show much more dynamic usage. These are primarily charged during midday, when PV generation is at its highest, allowing the system to absorb surplus solar energy that would otherwise be curtailed or exported at low prices. Interestingly, BESS are also discharged during the same higher price windows when EV charging is paused (01:00–02:00, 05:00–06:00, and 19:00–20:00), ensuring local demand and reducing reliance on the grid. Discharging typically continues into the evening hours, coinciding with rising demand and higher prices. This strategy improves self-consumption and reduces community costs by prioritizing internal supply.

The SoC evolution also reveals prioritization logic: EVs are charged conservatively, ensuring feasibility for mobility requirements, while batteries are cycled more aggressively, maximizing economic benefit. Notably, every BESS operates at near full cycles, taking full advantage of midday PV surpluses and discharging opportunistically during high price intervals.

Figure B.1 shows the binary status variables for EVs, connected ($u_{\text{connected}}$), charging (u_{ch}), and discharging (u_{dch}). The model ensures that EVs are only charged when connected, and the transitions between charging and discharging are governed by both technical constraints and market signals. No overlap occurs, confirming correct constraint handling. It is also observable that some EVs bearly discharge, reflecting either short availability windows or that discharging is not economically justified under the prevailing conditions.

4.2.3 Market Interactions and Price Impact

This subsection provides an analysis of the optimization outcomes regarding energy exchanges within the cVPP and with the external grid. Figure 4.4 presents the stacked hourly power flow over a 24-hour period, capturing grid imports, internal trading, self-consumption, and exports.

During the early morning hours (00:00–06:00), the community's total energy demand is driven primarily by household loads and the initiation of EV charging cycles. In this configuration, the cVPP relies on the external grid between 00:00–01:00, 02:00–05:00, and 06:00–07:00, when prices are comparatively low (≈€0.10–0.11/kWh). When the price rises slightly above these values (close to €0.12/kWh), the optimizer suppresses imports and instead relies on self-consumption and internal trades, with BESSs discharging to supply local demand (see Section 4.2.2). This pattern reflects a price responsive strategy that defers purchases during small periods of price increases while keeping EV charging feasible within the availability windows.

Between 07:00 and 11:00, as PV production increases and the community reduces grid reliance. A

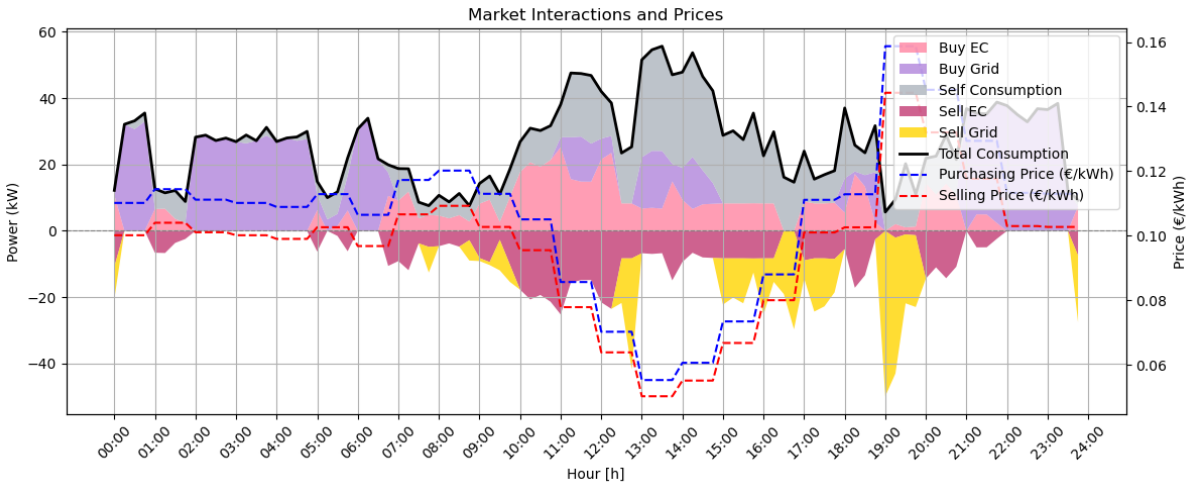

Figure 4.4: Stacked power flow showing market interactions, local trading, and consumption

growing share of demand is covered through PV energy generation and local energy sharing among participants, and some energy is even exported to the grid, indicating that individual surpluses coexist with internal sharing.

From 11:00 to 15:00, PV generation continues to rise but the community does not achieve a full surplus. Grid imports occur jointly with energy sharing within the cVPP, meaning that some participants have surplus while, in aggregate, the community faces a shortage in parts of this interval. Prices in this period are not zero, and the optimizer balances moderate imports with internal exchanges. From 15:00 to 18:00, PV generation jointly with available storage charging capacity of BESS creates a surplus, leading to exports to the external grid, while prices rise from roughly €0.06 to €0.11/kWh.

After 19:00, a critical transition occurs. With BESS largely full and prices at their daily maximum, the optimizer dispatches batteries to supply internal demand and even sells part of that energy to the grid to reduce community costs. From 20:00 to 21:00, self-consumption and internal trades continue without reliance on external energy. As prices start to fall and BESS become depleted, the community resumes importing from the grid. This sequencing underscores the alignment of storage operations with both technical constraints and the prevailing price signals.

Overall, this dynamic behavior illustrates the core principle of the VPP model: to shift consumption toward periods of low prices and utilize local renewable production and storage to buffer the community against high external prices. The coordination between prosumers trading, battery management, and EV charging confirms the effectiveness of the model in responding to both technical and economic constraints.

Table 4.3: Aggregate grid exchanges and costs

Metric	Value
Energy purchased from the grid	271.28 kWh
Energy sold to the grid	97.47 kWh
Net grid import (buy − sell)	180.69 kWh
Total purchase cost	€29.00
Total revenue from sales	€10.20
Net energy cost (cost − revenue)	**€18.80**
Average grid purchase price	€0.1069 / kWh
Average grid selling price	€0.1046 / kWh
Community-level cost per kWh	€**0.02928** / kWh

To contextualize, the community's total electricity consumption over the horizon is 642.13 kWh. The share supplied by the grid is:

$$\frac{271.28 \text{ kWh}}{642.13 \text{ kWh}} = 42.25\%,$$

implying a self-sufficiency ratio of 57.75%.

It is important to clarify that the community-level cost per kWh reported in Table 4.3 (€0.02928 / kWh) is computed as the total net energy cost divided by the total community consumption, including the energy produced locally at zero marginal cost, such as photovoltaic generation. Consequently, this indicator does not reflect the marginal grid price that guides operational decisions.. This value represents a weighted average of all participants' energy costs, where each participant's impact is proportional to their energy consumption. It offers a realistic and representative indicator of the overall energy cost efficiency achieved by the community.

Operational decisions such as battery dispatch rely not on average costs but on marginal grid prices. In the benchmark case, the battery discharges mainly between 00:00–08:00 and 19:00–22:00, during which the purchasing price from the grid consistently exceeds €0.04 / kWh. Since the degradation coefficient γ equals €0.04 / kWh, discharging during these hours remains economically justified. Moreover, the battery often charges using surplus photovoltaic generation or other zero-cost local energy, further enhancing its performance.

Therefore, even though the overall community cost per kWh is below the degradation threshold, the observed BESS operation remains coherent. The model bases its dispatch decisions on time-varying prices, not on aggregated averages. This ensures cost minimization and promotes efficient use of local renewable resources.

This benchmark will serve as a reference in the analysis of future scenarios, where grid dependence and energy cost efficiency will be revisited under different operating conditions.

4.3 Optimal Threshold Method

This section presents the results of the iterative method presented in section 3.2, which incorporates the iterative threshold strategy to control the participation of external EVs in the community energy system. The threshold mechanism ensures that external EVs can only access community energy once all internal EVs, charging at a given time, have reached a specific threshold determined by the iterative model, as it was explained in 3.2.

The analysis is structured to cover the following key aspects: EV scheduling data, system demand and supply profiles, market interactions among participants and the external grid, operational behavior of EVs, and the iterative optimization process results.

4.3.1 EV Scheduling

Table 4.4 presents the charging parameters and schedule for all EVs within the community, where participants 13 to 16 correspond to external EVs. These configurations define the specific time windows in which each vehicle is connected and the corresponding flexibility in charging operations.

As established in the 4.1.1, different battery capacities were assigned to the EVs, along with individualized maximum and minimum charging powers. These limits are influenced not only by the technical specifications of the vehicles themselves but also by external constraints, such as the limitations of the household electrical installation (in case of internal participants) and user defined boundaries configured via smart charging applications.

User ID	$P_{ch,max}$ (kW)	$P_{ch,min}$ (kW)	E_{max} (kWh)	E_{min} (kWh)	E_{init} (kWh)	$E_{final\ desired}$ (kWh)	Connect (h)	Disconnect (h)
1	11	1.38	58.0	5	10.0	58.0	0	8
2	7.4	1.38	48.1	8	14.4	45.7	18	24
3	11	1.38	75.0	5	10.0	56.3	0	7
4	3.6	1.38	39.0	5	10.0	35.1	6	13
5	11	1.38	64.8	6	15.0	47.0	19	24
6	11	1.38	72.5	10	10.0	72.5	9	17
8	22	1.38	52.0	5	10.0	49.5	9	13
10	11	1.38	66.5	5	19.9	53.7	17	24
13	22	1.38	60.0	5	18.0	45.0	12	16
14	11	1.38	77.0	8	20.0	70.0	11	16
15	11	1.38	37.9	6	11.4	30.5	8	12
16	11	1.38	64.0	8	19.2	60.0	9	18

Table 4.4: EV scheduling and energy parameters (Threshold Method).

4.3.2 Iterative Threshold Optimization

As introduced in 3.2, the iterative process was executed to determine the optimal SoC threshold x at which external EVs are allowed to charge using energy from the community. The objective of this process was to achieve a balanced trade-off between prioritizing internal participants, maximizing the

use of energy surplus within the community, and minimizing the amount of energy exported to the external grid.

Throughout the iterations, three key decision metrics were tracked:

- The amount of community energy consumed by external EVs;
- The amount of community energy consumed by internal EVs;
- The total surplus energy sold to the external grid.

Figure 4.5 presents the evolution of the composite score across the different threshold values tested. The highest value was recorded for $x = 50\%$, which was selected as the optimal threshold. This score was calculated using Equation 3.27, where the weights assigned to the normalized decision variables were $w_1 = 0.3$, $w_2 = 0.5$, and $w_3 = 0.2$, in accordance with the priorities defined within the cVPP.

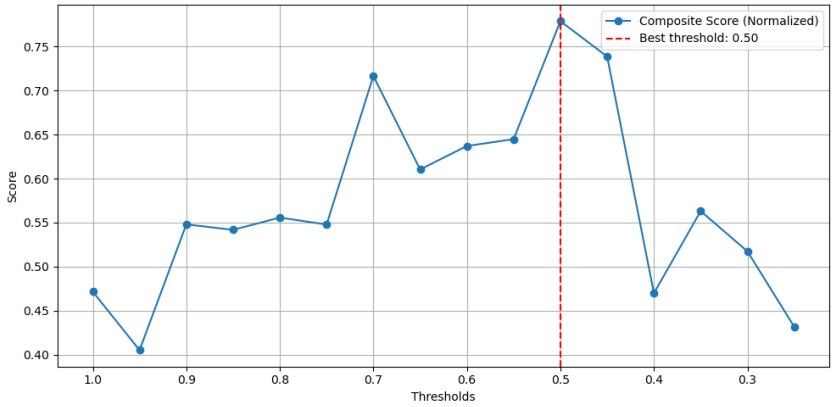

Figure 4.5: Normalized composite score for different threshold values.

To complement this analysis, a three dimensional visualization of the multi-criteria evaluation is provided in Figure 4.6. This plot offers a clearer representation of the trade-offs among the three decision variables. At the identified optimal threshold of 50%, external EVs consumed a total of 50.91 kWh of energy from the community, while 9.13 kWh of surplus was sold to the grid while external EVs were charging.

Although internal users have the highest priority when it comes to accessing community energy, through the weighting strategy adopted in the iterative function (with a weight of 0.5), it was still possible to ensure a significant allocation of energy to external users without compromising internal consumption. Notably, the energy consumed by internal participants from the community almost reaches its maximum, as illustrated in Figure 4.6, and the amount of energy purchased from the grid by internal participants approaches its minimum, differing by only 3% from the lowest possible value. This observation is reinforced in Figure 4.7.

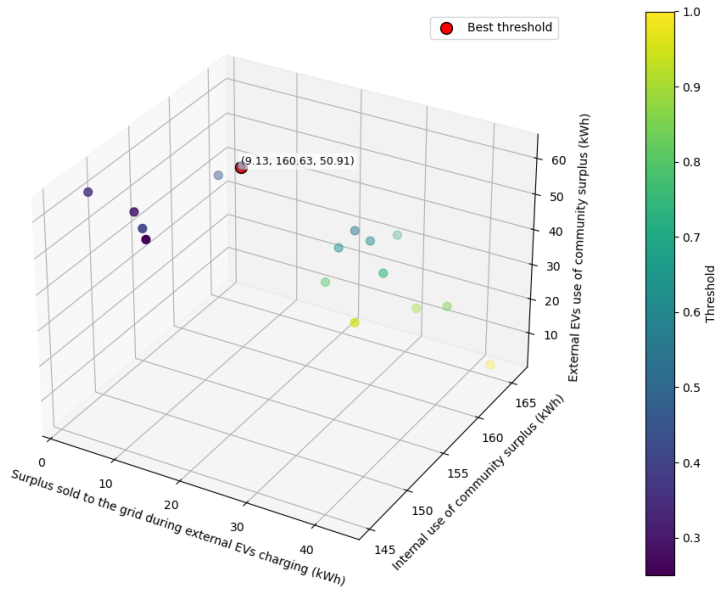

Figure 4.6: 3D multi-criteria analysis of threshold values: community energy used by externals and internals, and grid sales.

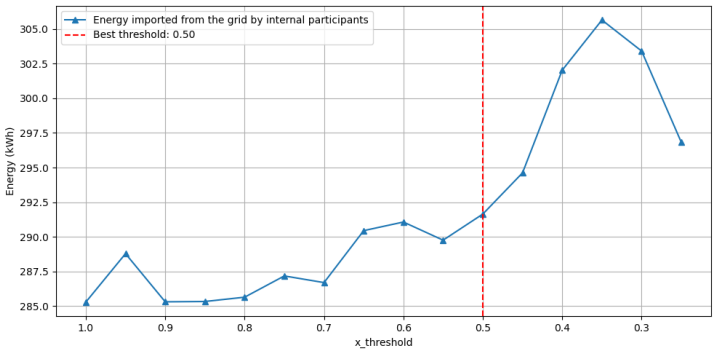

Figure 4.7: Energy purchased from the grid by internal participants.

Although the behavior of the system across threshold values is not strictly linear, a clear trend emerges, the total amount of energy sold to the external grid tends to decrease as the threshold becomes less restrictive. This is an expected outcome, given that a lower threshold allows external EVs to access community energy earlier, absorbing surplus that would otherwise be exported. This behavior is further illustrated in Figure 4.8, which consolidates both the total energy sold to the grid and the portion sold during external EV charging events.

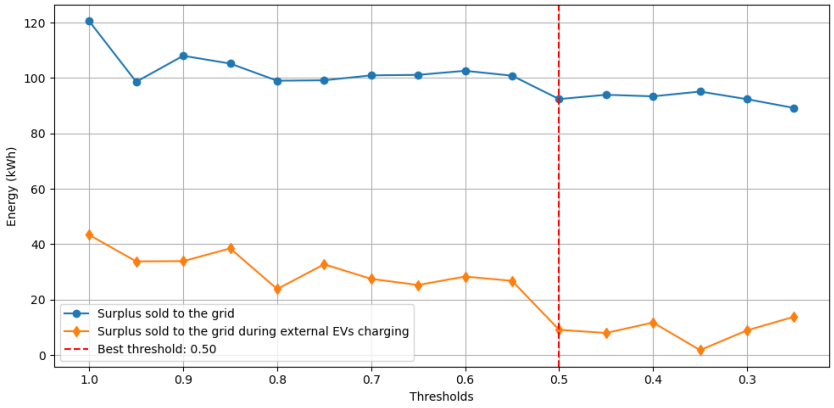

Figure 4.8: Surplus energy sold to the external grid, including sales during external EV charging.

4.3.3 Demand and Supply Analysis

The inclusion of external EVs and the enforcement of a threshold mechanism significantly influences the community's energy flow patterns. The aggregated community demand, displayed in Figure 4.9, is composed of the sum of household consumption, EV charging, and battery storage charging. A notable increase in load is observed between 10:00 and 16:00, predominantly driven by the charging cycles of both internal and external EVs.

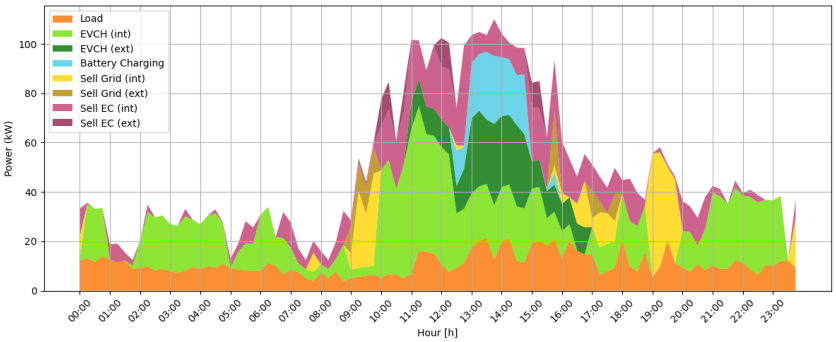

Figure 4.9: Total community demand, disaggregated into household load, EV charging, and battery charging components.

The corresponding generation profile is shown in Figure 4.10. The total energy supply derives from photovoltaic generation and discharging events from both EV and battery storage systems. PV output ramps up from around 07:30, peaks between 14:00 and 16:00, and fades stops around 20:00. Battery discharging is concentrated overnight and at the evening peak, short discharges occur between 00:00–02:00 and 05:00–06:00, and a major discharge around 19:00–20:30, supplying local demand when solar energy is fading and prices are higher. EV discharging is intermittent and price responsive, with clusters before and during the PV ramp (≈07:00–08:00 and 08:30–10:30), further events

from roughly 12:00 to 16:30 overlapping the PV plateau (including the day's largest spike), and shorter episodes near 19:00–20:00 and around 23:30. Taken together, EV discharges and BESS discharges act as a buffer, smoothing the community's net demand by covering high-price, low-solar windows and enabling limited exports during midday abundance.

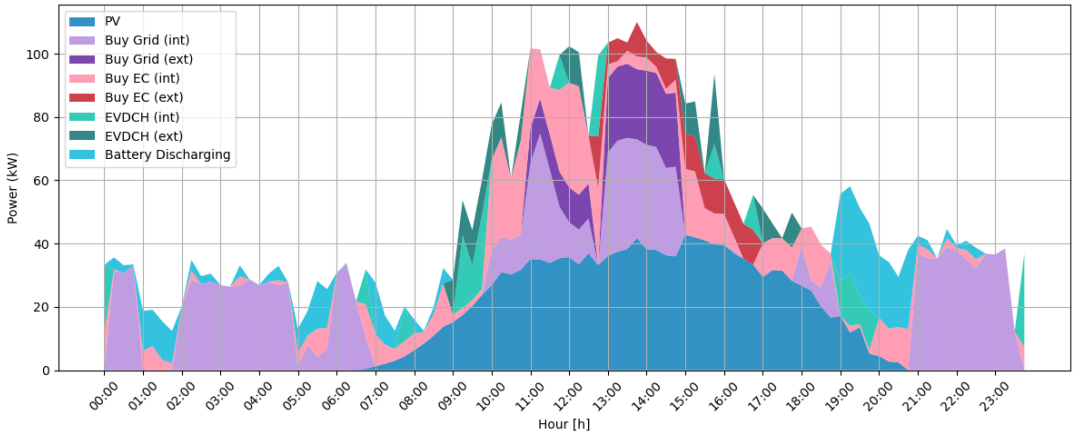

Figure 4.10: Total generation from PV, EV discharging, and battery discharging

4.3.4 Market Interactions and Community Energy Flow

The integration of external EVs, combined with the optimal threshold strategy, led to significant changes in the community's energy flow dynamics. Figure 4.11 illustrates the temporal distribution of market interactions, now with the participation ox external EVs, throughout the 24-hour period, highlighting the relationship between community energy usage, grid transactions, and hourly price variations.

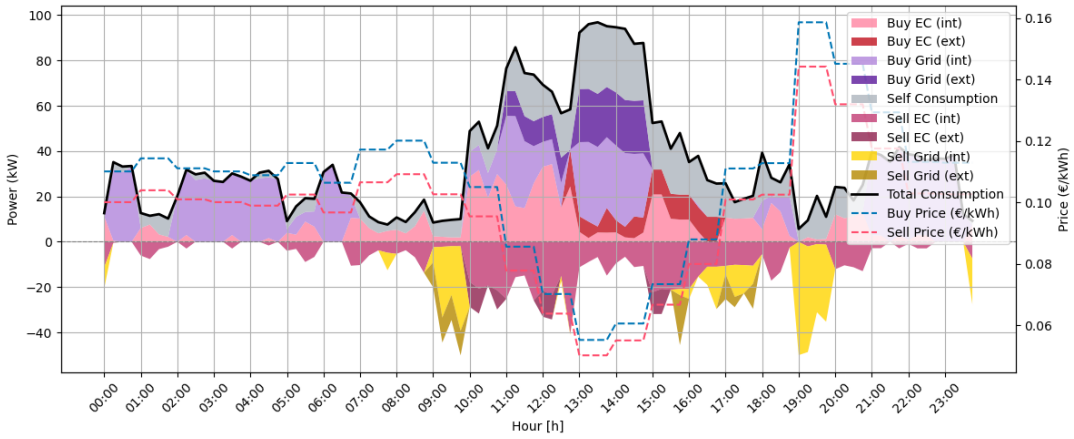

Figure 4.11: Community market interactions and energy price evolution throughout the day.

Between 00:00 and 02:00, imports dominate the first hour and then decrease. Specifically, the VPP relies on the external grid between 00:00–01:00, while from 01:00–02:00 demand is largely covered by self-consumption and internal exchanges supported by BESS (the negative “Sell EC”/reduced “Buy Grid” in Figure 4.4). This pattern reflects the small price step-up around 01:00, to which the optimizer reacts by briefly curtailing imports.

From 02:00 to 08:00, community batteries are depleted and the model shifts to external sourcing. Imports resume from 02:00–05:00 and again from 06:00–07:00, consistent with lower purchase prices (blue dashed line in Figure 4.4). Around 07:00–08:00, the reliance on imports begins to soften as PV starts to ramp and short EV discharging events provide additional internal supply.

Between 08:00 and 18:00, consumption is predominantly covered by local generation and community trading. Participants 3 and 5 are basically self-sufficient in this window (just a residual grid purchase), meeting their needs with their own PV and storage (Figures 4.12 and 4.13). Participant 4 supplies demand through a mix of self-generation and internal purchases, with occasional small imports. Importantly, the Figure 4.17 also shows bands from about 10:00 to 15:00 reflecting some imports while PV ramps. These imports are also associated with external EVs, as seen in Figure 4.14, Participant 16 buys from the grid during the 12:00–16:00 charging block, and Participant 13 does so mainly between 13:00–15:00. In the same interval, part of the traded energy originates from EV discharging by externals (e.g., Participant 16 around 10:00–11:00), so that EV discharges together with BESS act as a buffer that reinforces community supply.

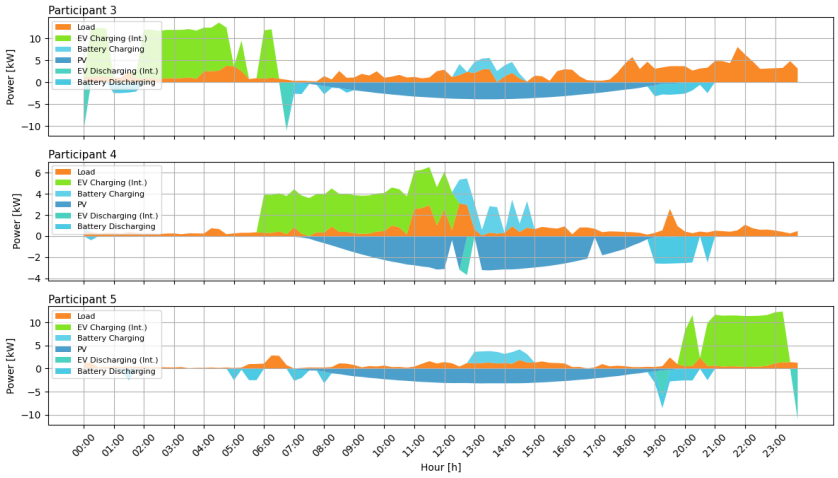

Figure 4.12: Energy Flows - Participant 3, 4 and 5

Between 13:00-15:00, community BESS begin to charge, absorbing PV and, in a small scale, energy from internal trades. Some grid purchases still occur, again linked to sustained external EV charging (Participants 13 and 16 in Figure 4.14). From roughly 15:00 to 18:00, PV and available storage capacity generate a clear surplus that is exported to the grid, while selling prices rise from about €0.06 to €0.11/kWh (Figure 4.4). Finally, from 18:00 to the end of the day, solar energy start to decrease and prices rise. With BESS near full, the optimizer dispatches storage during the 19:00–20:00 price peak, supplying internal demand and even exporting part of this energy, thereby reducing costly purchases. From 20:00 to 21:00, self-consumption and internal trades satisfy demand without external energy. As prices fall thereafter and storage becomes depleted, the VPP gradually resumes imports.

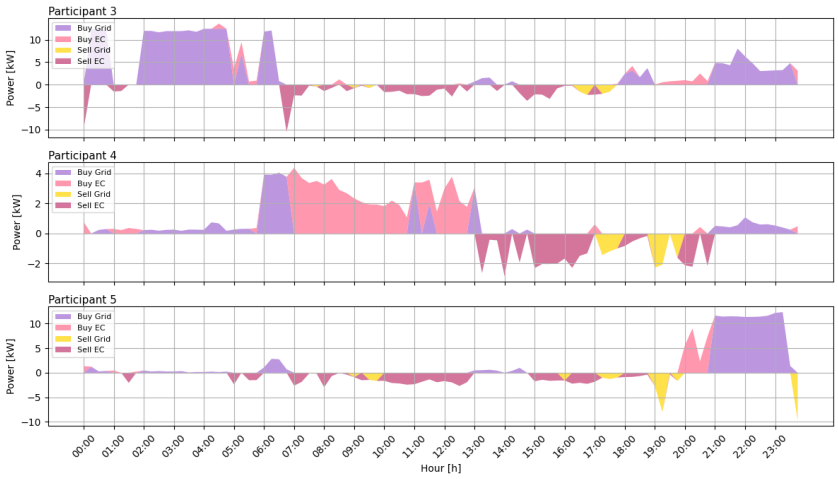

Figure 4.13: Market Interactions - Participant 3, 4 and 5

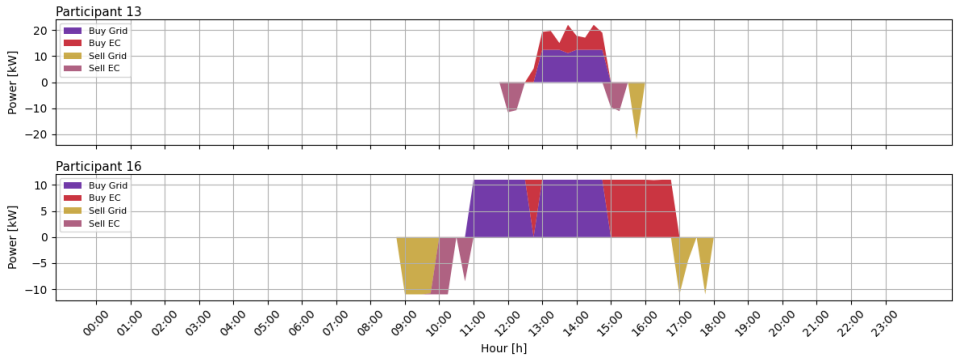

Figure 4.14: Market Interactions - Participant 13 and 16

4.3.5 EV Operational Behavior

This section provides a detailed analysis of the operational behavior of EVs within the VPP. Both internal and external participants are examined with regard to their connection schedules, charging and discharging events, and compliance with the threshold rule prioritizing internal EVs. This behavior reflects the model's capacity to enforce fairness while optimizing community energy usage.

Charging Priority Logic and u_{ext} Activation

As described in section 3.2, external EVs are only allowed to charge from the community once all current connected internal EVs have reached an optimal threshold, which in this case corresponds to 50% of SoC. This logic is enforced through the binary variable $u_{ext}[t]$, which is activated only when the condition is satisfied.

Figure 4.15 illustrates the evolution of $u_{ext}[t]$ over time for external EVs, clearly indicating the instants when the rule is met. For example, at t = 12:30, all connected internal EVs have already surpassed the threshold, and charging through the community is consequently permitted for external EV's.

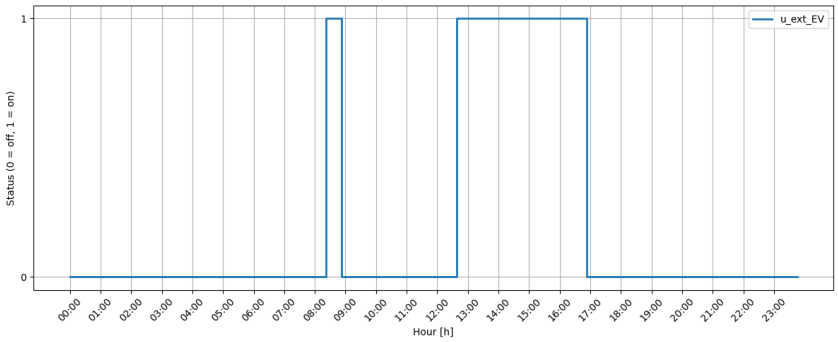

Figure 4.15: Binary variable $u_{ext}[t]$

Validation and Activation of u_{ext} Logic

The validation of the u_{ext} activation rule is confirmed through the observation of the SoC levels of internal EVs. Figure 4.16 illustrates the evolution of SoC across all EVs. At 12:45, all internal EVs that were connected had surpassed the defined SoC threshold of 50%, resulting in the activation of u_{ext}. Furthermore, at 17:00, the reason why u_{ext} goes to 0 is because participant 10 connects the car and the SoC is lower than 50%. This mechanism guarantees that external EVs do not prematurely access energy from the community, thereby safeguarding internal user priority.

It is important to highlight that this control logic does not compromise the ability of external EVs to achieve their final desired SoC. Rather than restricting their charging processes, it simply governs the source of the energy they consume. For example, as shown in Figure 4.17, participants 16 and

14 start charging from the grid at 11:00 and, once u_{ext} is activated (12:45h), a transition to community sourced energy occurs. In contrast, participant 15 only gained access to community energy between 8:00 and 9:00 since it was disconnected at 12:00. Regarding external EV's discharges, since there is no restriction on this matter, they can occur at any moment, which was the case of this simulation as the case of participant 16. These results confirm that the threshold rule is being correctly enforced, as well as the updated objective function, ensuring internal priority while maintaining external feasibility.

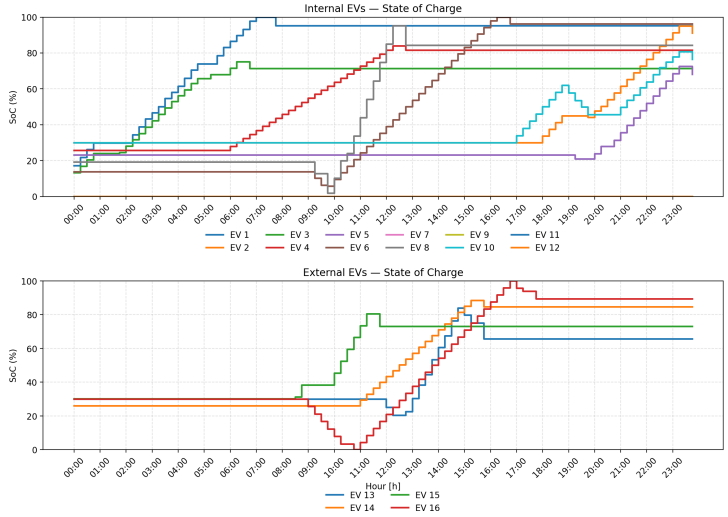

Figure 4.16: SoC of EVs and BESS across participants, including $u\_connected$ status.

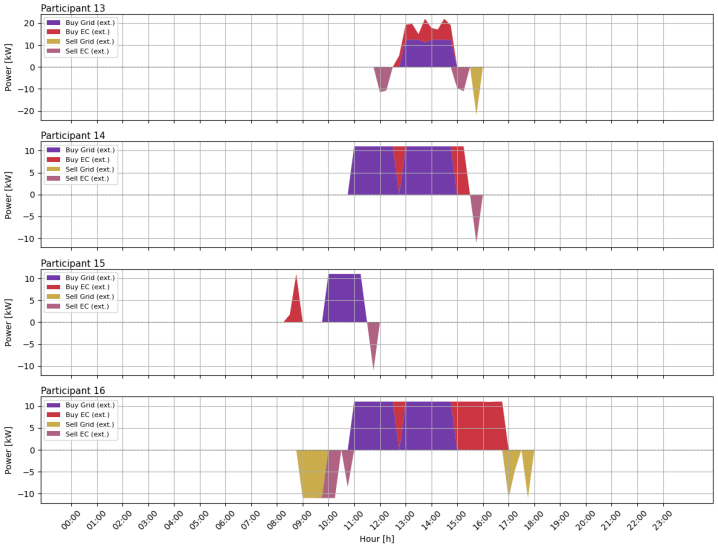

Figure 4.17: External EVs' market interactions: grid vs. community access.

4.3.6 Feasibility of EV Charging Targets

To ensure that the imposed threshold does not compromise EV user requirements, Table 4.5 shows the relaxation values for final SoC constraints across all participants. All EVs except for participants 4 and 14 reach their target SoC levels without any infeasibility. Even in this case, the deviation remains minimal and is attributed to physical limitations, specifically, restricted charging durations that prevent full completion of the charging process.

Table 4.5: Relaxation values for final SoC constraints (in kWh).

Participant	Relaxation	Participant	Relaxation
1	0.00	9	0.00
2	0.00	10	0.00
3	0.00	11	0.00
4	2.40	12	0.00
5	0.00	13	0.00
6	0.00	14	1.99
7	0.00	15	0.00
8	0.00	16	0.00

The operational dynamics observed confirm that the model effectively balances internal user protection and external participation. Charging behaviors align with participant preferences, energy availability, and community rules. External EVs operate under the same physical constraints as internal ones, and the prioritization mechanism via u_{ext} is enforced without compromising user satisfaction or network efficiency.

4.3.7 Cost Analysis

Table 4.6 summarizes the average grid-related indicators for internal participants (IDs 1–12), external participants (IDs 13–16), and for the community as a whole.

Table 4.6: Average unit values by segment

Segment	Avg Grid Unit Cost [€/kWh]	Avg Grid Unit Revenue [€/kWh]	Compensation (€)	Net Cost per kWh
Internals (1–12)	0.1044	0.1182	0.9581	**0.0278**
Externals (13–16)	0.0700	0.0936	-0.9581	**0.0426**
Community Total	**0.0941**	**0.1146**	-	**0.0308**

The results confirm the benefits of integrating external participants. For internal members, the average net cost per kWh (0.0278 €/kWh) is lower than in the case that only considers internal participants (0.0293 €/kWh), indicating improved economic efficiency through enhanced energy exchange and system flexibility. External participants also benefit, with a unit cost (0.0426 €/kWh) well below minimum grid tariffs, reinforcing the advantage of charging within the community framework.

The iterative process begins with a 100% threshold, corresponding to a scenario where external EVs are excluded from community interaction. Since this configuration was not selected, it implies that allowing partial participation of external EVs leads to a better outcome for both internal and external participants. This is because external EVs occasionally discharge into the community, contributing to internal supply and reducing grid imports. This cooperation enhances flexibility and lowers total system costs.

As illustrated in Figure 4.14, short discharge periods from external EVs to the community are followed by recharging within the community rather than from the external grid. This bidirectional interaction reinforces the collaborative logic of the system and improves its overall performance.

In summary, the integration of external EVs results in a mutually beneficial configuration: internal members enjoy lower costs supported by external discharges, while external users gain access to a cleaner and more cost-effective charging environment.

Results of the Compensation Mechanism

Following the introduction of the compensation mechanism described in Section 3.2, a simulation was carried out where the charging profiles of the four external EVs were configured to prevent any discharging to the community and consequently triggering the payment condition in every external participant.

The results showed that the average unit energy cost for internal participants slightly decreased to €0.0268/kWh compared to the previous case with some external discharges, indicating only a marginal difference. As expected, the average unit cost for external EVs increased to €0.07228/kWh. Nevertheless, this value remains approximately 13% lower than the average market price between 8:00 and 18:00, the typical charging window for external EVs, set at €0.08262/kWh.

These results confirm that the mechanism preserves the economic advantage for the community while ensuring fairness between internal and external participants. Externals who discharge continue to benefit from free access, while non-contributing users are charged a reasonable, market-aligned rate. This approach reinforces balanced participation and aligns with European principles of fairness and shared benefit in renewable energy communities.

4.4 Sensitivity Analysis on the Optimal Threshold Method

A sensitivity analysis was conducted to evaluate the behavior and robustness of the proposed model under varying operating conditions. The objective of this analysis is to examine how different external factors affect the optimal threshold strategy and the overall performance of the cVPP. Three representative scenarios were designed to capture distinct system dynamics.

The first scenario simulates a winter day with limited solar irradiation, leading to a significant reduction in photovoltaic generation. The second scenario represents an opposite condition, characterized by excess of PV production and energy surplus within the community. Finally, the third scenario explores a pricing environment with atypical dynamics, where market prices reach zero during certain periods, testing the model's capacity to adapt to extreme market signals.

4.4.1 Scenario A - Shortage of PV Generation

In this low generation scenario, where a shortage of 50% was set (compared to 4.3), the optimal threshold for allowing external EVs to access community energy is obtained directly from the 3D multi-criteria view in Figure 4.18, the red marker identifies the selected optimum at $x = 70\%$.

The position of the optimal point clarifies the trade-off under scarcity: Internal participants consumption from community surplus stays near the upper envelope for this scenario (114.58 kWh), while external usage of community surplus remains modest (24.93 kWh on the z-axis), and the surplus exported while external EVs are charging is kept near zero. A higher threshold therefore delays external access until sufficient headroom is secured, protecting internal charging schedules when PV is limited.

Consistent with the constrained supply, the accounting results show that grid purchases by internals rise relative to the full generation case, exceeding 370 kWh versus 291 kWh in the baseline, reflecting the lower availability of community solar. Even so, the threshold identified by Figure 4.18 maintains internal priority while still enabling a controlled level of external participation and minimizing exports during their charging periods.

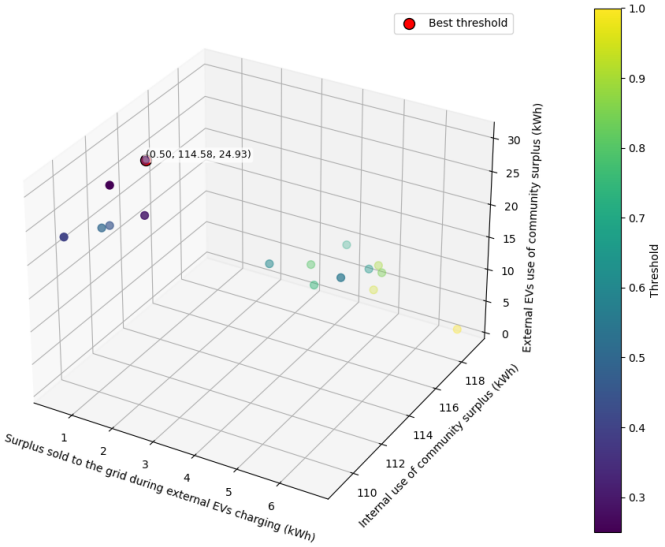

Figure 4.18: 3D multicriteria analysis — internal vs. external community usage and grid export across thresholds; the red marker indicates the selected optimum at $x = 70\%$.

Community Demand and Supply Balance

Figures 4.19 and 4.20 illustrate the total generation and demand of the community under this low-generation scenario.

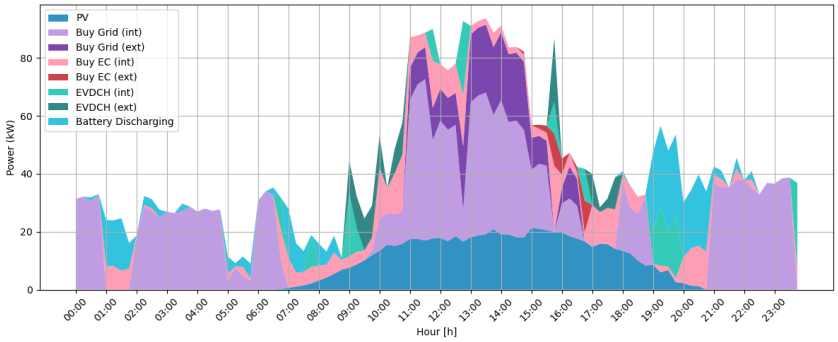

Figure 4.19: Total community generation (PV + EV + Battery Discharging) – 50% PV Scenario

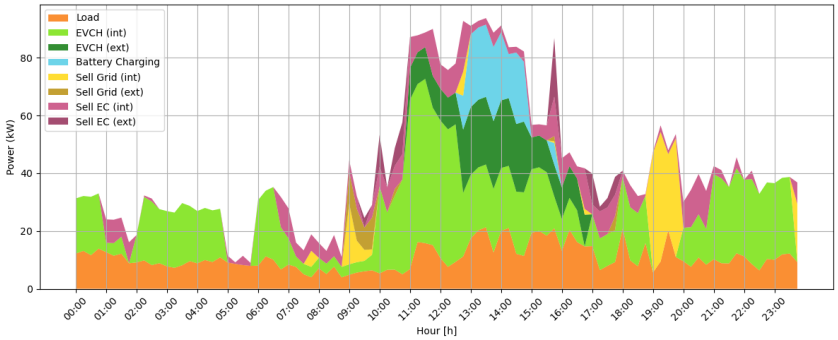

Figure 4.20: Total community demand (Load + EV Charging + Battery Charging) – 50% PV Scenario

The reduction in generation is clearly reflected in the PV profile, which peaks at around 20 kW, substantially lower than the 40kW observed in the baseline scenario. This limited supply imposes additional constraints on the energy available for community distribution and storage.

EV discharging behavior also adapts accordingly: the total discharged energy by external EVs, for example, dropped from 47.00 kWh to 36.25 kWh, representing a 30% reduction compared to the original scenario. This is a strategic decision by the optimizer, if EVs discharged at the same levels as before, they would later require recharging with grid energy due to the lack of surplus PV. Thus, the system avoids unnecessary discharging events that cannot be compensated by local production.

Battery systems still manage to participate actively in energy balancing. However, their charging power is slightly reduced, with a 84.3 kWh of discharged energy, 7kWh less than in the baseline. Despite this drop, batteries are still able to store energy during moderate PV hours and discharge during high demand or high price periods.

Overall, the optimizer demonstrates adaptability to the reduced supply by dynamically adjusting discharging events and charging rates across EVs and batteries, thus minimizing grid dependency while maintaining energy prioritization rules.

4.4.1.A Market Interaction Patterns

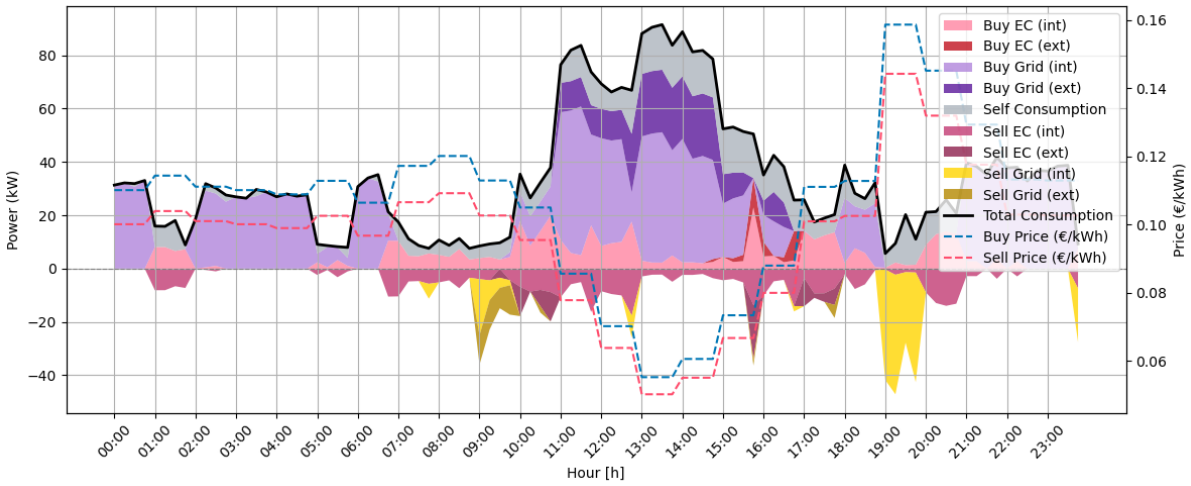

Figure 4.21: Community market interactions and energy price evolution throughout the day (Scenario A – 50% PV).

As illustrated in Figure 4.21, the reduction in PV generation has a direct and substantial impact on the energy exchange behavior of the community. Notably, grid consumption becomes the dominant source of supply across the entire day. From 00:00 to 08:00, the behavior is consistent with previous scenarios, imports from the grid remain high as no PV generation occurs during these early hours.

However, beyond 08:00, the impact of reduced generation becomes more evident. The proportion of self-consumed energy is significantly lower compared to the normal generation case, and trades between participants also decrease considerably, specially between internal and external participants that is almos inexistent. With limited energy surplus available, the opportunity for energy exchange shrinks, almost no energy is sold to the external grid, confirming that most local production is either self-consumed or insufficient to meet community demand.

Interestingly, the model still preserves a strategic approach to grid interaction. Grid purchases are concentrated during off-peak periods, particularly between 02:00 and 08:00 and again from 11:00 to 17:00, aligning with the lowest buy price slots. On the other hand, during high-price intervals (e.g., after 19:00), battery discharge and residual PV generation attempt to buffer demand, even though with limited capacity due to the initial generation deficit.

These results confirm that, although the volume of community-based energy trading is reduced under limited PV availability, the model maintains its cost-aware optimization logic. Priority is still given to

minimizing purchase costs through price sensitive scheduling and maximizing local energy use.

4.4.1.B EV Operational Behavior under Limited Generation

This section examines the behavior of EVs under the constrained generation conditions imposed by the 50% PV scenario. The goal is to assess whether the optimization model remains feasible and robust, and whether internal participants retain priority access to community energy, even with limited supply.

Model Feasibility and Charging Completion — Despite the reduction in photovoltaic generation, the optimizer ensures that all external EVs reach their final desired SoC. Feasibility is preserved, but, given the scarcity of community surplus, external users rely predominantly on grid energy, with only short intervals of community supply when allowed by the priority logic.

Charging Activation Rule and u_{ext} Logic — Figure 4.22 shows that the $u_{\text{ext}}[t]$ binary variable is activated once, in a single continuous window between 14:15 and 17:00. No activation is observed during the whole morning. This afternoon window coincides with the PV plateau and with sufficient internal headroom, which is consistent with the threshold policy that protects internal users and only grants access to externals when community's conditions are favorable.

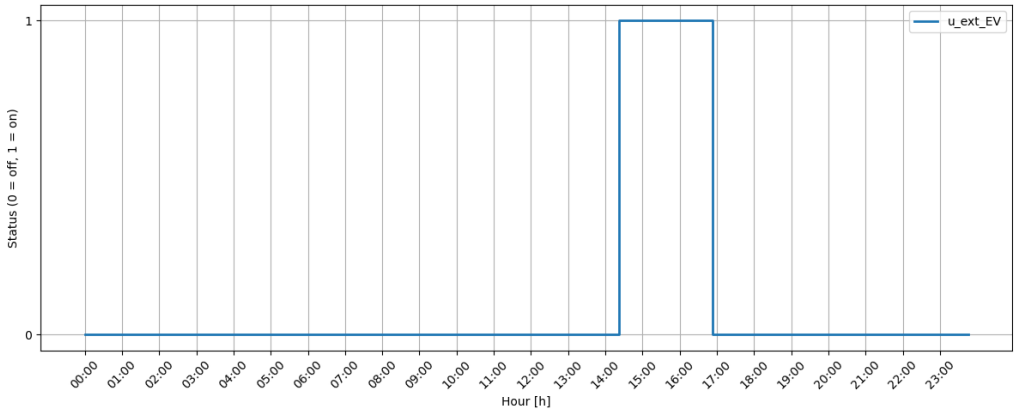

Figure 4.22: Activation of u_{ext} for external EV charging from the community.

Charging Source Distribution — The updated behavior is reflected in Figure 4.21. Across external participants, charging is mainly supplied by the external grid. Community energy ("Buy EC Ext.") appears only within the u_{ext} activation window representing a very small area of all market interactions in the chart. This pattern confirms that community energy is released to externals only in the permitted interval and in limited amounts, preserving internal priority.

Internal Protection and Trade-Offs — With reduced PV availability, the threshold policy delays and compresses access for external users into a single afternoon window, ensuring that internal EVs and household loads are not exposed to scarcity. The trade-off is a lower utilization of community energy

by externals and greater reliance on grid purchases during their charging sessions, but the approach maintains fairness and technical feasibility without relaxing the charging constraints.

4.4.2 Scenario B – Surplus of PV Generation

In this high generation scenario and with the demand profile unchanged relative to previous cases, the optimal threshold for external EV access is obtained from the 3D multi-criteria analysis in Figure 4.23, the red marker indicates the selected optimum at $x = 35\%$.

The position of this point reflects abundance rather than scarcity, internal community surplus usage remains near the maximum value for this scenario, with a total consumption of surplus of 166.37kWh. The surplus energy consumed by externals is substantial (68.89 kWh), and the surplus exported during external participants charging windows is comparatively low (12.35 kWh). A moderately low threshold therefore broadens access for external users while preserving internal headroom and curtailing exports during their charging periods.

Overall, the chosen setting leverages the extra PV to raise self-consumption and participation without affecting internal priority.

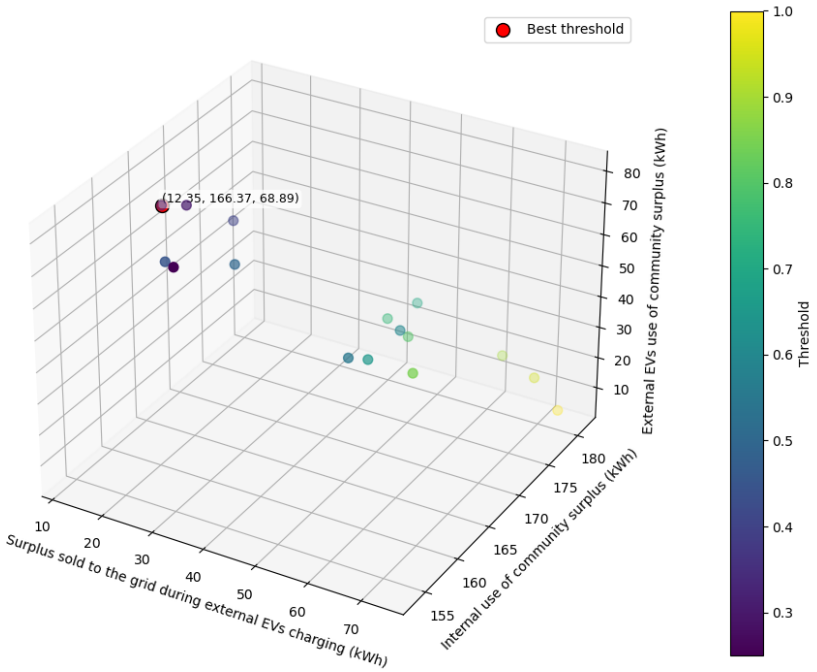

Figure 4.23: 3D multicriteria analysis; the red marker indicates the selected optimum at $x = 35\%$.

4.4.2.A Market Interactions and Grid Dependency

Figure 4.24 shows the energy exchange dynamics and price evolution for the community under the 120% PV scenario.

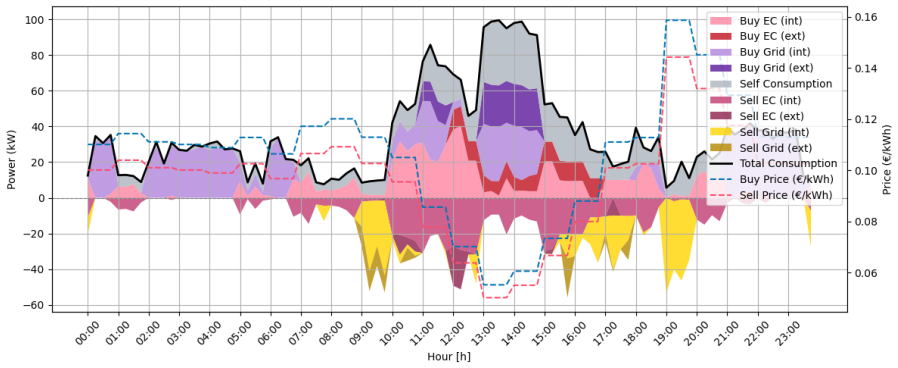

Figure 4.24: Community market interactions and energy price evolution throughout the day (Scenario B – 120% PV).

With higher PV availability, internal supply dominates a larger share of the day. From about 10:00 to 17:00 the stack shows strong self-consumption and local trades, with total internal supply approaching 40–60 kW near the midday plateau. As PV ramps in the morning (≈09:00–11:00) and again after 15:00, surplus appears and is either shared within the community ("Sell EC") or sold to the grid ("Sell Grid"), while internal demand is largely covered locally.

A notable difference relative to the baseline is the midday import block from roughly 13:00 to 15:00, where "Buy Grid" rises to meet the combined peak load, this aligns with the day's lowest purchase prices (blue dashed curve at ≈€0.05–0.06/kWh), showing the optimizer's price responsiveness. Before and after this trough, imports reduce and exports or local trades increase as PV and storage cover demand.

Grid purchases remain concentrated in the low-price early-morning window (≈02:00–07:00). During the evening price spike (≈18:30–19:30) imports are tempered by local trading and storage dispatch (visible as "Sell EC" and limited "Buy Grid"), with small imports resuming once prices fall later at night.

Overall grid energy purchased in Scenario B is 378.8 kWh, which is 37 kWh lower than in the normal generation scenario. This reduction is consistent with the larger midday self-consumption, the targeted midday imports at minimum prices, and the use of local energy sharing to buffer higher price hours.

4.4.2.B EV Operational Behavior under Abundant Generation

With PV at 120%, external EV charging remains feasible and all vehicles reach their target SoC. The higher generation reduces dependence on the grid and creates additional opportunities to allocate community energy to externals without penalizing internal priority.

Activation windows and u_{ext} logic — Figure 4.25 shows three authorized windows for external access, an early pulse around 08:00–09:00, a longer block from 12:00 to 17:00 and a small window from 17:15-18:00. These intervals track the PV ramp and afternoon plateau, i.e., precisely when internal headroom is maximized.

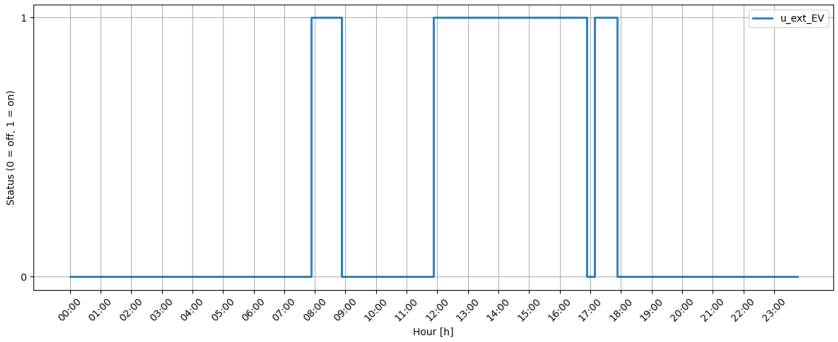

Figure 4.25: Activation of u_{ext} for external EV charging from the community (120% PV)

Charging source distribution — The purchasing profiles in Figure B.2 reveal a clear shift toward community energy within those windows. Participant 15 remains predominantly supplied by the grid, aside from a small morning intake during the first window. Participant 16 transitions from grid purchases late morning to a substantial community share in mid-afternoon. Participant 13 shows mixed sourcing across the long afternoon window, combining grid energy with community trades. Participant 16 shows the largest and most sustained "Buy EC" contribution during midday and early afternoon.

Implications — Relative to the limited generation case, abundant PV produces three effects: (i) a broader eligibility horizon for externals (three windows instead of two) and (ii) a higher share of community energy within those windows, particularly for Participants 14 and 16. The dispatch therefore preserves internal priority while using external EVs as an allocation for midday surplus, lowering exports and moderating grid purchases during the most favorable hours.

4.4.3 Scenario C – Zero Mid-Day Prices

With the demand profile unchanged relative to previous scenarios, the distinctive feature here is the price structure: buy and sell prices collapse to zero throughout most of the solar window (Figure 4.26). The objective is to assess how the optimizer reconfigures operations under these tariffs and whether the threshold policy remains stable when energy has no market value for several hours.

4.4.3.A Price Regime

Figure 4.26 shows a prolonged mid-day interval (approximately 11:00–18:30) in which both λ_{buy} and λ_{sell} approach zero. In such conditions, arbitrage incentives disappear, and the economically meaningful

decisions shift to, when to import at non-zero prices and how to allocate community PV generation between internal loads, storage, and external EVs.

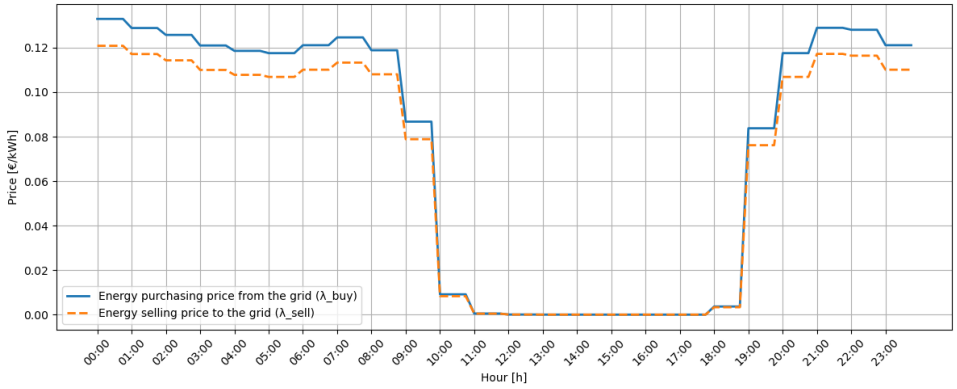

Figure 4.26: Energy purchase and sale prices — Scenario C (zero mid-day prices).

4.4.3.B Market Interactions and Grid Dependency

The resulting exchanges are depicted in Figure 4.27. During the zero-price period, the optimizer allows imports to occur (when needed) without cost penalty, while prioritizing self-consumption and community exchanges over exports, which yield no revenue. Stationary batteries are charged within this interval and held for later discharge in the evening ramp when λ_{buy} increases again. Early-morning imports are concentrated in the lowest positive price window, while evening purchases are guaranteed by stored energy and local flexibility. Overall grid dependency is marginally reduced compared with Scenario B, since low-price imports substitute for costly evening energy while maintaining high self-sufficiency levels.

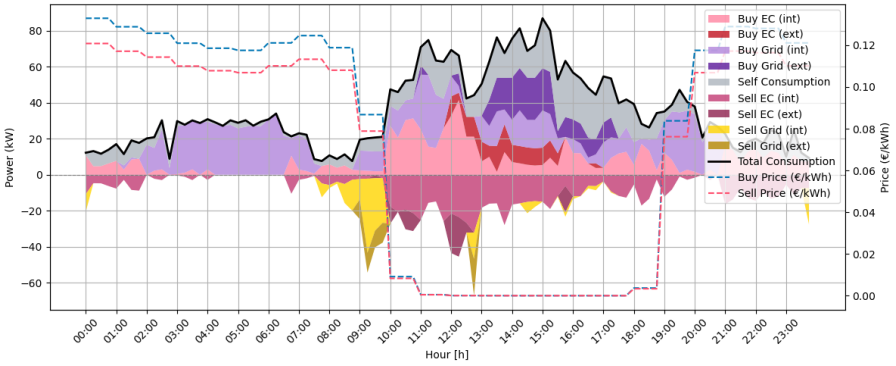

Figure 4.27: Community market interactions and price trajectory — Scenario C.

4.4.3.C Threshold Optimization

The three-dimensional analysis in Figure 4.28 shows the multi-criteria surface computed for different threshold levels. The selected optimum remains $x = 60\%$, identical to the one in section 4.3 case

despite the altered price structure. This stability indicates that once both buy and sell prices collapse to zero mid-day, the optimum is governed primarily by technical headroom and availability constraints (SoC limits, connection windows, and PV production envelope) rather than by absolute price levels. At $x = 60\%$, internal usage remains close to its upper bound, external participation remains significant, and exports during external charging periods are minimized.

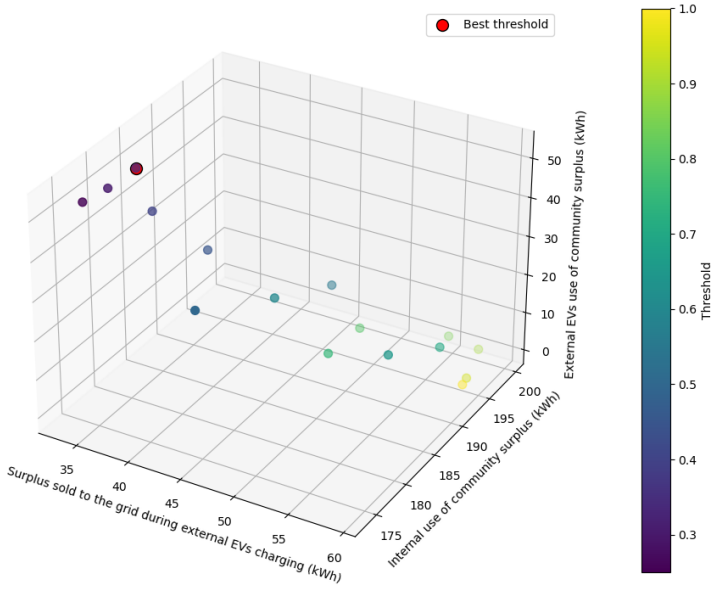

Figure 4.28: 3D multi-criteria analysis across thresholds — Scenario C; the red marker denotes the optimum at $x = 60\%$.

4.4.3.D Implications

When prices drop to zero in the middle of the day, the optimization behaves intuitively and in line with what would be expected from a rational energy manager. It naturally shifts charging and imports to those hours when electricity is free, avoids exporting energy that has no market value, and reserves stored energy for periods when prices rise again.

Interestingly, the externals access rule also proves remarkably stable: with the threshold at $x = 60\%$ continues to achieve a good balance between protecting internal members and allowing participation from external vehicles, even under such an extreme market condition.

From a broader design perspective, what truly shapes the system's performance is not the temporary price collapse itself, but how well external EV availability matches the solar generation peak and how much flexibility remains in internal SoC levels. In other words, ensuring that vehicles are connected during the PV production window and maintaining sufficient storage space have a far greater impact on community performance than the mid-day price depression alone.

5

Conclusion

Contents

Energy systems are shifting from centralized supply to community oriented coordination. The increasing penetration of DERs, particularly rooftop PV and the growing willingness of citizens to participate directly in local energy management motivate arrangements that respect community preferences while preserving technical feasibility. Among these, cVPPs optimize local generation, storage, and flexible demand to reduce cosEVs that may wish to charge using community energy. This dissertation assesses a cVPP design that admits external participants into the sharing process while protecting internal members' priority. The proposed mechanisms, an adaptive SoC access rule and a simple compensation term, in order to minimize community costs, align incentives, and improve operational flexibility without compromising physical feasibility.

5.1 Main Conclusions

This work simulated a cVPP first with twelve internal participants and later with four additional external participants. In the internal only case, each participant had a demand profile, a rooftop PV, some owned BESS and EVs. Energy was shared within the community, while imports and exports were settled at market buy and sell prices. The model shifted EV charging, when feasible, toward hours with higher PV production or lower market prices, and scheduled battery discharge during price peaks or when PV was unavailable. Overall, the formulation behaved consistently and delivered an average energy cost for members that was markedly below the minimum market price observed over the horizon.

In the second stage, four external EVs were introduced together with the corresponding constraints. Charging windows with different characteristics were selected to test behavior across the day, and one external EV was deliberately kept connected during almost all daylight hours to assess potential contribution dischaging energia using V2G technology. Results remained positive: energy management continued to respond to price and availability signals, and external EVs began drawing from the community only after all internal members had reached the required SoC threshold, confirming correct enforcement of the priority rules. This inclusion was beneficial for both groups: internal members experienced a reduction in unit energy cost relative to the internal only case, and external users paid a unit cost below the minimum market price prevailing during their charging windows, making community charging preferable to grid-only charging.

A further robustness check prohibited any external discharge. In that setting, external users compensated the community for the energy they consumed. The advantages for both groups persisted: the internal unit energy cost remained low and essentially unchanged relative to the case with external discharging, while the external unit cost increased compared with that case but still stayed below the average market price over the same charging periods. Connecting to the community therefore remained economically benefitial for external users.

Finally, sensitivity analyses were performed to assess robustness under production shortages, production surpluses, and a case with zero prices during daylight hours. Under shortage, external EVs were admitted to charge later than in the normal scenario, confirming that internal priority is kept when energy is scarce. Under surpluses, external users gained earlier access to community energy, following the same logic in the opposite direction. In the zero-daytime-price case, the model behaved appropriately by reducing exports to the grid, since the selling price was zero, and conserving energy whenever possible.

Overall, this work shows that a cVPP can admit external EVs without penalizing internal members welfare by combining an adaptive, SoC, based priority with a simple compensation rule. These mechanisms align external demand with surplus periods, preserve low unit energy costs for members, and maintain physically consistent dispatch, while relying only on quantities that operators can observe or forecast. The formulation proved robust across production shortages and surpluses, and even under zero daytime prices, indicating practical readiness for pilot deployment. The natural next step is to validate the approach under forecast uncertainty and distribution network constraints, so that the modeled gains translate into dependable day-to-day practice in live energy communities.

5.2 Future Work

Building on these results, several extensions are natural. First, uncertainty should be incorporated through stochastic or rolling-horizon clearing so that variability in PV generation, loads, and EV arrivals is addressed explicitly. This will quantify the value of flexibility and test the resilience of the adaptive threshold under imperfect foresight. Second, market decisions should be coupled with network-feasible dispatch, either by co-optimizing with power-flow constraints or by calibrating fees and penalties against validated AC checks, ensuring that price and priority signals remain compatible with voltage and line limits. Third, the design of visitor pricing and compensation can be incorporated under welfare and participation constraints to formalize fairness while preserving efficiency. Incorporating battery and EV degradation costs and user elasticities will better capture long-run cycling and behavioral response. Finally, a field pilot in a live energy community, scaling beyond twelve participants, would allow assessment of cost savings, welfare distribution, participant acceptance, and solver performance under real telemetry and forecasting conditions, and would validate the adaptive threshold and compensation rules in operation.

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A

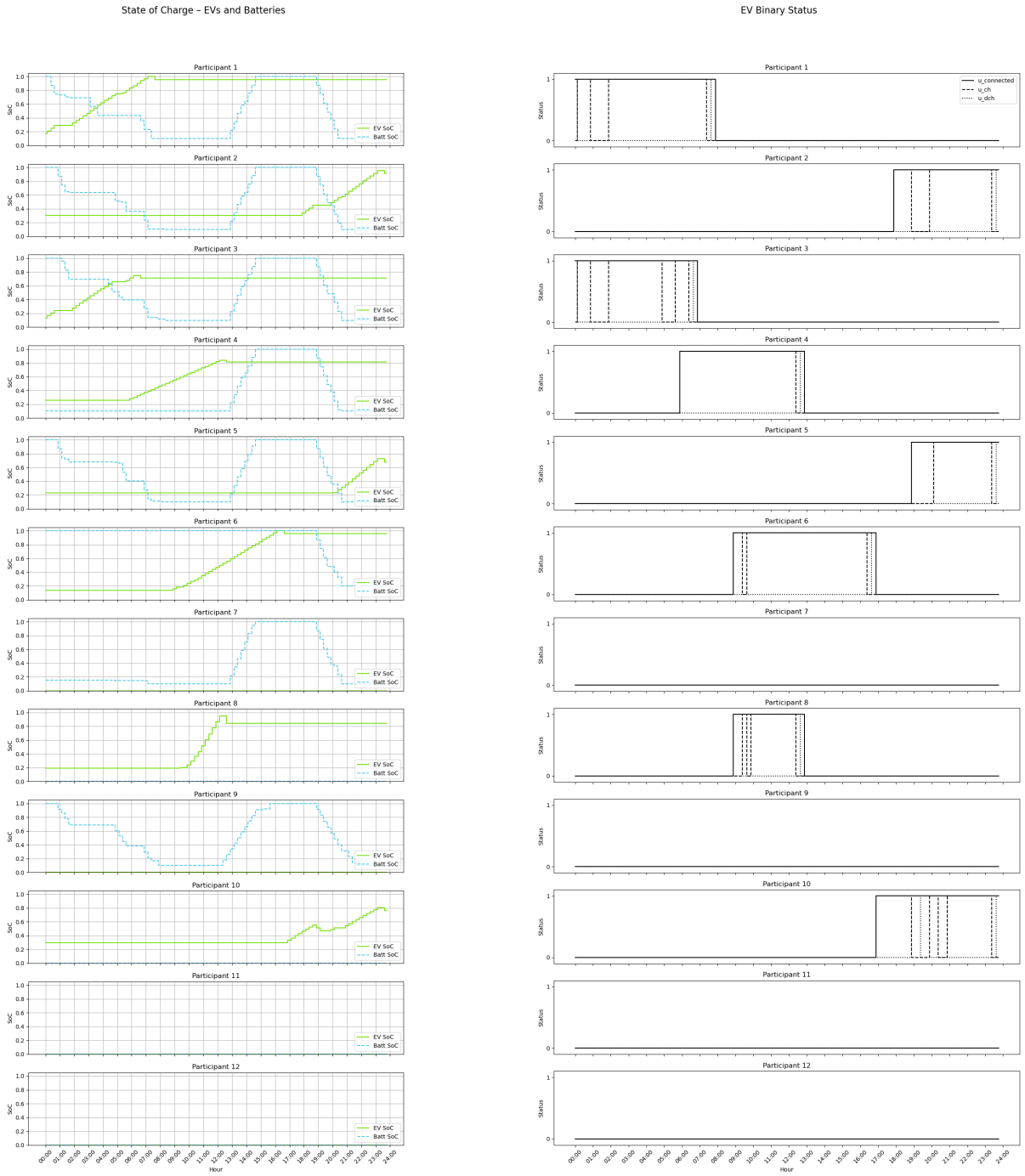
Appendix A

User ID	Electric Vehicle Model
1	VW ID.3 Pro (58 kWh)
2	Peugeot e-208 (MY24)
3	Tesla Model 3 LR (EU)
4	Nissan Leaf 40
5	Kia Niro EV (64.8 kWh)
6	Tesla Model Y LR (EU)
8	Renault Zoe ZE50
10	Mercedes EQA 250

Table A.1: Mapping between participant IDs and corresponding EV models.

B

Appendix B



((a)) State of Charge (SoC) of EVs and batteries.

((b)) EV status: connected, charging, discharging.

Figure B.1: Behavior and operational status of flexible storage systems.

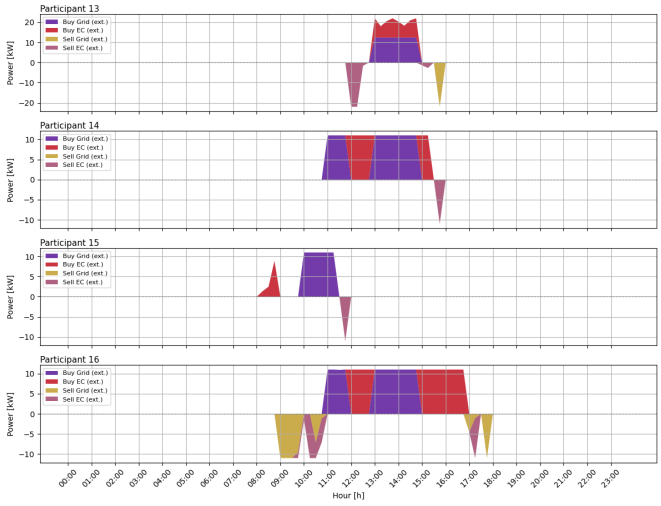


Figure B.2: Charging sources for external EVs (grid vs. community) — Participants 13–16, 120% PV.