# The Cost of Ignoring Uncertainty: How Stochastic Optimization Enhances Modelling of Energy Communities' Outcomes

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# DECLARATION

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

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# Abstract

The increasing complexity of modern energy markets, driven by the transition to renewable energy sources and the rise of decentralized energy production, requires innovative approaches to modelling and optimizing energy communities. This thesis aims to investigate how uncertainties in load, solar generation, and electricity prices influence the outputs of peer-to-peer (P2P) energy communities.

A centralized optimization model for a P2P energy community was developed, capturing the interactions between multiple consumers, prosumers, and shared storage systems within a community-based trading network. Using real-world data from Portugal, five optimization approaches were implemented, accounting for uncertainty and attitude towards risk: deterministic optimization with a single average scenario and with multiple scenarios, stochastic optimization, least regret, and robust optimization.

The findings demonstrate that incorporating uncertainty into optimization models significantly enhances operational robustness and economic performance. Stochastic methods provide greater confidence in consistently attaining higher positive welfare outcomes, particularly in high-uncertainty scenarios. Expected welfare gains from stochastic methods can reach approximately 6 times higher than deterministic approaches in winter scenarios, underscoring the essential role of uncertainty modelling for resilient energy communities. Each method exhibited distinct trade-offs between performance and reliability, offering practical insights for selecting optimization strategies tailored to the specific objectives of each energy community.

The results provide evidence-based guidance for energy community modelling and policymakers, emphasizing the critical importance of uncertainty modelling for sustainable and economically efficient energy communities.

**Key-words**: Energy Communities; Uncertainty Modelling; P2P Markets; Stochastic Optimization; Load Flexibility; Clustering.

# Resumo

A crescente complexidade dos mercados energéticos modernos, impulsionada pela transição para fontes de energia renováveis e pelo aumento da produção descentralizada de energia, exige abordagens inovadoras para modelizar e otimizar comunidades de energia. Este trabalho analisa a influência das incertezas no consumo, produção solar e preços da eletricidade nos resultados das comunidades de energia *peer-to-peer* (P2P).

Desenvolveu-se um modelo de otimização centralizado para uma comunidade de energia P2P, capturando interações entre múltiplos consumidores, *prosumers* e sistemas de armazenamento partilhados. Utilizando dados reais de Portugal, implementaram-se cinco abordagens de otimização, considerando a incerteza e atitude em relação ao risco: otimização determinística com um cenário médio e com múltiplos cenários, otimização estocástica, menor arrependimento e otimização robusta.

Os resultados demonstram que incorporar incerteza na otimização aumenta significativamente a robustez operacional e o desempenho económico. Os métodos estocásticos aumentam a confiança na obtenção de resultados positivos de bem-estar, particularmente em cenários de elevada incerteza. No inverno, os métodos estocásticos proporcionam ganhos de bem-estar aproximadamente seis vezes superiores aos obtidos com abordagens determinísticas, sublinhando o papel essencial da modelação de incertezas para comunidades de energia resilientes. Cada método revelou compromissos distintos entre desempenho e fiabilidade, proporcionando contributos relevantes na escolha de estratégias de otimização alinhadas com os objetivos de cada comunidade.

Os resultados fornecem orientações para a modelação de comunidades de energia e para os decisores políticos, salientando a importância crítica da modelação da incerteza para comunidades sustentáveis e economicamente eficientes.



**Palavras-chave**: Comunidades de Energia; Modelação da Incerteza; Mercados P2P; Otimização Estocástica; Flexibilidade de Carga; *Clustering*.

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# List of Acronyms and Abbreviations

| | |
|---|---|
| AMS | Average of Multiple Scenarios |
| AS | Average Scenario |
| BESS | Battery Energy Storage System |
| CCO | Chance-Constrained Optimization |
| CEP | Clean Energy for all Europeans Package |
| $CO_2$ | Carbon Dioxide |
| CV | Coefficient of Variation (%) |
| DER | Distributed Energy Resources |
| DLS | Degree of Local Sufficiency |
| DO | Deterministic Optimization |
| DRO | Distributionally Robust Optimization |
| DS | Demand Shifting |
| EC | Energy Community |
| ERSE | Entidade Reguladora dos Serviços Energéticos (Portuguese Energy Services Regulatory Authority) |
| EVES | Expected Value of the Expected Solution |
| EVLRS | Expected Value of the Least Regret Solution |
| EVPI | Expected Value of Perfect Information |
| EVRS | Expected Value of the Robust Solution |
| EVP | Expected Value Problem |
| EVSS | Expected Value of the Stochastic Solution |
| EVWMS | Expected Value of the Weighted Mean Solution |
| GHG | Greenhouse Gases |
| GT | Game-Theory |
| KPI | Key Performance Indicator |
| LEM | Local Energy Market |
| LR | Least Regret |
| MIBEL | Electricity Iberian Market |
| MILP | Mixed Integer Linear Programming |
| MMT | Matching Markets Theory |

| | |
|---|---|
| OMIP | Operador do Mercado Ibérico de Energia (Iberian Energy Market Operator) |
| P2P | Peer-to-Peer |
| PLR | Peak Load Reduction |
| PoR | Price of Robustness |
| PV | Photovoltaic |
| PVGIS | Photovoltaic Geographical Information System |
| QP | Quadratic Programming |
| RES | Renewable Energy Sources |
| RO | Robust Optimization |
| RV | Regret Value |
| SCR | Self-Consumption Ratio |
| SIV | Stochastic Integration Value |
| SO | Stochastic Optimization |
| SOC | State of Charge |
| SSR | Self-Sufficiency Ratio |
| VSS | Value of Stochastic Solution |
| WCSS | Within-Cluster Sum of Squared Errors |
| WSV | Wait-and-See Value |

# Nomenclature

### Indices and Sets

| | |
|---|---|
| $t \in T = \{0,1, \dots, 23\}$ | Set of hourly time periods in a day |
| $j \in C = \{0,1, \dots, N_C\}$ | Set of consumers, where 0 represents the grid |
| $i \in P = \{0,1, \dots, N_P\}$ | Set of prosumers, where 0 represents the grid |
| $k \in B = \{0,1, \dots, N_B\}$ | Set of batteries |
| $\mathrm{s} \in \mathrm{S} = \{0,1, \dots, N_S\}$ | Set of scenarios |

### Parameters

| | |
|---|---|
| $a_{j,t}$ | Utility function coefficient (intercept) for consumer $j$ at time $t$ (€/kWh) |
| $b_{j,t}$ | Utility function coefficient (slope) for consumer $j$ at time $t$ (€/kWh²) |
| $c_{i,t}$ | Cost function coefficient (intercept) for producer $i$ at time $t$ (€/kWh) |
| $d_{i,t}$ | Cost function coefficient (slope) for producer $i$ at time $t$ (€/kWh²) |
| $prob_s$ | Probability of scenario $s$ |
| $P_{reg}$ | Regulated electricity price (€/kWh) |
| $p_t^{OMIP}$ | Wholesale market price at time $t$ (€/kWh) |
| $y_{j,t}^{historical}$ | Historical consumption of consumer $j$ at time $t$ (kWh) |
| $\mathrm{y}_{j,t}^{self-consumption}$ | Self-consumed energy by prosumer $j$ at time $t$ (kWh) |
| $\eta_{\text{charge}}$ | Charging efficiency of battery (%) |
| $\eta_{\text{discharge}}$ | Discharging efficiency of battery (%) |
| $B^{capacity}$ | Battery capacity (kWh) |
| $B^{max\_charge}$ | Maximum battery charge (kW) |
| $B^{max\_discharge}$ | Maximum battery discharge (kW) |
| $\omega$ | Penalty factor for flexibility deviations |
| $E_p$ | Price elasticity of demand |

**Variables**

| | |
|---|---|
| $x_{i,t}$ | Energy sold by producer (grid or prosumer) $i$ at time $t$ (kWh) |
| $y_{j,t}$ | Energy purchased by consumer $j$ at time $t$ (kWh) |
| $\delta_{s,j,t}$ | Flexibility deviation for consumer $j$ at time $t$ in scenario $s$ (kWh) |
| $b_{k,t}^{charge}$ | Charge amount of battery $k$ at time $t$ (kW) |
| $b_{k,t}^{discharge}$ | Discharge amount of battery $k$ at time $t$ (kW) |
| $b_{k,t}^{soc}$ | State of charge of battery $k$ at time $t$ (kWh) |
| $p_t$ | Market clearing price at time $t$ (€/kWh) |
| $\lambda_t$ | Dual variable of energy balance constraint at time $t$ (€/kWh) |
| $z$ | Auxiliary variable for robust optimization |

**Functions**

| | |
|---|---|
| $U(y_{j,t})$ | Utility function for consumer $j$ at time $t$ (€) |
| $C(x_{i,t})$ | Cost function for producer $i$ at time $t$ (€) |
| $welfare(s)$ | Welfare for scenario $s$ (€) |
| $regret(s)$ | Regret for scenario $s$ (€) |
| $Penalty(\delta)$ | Penalty function for flexibility deviations (€) |

**Performance Metrics**

| | |
|---|---|
| $SSR$ | Self-Sufficiency Ratio (%) |
| $\Delta C$ | Energy cost saving (€) |
| $PLR$ | Peak Load Reduction (%) |
| $DS$ | Demand Shifting (%) |
| $\Delta CO_2$ | $CO_2$ emissions reduction ($tCO_2e$) |

# 1. Introduction

## 1.1 Context and Motivation

The global push for decarbonization and the energy transition, has driven initiatives like the Clean Energy for all Europeans Package (CEP), which aims to reduce greenhouse gas (GHG) emissions by more than half by 2030, and promote renewable energy adoption, namely by achieving carbon neutrality by 2050. This comprehensive legislative framework, published in 2019, comprises eight acts focused on energy performance of buildings, renewable energy, energy efficiency, governance, and electricity market design [1].

Pointed as critical to this energy transition is the emergence of Energy Communities (ECs), which have evolved from isolated initiatives into significant contributors to Europe's clean energy landscape. The CEP officially recognizes and reinforces the central role that citizens and communities can and must play in the energy transition by actively participating in the energy market, with energy poverty considerations embedded in many of its legislative acts.

ECs are groups of stakeholders, individuals or organizations, who collaborate to collectively produce, consume, and manage their own energy in a decentralized manner [2]. These communities can consist of different participants, like households, businesses, and even local authorities, working together to share and optimize energy resources. Their main goals often focus on optimizing renewable energy production and consumption, reducing greenhouse gas emissions, pursuing energy independence and security, and creating economic and social benefits for their members [3].

Although the exact definition of an ECs may vary, these entities aim to provide environmental, economic, or social benefits to the community, with a focus on empowering citizens rather than maximizing profit, while enabling citizens to participate collectively in the energy system [4].

In these markets, prosumers - a term used to describe individuals able to generate and/or store energy - can directly exchange energy with each other. This local trading system creates a consumer-centric approach where members of the community have more control over their energy choices, fostering collaboration and enhancing community resilience.

In this decentralization trend, local electricity markets (LEM) have emerged, offering an alternative to the traditional centralized wholesale and retail models [2]. An example of a commonly adopted LEM is the peer-to-peer (P2P) market, a model where prosumers can directly exchange energy with each other, fostering a consumer-centric and bottom-up approach that empowers consumers to select their preferred energy sources and manage the energy system collaboratively [5].

This structure not only provides economic benefits but also facilitates the integration of renewable energy sources (RES), which are often intermittent. By trading surplus renewable energy within the community, P2P markets help optimize local energy use and minimize reliance on external sources. They also offer a platform where the excess renewable energy generation can be sold to other participants, which constitutes an incentive for energy conservation and the adoption of energy-efficient technologies, enabling consumers without distributed energy resources (DER) to participate in low-cost energy trading [6].

The integration of P2P markets within ECs presents opportunities and challenges. While these markets empower consumers, stabilize energy prices, and promote renewable energy adoption, they also bring complexity in terms of regulation, technical infrastructure, and energy flow management. Effective coordination is essential to ensure these markets operate efficiently while meeting the energy needs of the community.

In this context, P2P markets are just one of several market models that an EC might implement. Some may focus on collective self-consumption, where members prioritize the local use of energy generated within the community. Others, like those engaging in P2P markets, encourage active trading of energy among participants. Both approaches allow for a more flexible and decentralized energy system, but P2P markets offer greater autonomy and innovation in managing energy flows. While various pilot projects are currently underway worldwide to assess P2P market models, further research is needed to effectively implement P2P sharing models in the electricity market and deliver the promised benefits. Ongoing research explores integrating P2P markets with existing wholesale and retail markets, enabling consumer flexibility, exploring the involvement of system operators in P2P markets, and ensuring reliable power systems through distributed reserve supply and improved negotiation processes [6].

### 1.1.1 Uncertainties affecting Energy Communities

The success of ECs is strongly influenced by system configuration, component sizing, and operational strategies. Well-designed systems can achieve significant reductions in operational costs and GHG emissions [7]. Additionally, the chosen LEM model and the surrounding regulatory framework play crucial roles in determining the long-term viability of the community [8].

A major challenge facing ECs is the inherent uncertainty present in energy systems. Many existing models assume perfect knowledge of key parameters, yet these parameters exhibit significant variability in real-world conditions. Solar power generation depends directly on weather conditions, while consumer demand fluctuates due to behavioural and contextual factors. Similarly, electricity prices can vary considerably based on market dynamics and regulatory changes. Therefore, accounting for these uncertainties is critical to accurately assess the performance and robustness of ECs.

These uncertainties may stem from diverse sources, including technical and operational variability, economic and regulatory shifts, and environmental or social influences. For instance, technical uncertainties may involve fluctuations in DER availability, which can compromise system stability and energy balance [8], [9]. Similarly, economic and regulatory uncertainties such as changes in market rules, tariffs, or incentive structures can affect financial performance and investment attractiveness [10]. Environmental events like storms or heatwaves, and social dynamics like shifting attitudes toward renewable energy, can also introduce unpredictability into system planning and operation [9]. Ignoring these factors can lead to suboptimal decisions that jeopardize the community’s goals.

## 1.2 Research Hypothesis and Objectives

The performance and outputs of ECs can vary considerably depending on several structural and operational characteristics, such as the number and type of participants, the availability of solar resources, and the specific energy market model adopted. Despite this inherent variability, many existing models in the literature assume perfect foresight, relying on deterministic data for key parameters such as energy demand, solar generation, and market prices. This simplification does not account for uncertainties, which are inherent in real-world energy systems. If these uncertainties are not properly identified and handled, the actual economic and operational performance of the designed distributed energy system may deviate from the optimal predictions. Understanding and quantifying the impact of uncertainty is critical for the successful design and operation of ECs. As such, the research question of this work can be defined as:

*To what extent do uncertainties on load, solar generation and electricity prices influence the outcomes of P2P energy communities?*

This work investigates the implications of relaxing the perfect-information assumption by explicitly incorporating uncertainty into EC' modelling. Specifically, it analyses how uncertainties in load demand, solar production, and electricity price mechanisms affect the performance of a P2P EC market. Different optimization approaches, including deterministic and stochastic models, are employed to evaluate the influence of uncertainty on optimal decisions of community agents. This study examines these effects through multiple analyses, including economic welfare, decision variables, and performance metrics, offering a holistic perspective on the implications and highlighting the value of uncertainty-model methodologies in P2P EC planning and operation.

The specific objectives of this research are to:

- Design, dimension and model a P2P energy community model that accounts for uncertainties in different parameters;
- Conduct a deterministic analysis followed by incorporation of uncertainties into the model with different techniques (e.g., stochastic optimization);
- Assess the impact of different sources of uncertainty and modelling strategies in economic, technical, and environmental outcomes of communities.

## 1.3 Structure

This thesis is organized into five chapters. Following this Introduction section, Chapter 2 reviews literature on P2P energy markets, EC modelling, and uncertainty handling techniques, identifying the research gap this work addresses. Chapter 3 details the methodology, including data processing, community modelling, and optimization formulations. Chapter 4 analyses results obtained across different optimization approaches for different seasonal scenarios, focusing on their performance under uncertainty. Finally, Chapter 5 summarizes the key findings and their implications, also outlining potential directions for future research.

# 2. Literature Review

The growing interest in EC has encouraged numerous studies exploring their potential benefits, challenges, and opportunities. EC have shown to enhance renewable energy generation, improve energy efficiency, and create social and economic value for its members. However, realizing these benefits requires addressing several key challenges, including regulatory and policy barriers, technical and operational difficulties, and securing adequate financing and support.

Research into EC often focuses on technical aspects such as the integration of DER or energy storage management ([11]). Additionally, economic and regulatory analyses have examined the role of policy incentives, the development of sustainable business models, and the impact of EC on traditional energy markets. A particular area of focus in this context is the LEM design, where EC can adopt different models depending on the specific objectives and structure ([12], [13], [14]).

## 2.1 Energy Communities

One possible LEM is P2P markets, which have gained momentum due to the emergence of DER, such as solar panels and storage equipment, as well as advancements in information and communication technology (ICT) [15]. In this context, three primary P2P market types are identified in the literature: full P2P, community-based markets, and hybrid markets [2]. Full P2P markets involve direct energy trading between peers without centralized oversight. Community-based markets are more structured, with a community manager coordinating transactions, making them suitable for microgrids. Hybrid markets allow for a combination of these approaches, offering scalability and flexibility in energy trading. Each of these market types offers its own set of advantages and disadvantages, and the most appropriate type may depend on the specific needs and goals of the market participants. This classification is presented in the “Market Type” column of Table 1, which offers an overview of the market models adopted in the 72 studies reviewed for this work.

In general, P2P energy markets offer significant advantages across the energy ecosystem. For grid operations, these markets enhance localized network performance through improved voltage management and capacity utilization, while reducing peak demand to potentially defer infrastructure investments and providing flexibility for emerging electrification demands [16]. Simultaneously, DER owners benefit economically through reduced energy costs and revenue generation from surplus energy, while gaining opportunities to participate in clean energy distribution, strengthen community relationships, and achieve meaningful autonomy in energy management [17].

While the benefits of P2P markets provide the foundation for understanding EC, examining how these structures are mathematically modelled offers deeper insights into their operational dynamics and decision-making frameworks.

## 2.2 EC Modelling with Utility and Cost Functions

A significant share of literature on EC adopts optimization-based approaches, where utility or cost functions are explicitly defined to guide decision-making. However, this represents only a subset of the broader EC research landscape, as many studies pursue alternative methodologies that do not rely on such functions. Despite this methodological diversity, the present review focuses specifically on models that formulate utility and/or cost functions, forming the foundation for the centralized optimization framework developed in this study. A full list of the 72 reviewed papers is provided in the Table 1.

This review reveals that these works typically aim to maximize social welfare, maximize individual or collective profits, or minimize operational costs. Within this subset, a variety of optimization frameworks are applied, with deterministic methods (DO) dominating the landscape (76%), while stochastic (SO) and robust (RO) approaches remain considerably less common. Recent studies have demonstrated the effectiveness of optimization-based approaches in modelling P2P energy communities. Deterministic optimization methods have been widely adopted, with quadratic utility functions commonly used to represent consumer preferences and market behaviours, explicitly defined to guide decision-making [17]. For instance, Khorasany et al. [18] employed quadratic utility functions to model decentralized bilateral energy trading systems, while Seyfi et al. [19] utilized quadratic formulations for prosumer demand response programs. Similarly, Paudel et al. [20] and Moradi et al. [21] implemented optimization frameworks with quadratic utility functions to analyse peer-to-peer energy trading considering network constraints.

Notably, 39% of the studies incorporate game-theoretic (GT) elements to capture strategic interactions among agents (such as prosumers or aggregators) particularly in decentralized or non-cooperative settings. Additionally, 18% of the studies explore market-based coordination mechanisms (MMT), including auctions and peer-to-peer trading systems.

However, these deterministic approaches often assume perfect foresight of key parameters such as energy demand, solar generation, and market prices, which may not reflect real-world uncertainties. While studies like Sun et al. [22], Chen et al. [23], and Sadati et al. [24] demonstrate sophisticated optimization frameworks, they predominantly rely on deterministic assumptions. This gap is particularly significant given that energy communities face substantial uncertainties in demand patterns, renewable generation, and electricity prices.

Although optimization-based approaches using utility and cost functions are widely used in the literature, the effectiveness of these models depends critically on how they address the inherent uncertainties in energy systems.

## 2.3 Uncertainty Modelling

To model and optimize P2P energy communities effectively, uncertainties must be explicitly integrated into the decision-making framework. The literature offers several methodologies for handling uncertainty in energy systems, with the aim to improve their operational resilience and adaptability, ensuring continued performance even when conditions deviate from expectations.

The literature reviewed in Table **1** reveals that uncertainty is typically addressed through stochastic or robust optimization techniques, but such approaches appear in only a minority of studies. Stochastic optimization (SO) appears in just 14% of papers, most based on expected value optimization, seeking to maximize performance under average conditions. Similarly, chance-constrained optimization (CCO) is used in only 8% of the papers to ensure constraint satisfaction with high probability. Robust optimization (RO), which emphasizes resilience by guaranteeing feasibility under worst-case scenarios, is found in merely 8% of papers. More flexible extensions, such as distributionally robust optimization (DRO), addressing ambiguity in probability distributions, appear in just 3% of the papers.

Examining specific applications of these uncertainty approaches reveals their diverse implementations in energy community contexts. For instance, Niromandfam et al. ([25], [26]) applied stochastic optimization to model demand response considering wind profit maximization under uncertain renewable generation. Mohan et al. [27] employed stochastic programming for realistic energy commitments in P2P markets with risk-adjusted prosumer welfare maximization. In the robust optimization domain, Xia et al. [28] developed a robust framework for P2P energy trading that preserves operation privacy while handling uncertain distributed energy resources. Mehdinejad et al. [29] designed robust decentralized energy transaction frameworks for active prosumers in local electricity markets. Regarding chance-constrained approaches, Guo et al. [30] implemented chance-constrained peer-to-peer joint energy and reserve markets considering renewable generation uncertainty, while Xia et al. [31] utilized CCO for P2P energy trading in ancillary service markets.

A key limitation in the current literature is that most papers address uncertainty in only one or two variables (typically demand or generation) with only about 10% of the papers accounting for all three critical dimensions: energy supply, demand, and market prices simultaneously. This represents a significant gap, as real-world energy communities face uncertainty across all these dimensions concurrently.

Additionally, based on the comprehensive analysis presented in Table **1**, which details the mathematical models, decision variables, utility functions, market types and uncertainty modelling approaches across the reviewed literature, the decision space considered in most studies is narrower than required for comprehensive modelling. A complete analysis should include local PV generation, electricity load, demand response and load shifting, peer-to-peer trading volumes, and the full operation of battery energy storage systems (BESS), including charging and discharging decisions, with dynamic price signals modelled through demand and supply curves. Such a comprehensive scope is necessary to capture the multi-dimensional flexibility and interdependencies inherent to EC under uncertainty.

Table 1: Studies modelling EC through utility and/or cost functions.

| Reference | Year | Resources | | | | | | Optimization Method | Game Theory, Matching Markets Theory | Uncertainty | | | | | | Objective Function | | | | Decision Variables | | | | | | | | Utility Function<br>Quadratic = quad<br>Logarithmic = log<br>Exponential = exp | Cost Function | Market Type | | | Data | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | DER/RES | PV | Wind | Conventional | Storage | DSM/DR | | | Supply | Demand | Price | No Uncertainty | Scen. Optimization | Scenarios Testing | Max(Welfare) | Max(Utility) | Min(Cost) | Max(Profit) | Trading | Generation | Consumption | Storage | Pricing | DSM/DR | Grid Exports | Grid Imports | | | Community | Full P2P | Hybrid | Real observations | Simulated | Test system |
| [32] | 2010 | √ | | | √ | | √ | DO | | | | | √ | | | √ | | | | | √ | √ | | √ | √ | | √ | quad | quad | | √ | | | √ | |
| [33] | 2014 | | | | | | √ | DO | | | | | √ | | √ | √ | √ | √ | | | | √ | | √ | | | √ | log | quad | | √ | | | √ | |
| [34] | 2014 | √ | | | √ | | √ | DO | | | | | √ | | | √ | | | | | √ | √ | | √ | √ | | √ | quad | quad | | √ | | | | √ |
| [35] | 2015 | | | | | | √ | DO | | | | | √ | | | √ | | | | √ | √ | √ | | √ | √ | | √ | quad | quad | | √ | | | √ | |
| [36] | 2016 | √ | | | | | | DO | | | | | √ | | | √ | | | | √ | √ | √ | | √ | | | | quad | quad | √ | √ | | | √ | |
| [37] | 2016 | √ | | | √ | | √ | DO | | | | | √ | | | √ | | | | √ | √ | √ | | √ | √ | | | quad, linear, log | quad | | √ | | | √ | √ |
| [38] | 2017 | √ | | | √ | | √ | DO | | | | | √ | | √ | √ | √ | √ | | | √ | √ | | √ | √ | | | quad | quad | | | √ | | √ | √ |
| [39] | 2017 | | | | √ | | √ | DO | | | | | √ | | | √ | | | | √ | √ | √ | | √ | √ | | | quad | quad | | √ | | | √ | √ |
| [40] | 2017 | √ | | | | | √ | DO | | | | | √ | | | √ | | | | √ | √ | √ | | √ | √ | | | quad | quad | | | √ | | √ | √ |
| [41] | 2017 | √ | | | | | | DO | | | | | √ | | √ | √ | | | | √ | | √ | | √ | | | √ | quad | quad | | √ | | | √ | √ |
| [42] | 2018 | √ | | √ | √ | | √ | DO | | | | | √ | | | √ | | √ | | | √ | √ | | | √ | | √ | quad | quad | √ | | | √ | | |
| [20] | 2020 | | | | √ | | √ | DO | | | | | √ | | √ | √ | | | | √ | √ | √ | | √ | √ | | | quad | quad | | √ | | | √ | √ |
| [18] | 2020 | √ | √ | √ | √ | √ | √ | DO | | | | | √ | | √ | √ | | | | √ | √ | √ | | √ | √ | √ | √ | quad | quad | | √ | | | √ | √ |
| [19] | 2021 | √ | | | | | √ | DO | | | | | √ | | | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | quad | quad | | √ | | | √ | √ |
| [43] | 2022 | | | | | | √ | DO | | | | | √ | | √ | | √ | | √ | | | √ | | √ | √ | | √ | quad, log, exp | no cost | √ | | | √ | | |
| [22] | 2022 | √ | √ | | | √ | √ | DO | | | | | √ | | √ | | | | √ | | | √ | | √ | √ | | √ | exp | linear | √ | | | √ | | |
| [44] | 2023 | | | | | | | DO | | | | | √ | | √ | √ | | | | √ | | √ | | √ | | | | quad | quad | | √ | | | √ | |
| [45] | 2023 | √ | √ | √ | √ | √ | √ | DO | | | | | √ | | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad, linear | | √ | √ | √ | √ | |
| [23] | 2023 | √ | √ | √ | √ | √ | √ | DO | | | | | √ | | | √ | | √ | | √ | √ | √ | | √ | | | | quad | quad | √ | √ | √ | | √ | √ |
| [46] | 2023 | √ | √ | | √ | | | DO | | | | | √ | | √ | √ | | | | √ | | | | √ | | √ | √ | quad | quad | | | √ | | | √ |
| [24] | 2023 | √ | | | | √ | √ | DO | | | | | √ | | | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | quad | quad | | √ | | | √ | |
| [47] | 2024 | √ | √ | | | √ | √ | DO | | | | | √ | | | √ | √ | √ | | √ | √ | √ | √ | √ | √ | √ | √ | quad | linear | | √ | | | √ | √ |
| [48] | 2024 | | | | | | √ | DO | | | | | √ | | √ | | √ | | | | | √ | | √ | √ | | √ | power | linear | √ | | | | | √ |
| [49] | 2024 | √ | √ | | | | √ | DO | | | | | √ | | √ | √ | √ | √ | √ | √ | √ | √ | | √ | √ | | √ | linear | linear | | √ | | √ | √ | √ |
| [50] | 2024 | √ | | √ | √ | | √ | DO | | | | | √ | | √ | | | √ | | √ | √ | √ | | | √ | | | quad | quad | | √ | | √ | | √ |
| [51] | 2024 | √ | √ | | | √ | | DO | | | | | √ | | √ | √ | | | | √ | √ | √ | | √ | | √ | √ | quad | quad | | √ | | | √ | √ |
| [52] | 2012 | | | | √ | | √ | DO | GT, MMT | | | | √ | | | √ | | | | | √ | √ | | √ | √ | | √ | quad | quad | √ | | | | √ | |
| [53] | 2013 | | | | √ | | √ | DO | GT | | | | √ | | √ | √ | √ | | √ | | √ | √ | | √ | √ | | | quad | quad | √ | | √ | √ | √ | |
| [54] | 2014 | √ | | | √ | | √ | DO | GT | | | | √ | | | | √ | | √ | √ | √ | √ | | √ | √ | | √ | quad | quad | | √ | | | √ | |
| [55] | 2014 | √ | | | | √ | | DO | GT, MMT | | | | √ | | | | √ | | √ | √ | | | √ | √ | | | | other | quad | | √ | √ | | √ | |
| [56] | 2014 | √ | √ | | | √ | | DO | GT, MMT | | | | √ | | | √ | | | | √ | | √ | | √ | | | | log | quad | √ | √ | √ | | √ | |
| [57] | 2015 | √ | √ | √ | | √ | | DO | GT | | | | √ | | | | √ | √ | | √ | | √ | √ | √ | | √ | √ | log | quad, linear | | √ | | √ | √ | |
| [58] | 2016 | √ | √ | √ | | √ | | DO | GT | | | | √ | | | √ | √ | | | √ | | | | | | | √ | log | no cost | √ | | | | √ | |
| [59] | 2016 | √ | √ | | | | | DO | GT, MMT | | | | √ | | | √ | √ | | √ | √ | √ | √ | | √ | | | | log | no cost | √ | | | | √ | |
| [60] | 2017 | √ | | | √ | | √ | DO | GT | | | | √ | | | √ | | | | √ | √ | √ | | | √ | | √ | quad | quad, linear | | √ | | | | √ |
| [61] | 2019 | √ | √ | | | √ | √ | DO | GT | | | | √ | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad | | √ | | √ | √ | |
| [62] | 2019 | √ | √ | | √ | √ | √ | DO | GT | | | | √ | | | √ | | √ | | √ | √ | √ | √ | √ | √ | √ | √ | log | quad | | √ | | √ | √ | |

| Reference | Year | Resources | | | | | | Optimization Method | Game Theory, Matching Markets Theory | Uncertainty | | | | | | Objective Function | | | | Decision Variables | | | | | | | | Utility Function<br>Quadratic = quad<br>Logarithmic = log<br>Exponential = exp | Cost Function | Market Type | | | Data | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | DER/RES | PV | Wind | Conventional | Storage | DSM/DR | | | Supply | Demand | Price | No Uncertainty | Scen. Optimization | Scenarios Testing | Max(Welfare) | Max(Utility) | Min(Cost) | Max(Profit) | Trading | Generation | Consumption | Storage | Pricing | DSM/DR | Grid Exports | Grid Imports | | | Community | Full P2P | Hybrid | Real observations | Simulated | Test system |
| [63] | 2019 | √ | √ | | √ | √ | √ | DO | GT, MMT | | | | √ | | | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | other | quad | √ | √ | | | | √ |
| [64] | 2020 | √ | √ | | | √ | | DO | GT, MMT | | | | √ | | | | | √ | | √ | | √ | √ | √ | | | √ | log | quad | | | √ | √ | √ | |
| [65] | 2024 | √ | √ | | | √ | √ | DO | GT | | | | √ | | √ | | | √ | | √ | √ | √ | √ | √ | √ | √ | | quad | quad, linear | | √ | | √ | | |
| [66] | 2024 | √ | √ | | √ | | √ | DO | GT | | | | √ | | √ | | | | √ | √ | √ | √ | | √ | √ | √ | √ | quad | quad | | √ | √ | √ | | |
| [67] | 2024 | √ | √ | √ | √ | √ | √ | DO | GT | | | | √ | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad, linear | | | √ | | √ | |
| [68] | 2017 | √ | | | √ | √ | √ | DO | | √ | √ | | | | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad | | √ | | | √ | √ |
| [69] | 2020 | | | | | | √ | DO | MMT | | √ | | | | √ | | √ | √ | √ | √ | | √ | | √ | √ | | √ | custom | linear | √ | | | √ | | |
| [70] | 2022 | | | | | | √ | DO | | | √ | √ | | | √ | √ | | | | | | √ | | √ | √ | | | exp | linear | √ | | | √ | | |
| [16] | 2023 | | | | | | √ | DO | | | √ | √ | | | | | √ | √ | √ | | | √ | | √ | √ | | √ | quad, linear, log, exp | quad, linear | √ | | | √ | | |
| [21] | 2024 | √ | √ | √ | √ | √ | √ | DO | | √ | √ | √ | | √ | √ | √ | | | | √ | √ | √ | √ | | √ | √ | √ | quadratic | quad, linear | √ | | | √ | √ | √ |
| [71] | 2013 | √ | √ | √ | √ | √ | √ | DO | GT | √ | | | | | | | | | √ | √ | √ | √ | √ | √ | √ | √ | √ | no utility | quad | | √ | | | √ | √ |
| [72] | 2022 | √ | √ | | | | | DO | GT | √ | √ | | | | √ | √ | | | | √ | √ | √ | | √ | | | √ | log | linear | √ | | | | √ | |
| [73] | 2023 | √ | √ | √ | | √ | | DO | GT | √ | √ | √ | | | | √ | | | | √ | √ | √ | √ | √ | | √ | √ | linear | linear | √ | | | √ | | |
| [74] | 2018 | √ | √ | | | √ | √ | DO, SO | GT | √ | √ | √ | | √ | √ | | √ | | √ | √ | | √ | √ | √ | √ | √ | √ | log | linear | √ | | | √ | √ | |
| [75] | 2015 | √ | | √ | √ | | √ | DO, CCO | | √ | | | | | √ | √ | | | | | √ | √ | | | √ | | √ | quad | quad | √ | | | √ | √ | |
| [76] | 2024 | √ | √ | | | √ | √ | DO, CCO | MMT | √ | √ | | | | √ | √ | √ | √ | | √ | √ | √ | | | √ | √ | √ | quad | quad | √ | | | | √ | √ |
| [29] | 2022 | √ | | | √ | √ | √ | DO, RO | | | | √ | | | | √ | √ | | √ | √ | √ | √ | √ | √ | √ | | √ | quad | quad | | √ | | √ | | |
| [26] | 2020 | √ | | √ | √ | | √ | SO | MMT | √ | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | quad, exp | linear | √ | | | √ | √ | √ |
| [77] | 2020 | √ | | √ | | √ | √ | SO | | √ | | | | √ | √ | √ | | | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad, exp | linear | √ | | | √ | √ | √ |
| [27] | 2021 | √ | √ | √ | | | | SO | MMT | √ | | | | | | √ | | | √ | √ | √ | √ | | √ | | √ | √ | quad | no cost | √ | | | √ | √ | √ |
| [78] | 2022 | | | | | | √ | SO | | | √ | | | √ | √ | √ | √ | | | | | √ | | √ | √ | | √ | log | quad | √ | | | | √ | |
| [79] | 2019 | √ | √ | | √ | | √ | SO | GT, MMT | √ | √ | √ | | √ | √ | | √ | | √ | √ | √ | √ | | √ | √ | | | linear | quad, linear | | √ | | √ | √ | √ |
| [80] | 2020 | √ | √ | | | √ | √ | SO | GT | √ | | | | √ | √ | | | | √ | √ | √ | √ | √ | | √ | √ | √ | quad | linear | √ | | | √ | √ | |
| [81] | 2021 | √ | √ | √ | √ | | √ | SO | GT | √ | √ | | | √ | √ | √ | | √ | √ | √ | √ | √ | | √ | √ | √ | √ | quad | quad | | √ | | √ | √ | |
| [82] | 2022 | √ | | | | | √ | SO | GT | √ | √ | √ | | √ | √ | √ | √ | √ | √ | √ | | √ | | √ | √ | | √ | quad | linear | √ | | √ | √ | √ | |
| [83] | 2023 | √ | √ | | | √ | √ | SO, CCO | GT, MMT | √ | | | | | | | √ | | | √ | √ | √ | √ | √ | √ | √ | √ | other | quad, linear | | √ | | | | √ |
| [30] | 2021 | √ | | √ | √ | | | CCO | | √ | | | | √ | √ | | | √ | | √ | √ | √ | | √ | | | | quad | quad | | √ | | √ | √ | √ |
| [31] | 2024 | √ | √ | √ | √ | √ | √ | CCO, RO, DRO | GT | √ | √ | | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad, linear | | | √ | | √ | √ |
| [84] | 2024 | √ | √ | | √ | √ | √ | CCO, RO, DRO | GT, MMT | √ | √ | √ | | | | | | √ | | √ | √ | √ | √ | √ | √ | √ | √ | other | quad | | √ | | | √ | √ |
| [85] | 2010 | | | | | | √ | RO | | | | √ | | | | | √ | √ | | | | √ | | | √ | | | linear | linear | √ | | | √ | | |
| [86] | 2014 | √ | | √ | √ | | √ | RO | | √ | √ | | | | √ | √ | √ | √ | √ | √ | √ | √ | | √ | √ | | √ | quad | quad | | √ | √ | | | √ |
| [87] | 2021 | | | | | | √ | RO | | | √ | | | | | √ | √ | √ | | √ | | √ | | √ | √ | | | quad | quad | √ | | | | √ | |
| [17] | 2022 | √ | √ | | √ | √ | √ | RO | | √ | √ | | | | | √ | | | | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad | √ | | | | √ | √ |
| [28] | 2022 | √ | √ | √ | √ | √ | √ | RO | GT | √ | | | | √ | √ | | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | quad | quad, linear | | √ | | | √ | √ |
| **This work** | **2025** | √ | √ | | | √ | √ | **DO, SO, LR, RO** | | √ | √ | √ | | √ | √ | √ | | | | √ | √ | √ | √ | √ | √ | √ | √ | **quadratic** | **quadratic** | √ | | | √ | √ | |

### 2.3.1 Clustering Methods for Scenario Generation

A closer look at how uncertainty is introduced into models reveals varying practices in scenario generation. In this literature review, a clear majority (60%) adopt a fully deterministic framework, omitting any explicit treatment of uncertainty (blue column in Table **1**). The remaining 40% introduce uncertainty into their models. However, only 17% of the studies embed scenarios directly within the optimization formulation (column "Scen.Optimization" in Table **1**).

In the set of 72 papers, 50% of the papers (of which half are deterministic, and the other half are stochastic studies) use scenario sets for benchmarking or sensitivity testing (column "Scenarios Testing" in Table **1**). Notably, all papers that generate scenarios for the optimization itself also leverage those same scenarios for comparative analysis and testing of different modelling approaches.

Among the studies using scenarios, three broad approaches to scenario generation emerge:

1. **Historical Data Sampling** ([78], [79], [81], [82]): This method emerges as the predominant scenario-generation technique in EC modelling. It builds directly on measured time series, such as household loads, market prices, or renewable outputs records and then group days into representative or "typical" clusters, employing random sampling or clustering algorithms of historical patterns. This approach combines empirical fidelity with ease of implementation, making it a practical foundation for scenario-based optimization.
2. **Probabilistic Time-Series Forecasting** ([25], [70], [76]): A second group fits statistical models (ARIMA/SARIMA or Gaussian processes) to capture temporal correlations and generate predictive distributions. Then, by using Monte Carlo sampling of forecast-error distributions around expected demand, prices or renewables, generate large scenario ensembles (often hundreds to thousands) that serve as statistically robust inputs for stochastic and chance-constrained optimization models.
3. **Distribution-Based and Machine-Learning Methods** ([21], [26], [30], [31], [69], [80]): A third strand employs parametric distributions (Rayleigh or Weibull for wind and solar, uniform or mixture models for price and load errors) or generative machine-learning tools (LSTM networks, Gaussian mixture models) to approximate the full uncertainty space. Scenarios are then sampled from these fitted distributions. In some cases, specialized scenario-reduction tools (SCENRED in GAMS) or moment-matching techniques are used to prune large ensembles down to a tractable subset.

These categories are not mutually exclusive, as many studies adopt a hybrid approach, typically starting from historical sampling and complementing it with probabilistic or distribution-based methods for selected variables.

## 2.4 EC Key Performance Indicators

Given the diverse benefits that EC aim to deliver, in comparison to a traditional market where agents only buy energy from the grid, it is essential to define evaluation metrics to assess their actual performance. Table **2** synthesizes the key performance indicators (KPIs) most frequently used in recent literature on EC modelling. This synthesis is derived from a focused review of 23 papers that explicitly reference both "KPI" and "energy community." Only KPIs mentioned in more than five studies were retained for detailed analysis.

The analysis reveals distinct categories of performance metrics crucial for EC evaluation, aligned with the multifaceted objectives that energy communities typically pursue. In the energy performance domain, Grid Imports (kWh/year) emerges as the most frequently cited indicator (18 papers), measuring the community's reliance on external energy sources. For economic assessment, Energy Cost Savings (€/year) represents the primary financial benefit metric (12 papers), quantifying tangible monetary advantages for community participants. From a grid and technical perspective, Demand Shifting (%) appears as a significant indicator (7 papers), reflecting the community's capability to adjust consumption patterns in response to grid conditions or price signals, while Peak Load Reduction (%) demonstrates the ability to decrease maximum demand during critical periods (5 papers). Finally, $CO_2$ Emissions Reduction ($kgCO_2eq$/year) stands as the predominant environmental indicator (13 papers), directly measuring the climate change mitigation potential of energy communities.

These metrics collectively provide a comprehensive evaluation framework that balances technical performance with socioeconomic and environmental considerations, reflecting the multifaceted nature of energy community objectives documented in the literature. By grounding the KPI selection in a structured literature review, this study provides a balanced and multidimensional approach to assessing EC performance across energy, economic, operational, and environmental dimensions.

Table 2: Studies referencing KPIs in the context of energy community modelling.

| Group | KPI | Description | Unit | [88] | [89] | [90] | [91] | [92] | [93] | [94] | [95] | [96] | [97] | [98] | [99] | [100 | [101 | [102 | [103 | [104 | [105 | [106 | [107 | [108 | [109 | [110 | This work | # |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Energy Performance** | Grid Imports | Energy imported from the grid | kWh/y | √ | | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | | √ | √ | √ | √ | | 18 |
| | Grid Exports | Energy exported to the grid | kWh/y | | | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | √ | | √ | √ | √ | | √ | √ | √ | √ | | 17 |
| | Energy Interaction with the Grid | Net energy exchange with the grid | % | √ | | √ | √ | | | | | √ | | √ | √ | √ | √ | | √ | √ | √ | | √ | √ | √ | √ | | 15 |
| | Self-Consumption Ratio (SCR) | % of locally generated energy locally used | % | | | √ | √ | | √ | √ | √ | √ | | | √ | | √ | √ | | √ | √ | | | √ | √ | | | 13 |
| | Self-Sufficiency Ratio (SSR) | % of energy demand covered by local generation | % | | | √ | √ | | √ | | √ | √ | | | √ | √ | | √ | | √ | √ | | √ | √ | √ | | √ | 13 |
| | Total Energy Generation | Total energy produced by REC assets | kWh/y | √ | | √ | √ | | | √ | | √ | √ | | | √ | √ | | √ | | | | √ | √ | | | | 11 |
| **Economic** | Energy Cost Savings | Reduction in energy expenditure | €/y | √ | | √ | √ | | √ | √ | √ | | | | | | | √ | √ | √ | √ | | | √ | √ | | √ | 12 |
| | Initial Investment Cost | Total capital expenditure | € | √ | | √ | √ | | √ | | √ | √ | | √ | | | √ | | √ | | √ | | √ | | √ | | | 12 |
| | Operation & Maintenance Costs | Annual costs for system upkeep | €/y | √ | | √ | √ | | √ | | √ | √ | | √ | | | √ | | √ | | √ | | | | √ | | | 11 |
| | Net Present Value (NPV) | Present value of all cash flows | € | | | √ | √ | | √ | | | √ | | √ | | | | | | | √ | | | | √ | | | 7 |
| **Grid and Technical** | Storage Utilization | Degree of storage capacity utilization | % | | √ | | | | | | √ | √ | | √ | √ | | √ | | √ | √ | | √ | √ | | √ | | | 11 |
| | Grid Impact | Effect on local distribution infrastructure | % or V | | | √ | √ | | √ | | | | | | √ | | √ | | √ | | √ | | √ | √ | | | | 9 |
| | Demand Shifting | Measure of load shifting capability | % | | √ | | | | | | √ | | | | | | | √ | √ | √ | | √ | | √ | | | √ | 7 |
| | Peak Load Reduction | Percentage reduction in peak load | % | | | | | √ | | | | | | | | | √ | √ | √ | | | | | √ | | | √ | 5 |
| **Environmental** | CO2 Emissions Reduction | GHG emissions avoided | $kgCO_2eq/y$ | √ | | | | √ | √ | | √ | √ | | √ | √ | | √ | √ | √ | | √ | | √ | | √ | | √ | 13 |

## 2.5 Knowledge gap and Contributions

Unlike most studies that focus on only one or two uncertain variables, this work simultaneously models uncertainty in demand, supply, and market prices, providing a more realistic representation of the challenges faced by ECs. It also introduces a seasonal dimension, showing how uncertainty differs between summer and winter and how this affects overall system performance.

This work makes several original contributions by examining the role of uncertainty in shaping the outcomes of P2P ECs. The core contribution lies in a comprehensive and comparative evaluation of five optimization approaches: deterministic optimization with a single average scenario (AS) and with an average of multiple scenarios (AMS), stochastic optimization (SO), robust optimization (RO), and least regret (LR). These approaches are applied consistently to a common set of real-world scenarios derived from two years of data on electricity demand, PV generation, and market prices.

Performance is evaluated using a diverse set of indicators, such as welfare, energy costs, self-sufficiency, peak load reduction, and $CO_2$ emissions, offering a multi-dimensional perspective on how different methods affect ECs outcomes, while highlighting trade-offs between maximizing expected performance (optimality) and ensuring resilience under uncertainty (robustness).

# 3. Methodology

This study presents a comprehensive optimization framework for P2P ECs, designed to maximize overall community welfare under uncertainty. The framework optimizes the operation of ECs equipped with DER - specifically solar photovoltaic (PV) systems and battery energy storage systems (BESS) - while incorporating demand flexibility capabilities of community participants.

The methodology employed in this study is grounded in an optimization problem where key variables including electricity consumption patterns, solar radiation, and electricity market prices are subject to uncertainty. Given the critical impact of these uncertainties on ECs operations and welfare, uncertainty is addressed through two complementary mechanisms: scenario construction and evaluation of different optimization methods.

During scenario construction, historical data is processed using two-layer clustering techniques to develop representative scenarios that capture the inherent variability in multi-year demand patterns, solar generation, and electricity prices. Firstly, data is separated by season (summer or winter). Then, within each of the resulting clusters, representative days are selected for running the optimizations. This hybrid design preserves the empirical grounding and simplicity of classical clustering approaches, ensures coverage of seasons, yielding a scenario set small enough to support efficient, multi-stage decision making. These scenarios form the foundation for all subsequent optimization analyses. Building upon this scenario framework, the second dimension of the uncertainty treatment involves the selection and application of different optimization approaches.

The optimization methodology includes two approaches: a deterministic analysis and, for further comparison with uncertainty consideration, three different stochastic methods are employed:

i) Stochastic Optimization (SO) – Maximizes the average performance across scenarios.
ii) Least Regret (LR) – Minimizes the worst-case deviation from optimal decisions.
iii) Robust Optimization (RO) – Maximizes performance under worst-case conditions.

These three stochastic approaches reflect varying levels of risk sensitivity - ranging from the risk-neutral stance of SO to the moderate risk aversion of LR, and the strong risk aversion characteristic of RO. Although all three methods explicitly incorporate uncertainty and operate over multiple scenarios, the term “Stochastic Optimization (SO)” will hereafter refer specifically to the first approach, consistent with its wide usage in the literature.

Each optimization approach is designed to increase community welfare and is further evaluated through operational decision variables and a set of performance metrics (in literature often named KPIs) including renewable self-sufficiency, economic savings, $CO_2$ emissions and grid interaction.

This multi-faceted evaluation enables the assessment of both the overall benefits for the EC and the specific contributions of individual components, such as batteries and demand flexibility.

By comparing solutions from stochastic optimization (which explicitly accounts for uncertainty) with those from deterministic approaches, the methodology provides valuable insights into the impact of uncertainty on optimal operational decisions within P2P ECs. This dual approach to uncertainty treatment , through both scenario construction and use of multiple optimization approaches, allows for a more comprehensive understanding of how energy communities can effectively respond to the inherent variability in renewable energy systems.

## 3.1 Model Framework and Implementation

The optimization model for this research was implemented in Python using Gurobi [111], a robust mathematical programming solver designed for large-scale Mixed Integer Linear Programming (MILP) and Quadratic Programming problems. This implementation choice was motivated by the need to efficiently solve large-scale quadratic programming problems that characterize P2P energy trading. Python's extensive data analysis capabilities, combined with Gurobi's advanced algorithms for handling complex constraint systems, provided an effective computational environment for this optimization.

The methodology workflow presented in Figure 1 details a comprehensive and systematic framework to optimizing P2P ECs under uncertainty, capturing both the technical complexities of DER and the economic dynamics of P2P energy trading.

The methodological approach begins with data preparation from multiple sources, followed by an initial optimization for community's resources dimensioning. To manage computational complexity while preserving statistical fidelity of data, clustering techniques that identify representative operational patterns from the dataset were employed. Then, deterministic and stochastic optimization approaches were explored, enabling comparison between different decision-making strategies under varying uncertainty conditions.

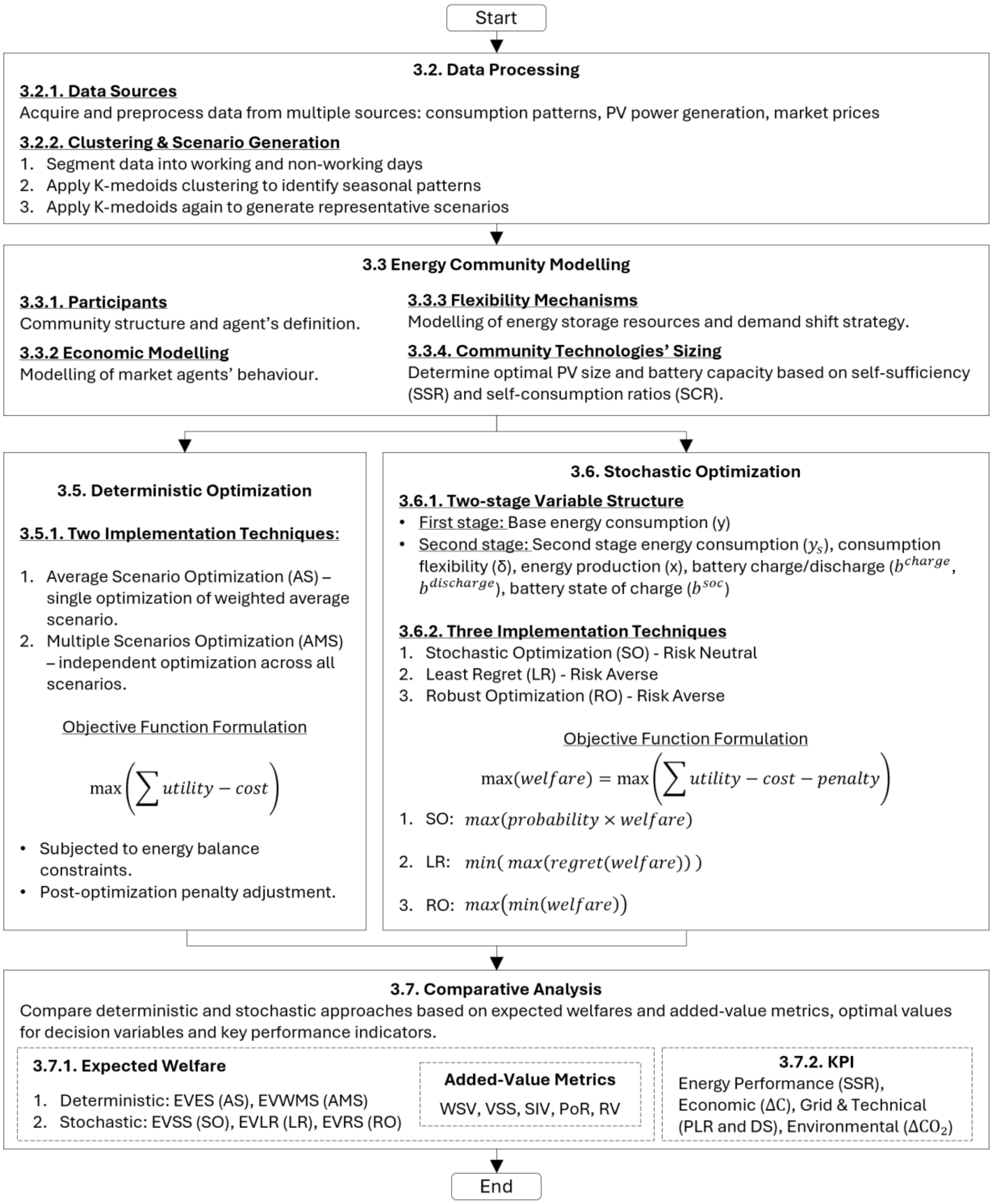


**Figure 1: Methodology Flowchart.**

Each step presented of the Methodology Flowchart is detailed in the next subchapters.

## 3.2 Data Processing

### 3.2.1 Data Sources

The initial stage of the methodology involves comprehensive data acquisition and preprocessing from multiple sources:

- **Consumption data:** Historical consumption profiles for three distinct household types, representing different consumption patterns with varying peak loads, base loads, and daily usage profiles, are obtained from [112]. While these consumption profiles originate from measurements taken in 2015, it was assumed that residential sector demand patterns remained sufficiently stable to apply these profiles to the 2022-2023 period analysed. To expand the data set while preserving realistic consumption patterns, three supplementary consumption profiles were generated by averaging these original profiles in pairs (households 1-2, 1-3, and 2-3).
- **Market price data:** Retail electricity price data was obtained from the Electricity Iberian Market (MIBEL [113]), consisting of hourly time series corresponding to the real OMIP [114] prices from January 1, 2022, to December 31, 2023. These wholesale prices capture hourly market fluctuations and serve as a price floor for P2P transactions.
- **Renewable generation data:** Solar PV production data was obtained from the European Commission's Photovoltaic Geographical Information System (PVGIS) [115] database for Lisbon, Portugal (latitude 38.7167, longitude -9.1333). The PVGIS data provides hourly PV power output estimates along with associated irradiation, temperature, and wind velocity. These estimates account for various factors including panel orientation, tilt angle, and technology type (crystalline silicon was selected as the primary technology). The PV output data serves as direct input to the model rather than being calculated internally, with the output scaled according to the system capacity determined in the dimensioning phase.

All data was collected at hourly resolution for a two-year period (2022-2023), providing 17,520 data points (24 hours × 730 days) for each variable. This extended time horizon captures seasonal variations, weather anomalies, price volatility patterns, and changing consumption behaviours, ensuring that the subsequent analysis accounts for a wide range of operational conditions.

### 3.2.2 Clustering and Scenario Generation

To account for the inherent variability in energy production, consumption, and electricity prices, a clustering methodology was implemented to capture different representative patterns of these three variables simultaneously, capturing diverse conditions faced by the EC throughout the timeframe chosen.

*Initial Segmentation*

First, an initial analysis of the 730 daily observations was developed, which revealed statistically significant differences between working days and non-working days across several variables, particularly in terms of consumption patterns. Detailed hourly distribution charts with statistical variations or all three household consumption profiles and electricity prices are presented in the Appendix section *Clustering: Working vs Non-working Days*. The key findings from this analysis are summarized below:

- During early morning hours, consumption was typically higher on working days, likely due to earlier wake-up times, while during daytime hours on non-working days, domestic consumption increased as people remained at home. Evening consumption patterns showed convergence between working and non-working days, suggesting similar household activities regardless of day type. The analysis identified minimal differences in consumption during sleeping hours regardless of season or day type, establishing a baseline consumption level that remains relatively constant.
- Regarding PV generation, expected seasonal and daily variations were observed, with peak production occurring during midday hours and summer months, which were not influenced by being working or non-working days.
- Electricity prices exhibited consistently higher values on weekdays compared to weekends during active hours, reflecting the influence of commercial and industrial demand on market prices.

Figure 2 presents the hourly consumption patterns for one of the household profiles, clearly highlighting the contrast between weekdays and holidays. To improve data visualization, the outliers of the dataset were excluded from the graphs.

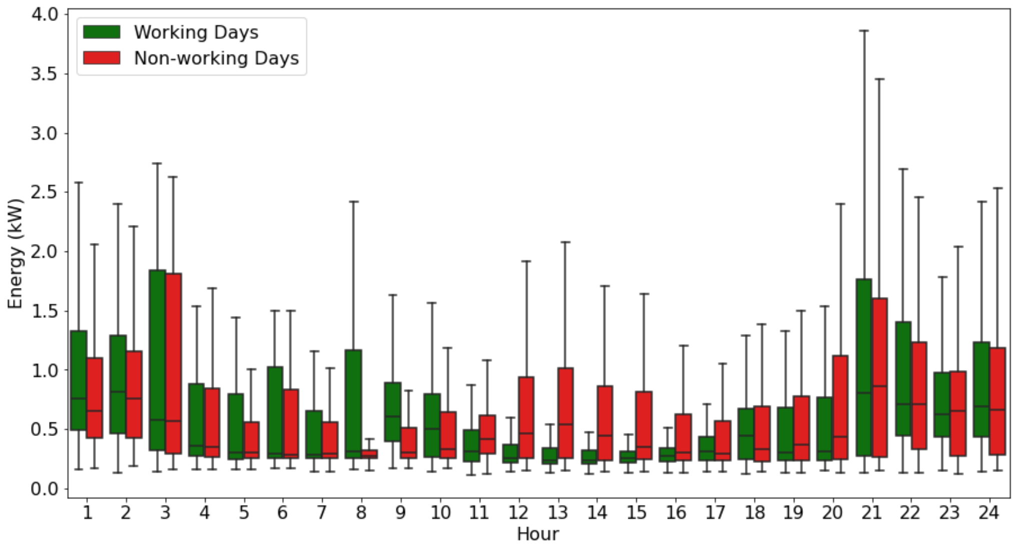


Figure 2: Statistical Variation of Input Variables – Consumption Profile of Household 2

These findings supported the decision to segment the dataset into distinct groups for the subsequent clustering and scenario generation process:

- Working days (representing business days – also denoted as “B” in the figures)
- Non-working days (representing holidays and weekends – also denoted as “H” the figures)

This initial segmentation approach provides substantial analytical advantages, as clustering the full dataset without this initial division would risk having inter-group variability overshadowing important intra-group patterns.

*Two-stage Clustering Process*

I. Seasonal Pattern Identification

After segmenting the data into working and non-working days, K-Medoids clustering algorithm is applied separately to each subset. This technique of clustering uses actual data points (medoids) as cluster centres, maintaining the original data.

The clustering process considered three variables simultaneously - consumption, production, and prices - to capture interdependencies and multidimensional patterns. Prior to this process, standardization is applied to address differences in scale among these variables, with equal weights assigned to each dimension to ensure balanced representation in the clustering algorithm.

The optimal number of seasonal clusters was determined using traditional clustering evaluation metrics - Silhouette Score and Elbow Method. The Silhouette Score measures cluster cohesion and separation by comparing each point's similarity to its assigned cluster versus other clusters:

$$S(i) = \frac{b(i) - a(i)}{\max\big(a(i), b(i)\big)} \tag{1}$$

where $a(i)$ is the average distance from point *i* to all other points in its cluster, and $b(i)$ is the minimum average distance to points in any other cluster. The overall silhouette score averages all individual values, with higher scores indicating better-defined clusters.

Concurrently, the Elbow Method was employed to evaluate the within-cluster sum of squared errors (WCSS), calculated as:

$$WCSS = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{2}$$

where $C_i$ is a cluster, $\mu_i$ is its centroid, and $\|x - \mu_i\|^2$ is the squared Euclidean distance between a point and its cluster centroid. This metric identifies the point where adding more clusters provides decreasing returns in reducing variance.

The detailed analysis of this metrics is provided in the Appendix, section Clustering: Seasonal Patterns.

Figure 3 represents the optimal number of clusters identified for each subset. For working days, the analysis identifies three distinct clusters (labelled in the graph as B0, B1 and B2) that correspond to summer, mid-season (spring/autumn), and winter periods, respectively. This three-cluster solution provides balanced group sizes and interpretable results that align with expected seasonal energy patterns.

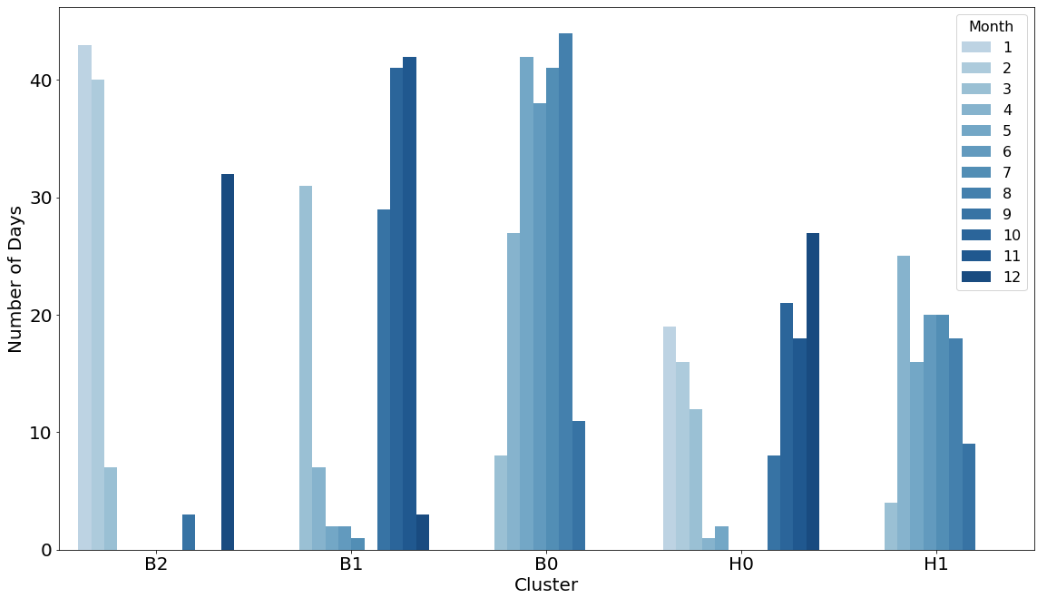


Figure 3: Seasonal Patterns in Overall Dataset

For non-working days, two clusters (labelled in the graph as H0 and H1) representing summer and winter seasons prove sufficient to capture the key seasonal variations, with transitional seasons showing less distinctive patterns compared to working days.

It is also worth noting that an alternative methodological approach involving independent clustering of each variable was explored but ultimately abandoned. While this alternative approach potentially offered more homogeneous variable-specific groups, it proved less appropriate for capturing the complex interdependencies between consumption, production, and price variables. The chosen approach preserves these critical interdependencies, enabling a more realistic representation of energy community dynamics.

## II. Scenario Construction

For the final stage of clustering, the methodology focuses on the two most distinct seasonal clusters for working days - B0 and B2, representing summer and winter - to capture extreme operational scenarios. From this point on, these two groups will be called the “Summer Cluster” (B0) and the “Winter Cluster” (B2). Within each of these clusters, K-medoids clustering is applied once more to identify representative daily profiles (scenarios), creating a comprehensive representation of possible operating conditions.

In this process, the optimal number of daily representative scenarios was determined using common metrics in the literature for scenario reduction – the Kullback-Leibler and the Method of Moments. The Kullback-Leibler (KL) Divergence measures the information loss between original data distributions and their clustered representations:

$$D_{KL}(P||Q) = \sum_{x} P(x) \times \log \frac{P(x)}{Q(x)} \tag{3}$$

where $P(x)$ represents the original distribution and $Q(x)$ the scenario approximation.

The Method of Moments (MM) difference evaluates how accurately the scenarios capture the statistical characteristics of the original data:

$$\mathrm{MM} = |\hat{\mu}_Q - \hat{\mu}_P| + |\hat{\sigma}_Q^2 - \hat{\sigma}_P^2| + |\hat{\gamma}_1^Q - \hat{\gamma}_1^P| + |\hat{\gamma}_2^Q - \hat{\gamma}_2^P| \tag{4}$$

where $\hat{\mu}, \hat{\sigma}^2, \hat{\gamma}_1, \hat{\gamma}_2$ represent the mean, variance, skewness, kurtosis, respectively, of the selected scenarios (Q) or original data distribution (P).

Both metrics typically decrease as the number of scenarios increases, with diminishing returns beyond a certain point. The optimal number of scenarios occurs where these metrics stabilize, indicating that additional scenarios would provide minimal improvement in representing the underlying distributions while increasing computational complexity.

For the Summer Cluster, eight representative scenarios (Figure 4) are selected based on the two metrics applied. For the Winter Cluster, nine representative scenarios are identified (Figure 5).

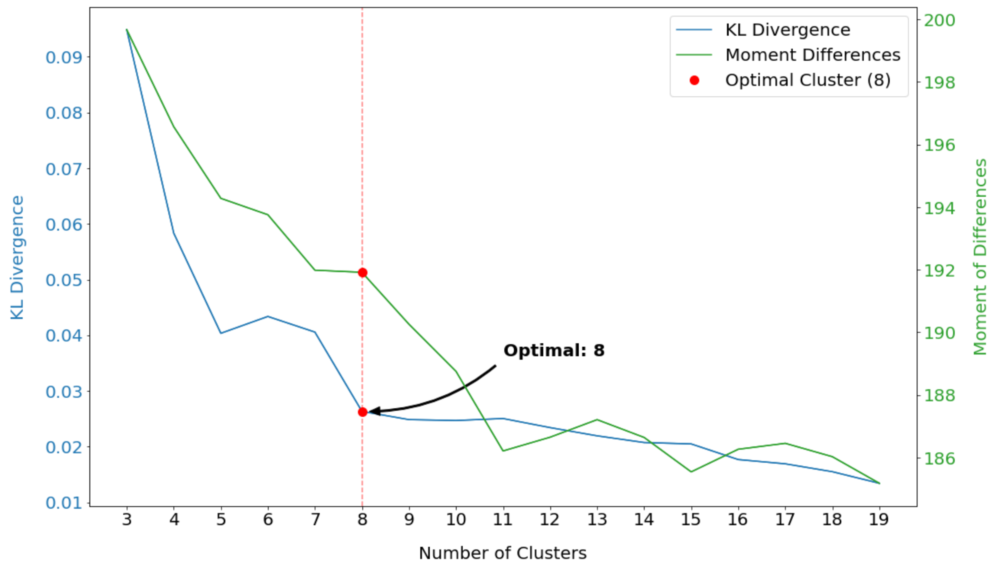


**Figure 4: Optimal Number of Scenarios for Summer Cluster**

Each scenario includes complete 24-hour profiles for all relevant variables (consumption patterns, PV generation, and OMIP prices) along with boundary conditions for operational constraints and is assigned a probability weight based on the number of observations it represents within its parent clusters.

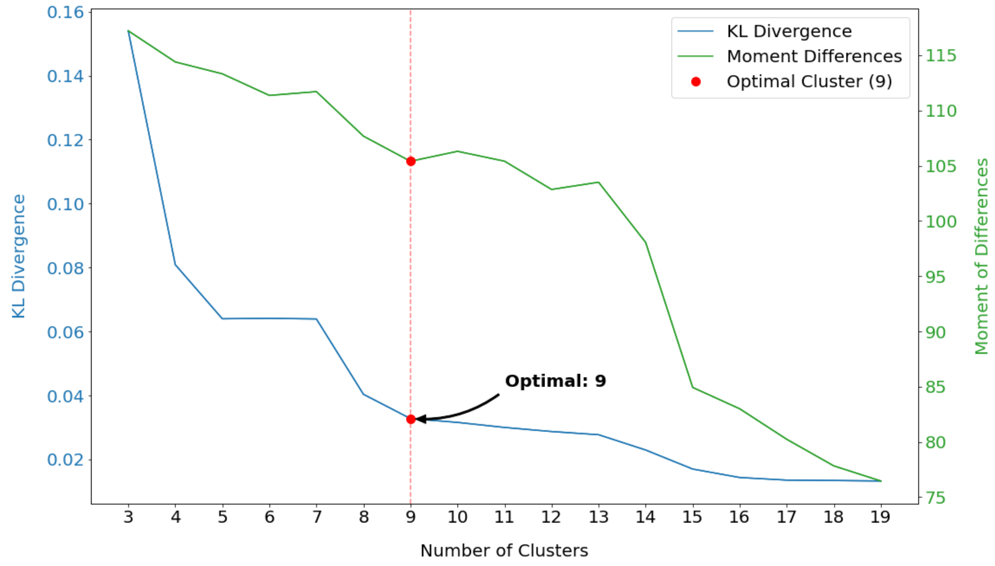


**Figure 5: Optimal Number of Scenarios for Winter Cluster**

The resulting scenarios, illustrated in Figure 6 and plotted against the 5th-95th percentile ranges of the original data, provide a statistically basis for the subsequent optimization phases, supporting both deterministic analysis based on a representative scenario and stochastic optimization that simultaneously accounts for uncertainty in all scenarios. Each scenario is assigned a specific probability, derived from its relative frequency within the clustered dataset, as represented in

**Table 3: Probability of occurrence of each scenario (%)**

| Scenario | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| Summer | 2.4 | 29.4 | 15.2 | 16.6 | 9.0 | 4.3 | 16.6 | 6.6 | N/A |
| Winter | 5.6 | 4.0 | 16.0 | 16.8 | 9.6 | 11.2 | 6.4 | 10.4 | 20.0 |

Additionally, a weighted average scenario (represented in Figure 6 as the dashed black line) is calculated for each cluster. This average scenario captures the dominant trends across all variables while smoothing extreme variations, serving as a baseline for the simplest deterministic approach.

The representative scenarios exhibit distinct patterns across both seasonal clusters, with notable differences between summer and winter consumption profiles. Consumption Profile 1 demonstrates relatively low and stable consumption (0.1-0.8 kW) with slight evening peaks, while Consumption Profiles 2 and 3 show greater variability and higher overall consumption (0.0-4.0 kW), particularly during morning and evening hours. OMIP prices exhibit significant intraday variability across scenarios, with winter prices showing higher volatility. In both seasonal clusters, a bimodal distribution emerges, characterized by price peaks during morning and evening hours. PV power generation follows a consistent bell-shaped curve with maximum output occurring around midday, though with considerable variability, namely in the winter cluster, as indicated by the 5th-95th percentile range and the scenarios dispersion.

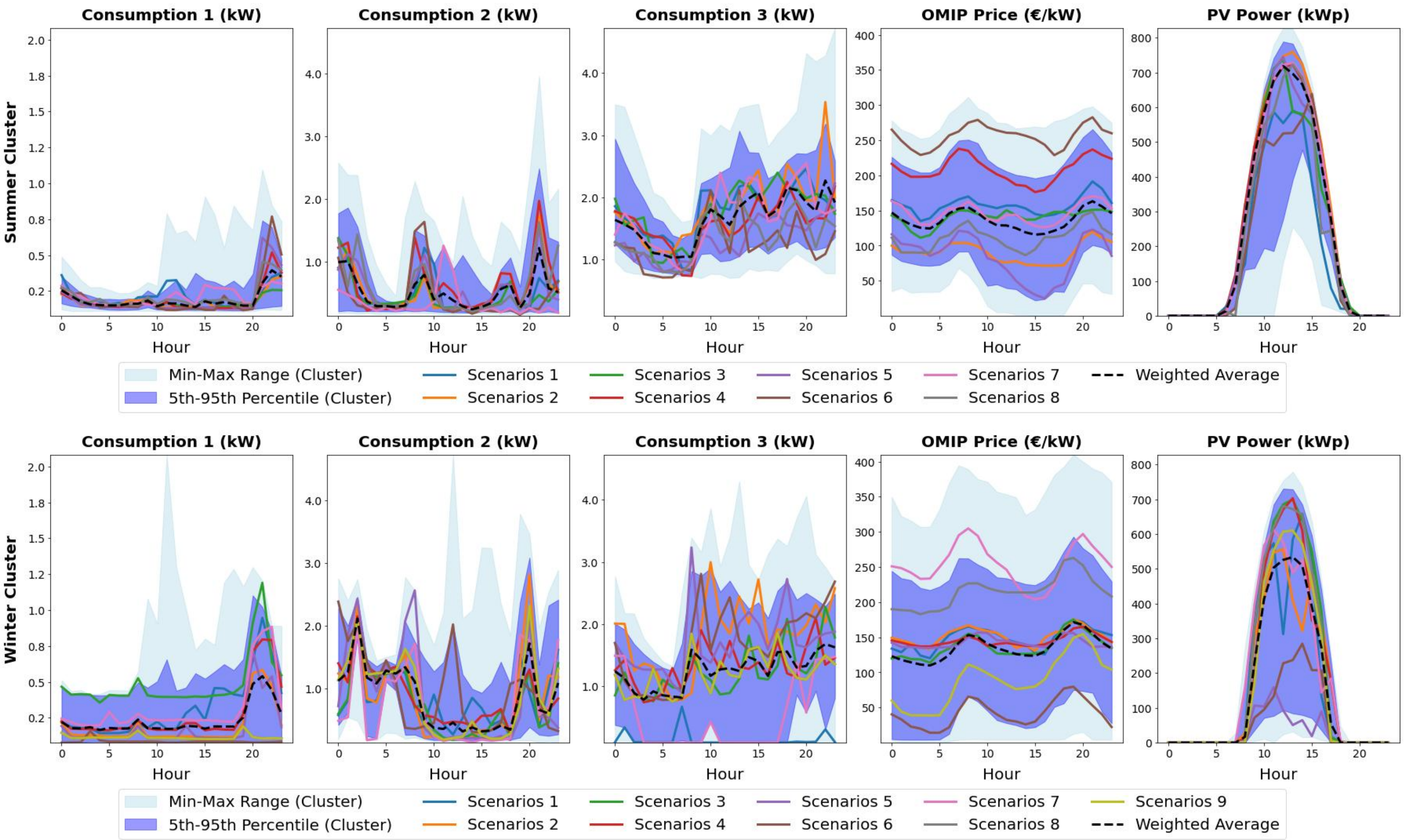


Figure 6: Scenarios Plotted Against Cluster's Boundaries and 5th-95th Percentile – Summer (top row) and Winter (bottom row)

## 3.3 Energy Community Modelling

### 3.3.1 Participants

The EC model considers multiple participants with different roles within the community. Agents are classified into two primary categories based on their energy production and consumption capabilities, and cannot have different roles simultaneously:

- **Consumers** are participants who only consume energy and do not have generation capabilities. These agents rely entirely on energy purchases, either from community producers or from the external grid, to meet their demand. In the model, consumers are represented with unique demand profiles derived from utility functions that characterize their willingness to pay for energy.
- **Prosumers** represent the distinctive feature of modern energy communities - participants who both consume and produce energy. These agents own photovoltaic systems that enable them to generate electricity for self-consumption and potentially sell excess production to other community members. Depending on their instantaneous production-consumption balance, prosumers dynamically transition between different roles: (i) when production exceeds consumption, they act as net producers (sellers) in the P2P market; (ii) when consumption exceeds production, they become buyers; (iii) at the break-even point, they satisfy their internal demand with self-consumption with no market participation.

The EC model in this study consists of a total of 6 participants: 3 consumers ($N_C$ = 3) and 3 prosumers ($N_P$ = 3), one community battery and the main grid, which serves as both a seller (providing energy at regulated retail tariffs) and a buyer (purchasing excess community generation at wholesale market prices) (Figure 7). This balanced composition allows for meaningful analysis of P2P interactions and community dynamics.

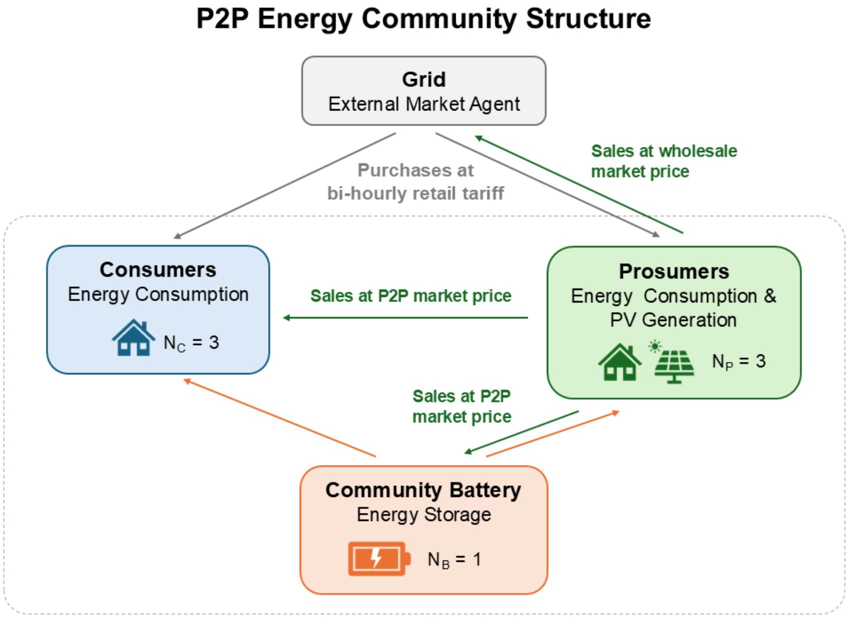


Figure 7: Energy Community Framework

This classification models the foundation for modelling energy transactions within the community, where each agent's behaviour is governed by individual preferences (represented by utility functions), technical capabilities (PV size and battery capacity), and economic considerations. The model assumes perfect competition in the P2P market, with no strategic behaviour or market power by any participant.

### 3.3.2 Economic Modelling

The model considers the following mathematical sets and indices:

- $T = \{0, 1, \ldots, 23\}$: Set of hourly time periods ($t$) in a day.
- $C = \{0, 1, \ldots, N_C\}$: Set of consumers (*j*), where 0 denotes the grid, 1-3 denote conventional consumers, and 4-6 denote prosumers acting in consumer mode.
- $P = \{0, 1, \ldots, N_P\}$: Set of prosumers (*i*), where 0 represents the grid and 1-3 represent community producers.
- $B = \{0, 1, \ldots, N_B\}$: Set of batteries (*k*), assumed to be one battery in this case study.
- $S = \{0, 1, \ldots, N_S\}$: Set of scenarios ($s$) in each season (winter or summer).

Some community members (namely, prosumers) can function either as consumers or sellers in a given period, but not both simultaneously. Their role depends on their generation capabilities and current operational state.

*Consumer Demand Curve*

The hourly energy demand from each consumer is modelled using a quadratic utility function that captures diminishing marginal utility as consumption increases [29], in euros (€):

$$U(y_{j,t}) = a_{j,t} \times y_{j,t} - b_{j,t} \times {y_{j,t}}^2 \tag{5}$$

where $y_{j,t}$ represents energy consumption of consumer *j* at hour *t*, while $a_{j,t}$ and $b_{j,t}$ are parameters that characterize the consumer's preferences. The parameter $a_{j,t}$ represents the maximum willingness to pay (the intercept of the marginal utility curve), while $b_{j,t}$ determines how quickly marginal utility diminishes with increased consumption.

From the utility function's first derivate, the demand curve can be expressed as:

$$P = a_{j,t} - 2b_{j,t} \times y_{j,t} \tag{6}$$

The demand curve parameters are derived based on the price elasticity of demand ($E_p$), which measures how sensitive the quantity demanded of a good ($y_{j,t}$) is to changes in its price ($P$). For the linear demand function in equation (6), the price elasticity ($E_p$) at any specific point can be expressed as:

$$E_p = \frac{\frac{dy_{j,t}}{y_{j,t}}}{\frac{dP}{P}} = \frac{\frac{dy_{j,t}}{y_{j,t}}}{\frac{-2b_{j,t} \times dy_{j,t}}{P}} = \frac{P}{y_{j,t}} \times \frac{1}{-2b_{j,t}} \tag{7}$$

Simplifying:

$$E_p = -\frac{P}{2b_{j,t} \times y_{j,t}} \tag{8}$$

Since the dataset provides the consumption–price pair $(P_{reg}, y_{j,t})$ for each consumer j at hour h, the market price $(P)$ is substituted by the regulated price $(P_{reg})$, allowing parameter calibration using observed data. Rearranging equation (8) to isolate $b_{j,t}$:

$$b_{jh} = -\frac{P_{reg}}{2y_{j,t} \times E_p} \tag{9}$$

Similarly, by substituting this expression for $b_{j,t}$ into equation (6) and solving for $a_{j,t}$, we obtain:

$$a_{j,t} = P_{reg}\left(1 - \frac{1}{E_p}\right) \tag{10}$$

where $P_{reg}$ is the regulated electricity price, $y_{j,t}$ is the baseline consumption, and $E_p$ is the price elasticity of demand. This formulation allows the model to capture how consumers adjust their consumption in response to price variations within the P2P market.

*Producer Supply Curve*

On the supply side, the energy available to be sold by each seller, produced from solar photovoltaic (PV) technologies, is modelled using a quadratic cost function [29], in euros (€):

$$\boldsymbol{C(x_{i,t}) = c_{i,t} \times x_{i,t} + d_{i,t} \times x_{i,t}^2} \tag{11}$$

where $x_{i,t}$ represents the energy production of seller *i* at hour *t*, while $c_{i,t}$ and $d_{i,t}$ are parameters that characterize the producer's supply $(P = c_{i,t} + 2d_{i,t} \times x_{i,t})$, shaped by individual preferences and the varying conditions of solar energy generation. The parameter $c_{i,t}$ represents the minimum price at which net supply begins, while $d_{i,t}$ determines how quickly this inferred price increases with supply.

For prosumers, three distinct cases emerge based on the relationship between PV generation capacity and self-consumption:

1. When PV capacity exceeds the maximum internal demand $\left(PV \geq \min\left(y_{max'}, \frac{a'}{2b'}\right)\right)$, the prosumer consistently acts as a net seller. Their residual supply curve begins at $x_{min} = PV - \min\left(y_{max'}, \frac{a'}{2b'}\right)$ for zero price and increases with a positive slope of $\frac{1}{2b'}$. In this case, the residual demand is zero across all prices (i.e., $y = 0$ for all $P$), indicating no market participation on the demand side.
2. When PV capacity falls below maximum internal demand but exceeds minimum demand $\left(y_{min'} < PV < \min\left(y_{max'}, \frac{a'}{2b'}\right)\right)$, market behaviour varies according to price levels relative to their break-even point $(P = a' - 2b'PV)$:

(i) At the break-even price, prosumers satisfy internal demand through self-consumption with no market participation.

(ii) Below the break-even price, they act as net buyers, purchasing additional energy to meet their demand (exhibiting a downward sloping demand curve and inelastic supply at $x = 0$).

(iii) Above the break-even price, they act as net sellers, reducing consumption to sell excess production to the market (exhibiting an upward sloping supply curve and inelastic demand at $y = 0$).

3. When the minimum internal demand exceeds PV capacity ($y_{min'} > PV$), the prosumer remains a net buyer across all price levels. Their generation capacity cannot satisfy minimum demand, imposing consistent market purchases, starting at $y_{min} = y_{min'} - PV$ for zero price, and decreases with a negative slope of $-\frac{1}{2b'}$, while no market supply is offered ($x = 0$ for all prices). The optimal market participation decision focuses exclusively on determining the optimal level of energy to purchase from the market, with demand bounded between $y_{min} = y_{min'} - PV$ and $y_{max} = \min\left(y_{max'}, \frac{a'}{2b'}\right) - PV$.

These different scenarios of prosumer behaviour can be summarized in Table 4.

Table 4: Prosumers Behaviour in Relation to PV Power

| | **PV Power** | **Price** | **Behaviour** | **Market Demand (y)** $P = a - 2by$ | **Market Supply (x)** $P = c + 2dx$ |
|---|---|---|---|---|---|
| 1 | $PV \geq \min\left(y_{max'}, \frac{a'}{2b'}\right)$ | All prices | Net Seller | $y = 0$<br>$y_{min} = 0$<br>$y_{max} = 0$ | $P = (a' - 2b'PV) + 2b'x$<br>$x_{min} = PV - \min\left(y_{max'}, \frac{a'}{2b'}\right)$<br>$x_{max} = PV - y_{min'}$ |
| 2 | $y_{min'} < PV < \min\left(y_{max'}, \frac{a'}{2b'}\right)$ | Depends on price level | Buyer or Seller (not both) | $P = (a' - 2b'PV) - 2b'y$<br>$y_{min} = 0$<br>$y_{max} = \min\left(y_{max'}, \frac{a'}{2b'}\right) - PV$ | $P = (a' - 2b'PV) + 2b'x$<br>$x_{min} = 0$<br>$x_{max} = PV - y_{min'}$ |
| 2.i | | $P = a' - 2b'PV$ | Break-even | No buying ($y = 0$) | No selling ($x = 0$) |
| 2.ii | | $P < a' - 2b'PV$ | Net Buyer | Demand > 0 ($y > 0$) | No selling ($x = 0$) |
| 2.iii | | $P > a' - 2b'PV$ | Net Seller | No buying ($y = 0$) | Supply > 0 ($x > 0$) |
| 3 | $y_{min'} > PV$ | All prices | Net Buyer | $P = (a' - 2b'PV) - 2b'y$<br>$y_{min} = y_{min'} - PV$<br>$y_{max} = \min\left(y_{max'}, \frac{a'}{2b'}\right) - PV$ | $x = 0$<br>$x_{min} = 0$<br>$x_{max} = 0$ |

This table illustrates how prosumers transition between buying and selling roles based on their generation capacity and market prices, highlighting the dynamic nature of peer-to-peer energy trading. From this table, it is possible to describe the formulas for the supply function parameters $c_{i,t}$ and $d_{i,t}$, which are:

$$\boldsymbol{c_{i,t}} = a_{j,t} - 2b_{j,t} \times PV \tag{12}$$

$$d_{i,t} = b_{j,t} \tag{13}$$

where $a_{j,t}$ and $b_{j,t}$ are the original demand function parameters, and $PV$ is the photovoltaic generation capacity.

*Pricing Mechanisms and Elasticity Concepts*

The parameters of the utility functions are calibrated using historical consumption of different households, regulated prices data, and price elasticity of demand which plays a crucial role in the model, reflecting how consumption changes in response to price variations. A short-term price elasticity value of -0.221 was employed, supported by comprehensive meta-analysis of electricity price elasticities in the literature [116], resulting in a 2.21% consumption reduction for every 10% price increase. The authors in [116] state that this value captures the dynamic nature of consumer adaptation while accounting for various influencing factors such as geographic location, temporal considerations, and methodological variations in the underlying studies. This suggests that this specific elasticity value provides a realistic basis for estimating consumer responsiveness to price changes and supports the economic validity of the modelled demand behaviour.

Additionally, the model incorporates pricing mechanisms that reflect both market dynamics and regulatory frameworks. The regulated electricity price considers a bi-hourly tariff (0.1956 €/kWh for peak hours and 0.1090 €/kWh for off-peak hours, values from ERSE 2023 tariff [117]) which serves as a reference point for market transactions, establishing a ceiling for P2P energy prices. The grid then acts as both a seller (at the regulated tariff) and a buyer (at the wholesale market price). This dual role creates boundary conditions for the P2P market, where internal community prices must position advantageously relative to these external reference points to incentivize local energy trading. Since consumers can always purchase from the grid at the regulated price, community producers must price their energy competitively below this threshold to attract buyers. However, no prosumer will sell within the P2P market at a price below the wholesale market price, as a perfectly elastic demand from the grid provides no incentive to price lower.

### 3.3.3 Flexibility Mechanisms

*Energy Storage (Batteries)*

Batteries play a critical role in optimizing energy use within the community by enabling temporal arbitrage and enhanced self-consumption of renewable generation. The optimization model incorporates detailed battery constraints that govern charging, discharging, and state-of-charge dynamics:

1. **Battery dynamics:** Battery state of charge (SOC) evolves according to:

$$b_{k,t+1}^{soc} = b_{k,t}^{soc} + b_{k,t}^{charge} \times \eta_{\text{charge}} - \frac{b_{k,t}^{discharge}}{\eta_{\text{discharge}}} \quad \forall k \in B, t \in T \tag{14}$$

where $b_{k,t}^{soc}$ represents the state of charge of battery *k* at time *t*, $\eta_{\text{charge}}$ and $\eta_{\text{discharge}}$ are the charging and discharging efficiencies respectively, set to $\eta = 90\%$ ([118]), and $b_{k,t}^{charge}$ and $b_{k,t}^{discharge}$ are the charging and discharging rates. This constraint models the energy storage dynamics, accounting for charging and discharging efficiencies.

2. **Initial and Final State of Charge:**

$$b_{k,1}^{soc} = b_{k,T+1}^{soc} = 0.1 \times B^{capacity} \quad \forall k \in B \tag{15}$$

This constraint ensures that the battery begins and ends with a specified state of charge, preventing the optimization from depleting the battery at the end of the planning horizon. It is established that the initial and final state of charge conditions are 10% of the battery capacity to ensure operational continuity and prevent terminal depletion strategies that would be impractical in ongoing operations

3. **Variable's bounds:**

$$B^{max\_charge} = B^{max\_discharge} = \frac{1}{3} \times B^{capacity} \quad \forall k \in B, t \in T \tag{16}$$

$$0 \leq b_{k,t}^{charge} \leq B^{max\_charge} \quad \forall k \in B, t \in T \tag{17}$$

$$0 \leq b_{k,t}^{discharge} \leq B^{max\_discharge} \quad \forall k \in B, t \in T \tag{18}$$

$$0 \leq b_{k,t}^{soc} \leq B^{capacity} \quad \forall k \in B, t \in T \tag{19}$$

However, as a limitation, this battery model does not account for degradation, temperature effects, or non-linear efficiency characteristics, which could affect long-term performance.

*Demand Shifting*

Consumers can manage their energy consumption through demand shifting (DS), a strategy aimed at redistributing energy use throughout the day without altering total daily consumption. The primary objectives of DS are to smooth the demand curve over time, reduce market price volatility, and enhance overall community welfare. By shifting energy consumption to different hours, consumers can take advantage of lower prices or avoid peak-hour surcharges, optimizing their energy use in response to price variations and incentives.

In this model, consumers adjust the timing of their energy consumption while ensuring that total daily usage remains constant. The key constraint for DS is the *Daily Consumption Constraint*, which states that total consumption over a 24-hour period must remain unchanged:

$$\sum_{t=1}^{24} y_{j,t} = \sum_{t=1}^{24} y_{j,t}^{historical} \tag{20}$$

where $y_{j,h}$ represents the optimized consumption of buyer *j* at time *t* and $y_{j,t}^{historical}$ represents the historical consumption buyer *j* at time *t* from data sources consumption profiles.

While DS offers flexibility, practical limitations exist on how much load can be shifted within each hour. To model these real-world constraints, the following condition was implemented:

$$\left| y_{j,t}^{historical} - y_{j,t} \right| \leq 0.1 \times \max\left\{ y_{j,t}^{historical} \right\} \tag{21}$$

This constraint ensures that for each hour, the absolute difference between historical and optimized consumption does not exceed 10% of the consumer's daily peak load, a threshold set by assumption. The parameter $\max\{y_{j,t}^{historical}\}$ represents the maximum hourly consumption for consumer *j* across all hours of the day.

In theory, it is expected that when prices are high (during peak hours), participants typically reduce their consumption, shifting demand downward and decreasing the quantity demanded at each price point. Conversely, during off-peak hours, when prices are lower, they increase consumption, shifting demand upward. This redistribution influences market equilibrium, leading to adjustments in both price and quantity in DS scenarios compared to a scenario without DS.

#### 3.3.4 Community Technologies' Sizing

A critical aspect of energy community planning is determining the optimal size of renewable generation and storage resources to maximize welfare and operational efficiency namely the PV panels and battery storage. This section details the methodology used to dimension the sizes of these technologies.

*Dataset's Average Scenario*

This process begins with the creation of a representative average scenario that serves as a standardized basis for the dimensioning analysis. Using the comprehensive two-year historical dataset, the methodology computes a representative 24-hour profile for each critical variable in the model: consumer load patterns, market prices, and PV generation potential.

For each hour of the day, the average scenario incorporates the mean value of each variable across the entire dataset, creating a synthetic but representative daily profile. Additionally, the procedure establishes boundary conditions for operational constraints, particularly the minimum and maximum consumption values that define the feasible region for the optimization model.

*Sizing Criteria and Metrics*

The community dimensioning process was guided by several technical and economic indicators:

- **Self-Sufficiency Ratio (SSR):** This metric measures the proportion of community consumption covered by locally generated energy and is defined as the ratio of self-consumed renewable energy to the total community consumption:

$$SSR = \frac{\sum_{t=1}^{24} E_{SC,t}}{\sum_{t=1}^{24} E_{C,t}} \tag{22}$$

where $E_{SC,t}$ represents the self-consumed energy at hour *t,* and $E_{C,t}$ represents the total community consumption at hour *t*.

- **Self-Consumption Ratio (SCR):** This metric measures the proportion of locally generated energy that is consumed within the community and is defined as the ratio of self-consumed renewable energy to the total renewable production:

$$SCR = \frac{\sum_{t=1}^{24} E_{SC,\mathrm{t}}}{\sum_{t=1}^{24} E_{PV,t}} \tag{23}$$

where $E_{PV,t}$ represents the total PV energy production at hour *t*.

- **Economic Welfare:** This metric captures the overall economic benefit to the community and is defined as the difference between consumer utility and producer cost:

$$\sum_{t=1}^{24} \left( \sum\nolimits_{j \in C} U_{j,t}(y_{j,t}) - \sum\nolimits_{i \in S} C_{i,t}(x_{i,t}) \right) \tag{24}$$

where $U_{j,t}(y_{j,t})$ is the utility function for consumer *j* at time *t*, and $C_{i,t}(x_{i,t})$ is the cost function for producer *i* at time *t*. The welfare function represents the net economic benefit to the community from the P2P energy trading arrangement.

The optimal dimensioning seeks to balance these metrics, recognizing that they often involve trade-offs. For example, increasing PV capacity typically improves SSR but may reduce SCR if the additional generation cannot be effectively utilized within the community.

*Optimal Resource Sizing*

With the representative average scenario established, a parametric analysis framework combined with deterministic optimization was employed to determine the optimal PV and BESS dimensions [119].

The frameworks evaluated PV system sizes ranging from 9 to 13 kWp per prosumer with 1 kWp increments, and battery storage capacities ranging from 50 to 80 kWh for the community with 5 kWh increments. For each possible combination of PV and battery capacity, the model updates the system parameters with the specific resource dimensions and executes a deterministic optimization to calculate key performance metrics. The dimensioning algorithm employs a two-stage approach based on these metrics. The optimal PV size is determined at the point where the difference between SSR and SCR changes from negative to positive. This corresponds to the point where the two metrics are equal, meaning their difference is zero (Figure 8).

Linear interpolation between adjacent PV sizes is applied to estimate the precise zero crossing point and the final optimal PV size is then rounded to a standard incremental step (1 kWp), as these modules are not infinitely discretized. The optimal PV size is found for 10 kWp per prosumer. This inflection point represents a balance between self-sufficiency and self-consumption, where increases in PV capacity begin to yield diminishing returns in terms of self-consumed energy.

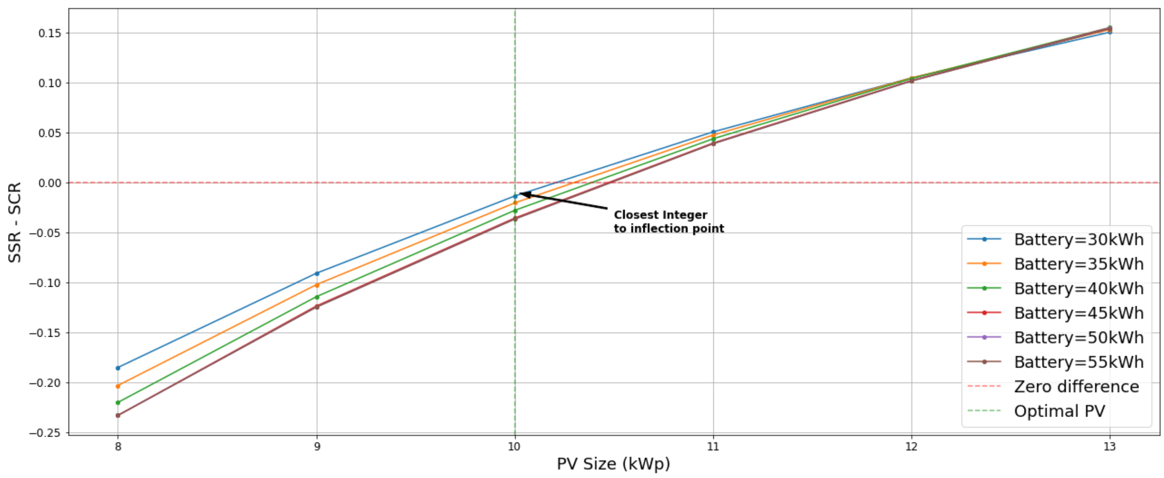


Figure 8: SSR-SCR vs PV Size

Once the optimal PV size is determined, the second stage identifies the optimal battery capacity by analysing welfare at this PV size across different battery capacity. The optimal battery capacity is identified at the point where incremental welfare gains, from additional storage capacity, begin to flatten, indicating diminishing economic returns on storage investment (Figure 9). The optimum value for the community battery capacity was found to be 45 kWh.

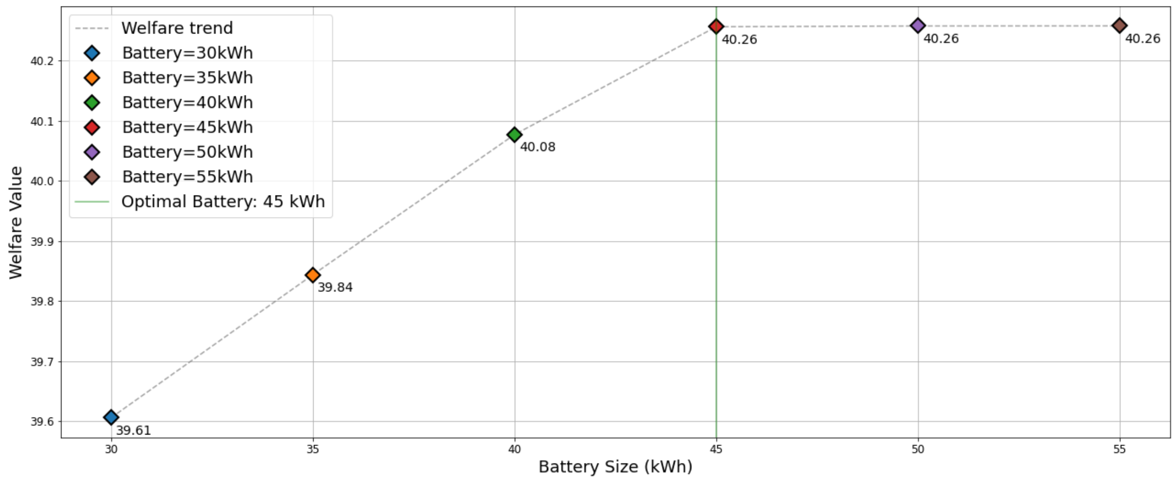


Figure 9: Welfare vs Battery Size for Optimal PV

This dimensioning methodology ensures a balanced optimization that considers both supply-side efficiency (SCR) and demand-side autonomy (SSR) while maximizing the community welfare.

## 3.4 Optimization Model Formulation

### 3.4.1 Objective Function

The optimization model is formulated as a quadratic programming problem designed to maximize social welfare over a 24-hour period, capturing the economic value created through P2P energy trading. Social welfare, defined in Equation 24, balances the utility gained by consumers (Equation 5) with the opportunity costs of producers (Equation **11**) and the interactions with external energy agents i.e. the grid (regulated and wholesale market). Mathematical, this objective function is expressed as:

$$\max\left(\sum_{t} welfare(t)\right) \tag{25}$$

where:

- $a_{j,t}$ and $b_{j,t}$ represent the utility function coefficients for consumer *j* at time *t*
- $c_{i,t}$ and $d_{i,t}$ represent the cost function coefficients for producer *i* at time *t*
- $x_{i,t}$ is the energy sold by producer *i* at time *t*
- $y_{j,t}$ represents energy purchased by consumer *j* at time *t*

Energy transactions ($x_{i,t}$ and $y_{j,t}$) represent the economic interactions within the community. These variables not only quantify energy exchanges but also reflect the dynamic pricing mechanisms and individual agent preferences that drive P2P trading. In addition, demand flexibility ($ds_{j,t}$) introduces a critical mechanism for optimizing energy consumption. This variable enables consumers to strategically redistribute their energy demand across different hours, responding to price signals and system constraints.

### 3.4.2 Constraints

The optimization problem is subject to a set of constraints that reflect the physical, economic, and operational realities of the energy community. The fundamental energy balance constraint ensures that total energy supply matches demand, accounting for energy transactions, consumption, and storage:

$$\sum_{i} x_{i,t} = \sum_{j} \left(y_{j,t} + ds_{j,t}\right) + \sum_{k} \left(b_{k,t}^{charge} - b_{k,t}^{discharge}\right), \forall\, t \in T \tag{26}$$

This constraint captures the real-time equilibrium between energy generation, consumption, and storage, reflecting the dynamic nature of P2P energy markets. Moreover, it is ensured that the energy bought by consumers is maintained within the technical bounds of each community participant.

Additional constraints include:

1. **Demand Shifting**: Total daily consumption for each consumer (excluding self-consumption) remains constant:

$$\sum_{t\in T} y_{j,t} = \sum_{t\in T} \left(\mathrm{y}_{j,t}^{hist} - \mathrm{y}_{j,t}^{self-consumption}\right), \forall\, j \in C\backslash\{0\} \tag{27}$$

These constraints allow for intra-day load shifting while maintaining the total daily energy consumption, representing the flexibility of consumers to adjust their consumption patterns without changing their overall energy needs.

2. **No arbitrage**: These constraints prevent buying from the grid solely to resell:
   The total amount of energy sold to the grid, accumulated over time, must not exceed the total energy produced locally by the PV system over the same period:

$$\sum_{t=1}^{h} y_{0,t} \leq \sum_{i \in S \setminus \{0\}} \sum_{t=1}^{h} x_{i,t} \quad \forall h \in T \tag{28}$$

   The battery can only be charged using the locally produced PV energy in the same period, which also means that it is not possible to charge it using energy purchased from the grid:

$$\sum_{k \in B} b_{k,t}^{charge} \leq \sum_{i \in S \setminus \{0\}} x_{i,t} \quad \forall t \in T \tag{29}$$

   The energy sold to the grid in each time period plus the energy used for battery charging must not exceed the locally produced PV energy in that same period:

$$\sum_{t=1}^{h} y_{0,t} + \sum_{k \in B} b_{k,t}^{charge} \leq \sum_{i \in S \setminus \{0\}} x_{i,t} \quad \forall t \in T \tag{30}$$

3. **Variables' bounds**:

$$y_{j,t}^{min} \leq y_{j,t} \leq y_{j,t}^{max} \quad \forall j \in C, t \in T \tag{31}$$

$$x_{i,t}^{min} \leq x_{i,t} \leq x_{i,t}^{max} \quad \forall i \in S, t \in T \tag{32}$$

These constraints define the feasible ranges for the decision variables, ensuring that physical and operational limits are respected.

### 3.4.3 Market Clearing Price

In the P2P energy market model, the market clearing price emerges from the optimization process as the dual variable (Lagrange multiplier) associated with the energy balance constraint:

$$p_t = \lambda_t \quad \forall t \in T \tag{33}$$

where $\lambda_t$ is the dual variable of the energy balance constraint at time *t.*

This price represents the marginal cost of energy in the community at each time period and serves as the basis for financial settlements between community members. It is bounded by the retail market price (upper bound) and the wholesale price (lower bound):

$$p_t^{OMIP} \leq p_t \leq p_t^{ERSE} \, \lambda_t \quad \forall t \in T \tag{34}$$

The market clearing process ensures that all trades in the community are financially balanced, with the total payments by consumers equal to the total revenues of producers.

## 3.5 Deterministic Optimization

The deterministic optimization serves as baseline technique for addressing energy community dynamics and resource allocation. Unlike stochastic approaches that explicitly incorporate uncertainty, deterministic methods solve the optimization problem using fixed, known parameter values. This study employs two distinct deterministic approaches - optimization of Average Scenario (AS) and optimization of the Averaging of Multiple Scenarios (AMS) - that differ on how they process scenario data while maintaining the same underlying model structure and objective function.

### 3.5.1 Implementation Techniques

Both deterministic approaches (AS and AMS) share the same objective function - maximizing community welfare. However, they differ significantly in how they handle input scenarios and how optimization results are processed. The following step-by-step diagrams illustrate the algorithmic flow of each approach:

**Table 5: Deterministic Approaches' Pseudocode.**

| Approach 1: AS Optimization | Approach 2: AMS Optimization |
|---|---|
| // Step 1: Scenario data preparation<br>input: Scenario set S = {$s_1$, $s_2$, ..., $s_n$} with probabilities P = {$p_1$, $p_2$, ..., $p_n$}<br><br>// Step 2: Compute weighted average scenario<br>avgScenario → ∑($p_i$ × $s_i$) for all i ∈ {1,2,...,n}<br><br>// Step 3: Initialize model parameters<br>Set objective function: max(welfare)<br><br>// Step 4: Perform single optimization<br>avgSolution → Optimize(avgScenario)<br>Extract optimal decisions: $y$, $x$, $b^{charge}$, $b^{discharge}$, $b^{soc}$<br><br>// Step 5: Evaluate performance across all scenarios<br>Initialize totalWelfare → 0<br>**FOR EACH** scenario s in S with probability p **DO**:<br>// Fix decisions to optimal values from average scenario<br>Fix $y \rightarrow y^*$<br>Fix $x \rightarrow x^*$<br><br>// Compute scenario-specific welfare using fixed decisions<br>scenarioWelfare → Calculate_Welfare($s$, $y^*$, $x^*$) | // Step 1: Scenario data preparation<br>input: Scenario set S = {$s_1$, $s_2$, ..., $s_n$} with probabilities P = {$p_1$, $p_2$, ..., $p_n$}<br><br>// Step 2: Initialize result containers<br>Initialize solutionSet → {}<br><br>// Step 3: Perform independent optimizations<br>**FOR EACH** scenario s in S with probability p **DO**:<br>Set objective function: max(welfare)<br><br>scenarioSolution → Optimize(s)<br>Extract optimal decisions: $y$, $x$, $b^{charge}$, $b^{discharge}$, $b^{soc}$<br><br>scenarioWelfare → Calculate_Welfare($s$, $y$, $x$)<br><br>Add scenarioSolution to solutionSet<br>END FOR<br><br>// Step 4: Calculate weighted average of results<br>avgDecisions → {<br>x_avg: ∑($p_i$ × $solutionSet_i$.x) for all i∈{1,2,...,n},<br>y_avg: ∑($p_i$ × $solutionSet_i$.y) for all i∈{1,2,...,n},<br>}<br>// Step 5: Evaluate avgDecisions across all original scenarios<br>Initialize TotalWelfare → 0<br>**FOR EACH** scenario s in S with probability p **DO**:<br>// Fix decisions to weighted average of results<br>finalScenarioWelfare → Calculate_Welfare(s, avgDecisions)<br><br>TotalWelfare → TotalWelfare + p × finalScenarioWelfare |

| | |
|---|---|
| // Accumulate weighted welfare<br>totalWelfare → totalWelfare + p × scenarioWelfare<br><br>END FOR<br><br>**RETURN** avgSolution, totalWelfare | END FOR<br><br>**RETURN** solutionSet, avgDecisions, TotalWelfare |

The distinction between these approaches lies in when and how the scenario aggregation occurs. While the AS approach aggregates scenarios before optimization, deriving a single representative scenario on which to base decisions, the AMS approach performs separate optimizations for each scenario independently, and then aggregates the scenario-specific optima using their probabilities, yielding an expected, probability-weighted solution.

These differences have important implications for computational efficiency and solution quality. The first approach only requires a single optimization run, making it computationally efficient but potentially less robust to scenario variability. The second approach requires separate optimizations, increasing computational requirements but potentially capturing scenario-specific optimal responses more accurately.

The deterministic approaches serve as important benchmarks against which to evaluate the more complex stochastic optimization methods described in the subsequent section, which explicitly account for uncertainty in the decision-making process.

## 3.6 Stochastic Optimization

In this methodology, uncertainty in energy markets is addressed through different stochastic optimization techniques, that are different in relation to the participant's attitude towards risk: stochastic optimization (where participants are risk neutral), robust optimization and least regret (where participants are risk averse). These different techniques share the same model structure, consider multiple possible scenarios simultaneously, but differ in their objective functions. Unlike deterministic models that assume perfect information, stochastic models are designed to deliver solutions that remain effective across a range of possible future outcomes.

### 3.6.1 Two-Stage Decision Framework

In the stochastic formulation, variables are divided in two stages, representing decisions made at the instant *t* (first-stage variables) while considering multiple possible future scenarios (second-stage variables). First-stage variables are fixed variables across all scenarios and decided before knowing which scenario will occur, representing advance commitments. Second-stage variables are flexible and scenario-dependent, allowing adaptation to the specific conditions of each realization. In this context, future scenarios refer to the evolution of key uncertain parameters – such as energy consumption, market prices, and PV generation - over a 24-hour horizon, with each scenario capturing different possible trajectory of these variables throughout the day. This structure allows the model to account for short-term volatility and makes decisions that remain effective across a range of day-ahead outcomes.

In the P2P energy community context, the first-stage decisions, also called "here-and-now" decisions, are the initial consumption scheduling plans:

$$y_{j,t} \quad \forall j \in C, t \in T \tag{35}$$

The second-stage decisions, also mentioned as "recourse decisions" in the literature because they react to the first-stage decisions, include:

- Consumption adjustments:

$$\delta_{s,j,t} \quad \forall s \in S, j \in C, t \in T \tag{36}$$

- Energy production:

$$x_{s,i,t} \quad \forall s \in S, i \in P, t \in T \tag{37}$$

- Battery operations:

$$b_{s,k,t}^{charge}, b_{s,k,t}^{discharge}, b_{s,k,t}^{soc} \quad \forall s \in S, k \in B, t \in T \tag{38}$$

An additional key component to this optimization is the inclusion of a quadratic penalty function designed to discourage excessive flexibility deviations $(\delta)$ between first-stage and second-stage decisions. This penalty represents the economic cost of deviating from the decisions made before the market opened and is incorporated directly into the objective function:

$$Penalty(\delta) = \omega \times \sum_{s,j,h} prob_s \times \delta_{s,j,t}^2 \tag{39}$$

where $\omega$ represents the penalty factor, $prob_s$ is the probability of scenario $s$ and $\delta_{s,j,t}^2$ is the flexibility deviations for consumer *j* at hour *t* in scenario *s*. This quadratic formulation $\delta_{s,j,t}^2$ penalizes larger deviations more heavily than smaller ones, reflecting the non-linear increase in difficulty and cost associated with implementing larger adjustments.

A sensitivity analysis was conducted to determine the optimal penalty factor value, testing $\omega = \{0.05, 0.1, 0.15, 0.2\}$ across all stochastic methods, allowing for fair comparison between their results. Based on this analysis, $\omega = 0.1$ was selected as the optimal value, providing an effective balance between economic efficiency and flexibility management, with penalty prices appropriately scaled relative to the wholesale market average price. The detailed results and justification for this selection are presented in the Appendix - Penalty Factor ($\omega$) Sensitivity Analysis.

This penalty mechanism serves different purposes:

- **Stability** : The penalty discourages excessive adjustments between the initial consumption schedule (first-stage decisions) and the scenario-specific adjustments (second-stage decisions), promoting more stable and practical solutions.
- **Practical Implementation**: In real-world operations, large deviations between planned and actual consumption can create operational challenges. The penalty represents the practical costs and difficulties associated with significant last-minute adjustments. In practical energy system operation, such deviations may trigger imbalance settlement costs, activate reserve capacity, or strain distribution infrastructure, particularly when large, abrupt adjustments are required. These costs are typically non-linear, with minor deviations being manageable, while larger adjustments incur disproportionately higher economic and technical burdens.

In stochastic methods, these adjustments are embedded in the objective function, enabling the model to internalize the trade-offs between flexibility and operational cost. In contrast, deterministic methods (AS and AMS) optimize based on a single representative or average scenario, assuming perfect foresight. As such, they neglect variability during optimization - a limitation given that real-world outcomes rarely match forecasted conditions. To ensure a fair comparison with stochastic optimization, an *ex-post* penalty is applied to the deterministic solutions. These adjustments, based on the mismatch between scheduled and actual values, reconcile consumption and supply across scenarios. Although these corrections are not part of the optimization process itself, they are essential to properly assess and compare the resulting welfare across methodologies.

### 3.6.2 Implementation Techniques

*Stochastic Optimization (SO)*

This technique aims to maximize the expected welfare across all scenarios, weighting each scenario's welfare by its probability of occurrence. The objective function takes the form:

$$max\left(\sum_{s\in S} prob(s) \times welfare(s)\right) \tag{40}$$

where $prob(s)$ represents the probability of scenario $s$ to occur, and $welfare(s)$ is the calculated welfare for that scenario. It optimizes across all scenarios simultaneously while weighting each scenario's contribution to the objective value by its probability.

This approach adopts a risk-neutral attitude, focusing on average-case performance rather than extreme scenarios, and is used when decision-makers are mainly concerned with long-term average performance rather than performance in a specific scenario. It properly accounts for the uncertainties and produces a solution that is expected to be optimal over all scenarios.

*Least Regret (LR)*

This technique, also known as minimax regret optimization, provides an approach between expected value and robust optimization. This method first determines the best possible welfare for each scenario, assuming perfect foresight, using the results from the deterministic optimization. It then seeks to minimize the maximum regret across all scenarios. Regret, in this context, represents the opportunity cost of a decision and is defined for each scenario as the difference between the best possible welfare and the welfare achieved by the chosen first-stage decisions:

$$regret(s) = welfare_{optimal}(s) - welfare_{actual}(s) \tag{41}$$

The objective function is then described as:

$$min\left(\max_{s\in S}\big(regret(s)\big)\right) \tag{42}$$

To implement this framework, a maximum regret variable is introduced to capture the worst-case deviation from optimal welfare. The first-stage decision variables are then established, ensuring consistency across all scenarios. In the second stage, scenario-specific adaptations are allowed to account for varying conditions. The welfare achieved under the chosen first-stage decisions is computed for each scenario, and regret is determined as the difference between the optimal and actual welfare. A constraint is imposed to ensure that the maximum regret reflects the worst-case regret across all scenarios. Finally, the objective function minimizes the maximum regret, promoting a more robust decision-making process.

This optimization reflects a risk-averse attitude, seeking to avoid solutions that might perform very well in one scenario but poorly in others. It aims to find solutions that perform reasonably well across all scenarios without sacrificing too much performance in any single case. This approach is particularly useful when decision-makers wish to balance between maximizing expected returns and limiting potential disappointment or underperformance relative to what could have been achieved. It is also less conservative than the robust optimization solution, while providing some protection against unfavourable scenarios.

*Robust Optimization (RO)*

This technique adopts a more conservative attitude toward uncertainty. This approach maximizes the minimum welfare across all scenarios, focusing on ensuring an adequate performance even in the worst-case scenario. This means the solver is finding the first-stage decisions that maximize the worst-case welfare across all scenarios, and that the resulting solution guarantees a minimum level of welfare no matter which scenario occurs. The objective function can be expressed as:

$$min\left(\sum\nolimits_{s\in S} welfare(s)\right) \tag{43}$$

This min-max problem can be reformulated as a standard maximization problem using an auxiliary variable ($z$) that represents the minimum welfare across all scenarios:

$$max(z) \tag{44}$$

$$welfare(s) \geq z \tag{45}$$

Unlike the SO approach, RO typically does not account for scenario probabilities into its objective function, treating all scenarios as equally possible. This approach is particularly valuable in contexts where resilience against adverse conditions is critical or where the consequences of poor performance in any scenario are severe. The resulting decisions tend to be more conservative but guarantees a solution that performs acceptably even in the worst-case scenario.

*Solver Configuration*

All optimization models were implemented using the Gurobi optimization solver (version 10.0) through its Python API (gurobipy). The following solver configurations were used:

**Table 6: Gurobi Parameters Configuration**

| Parameter | AS & AMS | SO | LR | RO |
|---|---|---|---|---|
| **Problem type** | Quadratic Programming (QP) | Quadratic Programming (QP) | Mixed Integer Quadratic Programming (MIQP) | Quadratic Programming with Non-Convex objectives (QCP) |
| **Time limit** | None (solve to optimality) | None (solve to optimality) | 10800 seconds | 7200 seconds |
| **MIP Gap** | n/a | n/a | 0.001<br>(5% optimality gap) | 0.001<br>(2% optimality gap) |
| **Non-Convex** | n/a | n/a | 2 (enable non-convex QP solution) | 2 (enable non-convex QP solution) |
| **Numeric Focus** | n/a | n/a | 3 | 3 |

The implementation includes careful error handling and fallback mechanisms to ensure robust operation even in challenging numerical conditions.

## 3.7 Comparative Analysis

### 3.7.1 Welfare Optimization Metrics

As seen, this study employs three different approaches for analysing the energy community behaviour under uncertainty:

a. deterministic optimization with a single scenario selected through clustering (AS),
b. deterministic optimization with multiple scenarios (AMS), and
c. stochastic optimization with three sub-methods related to the objective function (SO, LR, RO).

For each approach, specific metrics were applied to comprehensively evaluate welfare outcomes.

*Deterministic Optimization*

For the deterministic optimization two approaches were used. The first approach used a single representative scenario, where two primary metrics were calculated:

- **Expected Value Problem (EVP)**: represents the optimal welfare obtained from solving the AS problem. This quantifies the solution performance when assuming the uncertain parameters would constantly equal their average values.
- **Expected Value of the Expected Solution (EVES)**: Evaluates the performance of the EVP solution when implemented across all possible scenarios. This metric provides insight into how a solution optimized for average conditions performs under varying conditions.

The second approach employed differs fundamentally from the others as each scenario is solved deterministically and independently, with the result being the weighted average of individuals solutions based on scenario probabilities. Two key metrics were applied:

- **Wait-and-See Value (WSV):** Involves solving each scenario independently as separate deterministic optimization problems (assuming perfect information) and calculating the probability-weighted average of these optimal values. This represents the theoretical maximum expected objective value achievable if the community had perfect knowledge about which scenario would occur. Because of this, it is considered the upper bound on what any decision-making approach under uncertainty can achieve.
- **Expected Value of the Weighted Mean Solution (EVWMS):** Assesses the performance of the weighted solution derived from optimizing each scenario deterministically when implemented across all scenarios with their respective probabilities. This process involves: (1) optimizing each scenario deterministically, (2) calculating a weighted average solution using scenario probabilities, (3) fixing these decision variables, (4) evaluating the welfare for each scenario, and (5) computing the probability-weighted sum of these values. This metric helps determine whether the weighted averaging approach performs as expected when implemented in practice.

*Stochastic Optimization*

For the stochastic optimization approach, three metrics are applied, each corresponding to a specific sub-method, and being implemented across all respective scenarios given each probability:

- **Expected Value of the Stochastic Solution (EVSS):** Represents the objective value obtained from solving the stochastic optimization problem. This metric quantifies the expected welfare of the solution that optimally balances performance across all scenarios without perfect information.
- **Expected Value of the Least Regret Solution (EVLRS):** Assesses how effectively the solution derived from the least regret approach performs across all scenarios with their respective probabilities.
- **Expected Value of the Robust Solution (EVRS):** Evaluates the performance of the solution derived from the robust optimization approach when implemented across all scenarios with their respective probabilities.

To facilitate comparison across different scenarios and approaches, normalized metrics are calculated by expressing each welfare value as a percentage of the theoretical maximum (WSV):

$$Normalized\ Metric = \frac{Metric}{WSV} \times 100 \tag{46}$$

This normalization allows for meaningful comparison even when the absolute welfare values differ significantly across scenarios.

*Value-Added Metrics*

In addition to the direct welfare metrics described above, several value-based metrics are calculated to quantify the specific benefits of each approach:

1. **Value of Stochastic Solution (VSS)** [120]: Improvement from using stochastic optimization over the expected value solution.

   $$VSS = EVSS - EVES \tag{47}$$

   This metric quantifies the value of explicitly considering uncertainty in the decision-making process.

2. **Stochastic Integration Value (SIV)**: Improvement from using stochastic optimization over the weighted mean solution.

   $$\mathrm{SIV} = \mathrm{EVSS} - \mathrm{EVWMS} \tag{48}$$

   This metric quantifies the value of integrating scenarios into a single optimization problem rather than averaging independent solutions.

3. **Expected Value of Perfect Information (EVPI)** [120]: Difference between expected welfare with perfect information and expected welfare with uncertainty.

   $$\mathrm{EVPI} = \mathrm{WSV} - \mathrm{EVSS} \tag{49}$$

   This metric quantifies how much an EC would be willing to pay for perfect forecasts of uncertain parameters (solar radiation, grid prices, consumer demand).

4. **Price of Robustness (PoR)**: Cost of robustness compared to stochastic optimization.

   $$PoR = EVSS - EVR \tag{50}$$

   This metric quantifies the expected welfare reduction needed to achieve robustness against worst-case scenarios.

5. **Regret Value (RV)**: Performance gap between least regret and stochastic optimization.

   $$RV = EVSS - EVLRS \tag{51}$$

   This metric quantifies the cost of minimizing maximum regret instead of maximizing expected welfare.

### 3.7.2 Key Performance Indicators

Key Performance Indicators (KPIs) are essential metrics used to evaluate the effectiveness of energy communities. These indicators are typically grouped into four categories: Energy Performance, Economic, Grid and Technical, and Environmental indicators. Energy communities use these metrics to measure progress toward goals such as increasing self-consumption, reducing costs, ensuring grid stability, and/or decreasing carbon emissions. The optimization outputs allow the calculation of several KPIs that help quantify the benefits and performance of the energy community model:

- **Energy Performance**:
  - Self-sufficiency rate (%): indicates the community's ability to meet its own energy demands using local production.
- **Economic**:
  - Energy cost savings (€): demonstrate how much money participants save through local energy trading and self-consumption.
- **Grid and Technical**:
  - Peak load reduction (%): evaluates how well the community reduces stress on the grid.
  - Demand shift: tracks improvement in consumption efficiency through better habits or technology upgrades.
- **Environmental**:
  - $CO_2$ emissions reduction (kg$CO_2$eq): measures the impact of the energy community in decarbonization its consumption. For calculations, Portugal's emission factor (as of 2022) is approximately 0.124 kg $CO_2$ per MWh [121].

Table 7: Summary Table for KPIs

| Category | KPI | Mathematical Formulation |
|---|---|---|
| Energy Performance | Self-Sufficiency Ratio - SSR (%) | $SSR = \frac{E_{renewable,consumed}}{E_{total,consumed}} \times 100\%$ |
| Economic | Energy Cost Saving - $\Delta C$ (€) | $Baseline\ Cost\ (€) = \sum_t (Load_t \times Grid\ Price_t)$ <br> $Actual\ Cost\ (€) = \sum_t (Grid\ purchases_t \times Grid\ Price_t - OMIP\ purchases_t \times P2P\ Price_t) + Penalty$ <br> $\Delta C(€) = Baseline\ Costs(€)\ - Actual\ Cost\ (€)$ |
| Grid and Technical | Peak Load Reduction - PLR (%) | $PLR = \frac{\Delta P_{peak}}{P_{baseline}} \times 100\%$ |
| | Demand Shifting DS – (%) | $DS = \frac{\frac{\lvert DS^{+} + DS^{-} \rvert}{2}}{y^{hist}} \times 100\%$ |
| Environmental | $CO_2$ emissions reduction - $\Delta CO_2$ (kg$CO_2$e) | $\Delta CO_2 = CO_{2,without\ P2P} - CO_{2,with\ P2P}$ |

To following statistic measures were used across the different analysis:

- Weighted average ($\mu$)

$$\mu = \sum_{s=1}^{N_S} prob_s \times x_s \tag{52}$$

where $x_s$ is the variable value in scenario $s$, $prob_s$ is the probability of scenario $s$, and $N_S$ is the number of scenarios.

- Coefficient of Variation ($CV$)

$$CV = \frac{\sigma}{|\mu|} \times 100 \tag{53}$$

$$\sigma = \sqrt{\sigma^2} \tag{54}$$

$$\sigma^2 = \sum_{s=1}^{N_S} prob_s \times (x_s - \mu)^2 \tag{55}$$

where $\sigma$ is the standard deviation and $\sigma^2$ is the variance.

# 4. Results Analysis

This chapter examines the implications of incorporating uncertainty into the optimization of an EC, composed of PV prosumers, conventional consumers, and flexibility mechanisms. EC's agents interact with both the P2P market and the electricity grid (through retail market and the wholesale market - OMIP).

In some analysis, a baseline is also computed for benchmark, which assumes no EC implementation – all agents are pure consumers who purchase electricity exclusively from the retail market, and no energy is sold to the wholesale market.

Five optimization models are compared across two seasonal clusters (summer and winter), using hourly data on energy consumption, PV generation, and wholesale electricity prices: Average Scenario (AS), Average Multiple Scenario (AMS), and three stochastic formulations - Stochastic Optimization (SO), Least Regret (LR), and Robust Optimization (RO).

## 4.1 Welfare Optimization Analysis

This section evaluates the performance of the different optimization methods regarding the expected welfare as formalized in 3.7.1. Substantial differences emerge between deterministic and stochastic approaches, particularly under heightened uncertainty conditions.

### 4.1.1 Comparative Performance Analysis

In summer scenarios (Figure 10), characterized by more predictable generation and consumption patterns, stochastic methods achieve relatively high welfare performance with EVSS achieving 96.3% of theoretical optimal welfare (WSV). This demonstrates enhanced alignment with theoretical welfare expectations compared to deterministic approaches, which reach moderate performance levels (50.8% for EVES and 64.8% for EVWMS). The modest EVPI of 3.7% suggests limited potential gains from perfect forecasting during summer conditions.

Conversely, winter scenarios reveal considerably different results (Figure 11), emphasizing the impact of greater uncertainty. Deterministic methods perform exceptionally poorly, showing lower welfare values (11.6% for EVES and 39.5% for EVWMS) indicating substantial performance degradation when optimization decisions are applied across all possible scenarios. This is also reflected in both high VSS (63.7%) and SIV (35.8%) values, demonstrating the critical importance of stochastic approaches during high-uncertainty periods. The significantly higher EVPI (24.7%), in comparison to summer scenarios, indicates that perfect information would be substantially more valuable in winter scenarios.

Among the stochastic methods, EVSS maintains the strongest performance in both seasons (96.3% in summer and 75.3% in winter), while EVLRS and EVRS show respectable performance in summer (95.2% and 89.7% respectively) but experience more significant degradation in winter conditions (61.4%

and 58.6%). The RV (1.1% in summer versus 13.9% in winter) indicates that the ability to adapt decisions based on realized uncertain parameters becomes critically important during winter periods. Similarly, the PoR increases from 6.6% in summer to 16.6% in winter, quantifying the higher cost of implementing solutions that maintain feasibility across all scenarios during more uncertain conditions. All these metrics highlight the impact of seasonal uncertainty on optimization outcomes.

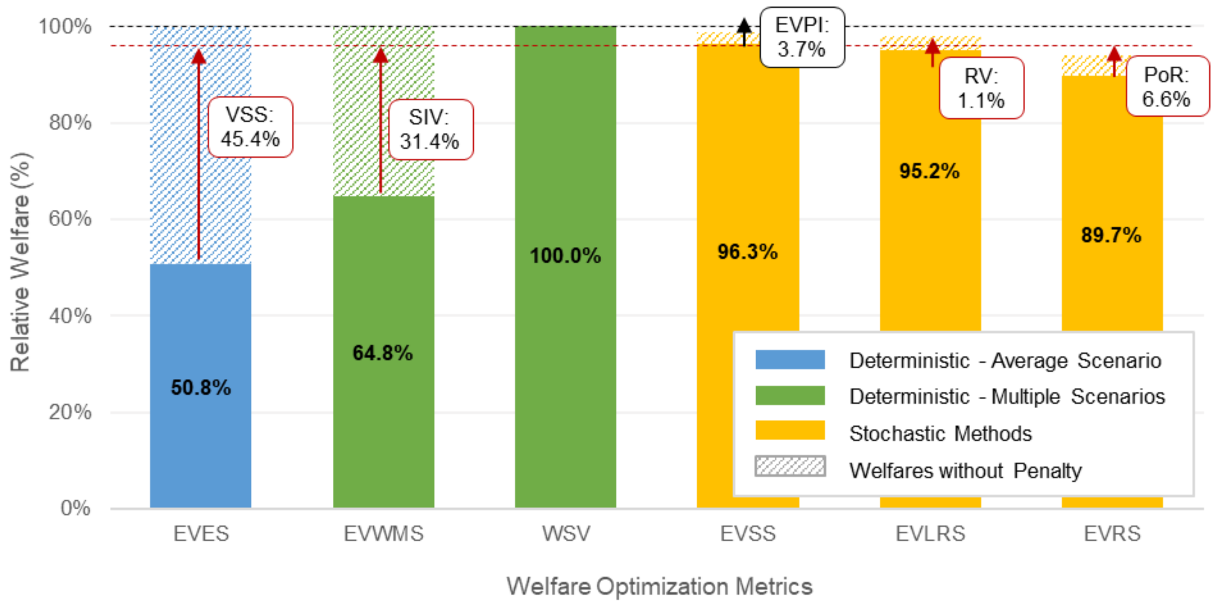


Figure 10: Comparative Performance of Relative Welfares for Summer Cluster

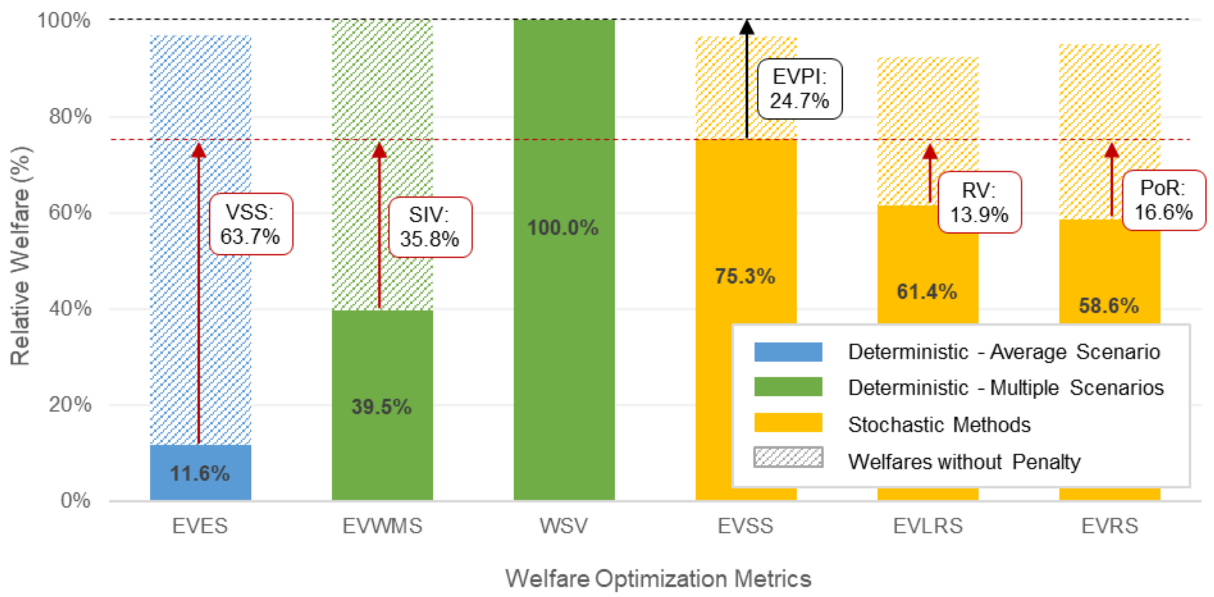


Figure 11: Comparative Performance of Relative Welfares for Winter Cluster

#### 4.1.2 Welfare Performance Statistics

To provide deeper insights into method performance, a detailed analysis of individual scenario outcomes and comprehensive statistical metrics is conducted, examining both the distribution of welfare values across scenarios (Figure 12) and the complete statistical characterization of each approach (Table 8).

Figure 12 provides a comprehensive visualization of welfare distributions across all scenarios, illustrating the outcomes' range for each optimization method under both summer and winter conditions.

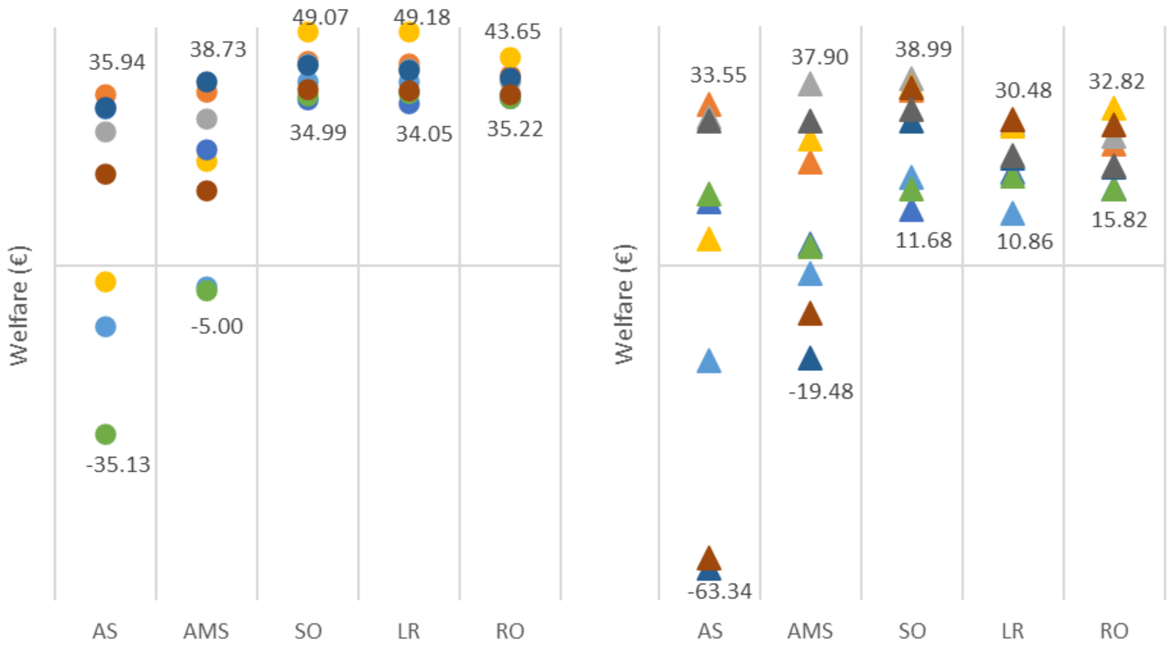


Figure 12: Welfare across Scenarios - Summer Cluster (left) and Winter Cluster (right)

The scatter plot reveals significative differences not only between seasons but also between optimization approaches. In summer (left plot), all stochastic methods show relatively clustered outcomes, while deterministic approaches exhibit wider vertical dispersion with negative values. The winter scenario plot (right plot) illustrates the fundamental difference between deterministic and stochastic approaches under uncertainty. Deterministic methods show extreme dispersion, reaching extremely high negative values, in comparison to stochastic methods that maintain positive welfare across all scenarios. It is also notable that RO delivers the most consistent performance with the tightest vertical distribution (min-max range). This visual representation demonstrates how deterministic approaches can catastrophically fail under winter uncertainty, while stochastic methods preserve positive welfare even in the most challenging scenarios.

The complete statistical characterization of method performance, including expected values, variability measures, and extreme outcomes, is presented in Table 8. Regarding summer scenarios:

- SO achieves the highest expected welfare at 42.20€, coupled with moderate variability (CV of 9.58%) with a minimum value of 34.99€, indicating both high expected returns and resilience under uncertainty.

- RO delivers a competitive expected welfare of 39.31€, paired with excellent stability (CV of 6.52%) and a robust worst-case outcome of 35.22€, highlighting how optimizing for downside protection can simultaneously enhance overall stability.
- LR approach results in a competitive expected welfare of 41.71€, with a minimum value of 34.05€, showing a favourable balance between expected performance (SO solution) and downside protection (RO solution)
- In contrast, deterministic methods (AS and AMS) exhibit considerable variability (CV values of 86.17% and 40.07%, respectively) with significantly negative minimum values (-35.13€ for AS and -5.00€ for AMS), indicating their vulnerability to scenario uncertainty.

Table 8: Welfare Performance Metrics by Optimization Method (€/day)

| | | SUMMER | | | | | WINTER | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | AS | AMS | SO | LR | RO | AS | AMS | SO | LR | RO |
| Welfare (Net) | Expected Welfare | 22.29 | 28.42 | 42.20 | 41.71 | 39.31 | 4.66 | 15.84 | 30.19 | 24.62 | 23.52 |
| | CV (%) | 86.17 | 40.07 | 9.58 | 10.13 | 6.52 | 702.43 | 115.38 | 31.72 | 22.45 | 26.12 |
| | MIN | -35.13 | -5.00 | 34.99 | 34.05 | 35.22 | -63.34 | -19.48 | 11.68 | 10.86 | 15.82 |
| | MAX | 35.94 | 38.73 | 49.07 | 49.18 | 43.65 | 33.55 | 37.90 | 38.99 | 30.48 | 32.82 |
| Penalty (ω = 0.1) | μ | 21.16 | 15.15 | 1.06 | 1.23 | 1.89 | 34.78 | 24.06 | 8.55 | 12.45 | 14.57 |
| | CV (%) | 97.21 | 73.71 | 29.98 | 23.30 | 35.37 | 96.44 | 72.10 | 65.78 | 14.63 | 23.68 |
| | MIN | 3.09 | 4.24 | 0.63 | 0.78 | 0.60 | 7.38 | 7.47 | 4.65 | 9.98 | 8.50 |
| | MAX | 72.87 | 44.61 | 1.48 | 1.61 | 2.87 | 107.80 | 57.19 | 22.72 | 15.28 | 19.60 |

**Notes**:
All values are expressed in euros per day (€/day) except CV in %
μ: Weighted Average
CV: Coefficient of Variation (%)
MIN: Minimum welfare across all scenarios
MAX: Maximum welfare across all scenarios

Under winter conditions, the performance of the evaluated methods exhibits significant variation in terms of expected welfare outcomes and associated risk:

- SO approach demonstrates superior average performance with the highest expected welfare of 30.19€, but this comes at the cost of significantly higher variability (CV of 31.72%) and poor worst-case protection (11.68€).
- LR approach offers a balanced middle ground with an expected welfare of 24.62€ and moderate stability (CV of 22.45%), though it provides limited worst-case protection (10.86€), reflecting its focus on minimizing maximum regret rather than downside risk.
- RO delivers the most robust worst-case outcome of 15.82€, successfully fulfilling its primary objective of maximizing worst-case welfare, while maintaining reasonable expected performance (23.52€) and acceptable variability (CV of 26.12%) under winter uncertainty.

- The deterministic approaches perform significantly worse (expected welfares of 4.66€ and 15.84€ for AS and AMS respectively), accompanied by CVs of 702.43% and 115.38%, respectively, indicating extreme volatility and unreliability in this season.

*Delta Variability and Penalty Analysis*

This welfare performance analysis incorporates a penalty component ($\omega$ = 0.1) that captures costs associated with second-stage adjustments when initial decisions prove suboptimal. A deeper examination of these penalty costs reveals important insights into each method's adaptability under uncertainty.

In summer, SO, LR, and RO methods incur modest average penalties (1.06€, 1.23€, and 1.89€ respectively). However, in winter scenarios, these penalties increase substantially to 8.55€, 12.45€, and 14.57€, reflecting the higher adjustment costs necessitated by greater uncertainty.

The winter penalty CV reveal that SO experiences the highest relative variability in adjustment costs (65.78%), while LR demonstrates superior stability (14.63%), suggesting consistent and predictable recourse actions regardless of scenario realization. RO approach shows moderate variability (CV of 23.68%) , reflecting its balanced approach between maintaining robustness and managing adjustment flexibility.

These penalty patterns help explain the welfare differences observed earlier: methods with more variable adjustment costs tend to exhibit greater overall performance volatility, while those with stable penalty structures maintain more consistent welfare outcomes.

These penalty dynamics are visually reinforced by the patterns observed in Figure **13**, which compares δ-adjustments across hours and scenarios for deterministic methods (AMS, top row) and the Stochastic Optimization (SO) approach (bottom row). In summer, AMS (top-left) methods show moderate variation, with occasional sharp corrections during midday, while in winter (top-right), the volatility intensifies significantly, with several scenarios exhibiting δ-adjustments exceeding 10 kW during peak hours, evidence of substantial recourse effort due to the inability to anticipate uncertainty.

Conversely, SO maintains consistently smoother δ-adjustments across both seasons (bottom row), with adjustments tightly clustered around zero in summer and moderate variability in winter. This reflects SO's capacity to internalize uncertainty and optimize flexibility without incurring disruptive operational costs.

Thus, the visual patterns in Figure 13 corroborate the welfare results: deterministic methods exhibit significant performance degradation when penalties are applied ex-post, as these costs are not integrated into their initial optimization frameworks. SO, by contrast, sustains superior performance by proactively managing uncertainty, confirming that the penalty mechanism meaningfully captures real-world costs and justifying the use of adaptive, scenario-aware optimization for energy community planning.

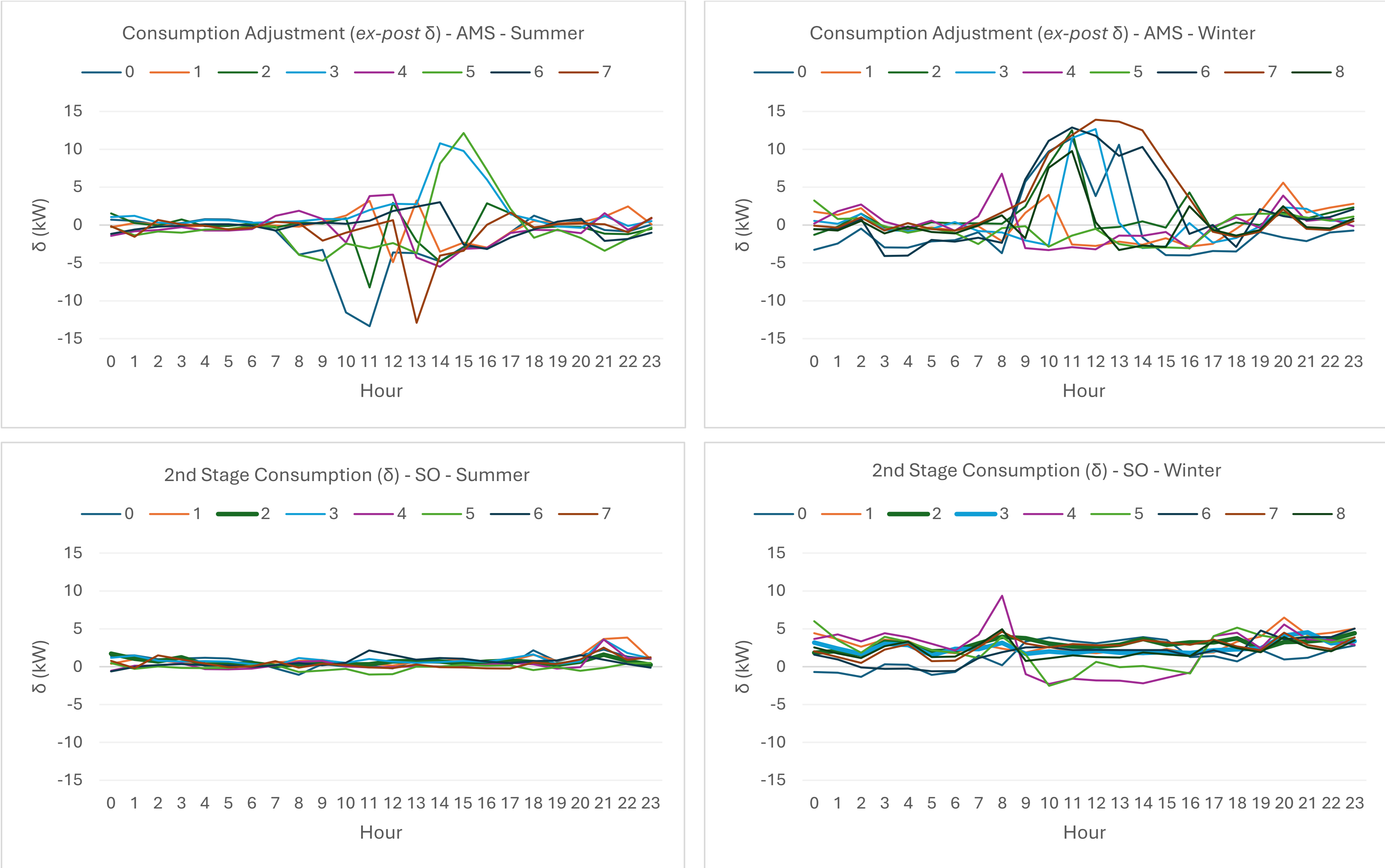


Figure 13: Delta Adjustments for AMS (top) and SO (bottom) - Summer (left) and Winter (right)

*Expected Welfare Trade-Off Analysis*

This analysis examines the trade-offs between expected welfare and performance characteristics across optimization methods, evaluating three key dimensions: stability through CV (Figure 14), downside protection via minimum welfare outcomes (Figure 15), and outcome dispersion measured by min-max range (Figure 16).

As shown in Figure 14, there is a clear trade-off between welfare and stability. Stochastic methods demonstrate stronger theoretical foundations and provide more reliable welfare outcomes across both seasons, with the difference becoming particularly pronounced in winter conditions (blue triangles) where deterministic approaches experience extreme volatility (AMS achieves a CV of 702%). This visualization clearly demonstrates the Pareto efficiency of stochastic methods, particularly SO, which achieves both higher expected welfare and higher stability (lower CV) compared to deterministic approaches.

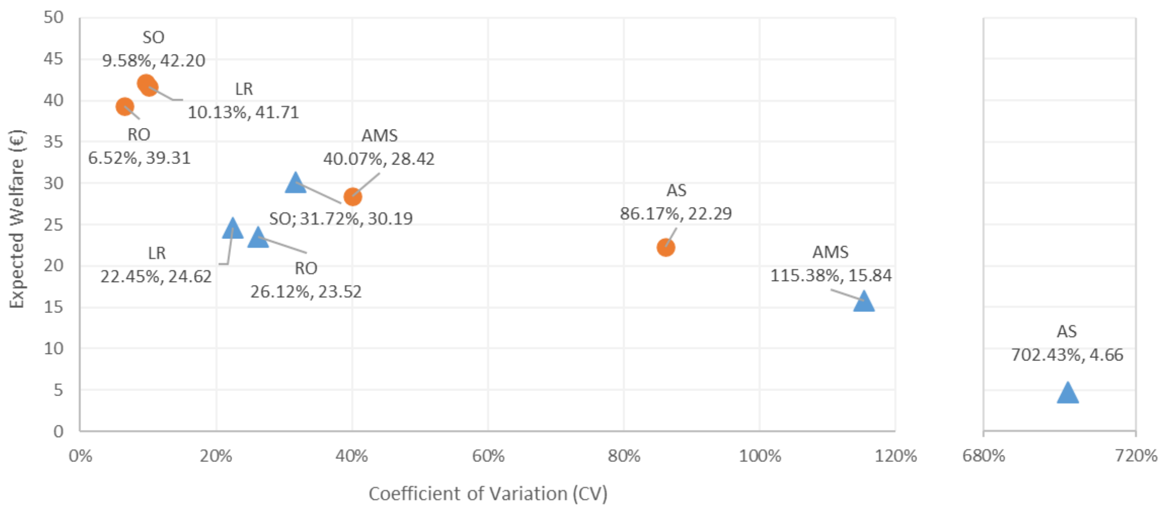


Figure 14: Expected Welfare (€) vs Coefficient of Variation (CV) - Summer (orange) and Winter (blue)

Figure 15 further illustrates this relationship by plotting expected welfare against minimum welfare, highlighting the severe downside risk faced by deterministic approaches, especially in winter scenarios where they can experience significant negative welfare values. This perspective emphasizes the worst-case performance, showing that while SO, LR, and RO maintain positive minimum welfare values in all conditions, deterministic approaches risk substantial financial losses in adverse scenarios. Notably, the analysis confirms RO's theoretical objective to maximize worst-case welfare, as evidenced by its superior minimum welfare in both seasons (35.2€ in summer and 15.8€ in winter).

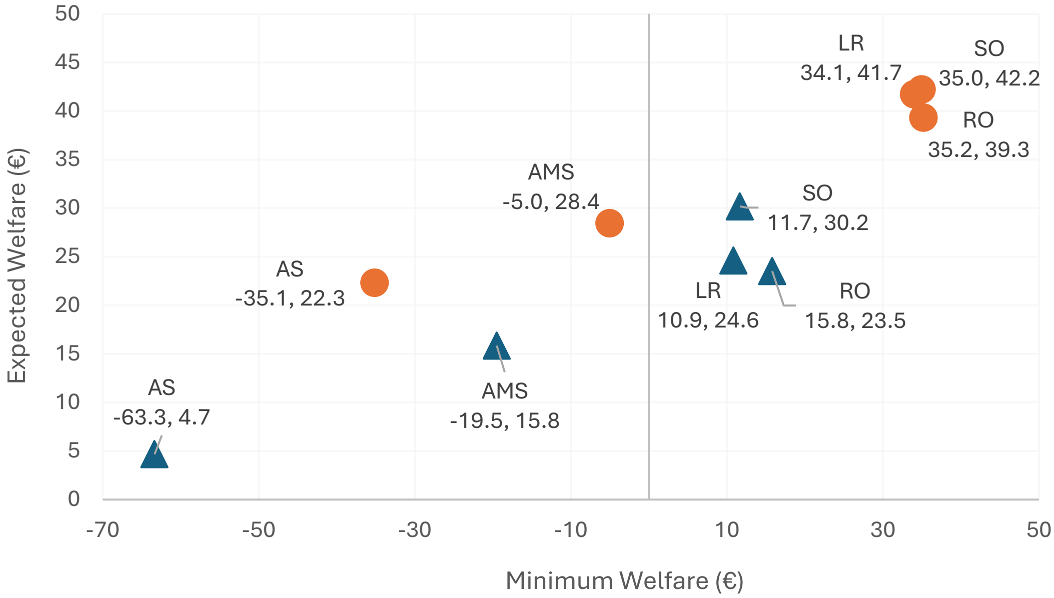


Figure 15: Expected Welfare (€) vs Minimum Welfare (€)

Figure 16 provides an additional valuable perspective by plotting expected welfare against welfare range (max-min). In summer, deterministic approaches not only have lower expected welfare but also exhibit substantially wider ranges (71.1€ for AS), revealing their higher dispersion in comparison to stochastic approaches (8.4€ for RO). In winter scenarios, the contrast becomes even more pronounced, with deterministic approaches showing extreme ranges (96.9€ for AS) compared to the much narrower bands of stochastic methods (17.0€ for RO).

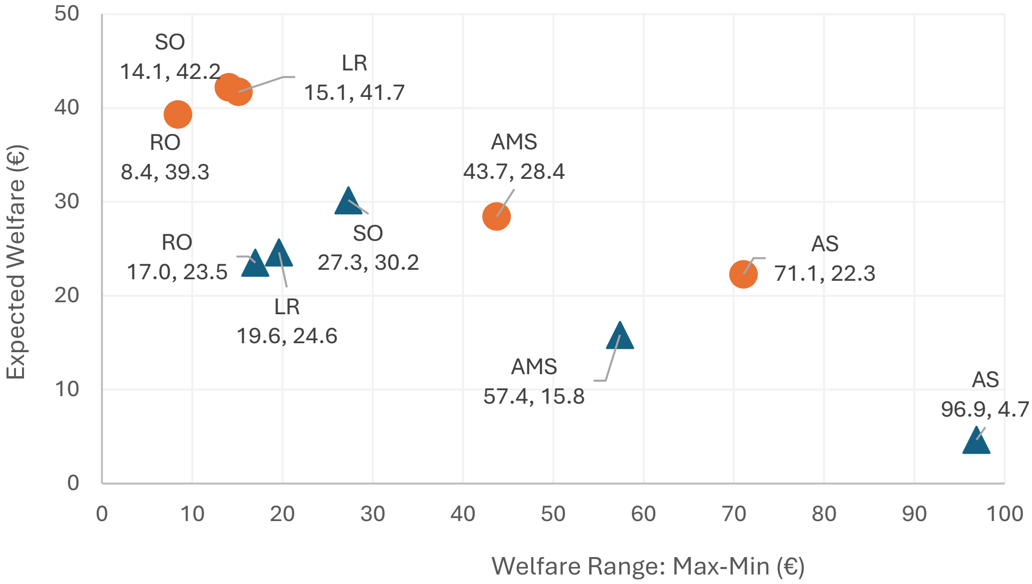


Figure 16: Expected Welfare vs Welfare Range (€)

These detailed welfare metrics provide compelling evidence that stochastic optimization methods not only maintain positive expected welfare under challenging conditions but also deliver significantly superior worst-case performance compared to deterministic approaches, with this advantage becoming even more pronounced under winter's high-uncertainty conditions.

## 4.2 Decision Variables Analysis

To complement the welfare optimization analysis, this section shows the optimal values of key decision variables, namely external market transactions, battery management, and P2P energy exchanges, under two representative optimization strategies: AMS (deterministic average of multiple scenarios) and SO (stochastic optimization, which demonstrated superior performance in prior analysis). A full report of detailed statistics in all decision variables in also provided in the last section. Analysing these operational decisions helps explain why the methods perform differently and reveals how effectively each approach handles uncertainty.

### 4.2.1 Hourly Decision Patterns

The hourly expected decision patterns between SO and AMS approaches reveal differences due to modelling structure, scenario characteristics, and the nature of the objective function, as illustrated in Figure 17 to Figure 20.

Regarding OMIP exports (green bars), in summer, AMS produces a smooth export profile peaking at hour 13 with consistent moderate levels, while SO creates a volatile pattern with a peak at hour 12 and then drops after hour 14. Winter amplifies these differences: AMS maintains its gradual transitions, whereas SO exhibits irregular behaviour by adapting to uncertainty of different scenarios. For regulated market imports (dark blue bars), both approaches follow similar daily patterns with high morning imports decreasing to near-zero during midday solar hours, then resuming evening imports. SO shows better grid independence with no imports during peak solar hours (8-16) in summer, while AMS maintains minimal residual imports in the same period. In winter, SO demonstrates superior optimization with lower evening imports compared to AMS, reflecting how simultaneous scenario optimization achieves more efficient grid interaction than the averaging approach.

Regarding battery management, in summer, both approaches show similar midday charging patterns (light blue bars) although SO achieves higher charging rate at hour 15 and higher evening discharge (orange bars). Winter operations reveal that SO maintains active battery management with substantial charging activity across all peak hours and significant evening discharging, whereas AMS is more conservative with minimal battery utilization in some of these periods.

In AMS, decision variables are computed as the weighted average of optimal solutions from individual deterministic optimizations, resulting in a single scenario, which is delivering an averaged behaviour that reduces extreme values but might omit important scenario-specific insights.

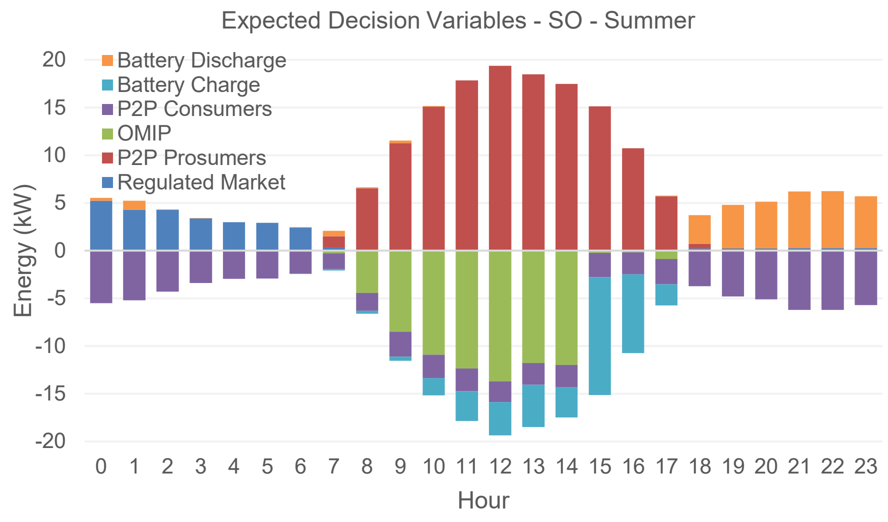


Figure 17: Expected Decision Variables - SO – Summer

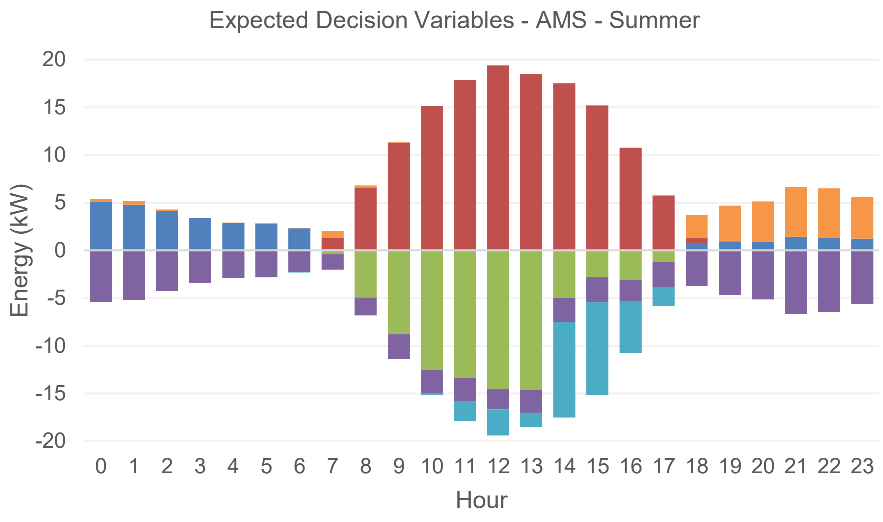


Figure 18: Expected Decision Variables - AMS - Summer

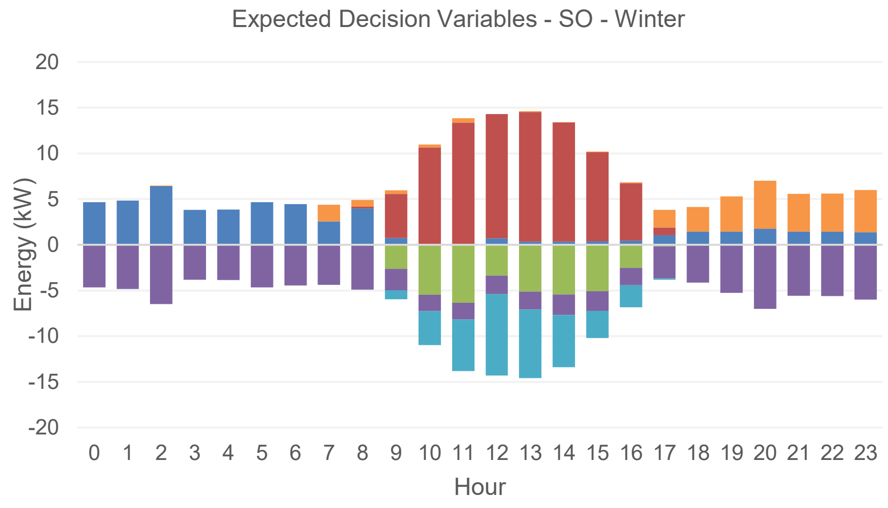


Figure 19: Expected Decision Variables - SO – Winter

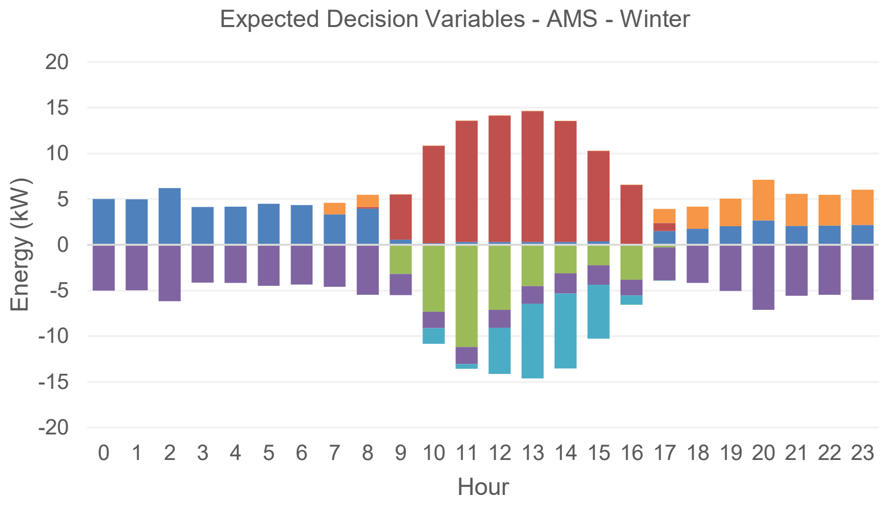


Figure 20: Expected Decision Variables - AMS - Winter

In contrast, SO formulates an integrated problem where the objective is to maximize expected welfare across all scenarios simultaneously. One might expect this adaptability to produce more varying decision variables, reflecting scenario-specific optimal adaptations, which is also presented in the next section.

### 4.2.2 Cross-Scenario Decision Variability

This analysis provides more insights into how the SO approach handles uncertainty across multiple scenarios, clearly presenting the decision variables under different conditions. This is particularly important for understanding how this method prepares for various possible outcomes rather than optimizing for a single expected scenario.

Summer scenarios demonstrate remarkably high convergence regarding grid imports (positive values) and exports (negative values), as shown in Figure 21. All scenarios show consistent export to OMIP during peak solar hours (7-15) with tight clustering of scenarios lines. Morning hours (0-7) exhibit stable imports, with smooth scenario variation, suggesting that the early morning operational strategy is relatively insensitive to scenario conditions. A notable exception is Scenario 0 (dark blue line), which shows distinct behaviour during evening hours (18-23) with higher imports (~5 kW) while other scenarios remain near zero, indicating that certain extreme scenarios may require different evening operational strategies.

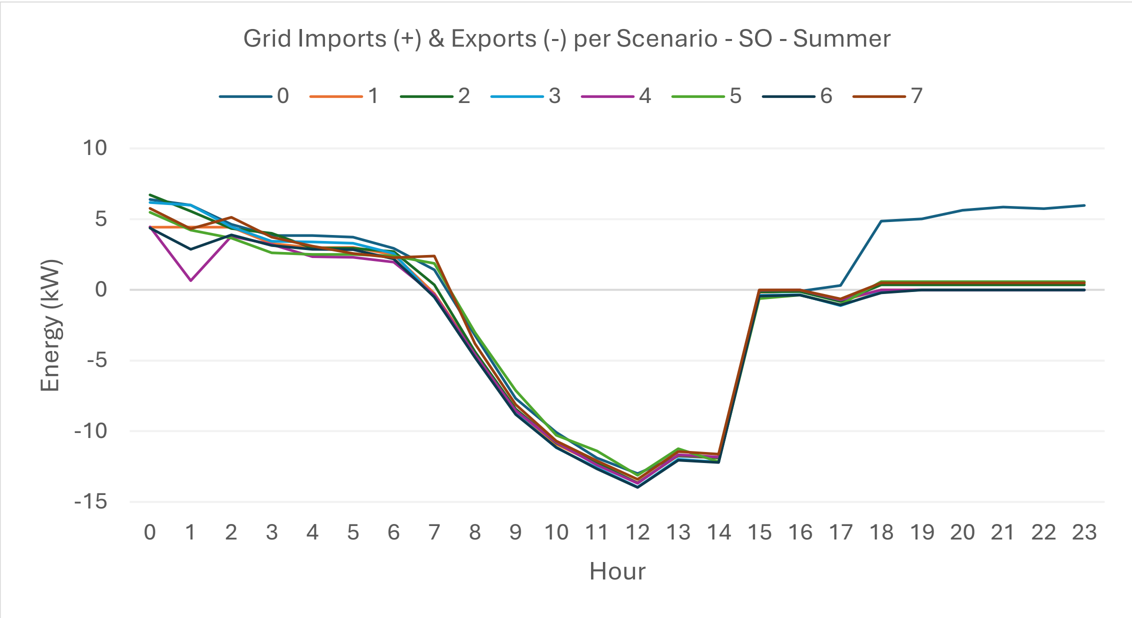


Figure 21: Grid Imports (+) & Exports (-) per Scenario - SO - Summer

On the other hand, winter operations reveal significantly greater cross-scenario divergence compared to summer, as demonstrated in Figure 22. Midday hours (8-17) exports vary up to 10 kW across scenarios, showing much less harmony than summer operations. Evening imports demonstrate substantial diversity, ranging from 2-8 kW depending on scenario conditions, indicating that winter operational strategies must be more adaptive to varying conditions. Scenarios 4 and 5 show distinctly different operational patterns, indicating that their PV power generation profiles deviate significantly from the other scenarios, which directly impacts grid dependency.

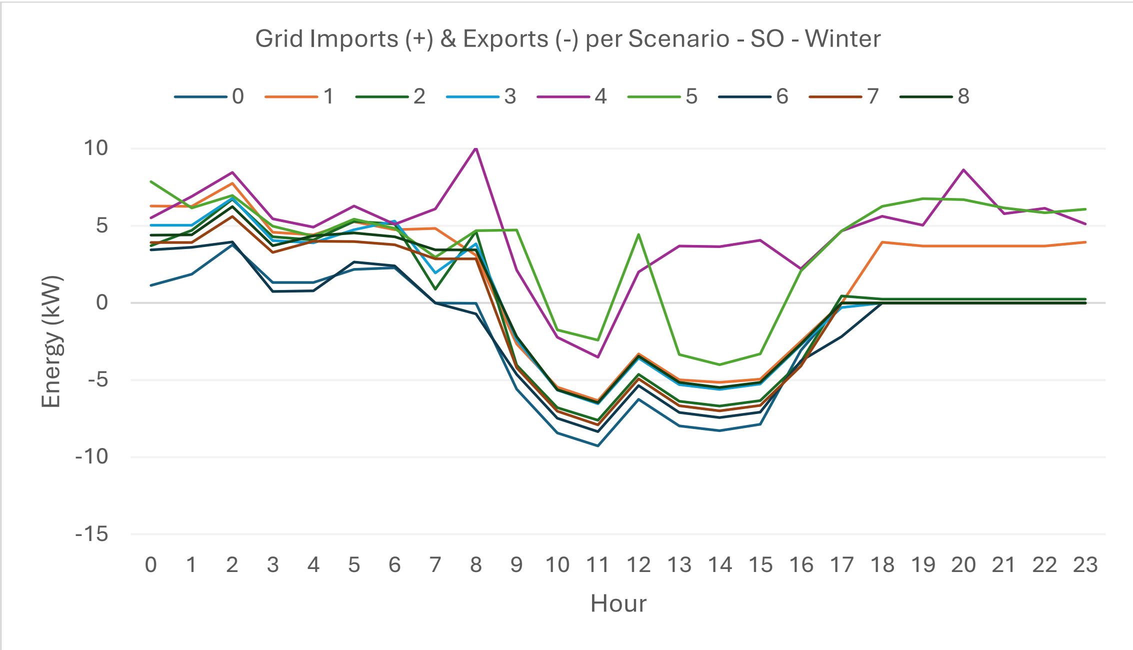


Figure 22: Grid Imports (+) & Exports (-) per Scenario - SO – Winter

Battery operations during summer show synchronized behaviour as all scenarios maintain similar timing for charge/discharge cycles despite magnitude variations, as illustrated in Figure 23. Most scenarios charge during midday hours (10-17) reaching peak charging around hour 15, followed by evening discharge from hours 18-23. However, scenarios 4 and 5 exhibit distinctly different operational patterns, with scenario 4 showing early discharge at hour 1 and reduced charging intensity, while scenario 5 demonstrates irregular charging behaviour during hours 8-12. This suggests that while most scenarios maintain robust timing for battery operations, certain PV generation conditions require significantly different battery management strategies to optimize system performance.

For winter scenarios, synchronization becomes less evident with greater operational variability across scenarios, as shown in Figure 24. During midday hours (10-16), scenarios exhibit significantly divergent battery operations, indicating scenario-specific adaptation to varying winter solar conditions. Between hours 18-23 the convergence across scenarios is more evident and similar to summer storage strategy.

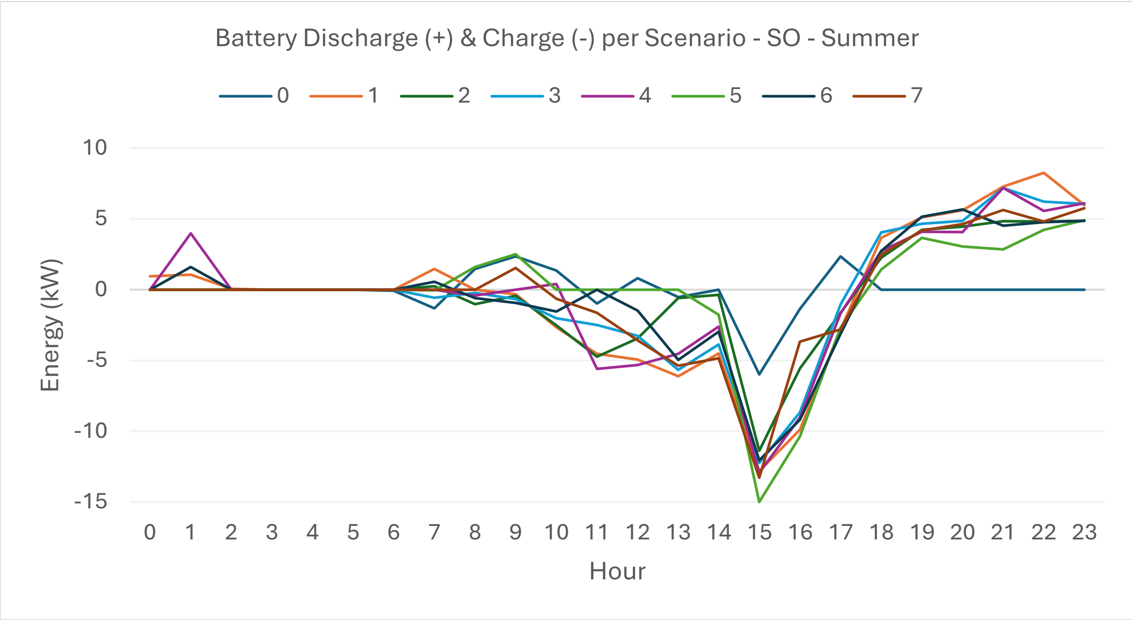


Figure 23: Battery Discharge (+) & Charge (-) per Scenario - SO - Summer

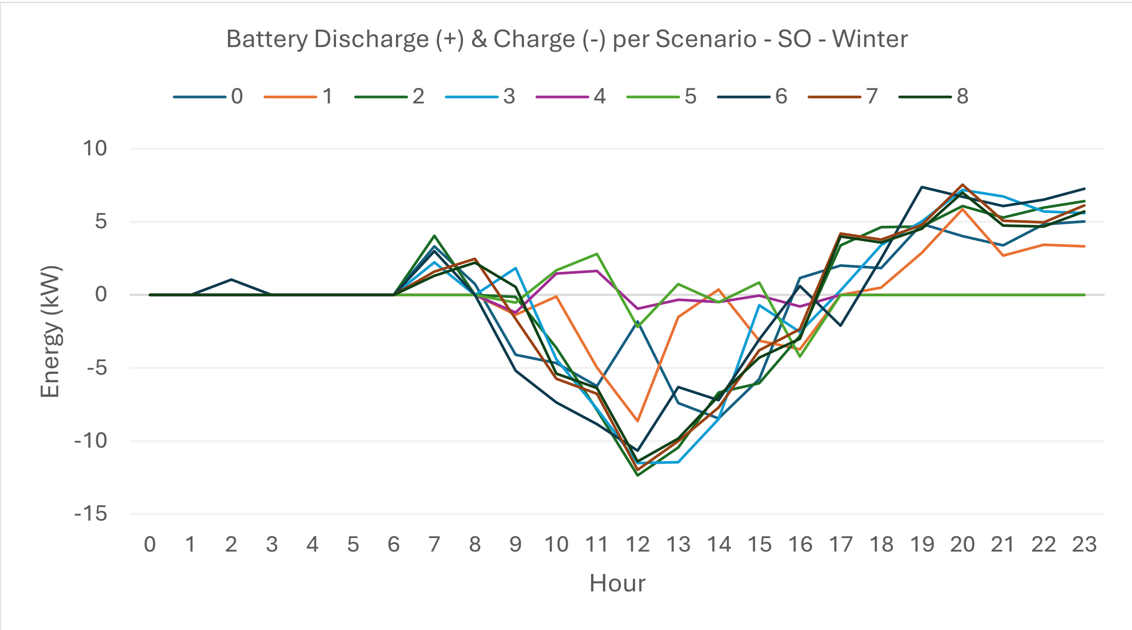


Figure 24: Battery Discharge (+) & Charge (-) per Scenario - SO - Winter

The observed decision variability is directly explained by underlying price volatility, which is determined endogenously in the optimization through market equilibrium dynamics, as illustrated in Figure 25 and Figure 26. These prices are bounded above by the regulated retail tariff (approximately 0.2 €/kWh) and below by the OMIP wholesale prices, creating a price range within which P2P transactions can occur economically. This mechanism drives the scenario-specific operational differences, as the optimization responds to varying price signals by adjusting battery management and grid transactions to maximize economic benefits under each scenario's unique market conditions.

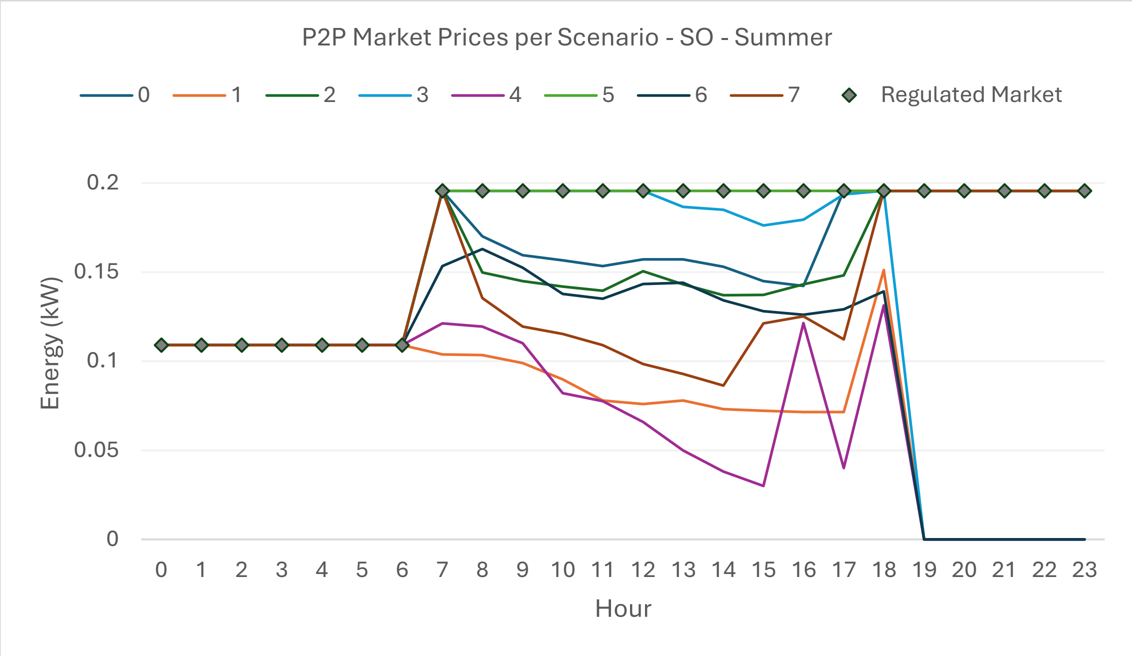


Figure 25: P2P Market Prices per Scenario - SO - Summer

During summer (Figure 25), P2P prices following similar patterns, remaining consistently below the 0.2 €/kWh regulated tariff ceiling, making P2P transactions economically attractive for consumers compared to grid purchases. The general drop to near-zero after hour 18 reflects the lack of need for buying energy during these hours, as storage accommodates demand.

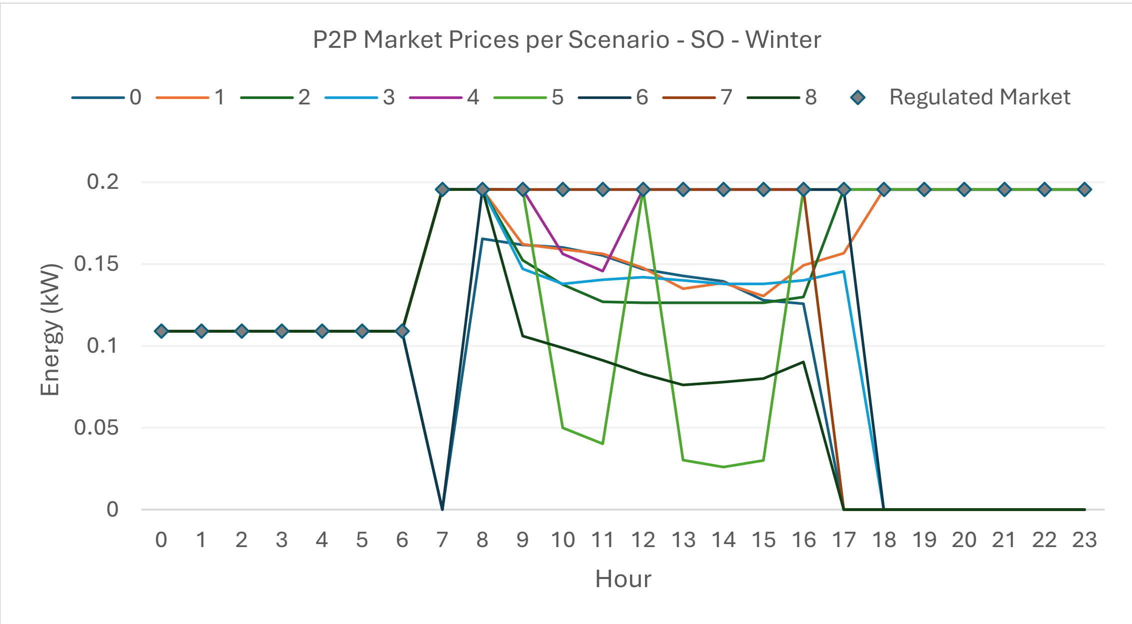


Figure 26: P2P Market Prices per Scenario - SO - Winter

Winter prices (Figure 26), however, display more complex dynamics, with P2P prices extreme volatility during midday hours. Some scenarios show price spikes up to 0.20 €/kWh, reaching the regulated tariff ceiling at hour 12 and indicating that PV generation does not meet all the demand in this season.

### 4.2.3 Decision Variables Statistics

This section extends the analysis to all five optimization approaches (AS, AMS, SO, RO, LR), providing comprehensive statistics that reveal how deterministic versus stochastic methodologies fundamentally differ in their operational decision-making under seasonal variations. A summary of the descriptive statistics - expected value (**μ**), coefficient of variation (CV) and minimum (MIN) and maximum (MAX) values - of the decision variables is presented in Table 9.

PV power output remains constant across optimization approaches at 7.00 kWh (summer) and 4.31 kWh (winter), being scenario-dependent and exogenous to the optimization process. These seasonal patterns in generation influence other endogenous operational decisions, particularly self-consumption, which varies from 1.04–1.19 kWh (summer) to 0.66–0.73 kWh (winter) based on optimization-specific strategies and price-responsive demand behaviour (calibrated with -0.221 price elasticity). Consequently, P2P prosumer supply, calculated as the difference between PV output and self-consumption, reaches approximately 5.8 kWh in summer and 3.6 kWh in winter.

The most sensitive variables to both seasonality and optimization approach are retail market imports, OMIP exports, and battery operations, all of which exhibit marked differences in expected values and variability:

- Retail imports decrease substantially from baseline levels (4.69 kWh summer, 4.67 kWh winter) across all methods, indicating strategic load-shifting toward local generation and flexibility mechanisms. In summer, imports range from 1.10 kWh (AS) to 1.34 kWh (AMS), while in winter, they increase slightly, ranging from 1.62 kWh (SO) to 2.39 kWh (AMS). The values are lowest under stochastic methods (SO, LR, RO), underscoring their stronger capacity for managing uncertainty and promoting local energy reliance. In addition, CV reveals significantly higher volatility in winter, especially for deterministic methods (e.g., AS: 81.51%) compared to stochastic approaches (SO: 59.67%; LR: 56.66%; RO: 61.42%), indicating improved decision stability under uncertainty-aware frameworks.
- OMIP exports show relatively stable expected values across methods during summer (~3 kWh) but diverge substantially in winter, reflecting heightened uncertainty management. The stochastic methods (SO, LR, RO) cluster around 1.42–1.51 kWh, suggesting a more consistent strategy for managing excess energy under uncertainty. The coefficient of variation (CV) for OMIP exports in winter skyrockets to 193.70% for AS and 77.75% for AMS, revealing extreme sensitivity to uncertainty. Even the stochastic methods show notable, though more moderate, increases: SO: 40.64%, LR: 47.16%, RO: 49.96%. These stark differences indicate that

deterministic methods struggle to maintain stability under uncertain winter conditions, while stochastic models, although not immune, offer significantly lower and more controlled variability. Among them, SO maintains the lowest winter CV, suggesting a better balance between responsiveness and robustness.

- Battery charging and discharging activities increase and become more variable in winter, reflecting greater reliance on storage during periods of reduced solar availability. For instance, winter charging ranges from 1.27-2.07 kWh , compared to 1.40–1.78 kWh in summer. Stochastic methods maintain more consistent expected values across methods and lower CVs in both seasons, highlighting their ability to deliver more stable storage behaviour under uncertainty. The observed asymmetry between charging and discharging values results from the 90% process efficiency in both directions, which introduces losses and prevents perfect symmetry, even when initial and final state-of-charge levels are identical.

Table 9: Decision Variables Metrics by Optimization Method (kWh/day)

| | | | | **SUMMER** | | | | | **WINTER** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | **AS** | **AMS** | **SO** | **LR** | **RO** | **AS** | **AMS** | **SO** | **LR** | **RO** |
| **DECISION VARIABLES** | **Supply (x)** | **Retail Market Imports (kWh)** | **μ** | 1.10 | 1.34 | 1.14 | 1.30 | 1.16 | 1.62 | 2.39 | 2.17 | 2.15 | 2.09 |
| | | | **CV (%)** | 61.90 | 47.44 | 26.90 | 23.27 | 25.56 | 81.51 | 44.65 | 59.67 | 56.66 | 61.42 |
| | | | **MIN** | 0.88 | | 0.78 | 0.96 | 0.74 | 0.84 | | 0.58 | 0.57 | 0.57 |
| | | | **MAX** | 2.69 | | 2.77 | 2.85 | 2.64 | 4.63 | | 4.90 | 4.87 | 4.91 |
| | | **P2P Prosumers (kWh)** | **μ** | 5.82 | 5.82 | 5.80 | 5.83 | 5.96 | 3.59 | 3.65 | 3.61 | 3.59 | 3.59 |
| | | | **CV (%)** | 66.71 | 66.72 | 66.72 | 66.72 | 66.72 | 67.64 | 68.17 | 68.08 | 68.13 | 68.08 |
| | | | **MIN** | 4.00 | | 2.89 | 4.06 | 4.18 | 0.33 | | 0.40 | 0.38 | 0.41 |
| | | | **MAX** | 6.22 | | 8.54 | 6.24 | 6.34 | 4.86 | | 4.76 | 4.76 | 4.76 |
| | | ***TOTAL SUPPLY*** | | *6.91* | *7.16* | *6.94* | *7.13* | *7.12* | *5.20* | *6.04* | *5.79* | *5.74* | *5.68* |
| | **Demand (y)** | **OMIP Exports (kWh)** | **μ** | 3.07 | 3.38 | 3.14 | 3.32 | 3.14 | 0.86 | 1.79 | 1.51 | 1.48 | 1.42 |
| | | | **CV (%)** | 28.90 | 24.61 | 3.02 | 2.87 | 5.15 | 193.66 | 77.75 | 40.64 | 47.16 | 49.96 |
| | | | **MIN** | 1.13 | | 2.92 | 3.04 | 2.73 | 0.00 | | 0.24 | 0.22 | 0.25 |
| | | | **MAX** | 5.03 | | 3.26 | 3.45 | 3.35 | 4.43 | | 2.37 | 2.36 | 2.40 |
| | | **P2P Consumers (kWh)** | **μ** | 3.51 | 3.51 | 3.49 | 3.52 | 3.64 | 3.95 | 4.01 | 3.97 | 3.95 | 3.95 |
| | | | **CV (%)** | 83.34 | 83.34 | 83.34 | 83.34 | 83.35 | 83.11 | 83.38 | 83.38 | 83.38 | 83.38 |
| | | | **MIN** | 2.79 | | 2.87 | 2.86 | 2.87 | 2.23 | | 2.19 | 2.18 | 2.18 |
| | | | **MAX** | 3.77 | | 3.79 | 3.82 | 3.97 | 4.96 | | 5.02 | 5.00 | 5.04 |
| | | **Battery Charge (kWh)** | **μ** | 1.76 | 1.40 | 1.65 | 1.52 | 1.78 | 2.07 | 1.27 | 1.59 | 1.61 | 1.64 |
| | | | **CV (%)** | 47.93 | 54.49 | 19.80 | 23.41 | 14.52 | 58.10 | 70.73 | 45.78 | 43.14 | 45.37 |
| | | | **MIN** | 0.00 | | 0.41 | 0.21 | 0.76 | 0.00 | | 0.16 | 0.16 | 0.16 |
| | | | **MAX** | 2.08 | | 2.03 | 1.93 | 206 | 2.08 | | 2.11 | 2.11 | 2.07 |
| | | **Battery Discharge (kWh)** | **μ** | 1.43 | 1.13 | 1.34 | 1.23 | 1.44 | 1.68 | 1.03 | 1.29 | 1.30 | 1.33 |
| | | | **CV (%)** | 47.93 | 54.49 | 19.80 | 23.41 | 14.52 | 58.10 | 70.73 | 45.78 | 43.14 | 45.37 |
| | | | **MIN** | 0.00 | | 0.33 | 0.17 | 0.62 | 0.00 | | 0.13 | 0.13 | 0.13 |
| | | | **MAX** | 1.69 | | 1.64 | 1.56 | 1.67 | 1.69 | | 1.71 | 1.71 | 1.68 |
| | | ***TOTAL DEMAND*** | | *6.91* | *7.16* | *6.94* | *7.13* | *7.12* | *5.20* | *6.04* | *5.79* | *5.74* | *5.68* |

| | | | SUMMER | | | | | WINTER | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | AS | AMS | SO | LR | RO | AS | AMS | SO | LR | RO |
| Parameter | PV Power (kWh) | μ | 7.00 | | | | | 4.31 | | | | |
| | | CV (%) | 66.71 | | | | | 67.73 | | | | |
| | | MIN | 5.20 | | | | | 0.87 | | | | |
| | | MAX | 7.51 | | | | | 5.55 | | | | |
| Decision Variable | Self-Consumption (kWh) | μ | 1.18 | 1.18 | 1.19 | 1.17 | 1.04 | 0.73 | 0.66 | 0.70 | 0.72 | 0.72 |
| | | CV (%) | 66.77 | 66.74 | 66.75 | 66.76 | 66.80 | 70.10 | 67.26 | 67.26 | 67.31 | 67.42 |
| | | MIN | 0.94 | | 0.87 | 0.88 | 0.82 | 0.31 | | 0.36 | 0.36 | 0.31 |
| | | MAX | 1.28 | | 1.30 | 1.27 | 1.19 | 1.02 | | 1.11 | 1.16 | 1.21 |

In summary, the combined analysis of expected values and CVs confirms that seasonal uncertainty (particularly in winter) amplifies operational unpredictability, highlighting the importance of method selection. Stochastic approaches (SO, LR, RO) not only reduce reliance on external imports and a more balanced storage behaviour, but also consistently minimize variability in key decision variables, as visually shown in Figure 27. By incorporating scenario diversity, they produce more robust and stable operational outcomes under uncertain conditions.

| | Summer Cluster | | | | | Winter Cluster | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | AS | AMS | SO | LR | RO | AS | AMS | SO | LR | RO |
| Retail Market (kWh) | 61.90 | 47.44 | 26.90 | 23.27 | 25.56 | 81.51 | 44.65 | 59.67 | 56.66 | 61.42 |
| OMIP (kWh) | 28.90 | 24.61 | 3.02 | 2.87 | 5.15 | 193.66 | 77.75 | 40.64 | 47.16 | 49.96 |
| Battery Charge (kWh) | 47.93 | 54.49 | 19.80 | 23.41 | 14.52 | 58.10 | 70.73 | 45.78 | 43.14 | 45.37 |
| Battery Discharge (kWh) | 47.93 | 54.49 | 19.80 | 23.41 | 14.52 | 58.10 | 70.73 | 45.78 | 43.14 | 45.37 |

Figure 27: Heat map of CV (%) for Summer (left) and Winter (right) Scenarios.

Lighter colours indicate more consistent performance (lower CV), while darker colours represent higher variability (higher CV). This evidence confirms that seasonal uncertainty amplifies the range and unpredictability of operational decisions, namely in winter scenarios which show more variability, requiring methods that account for fluctuations.

## 4.3 KPIs Analysis

This section presents a detailed analysis of the Key Performance Indicators (KPIs) used to evaluate the effectiveness of different optimization approaches under summer and winter scenarios for the EC. KPIs were selected to reflect four key dimensions of EC: energy performance through self-sufficiency ratio (SSR), economic viability via cost savings (ΔC), grid stability through peak load reduction (PLR) and demand shifting (DS), and environmental impact via $CO_2$ emissions reduction ($\Delta CO_2$), as described in Section 3.7.2.

The analysis compares the outcomes of the five optimization methods across both seasonal clusters, using quantitative values (Table 10) and normalized radar charts (Figure 28). Results are benchmarked against a baseline scenario, where all agents operate as conventional consumers without local generation, P2P trading or grid exports. These indicators complement the welfare analysis by translating economic optimization into physically meaningful outcomes.

**Table 10: Summary of Key Performance Indicators**

| Category | KPI | Summer Cluster | | | | | Winter Cluster | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | AS | AMS | SO | LR | RO | AS | AMS | SO | LR | RO |
| Energy Performance | $SSR$ (%) | 58% | 58% | 77% | 74% | 77% | 33% | 32% | 56% | 57% | 58% |
| Economic | $\Delta C$ (€) | 7.18 | 13.20 | 19.16 | 19.07 | 17.82 | -17.27 | -6.56 | 17.21 | 13.36 | 11.27 |
| Grid and Technical | $PLR$ (%) | -143% | -68% | 16% | 17% | 23% | -177% | -154% | 9% | 12% | 9% |
| | $DS$ (%) | 2.5% | 2.5% | 2.9% | 1.8% | 4.8% | 1.5% | 1.5% | 3.7% | 5.3% | 5.6% |
| Environmental | $\Delta CO_2$ ($kgCO_{2eq}$) | 0.74 | 0.78 | 1.06 | 1.01 | 1.05 | 0.22 | 0.39 | 0.74 | 0.75 | 0.77 |

*Summer Performance*

All stochastic formulations demonstrate enhanced solution stability and consistency relative to deterministic methods. SO attains the highest SSR (77%), clearly reducing grid dependence compared to AS and AMS (both with 58%). This superior performance translates directly into economic benefits, with SO delivering the greatest cost savings (ΔC = 19.16€), approximately 40% above AMS and 2.5 times greater than AS. RO provides the greatest grid stress reduction (PLR = 23%), reflecting its worst-case optimization focus, while also providing the highest demand flexibility (DS ≈ 5 %). All three stochastic approaches avoid around 1 kg of $CO_2$ daily emitted, more 30% than deterministic, through superior utilisation of local PV generation.

*Winter Performance*

Higher uncertainty in this season lowers all KPIs, yet the performance gap between stochastic and deterministic approaches persists. Deterministic methods show severe limitations: lower SSR (~32%), negative economic outcomes (ΔC<0) due to post-optimization penalties, indicating cost increases rather than savings, and grid stress amplification (PLR ≈ -160%). These results demonstrate the fragility of deterministic solutions under high variability conditions. Conversely, SO, LR and RO maintain robust performance with SSR between 56-58%, positive savings of 11–17€, continued peak reduction (PLR = 9-12%), and $CO_2$ emissions reduction almost twice the deterministic values.

Performance differentiation aligns with each method's objective function: SO achieves the largest cost savings in both seasons, whereas the risk averse formulations (RO and LR), excel in minimizing peak grid stress and demonstrate superior demand shifting operation, distributing load adjustments more effectively across scenarios.

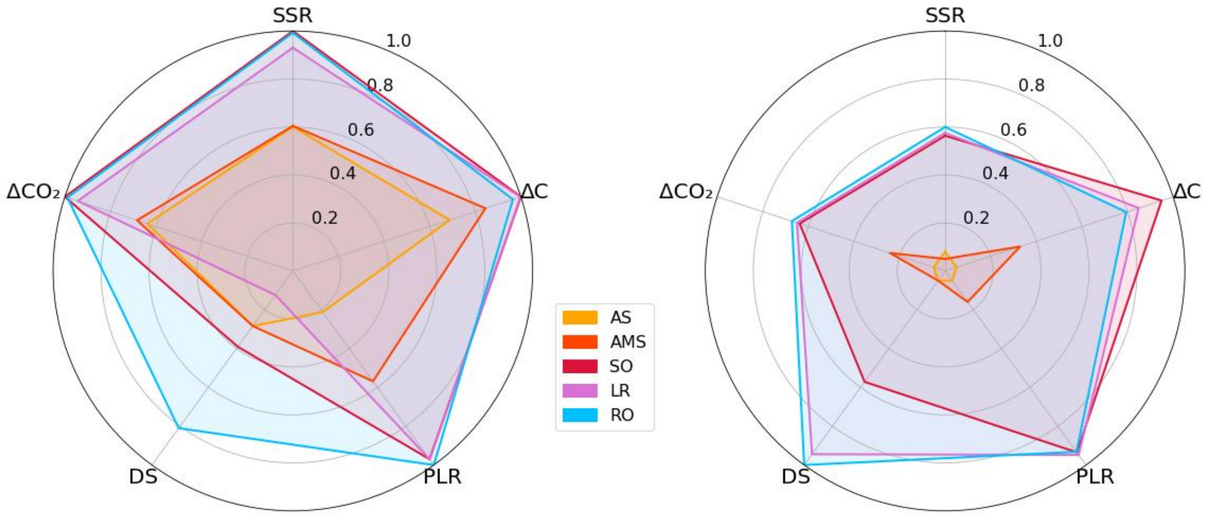


Figure 28: Normalized KPIs Performance - Summer (left) vs Winter (right) scenarios

Figure 28 illustrates these performance patterns, clearly showing that incorporating scenario uncertainty is fundamental to reliable community operation.

Overall, KPI analysis corroborates the welfare-based findings: deterministic, single-scenario planning proves inadequate for renewable ECs operating under uncertainty. Stochastic optimization approaches consistently deliver measurable improvements in energy autonomy, cost efficiency, and system reliability. While trade-offs exist between methods, with SO optimizing economics, RO reducing peak grid stress, and LR offering a balanced performance. All stochastic approaches exhibit stronger solution reliability than deterministic alternatives, particularly under high-uncertainty winter conditions.

## 5. Conclusions

This thesis developed and applied a comprehensive modelling framework to evaluate how uncertainty in load, generation, and electricity prices affects the performance of P2P energy communities. The framework integrates DERs along with demand flexibility from community participants to optimize operational decisions under uncertainty. A two-stage stochastic optimization model was implemented and tested using real-world data, comparing five optimization approaches - two deterministic and three stochastic - across seasonal clusters. The analysis covered welfare outcomes, decision variable behaviour, and KPIs, aiming to identify the operational and economic implications of explicitly modelling uncertainty in energy community planning.

The findings of this study highlight the importance of considering uncertainty in the planning and operation of P2P energy communities. The comparative analysis between optimization approaches reveals significant differences in welfare outcomes, operational performance, and resilience under varying conditions. In terms of expected welfare, stochastic models consistently provide greater confidence in attaining a higher proportion of theoretical welfare outcome, achieving over 1.8 times higher values in summer and more than 6 times higher in winter, showcasing their clear advantage under uncertainty. Deterministic optimization, while simpler, fails to ensure robust performance under high volatility, particularly in winter scenarios characterized by stronger unpredictable generation, consumption, and market dynamics. These limitations are reflected in negative deterministic welfare in summer and extreme volatility in winter (CV exceeding 700%), compared to more stable stochastic values (CVs under 32%). This clearly indicates that methods which ignore uncertainty modelling are not well-suited for ensuring robust and resilient EC operation. In contrast, stochastic optimization methods achieve outcomes with greater operational stability, offering enhanced adaptability and sustained welfare even under adverse conditions. Additionally, considering uncertainty enhances local value creation by reducing dependence on external energy sources and enabling more strategic storage management, contributing to improved autonomy and cost-efficiency. These results clearly demonstrate the practical value of considering uncertainty in the development and management of ECs.

Among the stochastic approaches analysed, SO delivers the highest expected welfare, RO provides stronger protection against worst-case scenarios, and LR offers a balanced trade-off between performance and risk aversion. These distinctions suggest that the selection of optimization strategy should align with the community's specific preferences regarding risk and performance. Operational analysis reinforces these conclusions: stochastic methods are more responsive to scenario-specific conditions, particularly in leveraging battery systems and wholesale market interactions. SO, for example, stands out for its ability to adjust real-time decisions in response to price signals, whereas deterministic models incur notable performance penalties due to their inability to respond dynamically to real-world requirements. Seasonal analysis further highlights these distinctions, with winter conditions magnifying the advantages of stochastic optimization.

Beyond welfare optimization, the analysis of KPIs demonstrates that stochastic methods, particularly SO and RO, consistently outperform deterministic approaches in enhancing self-sufficiency, reducing

$CO_2$ emissions, cutting costs, and mitigating grid impacts in P2P ECs, emphasizing the importance of incorporating uncertainty in operational planning. SO proves effective for achieving both economic (e.g. 17.21 € vs. –17.27 € with AS in winter) and environmental objectives, while RO excels in reducing peak load reduction and enhancing demand shifting (e.g. +23% vs. –143% for AS in summer), making each method suitable for different planning priorities. Seasonal variations further highlight the need for context-sensitive and adaptive strategies. As no single method optimizes all KPIs, the use of multi-criteria decision-making tools is essential for balancing economic, environmental, and technical trade-offs.

In conclusion, this work demonstrates that modelling uncertainty is not merely a theoretical enhancement but a practical necessity for modern energy communities. Deterministic models are insufficient in volatile environments, while stochastic approaches enable both robust welfare outcomes and flexible, adaptive operations. The future of resilient ECs should focus on embedding scenario-based planning, leveraging flexibility mechanisms, and aligning policy with the inherently uncertain nature of distributed energy systems. As such, ECs should be conceived and supported as dynamic, uncertainty-sensitive systems within the evolving energy landscape.

## 5.1 Recommendations

From a strategic perspective, ECs should adopt stochastic optimization as a standard element for their planning frameworks, particularly for day-ahead operations during high-uncertainty periods, such as winter. Robust optimization can play a complementary role in real-time decision-making, minimizing exposure to adverse outcomes when uncertainty materializes. A dynamic, seasonal approach is advisable: communities should adjust between different stochastic approaches, depending on expected variability. Moreover, continuous monitoring of second-stage penalties and scenario-specific adjustments should be integrated into planning processes, providing feedback to enhance decision-making over time and strengthen long-term operational robustness.

At the policy level, regulators should promote the adoption of uncertainty-aware optimization practices through tailored incentives, especially in regions characterized by high renewable penetration or price volatility. Given the clear seasonal asymmetries observed in EC performance, regulatory frameworks should incorporate differentiated requirements, for instance, stricter performance guarantees and enhanced storage mechanisms in periods of greater uncertainty. In addition, public and private investment in flexibility resources, including batteries, demand response technologies, and digital infrastructure, will be essential to unlock the full value of scenario-based planning. These investments not only support greater flexibility but also position these energy systems to operate more effectively within the evolving challenges of decentralized, renewable energy landscape.

## 5.2 Limitations and Future Developments

A limitation of this work lies in its two-stage stochastic formulation, which, while effective for initial modelling, simplifies the sequential nature of operational decisions in dynamic environments. This restricts its ability to fully capture real-time flexibility management and evolving uncertainties in P2P energy systems.

A promising direction for future research would be the development of a multi-stage stochastic or hybrid stochastic-robust optimization model. Such a framework would enable more realistic modelling of decision-making over time, particularly in systems with flexible resources and price-responsive users. In this context, the design and empirical validation of non-linear penalty mechanisms for deviations could enhance the accuracy of operational cost representation and improve responsiveness to real-world grid constraints. Additionally, extending the model to a distributed or agent-based structure could support the analysis of decentralized ECs with heterogeneous actors. This would allow for the exploration of strategic behaviour, privacy-preserving coordination, and the social dimension of energy sharing, laying the foundation for policy-relevant insights and practical implementation strategies.

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# Appendix

*Clustering: Working vs Non-working Days*

To improve data visualization, the outliers of the dataset were excluded from the graphs.

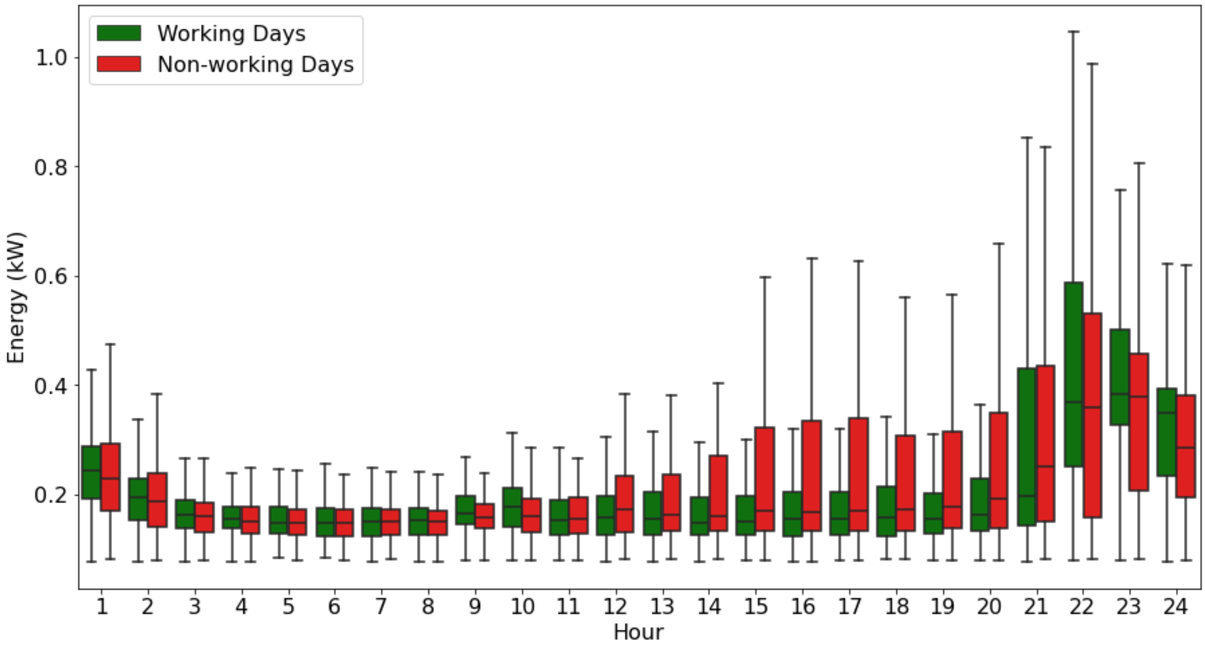


Figure 29: Statistical Variation of Input Variables – Consumption Profile of Household 1

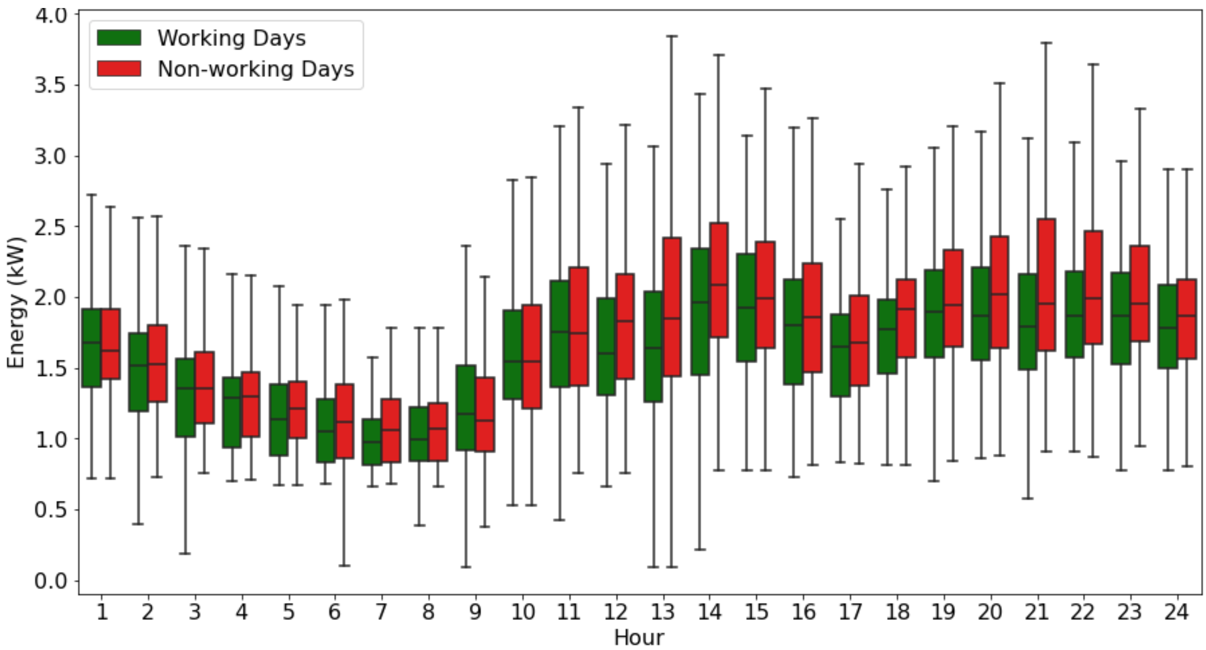


Figure 30: Statistical Variation of Input Variables – Consumption Profile of Household 3

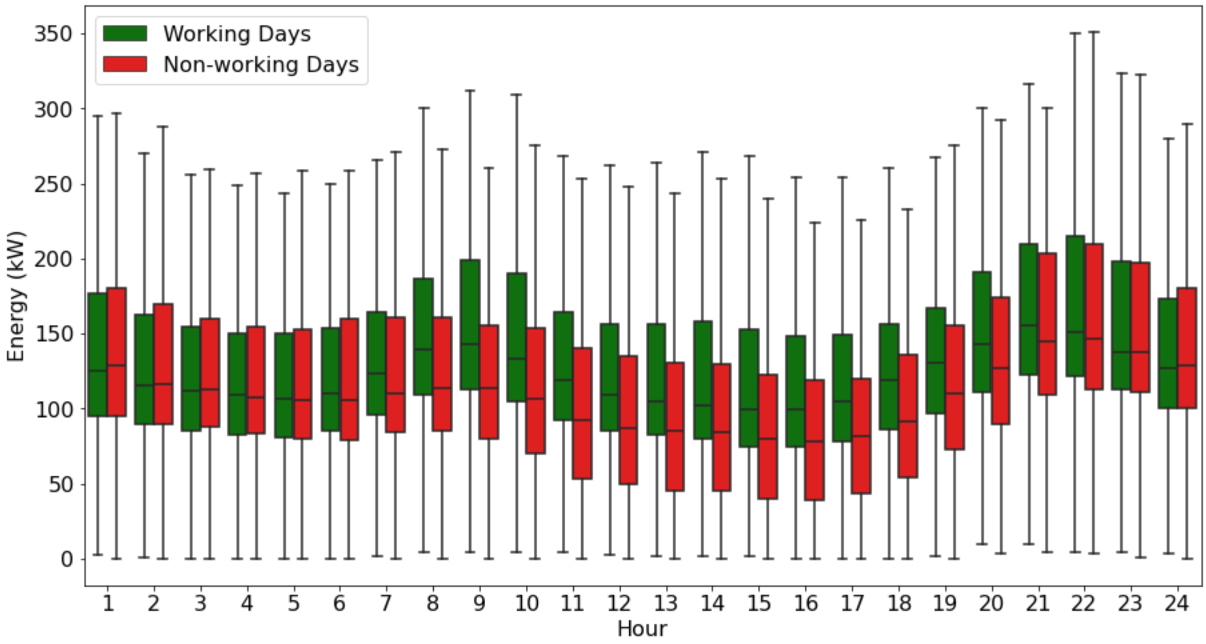


Figure 31: Statistical Variation of Electricity Prices

*Clustering: Seasonal Patterns*

After segregating the data into working and non-working days, K-Medoids clustering was applied to each subset to identify further intra-group patterns. Depending on the number of clusters, this clustering technique revealed seasonal distinctions on the subsets:

1. **Two Clusters**: Observations were divided into winter (October to January) and summer (February to September).

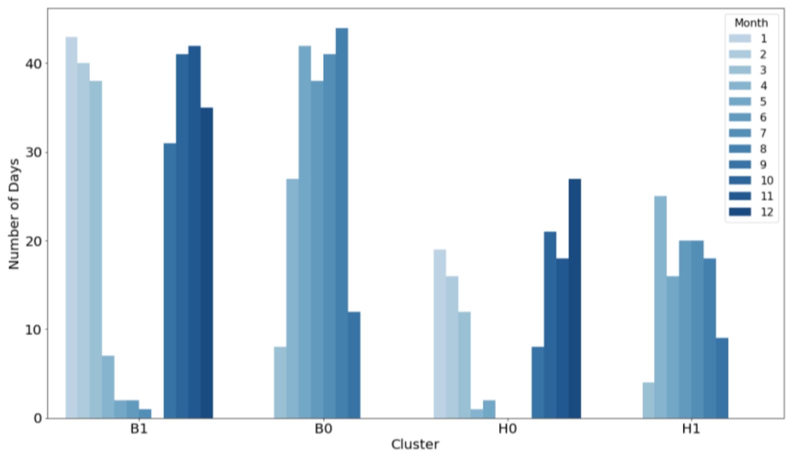


Figure 32: Seasonal Patterns in Overall Dataset (2-2 clusters)

2. **Three Clusters**: Observations from transitional months (February, March, September, and October) formed a third "mid-season" cluster.

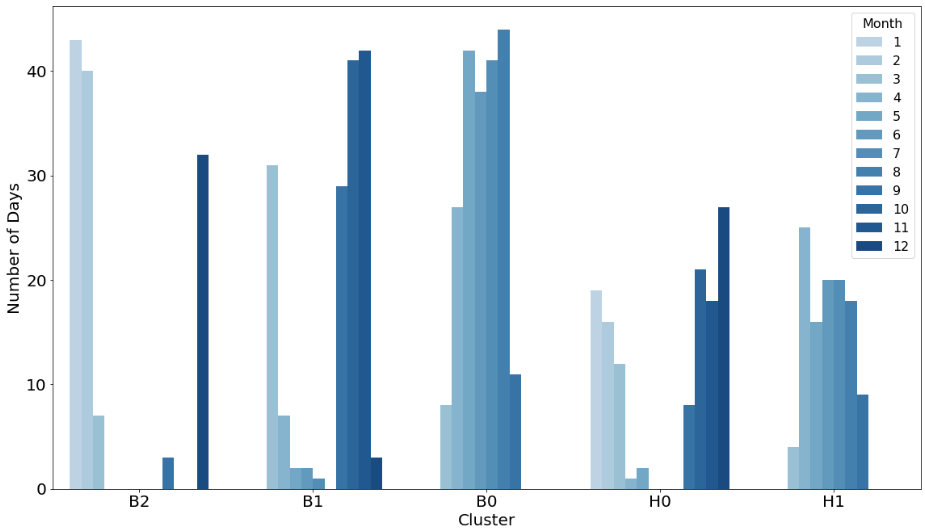


Figure 33: Seasonal Patterns in Overall Dataset (3-2 clusters)

3. **Four Clusters**: While summer and winter clusters became more distinct, the mid-season clusters remained difficult to differentiate.

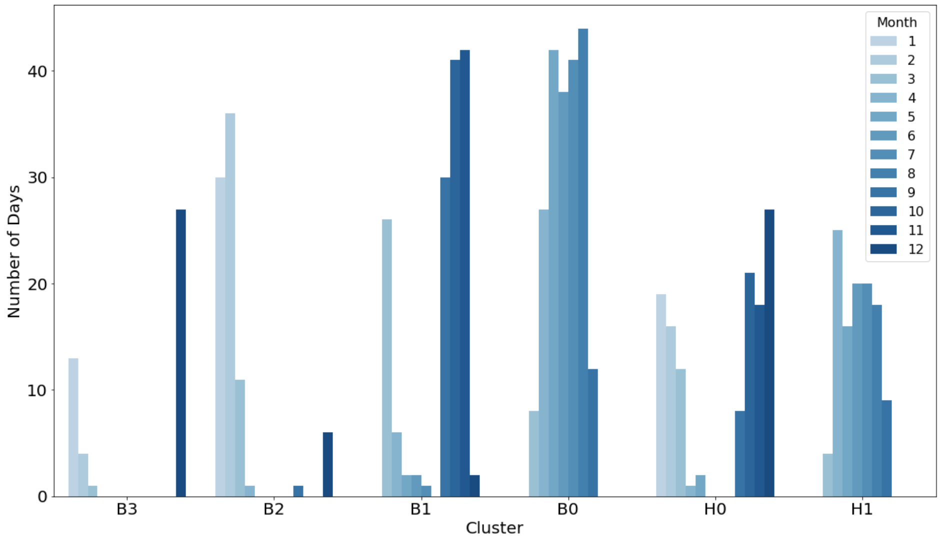


Figure 34: Seasonal Patterns in Overall Dataset (3-3 clusters)

After analysing these results, and applying the Silhouette Method to identify the optimal number of clusters, the following numbers are chosen to proceed with the analysis:

- For working days: three clusters – B0, B1, B2 – represent winter, summer, and mid-season, which provided balanced group sizes and interpretable results.
- For non-working days: two clusters – H0 and H1 – that represent summer and winter are sufficient.

Although Silhouette Score might indicate 2 clusters as the optimal number, the previous bar graphs show a clear distinction between 3 seasons (winter, summer and spring/autumn).

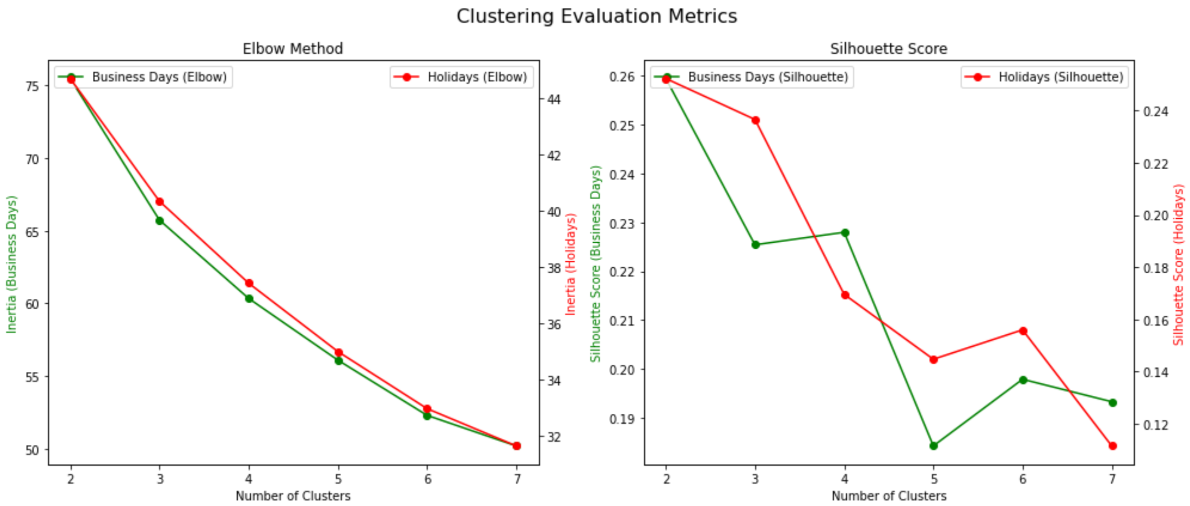


**Figure 35: Statistical Metrics for Cluster Generation**

This choice ensured meaningful representation while avoiding overfitting or excessive complexity of the data set. With this approach, it is also assumed that the agents of this community can identify beforehand the applicable season for the given time horizon.

*Penalty Factor ($\omega$) Sensitivity Analysis*

The definition of an appropriate penalty factor ($\omega$) in stochastic energy market modeling involves balancing economic performance with operational realism. Given the lack of empirical benchmarks and limited guidance from the literature, a sensitivity analysis was carried out, not as an optimization procedure, but as a systematic approach to identifying a reasonable and justifiable value. This analysis was performed for the SO, LR, and RO approaches across both seasonal clusters (Summer and Winter), considering the range $\omega = \{0.05. 0.1. 0.15.0.2\}$.

For the summer cluster, a penalty factor of $\omega = 0.1$ demonstrates a well-balanced performance:

- The SO approach achieves 42.258 € of expected welfare with modest welfare loss (3%)
- The penalty price represents 41% of the average OMIP market price (0.149 €/kWh)
- Maximum delta values show meaningful reduction (0.880 kWh for SO) compared to lower penalty factors

This value strikes an appropriate balance between economic considerations and flexibility management, as it establishes a meaningful penalty without excessive welfare degradation.

For the Winter cluster with the same penalty factor:

- The SO approach achieves 30.885 € in expected welfare with 20% welfare loss
- The penalty price represents 90% of the average OMIP market price (0.147 €/kWh)

- Delta values show some reduction (1.427 kWh maximum delta for SO) from the 0.05 factor

While the Winter cluster exhibits higher sensitivity to penalty factors, a penalty factor of $\omega = 0.1$ still represents a reasonable compromise between welfare losses and flexibility benefits.

Among the three stochastic approaches (SO, LR, RO) with $\omega = 0.1$:

- SO maintains good welfare performance (3% loss for Summer, 20% for Winter).
- LR shows similar performance for Summer (3% welfare loss) but higher losses for Winter (31%).
- RO exhibits more significant welfare losses (7% for Summer, 42% for Winter).

The selection of $\omega = 0.1$ as the optimal penalty factor is consequently justified by:

- **Market-Based Penalty Pricing**: At $\omega = 0.1$. the penalty prices range from 41-90% of OMIP market prices across seasons, establishing an economically sound relationship between flexibility deviations and market conditions.
- **Meaningful Flexibility Management**: This factor creates sufficient incentive to reduce deviations without overly constraining the model, as evidenced by the moderate reductions in maximum delta values.
- **Acceptable Economic Impact**: While welfare losses increase compared to lower penalty factors, they remain within reasonable bounds (3-20% for SO) that can be justified given the flexibility benefits.

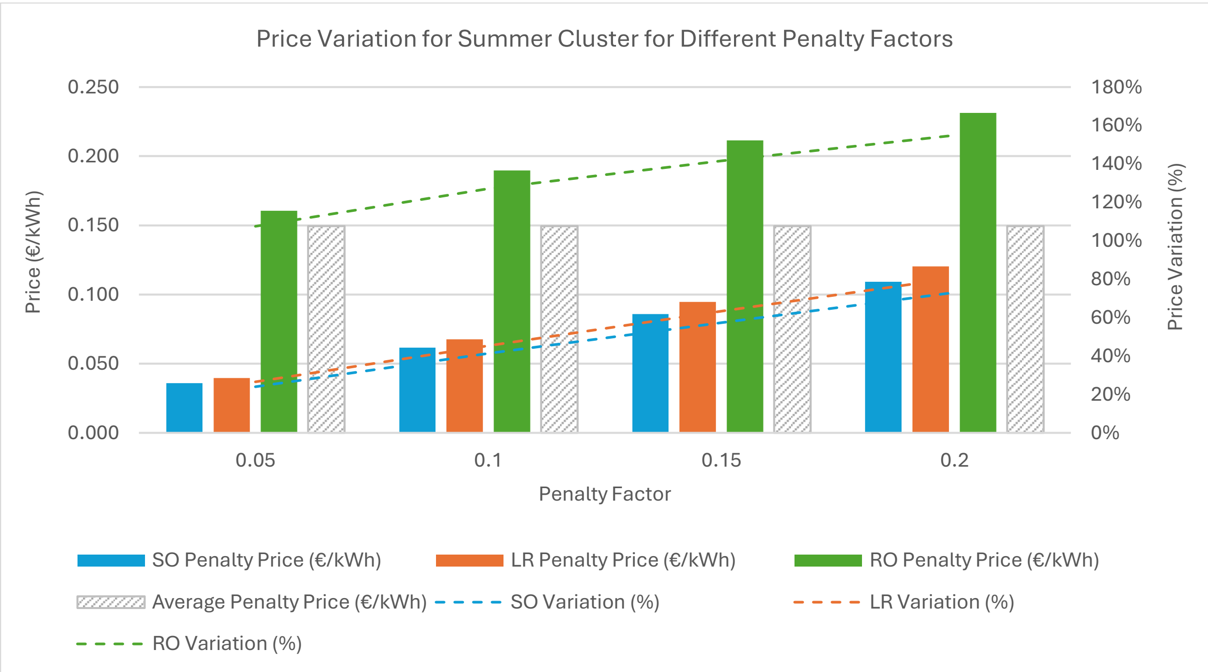


Figure 36: Price Variation for Summer Cluster for Different Penalty Factors

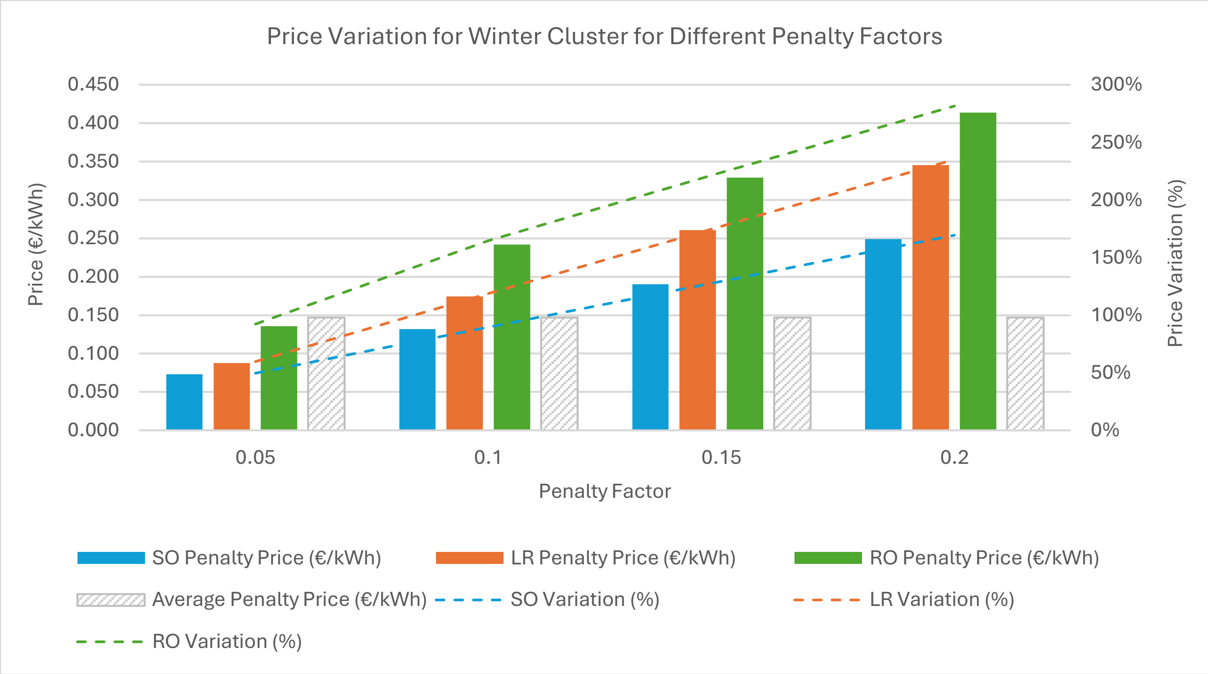


Figure 37: Price Variation for Winter Cluster for Different Penalty Factors