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Peer-to-Peer Energy Trading Strategies for Decentralized Residential Energy Systems

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Abstract

This work investigates peer-to-peer (P2P) energy trading within residential local energy markets (LEMs) assessing how decentralized bilateral matching mechanisms can increase renewable self-consumption, reduce reliance on the upstream grid, and affect distributional and network outcomes. Two bilateral matching strategies are formalized and implemented: a time-varying Supply–Demand Matching strategy (ST1), which privileges temporal complementarity between surplus and deficit, and a time-invariant Distance-Based Matching strategy (ST2), which privileges geographically proximate trades to reduce distribution losses. Both strategies are embedded in a decentralized market-clearing framework solved via the Alternating Direction Method of Multipliers (ADMM) and implemented in Python using CVXPY with the SCS solver. Experiments are conducted on a synthetic community of ten households derived from real household generation and load data, including photovoltaic and wind profiles.

Simulation results show that both ST1 and ST2 materially decrease community grid imports and overall procurement costs compared with the baseline, while producing distinct trade-offs. ST1 attains higher adaptability to temporal variability and delivers greater economic savings and improved renewable utilization in scenarios with pronounced intermittency, at the expense of increased computational and coordination complexity and less stable pairing patterns. ST2 yields more stable, locality-constrained exchanges that tend to reduce distribution losses and operational complexity, though with reduced responsiveness to dynamic supply–demand fluctuations. Sensitivity analyses (varying grid tariffs and local generation capacity) indicate that the relative benefits of P2P trading are amplified under higher grid prices and greater local renewable penetration. The findings provide empirical guidance for the design of scalable, equitable, and technically robust P2P mechanisms and inform policy and DSO considerations for integrating local markets into existing distribution systems.

Keywords: Peer-to-peer energy trading, Local energy markets, Decentralized systems, Renewable energy, Community energy, Energy equity.

Resumo

Este trabalho investiga o comércio de energia ponto a ponto (P2P) nos mercados locais de energia residencial, avaliando como os mecanismos de correspondência bilateral descentralizados podem aumentar o autoconsumo renovável, reduzir a dependência da rede e afetar os resultados distributivos da rede. Duas estratégias de correspondência bilateral são formalizadas e implementadas: uma estratégia de correspondência de oferta e procura variável no tempo (ST1), que privilegia a complementaridade temporal entre excedentes e déficits, e uma estratégia de correspondência baseada na distância invariante no tempo (ST2), que privilegia transações geograficamente próximas para reduzir as perdas de distribuição. Ambas as estratégias estão incorporadas numa estrutura descentralizada de compensação de mercado resolvida através do Método de Direção Alternada de Multiplicadores (ADMM) e implementada em Python usando CVXPY com o solucionador SCS. As simulações são realizadas numa comunidade sintética de dez famílias derivadas de dados reais de produção e carga doméstica, incluindo perfis fotovoltaicos e eólicos.

Os resultados da simulação mostram que tanto o ST1 quanto o ST2 reduzem significativamente as importações da rede comunitária e os custos gerais de aquisição em comparação com a linha de base, ao mesmo tempo em que produzem compensações distintas. O ST1 alcança maior adaptabilidade à variabilidade temporal e proporciona maiores poupanças e melhor utilização de energias renováveis em cenários com intermitência pronunciada, em detrimento de uma maior complexidade computacional e de coordenação e padrões de emparelhamento menos estáveis. O ST2 produz trocas mais estáveis e limitadas pela proximidade, que tendem a reduzir as perdas de distribuição e a complexidade operacional, embora com menor capacidade de resposta às flutuações dinâmicas da oferta e da procura. Análises de sensibilidade (variando tarifas da rede e capacidade de produção local) indicam que os benefícios relativos do comércio P2P são amplificados sob preços mais altos da rede e maior penetração local de energias renováveis. As conclusões fornecem orientação empírica para a conceção de mecanismos P2P escaláveis, equitativos e tecnicamente robustos e informam considerações políticas e de DSO para integrar mercados locais em sistemas de distribuição existentes.

Palavras-chave: negociação ponto a ponto, mercados locais de energia, sistemas descentralizados, energias renováveis, energia comunitária, equidade energética.

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Acronyms

2DECS Development approach for Decentralized Control Systems.

ADMM Alternating Direction Method of Multipliers.

AI Artificial Intelligence.

BESS Battery Energy Storage System.

BFS Breadth-First Search.

CVXPY Python-embedded modelling language for convex optimization.

DCP Disciplined Convex Programming.

DER Distributed Energy Resource.

DOE Dynamic Operating Envelope.

DSO Distribution System Operator.

ECOS Embedded Conic Solver.

FADMM Fast Alternating Direction Method of Multipliers.

IoT Internet of Things.

KPI Key Performance Indicator.

LEM Local Energy Market.

MOSEK MOSEK Optimization Suite.

OSQP Operator Splitting Quadratic Program.

P2P Peer-to-Peer.

P2P-ETP P2P Energy Trading Platform.

PoA Proof of Authority.

PV Photovoltaic.

QoT Quality of Transaction.

RES Renewable Energy Sources / Renewable Energy Resources.

SCS Splitting Conic Solver.

ST1 Supply–Demand Matching Strategy.

ST2 Distance-Based Matching.

TDSO Transmission and Distribution System Operator.

TSO Transmission System Operator.

LIST OF SYMBOLS

$\gamma_{ij,t}$	Bilateral trading coefficient between households i and j at time t.
ϵ_p	Tolerance for primal residual.
ϵ_d	Tolerance for dual residual.
λ^{buy}	Price for buying energy from the grid at time t.
λ^{sell}	Price for selling energy to the grid at time t.
$\mu_{i,t}$	Perceived energy price by household i at time t.
$\xi_{ij,t}$	Dual variable in ADMM between i and j at time t.
ρ	Penalty parameter in the ADMM algorithm.
Γ	Matrix of bilateral trading coefficients.
$\Gamma^{b,rel}$	Normalized matrix for buying in ST1.
$\Gamma^{s,rel}$	Normalized matrix for selling in ST1.
Δt	Time interval.
Ξ_t	Matrix of trading prices at time t.
$d_{ij,t}$	Energy traded between households i and j at time t.
$dist_{ij}$	Distance between houses i and j in the network topology.
$p_{i,t}$	Net power exchange of household i at time t.
$p_{buy,i,t}$	Energy bought from the grid by household i at time t.
$p^g_{i,t}$	Power exchanged with the grid by household i at time t.
$p_{sell,i,t}$	Energy sold to the grid by household i at time t.
r^k	Primal residual in ADMM at iteration k.
s^k	Dual residual in ADMM at iteration k.

C	Global variable for trading quantities in ADMM.
$C^{g}_{i,t}(p_{i,t}{}^{g})$	Cost function for household i at time t for grid interaction.
D	Local trading quantities schedule for household i.
D_t	Matrix of trading quantities at time t.
M	Set of trading partners for a household, indexed by j.
N	Set of nodes (households).
P^{buy}	Matrix of power that households want to buy.
P^{sell}	Matrix of power that households want to sell.
P^{net}	Net budget matrix (power surplus or deficit).
$P^{l}_{i,t}$	Baseload demand of household i at time t.
$P^{Pv}_{i,t}$	Photovoltaic (PV) power generation of household i at time t.
$P^{W}_{i,t}$	Wind generation of household i at time t.
T	Set of time steps.

1 Introduction

The accelerating deployment of distributed energy resources and the digitalization of electricity systems are creating new opportunities for local coordination and market formation at the residential scale. Communities equipped with rooftop photovoltaics, small-scale storage, and controllable loads can potentially satisfy a larger share of their demand locally, reducing exposure to wholesale price volatility and enhancing resilience against external disturbances. At the same time, the proliferation of such resources raises complex technical and economic questions: how should bilateral exchanges be organized so that local benefits are realized without creating unacceptable operational impacts on distribution networks, and how can market mechanisms be designed to balance efficiency with fairness among heterogeneous participants?

Energy communities are local entities, organized by citizens, small businesses, or local authorities that collectively produce, consume, store, and exchange energy, typically from renewable sources. EU policy distinguishes legal forms such as Renewable Energy Communities (RECs) and Citizen Energy Communities (CECs), which differ in scope and permitted activities but share objectives of increasing local renewable uptake, enabling collective self-consumption, and redistributing economic benefits within the community. Operationally, these communities coordinate PV generation, storage dispatch, flexible loads, and internal peer-to-peer (P2P) exchanges, and may aggregate flexibility for participation in wider markets. Doing so requires measurement and verification, clearing/optimization algorithms, and governance arrangements that align individual incentives with network constraints [1].

This study is framed by the European policy context: the recast Renewable Energy Directive (EU/2023/2413), which entered into force in November 2023, embeds energy-community concepts in EU law and sets an EU-level renewables target (at least 42.5% by 2030, with an indicative objective of 45%) [1]. The Directive also includes measures to accelerate renewables deployment and streamline permitting factors that both incentivize the growth of energy communities and create new technical and regulatory constraints that market designs must respect. National transposition choices (tariffs, network charges, access rules, permitting) therefore materially influence which coordination mechanisms are feasible in practice [1].

Accordingly, the problem addressed in this work, the design and evaluation of coordination and market mechanisms for P2P exchanges in residential communities, sits at the intersection of engineering and market design. The work evaluates mechanisms not only by aggregate metrics (total traded energy, community cost savings) but also by spatial and distributional outcomes. Emphasis is placed on comparative, reproducible experiments that reveal trade-offs among efficiency, locality, equity, and distribution-network impacts, producing evidence useful to distribution system operators, regulators, and community initiatives for designing pilots and informing national transposition choices. The subsequent sections formalize the study's background, precise objectives, and the thesis structure used to analyze these issues.

1.1 Background

The emergence of local energy markets (LEMs) and P2P (Peer-to-Peer) trading is driven by three interacting trends: (i) the increasing penetration of small-scale renewable generation at the household level, (ii) the availability of fine-grained metering and (iii) communication infrastructures that enable near-real-time coordination, and algorithmic advances in convex optimization and distributed algorithms that make decentralized market clearing tractable and reproducible. In such markets, prosumers can act simultaneously as producers and consumers, creating opportunities to match local surplus with local demand and to internalize part of the value traditionally captured by the centralized supply. While various auction mechanisms and bidding strategies have been investigated [2], a comprehensive comparative analysis of how different market structures influence local energy system performance remains critical. Two primary market structures analyzed are centralized and decentralized markets [2].

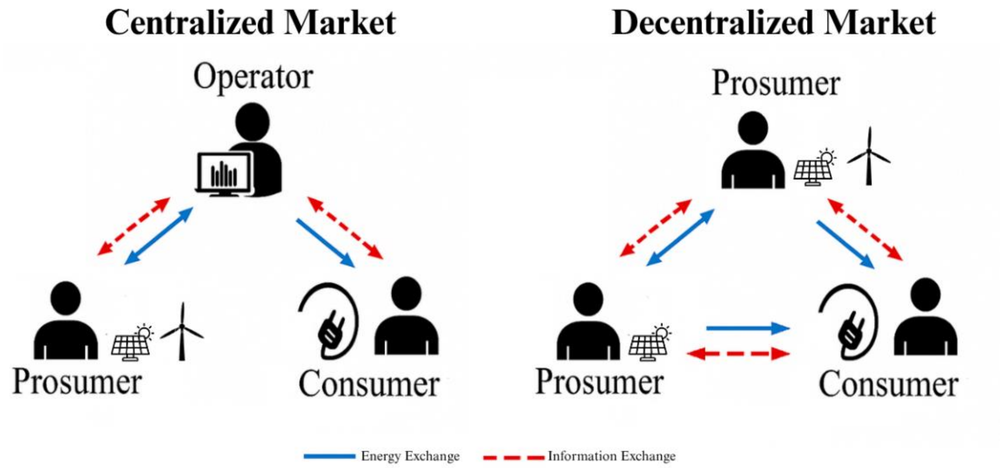

Figure 1.1-Market structures.

A centralized market design typically involves a central manager who collects information from all participants to formulate and solve a centralized optimization problem [3]. This manager-based market facilitates trading within the community and with external communities. In contrast, decentralized market designs, such as P2P energy trading based on a continuous double auction, allow prosumers and consumers to trade energy directly without an intermediary [3], [4]. For energy self-sustaining communities, P2P energy trading can be a superior design due to its decentralized, flexible, and privacy-preserving attributes [3]. However, a potential drawback is that some electricity may be sold directly to the grid due to unmatchable bids and asks [2]. Nevertheless, with ex post security verification, P2P energy trading can also guarantee secure network operation [3].

Both market designs, along with their network security verification, have been quantitatively compared in terms of social welfare, total payment, and energy trading volume [3]. Distribution system operators (DSOs), transmission system operator (TSO), and transmission and distribution system operator (TDSO), also play a role in overseeing transactions to ensure system operations are maintained [4].

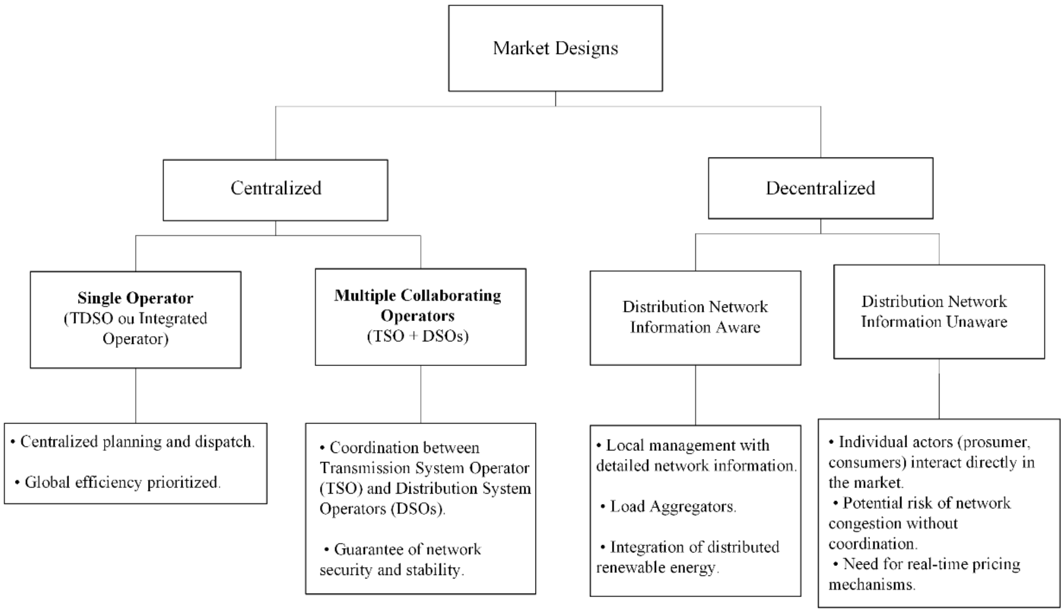

Figure 1.2-Market designs.

1.2 Objectives

The research pursues three interrelated objectives. First, to formalize and implement two bilateral matching strategies, one exploring supply–demand matching and the second one, distance-based matching, seeking the minimization of distribution losses, within a decentralized market-clearing framework that preserves data locality and produces verifiable convergence diagnostics. Second, to quantify the technical and economic impacts of these strategies through a series of representative experiments, including Summer and Winter operating weeks, using community-level indicators (grid imports/exports, P2P traded energy, self-consumption) and per-household metrics that reveal distributional effects. Third, to assess the robustness of the observed outcomes through sensitivity scenarios that vary grid purchase tariffs and local generation capacity, thereby identifying which policy or infrastructure levers most effectively increase traded volumes and economic gains.

1.3 Thesis structure

The thesis is organized to guide the reader from conceptual foundations to modelling details, empirical evaluation, and prescriptive conclusions. Chapter 2 reviews the state of the art in P2P market designs, relevant optimization techniques, and socio-regulatory considerations that frame the study.

Chapter 3 formalizes the mathematical model, introduces notation, and presents the Alternating Direction Method of Multipliers, ADMM, decomposition alongside the two bilateral matching strategies and their parameterizations.

Chapter 4 describes the case study, the generation of the synthetic household dataset, the network topology used for distance-based matching, and the experimental assumptions. Chapter 5 presents the results of day and week-scale experiments, including per-household analyses and an interpretative discussion of trade-offs between efficiency, locality, and fairness. Chapter 6 reports sensitivity analyses that explore higher grid tariffs and expanded local generation, together with numerical robustness checks. Chapter 7 concludes with a concise summary of findings, practical recommendations, and a research agenda for future work.

2 State of The Art

This chapter examines the technological, market, economic, regulatory, and social aspects of Peer-to-Peer (P2P) energy trading, highlighting its potential to revolutionize decentralized energy systems. P2P energy trading leverages technologies like blockchain and smart contracts to enable secure, transparent, and automated direct electricity exchanges among consumers, reducing reliance on traditional centralized models [6], [7]. Despite benefits such as enhanced energy balancing, grid impact mitigation, and incentivizing renewable energy adoption [7], [8], challenges in scalability, interoperability, transaction speed [10], and synchronization persist [10]. Market structures, including centralized and decentralized designs, alongside various pricing and bidding mechanisms, are analyzed for their impact on efficiency and fairness in the work performed in [11]. Decentralized algorithms are crucial for optimizing P2P market clearing while preserving privacy [12], [13]. Economically, P2P trading offers revenue generation and cost savings for prosumers, alongside grid stress reduction [13], [14]. However, current regulatory frameworks, designed for centralized markets, require adaptation to accommodate P2P trading, with regulatory sandboxes being explored for testing innovative models [15], [16]. Socially, P2P energy trading fosters community engagement and collective responsibility in energy management [8]. While the potential is significant, large-scale commercial deployment remains limited, underscoring the need for further research and policy development [17], [18].

Technological Enablers of P2P Energy Trading

Peer-to-Peer (P2P) energy trading depends on a suite of advanced technologies that together enable secure, auditable, and automated transactions as well as real-time monitoring and system optimization [16]. Innovations such as blockchain, smart contracts, internet of things, and artificial intelligence are crucial for transitioning from traditional centralized energy systems to more decentralized, efficient, and resilient energy ecosystems, as briefly summarized hereinafter.

- Blockchain Technology

Blockchain provides a distributed ledger for many P2P energy frameworks by recording transactions in a tamper-resistant, transparent manner that reduces reliance on centralized intermediaries and improves market integrity [5], [9]. By immutably logging exchanges, blockchain can help address inefficiencies and pricing opaqueness in traditional markets while strengthening data integrity, reliability, and privacy controls, factors that support more robust and sustainable local energy markets [19], [20].

However, mainstream blockchain architectures bring disadvantages, and questions remain about technical maturity, scalability, and many public blockchains suffer from high energy use and limited transaction throughput [5], [9], [20]. To mitigate these issues, researchers and practitioners propose layered or hybrid designs. Examples include off-chain trading layers combined with on-chain settlement, semi-private or permissioned networks that use lightweight consensus (e.g., Proof of Authority) to accelerate validation for community deployments, and multi-layer semi-permissioned platforms augmented by

Quality of Transaction (QoT) modules to improve verification, privacy, and scalability [19], [9]. Alternative economic models, such as "credit blockchain" schemes, have also been suggested to reduce on-chain update frequency (lowering energy and latency costs) and to incorporate utility actors as liquidity or service providers to increase participation [20].

- Smart Contracts

Smart contracts are self-executing programs deployed on distributed ledgers that automatically enforce the rules of energy transactions, eliminating the need for manual settlement or trusted intermediaries and enabling consumers to act directly as market participants [5]. By encoding trade logic on-chain, these contracts increase automation, transparency, and tamper-evident auditability of exchanges, strengthening both security and trust in decentralized energy arrangements [16], [19]. As an emergent enabling technology for P2P energy markets, smart contracts support rapid, rule-based clearing, billing, and dispute resolution, and they open the door to innovative, consumer-centered market designs [21].

- Internet of Things (IoT)

IoT devices are a fundamental part of P2P energy markets by supplying real-time sensing, metering, and actuation needed to match local supply, demand, and to drive automated settlement mechanisms. Embedded sensors, smart meters, and controllable resources continuously deliver telemetry and status signals that feed matching engines and on-chain logic, enabling timely trade execution, verification, and auditing. Because these devices provide low-latency measurements and control hooks, they are essential for secure, transparent automated transactions and for maintaining the responsiveness and efficiency of decentralized energy systems [16].

- Artificial Intelligence (AI)

Artificial intelligence (AI) functions as a core enabling layer for P2P energy markets by providing data-driven forecasting, decision-making, and optimization capabilities that improve market performance [16]. Machine-learning and optimization methods support accurate short-term predictions of generation and load, adaptive price formation, and automated matching of supply and demand under uncertainty. These techniques can power dynamic pricing, participant-level bidding strategies, and automated control policies that increase allocation efficiency, reduce imbalances, and raise overall system responsiveness [16]. AI is therefore recognized as a rapidly emerging trend in P2P energy research and practice, because it systematically converts large streams of meter and IoT data into actionable models and optimization routines that enhance both economic and operational outcomes [21].

2.1 Resource Integration in P2P Systems: DERs and Energy Storage

The widespread adoption of distributed energy resources (DERs) and advancements in computing and communication technologies are driving the electricity sector towards more decentralized operations [22]. P2P energy trading emerges as a key paradigm in this evolving landscape, enabling customers with DERs to directly trade and share electricity, promoting autonomous participation while preserving privacy [12], [17], [23].

P2P energy trading significantly facilitates the integration and effective management of various DERs, such as photovoltaic (PV) systems, particularly when combined with battery energy storage systems (BESS) [7]. Studies demonstrate that well-designed combinations of PV and BESS, coupled with effective P2P trading mechanisms, can substantially enhance residential energy efficiency and establish viable revenue models for participants [7]. For example, the interaction between energy storage and P2P trading in an Indian residential community led to a significant reduction in grid power consumption bills [23].

The integration of DERs and energy storage via P2P mechanisms offers several advantages:

- **Enhanced Energy Balancing and Efficiency**

P2P energy trading facilitates local power and energy balance [17]. By modeling DERs, mainly PV, and BESS, P2P systems aim to maximize energy savings while minimizing network stress [7]. Market frameworks developed for P2P trading are designed to achieve market equilibrium and global optimality for all participants, ensuring grid constraint satisfaction and considering ancillary services [12].

- **Grid Impact Mitigation**

The inclusion of peak demand constraints within P2P market models can effectively reduce network stress with minimal impact on trading and operating costs, showing notable cost benefits in low-voltage distribution networks [7]. This highlights P2P trading's potential to manage the rapidly increasing number of DERs as part of the net-zero transition [17].

- **Increased Resilience and Sustainability**

Beyond economic benefits for prosumers, P2P sharing enhances energy resilience and sustainability, allowing communities to better leverage local resources and fostering collective responsibility in energy management [22].

Despite these benefits, large-scale commercial deployment of P2P energy trading via public power networks remains limited [17], indicating that research in this area is still exploratory [22], with ongoing efforts to identify challenges and develop solutions.

2.2 Market Structures and Mechanisms for P2P Trading

Carefully engineered market mechanisms are essential both for maintaining real-time balance between electricity supply/demand and for maximizing social welfare. This requirement becomes especially important in P2P energy systems, which are commonly deployed to raise local photovoltaic self-consumption and so change how energy is traded locally [2], [3].

Pricing Mechanisms and Bidding Strategies

Common pricing rules used in P2P proposals, for example, mid-market rates, supply–demand ratio pricing, and bill-sharing schemes, are intended to lower consumer bills and increase participant revenues as verified in [11]. In practice, these simple rules do not always produce fair or welfare-maximizing outcomes, because they typically ignore strategic behavior, heterogeneous incentives, and behavioral traits (e.g., fairness preferences or selfishness) that shape how prosumers bid and trade [11].

As seen in [11], to capture and mitigate those effects, several works adopt game-theoretic formulations that explicitly model strategic interactions. Such models can be used to derive pricing and incentive schemes that lower system costs and encourage active local trading. Different game theoretical frameworks have been proposed to suit alternative P2P market rules and objectives.

Another approach, like the one presented in [4], involves an optimal exchange price by solving an optimization problem that enforces network feasibility while clearing trades. In one representative design, winners in the P2P clearing trade at the computed exchange price, whereas non-winning participants retain the option to transact with the utility, sellers at an excess-energy rate, and buyers at time-of-use tariffs, so that all agents have feasible fallback transactions and the P2P market does not violate network constraints. This optimization-based clearing guarantees both operational feasibility and a principled exchange price for matched participants.

According to [24], when power-flow limits or voltage bounds are binding, locational differences can cause market-clearing prices to diverge across the grid. To preserve fairness in such cases, uniform pricing schemes combined with methods like Dynamic Operating Envelopes (DOEs) decompose global thermal and voltage limits into local envelopes for each prosumer, doing so enforces network security while maintaining a single clearing price across locations. Numerical experiments have been used to benchmark these market designs when voltage constraints are active.

For decentralized market implementations, adaptive bidding strategies based on learning algorithms outperform naive or random bidding rules and improve market performance [2]. Research has therefore focused on developing learning-based bidding policies suited to decentralized architectures, while centralized markets often rely on prescribed pricing mechanisms and centralized clearing rules [2].

Decentralized Algorithms and Optimization for P2P Market Clearing

Rising penetration of distributed energy resources (DERs) is driving distribution networks toward decentralized operation. P2P energy trading is a primary mechanism enabling autonomous, privacy-preserving participation of DER owners in local markets [12]. Such systems require market designs that support consumer-centric, bilateral matching and that operate without a central coordinator, because decentralization helps address security, privacy, and real-time transaction challenges inherent to P2P markets [10], [25].

A class of decentralized optimization algorithms built on the Alternating Direction Method of Multipliers (ADMM) has become a leading solution for these markets. ADMM is well-suited to bidirectional trading and typically exhibits rapid practical convergence. It naturally decomposes global objectives and constraints so participants can compute locally and exchange only limited coordination information [13]. Recent ADMM-based market frameworks treat participants as nodal or P2P agents that iteratively reconcile local decisions to reach a market equilibrium while guaranteeing satisfaction of network constraints, global optimality, and preservation of prosumer privacy, autonomy, and anonymity [12]. These frameworks also permit explicit accounting and allocation of ancillary-service costs and rewards, and they reduce computational burdens when applied in real-time clearing simulations [10]. The variables produced by ADMM (local prices, power schedules, residuals) are useful both for settlement and for enabling decentralized learning of prosumer cost models [13].

According to [26], robust and accelerated ADMM variants extend these capabilities. For example, Fast ADMM (FADMM) and related robust-optimization formulations allow buyer prosumers with storage and demand-response flexibility to hedge against uncertain retail prices while preserving private data. Robust decentralized formulations can guarantee feasible solutions for every realization in an uncertainty set and optimize for worst-case outcomes, importantly, without requiring a supervising third party or disclosure of individual players' private information. These features make robust ADMM variants attractive when privacy, reliability, and explicit uncertainty handling are priorities.

Beyond ADMM, other decentralized techniques are proposed in [25] and [10]. These approaches can directly embed technical constraints (e.g., line-flow or voltage limits) into bilateral trading rules, enable product differentiation, and support welfare maximization while preventing network violations. Compared with some P2P methods, properly designed primal–dual and gradient-based schemes can reduce the volume of exchanged data and accelerate convergence, making them competitive alternatives in settings where communication overhead and speed are critical.

2.3 Economic Benefits and Sustainability of P2P Energy Trading

Peer-to-peer (P2P) energy trading is increasingly recognized as a sustainable and economically viable approach for managing distributed energy resources within local electricity markets and microgrids [7], [27]. This paradigm offers significant economic and technical feasibility, marking a crucial shift from traditional hierarchical power systems towards more decentralized models [7], [22]. The overall objective of P2P energy market platforms is to maximize the collective social welfare of energy providers and consumers by coordinating energy trading [10].

P2P energy trading provides substantial economic benefits, particularly for prosumers, by improving their financial prospects and serving as a viable revenue model [7], [22]. This system rewards proactive customers who generate their own energy, allowing them to trade excess energy with other individuals or the main grid [10], [14]. Furthermore, P2P trading platforms are anticipated to reduce energy consumption costs for both individual prosumers and the utility grid [14].

Beyond individual economic gains, P2P energy trading offers multiple advantages for the utility grid by minimizing peak load demand, reducing overall energy consumption costs, and eliminating network losses [14]. Studies such as the ones performed in [7]·have shown that the strategic deployment of PV and BESS systems can maximize energy savings while simultaneously minimizing network stress. The introduction of peak demand constraints, for instance, has been found to significantly reduce network stress with minimal effects on P2P trading and operating costs, leading to notable cost benefits in network analyses [7]. This highlights P2P's capacity to optimize energy flow and reduce strain on existing infrastructure.

As [22] says, the widespread adoption of distributed energy resources (DERs) necessitates innovative energy distribution models like P2P sharing, which enables communities to collaboratively manage their energy assets. The effectiveness of P2P sharing not only boosts the economic prospects for prosumers but also enhances overall energy resilience and sustainability. This approach empowers communities to better leverage local resources, fostering a sense of collective responsibility and collaboration in energy management. In essence, P2P energy trading demonstrates both technical and economic benefits, contributing to a more sustainable and efficient energy ecosystem [27].

2.4 Challenges and Practical Implementation Issues in P2P Energy Trading

According to [17], despite extensive research, the large-scale commercial deployment of peer-to-peer (P2P) energy trading remains limited globally, with no extensive implementation in electricity markets currently [18], [22]. This limited adoption is partly attributed to a scarcity of research on decision-making processes for selecting and implementing energy sharing scenarios [18].

Significant practical challenges exist for conducting P2P energy trading via public power networks, to which most distributed energy resources (DERs) are connected [17]. Installing P2P energy trading at a broader level introduces several modeling problems across both physical and virtual network layers [14]. Furthermore, ensuring efficient and safe operation is complicated by specific issues within the P2P market, including serious challenges related to security protection and real-time transactions [10]. A key implementation hurdle identified is the synchronization problem between peers during the market-clearing process [10]. Addressing these technological problems is crucial for the advancement of P2P energy trading within electrical networks [14]. To mitigate synchronization issues, a P2P Manager (P2PM) utility has been introduced, with real-time applications verifying its effectiveness in synchronizing market participants and improving power transactions [10].

Key implementation challenges and issues include key insights, as identified in Table 2.1.

Table 2.1-Key challenges and issues.

Challenge Category	Specific Issues	Relevant Sources
General Adoption	Limited large-scale commercial deployment; Lack of generalization; Research still in exploratory stage.	[12], [17], [22]
Implementation Decision-Making	Few works on selecting and implementing energy sharing scenarios.	[18]
Grid Integration & Network Modeling	Practical challenges via public power networks; Modeling problems in physical and virtual network layers for broader installation.	[14], [17]
Transaction & Operational Issues	Security protection, Real-time transaction issues; Synchronization problems between peers during market clearing.	[10]

2.5 Regulatory and Policy Frameworks for Decentralized Energy Markets

The widespread adoption of peer-to-peer (P2P) energy trading encounters significant regulatory and market challenges, as seen in [16]. Current regulatory frameworks, designed for traditional, centralized energy markets, often lack the necessary provisions to accommodate decentralized trading models. These emerging modes of energy transaction fundamentally defy established hierarchical structures based on vertical agreements between energy providers and consumers [28]. Key issues arising from this disparity include grid access, tariffs, consumer protection, and data privacy. Regulatory barriers vary significantly by region, directly influencing the pace of P2P adoption, making the design and implementation of P2P trading markets complex [16], [28].

Policy Adaptations and Solutions

To fully realize the potential of P2P energy trading and contribute to resilient, sustainable, and decentralized energy systems, adaptable policies and robust platforms are indispensable [16]. A policy approach fostering dialogue and innovation is crucial to reap societal benefits while mitigating considerable risks to infrastructure and individuals[15]. Essential market mechanisms for P2P energy trading success include dynamic pricing, demand response programs, and real-time settlement systems. The evolving role of aggregators and intermediaries also requires careful consideration and regulatory adaptation [16].

For P2P energy trading platforms (P2P-ETP) to foster a sustainable energy ecosystem, specific legal risks must be addressed through appropriate regulatory solutions. Smart contracts, a main component of P2P-ETPs, introduce legal uncertainties, particularly concerning their enforceability. Additionally, there is a risk of inadequate consumer protection regarding potential price manipulation, privacy violations, and data breaches [29]. Therefore, proposed policy implementations must establish clear principles for a legal and regulatory framework that supports a trusted P2P-ETP [33]. Policymakers and societies must understand and address considerations from social, market design, and regulatory viewpoints [15].

Regulatory bodies are actively exploring sandbox environments as a mechanism to test innovative P2P models [16]. The regulatory sandbox is proposed as the most appropriate tool to facilitate this innovation and promote dialogue, which can help prevent the breakdown of trust between policymakers and platform companies, an issue observed in other sectors of the sharing economy [15]. This approach is vital for addressing the complex considerations that policymakers and societies must navigate, especially given that P2P electricity trading is a novel data-driven business model currently being trialed within the energy sector [15].

2.6 Social and Stakeholder Perspectives of P2P Energy Trading

Peer-to-peer (P2P) energy trading is emerging as a new data-driven business model within the energy sector, currently undergoing trials [15]. This approach signifies a fundamental shift in how energy is consumed, traded, and utilized, moving from traditional hierarchical power systems towards more decentralized models [22]. P2P energy trading can be conceptualized as part of the sharing economy, with parallels drawn from experiences in other sectors [15]. This decentralized model allows prosumers to directly generate and exchange electricity, promoting local generation and consumption balancing and encouraging renewable energy use [16].

Regarding the Social Implications and Community Engagement, the introduction of P2P transactions to an essential service like energy supply carries significant implications for individuals and the grid [15]. P2P sharing models enable communities to collaboratively manage their energy resources, fostering a sense of collective responsibility and collaboration in energy management within communities [22]. While P2P energy trading pilots have demonstrated benefits for prosumer and renewable energy valorizations [18], the widespread implementation of these sharing models in current electricity markets is not yet extensive [22]. Empowering citizens to actively participate in energy markets is a key opportunity presented by the increasing penetration of Renewable Energy Resources (RES) [30].

Stakeholder Engagement and User Experience

Local P2P energy markets involve a range of stakeholders beyond just prosumers and consumers [31]. The coordination of energy trading between energy providers and consumers primarily aims to maximize their social welfare [10]. To account for the diverse interests of these individual stakeholders, existing methodologies for establishing and analyzing requirements for local energy markets have been extended and refined [31]. This includes applying the Development approach for Decentralized Control Systems (2DECS), which utilizes artifacts like User Stories, "Definitions of Done," Story Cards, and Acceptance Test Requirements for requirements elicitation [31]. The individual interests of market participants can also be rated based on their potential for conflict [31]. A multi-agent framework can be established to simulate the behavior and interaction of multiple entities in P2P energy trading [27].

3 Methodology

This chapter describes, in a reproducible and rigorous manner, the methodology adopted in this study. It integrates the mathematical modeling of the peer-to-peer (P2P) energy trading problem, the two bilateral matching strategies under analysis, named ST1 and ST2, the decentralized formulation solved via an optimization algorithm, the Alternating Direction Method of Multipliers (ADMM), implementation details, and evaluation metrics. The description is organized to facilitate reproducibility and to support the results presented in subsequent chapters.

3.1 Mathematical Model of the P2P Problem

This study considers a residential energy community composed of a set of nodes N, indexed by $i = 0, 1, ..., N$. Although a node can represent a household or a building within the distribution network, this study focuses solely on households. All households are connected to the main grid and can inject/withdraw power through that connection. Their electricity demand is known and described by a load profile. The baseload demand of household i at timestep t is denoted as $P_{i,t}^{l}$, and is assumed to be deterministic. The power withdrawn/injected from/to the grid is denoted as $p_{i,t}^{g}$ and is associated with a price λ^{buy} for energy bought from the grid and λ^{sell} for energy sold back to the grid. These prices are fixed on timestep t for all households in the community.

In P2P trading, each household can exchange a net amount of power with other households in the network. The net power exchange is denoted by $p_{i,t}$. A positive value indicates surplus power, i.e., power available for sale, and a negative value suggests residual demand, i.e., power that needs to be bought.

3.1.1 Energy Balance

The net power $p_{i,t}$, is determined by using an energy balancing formula as follows:

$$p_{i,t} = p_{i,t}^{g} + P_{i,t}^{pv} + P_{i,t}^{W} - P_{i,t}^{l} \tag{1}$$

where, $p_{i,t}^{g}$ is the power withdrawn/injected from/to the grid by household i at time t, according to the consumer criterion, $P_{i,t}^{pv}$ denotes the photovoltaic generation of household i at time t, $P_{i,t}^{W}$ the wind generation of household i at time t, and $P_{i,t}^{l}$ denotes the electrical load (demand) of household i at time t.

3.1.2 Local Cost Function

The net grid power, $p^g_{i,t}$, is decomposed into nonnegative import and export components: if $p^g_{i,t}$ is positive, we call it $p_{buy,i,t}$ if negative, $p_{sell,i,t}$.
The cost function for each household *i* in timestep *t* can be formulated as follows:

$$C^g_{i,t}\left(p^g_{i,t}\right) = \lambda^{\text{buy}}_t \; p_{buy,i,t} - \lambda^{\text{sell}}_t \; p_{sell,i,t} \tag{2}$$

where

$$\begin{cases} p_{buy,i,t} \geq 0 \\ p_{sell,i,t} \geq 0 \end{cases} \tag{3}$$

The $C^g_{i,t}\left(p^g_{i,t}\right)$ denotes the cost associated with grid interaction for household *i* at time *t*, λ^{buy}_t and λ^{sell}_t are the grid purchase and selling prices at time *t*, respectively. Variable $p_{buy,i,t}$, is the power bought from the grid by household *i* at time *t,* and $p_{sell,i,t}$ is the nonnegative power sold to the grid by household *i* at time *t*.

3.2 Mathematical Formulation of ADMM for Bilateral Trading

3.2.1 Centralized Problem

In this study, a P2P market model is employed as a particular instance of the unified formulation presented in [32]. This model enables the assignment of a unique bilateral trading coefficient to each trade, ensuring that every transaction is weighted according to its specific characteristics. It is assumed that all households on the network act as rational, nonstrategic market participants. The primary objective is to minimize the overall costs for all households (denoted by *N*) over a given time horizon (*T*). These costs encompass both the expenses (or revenues) associated with withdrawing power from or injecting power into the grid, as well as those arising from bilateral energy trading among households. The centralized cost minimization reads:

$$\min \sum_{t=0}^{T} \sum_{i=0}^{N} \left[C^g_{i,t}(p^g_{i,t}) + \sum_{j=0}^{M} \gamma_{ij,t} \left| d_{ij,t} \right| \right] \tag{4}$$

Let *M* denote the set of potential trading partners for household *i* (indexed by *j*). Household *i* expresses its bilateral trading preferences through a parameter $\gamma_{ij,t}$, which acts as the trading penalty/coefficient applied to transactions with partner *j*. The variable, $d_{ij,t}$, models the amount of energy exchanged between households *i* and *j*. subject to the local energy balance.

$$p_{i,t} = \sum_{j=0}^{M} d_{ij,t} \, , \quad [\mu_{i,t}] \quad \forall i \in N, t \in T, \tag{5}$$

For each time step *t*, the algebraic sum of energies that household *i* exchanges with all partners must match its net available power, given by (1). This requirement is imposed by constraint (5).

The dual variable $\mu_{i,t}$, calculated according to the formulation described in the next subchapter, corresponds to the energy price as perceived by household *i*. At the network level, $\mathbf{D_t}$ it collects all bilateral trade quantities at time *t*, while $\boldsymbol{\Xi}_t$ stores the associated dual prices.

Reciprocity of both traded quantities and prices is enforced by constraint (6) and holds at the optimization optimum.

$$\mathbf{D_t} = -\mathbf{D_t}^{\top} \quad [\boldsymbol{\Xi}_\mathbf{t}] \quad \forall t \in T. \tag{6}$$

3.2.2 Decentralized Formulation

In this study, a consensus formation was employed with the Alternating Direction Method of Multipliers (ADMM) to split the centralized problem in the equation (4) into a set of local subproblems. Each household independently optimizes its own subproblem, and then the individual solutions are reconciled to satisfy the global coupling constraints. After solving its local subproblem, every household produces its own optimal local trading quantities schedule $\mathbf{D}$, which is linked to the global variable $\mathbf{C}$. Following the convention used in [32], was defined:

$$\mathbf{D} = \frac{1}{2}\left(\mathbf{C} - \mathbf{C}^{\mathbf{T}}\right) \tag{7}$$

Here, $\mathbf{C}$ collects each household's proposals for bilateral trades at time *t* and acts as the global, aggregated consensus variable used by the ADMM coordinator to reconcile local solutions.

In this way, $\mathbf{D}$ represents the average between the proposal that *i* make for *j* and the reciprocal proposal from *j* to *i*. Consensus between households is achieved when both parties propose equal values for their bilateral trades, a condition ensured by the ADMM algorithm at convergence, since the underlying optimization problem in (4) is convex [32]. Importantly, the decentralized setup preserves agent privacy, locally measured series (generation, demand) remain private and are not shared across the network.

Leveraging this consensus constraint, the fully decentralized augmented Lagrangian for the bilateral trading model can be formulated, a fully decentralized augmented Lagrangian is a distributed optimization method where constraints are enforced through an augmented Lagrangian formulation, and all computations/communications are performed locally without any central coordinator [33]. For each iteration *k* and per household *i*, as follows:

$$\left(p_i^g, D_i\right)^{k+1} = \arg\min_{p_i^g, D_i} \sum_{t=0}^{T} \left[C_{i,t}^g\left(p_{i,t}^g\right) + \sum_{j=0}^{M} \left[\gamma_{ij,t} |d_{ij,t}^{(k+1)}| + \frac{\rho}{2}\left(\frac{d_{ij,t}^{(k)} - d_{ji,t}^{(k)}}{2} - d_{ij,t}^{(k+1)} + \frac{\xi_{ij,t}^{(k)}}{\rho}\right)^2 \right]\right] \tag{8}$$

Let $\rho > 0$ denote the ADMM penalty parameter and let ξ be the dual variable representing the price associated with each bilateral trade [33]. The dual variable ξ is updated at every ADMM iteration *k* according to the following expression.

$$\xi_{ij,t}^{(k+1)} = \xi_{ij,t}^{(k)} - \frac{\rho}{2}\left(d_{ij,t}^{(k+1)} + d_{ji,t}^{(k+1)}\right) \tag{9}$$

Convergence of the ADMM procedure, attainment of consensus, is declared when the algorithm satisfies the stopping conditions listed in the following expression:

$$\| \mathbf{r}^{(k)} \|_2 \leq \varepsilon_{\text{prim}}, \quad \| \mathbf{s}^{(k)} \|_2 \leq \varepsilon_{\text{dual}} \tag{10}$$

where $\mathbf{r}$ and $\mathbf{s}$ denote the primal and dual residuals, respectively, $\varepsilon_{\text{prim}}$ and $\varepsilon_{\text{dual}}$ are the prescribed tolerances for the primal and dual residuals. These tolerances are normally chosen to be very small values, as recommended in [33].

3.3 Bilateral Trading Strategies

To aggregate all bilateral trading coefficient values between any household and its peers in the network, a matrix of bilateral trading coefficients, $\boldsymbol{\Gamma}$, should be defined. This matrix is used to indicate preferred trading partners and enable product differentiation. According to the formulation, the smaller the value of $\gamma_{ij,t}$, the more favorable the associated trade with household j. In this approach, two strategies for defining the matrix $\boldsymbol{\Gamma}$ are proposed, a supply-demand matching strategy (ST1) and a distance-based matching strategy (ST2), being inspired by the work presented in [34].

The use of two distinct strategies is deliberate: each embodies a different market logic and therefore highlights different operational, economic, and equity effects that a local market design can produce.

In this study, ST1 is implemented as a time-varying matrix $\boldsymbol{\Gamma}$ to capture temporal and economic complementarity between households, whereas ST2 is implemented as a time-invariant (static) matrix $\boldsymbol{\Gamma}$ that reflects fixed geographic/topological proximity. This distinction is important: a time-varying $\boldsymbol{\Gamma}$ produces dynamic matching patterns and requires recomputation and coordination at each scheduling interval, potentially affecting traded volumes, sensitivity to forecast errors, and the computational/communication burden of the ADMM coordination; a static $\boldsymbol{\Gamma}$ reduces operational complexity but constrains matching to a fixed set of preferred partners.

3.3.1 Supply-Demand Matching Strategy (ST1)

In this strategy, the bilateral trading coefficients , $\gamma_{ij,t}$, are determined based on matching the power demand and surplus power generation of households [34]. ST1 privileges temporal and economic complementarity between houses. Under ST1, households are preferentially paired when one's surplus production temporally matches another's demand. The principal objective of ST1 is to maximize local utilization of renewable generation and minimize aggregate imports from the main grid by promoting trades that increase system-level self-consumption. Analysis under ST1, therefore, focuses on traded volumes aligned with generation profiles, reductions in grid dependence, sensitivity to forecasting errors, and distributional outcomes that arise from temporal complementarity.

To implement these assumptions in the bilateral trading coefficients, several steps are followed:

1. The expected net budget matrix $\boldsymbol{P^{net}}$, is determined, containing the net power of all households across all time steps.

2. From this matrix, two new matrices, $\boldsymbol{P^{Buy}}$ and $\boldsymbol{P^{Sell}}$, are defined, representing the amount of net power each household wants to buy or sell at every timestep.

3. Each row in $\boldsymbol{P^{Buy}}$ and $\boldsymbol{P^{Sell}}$ is normalized according to the maximum deficit and surplus budget in that row.

   Normalization makes preference values comparable across households of different scales, bounds the bilateral coefficients within a predefined range (0 to χ), and preserves temporal patterns of surplus/deficit while converting absolute energy amounts into relative trading preferences.

4. Subsequently, the matrices $\boldsymbol{\Gamma^{b,rel}}$ and $\boldsymbol{\Gamma^{s,rel}}$ are generated.

The matrices $\boldsymbol{\Gamma^{b,rel}}$ and $\boldsymbol{\Gamma^{s,rel}}$ represent the relative willingness of households to buy or sell energy, expressed by trading coefficients. The maximum baseline value for bilateral trading coefficients is defined by using parameter χ . Using $\boldsymbol{\Gamma^{b,rel}}$ and $\boldsymbol{\Gamma^{s,rel}}$**,** the final 3-D matrix of bilateral trading coefficients, $\boldsymbol{\Gamma}$, is constructed.

Functionally, χ ,with the value of 0.10, acts as an upper bound that prevents bilateral coefficients from attaining excessively large magnitudes, which could produce unrealistic P2P prices or destabilize exchange allocations. The χ value is obtained by empirical calibration using a trial-and-error procedure aimed at tuning the strategy for the studied scenario. In this way, this process seeks a practical compromise between matching efficiency and economic stability.

When $\gamma_{ij,t} = \chi$, households *i* and *j* are considered highly unlikely to engage in trading.

The complete procedure for this strategy (ST1) is outlined in Figure 3.1.

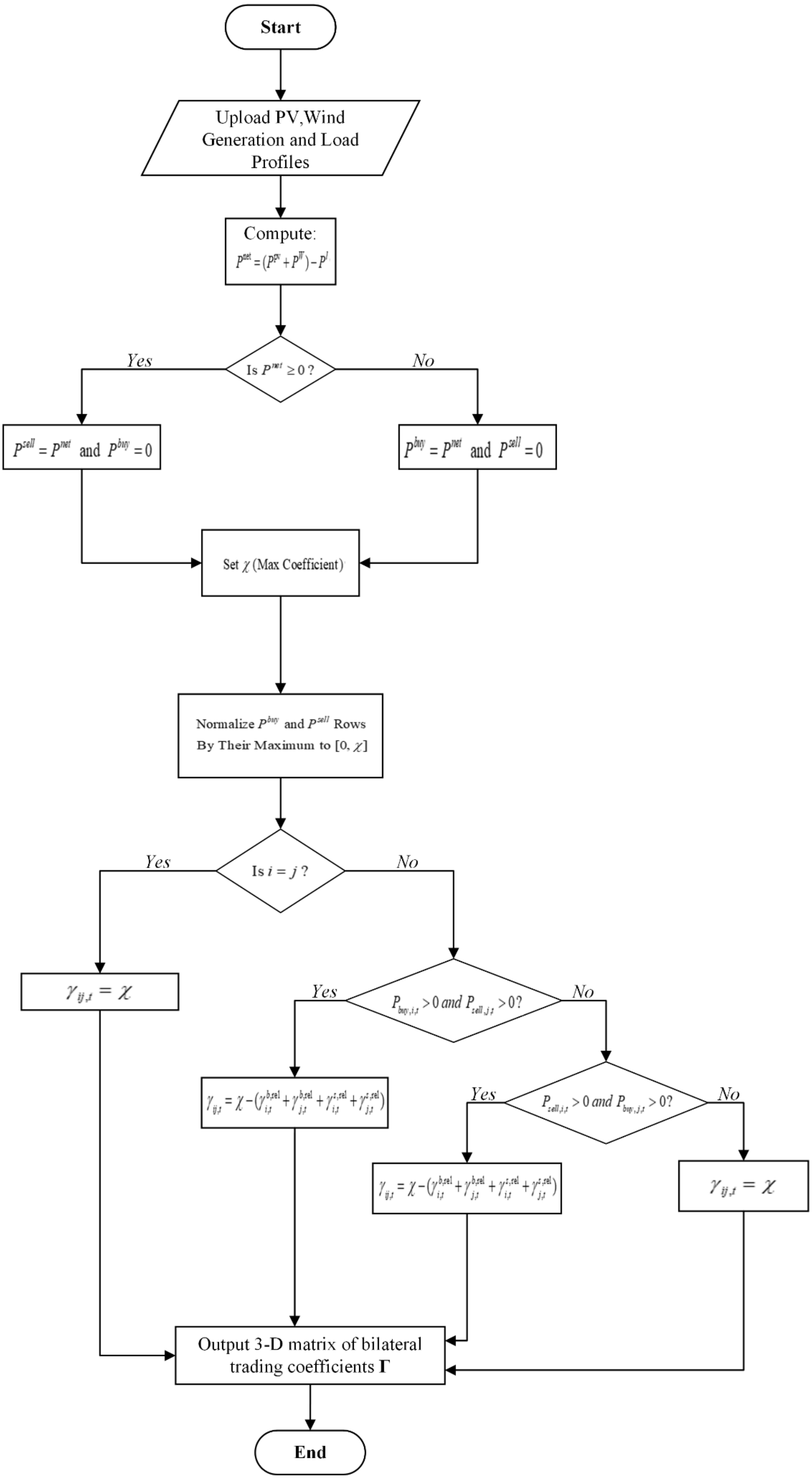

Figure 3.1-ST1 Flowchart.

3.3.2 Distance-Based Matching Strategy (ST2)

The second proposed strategy for matching energy trading between households is based on their distance within the network. ST2 privileges geographic or topological proximity. Under ST2, preference is given to nearby neighbors so that bilateral trades are physically short, which tends to reduce distribution losses, limit grid congestion on specific feeders, and lower certain transaction or metering costs. The objective of ST2 is to test how locality-constrained matching affects network performance, operational feasibility, and local fairness. Analysis under ST2 emphasizes whether restricting trading to proximate peers reduces or redistributes economic opportunities.

Here, distance is defined by the number of connections between households. The distance between households depends on the network topology, as proposed by the one represented in Figure 4.1.

The network depicted in Figure 3.2 follows a radial (tree) distribution topology. For clarity, all nodes are numbered in the figure: nodes 1–10 represent end-user households (leaf nodes), nodes 11–13 denote distribution cabinets that aggregate local connections, and node 14 corresponds to the transformer substation linking the distribution network to the upstream grid.

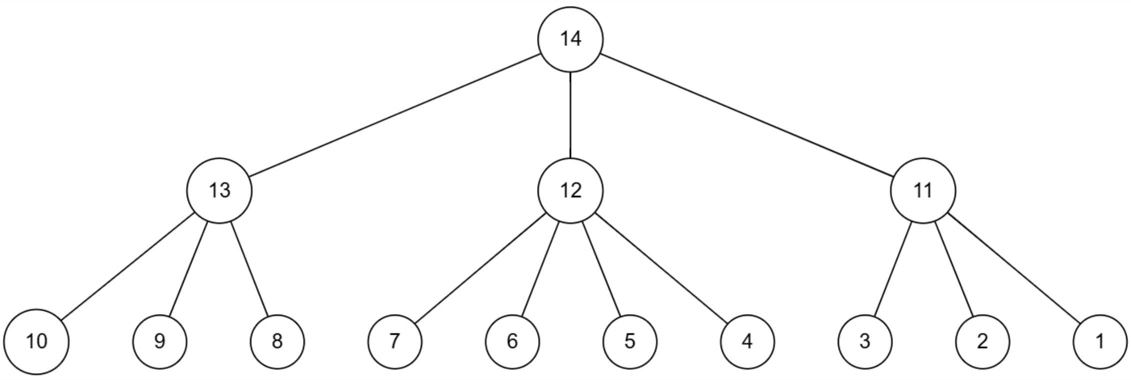

Figure 3.2-Network topology graph.

Unlike ST1, whose coefficients are time-varying to reflect temporal dynamics (generation availability and load profiles), ST2 uses time-invariant coefficients fixed over the analysis horizon. This is justified by the assumption of equal inter-house distances, so distance-based weights do not change with time.

To calculate the bilateral trading coefficient between household *i* and *j*, γ_{ij}, the following equation (11) is used:

$$\gamma_{ij} = \chi\left(\mathrm{dist}_{ij}\right) \tag{11}$$

where, dist_{ij}, is the distance between houses *i* and *j* in the network topology and χ is a fixed scale coefficient.

The parameter χ, with the value of 0.05, serves as a scaling factor applied to the bilateral coefficients in this approach. The raw bilateral coefficient is proportional to the topological distance (number of hops) between two households, because this distance is an integer-valued quantity, its unscaled magnitude would be incompatible with the numerical range of the other cost terms.

The parameter χ rescales the distance-based coefficients to a numeric interval that allows the distance penalty to meaningfully influence bilateral trade costs without dominating the objective function. The χ value was selected through calibration by trial and error to balance the penalization of long-distance trades with the viability of local exchanges.

As the distance increases, the bilateral trading coefficient, γ_{ij}, increases linearly, reflecting a higher "cost" or difficulty in negotiating between houses that are farther apart.

The distance dist_{ij} between two houses is determined by the Breadth-First Search (BFS) algorithm, detailed in section 3.4.5. The idea is to find the minimum number of hops needed to reach from node *i* (start) to node *j* (destination) in the network.

The process works as follows:

1. Initialization:
    - Start with a queue that contains the starting node with a distance of zero.
    - Maintain a set of visited nodes to avoid repetitions.
2. Processing:
    - While the queue is not empty, the algorithm removes the node at the front of the queue and checks if it is the destination.
    - If not, it adds the neighbors (that haven't been visited) of the current node to the queue, incrementing the distance by 1 for each neighbor.
3. Result:
    - If the destination node is found, the algorithm returns the distance (dist_{ij}).
    - If there is no path (the destination is unreachable), the function returns infinity, indicating that the houses are not connected in the provided topology.

In mathematical terms, the BFS algorithm isn't expressed by a single formula, but the result dist_{ij} is the length of the minimum path found between *i* and *j*.

This strategy prioritizes reducing long-distance electricity flows, potentially improving energy efficiency by encouraging P2P trading among nearby households. Detailed descriptions of the ST2 function are provided in Figure 3.3.

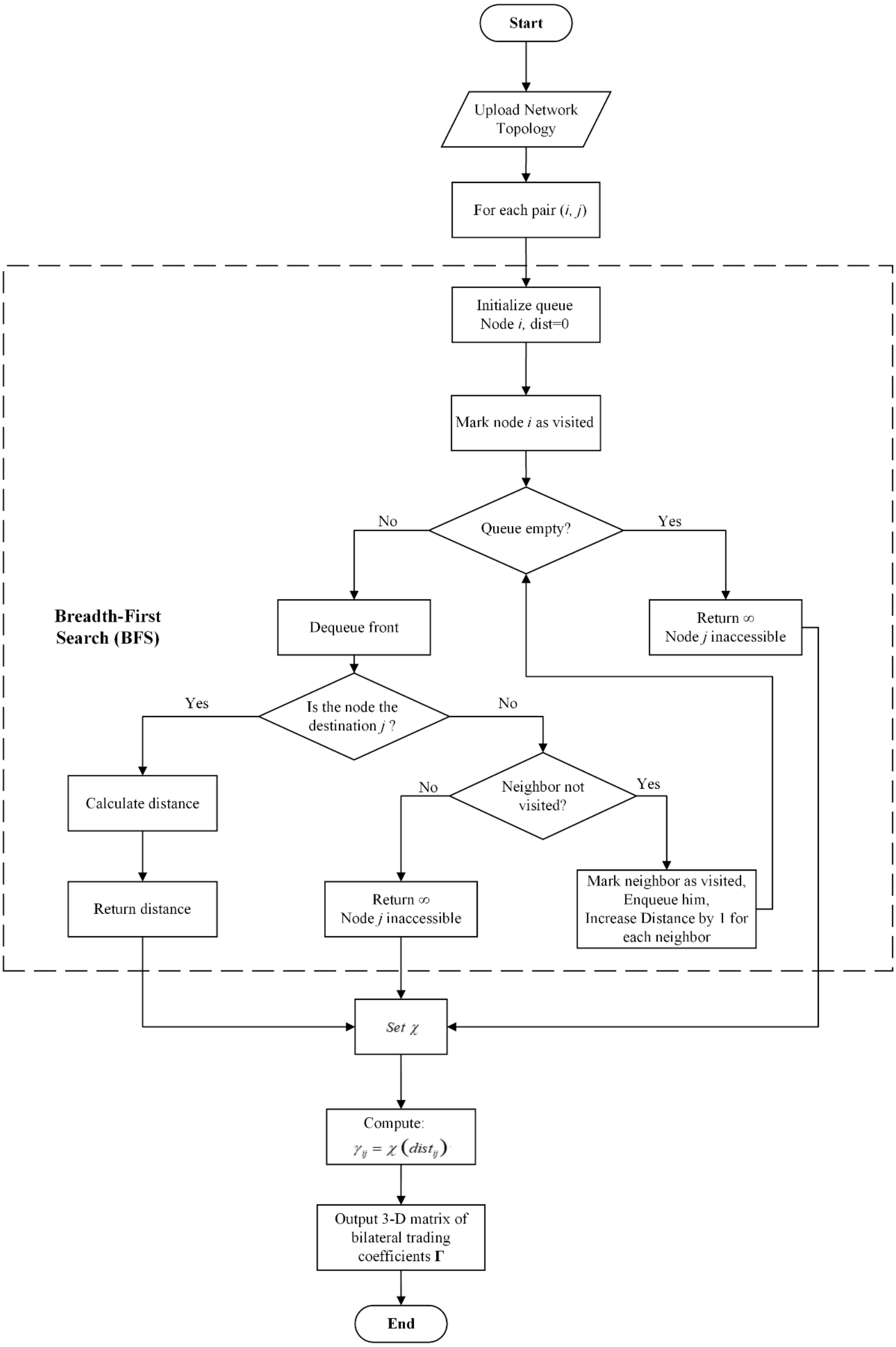

Figure 3.3-ST2 Flowchart.

3.4 Tools and Implementation

3.4.1 Programming Environment (Python 3)

All computational tasks for this study were carried out in Python 3, chosen because it is stable, widely adopted across the scientific community, and supported by extensive official documentation, factors that help make the codebase maintainable and reproducible. The implementation builds on the standard scientific Python stack. At the data and number-crunching core sits NumPy, which supplies multidimensional array types and vectorized operations that underpin data representation and most numerical computations [35]. NumPy also functions as the established interoperability layer connecting components of the scientific Python ecosystem. SciPy complements this by providing well-tested implementations of common numerical routines (e.g., linear algebra, interpolation, and signal-processing primitives), enabling concise, reliable preprocessing and analysis code [35], [36].

The study's optimization models were authored and executed inside the same Python environment using CVXPY, a mature domain-specific modelling language that turns high-level convex formulations into solver-ready conic representations and interfaces with multiple solvers [37]. This makes the translation from mathematical expressions to executable code clear and auditable. Keeping the entire workflow in a single language permitted seamless combination of data preparation, model definition, solver invocation, and visualization within scriptable, version-controlled pipelines, practices that strengthen reproducibility. Consistent with community recommendations seen in [38], [39], the project stores software versions and solver configuration in experiment metadata and adheres to standard reproducibility guidelines for computational research.

3.4.2 Modeling Framework (CVXPY)

CVXPY is an open-source, Python-embedded modeling language designed to let researchers express convex optimization problems in code that closely mirrors their mathematical form [37]. Rather than forcing users to hand-craft problems in a restrictive canonical representation required by many low-level solvers, CVXPY accepts natural, math-like expressions and automatically transforms them into the standard conic/solver format, a process that both speeds development and reduces translation errors from equations to executable models [37].

A core aspect of CVXPY is its enforcement of the Disciplined Convex Programming (DCP) ruleset [40]. By restricting how functions and operations may be composed, CVXPY can automatically check whether an expression is convex and warn when a modeling construct violates convexity requirements. This automatic convexity analysis protects correctness by ensuring that only legitimately convex problems are forwarded to convex solvers, and it rests on well-established DCP theory [40].

CVXPY also includes practical modeling features that make experimentation and scaling straightforward: named parameters for running repeated experiments without reconstructing the problem object, efficient support for sparse matrix data, vectorized operations for compact model expressions, and a solver-agnostic that lets users switch backends (e.g., SCS, OSQP, ECOS) with minimal code changes [37].

Because CVXPY sits naturally inside the Python scientific ecosystem, it simplifies the project's end-to-end workflow, from preprocessing and problem assembly to parameter sweeps, solver execution, and post-processing, all within a single scriptable environment [41]. Active maintenance, thorough documentation, and broad adoption in research and teaching further improve diagnosability and community validation.

For these reasons, transparent math-to-solver conversion, DCP safety checks, parameter and sparse-data support, solver flexibility, and tight Python integration, CVXPY was selected as the modeling framework for this work.

3.4.3 Solver (SCS)

The convex programs produced from our CVXPY models were solved using the Splitting Conic Solver (SCS). SCS is a first-order solver that applies an operator-splitting strategy to the homogeneous self-dual embedding of conic problems [42]. That formulation lets the solver return primal/dual solutions and, in cases of infeasibility, certificates proving infeasibility or unboundedness, while allowing the method to scale substantial and sparse instances [42].

SCS was selected for three practical, complementary reasons. First, as a first-order method, it has low memory overhead and favorable scaling behavior with problem dimensions, which makes repeated solves (e.g., parameter sweeps and ADMM subproblem solves) feasible without exhausting memory or compute resources. Second, SCS is directly supported and tightly integrated with CVXPY, so it can be invoked from the same high-level model code used to construct problems. This simplifies experimentation with model parameters and solver options. Third, SCS exposes tolerances and convergence diagnostics (e.g., primal/dual residuals, iteration counts, etc..), enabling coherent termination logic when SCS is nested inside higher-level algorithms such as ADMM and allowing us to align solver stopping criteria across algorithmic layers [41].

It is important to acknowledge the algorithmic tradeoffs: first-order solvers like SCS are designed to reach modest (but usually sufficient) accuracy quickly and with low memory use, but they do not typically attain the high numerical precision of interior-point (second-order) methods. For this work, where the emphasis was on many large-scale solves inside an ADMM loop and on comparative performance across scenarios rather than on obtaining ultra-high precision optimal values, SCS offered a pragmatic balance between speed, resource use, and acceptable accuracy. Solver parameters were tuned to match the ADMM stopping rules and are recorded with the experiment metadata to support reproducibility [42].

Finally, SCS is actively maintained, documented, and distributed with public source code, which helps with traceability and reproducibility. When higher accuracy or different numerical behavior is needed, the CVXPY modeling choices make substitutions for other compatible solvers (e.g., OSQP, ECOS, commercial solvers such as MOSEK) straightforward for future work.

3.4.4 Decentralized Algorithm (ADMM)

The Alternating Direction Method of Multipliers (ADMM) was adopted as the decentralized optimization engine for the P2P trading framework because it naturally decomposes a global convex optimization problem into local subproblems that can be solved independently by each agent, while a lightweight coordination step enforces consistency (consensus) across agents. In its canonical form, ADMM addresses problems of the type minimize $f(x)+g(z)$ subject to $Ax+Bz = c$ by alternating local minimization steps on x and z followed by a dual update. The algorithm, therefore combines the decomposability of dual ascent with the superior numerical robustness of the method of multipliers. This behavior and the standard ADMM iterations are described in detail by [33].

From a practical viewpoint for P2P energy trading, ADMM provides three decisive advantages. First, it maps directly to a distributed software architecture, where each household solves a local convex subproblem that depends only on local variables and a small set of coupling variables, which reduces computational burden and preserves data locality. Second, ADMM's iterative structure fits naturally with convex modelling tools (CVXPY) and first-order solvers (SCS) used in this study, enabling rapid prototyping and parameter sweeps inside the ADMM loop. Third, the algorithm's residual-based stopping criteria provide operationally meaningful diagnostics (primal and dual residuals) that are convenient both for terminating iterations and for monitoring convergence across experimental scenarios. These properties make ADMM a frequent choice in recent P2P and distributed energy studies [33], [43], [44].

The ADMM penalty parameter $\rho > 0$ controls the tradeoff between primal feasibility and dual progress, larger ρ tends to reduce primal residuals faster but can increase dual residuals, and vice versa. Selecting ρ is therefore important for practical performance. Heuristic adaptive schemes that adjust ρ based on the relative magnitude of primal and dual residuals are commonly used, however, these heuristics have limitations related to problem scaling and may need problem-specific tuning [45].

Although ADMM is widely used and robust for many classes of convex problems, its theoretical global convergence rate is not uniform across all problem classes and may be slow to reach very tight tolerances compared with interior-point methods; therefore the choice of solver, ρ , tolerances and maximum iterations must be aligned with the study's objectives (comparative experiments and scalability rather than extremely high precision optimal values). Readers are referred to foundational analyses and to recent reviews on distributed optimization in energy systems for further discussion and for examples of ADMM variants that address asynchrony, communication delays, and nonconvex extensions [33], [44].

3.4.5 Breadth-First Search (BFS)

Breadth-First Search (BFS) is a classical graph traversal algorithm that explores a graph layer by layer from a given source node, discovering all vertices at distance d before visiting vertices at distance $d + 1$. In unweighted graphs, BFS computes the shortest path length measured in number of edges (hops) from the source to every other reachable node, and it does so with linear time complexity $O(|V|+|E|)$ where $|V|$ and $|E|$ are the numbers of vertices and edges, respectively.

The algorithm is simple to implement using a queue and a visited/parent array to avoid revisiting nodes, its theoretical properties and standard pseudocode are covered in algorithmic texts [46].

The reasons for choosing BFS in this context are threefold. First, BFS is the canonical algorithm for shortest hop distances in unweighted graphs and thus matches precisely the definition of topological distance used in ST2. Second, BFS is inexpensive to run even when repeated N times to produce an all-pairs hop distance matrix, which is negligible for the modest network sizes considered here. Third, BFS is robust and deterministic, it produces identical results independent of implementation details (provided the graph representation is the same), which aids reproducibility and traceability of distance-based effects in the experiments [46], [47].

Reproducibility considerations

To ensure reproducibility, random seeds were fixed during the generation of synthetic household data, and all solver parameters and settings were documented. The codebase was structured in modular form, separating data preprocessing, model definition, and result analysis, thereby facilitating extension of the framework to other solvers, trading strategies, or community configurations.

4 Case Study Framework and Assumptions

This chapter introduces the case study adopted in this work, aiming to provide a platform to evaluate the performance of decentralized P2P trading strategies previously introduced. The case study consists of a synthetic residential community of ten households, including consumers and prosumers, nevertheless without storage. The deliberate exclusion of energy storage reflects current market realities, where installed residential battery systems remain comparatively costly and their adoption is limited, so modeling without storage better represents the present-day majority of households while remaining readily extensible for future studies. The analysis focuses on quantifying P2P trade volumes, grid import/export, self-consumption, and procurement cost. This scenario enables assessment of both economic efficiency and operational impacts on the local distribution network, which will be presented in the following chapters.

4.1 Synthetic Dataset Description

The case study used for this study originates from a real data set from a single residential household, covering a period of nearly five years (2014–2020) [48]. The complete data set comprises 201,604 observations recorded at 15-minute intervals. For this study, data corresponding to the period September 30, 2019, to September 30, 2020, is considered so that the analysis reflects contemporary consumption patterns while remaining computationally tractable. This high temporal resolution dataset provides detailed profiles of electricity consumption and distributed renewable generation and constitutes a robust foundation for modeling dynamic household energy behavior, with emphasis on three primary variables:

- **Electricity Load:** The total electricity consumption of the household.
- **Residential Wind Generation:** The energy produced by wind turbines installed at the household.
- **Residential Solar Generation:** The energy produced by solar photovoltaic (PV) panels.

According to the dataset, for the period under analysis, the annual values for the reference household amount to 917.04 kWh of electricity consumption, 2909.94 kWh of solar generation, and 5635.32 kWh of wind generation. These values reveal an unrealistic balance between consumption and production for a typical residential household, particularly given the disproportionately high levels of renewable generation. Consequently, it is necessary to construct synthetic data for the entire community of ten households by applying scaling factors to the one-year reference dataset, thereby generating profiles that yield more representative household-level consumption and generation patterns.

Synthetic profiles for the ten households are derived by scaling the original household dataset using predefined factors. This procedure introduces variation across households while preserving the temporal structure, statistical variability, and seasonal patterns of the source data, thereby ensuring realistic representations of both consumption and generation profiles and enabling community-wide analysis. The scaling factors applied to the original dataset to create synthetic households are presented in Table 4.1.

Table 4.1-Synthetic data generation for residential community.

House	Electricity Load	Residential Solar Generation	Residential Wind Generation
1	4.40	0.80	0.60
2	3.60	0.72	0.48
3	4.00	0	0
4	3.80	0	0
5	4.20	0	0
6	4.00	0.72	0.48
7	3.40	0.	0
8	4.60	0.80	0.56
9	3.52	0	0
10	4.00	0.72	0.56

The scaling factors applied highlight the variability introduced in energy consumption and renewable generation among households, providing a diverse yet realistic data set for simulation.

4.2 Annual Aggregation of Scaled Data

To quantify the impact of the scaling procedure on community-level energy demand and renewable generation, each of the ten households' time series was aggregated into annual totals, considering the period September 30, 2019, to September 30, 2020, for the three variables of interest, consumption, solar generation, and wind generation, as can be seen in Table 4.2.

The resulting annual figures enable:

- Direct comparison of electricity consumption across the synthesized households.
- Assessment of the absolute and relative contributions of the two renewable sources in each household.
- Identification of potential imbalances at the individual level.

By calibrating the scale factors against typical benchmark values from the literature, the community-level analysis is kept grounded in realistic energy profiles, thereby enhancing the validity of subsequent peer-to-peer trading and demand response studies.

Table 4.2-Annual totals of scaled electricity load and renewable generation (kWh).

House	Electricity Load (kWh)	Residential Solar Generation (kWh)	Residential Wind Generation (kWh)	Production vs Consumption (%)
1	4034	2327	3381	141,5
2	3301	2095	2704	145,4
3	3668	0	0	0
4	3484	0	0	0
5	3851	0	0	0
6	3668	2095	2704	130,7
7	3117	0	0	0
8	4218	2327	3155	129,7
9	3227	0	0	0
10	3668	2095	3155	143,1

Based on this distribution, the case study community consists of five prosumers (households that both consume and generate electricity) and five consumers (households that only consume electricity without generating any renewable energy).

4.3 Grid Topology

The community is composed of ten households, connected in a radial configuration to the low-voltage grid through a point of common coupling (PCC) located on the low-voltage side of a distribution transformer of the utility grid.

Among the ten households, five are modeled as prosumers, equipped with solar photovoltaic panels and small wind turbines, while the remaining five operate solely as consumers. Figure 4.1, depicts the prosumers with solar panels, representing households with photovoltaic generation, while the wind turbine icon denotes households with wind generation capacity. The blue lines indicate the traditional grid connections linking all participants to the transformer and subsequently to the utility electricity network. A more detailed schematic of the network topology is provided in Figure 3.2.

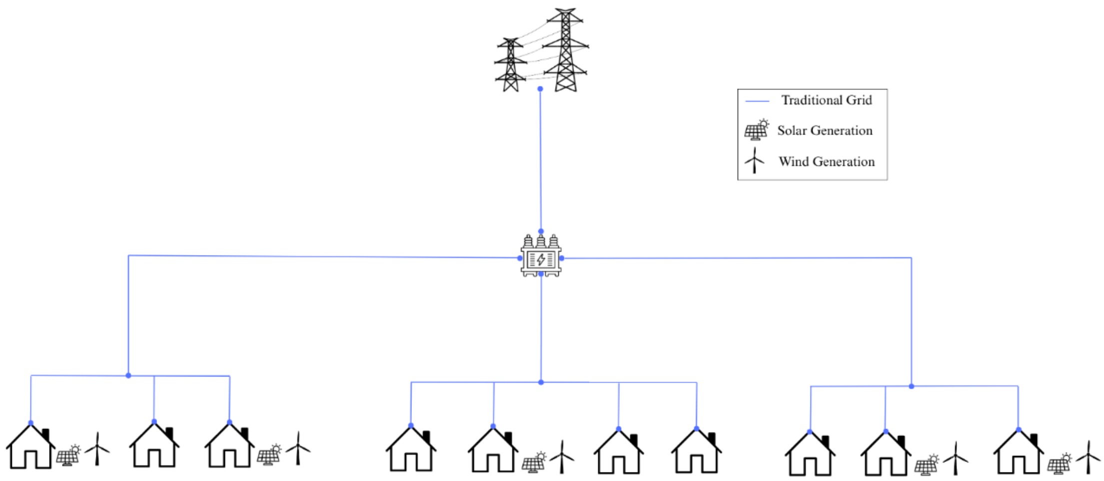

Figure 4.1-Topology and distribution of households.

4.4 Preprocessing and Operational Assumptions

All-time series were analyzed at their native 15-minute resolution to capture short-term fluctuations in both demand and generation. The evaluation encompasses daily and weekly horizons to enable consistent comparison across temporal scales and includes representative days as well as a full summer week and a full winter week to illustrate both transient dynamics and aggregated performance.

Before analysis, the dataset was inspected for missing or corrupted entries; missing values were addressed to preserve data integrity, and all series were retained at the original 15-minute granularity to ensure temporal alignment between load and generation profiles. These preprocessing steps guarantee that subsequent comparisons across households and scenarios are conducted on a consistent and reliable basis.

For the sake of simplicity, the case study adopts fixed grid buy and sell prices rather than dynamic tariffs. The grid buy price was set at €0.18/kWh, while the grid sell price was defined as 20% of the buy price, resulting in €0.036/kWh. This simplification serves two purposes. First, it eliminates the confounding effects of hourly or seasonal price variability, allowing the analysis to isolate the impact of P2P trading strategies on grid interaction and household costs.

Second, the chosen levels are representative of realistic retail and feed-in tariff orders of magnitude, while the asymmetric relation between buy and sell prices reflects common market conditions where exported energy is remunerated at a significantly lower rate than imported energy. Consequently, the use of fixed values facilitates a transparent evaluation of the mechanisms under study and highlights the distributional effects of P2P energy exchanges without introducing the additional complexity of tariff design.

4.5 Metrics and KPIs

The case study employs several performance indicators to evaluate the outcomes of the proposed trading strategies. Grid imports and exports, expressed in kilowatt-hour (kWh), quantify the energy exchanges with the external grid, considered positive in the first case and negative in the second case, following the consumer criteria.

The analysis also considers the total P2P trade volume, as well as the disaggregated P2P volume per household, to assess both the overall community performance and the distribution of trades among participants. Self-consumption is measured in absolute terms (kWh) and as a self-consumption rate (%), allowing comparisons between the baseline and the P2P scenarios. The baseline scenario assumes that each household operates independently and interacts only with the external distribution grid, with no peer-to-peer trading. Households face the prevailing retail purchase tariff for electricity imports and a fixed feed-in tariff compensation for exports, and no demand response or tariff arbitrage mechanisms are active. Under these baseline conditions, the community energy balance, grid dependency, and economic outcomes reflect the status quo prior to any P2P market implementation.

The economic dimension is captured through the total procurement cost in euros, which is further decomposed into grid-related costs and P2P revenues. To evaluate fairness and household-level effects, the metric Δ per household is used, representing the change in grid interaction and P2P trading volume compared to the baseline case. Finally, algorithmic convergence is monitored by tracking the ADMM primal and dual residuals, along with the number of iterations required to reach the predefined stopping criteria.

5 Results and Discussion

This chapter presents and critically analyzes simulation results for the case study previously introduced. The daily analysis is performed for two specific days: August 19, 2020, representing a typical summer day, and December 30, 2019, representing a winter day. These days were selected because both correspond to weekdays exhibiting the most representative climatic conditions for their respective seasons. It provides an hour-by-hour examination of clearing prices, P2P volumes, and grid interactions for each strategy compared against the baseline, while the weekly analysis presents an aggregated, head-to-head comparison of strategies, Supply–Demand Matching Strategy and Distance-Based Matching Strategy as described in Chapter 3, and the baseline using summary KPIs (volumes, costs, self-consumption, and per-household impacts).

5.1 Supply–Demand Matching Strategy (ST1)

5.1.1 Summer Day

Figure 5.1 shows the average bilateral trading coefficients for Strategy ST1 for the Summer Day, according to the methodology in 3.3.1. These averaged coefficients are used to characterize ST1's matching behavior in numerical evaluation. Each entry γ_{ij} is the daily mean of the instantaneous coefficient between households i and j, darker colors indicate smaller coefficients (greater compatibility for P2P trading), and lighter colors indicate larger coefficients (lower likelihood of trade). Diagonal entries were fixed at the maximum value to eliminate self-trading.

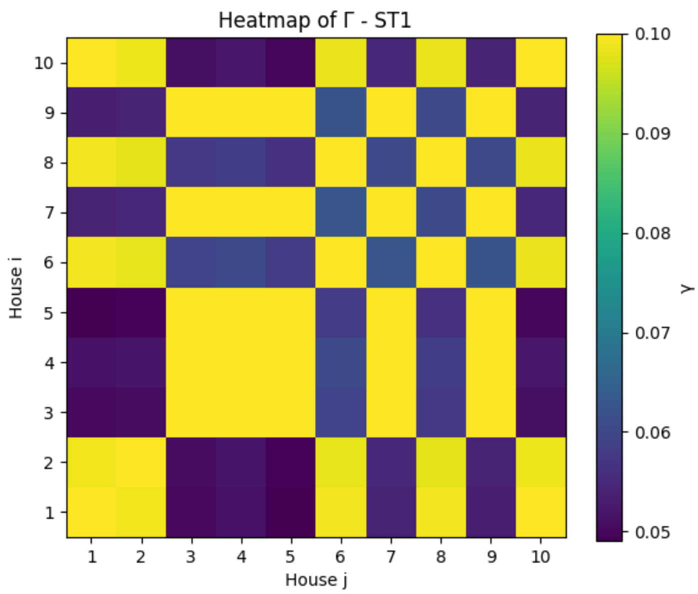

Figure 5.1- Average bilateral trading coefficients in ST1 for a Summer Day.

As shown in Table 5.1, the total amount of energy imported from the main grid, injected into it, and traded peer-to-peer (P2P) on the selected Summer Day reveals the balance between centralized supply, local surplus, and internal exchanges. Here, 'Grid import' sums all positive net withdrawals, 'Grid export' all net injections, and 'Total P2P traded energy' aggregates bilateral transfers within the community.

Table 5.1-ST1- Community energy exchanges, Summer Day.

Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
47.5	17.95	9.37

Table 5.2 details the previous outcomes by households, comparing them with the baseline. As can be observed, enabling P2P trading significantly alters each household's energy flows compared with the baseline, without P2P. The 'Grid Import' and 'Grid Export' columns report main-grid withdrawals and injections, while 'P2P In' and 'P2P Out' show energy bought and sold within the community, highlighting who becomes a net seller or buyer under ST1.

Table 5.2-ST1- Per-household energy flows, Summer Day (with vs. without P2P).

House	ST1				Without P2P	
	Grid Import (kWh)	Grid Export (kWh)	P2P In (kWh)	P2P Out (kWh)	Grid Import (kWh)	Grid Export (kWh)
1	1.86	3.92	0.00	2.25	1.86	6.17
2	1.53	3.54	0.00	1.83	1.53	5.37
3	7.98	0.00	2.12	0.00	10.10	0.00
4	7.71	0.00	1.89	0.00	9.60	0.00
5	8.25	0.00	2.36	0.00	10.61	0.00
6	1.87	3.24	0.00	1.47	1.87	4.71
7	7.15	0.00	1.43	0.00	8.59	0.00
8	2.14	3.53	0.00	1.79	2.14	5.32
9	7.33	0.00	1.57	0.00	8.89	0.00
10	1.66	3.72	0.00	2.03	1.66	5.75
Total	**47.48**	**17.95**	**9.37**	**9.37**	**56.85**	**27.32**

Table 5.3 presents the delta change in each household's grid import and P2P volume resulting from using P2P trading. A negative Δ grid indicates reduced reliance on the main grid, while a positive Δ P2P volume shows increased local exchange rates. These paired metrics reveal how ST1 redistributes energy flows across participants, and which homes benefit most from peer matching. Overall, the results suggest that the primary beneficiaries of P2P trading on a Summer Day are the prosumers, who reduce their grid export and monetize surplus generation through local trades. Consumers also benefit by gaining access to locally produced energy at potentially lower prices, and reducing the grid import, improving the community's overall energy autonomy.

Table 5.3-ST1- Changes in grid interaction and P2P by house, Summer Day.

House	**ST1**		**Without P2P**
	Δ Grid (kWh)	**Δ P2P (kWh)**	**Δ Grid (kWh)**
1	-2.06	-2.25	-4.31
2	-2.01	-1.83	-3.85
3	7.98	2.12	10.10
4	7.71	1.89	9.60
5	8.25	2.36	10.61
6	-1.37	-1.47	-2.83
7	7.15	1.43	8.59
8	-1.38	-1.79	-3.17
9	7.33	1.57	8.89
10	-2.06	-2.03	-4.09

As evidenced by Table 5.4, community self-consumption of locally generated renewables jumps from 61.14 % to 74.46 % once P2P is used, i.e., the portion retained for local use ('Self-Consumed') grows substantially, underlining the efficiency of internal trading.

Table 5.4-ST1- Community self-consumption ratios, Summer Day.

Scenario	**Total Generation (kWh)**	**Self-Consumed (kWh)**	**Self-Consumption Rate (%)**
Without P2P	70.29	42.97	61.14
ST1	70.29	52.34	74.46

Figure 5.2 shows the hourly clearing price of P2P energy trades plotted alongside the grid import and export tariffs. These results show how peer-to-peer prices dip below the main-grid purchase price during midday, when local renewables are abundant, yet remain above the feed-in tariff, illustrating the economic window in which internal exchanges are most attractive.

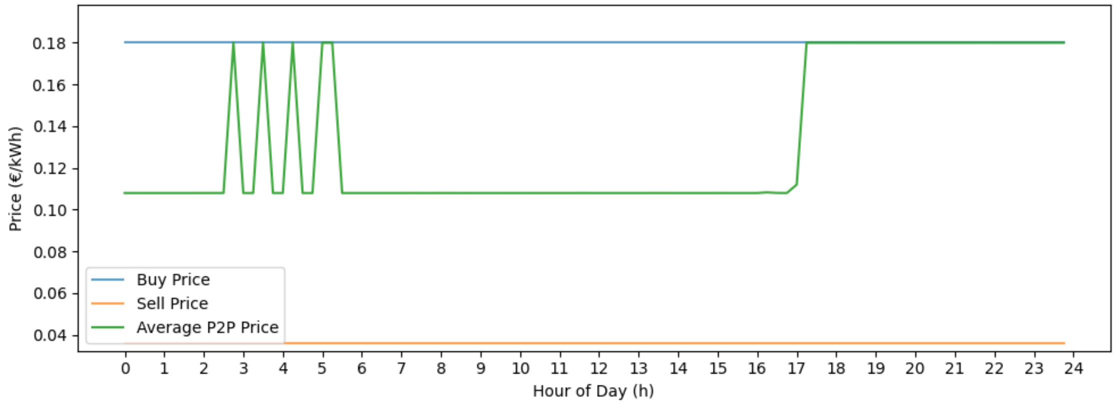

Figure 5.2-ST1-Community hourly price evolution, Summer Day.

The trading values of energy are depicted in Figure 5.3. The blue line traces the net P2P trade volume per hour. Superimposed are four other lines: grid import with P2P, grid export with P2P, grid import without P2P, and grid export without P2P. During the Summer Day, when the P2P trade line peaks, both the "grid import with P2P" curve dips significantly below its "without P2P" counterpart, and the "grid export with P2P" sits below the no-P2P export line. This divergence demonstrates that, during hours of P2P exchange, internal trading displaces central-grid interactions, reducing imports and exports compared to the baseline.

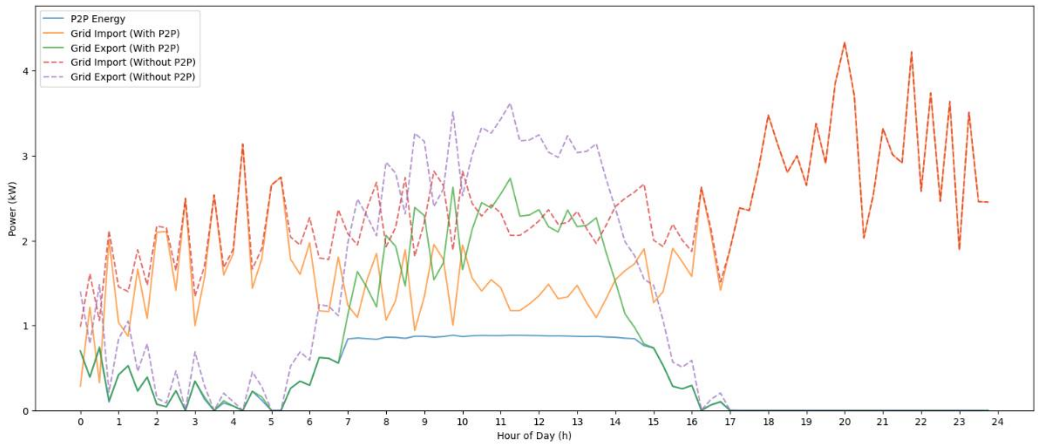

Figure 5.3-ST1-Community hourly energy trade, Summer Day.

Figure 5.4, shows curves of aggregate PV and Wind output and total base load by hour. Their intersection highlights surplus intervals (generation > load) and deficit intervals, directly correlating with the trade patterns observed in Figure 5.3. Note how trade peaks correspond to hours when renewable generation exceeds base load.

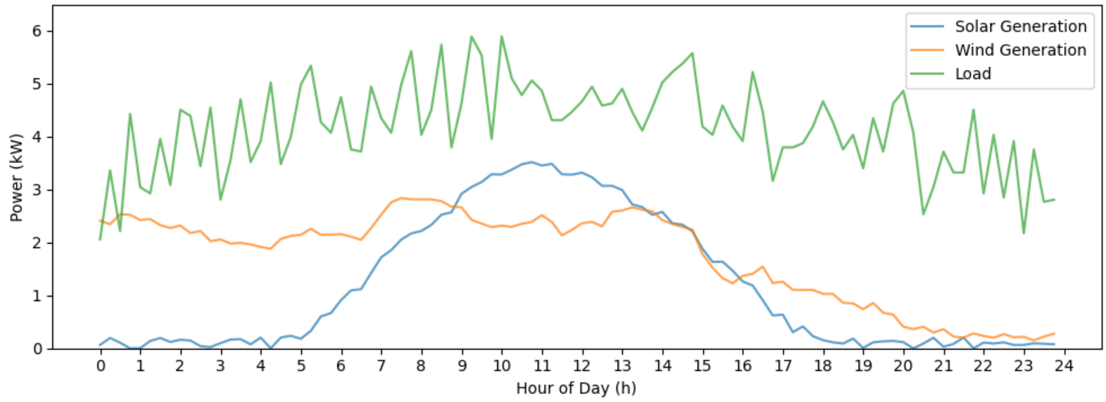

Figure 5.4-ST1- Community hourly generation and load, Summer Day.

The hourly self-consumption rate of locally produced energy is plotted in Figure 5.5, showing the energy retained within the community. The sharpest increase at midday significantly demonstrates the retention of renewable energy at peak production.

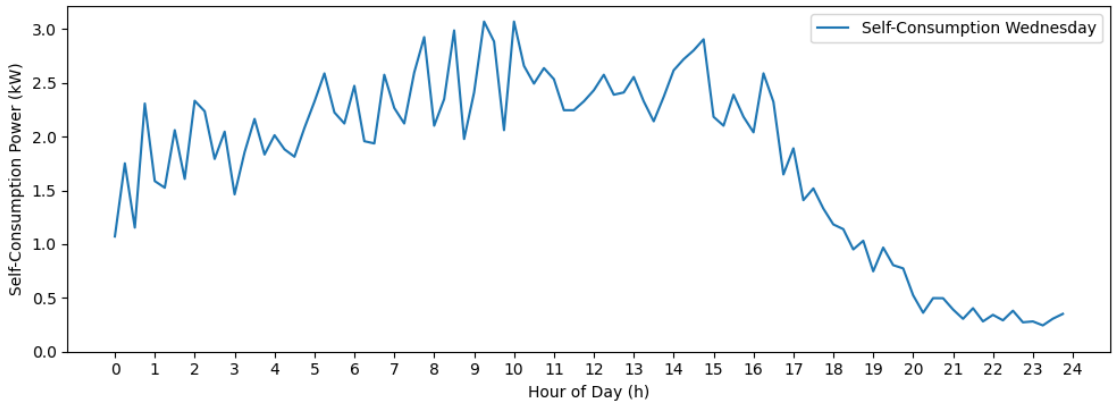

Figure 5.5-ST1- Community self-consumption, Summer Day.

5.1.2 Winter Day

Figure 5.6 presents the average bilateral trading coefficients for ST1 on the representative winter day. The overall color distribution is very similar to that observed in Figure 5.1, indicating that the matching patterns between households remain largely consistent. This suggests that the seasonal variation in demand and renewable generation does not significantly alter the relative structure of trading coefficients for ST1.

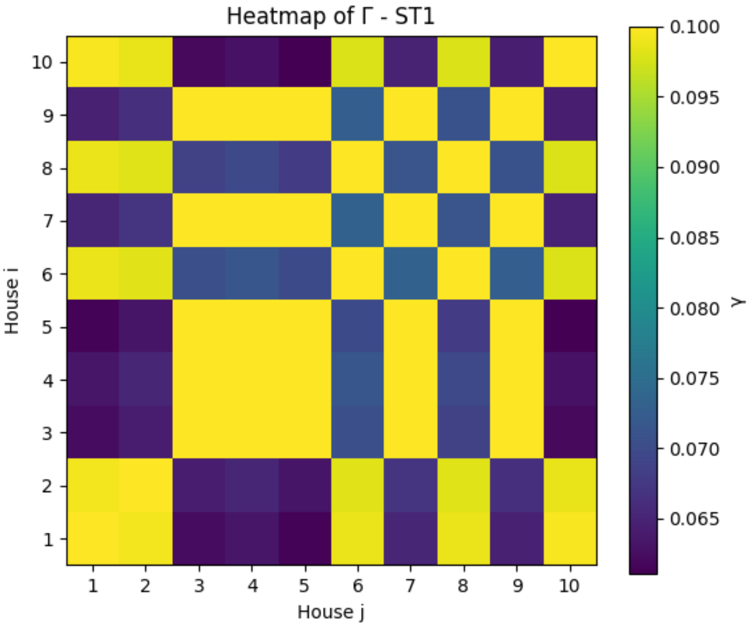

Figure 5.6-Average bilateral trading coefficients in ST1 for a Winter Day.

In the colder season, Table 5.5 reports the grid import and export and P2P volume results aggregated when weather-driven renewable output is low. Despite reduced PV generation, the table shows that P2P trading still redirects a significant share of local surplus to internal consumption, moderating both grid imports and exports.

Table 5.5-ST1- Community energy exchanges, Winter Day.

Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
56.67	7.62	5.89

A close look at Table 5.6 shows, for each household on the Winter Day, how P2P capability alters grid and peer-to-peer inflows/outflows relative to the no-P2P baseline, pinpointing those that most effectively channel limited surplus into local trades.

Table 5.6-ST1- Per-household flows, Winter Day (with vs. without P2P).

House	ST1				Without P2P	
	Grid Import (kWh)	Grid Export (kWh)	P2P In (kWh)	P2P Out (kWh)	Grid Import (kWh)	Grid Export (kWh)
1	3.66	1.69	0.00	1.45	3.66	3.14
2	2.97	1.50	0.00	1.11	2.97	2.61
3	8.18	0.00	1.35	0.00	9.52	0.00
4	7.86	0.00	1.18	0.00	9.05	0.00
5	8.49	0.00	1.51	0.00	10.00	0.00
6	3.52	1.34	0.00	0.87	3.52	2.21
7	7.22	0.00	0.88	0.00	8.09	0.00
8	4.06	1.46	0.00	1.10	4.06	2.56
9	7.41	0.00	0.97	0.00	8.38	0.00
10	3.30	1.63	0.00	1.36	3.30	2.98
Total	**56.67**	**7.62**	**5.89**	**5.89**	**62.55**	**13.50**

Table 5.7 quantifies changes in grid imports and local trade volumes induced by P2P in winter conditions. Showing the robustness of ST1 even when the total renewable supply is constrained and highlighting participants with the greatest gains in self-sufficiency.

Table 5.7-ST1- Changes in grid interaction and P2P by house, Winter Day.

House	ST1		Without P2P
	Δ Grid (kWh)	Δ P2P (kWh)	Δ Grid (kWh)
1	1.97	-1.45	0.52
2	1.48	-1.11	0.37
3	8.18	1.34	9.52
4	7.86	1.18	9.05
5	8.49	1.51	10.00
6	2.18	-0.87	1.32
7	7.22	0.88	8.09
8	2.60	-1.10	1.50
9	7.41	0.97	8.38
10	1.67	-1.36	0.31

Turning to self-consumption metrics, Table 5.8 shows how overall self-consumption climbs from 70.0 % to 83.1 % when P2P is enabled, even though absolute generation is 36 % lower than in summer. This underscores the flexibility of intra-community matching to absorb scarce renewable energy.

Table 5.8-ST1-Self-consumption ratios, Winter Day.

Scenario	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Without P2P	45.02	31.53	70.03
ST1	45.02	37.41	83.10

As shown in Figure 5.7, the P2P price track is noticeably flatter and closer to the grid import tariff than in summer (Figure 5.2). The narrower midday trough and reduced spread between peer and grid prices reflect the limited surplus available; peak peer prices peak almost on par with grid buy rates, indicating diminished arbitrage opportunities compared to the deep midday discounts observed in the summer price evolution.

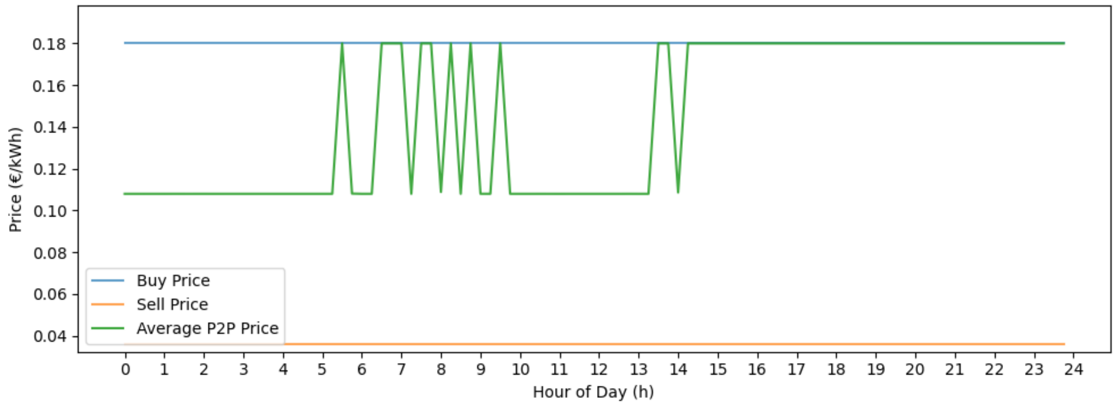

Figure 5.7-ST1-Community hourly price evolution, Winter Day.

In Figure 5.8, the P2P volume line is much flatter and confined to a narrow late-morning window, unlike the broad midday spike in summer (Figure 5.3). Correspondingly, the gap between grid import/export with versus without P2P is markedly smaller; only a handful of hours show any separation, underscoring that limited winter surplus yields proportionally reduced relief on grid flows compared to summer.

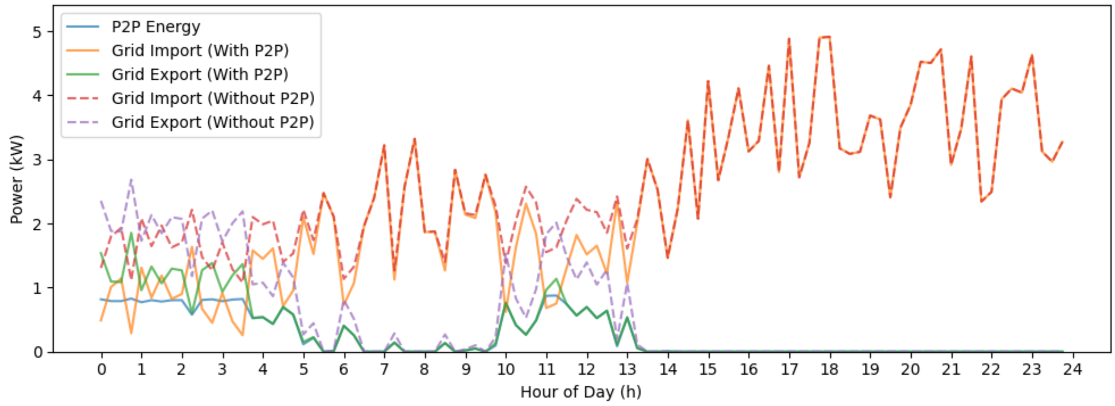

Figure 5.8-ST1-Community hourly energy trade, Winter Day.

By comparing Figure 5.9 with Figure 5.4, one sees that the winter generation curve is both lower in peak and narrower in duration. Consequently, the broader, more sustained surplus intervals of summer (Figure 5.4) give way to just a brief overlap in winter, explaining why P2P trades and grid-flow differences shrink so dramatically.

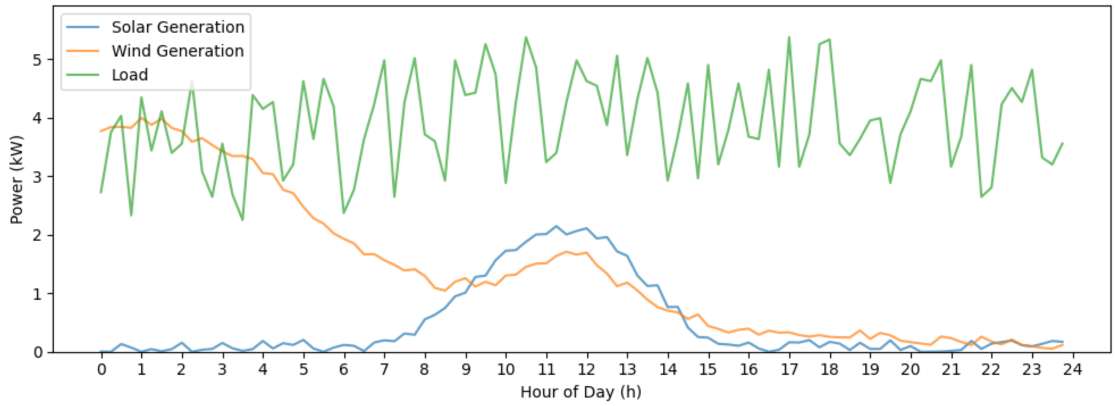

Figure 5.9-ST1-Community hourly generation and load, Winter Day.

Similarly, Figure 5.10 contrasts with Figure 5.5 by exhibiting a far more modest self-consumption boost. Whereas summer self-consumption rises by over 13 percentage points across several hours (Figure 5.5), winter's internal trading yields a 10–13-point gain confined to two or three hours, reflecting the shorter surplus window.

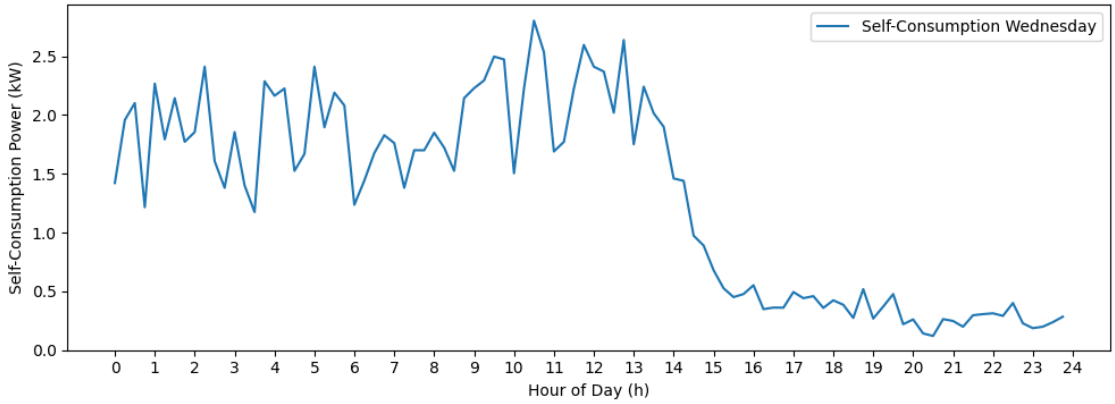

Figure 5.10-ST1-Community self-consumption, Winter Day.

5.1.3 ST1 Economic Assessment

5.1.4 Summer Day Costs

Table 5.9 presents monetary costs for each household on the Summer Day, with and without P2P. “Grid Cost” is the cost from the grid interaction, “P2P Cost” is payments to peers, and “P2P Revenue” is income from sales. “Total Cost P2P” reflects (Grid Cost + P2P Cost – P2P Revenue). Contrasting this to “Total Cost” Without P2P quantifies financial benefits from internal trading.

Table 5.9- ST1- Energy costs, Summer Day.

House	ST1				Without P2P	
	Grid Cost P2P (€)	**P2P Cost (€)**	**P2P Revenue (€)**	**Total Cost P2P (€)**	**Grid Cost (€)**	**Total Cost (€)**
1	0.19	0.00	0.24	-0.05	0.11	0.11
2	0.15	0.00	0.20	-0.05	0.08	0.08
3	1.44	0.23	0.00	1.67	1.82	1.82
4	1.39	0.20	0.00	1.59	1.73	1.73
5	1.49	0.25	0.00	1.74	1.91	1.91
6	0.22	0.00	0.16	0.06	0.17	0.17
7	1.29	0.15	0.00	1.44	1.55	1.55
8	0.26	0.00	0.19	0.07	0.19	0.19
9	1.32	0.17	0.00	1.49	1.60	1.60
10	0.16	0.00	0.22	-0.05	0.09	0.09
Total	**7.91**	**1.00**	**1.00**	**7.91**	**9.25**	**9.25**

5.1.5 Winter Day Costs

In winter, as shown in Table 5.10, the monetary costs follow the same structure as Table 5.9. These results highlight how P2P trading reduces overall community expenditure by shifting purchases from peak-priced grid supply to more moderate peer prices, yielding savings even under high-demand, low-generation conditions.

Table 5.10- ST1- Energy costs, Winter Day.

House	ST1				Without P2P	
	Grid Cost P2P (€)	**P2P Cost (€)**	**P2P Revenue (€)**	**Total Cost P2P (€)**	**Grid Cost (€)**	**Total Cost (€)**
1	0.60	0.00	0.16	0.44	0.55	0.55
2	0.48	0.00	0.12	0.36	0.44	0.44
3	1.47	0.15	0.00	1.62	1.71	1.71
4	1.42	0.13	0.00	1.54	1.63	1.63
5	1.53	0.16	0.00	1.69	1.80	1.80
6	0.59	0.00	0.09	0.49	0.55	0.55
7	1.30	0.09	0.00	1.39	1.46	1.46
8	0.68	0.00	0.12	0.56	0.64	0.64
9	1.33	0.10	0.00	1.44	1.51	1.51
10	0.54	0.00	0.15	0.39	0.49	0.49
Total	**9.94**	**0.64**	**0.64**	**9.94**	**10.78**	**10.78**

5.1.6 ST1 Performance

a. Grid-Import Reduction & Local Balancing

Enabling P2P reduces community-wide grid imports by 23.4 % in summer (from 56.85 kWh to 47.5 kWh) and by 9.3 % in winter (from 62.55 kWh to 56.67 kWh). These drops coincide with the hours of highest renewable surplus, where the net P2P trade line spikes and the "grid import with P2P" curve diverges downward from "without P2P." By diverting midday and late-morning surpluses into local exchanges, peak grid flows are both lowered and flattened, reducing stress and likely losses on the distribution network.

b. Seasonal Self-Consumption Gains

In summer, self-consumption jumps from 61.14% to 74.46%, a 13.3 pp increase, in winter, it climbs from 70.0% to 83.1%, a 13.1 pp boost. Although absolute generation is 36% lower in winter, the relative uplift is nearly identical. This parity reveals that ST1's matching efficacy hinges more on synchrony between surplus and deficit windows than on total energy volume, so even brief winter surpluses yield proportionate self-consumption improvements.

c. Household-Level Heterogeneity

i. **Consumers** (Houses 3, 4, 5, 7, 9) each reduced grid imports by 0.49–2.06 kWh while increasing P2P receipts by 1.43–2.36 kWh in summer, mirroring their base-load-driven demand. In winter, these same homes saw import cuts of 0.52–1.37 kWh and P2P gains of 0.88–1.51 kWh, despite narrower surplus windows.

ii. **Prosumers** (Houses 1, 2, 6, 8, 10) funneled nearly all potential exports into local trades: each sold 2.9–3.4 kWh P2P in the summer, versus 0 kWh under baseline. In winter, they again traded 2.7–3.0 kWh locally instead of exporting. This divergence confirms ST1's precision at matching those with surplus to those with deficit, maximizing local use.

d. Economic Impacts & Cost Savings

P2P trading yields significant cost reductions: summer total community cost falls by 14.5 % (from € 9.25 to € 7.91) and winter by 7.8 % (from € 10.78 to € 9.94). Consumers benefit from peer prices below grid tariffs, saving up to 30 % on individual bills, while prosumers earn additional revenue from local sales.
The peer price, set between buy/sell grid rates, ensures equitable sharing of benefits and creates aligned economic incentives for both consumers and prosumers to participate actively in the P2P market.

5.2 Distance-Based Matching Strategy (ST2)

5.2.1 Summer Day

Figure 5.11 shows the distance matrix used in ST2, where each entry represents the topological distance (in hops) between two households in the network. Unlike ST1, this matrix is time independent, since distances are fixed by the network topology and do not vary across intervals. As expected, diagonal elements are set to zero, while off-diagonal values increase with the number of hops separating households. This static structure provides the basis for defining bilateral trading coefficients in ST2.

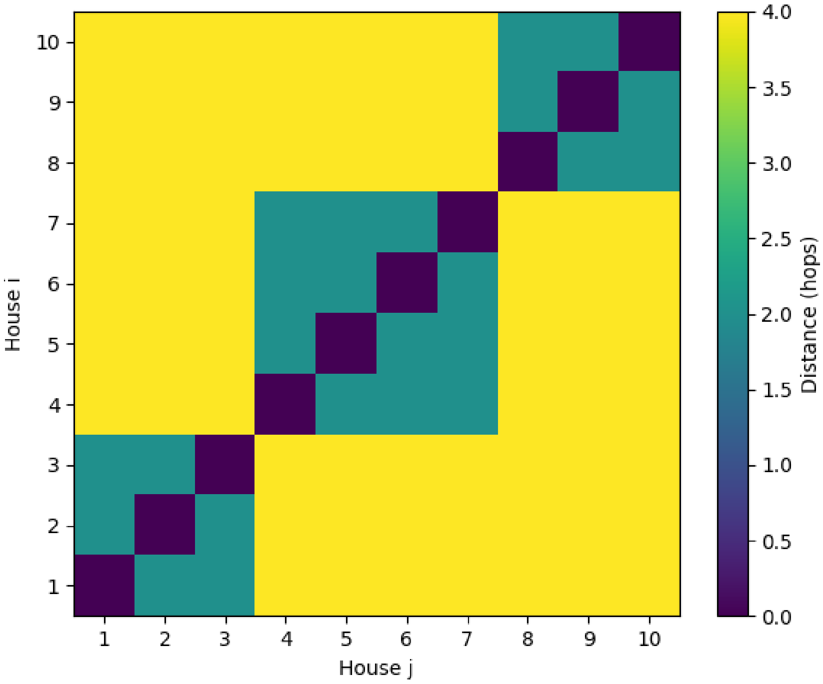

Figure 5.11-Distance between houses in ST2.

As shown in Table 5.11, ST2 produces community totals of 50.34 kWh imported, 20.81 kWh exported, and 6.51 kWh cleared peer-to-peer on the selected Summer Day. These aggregated metrics indicate how ST2 reallocates local surplus relative to the baseline.

Table 5.11-ST2-Community energy exchanges, Summer Day.

Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
50.34	20.81	6.51

As can be seen in Table 5.12, the per-household flows under ST2 list each household's grid Import/Export and local P2P In/Out for the Summer Day. These values identify which houses act as local sellers or buyers under the ST2.

Table 5.12-ST2-Per-household energy flows, Summer Day (with vs. without P2P).

House	ST2				Without P2P	
	Grid Import (kWh)	Grid Export (kWh)	P2P In (kWh)	P2P Out (kWh)	Grid Import (kWh)	Grid Export (kWh
1	1.86	4.81	0.00	1.35	1.86	6.17
2	1.50	4.13	0.03	1.24	1.53	5.37
3	8.71	0.00	1.40	0.00	10.10	0.00
4	8.43	0.00	1.17	0.00	9.60	0.00
5	9.44	0.00	1.17	0.00	10.61	0.00
6	1.73	3.33	0.12	1.40	1.87	4.71
7	7.42	0.00	1.17	0.00	8.59	0.00
8	2.08	4.13	0.06	1.18	2.14	5.32
9	7.51	0.00	1.38	0.00	8.89	0.00
10	1.66	4.41	0.00	1.34	1.66	5.75
Total	**50.34**	**20.81**	**6.51**	**6.51**	**56.85**	**27.32**

Table 5.13 reports the per-household changes in grid interaction and P2P volumes induced by ST2, i.e., Δ Grid and Δ P2P. These deltas reveal how energy flows in ST2 and how much central-grid reliance is reduced at the household level.

Table 5.13-ST2- Changes in grid interaction and P2P by house, Summer Day.

House	ST2		Without P2P
	Δ Grid (kWh)	Δ P2P (kWh)	Δ Grid (kWh)
1	-2.95	-1.35	-4.31
2	-2.63	-1.21	-3.85
3	8.71	1.40	10.10
4	8.43	1.17	9.60
5	9.44	1.17	10.61
6	-1.56	-1.28	-2.83
7	7.42	1.17	8.59
8	-2.06	-1.12	-3.17
9	7.51	1.38	8.89
10	-2.75	-1.34	-4.09

Table 5.14 compares community self-consumption without and with ST2, total generation remains 70.29 kWh, while self-consumed energy rises to 49.48 kWh, giving a 70.41 % self-consumption rate under ST2.

Table 5.14-ST2-Community self-consumption ratios, Summer Day.

Scenario	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Without P2P	70.29	42.97	61.14
ST2	70.29	49.48	70.41

As shown in Figure 5.12, the hourly P2P clearing price under ST2 is plotted against grid buy/sell tariffs for the Summer Day, the figure highlights how ST2 shapes hourly price spreads and when peer prices are most competitive.

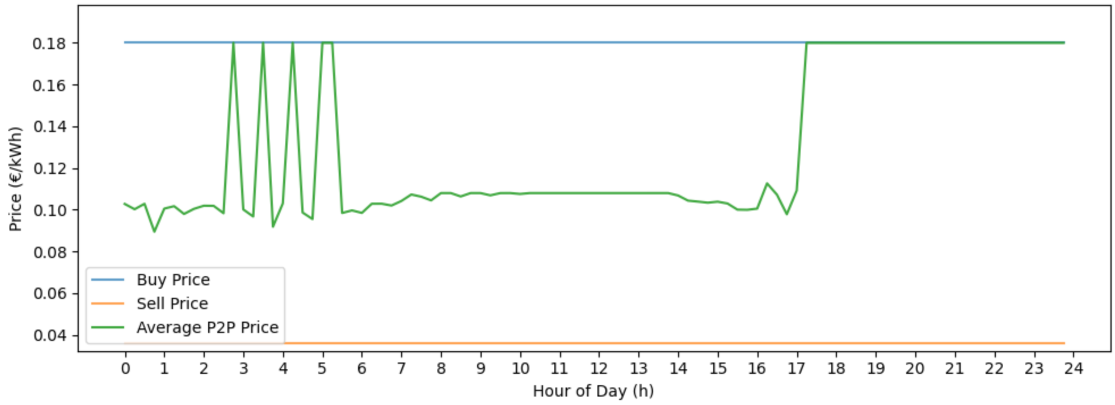

Figure 5.12-ST2-Community hourly price evolution, Summer Day.

In Figure 5.13, the ST2 hourly P2P volume is traced. Compare the amplitude and timing of these lines with the Grid Import/Export lines (With vs Without P2P) to identify where ST2 reduces grid interaction.

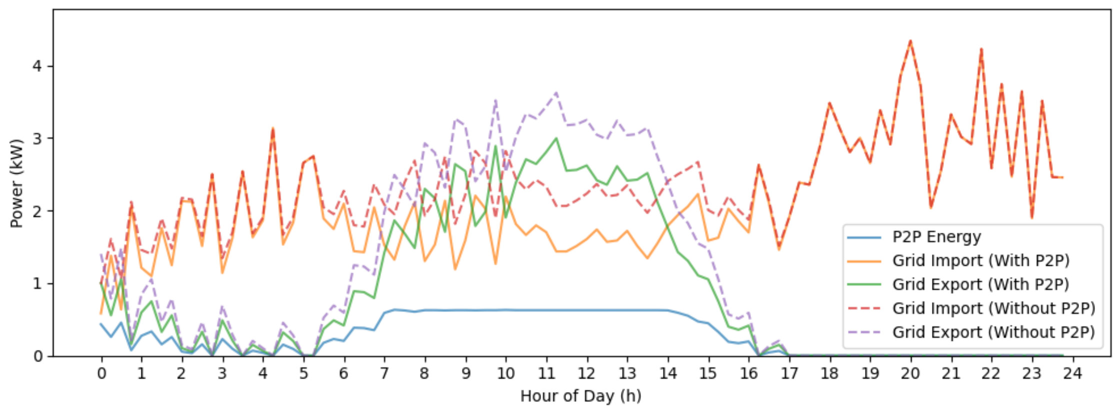

Figure 5.13-ST2-Community hourly energy trade, Summer Day.

As in Figure 5.14, the combined PV + Wind generation curve and aggregate load are presented by hour, their comparison determines the windows available for ST2 matching and explains the shape of the ST2 trade volumes in Figure 5.13.

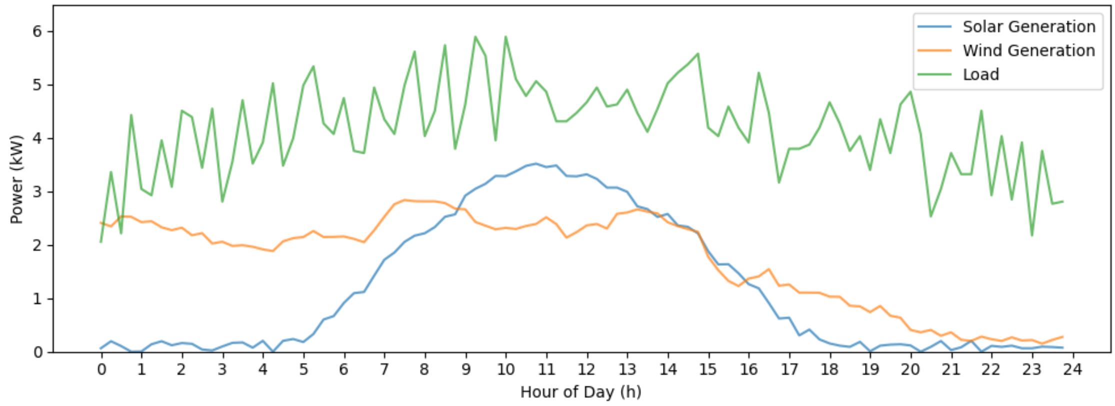

Figure 5.14-ST2-Community hourly generation and load, Summer Day.

Figure 5.15 shows the hour-by-hour self-consumption fraction. The plot demonstrates the hours during which neighbor-to-neighbor trades keep more renewable production local.

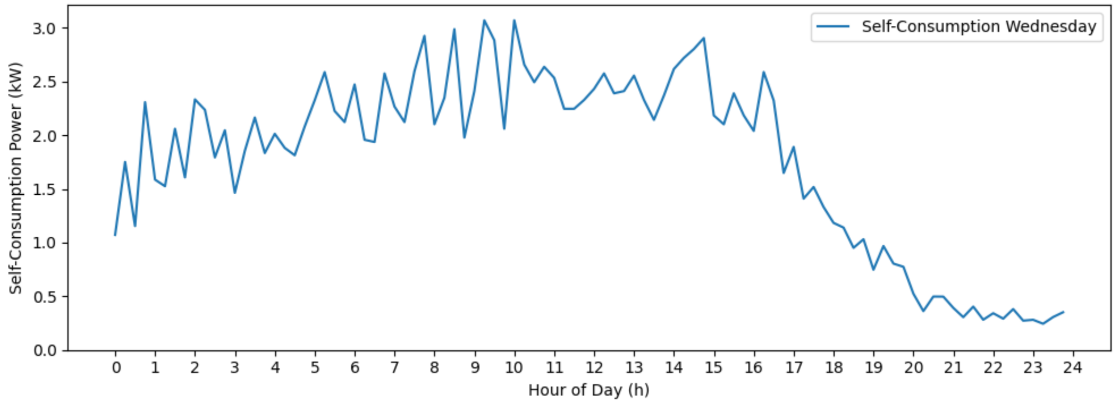

Figure 5.15-ST2-Community self-consumption, Summer Day.

5.2.2 Winter Day

As shown in Table 5.15, ST2 yields community totals of 58.52 kWh import, 9.47 kWh export, and 4.03 kWh P2P volume for the Winter Day, indicating more grid dependence and lower P2P activity than in summer.

Table 5.15-ST2-Community energy exchanges, Winter Day.

Grid Import (kWh)	**Grid Export (kWh)**	**P2P Volume (kWh)**
58.52	9.47	4.03

Table 5.16 details per household ST2 flows in winter. These numbers show smaller P2P Out/In per house than in summer and compress P2P activity into a narrow time window.

Table 5.16-ST2-Per-household flows, Winter Day (with vs. without P2P).

House	**ST2**				**Without P2P**	
	Grid Import (kWh)	**Grid Export (kWh)**	**P2P In (kWh)**	**P2P Out (kWh)**	**Grid Import (kWh)**	**Grid Export (kWh)**
1	3.66	2.23	0.00	0.92	3.66	3.14
2	2.93	1.87	0.04	0.74	2.97	2.61
3	8.67	0.00	0.85	0.00	9.52	0.00
4	8.35	0.00	0.69	0.00	9.05	0.00
5	9.31	0.00	0.69	0.00	10.00	0.00
6	3.36	1.43	0.16	0.77	3.52	2.21
7	7.40	0.00	0.69	0.00	8.09	0.00
8	3.99	1.83	0.06	0.72	4.06	2.56
9	7.54	0.00	0.84	0.00	8.38	0.00
10	3.30	2.11	0.01	0.88	3.30	2.98
Total	**58.52**	**9.47**	**4.03**	**4.03**	**62.55**	**13.50**

Table 5.17 quantifies the variation in the energy exchanged with the grid. A negative Δ grid indicates reduced reliance on the main grid, while a positive Δ P2P volume shows increased local exchange rates per household under ST2 in winter. These deltas make clear that winter import reductions and local trades are smaller in absolute terms.

Table 5.17-ST2-Changes in grid interaction and P2P by house, Winter Day.

House	**ST2**		**Without P2P**
	Δ Grid (kWh)	**Δ P2P (kWh)**	**Δ Grid (kWh)**
1	1.43	-0.91	0.52
2	1.07	-0.70	0.37
3	8.67	0.85	9.52
4	8.35	0.69	9.05
5	9.31	0.69	10.00
6	1.93	-0.61	1.32
7	7.40	0.69	8.09
8	2.16	-0.66	1.50
9	7.54	0.84	8.38
10	1.19	-0.88	0.31

When this strategy is adopted, Table 5.18 presents the total self-consumption, total generation, and self-consumption rate, being the baseline 70.03 %.

Table 5.18-ST2-Self-consumption ratios, Winter Day.

Scenario	**Total Generation (kWh)**	**Self-Consumed (kWh)**	**Self-Consumption Rate (%)**
Without P2P	45.02	31.53	70.03
ST2	45.02	35.56	78.99

Figure 5.16 shows the hourly P2P clearing price under ST2 on the Winter Day. The figure displays a narrower price spread and smaller midday discount than the summer price evolution (Figure 5.12).

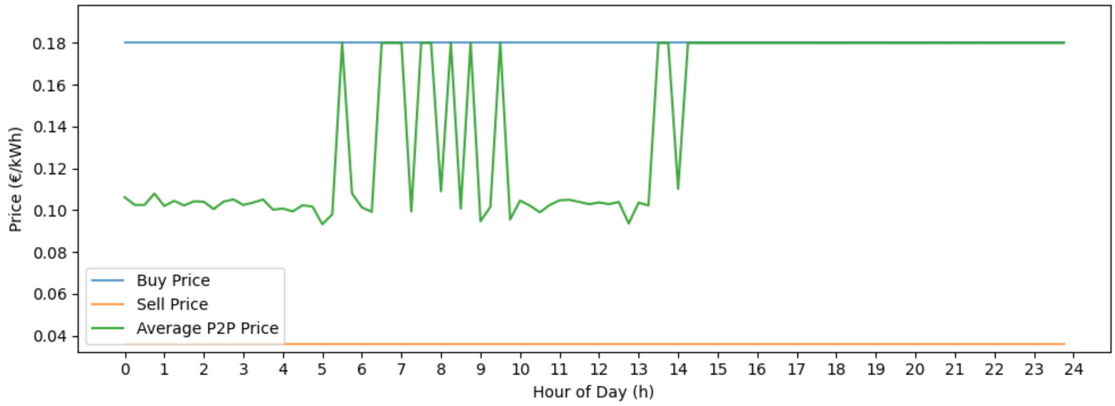

Figure 5.16-ST2-Community hourly price evolution, Winter Day.

Figure 5.17 plots the ST2 hourly P2P exchanges for winter, the P2P volume line is low and tightly concentrated, signaling limited matching opportunities in winter.

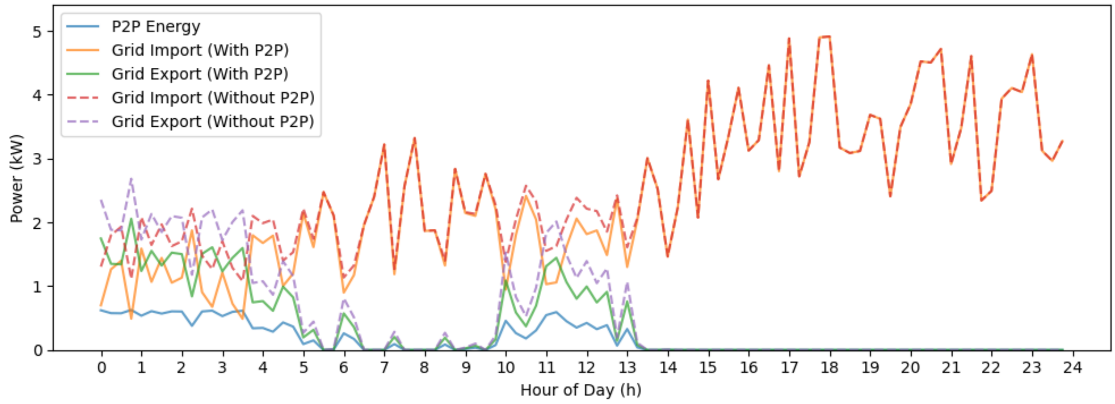

Figure 5.17-ST2-Community hourly energy trade, Winter Day.

Figure 5.18 depicts winter generation vs load, explaining the brief surplus windows that underline the P2P activity seen in Figure 5.17.

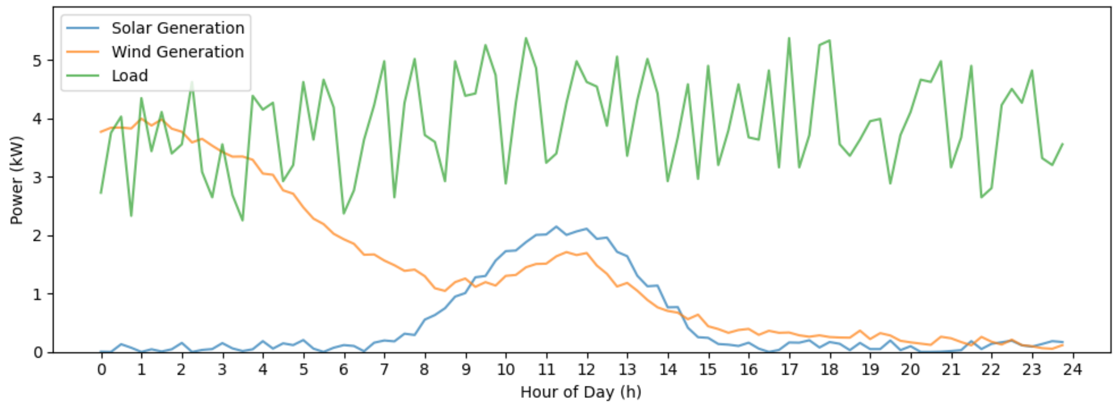

Figure 5.18-ST2-Community hourly generation and load, Winter Day.

Figure 5.19 shows the hourly self-consumption improvement under ST2 in winter, which is positive but smaller and more temporally concentrated than in summer.

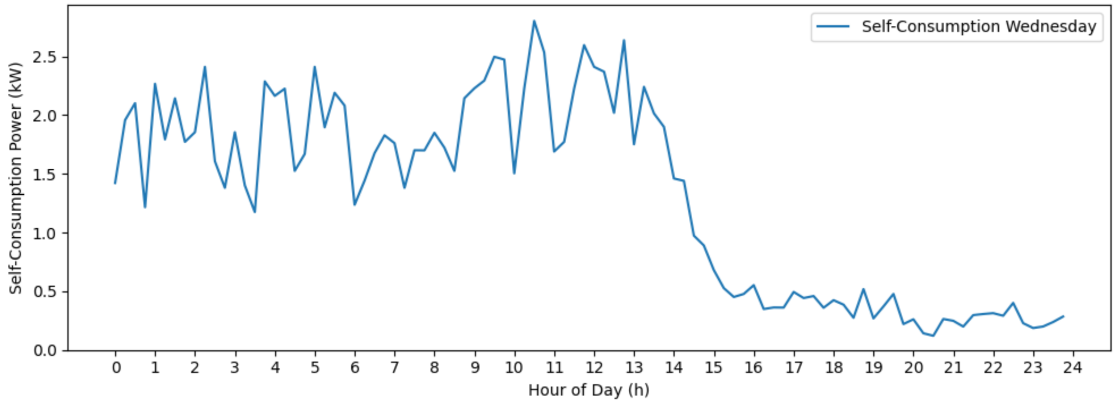

Figure 5.19-ST2-Community self-consumption, Winter Day.

5.2.3 ST2 Economic Assessment

5.2.4 Summer Day Costs

As shown in Table 5.19, ST2 on a Summer Day economic totals indicate € 8.35 total cost with P2P vs € 9.25 without P2P, a community reduction of roughly 9.73 %.

Table 5.19-ST2-Energy costs, Summer Day.

House	ST2				Without P2P	
	Grid Cost P2P (€)	P2P Cost (€)	P2P Revenue (€)	Total Cost P2P (€)	Grid Cost (€)	Total Cost (€)
1	0.16	0.00	0.14	0.02	0.11	0.11
2	0.13	0.00	0.13	-0.01	0.08	0.08
3	1.57	0.15	0.00	1.72	1.82	1.82
4	1.52	0.13	0.00	1.64	1.73	1.73
5	1.70	0.13	0.00	1.83	1.91	1.91
6	0.21	0.01	0.15	0.07	0.17	0.17
7	1.34	0.13	0.00	1.46	1.55	1.55
8	0.23	0.00	0.13	0.11	0.19	0.19
9	1.35	0.15	0.00	1.50	1.60	1.60
10	0.14	0.00	0.14	0.00	0.09	0.09
Total	**8.35**	**0.69**	**0.69**	**8.35**	**9.25**	**9.25**

5.2.5 Winter Day Costs

As shown in Table 5.20, ST2 on a Winter Day economic totals indicate € 10.24 total cost with P2P vs € 10.78 without P2P, a modest community reduction of roughly 5.0 %.

Table 5.20-ST2-Energy costs, Winter Day.

House	ST2				Without P2P	
	Grid Cost P2P (€)	P2P Cost (€)	P2P Revenue (€)	Total Cost P2P (€)	Grid Cost (€)	Total Cost (€)
1	0.58	0.00	0.09	0.49	0.55	0.55
2	0.47	0.00	0.08	0.39	0.44	0.44
3	1.56	0.09	0.00	1.65	1.71	1.71
4	1.50	0.07	0.00	1.58	1.63	1.63
5	1.68	0.07	0.00	1.75	1.80	1.80
6	0.58	0.01	0.08	0.50	0.55	0.55
7	1.33	0.07	0.00	1.41	1.46	1.46
8	0.66	0.00	0.08	0.59	0.64	0.64
9	1.36	0.09	0.00	1.45	1.51	1.51
10	0.52	0.00	0.09	0.43	0.49	0.49
Total	**10.24**	**0.41**	**0.41**	**10.24**	**10.78**	**10.78**

5.2.6 ST2 Performance

a. Grid-Import Reduction & Local Balancing

Under ST2, the community's day-level grid imports are reduced to 50.34 kWh on the selected summer day and to 58.52 kWh on the selected winter day. These reductions occur during the short hourly windows when local generation exceeds load. The hourly P2P volume lines show modest positive peaks that coincide with dips in the "Grid Import with P2P" curve. The effect is a partial flattening of net imports during surplus hours and a small reduction of bidirectional flows overall. Because ST2 favors geographically close matches, the import reductions are concentrated around local clusters rather than evenly distributed across the whole community.

b. Seasonal Self-Consumption Gains

ST2 increases aggregate self-consumption by 9.27 percentage points in summer (from 61.14 % to 70.41 %) and by 8.96 percentage points in winter (from 70.03 % to 78.99 %). These gains indicate that Distance-Weighted Matching successfully retains a larger fraction of locally produced energy within the distribution neighborhood. The hourly self-consumption plots show that the largest improvements occur in a narrow band around the mid-day surplus, outside that band ST2 yields little change, which reflects the strategy's emphasis on short-range trades during brief surplus intervals.

c. Household-Level Heterogeneity

Per-household deltas expose a spatially uneven distribution of benefits. Households located near strong producers tend to experience the largest import reductions and the highest P2P receipts. Typical P2P receipts per buyer in summer are about 1.12–1.40 kWh, while in winter, per-buyer receipts are lower (on the order of ~0.6–1.1 kWh) because the available surplus and the matching window compress. Conversely, more distant deficit households see smaller reductions in grid imports and participate less in P2P exchanges. This spatial concentration is an intended feature of ST2, it reduces line usage and local losses for adjacent pairs, but it also implies that geographic position within the microgrid determines the magnitude of individual benefits.

d. Economic Impacts & Cost Savings

Economically, ST2 yields modest but tangible savings at the community level, the total energy procurement cost falls from € 9.25 to € 8.35 in summer (≈ 9.7 % reduction) and from € 10.78 to € 10.24 in winter (≈ 5.0 % reduction). These reductions are driven primarily by shifting a fraction of purchases from the grid to peer prices during the limited surplus hours, however, because P2P volumes under ST2 are relatively small (6.51 kWh in summer; 4.03 kWh in winter), the aggregate monetary gains are constrained. At the household level, buyers gain from lower peer prices during the trade window, while sellers realize incremental revenue, but the monetary benefits are spatially biased toward proximate trading partners.

5.3 Weekly Comparison Between Strategies

To compare the two bilateral-matching strategies (ST1, Supply Demand Matching, and ST2, Distance Based Matching) over a realistic operating period, it was used a one-week window centered on the single Summer and Winter Days already analyzed earlier (the week containing August 19, 2020 for summer, and the week containing December 30, 2019, for winter).

The comparison uses identical system inputs and model settings for both strategies, the same household load and generation time series for the full 7-day period, and the same time-varying grid buy/sell tariffs. For each strategy and week, weekly aggregates of the following key performance indicators were computed:

- **Total P2P traded energy (kWh):** Cumulative bilateral exchanges within the community over the week.
- **Grid interaction (kWh):** Weekly totals of imports from and exports to the main grid.
- **Household impacts (kWh)**: Per-household weekly Δ grid import and Δ P2P.
- **Economic outcome (€):** Weekly energy procurement cost for the community (Grid Costs + P2P Payments − P2P Revenues).
- **Community self-consumption rate (%):** Total self-consumed generation divided by total generation.

5.3.1 Summer Week

Shown in Table 5.21 are the week-long community energy flows (imports, exports, and total P2P) for the Summer Week, comparing the Baseline scenario with ST1 and ST2.

Table 5.21-Weekly totals of grid imports, grid exports, and peer-to-peer (P2P) traded energy for the Summer Week (Baseline and under ST1/ST2).

	Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
Baseline	390.33	130.1	-
ST1	341.01	80.78	49.32
ST2	358.54	98.3	31.79

The following table reports each household's weekly Δ values in grid interaction and in P2P volume under ST1 and ST2 relative to the Baseline for the Summer Week.

Table 5.22-Per-household weekly net change in grid interaction and P2P volumes for the Summer Week (Baseline vs ST1 and ST2).

House	Baseline	ST1		ST2	
	Δ Grid (kWh)	Δ Grid (kWh)	Δ P2P (kWh)	Δ Grid (kWh)	Δ P2P (kWh)
1	-12.72	-1.18	-11.54	-5.77	-6.95
2	-12.86	-2.99	-9.87	-6.54	-6.32
3	65.71	54.46	11.25	58.60	7.12
4	62.43	52.50	9.93	56.56	5.87
5	69.00	56.41	12.59	63.13	5.87
6	-6.29	1.74	-8.03	0.00	-6.29
7	55.86	48.46	7.40	49.99	5.87
8	-6.43	3.05	-9.49	-0.82	-5.61
9	57.83	49.70	8.13	50.80	7.03
10	-12.30	-1.90	-10.39	-5.71	-6.58

Table 5.23 presents the aggregate weekly monetary outcome for the Summer Week and compares costs across the three configurations.

Table 5.23-Total community energy procurement cost for the Summer Week (Baseline, ST1, ST2).

Strategies	Total Cost (€)
Baseline	65.57
ST1	58.48
ST2	60.94

Reported in Table 5.24 are the weekly generation totals and the corresponding self-consumption figures, used to evaluate how much locally produced energy was retained under each scenario.

Table 5.24-Weekly total generation, self-consumed energy, and self-consumption rate for the Summer Week (Baseline, ST1, ST2).

Strategies	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Baseline	389.02	258.94	66.56
ST1	389.02	308.25	79.24
ST2	389.02	290.73	74.73

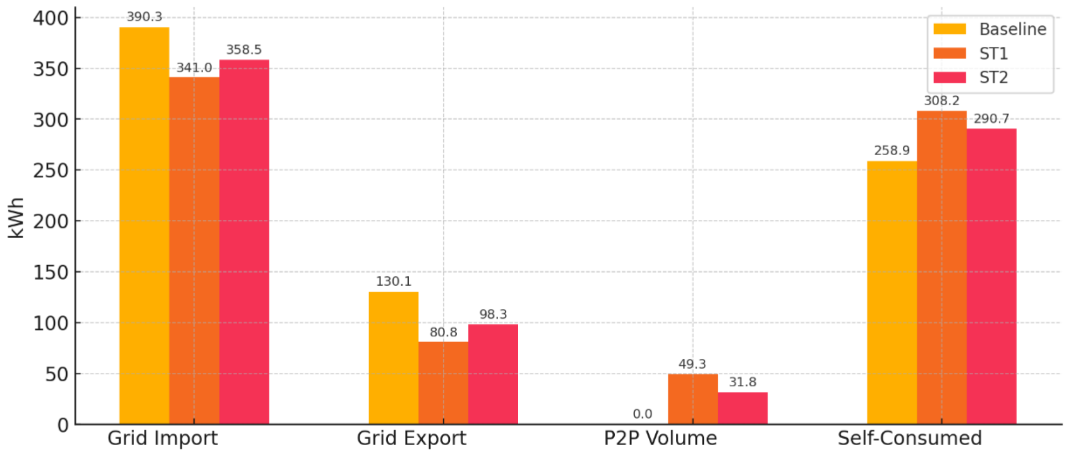

Figure 5.20-Graphical overview of weekly totals and indicators, comparing Baseline, ST1, and ST2 for the Summer Week.

5.3.2 Winter Week

Table 5.25 provides the Winter-Week analogue of Table 5.21, listing weekly imports, exports, and total P2P for Baseline, ST1, and ST2 to highlight seasonal differences.

Table 5.25-Weekly totals of grid imports, grid exports, and peer-to-peer (P2P) traded energy for the Winter Week (Baseline and under ST1/ST2).

	Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
Baseline	464.79	140.3	-
ST1	423.43	98.92	41.36
ST2	436.16	111.66	28.63

Displayed in Table 5.26 are the per-household weekly deltas (Δ Grid and Δ P2P) for the Winter Week, enabling analysis of distributional effects under constrained generation.

Table 5.26-Per-household weekly net change in grid interaction and P2P volumes for the Winter Week (Baseline vs ST1 and ST2).

House	Baseline	ST1		ST2	
	Δ Grid (kWh)	Δ Grid (kWh)	Δ P2P (kWh)	Δ Grid (kWh)	Δ P2P (kWh)
1	-5.26	5.07	-10.33	1.00	-6.26
2	-4.38	3.13	-7.51	1.04	-5.42
3	70.81	61.51	9.30	64.52	6.29
4	67.27	58.95	8.32	61.91	5.36
5	74.35	64.05	10.30	68.99	5.36
6	2.70	8.70	-6.00	8.30	-5.60
7	60.19	53.75	6.45	54.83	5.36
8	2.76	10.71	-7.95	7.91	-5.15
9	62.32	55.32	6.99	56.10	6.21
10	-6.27	3.31	-9.57	-0.10	-6.17

Table 5.27 reports the aggregated weekly cost (in €) for the Winter Week and permits a direct economic comparison between Baseline, ST1, and ST2.

Table 5.27-Total community energy procurement cost for the Winter Week (Baseline, ST1, ST2).

Strategies	**Total Cost (€)**
Baseline	78.61
ST1	72.66
ST2	74.49

Summarized in Table 5.28 are the Winter Week generation totals and the share consumed locally under each scenario, which serve as the primary technical efficiency indicators.

Table 5.28-Weekly total generation, self-consumed energy, and self-consumption rate for the Winter Week (Baseline, ST1, ST2).

Strategies	**Total Generation (kWh)**	**Self-Consumed (kWh)**	**Self-Consumption Rate (%)**
Baseline	375.13	234.84	62.6
ST1	375.13	276.2	73.63
ST2	375.13	263.47	70.23

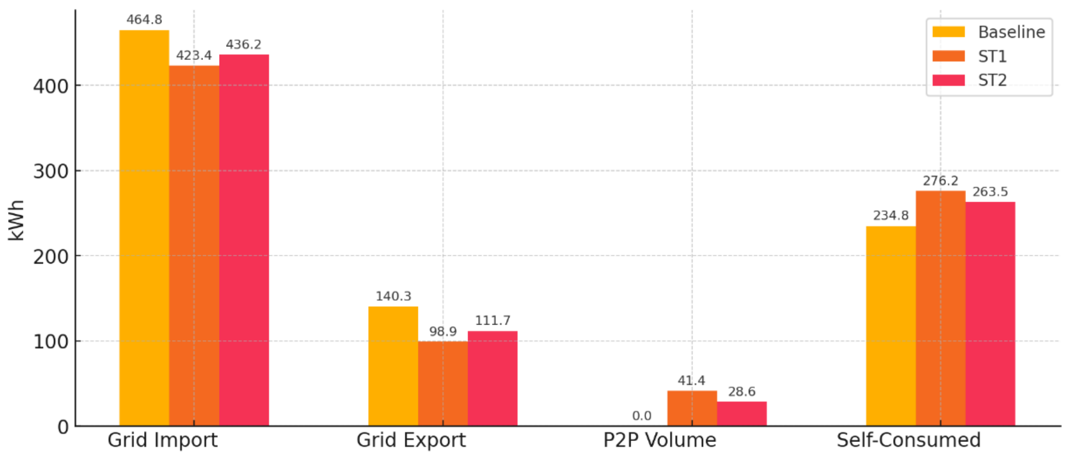

Figure 5.21-Graphical overview of weekly totals and indicators, comparing Baseline, ST1, and ST2 for the Winter Week.

5.3.3 Week-Long Performance Comparison: ST1 vs ST2

a. Summer-Week Summary: Over the Summer Week, baseline imports are 390.33 kWh, ST1 reduces imports to 341.01 kWh and clears 49.32 kWh P2P, while ST2 yields 358.54 kWh imports and 31.79 kWh P2P. Community self-consumption rises to 79.24 % under ST1 and to 74.73 % under ST2 (baseline 66.56 %). Weekly procurement costs fall from €65.57 (Baseline) to €58.48 (ST1) and to €60.94 (ST2). These values indicate that ST1 achieves a larger absolute P2P volume, stronger import reduction, and greater cost savings in the summer week.

b. Winter-Week Summary: For the Winter Week, the baseline imports are 464.79 kWh, ST1 reduces them to 423.43 kWh with 41.36 kWh P2P, while ST2 results in 436.16 kWh imports and 28.63 kWh P2P. Self-consumption reaches 73.63 % (ST1) and 70.23 % (ST2) compared with the Baseline of 62.6 %. Weekly community costs fall from €78.61 (Baseline) to €72.66 (ST1) and to €74.49 (ST2). Again, ST1 produces larger technical and monetary gains, though absolute benefits shrink in winter.

c. Technical Interpretation and Root Causes: ST1 maximizes matchable surplus–deficit pairs across the entire community, hence delivering the largest P2P volumes and the greatest uplift in self-consumption. ST2 enforces proximity, which reduces line lengths and likely reduces local losses, but it restricts cross-community matches and therefore lowers total traded energy. The seasonal reduction of absolute gains in winter reflects compressed surplus windows and lower renewable output, both strategies are effective, but ST1 exploits temporal complementarity more aggressively.

d. Economic Assessment: Monetary savings scale with traded volume and timing: ST1's larger P2P volumes produce higher weekly cost reductions (summer: €7.09 saved vs €4.63 for ST2; winter: €5.95 vs €4.12), so ST1 dominates in pure cost terms. However, ST2's narrower, locality-focused trades produce peer prices closer to grid tariffs (smaller arbitrage), explaining its reduced economic impact despite network-related benefits not captured in procurement cost alone (e.g., lower losses, reduced congestion).

e. Distributional (Equity) Effects: Per-household deltas show that ST2 concentrates benefits spatially: households near producers gain proportionally more under ST2, while ST1 distributes gains more broadly because longer matches are allowed. If community acceptance and fairness are priorities, ST2 may require compensatory mechanisms (credits or tariff adjustments) to avoid geographic winners and losers.

f. Recommendations and Practical Guidance:

i. If the primary objective is to maximize local renewable utilization and community cost savings, ST1 is preferable.

ii. If the primary objective is to reduce line flows, losses, and feeder stress (or to prioritize operational stability), ST2 is the better default.

iii. A pragmatic operational policy is a hybrid approach: apply a distance-weighted coefficient that still allows non-local matches when local surplus is insufficient (i.e., minimum proximity preference but not an absolute constraint). Complement either strategy with storage or demand flexibility to increase temporal matching and raise weekly gains.

g. Short note on robustness: Results are specific to the selected weeks and tariff structure, sensitivity analysis (varying tariffs, increasing generation…) is recommended before generalizing the recommendation to other neighborhoods.

6 Sensitivity Analysis

This chapter presents a sensitivity analysis of the proposed peer-to-peer (P2P) trading strategies (ST1 and ST2). The goal is to evaluate the robustness of the strategies with respect to two exogenous variations that are relevant for distribution system operation and market design: (1) an increase in the grid buy price to €0.20/kWh, and (2) a 20% increase in renewable generation for prosumers. For each scenario, the same simulation framework and algorithmic settings used in the main experiments are retained (ADMM penalty and tolerances, solver settings, random seed). Results are reported as absolute and relative changes with respect to the baseline scenario and analyzed at both community and household levels.

6.1 Scenario 1

In Scenario 1, the grid purchase price is raised to €0.20/kWh, while the grid sell price is kept proportional as $\lambda^{\text{sell}} = 0.20 \times \lambda^{\text{buy}} = €0.04 / kWh$. All other model settings (ADMM parameters, solver configuration, data, and topology) remain identical to the baseline to isolate the effect of the price change. The simulations are run for both representative weeks (summer and winter) and for both strategies (ST1 and ST2). It was expected that a higher retail purchase price will make local matching and P2P trades relatively more attractive, reducing net grid imports and increasing self-consumption and P2P volume. Results below quantify these effects at the community and household levels.

6.1.1 Summer Week

Table 6.1- Community energy exchanges comparison, between strategies in Baseline and Scenario 1, Summer Week.

Strategies	Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
Baseline	390.33	130.1	-
ST1- Base	341.01	80.78	49.32
ST2- Base	358.54	98.3	31.79
ST1- Scenario 1	337.03	76.79	53.3
ST2- Scenario 1	355.22	95	35.1

Table 6.2- Economic comparison between strategies in Baseline and Scenario 1, Summer Week.

Strategies	Total Cost (€)
Baseline	65.57
ST1	58.48
ST2	60.94
Baseline- Scenario 1	72.86
ST1- Scenario 1	64.34
ST2- Scenario 1	67.25

Table 6.3- Self-consumption ratios comparison between strategies in Baseline and Scenario 1, Summer Week.

Strategies	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Baseline	389.02	258.94	66.56
ST1- Base	389.02	308.25	79.24
ST2- Base	389.02	290.73	74.73
ST1- Scenario 1	389.02	312.23	80.26
ST2- Scenario 1	389.02	294.04	75.5

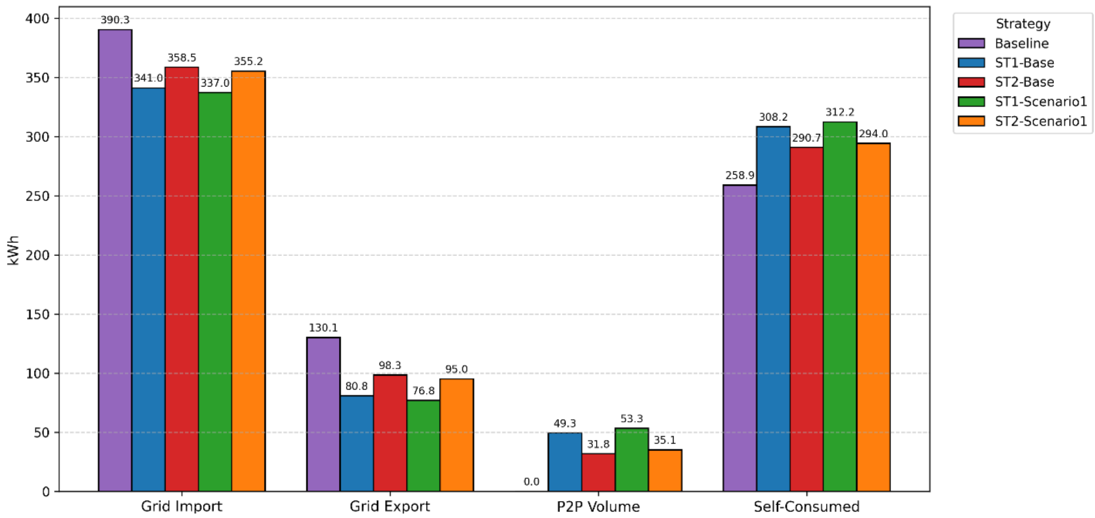

Figure 6.1-Weekly totals of P2P exchanges and grid balance in a Summer Week, Baseline vs Scenario 1.

6.1.2 Winter Week

Table 6.4-Community energy exchanges comparison, between strategies in Baseline and Scenario 1, Winter Week.

	Grid Import (kWh)	**Grid Export (kWh)**	**P2P Volume (kWh)**
Baseline	464.79	140.3	-
ST1- Base	423.43	98.92	41.36
ST2- Base	436.16	111.66	28.63
ST1- Scenario 1	418.62	94.13	46.17
ST2- Scenario 1	432.38	107.89	32.41

Table 6.5- Economic comparison between strategies in Baseline and Scenario 1, Winter Week.

Strategies	**Total Cost (€)**
Baseline	78.61
ST1- Base	72.66
ST2- Base	74.49
Baseline- Scenario 1	87.35
ST1- Scenario 1	79.96
ST2- Scenario 1	82.17

Table 6.6-Self-consumption ratios comparison between strategies in Baseline and Scenario 1, Winter Week.

Strategies	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Baseline	375.13	234.84	62.6
ST1- Base	375.13	276.2	73.63
ST2- Base	375.13	263.47	70.23
ST1- Scenario 1	375.13	281.01	74.91
ST2- Scenario 1	375.13	267.24	71.2

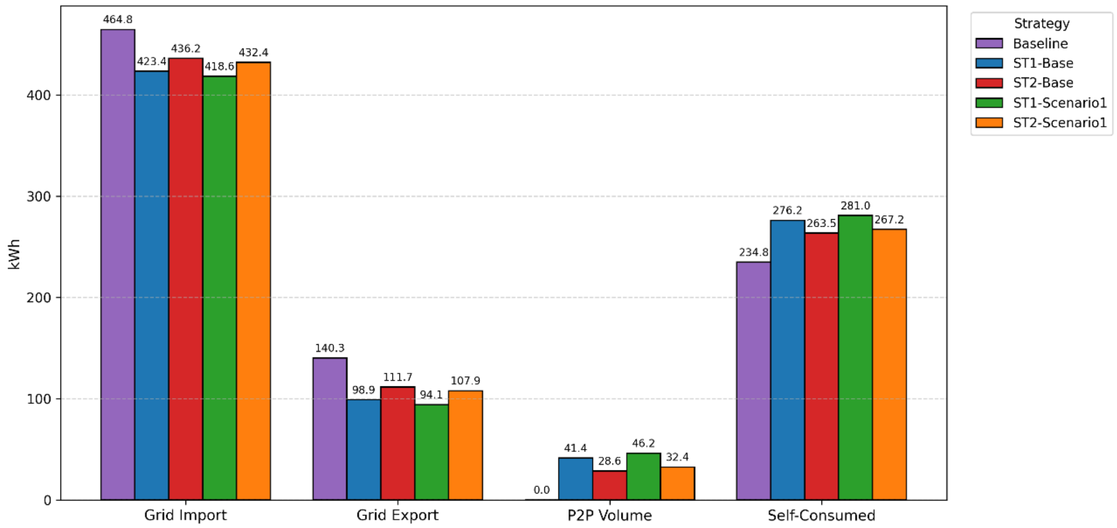

Figure 6.2-Weekly totals of P2P exchanges and grid balance in a Winter Week, Baseline vs Scenario 1.

6.2 Scenario 2

In Scenario 2, the grid prices are kept at their baseline values €0.18/kWh, while the renewable generation of all prosumer households (PV and Wind) is increased by 20%. This adjustment aims to capture the potential impact of technological improvements or favorable weather conditions on community energy dynamics. The simulations are again performed for both representative weeks (summer and winter) under ST1 and ST2, allowing a direct comparison with the Baseline scenario.

By enhancing local generation, more surplus energy becomes available for self-consumption and P2P exchanges, which is expected to reduce overall grid imports and increase community self-sufficiency.

6.2.1 Summer Week

Table 6.7-Community energy exchanges comparison, between strategies in Baseline and Scenario 2, Summer Week.

Strategies	Grid Import (kWh)	Grid Export (kWh)	P2P Volume (kWh)
Baseline	390.33	130.1	-
ST1- Base	341.01	80.78	49.32
ST2- Base	358.54	98.3	31.79
Baseline- Scenario 2	375.56	193.13	-
ST1- Scenario 2	312.19	129.77	63.37
ST2- Scenario 2	334.20	151.76	41.37

Table 6.8- Economic comparison between strategies in Baseline and Scenario 2, Summer Week.

Strategies	Total Cost (€)
Baseline	65.57
ST1	58.48
ST2	60.94
Baseline- Scenario 2	60.65
ST1- Scenario 2	51.52
ST2- Scenario 2	54.69

Table 6.9- Self-consumption ratios comparison between strategies in Baseline and Scenario 2, Summer Week.

Strategies	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Baseline	389.02	258.94	66.56
ST1- Base	389.02	308.25	79.24
ST2- Base	389.02	290.73	74.73
Baseline- Scenario 2	466.82	273.69	58.63
ST1- Scenario 2	466.82	337.06	72.2
ST2- Scenario 2	466.82	315.06	67.5

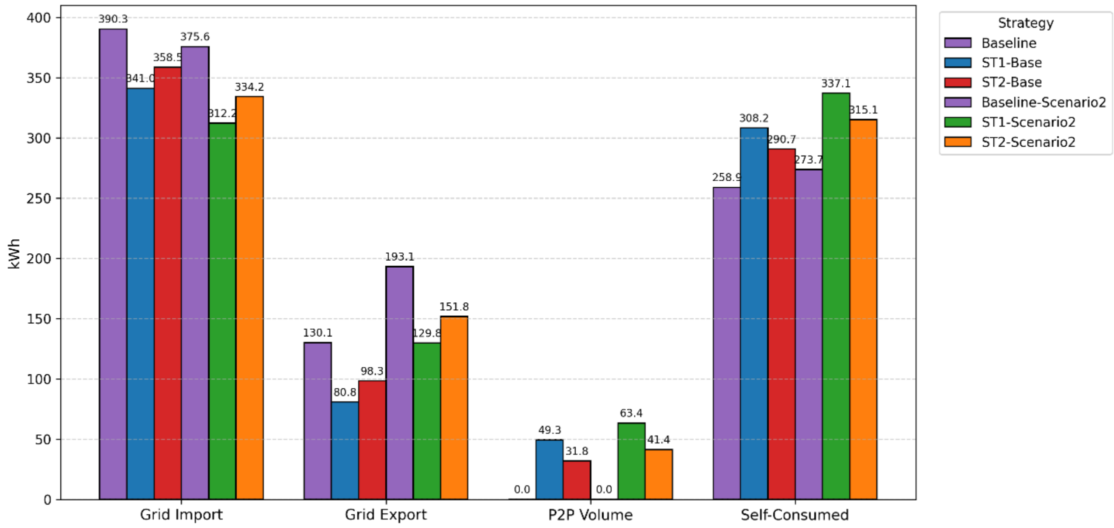

Figure 6.3-Weekly totals of P2P exchanges and grid balance in a Summer Week, baseline vs Scenario 2.

6.2.2 Winter Week

Table 6.10- Community energy exchanges comparison between strategies in Baseline and Scenario 2, Winter Week.

	Grid Import (kWh)	**Grid Export (kWh)**	**P2P Volume (kWh)**
Baseline	464.79	140.3	-
ST1- Base	423.43	98.92	41.36
ST2- Base	436.16	111.66	28.63
Baseline- Scenario 2	447.92	198.44	-
ST1- Scenario 2	399.05	149.58	48.87
ST2- Scenario 2	412.97	163.5	34.95

Table 6.11- Economic comparison between strategies in Baseline and Scenario 2, Winter Week.

Strategies	**Total Cost (€)**
Baseline	78.61
ST1- Base	72.66
ST2- Base	74.49
Baseline- Scenario 2	73.48
ST1- Scenario 2	66.43
ST2- Scenario 2	68.44

Table 6.12- Self-consumption ratios comparison between strategies in Baseline and Scenario 2, Winter Week.

Strategies	Total Generation (kWh)	Self-Consumed (kWh)	Self-Consumption Rate (%)
Baseline	375.13	234.84	62.6
ST1- Base	375.13	276.2	73.63
ST2- Base	375.13	263.47	70.23
Baseline- Scenario 2	450.16	251.72	55.92
ST1- Scenario 2	450.16	300.59	66.77
ST2- Scenario 2	450.16	286.67	63.68

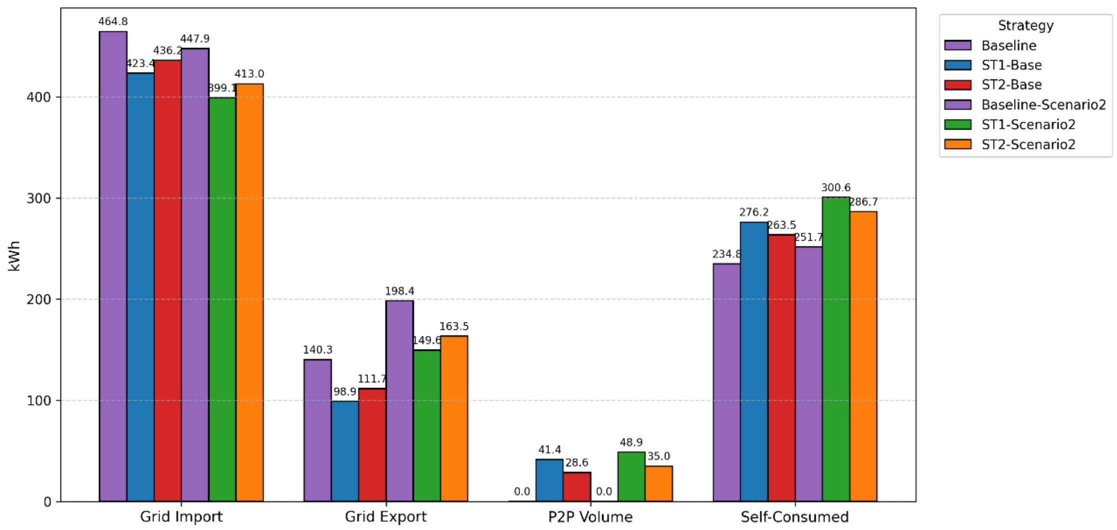

Figure 6.4-Weekly totals of P2P exchanges and grid balance in a Winter Week, Baseline vs Scenario 2.

6.3 Key Findings and Implications

The previous sections reported how peer-to-peer (P2P) energy exchanges respond to two sensitivity scenarios: (1) an increase in the grid purchase price and (2) a 20% increase in prosumer generation, with the explicit objective of quantifying differences in P2P behavior between the baseline and each sensitivity case. The main findings are as follows.

First, in terms of aggregated consumption versus production, raising the grid purchase price makes imported energy relatively more expensive and therefore increases the competitiveness of local P2P trades. For the analyzed summer week (ST1), the aggregated P2P volume increased (Table 6.1). The same pattern of modest but consistent P2P growth is also visible in the winter week's results for Scenario 1 (Table 6.4).

Second, increasing prosumer generation by 20% expands the physical availability of energy for local exchange and produces larger absolute increases in P2P volumes than the tariff change. For the analyzed winter week (ST1), P2P rose substantially when generation was increased (Table 6.10); the summer counterpart is reported in Table 6.7. Notably, in this scenario, the results show a simultaneous increase in P2P exchange volumes and a reduction in net imports from the grid, while exports to the grid also grow. This behavior reflects that the additional local generation expands the pool of surplus energy, a larger portion is matched locally through P2P (hence lower grid imports), but when local demand is insufficient to absorb the extra production, the residual surplus is exported upstream. The numerical magnitudes of these effects are reported in Table 6.7 and Table 6.10.

Seasonal and temporal effects moderate these responses. The tariff increase (Scenario 1) yields modest but consistent relative increases in P2P across both summer and winter weeks, acting primarily as an economic amplifier of trading activity. The generation increase (Scenario 2) produces larger absolute jumps in P2P, with the magnitude dependent on existing production levels and seasonal irradiance. The effect is particularly noticeable during periods that already present some generation potential, while remaining significant even in low-generation periods due to the expanded window of surplus energy.

The effect on self-consumption differs when viewed in absolute versus relative terms. Both scenarios increase local retention of energy, but with different patterns: under the tariff increase, the rate of self-consumption rises slightly, whereas the +20% generation case increases self-consumed energy in kWh but not necessarily the self-consumption percentage to the same degree, since total generation also grows.

From a drivers-of-change perspective, two conclusions stand out. First, the availability of local supply is the most powerful lever to raise absolute P2P volumes: increasing prosumer generation produced larger absolute increases in exchanged energy than the tariff change (Table 6.7 and Table 6.10). Second, economic signals (higher grid purchase prices or time-varying retail prices) are effective at shifting demand toward local markets but typically produce smaller absolute changes than comparable increases in local generation.

Mechanistically, the tariff increase improves arbitrage opportunities between grid imports and local purchases, incentivizing buyers to prefer local matches. Increased generation enlarges the set of candidate sellers and extends the hours with surplus energy available for P2P matching.

The analysis is robust for the studied configuration (topology, demand/generation profiles, ADMM parameters, and solver settings), but its quantitative outcomes depend on those assumptions. In particular, network losses, congestion costs, and detailed physical network constraints were not modelled; incorporating such effects could alter the attractiveness of long-distance matches and change the spatial pattern of P2P exchanges.

Practical recommendations focused on increasing P2P volumes are:

- If the objective is to maximize absolute P2P energy exchange, policies and incentives that increase local generation capacity (e.g., support for prosumer PV or micro-wind installations) are more effective than modest tariff adjustments.

- If the objective is to quickly shift consumption from the grid to the distributed energy sources, adjusting economic signals (higher purchase tariffs, time-varying retail prices) is an efficient and operationally simple instrument.

- The greatest efficacy is achieved by integrating expanded local generation with appropriate price signals and enabling technologies, specifically energy storage and demand flexibility, because increases in local supply will only translate into higher local utilization if adequate absorption capacity is present.

7 Conclusion and Future Work

Decentralized bilateral P2P markets can deliver meaningful technical and economic benefits while presenting clear design trade-offs that must be addressed before operational deployment. This work explored two strategies, the supply–demand matching strategy (ST1) and the distance-based matching strategy (ST2). Both of them reduce grid imports and increase community self-consumption relative to a no P2P baseline, but they do so through different mechanisms: ST1 maximizes matchable surplus–deficit pairs across the entire community and therefore achieves the largest traded volumes and the greatest absolute procurement cost reductions, whereas ST2 enforces locality and produces smaller absolute traded energy while concentrating exchanges among nearby agents, an outcome that is likely to reduce feeder flows and local losses when network physics are considered.

A related and important finding is that distributional effects depend strongly on the matching rule. ST1 tends to spread benefits more evenly because it allows long-range matches, while ST2 concentrates monetary and technical gains near producers so that a household's geographic position within the microgrid becomes a primary determinant of individual outcomes. If equitable benefit sharing is an objective, distance-based matching requires complementary mechanisms, such as credits, compensatory tariffs, or hybrid matching rules, to avoid creating persistent geographic winners and losers. The sensitivity analysis further indicates that increasing local generation capacity produces larger absolute increases in P2P volumes than comparable increases in grid tariffs, while economic signals (higher purchase prices) shift consumption more rapidly toward local matches but typically yield smaller absolute increases in exchanged energy. Combining supply expansion, price incentives, and enabling technologies such as storage and demand flexibility produces the largest aggregate gains.

The present work has modelling and implementation limitations that must be addressed in further research. The optimization model abstracts from detailed electrical network constraints (line impedances, voltage limits, and explicit loss accounting), an omission that could materially alter the attractiveness of long-distance matches when physical layer costs and constraints are internalized. The ADMM implementation evaluated here uses synchronous iterations and a solver chosen for repeatability (SCS); therefore, investigating alternative solver back-ends, asynchronous ADMM variants, and the effect of communication latency and privacy-preserving architectures will be important to validate algorithmic performance under realistic operational conditions.

Accordingly, the principal directions for future work are, extend the optimization model to incorporate distribution network physics (either via linearized power-flow or full AC formulations) so that losses, voltages and congestion are internalized in trading decisions, integrate storage devices and demand flexibility into the agent models and quantify their effect on temporal matching and the value of flexibility, investigate asynchronous and event-driven ADMM implementations and communication constraints, design and evaluate market-level fairness mechanisms and hybrid matching rules that balance locality with efficiency, scale experiments to larger and more heterogeneous communities, and, where feasible, implement field pilots in regulatory sandboxes to evaluate metering, settlement and consumer acceptance. Pursuing these lines of work will address the main gaps identified in this thesis and will provide the empirical and methodological evidence necessary to translate P2P market concepts into operational, equitable, and technically secure implementations.

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