Blockchain-Enabled Distributed Energy Management in Network-Constrained Microgrids

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Declaration

I hereby declare that this manuscript, entitled "Blockchain-Enabled Distributed Energy Management in Network-Constrained Microgrids," is the result of my own work, except for quotations and citations, which have been duly acknowledged.

I also declare that, to the best of my knowledge and belief, it has not been previously or concurrently submitted, in whole or in part, for any other degree or diploma at Nazarbayev University or any other national or international institution.

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Dedication

This paper is dedicated to those who continue fighting the same battle daily, even though no progress was made the previous day and the solution seems far away. This paper honors those who never stop exploring the unexplored. This paper appreciates engineers who need real results, not theories. This paper salutes people who attempt to make beautiful theories work, understanding that it takes many attempts for breakthroughs to happen.

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Lastly, to those who saw my potential even before proving anything, I hope I live up to your expectations.

Abstract

With the increasing penetration of DERs and energy storage, microgrids are moving towards becoming decentralized networks with agents exhibiting inter-temporal constraints and constraints imposed by the network. Centralized models have limitations with regard to scaling and security as well as the need for trusted third parties. However, peer-to-peer trading requires systems that ensure the feasibility of the transactions. In this study, we propose a decentralized energy management system that combines consensus-based ADMM optimization with blockchain-enabled post-clearing settlement. Our model is based on multi-period social welfare maximization considering bilateral P2P transactions and battery storage dynamics. The centralized formulation is decomposed into a consensus-based ADMM scheme, where agents solve local convex subproblems and a non-economic coordinator enforces network feasibility through projection. The approach is validated primarily on a modified IEEE 14-bus system, with additional scalability verification on the IEEE 33-bus system, over a 24-hour horizon. For the IEEE 14-bus, results show that the distributed solution closely matches the centralized benchmark, achieving welfare values of 14.10 versus 14.11 in the unconstrained case and 13.97 in both cases under network constraints, corresponding to gaps of 0.05% and 0.02%, respectively. All line limits are satisfied in the constrained scenario. For the post-clearing stage of the IEEE 14-bus system, 2,808 bilateral trades are generated by the constrained market-clearing stage. Of these, 2,795 verified bilateral trades, corresponding to around 276 kWh of total energy, are settled using simulated smart meter measurements generated within the system and a blockchain-based settlement layer developed using Hardhat, recording a settlement success rate of 100% without involving the optimization process.

Keywords:

Peer-to-peer energy trading; Distributed optimization; Network-constrained microgrids; Time-coupled storage; Blockchain-based settlement

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List of Abbreviations & Symbols

Abbreviation/ Symbol	Description
ADMM	Alternating Direction Method of Multipliers
BESS	Battery Energy Storage System
DC	Direct Current
DER	Distributed Energy Resource
NO	Network Operator
EMS	Energy Management System
ESS	Energy Storage System
IEEE	Institute of Electrical and Electronics Engineers
kW	Kilowatt
kWh	Kilowatt-hour
OPF	Optimal Power Flow
P2P	Peer-to-Peer
PTDF	Power Transfer Distribution Factor
SoC	State of Charge
VPP	Virtual Power Plant
$\mathcal{T}$	Set of time periods
$\mathcal{S}$	Set of sellers
$\mathscr{B}$	Set of buyers
$\mathcal{N}$	Set of agents, $\mathcal{N} = \mathcal{S} \cup \mathscr{B}$
$\mathscr{L}$	Set of network lines
t	Time index
i, j	Agent indices
ℓ	Line index
$x_i(t)$	Power generated by seller i

$y_j(t)$	Power consumed by buyer *j*
$p_i(t)$	Net power injection of agent *i*
$z_i(t)$	Consensus power injection
$c_i(t)$	Battery charging power
$d_i(t)$	Battery discharging power
$s_i(t)$	Battery state of charge
$f\ell(t)$	Power flow on line ℓ
$u_i(t)$	ADMM dual variable
α_i	Quadratic generation cost coefficient
β_i	Linear generation cost coefficient
γ_i	Fixed generation cost
ω_j	Utility scaling coefficient
δ_j	Marginal disutility coefficient
$\mathrm{PTDF}\ell_i$	Power transfer distribution factor
$\bar{f}\ell$	Line thermal limit
η^c	Battery charging efficiency
η^d	Battery discharging efficiency
Δt	Time step length
ρ	ADMM penalty parameter
ε^{pri}	Primal residual tolerance
ε^{dual}	Dual residual tolerance
K_{max}	Maximum number of ADMM iterations
$C\mathrm{Ci}\ ()$	Seller cost function
$U_j(\cdot)$	Buyer utility function

Chapter 1. Introduction

1.1 Background and Motivation

The increased penetration of DERs such as photovoltaic generation, battery energy storage systems, and flexible loads is changing the face of the power system. The microgrid is evolving from a centrally controlled system with a small number of controllable resources to a group of independent agents that can operate in a coordinated manner without relying on mutual trust and information disclosure. The coordination between these agents requires energy management systems that transcend the conventional centralized optimization techniques. In this thesis, the focus is placed on the coordination and market clearing between these agents, rather than the distribution network's electrical characteristics. Accordingly, a linearized DC power flow model is utilized to represent the network. The DC power flow model is a popular choice in electric market clearing and optimal power flow problems due to its simplicity and tractability [1]. The DC power flow model can capture active power flow and congestion in the network via the use of PTDF-based constraints.

Traditional centralized energy management systems (EMS) assume complete information availability and rely on a trusted central coordinator to optimize generation, consumption, and storage schedules. However, this model encounters numerous obstacles when applied to decentralized settings, in which prosumers and consumers may be unwilling to disclose their private cost functions, utility parameters, or operational constraints to any third party. A growing number of microgrid-related publications [2], [3] have identified limited centralized information sharing, participant scalability, and robustness against single points of failure as key features of future microgrid operations. Peer-to-peer (P2P) energy trading is one of the models that allow local energy trading among owners of distributed energy resources without the help of centralized intermediaries. Initially, most P2P models were designed around direct consumer-prosumer negotiations using bilateral trading schemes and game-theoretic mechanisms [4]. Although such models have shown great potential for economic gains, in many cases, they still depended on either simplified assumptions of the physical network or the use of central coordinators to guarantee the physical feasibility of the trades.

More recent work has incorporated network awareness into P2P markets by embedding power flow constraints directly into the market clearing process. Ullah and Park [2] developed a distributed dual-decomposition framework for network-constrained peer-to-peer local energy market clearing that explicitly accounts for bilateral power losses and network utilization charges using PTDF-based modeling. Their approach demonstrates exact convergence to the centralized optimum and scalability on IEEE 14-Bus, 33-Bus, 39-Bus, and 141-Bus systems with convergence in seconds and fewer than 200 iterations. However, the framework is limited to a single-period market and does not consider time-coupled storage or multi-period EMS coordination. Similarly, Xia et al. [3] developed a generalized Nash-in-Nash bargaining framework for peer-to-peer energy trading among buildings that jointly allocates traded energy, network usage costs, and transmission losses under distribution network constraints. While the model ensures fairness and incorporates decentralized ADMM-based clearing, price formation relies on negotiated bargaining outcomes rather than welfare-maximizing optimization with storage-driven intertemporal coupling.

Blockchain technology has been proposed as a means of enabling trustless and transparent energy trading without centralized intermediaries [5]. Several pilot projects and commercial platforms have demonstrated peer-to-peer energy trading using blockchain-based transaction records and smart contracts [6], [7]. However, most blockchain-based energy trading platforms treat market clearing as an external process. Optimization is either centralized, heuristic, or entirely absent, with the blockchain serving only as a settlement layer.

Hong et al. [8] reviewed the development of blockchains in the field of virtual enterprise networks and proposed conceptual roadmaps for their future development. The study notes a trend of interest in using blockchain for energy trading and data management. However, the authors do not consider optimization methods based on market clearing calculations, consideration of physical network constraints, time-related coordinated energy storage, and its use. Similarly, Shorya and Jagwani [9] propose a model for direct energy trading between users using blockchain, which combines device-level demand forecasting and energy generation methods with smart contracts for energy consumption planning. Although the method allows consumption prediction and increased market transparency, the authors do not present a formalized optimization-based model for market clearing and do not consider physical network constraints.

1.2 Problem Statement

For decentralized energy management to be deployable in microgrids, three requirements must be satisfied simultaneously:

Limited information disclosure: Agents should not be required to disclose cost functions, utility parameters, or internal constraints to a central operator or other participants.

Physical feasibility: Decentralized decisions must respect power balance, network constraints (line flow limits modeled via PTDF), and storage dynamics (state of charge evolution over time). Verifiable execution and settlement: Scheduled actions must be measurable and verifiable without relying on a trusted central authority.

Existing approaches address these requirements only partially. Distributed optimization methods, particularly those based on the alternating direction method of multipliers (ADMM), enable coordination with localized information sharing but often simplify or relax network constraints and typically assume trusted off-chain settlement [10], [11]. On the contrary, blockchain-powered energy trading systems offer transparent and automated settlements but consider market clearing as an outside operation. They depend on centralized or heuristic scheduling with weak integration of physical network constraints [6], [9]. As a result, most existing frameworks satisfy at most two of the three requirements.

Besides that, energy storage adds to intertemporal coupling which makes the problem more complicated to a great extent. The changes in storage state-of-charge (SoC) connect the scheduling decisions over different time periods, thus coordination mechanisms can handle both spatial coupling (via network constraints) and temporal coupling (via storage) should be employed [12], [13]. Several distributed market clearing methods rarely prove fast convergence and almost optimal performance in systems with many agents and time-coupled storage.

1.3 Objectives of the Study

The objective of this study is to develop and evaluate a distributed energy management framework for peer-to-peer electricity trading in network-constrained microgrids with time-coupled battery storage. The framework combines distributed optimization and blockchain-based settlement to coordinate autonomous agents while preserving physical grid feasibility.

The study is conducted and verified on the IEEE 14-bus and IEEE 33-bus network with a 24-hour period. The key aspect is to study the convergence behavior, economic efficiency, and the line flow constraints enforcement under distributed coordination.

Hence, the objectives are to:

1. Formulate a multi-period social welfare optimization problem that characterizes bilateral peer-to-peer trading, battery storage dynamics, and PTDF-based network constraints.

2. Develop a distributed solution method with consensus ADMM that permits agents to solve their local problems while a coordinating operator ensures network feasibility.
3. Compare the distributed results against the centralized benchmarks in terms of welfare recovery, convergence speed, and physical constraint satisfaction.
4. Use blockchain for post-clearing trade settlement verification without being part of the optimization loop.
5. Study how the system behaves in both constrained and unconstrained situations to evaluate the influence of network restrictions on economic performance.

1.4 Research Questions or Hypotheses

This thesis seeks to answer the following research questions:

RQ1: Can a consensus-based ADMM algorithm achieve fast convergence and near-optimal social welfare in microgrids integrated with network constraints that are time-coupled to a battery storage system and contain multiple autonomous agents?

RQ2: To what extent do the distributed ADMM solutions achieve social welfare levels close to the centralized benchmarks, both under network-constrained and unconstrained operating conditions over a 24-hour scheduling horizon?

RQ3: How does the addition of PTDF-based power network constraints influence the convergence behavior, welfare outcomes, and line utilization in peer-to-peer energy trading markets?

RQ4: Can the optimized peer-to-peer trading schedules be verified and settled using smart meters and blockchain-based smart contracts reliably at the scale of thousands of bilateral transactions?

1.5 Scope and Limitations

The scope of the study is defined as follows:

Network modeling: The power network is represented by a linearized DC power flow model with PTDF-based line flow constraints. The model is focused on active power balancing and line thermal limits, but it does not account for reactive power, voltage magnitude constraints, and losses only to the extent of linear approximations.

Market structure: The conceptual framework is based on peer-to-peer energy trading between autonomous agents who are either sellers or buyers. The distribution system operator, which acts strictly as a non-economic coordinator, has the sole role of network feasibility enforcement and is thus not involved in market optimization or price formation.

Time horizon: The simulations are based on a 24-hour period with discrete time intervals, which is a typical characteristic of day-ahead energy market coordination. The intraday or real-time market clearing is thus out of scope.

Energy storage: The dynamics of battery energy storage as related to the state of charge are captured by linear equations considering fixed charging and discharging efficiencies. But the battery degradation, aging effects, and stochastic behavior are the aspects not covered by the model.

Uncertainty: In the current study, the renewable energy sources' generation and the load demand are assumed to be perfectly known. This assumption is taken to focus on the coordination and feasibility issues of the distributed market clearing. This assumption avoids the added complexity of stochastic optimization. Therefore, the issues of uncertainty, errors, and optimization are not considered.

Blockchain implementation: The settlement layer is a blockchain test environment-based implementation with smart contracts and smart meters. The research is centered on the accuracy and scalability of the settlement process rather than blockchain consensus mechanisms, latency, or gas cost optimization on public networks.

Validation systems: The main numerical validation is conducted on the IEEE 14-bus benchmark network that has been modified with 25 agents and IEEE 33-bus network with 45 agents in this thesis.

1.6 Significance of Study

This study explores and contributes to the advancements in distributed optimization, peer-to-peer energy markets, and blockchain-based energy systems.

Methodological contribution: The thesis enhances network-constrained peer-to-peer market-clearing models [2], [3] by integrating battery storage systems' time-coupled dynamics explicitly through a multi-period consensual-based ADMM approach [11]. It breaks the limitation of single-period market clearing and thus allows for the intertemporal coordination between energy and storage that is necessary for a microgrid to run in real-life conditions.

Practical validation: The study supports its mathematical modeling with quantitative experiments on IEEE benchmark test systems, primarily focusing on a modified IEEE 14-bus network adjusted with 25 agents for a 24-hour period. Numerical results exhibit the distributed ADMM economic performance that is quite close to centralization across all scenarios, which shows that distributed ADMM can reach the economic optimality almost exactly without agents having to disclose their private information to a central authority.

System integration: By structurally combining distributed optimization with smart-meter-based verification and blockchain-based settlement, the present framework suggests that blockchain energy integration can be beyond just a conceptual trend, but rather an executable solution. The joint settlement of over 2,000 bilateral peer-to-peer energy transactions without failure shows real evidence of a scalable and trustworthy market implementation.

Implications for prosumer participation: According to the simulation results, local energy market participation is possible for prosumers and consumers without exposing their private cost functions and operational constraints, yet they can still achieve welfare outcomes close to centralized results. This provides a practical balance between decentralization and physical feasibility, thereby strengthening the case for wider DER participation in local energy markets.

Foundation for future research: The clearly defined modular separation between optimization, verification, and settlement layers can be seen as a launching pad for future work such as uncertainty modeling, real-time or intraday market clearing, demand response integration, and production-level deployment of blockchain networks.

1.7 Organization of the Thesis

This thesis develops and evaluates a framework for distributed energy management, specifically designed for network-constrained microgrids. In Chapter 2, the current literature on peer-to-peer trading, distributed optimization, and blockchain technology in the context of energy trading is discussed, with specific emphasis on the gaps in the current literature that have not considered the issues of physical feasibility, intertemporal storage, and verifiable trading.

In Chapter 3, a multi-period social welfare optimization is formulated as a centralized optimization problem to account for network constraints using PTDF and to incorporate intertemporal effects of battery storage. This chapter establishes the mathematical basis and serves as a benchmark for the proposed framework.

Chapter 4 presents the distributed solution to the optimization problem, leveraging the consensus-based ADMM. This allows for decentralized optimization with network feasibility.

Chapter 5 presents the verification and settlement mechanism using blockchain technology to ensure transparent and tamper-free execution of the market clearing mechanism.

Chapter 6 presents the simulation results of the framework, and Chapter 7 discusses the implications of the results. Finally, in Chapter 8, the conclusions and suggestions for further work are presented.

Chapter 2. Literature Review

This chapter provides an overview of recent studies related to peer-to-peer energy trading, distributed optimization methods for smart grids, and blockchain technology-based energy management systems. The summary highlights key achievements, deficiencies, and shortcomings of existing research findings which this research attempts to resolve.

2.1 Peer-to-Peer Energy Trading Models

Trading energy in a peer-to-peer system has become an effective way of conducting localized energy trades between owners of distributed energy resources by avoiding the need for a centralized facilitator. Initial P2P trade systems emphasized on developing means of conducting bilateral trading between producers and consumers, implying economic viability based on localized pricing information and efficient use of DERs [4], [5]. Such approaches made some assumptions like using a simple or unconstrained model of the electrical grid.

In order to increase scalability and economic viability, modern P2P trade systems utilize market-based modeling where P2P trade becomes an optimization problem. Sun et al. [4] introduced a decentralized P2P trading mechanism using bidirectional matching and multi-attribute decision-making. The model ensures autonomous trading with privacy preservation. Although economic viability is ensured, the electrical network is assumed unlimited, and congestion is not considered. This assumption is common with other P2P models, where prices are determined using negotiations. Moreover, recent research has also studied and analyzed the distributed peer-to-peer trading frameworks concerning industrial microgrids with complex operational processes and uncertainties related to renewable energy sources. Wu et al. [14] have presented a distributed P2P trading framework considering assembly processes in industrial microgrids, uncertainty related to renewable energy sources, and battery storage. The framework is analyzed based on microgrid levels without considering network constraints in the distribution network. Optimization-based trading frameworks similar to the above have also been presented for multi-microgrid systems under uncertainty; however, they are usually concerned with market coordination and often rely on trusted communication infrastructures without considering secure verification of transactions and decentralized settlement mechanisms [15].

Recently P2P models have started considering the electrical network constraints while solving P2P trading problems. Ullah and Park [2] introduced a P2P trading framework, where a social welfare maximization problem is formulated using PTDF-based line flow modeling and bilateral loss allocation. The problem is then solved using distributed dual decomposition. The model ensures convergence to optimal solutions with strict enforcement of power balance, line flow, and loss-dependent network usage charges. The model is tested with various IEEE test systems. Nevertheless, the model is applicable for a single period and does not include time-dependent storage.

Xia et al.'s [3] work extends the state-of-the-art in network-aware P2P energy trading by proposing a generalized Nash-in-Nash bargaining approach for the co-allocation of energy, network costs, and loss allocation, all while satisfying the constraints imposed by the distribution grid. The approach relies on PTDF-based line loading, satisfies voltage constraints, and considers congestion costs, all while solving the problem in a decentralized manner using an ADMM approach. Although the approach considers the interactions between different periods, the price formation is not based on the dual variables obtained by solving the welfare maximization problem but is derived from the Nash bargaining solution, while the role of storage is limited to the secondary level.

Other works have focused on the problem of P2P trading in other specialized domains, such as industrial microgrids and capacity planning, while incorporating the role of storage and considering the uncertainty associated with the problem, but the problem is solved in a centralized manner, and the price formation is heuristic in nature [16]. As such, the current state-of-the-art in the problem of P2P energy trading highlights the tension between economic decentralization and the physical reality of the problem, where the network-aware approaches are very rigorous from the physics point of view but are limited to the single period, while the approaches considering the multiperiod problem with significant emphasis on the role of storage are either too simplistic from the point of view of the electrical network or are solved in a centralized manner, highlighting the need for distributed network-constrained P2P markets while considering the time-coupled dynamics of the problem.

2.2 Distributed Optimization in Smart Grids

In the context of the smart grid, the emphasis in the development of the field of distributed optimization has been the promotion of the concepts of privacy, scalability, and practicality. The fundamental principle behind the field is the ability to have all the different entities retain their autonomy while, at the same time, coordinating to satisfy the requirements imposed by the constraints. This is accomplished by breaking down the complex problem into smaller subproblems, with the entities interacting with minimal information exchange to ensure coordination. Among the different methods used in the field, the alternating direction method of multipliers (ADMM) has been the one used the most, with the majority of the emphasis focused on its applicability to the field of distributed optimization due to its suitability for handling problems with convex objectives, separable constraints, and minimal coordination requirements [10], [17], all of which are significant requirements for the field of energy management and the coordination of markets. Recent distributed energy management schemes have shown the effectiveness of the alternating direction method of multipliers (ADMM) for handling the decentralized control of networked microgrids and DERs under decentralized decision-making; however, most of these works focus on operational-level coordination instead of decentralized markets [18].

There have been several works that have focused on the application of the field of distributed optimization to the problem of energy trading and scheduling, with some works simplifying the electrical network for the purpose of coordination. For instance, the work by Zheng and Wei [19] presented an approach for the development of a peer-to-peer energy trading method for the context of the multi-energy systems, using the principles of the Lyapunov optimization method along with the ADMM method for handling the uncertainty associated with the problem without the need for forecasting the uncertainty. While the approach enables online operation and storage coordination, the electrical network is modeled at an aggregate hub level, and nodal congestion and PTDF-based line constraints are not considered. Consequently, market results are not guaranteed to be physically feasible at the distribution network level.

Uncertainty about renewable resources and load demand has also been considered in peer-to-peer trading models. Alhasnawi et al. in their study [20] proposed a chance-constrained peer-to-peer trading strategy for multi-microgrid load scheduling in the presence of renewable resource uncertainties. The proposed strategy improves the robustness of load scheduling, but it does not explicitly consider distribution network constraints and congestion in market clearing.

Other work has focused on integrating uncertainty and network constraints within centralized or semi centralized formulations. Suthar and Pindoriya [21] developed a chance constrained co optimization framework that jointly clears a P2P market and distribution network operation under renewable and load uncertainty. Although voltage and line flow constraints are rigorously enforced, the market is cleared centrally and limited to single period operation, preventing privacy preserving distributed price formation and intertemporal storage coordination.

Decentralized transactive energy frameworks have also been proposed to couple market coordination with network feasibility. Abdolahinia et al. [22] introduced a decentralized transactive energy market in which agents coordinate trades through a primal dual algorithm and network feasibility is enforced using AC OPF based network usage fees. While the framework rigorously models voltage, congestion, and losses, it remains single period and does not incorporate time coupled storage dynamics or multi period market clearing.

A recurring limitation in much of the distributed optimization literature is the lack of intertemporal modeling. Zhao et al. [23] addressed this gap by proposing a decentralized P2P energy trading framework with shared energy storage coordinated over a multi period horizon using Stackelberg game modeling. However, physical distribution network constraints are abstracted, and pricing relies on heuristic supply demand ratios rather than optimization driven congestion aware prices.

More recent work has attempted to bridge distributed optimization, storage, and network constraints through hierarchical coordination. Habib et al. [10] proposed a tri level hierarchical optimization framework solved using hierarchical distributed ADMM to coordinate smart homes, microgrids, and the NO under network constraints and time coupled storage. While the framework enforces physical feasibility and intertemporal coupling, market coordination is hierarchical and price signals are imposed top down rather than emerging from distributed peer to peer market clearing.

Beyond electricity only systems, Schinke Nendza et al. [17] proposed a fully distributed ADMM based market clearing framework for coupled electricity and gas networks, where network operators and market agents iteratively negotiate quantities and prices while preserving privacy. Although the framework rigorously integrates network constraints and intertemporal flexibility through gas linepack and power to gas coupling, it is designed for transmission level coordination and does not consider distribution level P2P trading or battery-based storage. In a similar way, distributed optimization schemes that use integrated blockchain infrastructure for distributed power system operations have been proposed, but in all of these studies, blockchain is used for synchronizing/communicating between distributed controllers, not for decentralized market settlements [18].

In summary, distributed optimization has been widely applied to decentralized energy coordination, but existing approaches exhibit clear tradeoffs. Methods that rigorously enforce network constraints often rely on centralized or hierarchical coordination, while fully distributed approaches typically abstract the electrical network or restrict operation to single period markets. Frameworks that incorporate time coupled storage rarely integrate PTDF-based network constraints and congestion aware price formation within a distributed market clearing setting. These limitations motivate the need for a distributed market-clearing framework that simultaneously preserves agent privacy, enforces physical network feasibility through explicit constraints, and supports intertemporal coordination of storage decisions.

2.3 ADMM and Convex Optimization Methods

The alternating direction method of multipliers (ADMM) is a decomposing approach that breaks down a convex optimization problem into smaller subproblems that are easier to solve [11]. ADMM takes advantage of decomposability in dual decomposition and combines it with the great convergence performances of the method of multipliers. It is a very robust method regarding problem scaling and hence, it has been extremely successful in performing distributed large-scale optimizations together with non-smooth objective functions.

In practice, the energy system's agent could utilize the ADMM algorithm in dealing with their local optimization problem while remaining coordinated through shared variables, as well as dual variables (Lagrange multipliers). Boyd et al. [11] offer a detailed analysis on the alternating direction method of multipliers, considering the performance of the algorithm in dealing with convex optimization problems, as well as practical guidelines on how the algorithm's parameters could be tuned in order to increase the rate of convergence. The scaled form of the ADMM has become the most used form in practice due to its ease in handling the dual variables' updates. Recent works have also explored the integration of ADMM-based distributed optimization with blockchain technology for improved trust and data integrity in distributed coordination. However, these works mainly deal with the optimization problems in the operation of the grid, such as the optimal power flow problem, instead of energy trading and settlement [18].

Paudel and Gooi [24] propose a consensus-based ADMM algorithm in developing a distributed pricing mechanism in the context of a peer-to-peer energy trading system in a community microgrid. In the proposed system, a market operator is responsible in updating the prices while ensuring the privacy of the prosumers as well as the consumers. The proposed system successfully implements a welfare-maximizing price discovery in a distributed manner. However, the system does not consider the physical power network, as well as a single-period market without the need to consider the storage constraints in the different periods.

Existing studies have extensively demonstrated the utilization of the distributed optimization technique in the energy management system. In this regard, Xiong et al. [12] offered a comprehensive review on the distributed energy cooperative control and optimization, as well as the drawbacks of the centralized energy management system, highlighting the importance of the distributed optimization in dealing with the energy storage constraints. However, the review focuses on the control as well as the optimization, while the distributed market clearing, as well as the price formation, are not considered. In this thesis, a consensus-based ADMM algorithm is utilized in dealing with the bilateral peer-to-peer energy trading, the congestion in the energy networks, as well as the battery storage in a single welfare-maximizing market clearing.

2.4 Blockchain Applications in Energy Markets

Blockchain technology has been recognized as a key enabling technology for decentralized energy markets, as it can provide transparent, tamper-proof, and auditable transaction records without relying on central authorities [5], [6], [9]. For peer-to-peer energy trading, blockchain is recognized as a trust layer, as it can provide secure settlements, data integrity, and automated execution using smart contracts [6], [7]. Previous research has demonstrated the feasibility of blockchain-based peer-to-peer energy trading platforms, especially in terms of transaction recording and payment settlements [7], [9]. For example, Yang et al.[6] proposed a blockchain-based decentralized energy management system for a VPP, using time-linked storage scheduling with primal-dual optimization. However, the physical power grid was not considered, and there was no enforcement of market clearing with grid constraints, limiting its feasibility to conceptual validation. While early instances of blockchain-based local energy markets, such as actual demonstrations of microgrid-based trading, have been shown to be technically feasible, they often utilize simplistic market structures and do not involve optimization-based market clearing or constraints [25].

Similarly, systematic reviews of existing literature have pointed out certain limitations in existing blockchain-based energy trading systems. Andoni et al. [5] classify peer-to-peer energy trading as one of the main applications of blockchain technology in the energy sector. However, it is also noted by these researchers that many solutions proposed in this area mainly focus on transactional systems, digital marketplaces, etc. The above literature has demonstrated clearly that blockchain technology alone cannot provide efficient and physically feasible energy trading without proper integration with power system models and optimization methods.

Some blockchain-based trading frameworks with storage and multi-agent coordination have been proposed, but they still rely on heuristic pricing and negotiation. For example, Huo and Xun [26] proposed a blockchain-based peer-to-peer energy trading framework with time-coupled storage for interconnected microgrids, and Liu et al. [27] developed a blockchain-based platform for optimization and trading of multiple microgrids with a virtual power plant. Although optimization is performed, it is not done online, and constraints are not considered. The prices are determined either with centralized supervision or with external prices.

Some recent studies have focused on improving transparency and autonomy using forecasting and scheduling. For example, Umar et al. [7] and Shorya and Jagwani [9] developed blockchain-based energy trading platforms with smart meters, load forecasting, generation forecasting, and scheduling using smart contracts. Although these studies improve transparency and digital autonomy, they still do not formulate optimization problems, do not consider physical constraints, and do not include time-coupled storage. The feasibility of energy trading is not ensured.

Recent reviews have provided more insight into the application of blockchain technology in energy systems. For example, Hong et al. [8] provided a comprehensive review of blockchain applications in VPPs, along with conceptual roadmaps for their future development. Although they emphasized the application of blockchain technology as a data management and settlement layer, they did not address optimization-based market clearing mechanisms, physically feasible trading frameworks, and optimization problems. In addition to settlement applications, there has been an exploration of blockchain-based secure communication infrastructure for distributed control and coordination of microgrid systems; however, such investigations focus on cybersecurity and control aspects rather than on decentralized markets [28].

Most blockchain energy studies are limited as they consider the weak integration of physical energy delivery and digital settlement at the blockchain level. There are some centralized/heuristic approaches to market clearing which are done offline, while the blockchain is used to log-in transactions and execute payments. This separation creates layers of trust and loses the ability to trustless verify optimized schedules. Specifically, participants in the market lack the ability to re-solve an optimization problem to satisfy network constraints at the trade settlement level. There are only a few studies that found means of bringing in the physical and optimized schedules settlement without the need to re-run the optimization algorithm on chain. Furthermore, the lack of integration of blockchain and Distributed Optimization is owing to the computational expense of on chain optimization.

In summary, existing blockchain enabled energy trading frameworks primarily address transparency, auditability, and settlement, while relying on external optimization and simplified grid models. There remains a clear need for architectures that explicitly separate optimization from settlement while ensuring verifiable linkage through auditable and enforceable outcomes, enabling scalable, network-constrained, and optimization driven peer-to-peer energy markets with blockchain based enforcement. These observations motivate a framework in which optimization-based market clearing is performed off-chain under explicit network and storage constraints, while blockchain is used strictly as a verifiable settlement and enforcement layer.

2.5 Energy Storage and Intertemporal Coordination

This subsection reviews prior work on energy storage and multi-energy coordination only as far as it relates to intertemporal coupling and market coordination, rather than detailed modeling of non-electrical energy carriers. Energy storage has been widely studied as a key enabler of flexibility in future energy systems [12], enabling load shifting, renewable integration, and intertemporal optimization. Similar to the centralized microgrid energy management strategies, the potential for time-coupled storage scheduling has also been studied. In the study by Hai et al. [29], the authors presented a microgrid energy management strategy that incorporates renewable energy sources, battery storage devices, and price signals while accounting for the state-of-charge constraint over multiple time periods.

In terms of shared energy storage devices, their potential for coordinating energy consumption among multiple microgrids has also been studied. In the research by Gholami et al. [30], the authors presented a study on the centralized coordination of shared battery storage devices for residential and commercial microgrids and presented results on the potential for time-coupled storage scheduling to improve load balancing and reduce peak demand.

Several studies have investigated peer-to-peer or community-level energy trading with explicit modeling of storage and multi-energy interactions. Cheng et al. [13] proposed a two-stage P2P multi-energy market in which a centralized optimizer enforces power, gas, and heat network constraints, while bilateral electricity and heat trades are cleared through an iterative double-auction mechanism. Although the framework integrates coordinated storage and realistic network models, market clearing relies on centralized dispatch and rule-based auction pricing rather than distributed optimization with endogenous congestion-aware prices. Valipour et al. [31] have presented a powerful optimization tool for P2P trading among multiple microgrids, taking into consideration network constraints and storage effects, even in uncertain scenarios. Still, in these P2P transactions, they are co-optimized and settled based on external prices. Thus, the freedom of action of the participants is restricted, and price formation based on natural market forces is not possible.

Other researchers have studied hierarchical or operator-based coordination, particularly in scenarios with abundant storage. Zhang et al. [32] have proposed a bi-level robust energy management system based on a Stackelberg game structure among a community operator and residential prosumers, considering time-coupled battery storage and EV storage. Even though they have effectively accounted for intertemporal flexibility, they have neglected electrical network effects in their model. Also, they have given priority to the operator in determining prices. There is a common characteristic in all these studies. In scenarios with abundant storage capacity and multiple energy sources, it is natural to have a high degree of coordination. However, this coordination is usually based on hierarchical optimization. Even in scenarios with P2P trading, it is usually based on a secondary layer over hierarchical optimization or heuristic price determination [32]. This thesis differs from previous storage-centric approaches in that it incorporates time-coupled battery storage in a distributed P2P market-clearing model.

2.6 Comparative Insights from Survey Literature

There are several surveys and review articles that deal with distributed optimization, blockchain-based energy systems, and peer-to-peer energy trading in existing literature. These articles provide significant taxonomy and identify major challenges associated with distributed optimization, scalability, and coordination [33], [34]. These surveys also highlight that the existing literature is fragmented, and major components like market design, physical feasibility, storage coordination, and pricing are analyzed individually rather than in a comprehensive framework. Ahsan et al. in [33] provide a comprehensive taxonomy of networked microgrid pricing and trading strategies using optimization-based, game-theoretic, learning-based, and blockchain-based methods. The literature survey in [33] reveals that a small number of studies have dealt with network-constrained market clearing in conjunction with distributed optimization and time-coupled storage effects. Similarly, in another literature survey article, Wang et al. in [34] present a comprehensive overview of energy sharing mechanisms in virtual power plants and community energy systems. The literature survey reveals that several proposed models are based on hierarchical coordination and heuristic pricing without explicitly addressing distribution network constraints in a comprehensive framework. Although Davoudi et al. in [35] have focused mainly on centralized wholesale electricity markets, their literature survey reveals critical insights into the relationship between operational constraints and wholesale electricity prices. This is particularly relevant to peer-to-peer-based energy trading platforms, where network congestion and operational constraints should be represented in a comprehensive market clearing formulation to generate economically viable price signals.

2.7 Research Gaps

The literature review section points out that there is a major gap in terms of integration of network constraints, energy storage, and distributed coordination. Although there is research on network-constrained peer-to-peer markets [2], [3] and distributed optimization-based methods for energy management [10], [19], [22] only a few frameworks have been developed to integrate distributed coordination with network constraints using PTDF and multi-period battery storage with a scalable market-clearing mechanism. Although there is research on network-constrained P2P markets, it has been conducted only in a single period [1], whereas distributed optimization-based methods with battery storage often neglect the network or use a simple model of congestion [19], [22].

Quantitative assessment of distributed markets: Although there is a large number of research works on distributed optimization methods that focus on convergence and feasibility of distributed optimization methods, there is limited research on evaluating the economic performance of distributed markets regarding distributed optimization methods.

Third, the connection between optimization-based market clearing and blockchain-based settlement is still weak in the current literature. Although blockchain technology has been recognized as an important facilitator of peer-to-peer trading in microgrids [5], [6] in most frameworks, market clearing is considered as an independent process and blockchain is only applied to facilitate transaction recording and payment settlement [7], [9]. While blockchain-based trading platforms have shown promising features in transparent trading record-keeping and automated settlement through smart contracts, they still rely on externally derived trading decisions or market rules rather than optimization-based market clearing mechanisms [25], [36]. In addition, prior research on blockchain-based distributed optimization has mainly utilized blockchain as a communication tool and has not addressed the decentralized verification and settlement of peer-to-peer market outcomes [18].

This thesis fills these research gaps by proposing a blockchain-based decentralized energy management system for network-constrained microgrids. The system clearly separates market clearing and settlement and establishes a verifiable connection between them. The optimization-based market clearing is performed in a decentralized manner under explicit network and storage constraints, while blockchain-based smart contracts are applied to facilitate settlement in a verifiable and enforceable manner.

The proposed framework meets these objectives via the following steps:

- Development of a multi-period, network-constrained peer-to-peer market clearing model, considering time-coupled battery storage, and solving it via a consensus-based ADMM.
- Quantitative validation of the framework using a modified IEEE 14-bus test system, considering 25 agents, to attain an accuracy of 0.02% for welfare recovery, while ensuring the privacy of agents and scalability.
- Demonstration of the integration of off-chain optimization and on-chain smart contract settlement, allowing for the verification of thousands of energy trades without the need to execute computationally expensive optimization procedures.

To highlight the novelty of the proposed framework, Table 2.1 compares some of the prominent characteristics of the proposed framework and other representative works in the literature, considering market structure, network modeling, storage coordination, optimization, blockchain, and validation scale.

Table 2.1. Comparative literature summary

Ref.	**Market Type**	**Network Constraints**	**Time-Coupled Storage Modeling**	**Optimization Method**	**Blockchain Integration**	**Validation Scale**
[2]	P2P bilateral trading	PTDF-based line limits	Single period only	Dual decomposition	Not addressed	IEEE 14-Bus
[3]	P2P bargaining	PTDF and voltage constraints	Limited multi-period interaction; storage not fully integrated	ADMM-based	Not addressed	Building level
[19]	Hub-level P2P	Inter-hub power exchange limits	Time-coupled via Lyapunov optimization	ADMM	Not addressed	Multi-hub system

[10]	Hierarchical market	DC power flow and line limits	Time-coupled BESS and EVs	Hierarchical ADMM	Not addressed	IEEE 33 & 69-Bus
[8]	Review	Not modeled	Conceptual discussion	Not applicable	Conceptual roadmaps	Review paper
[9]	Forecast-driven scheduling	Not modeled	Not modeled	Rule-based scheduling	Smart contracts	Conceptual / small-scale validation
This work	**P2P social welfare maximization**	**PTDF-based line limits**	**Fully time-coupled SOC dynamics**	**Consensus ADMM**	**Smart contract settlement**	**IEEE 14-Bus, 25 agents**

As indicated by the literature review above, there is no existing framework that has successfully integrated all of the above-stated components of an energy system. Most of the existing research works have only focused on a subset of these components. For example, network-constrained P2P markets have not considered multi-period storage effects, while distributed optimization methods with storage integration often assume a simplified electrical grid or use a hierarchical coordination method. Similarly, blockchain-based energy trading systems have not considered optimization-based P2P market clearing. To fill this gap, Chapter 3 of this research work proposes a multi-period system model and a centralized social welfare maximization problem. This provides a mathematical foundation for the proposed framework and offers a reference solution to evaluate the feasibility of the subsequent distributed market-clearing method.

Chapter 3. System Model and Problem Formulation

Chapter 3 continues with the issues identified in Chapter 2, where the need for a unifying framework that can accommodate network constraints, storage, and distributed coordination was highlighted. Chapter 3 begins to take a rigorous mathematical approach, where a multi-period system model and a centralized social welfare optimization problem are presented.

3.1 Microgrid Architecture and Agent Types

We consider a networked microgrid system composed of a set of autonomous agents interconnected through a power network. Each agent is connected to a single bus and participates in a peer-to-peer energy trading market over a finite time horizon [2], [4].

Agents are classified into three categories:

- Sellers (prosumers with generation and optional storage),
- Buyers (consumers with flexible demand and optional storage),
- A passive Network Operator (NO).

The NO enforces network feasibility but does not participate in optimization, pricing, or welfare maximization. Table 3.1 summarizes the cost, utility, and operational parameters assigned to sellers and buyers in the simulations.

Table 3.1. Agent Parameters Used in the Simulation

Parameter	**Description**	**Sellers**	**Buyers**
α_i	Quadratic generation cost coefficient	✓	–
β_i	Linear generation cost coefficient	✓	–
γ_i	Constant cost per period (as implemented)	✓	–
ω_j	Utility scaling coefficient	–	✓
δ_j	Marginal disutility coefficient	–	✓
$x_i^{\min}, x_i^{\max}$	Generation limits (kW)	✓	–
$y_j^{\min}, y_j^{\max}$	Demand limits (kW)	–	✓
Storage flag	Indicates presence of battery storage	✓ / ✗	✓ / ✗
$s^{\min}, s^{\max}$	State of charge bounds (kWh)	✓ (if storage)	✗
s^0	Initial state of charge (kWh)	✓ (if storage)	✗
$s^{\text{final,min}}$	Minimum terminal state of charge (kWh)	✓ (if storage)	✗
$c^{\max}$	Maximum charging power (kW)	✓ (if storage)	✗
$d^{\max}$	Maximum discharging power (kW)	✓ (if storage)	✗
η_c	Charging efficiency	✓ (if storage)	✗
η_d	Discharging efficiency	✓ (if storage)	✗

All agent parameters are heterogeneous and loaded directly from the simulation data files. Cost and utility coefficients are selected to ensure convexity of the local optimization problems, while generation and demand limits reflect realistic operating constraints. Storage flags determine whether an agent is equipped with a battery system and subject to the storage dynamics defined in Section 3.6.

3.2 Time Horizon and Sets

The market is cleared over a discrete time horizon defined as

$$\mathrm{t} \in \mathcal{T} = \{1,2,\dots,\mathrm{T}\}, \quad \mathrm{T} = 24 \tag{3-1}$$

Let:

- $\mathcal{S}$ denote the set of sellers,
- $\mathcal{B}$ denote the set of buyers,
- $\mathcal{N} = \mathcal{S} \cup \mathcal{B}$ denote all agents,
- $\mathcal{L}$ denote the set of network lines.

3.3 Power Injection Model

For each agent $i \in \mathcal{N}$, the net active power injection at time t is denoted by $p_i(t)$.

Base Injection

For sellers without storage:

$$p_i(t) = x_i(t), i \in \mathcal{S} \tag{3-2}$$

For buyers without storage:

$$\mathrm{p_i(t)} = -\mathrm{y_i(t)}, \mathrm{i} \in \mathcal{B} \tag{3-3}$$

Injection with Storage

For agents equipped with battery storage:

$$\mathrm{p_i(t)} = \mathrm{p_i^{base}(t)} + \mathrm{d_i(t)} - \mathrm{c_i(t)} \tag{3-4}$$

where $c_i(t)$and $d_i(t)$denote charging and discharging power, respectively.

3.4 Seller Model

Each seller $i \in \mathcal{S}$ produces energy $x_i(t) \geq 0$.

Generation Constraints

$$x_i^{\min} \le x_i(t) \le x_i^{\max}, \forall t \in \mathcal{T} \tag{3-5}$$

If a time-varying generation profile is available:

$$x_i(t) \le \bar{x}_i(t), \forall t \in \mathcal{T} \tag{3-6}$$

Seller Cost Function

The generation cost is modeled as a convex quadratic function:

$$C_i(x_i(t)) = \alpha_i x_i(t)^2 + \beta_i x_i(t) + \gamma_i \tag{3-7}$$

This captures increasing marginal costs typical in generation units.

3.5 Buyer Model

Each buyer $j \in \mathcal{B}$ consumes energy $y_j(t) \ge 0$.

Demand Constraints

Buyer consumption is bounded by minimum and maximum demand:

$$y_j^{\min} \le y_j(t) \le y_j^{\max}, \forall t \in \mathcal{T} \tag{3-8}$$

If a time-varying load profile is available:

$$y_j(t) \le \bar{y}_j(t), \forall t \in \mathcal{T} \tag{3-9}$$

Buyer Utility Function

The buyer utility is modeled as:

$$U_j(y_j(t)) = \omega_j \log(1 + y_j(t)) - \delta_j y_j(t) \tag{3-10}$$

This function captures diminishing returns from increased energy usage and disutility from overconsumption [4].

3.6 Battery Energy Storage Model

For agents equipped with battery storage, the state of charge evolves according to:

$$s_i(t+1) = s_i(t) + \eta_c \Delta t\, c_i(t) - \frac{\Delta t}{\eta_d} d_i(t), \quad \forall t \in \mathcal{T} \tag{3-11}$$

Where:

Δt = duration of each time interval (hours). Charging and discharging are adjusted for efficiency losses.

Storage Constraints
The SoC must remain within its allowable range:

$$s_i^{\min} \leq s_i(t) \leq s_i^{\max}, \qquad \forall t \in \mathcal{T} \tag{3-12}$$

Initial and final SoC conditions are enforced to ensure proper cycling:

$$s_i(0) = s_i^{\text{init}}, \qquad s_i(T) \geq s_i^{\text{final}} \tag{3-13}$$

Charging and discharging power are limited:

$$0 \leq c_i(t) \leq c_i^{\max}, \quad 0 \leq d_i(t) \leq d_i^{\max}, \qquad \forall t \in \mathcal{T} \tag{3-14}$$

To preserve convexity, simultaneous charging and discharging is not explicitly prohibited in the model. Instead, a small penalty term is added to the objective function:

$$-\boldsymbol{\lambda_{cd}} \sum_{t \in \mathcal{T}} (\boldsymbol{c_i(t)} + \boldsymbol{d_i(t)}) \tag{3-15}$$

This discourages non-physical simultaneous operation without introducing binary variables, which would lead to a mixed-integer formulation and increase computational complexity. In practice, efficiency losses and the penalty term prevent this behavior from being binding in the simulation results.

3.7 Power Balance Constraint

At each time step, the total net power injection across all agents must equal zero:

$$\sum_{i \in \mathcal{N}} p_i(t) + p^{\text{imp}}(t) = 0, \qquad \forall t \in \mathcal{T} \tag{3-16}$$

A nonnegative grid import variable $p^{\text{imp}}(t) \geq 0$ is introduced to ensure feasibility of the optimization problem under all operating conditions. This variable represents external energy supplied from the upstream grid when local generation and storage are insufficient to meet demand.

3.8 Network Model Using PTDF

Line flows are calculated using Power Transfer Distribution Factors (PTDF), which provide a linear mapping between nodal injections and line flows under the DC power flow approximation [1], [2]. For each line $\ell \in \mathcal{L}$, the flow is given by:

$$f_\ell(t) = \sum_{i \in \mathcal{N}} \text{PTDF}_{\ell i}\ p_i(t), \quad \forall t \in \mathcal{T} \tag{3-17}$$

The PTDF matrix provides a linear sensitivity relationship between nodal injections and line flows under the DC power flow approximation.
In the implementation, injections are represented at the agent level rather than directly at buses. Each agent is mapped to a bus, so the nodal injection vector can be written as $p_{\text{bus}}(t) = M\,p_{\text{agent}}(t)$, where M is the agent-to-bus incidence matrix is. Consequently, line flows are computed as $f(t) = \text{PTDF}_{\text{bus}}\,p_{\text{bus}}(t) = (\text{PTDF}_{\text{bus}}M)\,p_{\text{agent}}(t)$, which is equivalent to using an agent-level PTDF matrix.

PTDF Matrix Construction

The PTDF matrix is computed based on the DC power flow formulation as [2], [3]:

$$\text{PTDF} = \text{B}_{\text{line}} \cdot \text{A} \cdot \text{B}^{-1} \tag{3-18}$$

where:

A: network incidence matrix

B_{line}: diagonal matrix of line susceptance

B^{-1}: inverse of the reduced admittance matrix (excluding slack bus)

The main test framework utilizes a modified version of the IEEE 14-bus benchmark system with 25 agents and 20 active lines, based on the MATPOWER implementation of the IEEE 14-bus test case [37]. The parameters of the network are used to compute the Power Transfer Distribution Factor matrix and to impose line flow limits on the market clearing problem.

The parameters of the lines of the modified IEEE-14 bus and IEEE-33 bus network used for the simulations are presented in Table 3.2. and Table 3.3 Line Parameters of the Modified IEEE-33 Bus Network The parameters include the line resistance r_ℓ, the line reactance x_ℓ, and the line capacity limits $\bar{f}_\ell$. In the DC power flow approximation used in the current study, only the reactance values are used to compute the network susceptance matrix.

Table 3.2 Line Parameters of the Modified IEEE-14 Bus Network

Line ℓ	From Bus	To Bus	r_ℓ(p.u.)	x_ℓ(p.u.)	Thermal Limit $\bar{f}_\ell$
1	1	2	0.01938	0.05917	15
2	1	5	0.05403	0.22304	5
3	2	3	0.04699	0.19797	2
4	2	4	0.05811	0.17632	2
5	2	5	0.05695	0.17388	8
6	3	4	0.06701	0.17103	9
7	4	5	0.01335	0.04211	6
8	4	7	0	0.20912	1.2
9	4	9	0	0.55618	0.76

10	5	6	0	0.25202	1.5
11	6	11	0.09498	0.19890	5
12	6	12	0.12291	0.25581	2
13	6	13	0.06615	0.13027	2
14	7	8	0	0.17615	20
15	7	9	0	0.11001	7
16	9	10	0.03181	0.08450	5
17	9	14	0.12711	0.27038	5
18	10	11	0.08205	0.19207	5
19	12	13	0.22092	0.19988	19
20	13	14	0.17093	0.34802	14

Table 3.3 Line Parameters of the Modified IEEE-33 Bus Network

Line ℓ	From Bus	To Bus	r_ℓ (p.u.)	x_ℓ (p.u.)	Thermal Limit $\bar{f}_\ell$
1	1	2	0.005753	0.002932	3.5
2	2	3	0.03076	0.015667	3.5
3	3	4	0.022836	0.01163	3.5
4	4	5	0.023778	0.01211	3.5
5	5	6	0.051099	0.044112	3.5
6	6	7	0.01168	0.038608	3.5
7	7	8	0.044386	0.014668	2.5
8	8	9	0.064264	0.04617	2.5
9	9	10	0.065138	0.04617	2.5
10	10	11	0.012266	0.004056	2.5
11	11	12	0.02336	0.007724	2.5
12	12	13	0.091592	0.072063	2.5
13	13	14	0.033792	0.04448	2.5
14	14	15	0.036874	0.032818	2.5
15	15	16	0.046564	0.034004	2.5
16	16	17	0.080424	0.107378	2.5
17	17	18	0.045671	0.035813	2.5
18	2	19	0.010232	0.009764	1.8
19	19	20	0.093851	0.084567	1.8
20	20	21	0.02555	0.029849	1.8
21	21	22	0.04423	0.058481	1.8
22	3	23	0.028152	0.019236	1.8
23	23	24	0.056028	0.044243	1.8
24	24	25	0.055904	0.043743	1.8
25	6	26	0.012666	0.006451	1.8
26	26	27	0.017732	0.009028	1.8
27	27	28	0.066074	0.058256	1.8
28	28	29	0.050176	0.043712	1.8
29	29	30	0.031664	0.016128	1.8
30	30	31	0.060795	0.060084	1.8
31	31	32	0.019373	0.02258	1.8
32	32	33	0.021276	0.033081	1.8

3.9 Line Capacity Constraints

Each line must operate within its thermal limits:

$$-\bar{f}_\ell \le f_\ell(t) \le \bar{f}_\ell, \quad \forall \ell \in \mathcal{L}, \quad \forall t \in \mathcal{T} \tag{3-19}$$

3.10 Centralized Social Welfare Maximization

The centralized benchmark problem maximizes total social welfare, following a standard formulation used in electricity market optimization and peer-to-peer energy trading models [2], [3], [4]:

$$\max_{\{x,y,c,d,s,p^{imp}\}} \sum_{t=1}^{T} \left(\sum_{j \in \mathcal{B}} U_j \left(y_j(t) \right) - \sum_{i \in \mathcal{S}} C_i\left(x_i(t)\right) - C^{\text{imp}} \cdot p^{\text{imp}}(t) \right) \tag{3-20}$$

A large penalty coefficient C^{imp} is assigned to grid import to discourage its use under normal conditions, ensuring that local generation and peer-to-peer trading are prioritized. The grid import variable is only utilized when necessary to maintain feasibility. The objective maximizes total social welfare defined as the difference between consumer utility and generation cost. The problem is convex and admits a globally optimal solution.

The centralized multi-period social welfare problem formulation is presented in Chapter 3, along with the physical and economic constraints of the system. This forms the basis and point of reference for the decomposition method. Chapter 4 follows this formulation and proposes a distributed solution based on a consensus ADMM.

Chapter 4. Distributed Optimization Using ADMM

In the last chapter, the centralized approach for the concept of social welfare over various time horizons was discussed. However, the problem with centralized optimization is the need for full information sharing and the complexity of the system when scaled. Thus, the limitations discussed in the last chapter provide the basis for the application of the proposed distributed approach based on consensus ADMM.

4.1 Distributed Market Clearing

The centralized welfare maximization problem in (3.20) requires full knowledge of agent-specific cost functions, utility parameters, and storage constraints. Such information is typically private and difficult to collect in practice. In addition, centralized optimization scales poorly with the number of agents and time periods [10], [11]. To address these challenges, this thesis adopts a consensus-based Alternating Direction Method of Multipliers (ADMM), which decomposes the centralized problem into local subproblems while guaranteeing convergence under convexity assumptions [11].

4.2 Variable Splitting and Consensus Constraint

To enable decomposition, each agent maintains a local estimate of its power injection $p_i(t)$, while a global consensus variable $z_i(t)$ is introduced [11].

The consensus constraint is defined as:

$$p_i(t) = z_i(t), \quad \forall i \in \mathcal{N}, \qquad \forall t \in \mathcal{T} \tag{4-1}$$

Constraint (4.1) enforces agreement between local agent decisions and system-wide feasible injections, enabling decentralized optimization while global feasibility is maintained through consensus.

4.3 Augmented Lagrangian Formulation

The augmented Lagrangian of the problem is given by, following the standard ADMM framework for convex optimization problems [11]:

$$\mathcal{L}_\rho = \sum_{t=1}^{T} \left(\sum_{j \in \mathcal{B}} U_j\left(y_j(t)\right) - \sum_{i \in \mathcal{S}} C_i\big(x_i(t)\big) \right) - \frac{\rho}{2} \sum_{i \in \mathcal{N}} \sum_{t=1}^{T} \parallel p_i(t) - z_i(t) + u_i(t) \parallel^2 \tag{4-2}$$

The augmented Lagrangian in (4.2) combines the social welfare objective with a quadratic penalty that discourages deviation from the consensus variables, where ρ controls the strength of coordination.

4.4 Local Agent Subproblems

At each iteration $k + 1$, agents solve local optimization problems and update consensus and dual variables according to the standard ADMM iterative procedure [13].

4.4.1 Seller Subproblem

For each seller $i \in \mathcal{S}$:

$$\max \sum_{t=1}^{T} \left(-C_i(x_i(t)) - \frac{\rho}{2} \parallel p_i(t) - z_i^{(k)}(t) + u_i^{(k)}(t) \parallel^2\right) \tag{4-3}$$

subject to (3.5)–(3.6), (3.12)–(3.17).

Each seller minimizes its generation cost while being softly penalized for deviating from the current consensus target.

4.4.2 Buyer Subproblem

For each buyer $j \in \mathcal{B}$:

$$\max \sum_{t=1}^{T} \left(U_j(y_j(t)) - \frac{\rho}{2} \parallel p_j(t) - z_j^{(k)}(t) + u_j^{(k)}(t) \parallel^2\right) \tag{4-4}$$

subject to (3.8)–(3.16).

Each buyer solves a local convex optimization problem that maximizes utility while maintaining consensus consistency.

4.5 NO Consensus Update Without Network Constraints

When network constraints are not enforced, the consensus update reduces to an averaging step:

$$\bar{q}^k(t) = \frac{1}{N} \sum_{j=1}^{N} (p_j^{k+1}(t) + u_j^k(t)), \qquad z_i^{k+1}(t) = (p_i^{k+1}(t) + u_i^k(t)) - \bar{q}^k(t) \tag{4-5}$$

In the absence of network constraints, the NO computes the consensus variable by averaging the shifted injections $(p_i + u_i)$. The update removes the system-wide mean so that the resulting consensus satisfies $\sum_i z_i\,(t) = 0$ at each time step. This corresponds to the standard scaled ADMM consensus step and enforces power balance while preserving dual consistency.

4.6 NO Projection with Network Constraints

When network constraints are enabled, the NO computes consensus injections by solving the following problem independently for each time step t:

$$\min_{\{z_i(t)\}} \sum_{i\in\mathcal{N}} \| z_i(t) - \hat{p}_i(t) \|^2$$

$$\text{s.t. } \sum_{i\in\mathcal{N}} z_i(t) = 0 \qquad (4\text{-}6)$$

$$-\bar{f}_\ell \le \sum_{i\in\mathcal{N}} \mathrm{PTDF}_{\ell i}\, z_i(t) \le \bar{f}_\ell, \qquad \forall \ell \in \mathcal{L}$$

Where;

$$\hat{p}_i(t) = p_i^{(k+1)}(t) + u_i^{(k)}(t) \qquad (4\text{-}7)$$

When network constraints are active, the NO computes feasible consensus injections by solving the projection problem in (4.6). This step minimally adjusts tentative agent injections to satisfy power balance and PTDF-based line flow limits. Agent-level bounds are enforced within the local subproblems, while the projection step enforces only coupled network constraints.

The structure of the distributed ADMM framework with network feasibility enforcement is illustrated in Figure 4.1.

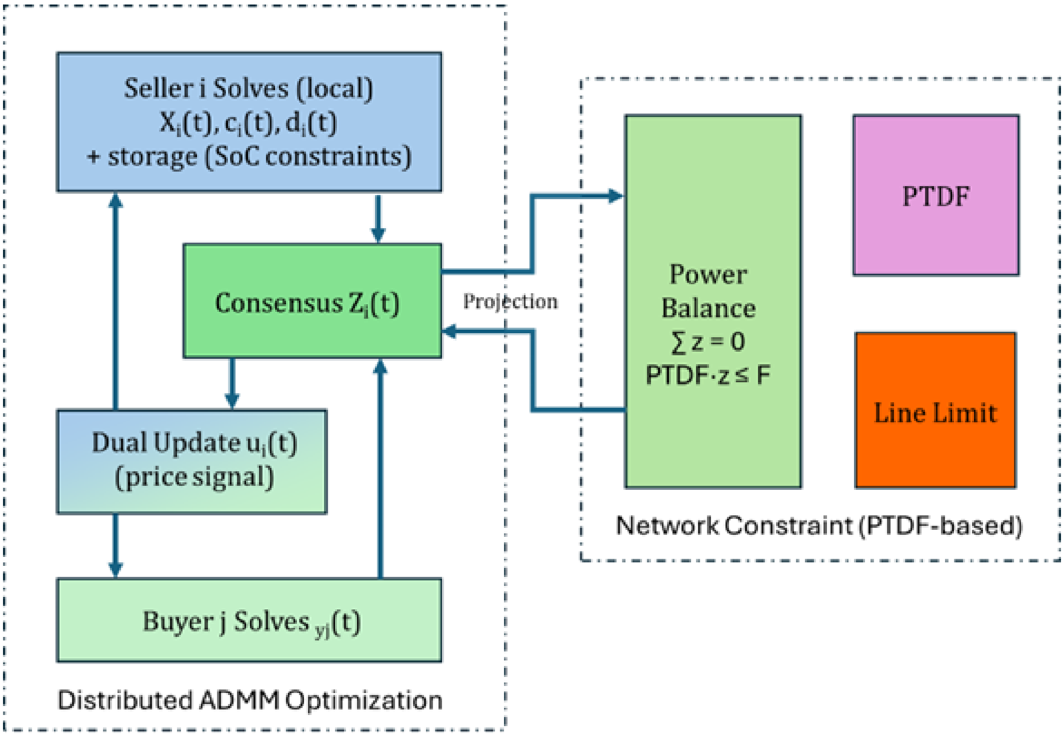


Figure 4.1. Distributed ADMM market clearing with PTDF-based network projection.

In the configuration shown in Figure 4.1, local optimization problems are solved for both sellers and buyers, while a distribution system operator performs a projection to meet the balance of power and satisfy line constraints based on PTDFs. The dual update serves as a price signal to drive the system to a consensus.

4.7 Dual Variable Update

The dual variables are updated as:

$$u_i^{(k+1)}(t) = u_i^{(k)}(t) + p_i^{(k+1)}(t) - z_i^{(k+1)}(t) \tag{4-8}$$

The algorithm uses scaled ADMM dual variables $u_i(t)$. In scaled form, the corresponding Lagrange multiplier is given by $\lambda_i(t) = \rho\, u_i(t)$, which represents the marginal value of enforcing the consensus constraint. In the implementation, a system-level price signal is recovered from the dual variables, while centralized benchmark prices are obtained directly from the power balance constraint dual.

4.8 Convergence Criteria

The convergence of the ADMM algorithm is evaluated using both primal and dual residuals, which measure consensus violation and dual feasibility, respectively. The primal gap is considered to be the difference between the local decision variables and the consensus variable, while the dual gap is considered to be the difference between the consensus variables at successive iterations. The convergence of the algorithm is reached when the gaps fall below the tolerance threshold.

$$\| r_{\text{pri}}^{(k)} \| \leq \varepsilon_{\text{pri}}, \| r_{\text{dual}}^{(k)} \| \leq \varepsilon_{\text{dual}} \tag{4-9}$$

Where;

$$r_{\text{pri}}^{(k)} = \sqrt{\textstyle\sum_{i\in\mathcal{N}} \sum_{t\in\mathcal{T}} \| p_i^{(k)}(t) - z_i^{(k)}(t) \|^2} \tag{4-10}$$

$$r_{\text{dual}}^{(k)} = \rho\sqrt{\textstyle\sum_{i\in\mathcal{N}} \sum_{t\in\mathcal{T}} \| z_i^{(k)}(t) - z_i^{(k-1)}(t) \|^2} \tag{4-11}$$

Additionally, line flow violations must satisfy:

$$\max_{\ell,t} \mid f_\ell(t) \mid \leq \bar{f}_\ell + \epsilon \tag{4-12}$$

In this study, the stopping tolerances are based on standard absolute and relative criteria, with $\varepsilon_{\text{abs}} = 10^{-4}$ and $\varepsilon_{\text{rel}} = 10^{-3}$. Accordingly, the primal and dual tolerances are computed at each iteration using these values rather than being fixed constants. These conditions ensure consensus consistency and physical feasibility simultaneously.

4.9 Selection of Penalty Parameter (ρ)

The penalty parameter ρ in the ADMM framework controls the trade-off between primal feasibility and dual convergence. It sets the importance of the consensus term in the Lagrangian multiplier and significantly influences the convergence rate and stability of the optimization process. When ρ is small, the convergence is very slow because the consensus is not properly enforced, while when ρ is high, oscillations may occur during the optimization process. In the current research work, a constant value of ρ is used throughout all experiments.

Algorithm 1
Distributed Peer-to-Peer Market Clearing with Network Constraints and Time-Coupled Storage

Input:
Sets $\mathcal{S}, \mathcal{B}, \mathcal{N}, \mathcal{L}, \mathcal{T}$;
Agent parameters (cost, utility, storage)
PTDF matrix and line limits
ADMM parameters ρ, $\varepsilon^{\{\text{pri}\}}$, $\varepsilon^{\{\text{dual}\}}$, K_{max}
Output:
Consensus injections $z_i^*(t)$
Agent schedules $x_i(t), y_j(t), c_i(t), d_i(t), s_i(t)$
Dual variables $u_i(t)$
Initialize $z_i^{(0)}(t) \leftarrow 0, u_i^{(0)}(t) \leftarrow 0\ \forall\ i \in \mathcal{N}, t \in \mathcal{T}$
Set iteration counter $k \leftarrow 0$
while $k < K_{max}$ and not converged **do**
    Local agent updates
    for each seller $i \in \mathcal{S}$ do
        Solve the seller subproblem (4.3) subject to constraints (3.5)–(3.6), (3.12)–(3.17).
        Update $p_i^{(k+1)}(t) \leftarrow x_i^*(t)$
    end for
    for each buyer $j \in \mathcal{B}$ do
        Solve the buyer subproblem (4.4) subject to constraints (3.8)–(3.16).
        Update $p_j^{(k+1)}(t) \leftarrow -y_j^*(t)$
    end for
    NO consensus update
    for each period $t \in \mathcal{T}$ do

if network constraints are not enforced then
  Update $z^{(k+1)}(t)$using (4.5)
else
  Compute $z^{(k+1)}(t)$ by solving the projection problem (4.6)
end if
end for
Dual variable update
for each agent $i \in \mathcal{N}$do
  Update dual variable:
  $u_i^{(k+1)}(t) \leftarrow u_i^{(k)}(t) + (p_i^{(k+1)}(t) - z_i^{(k+1)}(t))$
end for
Convergence check
Compute primal and dual residuals using (4.10)–(4.11)
(Optional) evaluate line flow violations using (4.12)
Update iteration counter $k \leftarrow k + 1$
end while
Return final consensus injections $z_i^*(t)$ and corresponding agent schedules.

Algorithm Overview

Algorithm 1 presents a consensus-based alternating direction method of multipliers (ADMM) framework, where local economic decisions are decoupled from system-wide feasibility. Here, both sellers and buyers perform local optimization problems using their own information, while a passive distribution system operator simply takes a projection onto power balance and line flows, as determined by PTDFs. The dual variables guide all agents toward consensus over time, with economic and physical convergence occurring simultaneously. To summarize the interaction between physical agents, the distributed optimization process, and the post-clearing settlement mechanism, the overall system architecture is illustrated in Figure 4.2.

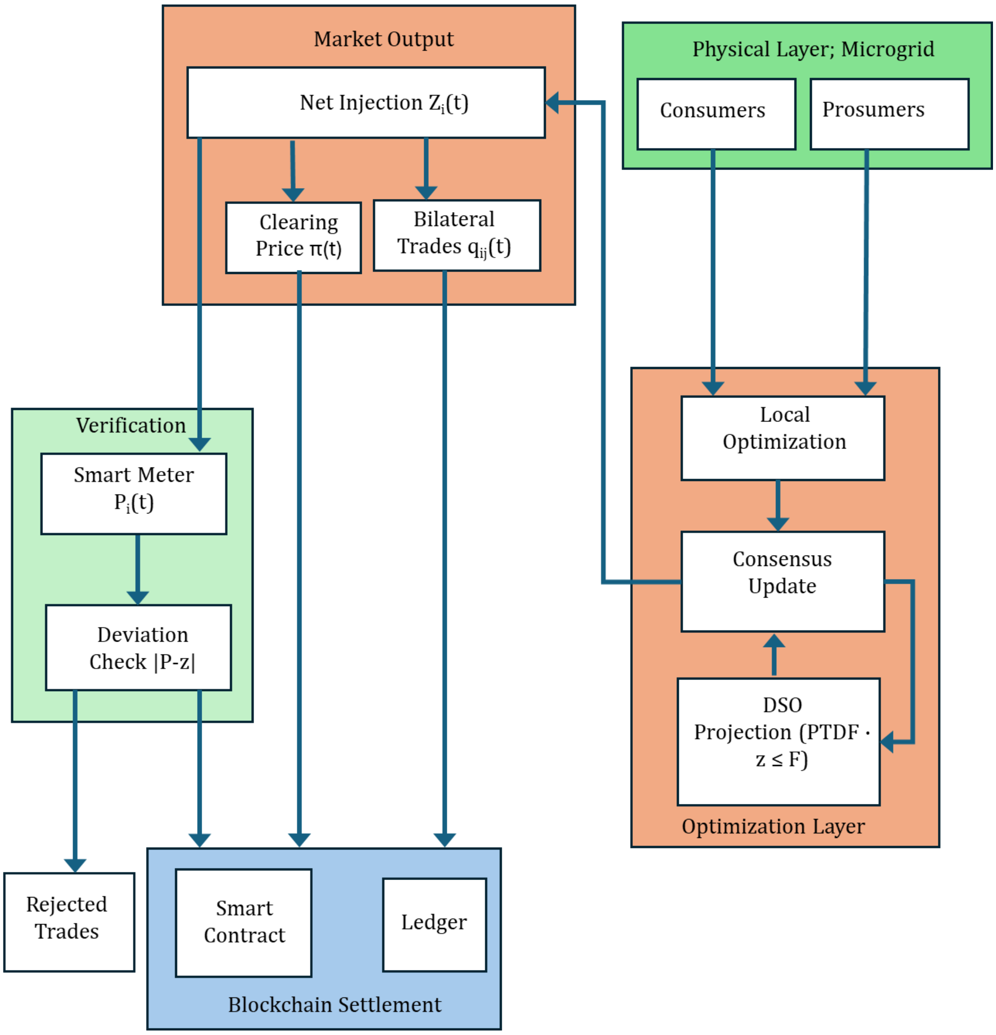


Figure 4.2 Blockchain-Enabled Distributed Energy Management System Architecture

Figure 4.2 shows Layered architecture of the proposed blockchain-enabled distributed peer-to-peer (P2P) energy management framework for network-constrained microgrids. The physical layer consists of consumers and prosumers participating in energy trading within the microgrid. In the optimization layer, each agent performs local optimization, followed by a consensus update coordinated through a NO projection step that enforces power balance and PTDF-based line flow constraints. The resulting market output includes net injections $z_i(t)$, clearing prices $\pi(t)$, and bilateral trades $q_{ij}(t)$. In the verification layer, smart meters measure actual injections $P_i(t)$, and deviations from scheduled injections are checked. Verified trades proceed to the blockchain settlement layer, where smart contracts record transactions on the ledger, while non-compliant trades are rejected.

Chapter 4 provides the distributed optimization framework and its guarantee for convergence and feasibility, but it does not address how the generated schedules are validated and implemented in practice. Chapter 5 provides the answer by introducing a blockchain-based settlement layer that enables verifiable and tamper-resistant execution of market results.

Chapter 5. Blockchain-Based Verification and Settlement

Chapter 5 builds on the proposed framework for distributed optimization, which is presented in Chapter 4 and ensures that the results are both feasible and optimal. However, these results must be verified and implemented in a decentralized manner. In the context of decentralized energy systems, there are several operational needs that must be met, such as trust and transparency among the participants, and the tamper-resistant recording of all transactions. One such technology is blockchain technology, which has the potential to provide verifiable results for the proposed market outcomes. In fact, the proposed use of smart contracts based on blockchain technology for the promotion of transparency in decentralized energy transactions and peer-to-peer electricity markets has been proposed [15], [38] . Thus, Chapter 5 discusses the mechanism for verification using blockchain technology.

5.1 Role of Blockchain in the Proposed Framework

The blockchain layer has the role of ensuring verifiable execution and tamper-resistant settlement of cleared market results. All economic decisions, including pricing, congestion management, and trade matching, are computed off-chain using the distributed alternating direction method of multipliers algorithm, as discussed in Chapter 4. This is done intentionally, because optimization requires iterative numerical computation, including the exchange of dual variables, which is not suitable for implementation on the blockchain platform considering latency and computational overhead constraints.

Distributed optimization methods, such as the alternating direction method of multipliers, have been extensively used for distributed control of distributed energy resources and microgrid energy management systems. This allows independent entities to solve their optimization problems while maintaining privacy and autonomy for the participants [15], [39].

On the same context, blockchain technology has been considered as a safe platform for the development of decentralized coordination and data exchange in the power system. Blockchain-based systems have been suggested for the development of trusted communication and synchronization between the distributed control elements in the energy systems[18], [40].

Instead of integrating the optimization process with the blockchain technology, the suggested architecture clearly defines the optimization and settlement processes. The optimization process occurs outside the blockchain technology, and the blockchain technology only records the results after the optimization process has converged. The integrated system has four layers, which work simultaneously with each other.

Optimization Layer: This layer performs distributed market clearing and computes feasible schedules that define the net power injections for all agents in a way that satisfies power balance and constraints of the networks. Distributed optimization is widely used to manage distributed energy resources and control microgrid operation [15], [41].

Metering Layer: Smart meters measure actual energy injection and withdrawal for all agents at each interval. Advanced metering infrastructure is at the heart of modern smart grids and is essential for monitoring, control, and decision-making [42].

Verification Layer: Actual values are compared with scheduled values obtained from the optimization layer before executing the settlement process.

Settlement Layer: Verified values are recorded and executed through smart contracts implemented via blockchain technology.

The interaction of all layers is presented in Figure 5.1, showing data exchange between the optimization process and smart contract execution.

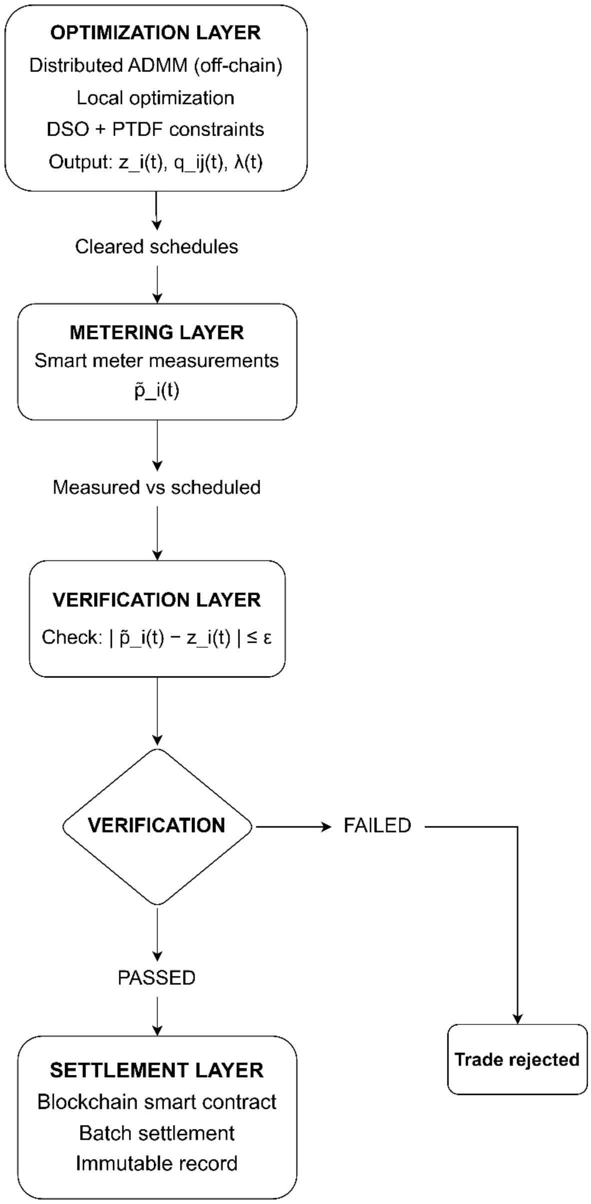


Figure 5.1 Data flow from distributed optimization to blockchain settlement.

The blockchain layer only receives trade schedules after convergence and is not involved in the determination of variables in the optimization process, updates of dual values, and enforcement of network feasibility constraints.

5.2 Trade Representation and Market Outputs

At convergence of the distributed algorithm, three main results are obtained:

- The total injection schedule of each agent
- The bilateral transactions between the sellers and the buyers
- The prices at each time step

The reference framework might influence the definition of the price. For example, in the context of centralized optimization problems, prices are considered to be related to the marginal cost of generation. For distributed ADMM-based approaches, prices are generally related to the dual variables of the power balance constraint. ADMM-based distributed approaches to the market-clearing problem have been widely used for the coordination of decentralized energy systems and P2P trading of electricity [43], [44].

To define the settlement price, the marginal cost of each seller is derived as the derivative of the cost function of each seller, which is quadratic.

$$\mathrm{MC_i(t)} = 2\alpha_\mathrm{i}\mathrm{x_i(t)} + \beta_\mathrm{i} \tag{5-1}$$

Based on these marginal costs, the settlement price is computed as a weighted average across all active sellers

$$\pi(t) = \frac{\sum_{i\in\mathcal{S}} MC_i(t)\, x_i(t)}{\sum_{i\in\mathcal{S}} x_i(t)} \tag{5-2}$$

This formulation ensures that the settlement price reflects the aggregated marginal cost of energy supply while remaining consistent with the dispatched generation schedules.

The bilateral trades are derived from the aggregate market results. The demand allocated by each buyer is distributed proportionally according to the generation contribution of each seller;

$$q_{ij}(t) = \frac{x_i(t)}{\sum_{k\in\mathcal{S}} x_k(t)}\, y_j(t) \tag{5-3}$$

Thus, the arrangement remains consistent with dispatched trades. Each buyer receives the demanded amount while each seller supplies the generated amount.

The monetary value of each transaction is derived from the quantity traded and the clearing price.

$$v_{ij}(t) = q_{ij}(t)\, \pi(t) \tag{5-4}$$

Each bilateral transaction can therefore be expressed as

$$\big(i, j, t, q_{ij}(t)\big) \tag{5-5}$$

The above results comprise the complete set of market outputs transmitted to the verification and blockchain settlement layer.

5.3 Smart Meter Verification Mechanism

For each agent i and time t, the smart meter reports measured power:

$$\tilde{p}_i(t) \tag{5-6}$$

Verification is performed by checking the consistency between cleared schedules and measured injections:

$$| \tilde{p}_i(t) - z_i(t) | \leq \epsilon \tag{5-7}$$

where ε denotes an allowable measurement tolerance.

This condition ensures that settlement reflects delivered energy rather than planned quantities alone. Trades failing the verification tolerance are rejected prior to contract execution.

Smart meters and advanced metering infrastructures are essential for enabling accurate measurement of distributed energy resources and supporting real-time monitoring of power systems [42], [45].

5.4 Smart Contract Structure and Batch Settlement

The smart contract has a well-structured, though restricted, repertoire of operations, consisting of:

- Registration of authorized agents, along with their corresponding smart meters.
- Submission of cleared tuples of bilateral trade.
- Verification of metered injections.
- Execution of settlement for verified trades.

To reduce the overhead of individual on-chain transaction costs, trades are settled in batches rather than individually. Let Q represent the set of verified trades over the market horizon. Then, the process of settling trades is given by:

$$\text{settle}(Q) \tag{5-8}$$

The process of batch execution combines trades within a single contract invocation, hence reducing the total number of trades and the corresponding computational costs.

In numerical experiments, the total number of bilateral trades verified and settled using the batch mechanism was 2,808, with no failures in the settlement process. The contract logic does not include optimization, pricing, or congestion management, and its only purpose is to ensure the settlement of the results, which were pre-clearing and verified. Smart contracts based on blockchain technology have been suggested for the purpose of automating the settlement process and promoting transparency in P2P electricity trading systems [38], [46]. The interaction between the wallet of the seller or buyer, the off-chain optimization engine, the metering entity, and the settlement process has been shown in Figure 5.2, which has been captioned "Sequence of Off-Chain Market Clearing and Wallet-Based Settlement."

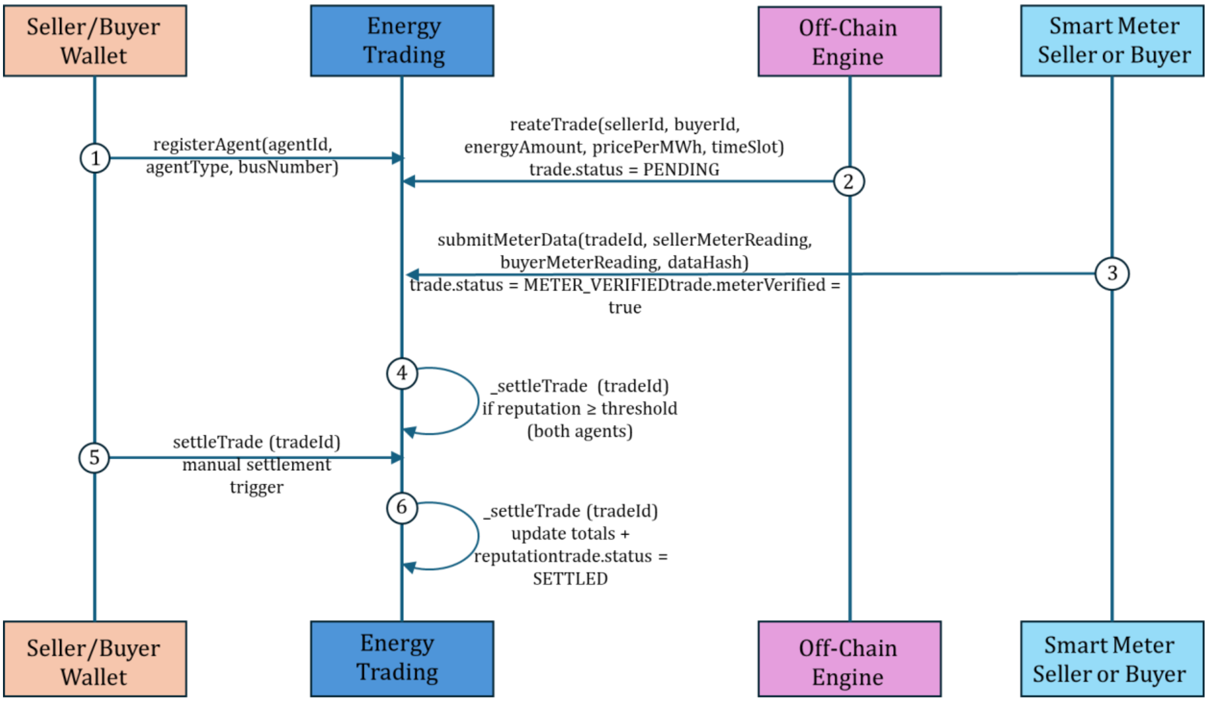


Figure 5.2. Sequence of off-chain market clearing and wallet-based settlement.

As shown in Figure 5.2, the trade requests are initiated by the wallet of the participants, and the process goes through the optimization engine and the settlement process as indicated.

5.5 Implementation Environment and Security Considerations

The settlement framework is executed in a blockchain development environment for functional verification. The evaluation criteria include:

- Correct execution of verification rules.
- Consistency and immutability of recorded trades.
- Viability of batch settlement at the level of testing.

Performance benchmarking of public networks, gas costs, and consensus latency is not considered in this work.

From the perspective of security, the framework offers:

- Protection against unilateral modification of cleared trades
- Immutable records of settlement outcomes
- Independent auditability of transactions

Blockchain technologies have been extensively recognized for offering benefits in terms of transparency, trust, and invariability in decentralized energy systems and peer-to-peer electricity markets [46], [47]. Privacy-critical information such as agent cost functions, internal constraints, and optimization variables remains outside the blockchain. Only verified outcomes of trades are recorded in the blockchain ledger. By separating optimization and settlement, verifiable execution is achieved without imposing computational burdens of blockchain implementation on the distributed market clearing process.

The next chapter presents numerical experiments for evaluating the framework's performance. Having discussed the framework's optimization and settlement layers, it is essential to assess its effectiveness. Therefore, Chapter 6 discusses numerical experiments for evaluating the framework's performance in terms of convergence rate, economic efficiency, feasibility of networks, and reliability of blockchain-based settlement outcomes.

Chapter 6. Simulation Results and Performance Analysis

This chapter extends the integrated optimization and settlement model that has been developed in Chapters 4 and 5. To evaluate the efficiency of the model that has been developed in this study, a quantitative analysis is necessary. For this purpose, numerical simulations of the model will be carried out.

6.1 Overview of Numerical Experiments

In this chapter, the evaluation of the proposed distributed peer-to-peer energy management framework is performed through numerical experiments on IEEE benchmark networks. The results include performance in terms of convergence, economic optimality, feasibility, scalability, and performance in the settlement layer. The simulation results are obtained based on the implementation provided in Chapter 5. The optimization layer is implemented in Python, utilizing the CVXPY library, while the CLARABEL and SCS libraries are used in the centralized and distributed optimization, respectively. The blockchain-based settlement layer is implemented in Solidity using a local Ethereum test environment via Hardhat, while the development environment is Visual Studio Code. The Python scripts are used to connect the optimization layer with the blockchain layer, allowing the experiments to be performed in a controlled environment. The results provided in this chapter are based on the results obtained by the solvers. The experiments are performed in four stages: centralized optimization, distributed optimization, network utilization, and blockchain-based experiments.

6.2 Test Systems and Simulation Setup

6.2.1 IEEE Test Networks

The experiments were performed on the IEEE 14-bus network as benchmark and IEEE 33-bus network. The IEEE 14-bus system was originally intended as a transmission test system. The IEEE 14-bus network is here intended as a proxy for the study of coordination, congestion, and market effects in a network-constrained environment. The choice of the system is motivated by the need for a meshed network that presents non-trivial power flow effects and congestion. The spatial distribution of agents in the network is shown in Figure 6.1.

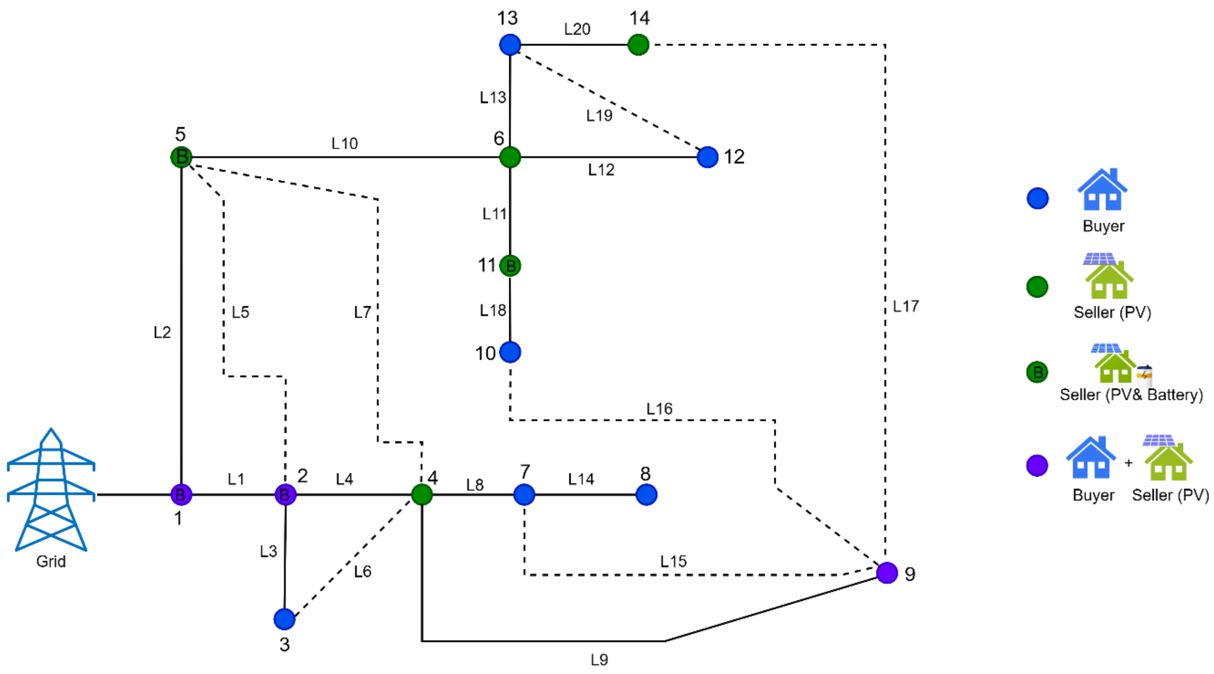


Figure 6.1. IEEE 14-bus benchmark network adapted, showing the grid connection point and locations of sellers and buyers.

6.2.2 Agents and Storage Configuration

Each network contains 25 heterogeneous agents. Sellers represent generation resources. Buyers represent flexible demand. Agent placement forces power transfers across multiple lines to activate network constraints.

Five sellers include battery storage. The remaining sellers operate generation only resources. Buyers do not include storage. Seller and storage parameters are defined at the agent level. These parameters include generation limits, storage capacity, charging and discharging limits, and efficiency coefficients. Representative seller configurations are summarized in Table 6.1. Buyer behavior is defined by time varying demand limits and price sensitivity coefficients. Representative buyer parameters are summarized in Table 6.2. Storage equipped sellers include time coupled state of charge dynamics and terminal feasibility constraints. These constraints enforce intertemporal consistency across the 24-hour horizon.

Table 6.1 Representative Seller and Storage Parameters

Agent ID	Bus	Storage?	P^{max} (kW)	E^{max} (kWh)	$P^{ch,max}$ (kW)	$P^{dis,max}$ (kW)	η_{ch}	η_{dis}
1	2	Yes	3.0	8.0	2.0	2.0	0.95	0.95
2	6	Yes	3.0	6.0	1.5	1.5	0.95	0.95
3	4	No	3.0	0.0	0.0	0.0	1.00	1.00
4	9	No	3.0	0.0	0.0	0.0	1.00	1.00
5	11	No	3.0	0.0	0.0	0.0	1.00	1.00

Table 6.2 Representative Buyer Parameters

Agent ID	Bus	Average demand (kW)	Time-varying profile	ω	δ
6	3	1.36	Yes	0.22	0.50
7	5	1.26	Yes	0.23	0.55
8	21	1.18	Yes	0.215	0.50
9	25	1.36	Yes	0.24	0.60
10	11	1.29	Yes	0.225	0.55

6.2.3 Network Constraints and Time Horizon

The network constraints are ensured through Power Transfer Distribution Factor (PTDF) matrices, which are based on a DC power flow. PTDF provides a measure of injections in terms of power flow with respect to a chosen slack bus. Thermal constraints are directly built into the optimization model, ensuring that schedules are physically feasible. All simulations have a common 24-hour day-ahead temporal scope with hourly granularity. Figure 6.2 illustrates aggregated load, supply, and resulting demand. Surpluses in mid-day create charging possibilities, whereas evening deficits create discharging possibilities with peer-to-peer transactions.

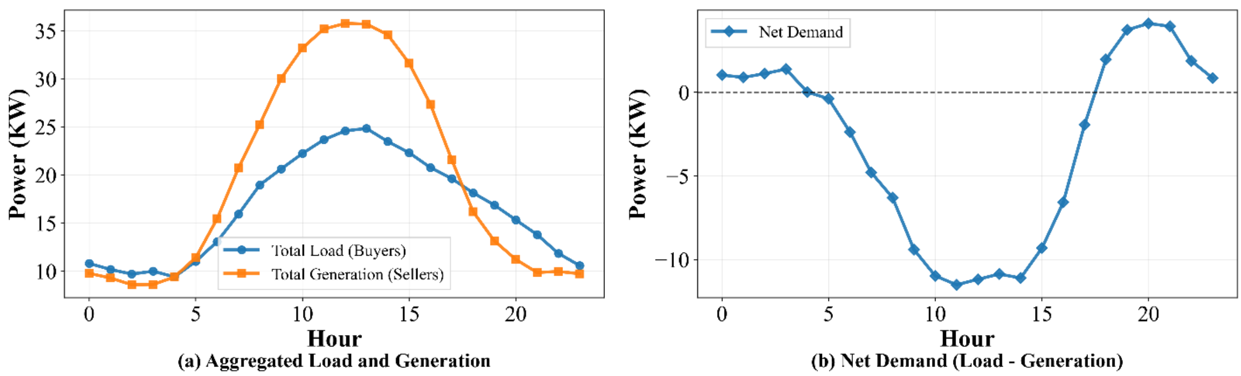


Figure 6.2 Aggregated load, generation, and net demand over the 24-hour horizon. (a) Total buyer load and seller generation. (b) Net demand defined as load minus generation.

The optimization algorithm is implemented in Python version 3.13 by means of matrix operations provided through NumPy library. Computation time is measured for simulations on a Dell Precision computer featuring an Intel Core i7 microprocessor and 16 GB RAM. Subproblems for agents are solved one after another using a single CPU core. In case of any divergent solution path, iterations are terminated at maximum value of $K_{max} = 500$. Simulation parameters are summarized in Table 6.3.

Table 6.3. Simulation Configuration Summary (IEEE 14-Bus and IEEE 33-Bus)

Parameter	IEEE 14-Bus	IEEE 33-Bus
Number of buses	14	33
Number of lines	20	32
Total agents	25	45
Sellers	12	20
Buyers	13	25
Sellers with storage	5	6
Buyers with storage	0	0
Planning horizon	24 hours	24 hours
Time resolution	1 hour	1 hour
Storage capacity	6–9 kWh	3.13–4.77 kWh
Charge/discharge limit	1.5–2.0 kW	0.82–1.70 kW
Round-trip efficiency	0.90	0.95
Network constraints	PTDF-based	PTDF-based

6.3 Centralized Benchmark Results

6.3.1 Centralized Optimization Formulation

The centralized benchmark represents an optimal solution for the overall issue of maximizing social welfare when there is full transparency with respect to information. The objective function maximizes the sum of utilities of the consumers minus the total cost of production from the producers, while considering various constraints such as power balance, generation capacity constraints, demand constraints, storage constraints, and flow constraints.

6.3.2 IEEE 14 Bus Centralized Results

Two central examples are considered. For the unconstrained scenario, no network constraints are considered, leading to welfare level 14.11. Imposing line limitations leads to reduced welfare level of 13.97, representing a reduction of 0.14 or around 0.99%, which can be considered the economic value of congestion in IEEE 14-bus test system.

For illustration purposes of market curves, the dispatch schedules of production and demand over 24 hours for all producers and consumers, as well as aggregate trajectories are presented in Figure 6.2. The computation time for the constrained example will necessarily be larger due to increased complexity associated with the spatial coupling caused by network constraints. As can be seen from the plots, dispatch schedule displays clear daily periodicity with growing total electricity demand throughout the day, and declining demand during evening period. Heterogeneity among agent behaviors is reflected through different shapes of the stacked areas, resulting from marginal costs, utility functions, and capacity restrictions faced by individual agents.

6.4 Distributed ADMM Performance

6.4.1 Algorithm Configuration

The distributed ADMM algorithm, as a framework, decomposes the centralized optimization problem into sub-problems, each representing the optimization problem faced by the individual agent. The optimization problem faced by each agent is subject to different constraints, while the global power balance is ensured by the coordinated layer based on PTDF (Power Transfer Distribution Factor) constraints. The convergence is checked by monitoring the scaled primal and dual residuals. The stopping criterion is based on the absolute tolerance, 1×10^{-4}, relative tolerance, 1×10^{-3}, and the maximum number of iterations, 500. The initial penalty parameter is fixed as $\rho = 0.1$.

6.4.2 Convergence Behavior

The reliability of the distributed algorithm's performance is ensured with respect to both unconstrained and constrained network conditions. For the unconstrained case (14-Bus network), the process converges within 84 iterations, with a runtime of 73 seconds. For the network-constrained case, the process converges after 119 iterations, with a runtime of 223 seconds, considering the added complexity of the PTDF-based line constraints. The performance of the distributed ADMM algorithm with respect to convergence and feasibility is provided in Table 6.4. For the unconstrained case, the process converges without considering the line capacities, which can lead to dispatch solutions that violate physical constraints. For the constrained case, the process takes longer with the inclusion of the line constraints based on the PTDF within the coordination layer.

The enforcement of network feasibility is based on the consensus injection variable z, which represents the projected solution that is consistent with the overall system. Hence, the assessment of feasibility is based on the flows obtained from the variable z. The local schedules p, which represent the ADMM-based intermediate variable, can become inconsistent with respect to feasibility before the projection operation, although they do not represent the final feasible solution.

Table 6.4. Distributed ADMM Convergence Metrics (IEEE 14 Bus)

System	Scenario	Iterations	Time (s)	Status
IEEE 14-Bus	No network constraints	84	72.960	Converged
IEEE 14-Bus	With network constraints	119	222.811	Converged
IEEE 33-Bus	No network constraints	80	91.674	Converged
IEEE 33-Bus	With network constraints	49	124.723	Converged

Figure 6.3 shows the convergence behavior of the distributed ADMM algorithm by plotting the primal and dual residual values for successive iterations. The figure validates the progressive reduction in residual values and the convergence behavior for both the constrained and unconstrained problems, matching the iteration counts provided in Table 6.4.

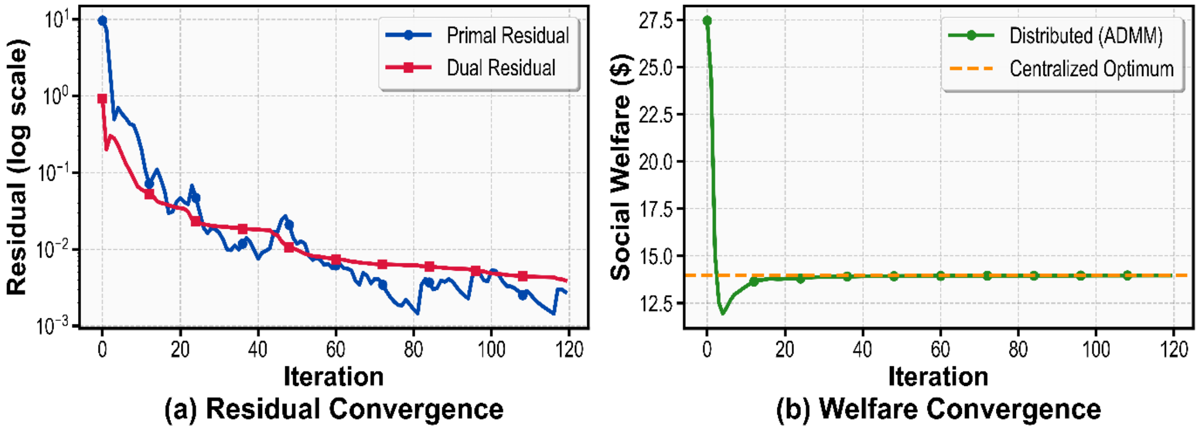


Figure 6.3: ADMM Primal and Dual Residual Convergence

Despite the success of all the cases tested where convergence occurred, the convergence of ADMM is not unconditional. Non-convergence may happen when the penalty parameters used are not well chosen or the interaction between the PTDF projection and the update by the local agents is unstable, which leads to oscillating primal and dual residuals and prevents convergence of the local schedule (p_i) to the consensus variable (z_i). If that happens, then the dispatch schedule will not converge, and hence neither a dual market price nor a trading schedule will be achieved.

6.4.3 Welfare Recovery Analysis

It has been observed that the distributed ADMM method is able to achieve welfare outcomes that closely approximate the centralized benchmark under unconstrained and network-constrained conditions. The comparison of welfare values with their centralized counterparts shows that the residual gap is negligible and is attributed to numerical convergence tolerances and not related to the structure of the distributed coordination mechanism. Table 6.5 shows the values of welfare obtained by centralized and distributed methods, along with their gaps, for both scenarios.

Table 6.5. Welfare Comparison and Gap Analysis

Case	Centralized Welfare ($)	Distributed Welfare ($)	Absolute Gap	Gap (%)
No network constraints	14.11	14.10	0.010	0.0466
With network constraints	13.97	13.97	0.003	0.0187

Figure 6.4 provides a visual comparison of the centralized and distributed welfare values under the network-constrained case, highlighting the near-optimal welfare recovery achieved by ADMM.

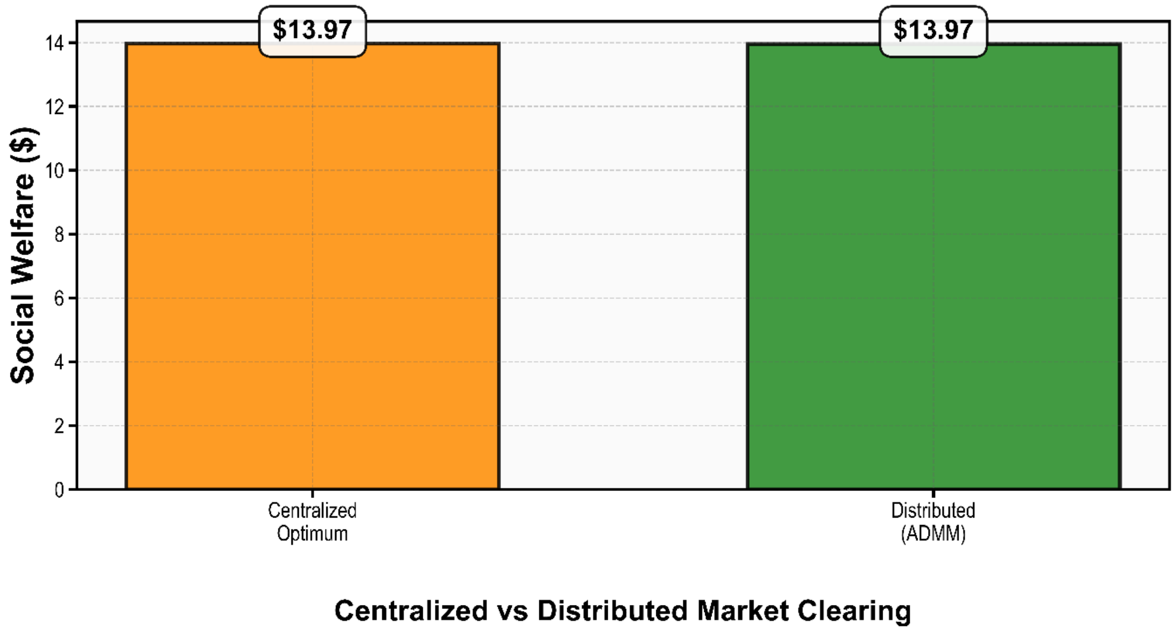


Figure 6.4: Centralized vs Distributed Market Clearing Welfare Comparison

The welfare achieved by distributed ADMM remains remarkably close to the centralized benchmark, confirming that decentralized coordination with privacy preservation introduces only a negligible loss relative to the global optimum.

6.5 Effect of Penalty Parameter on Convergence

The impact of the penalty parameter ρ on convergence performance is evaluated using the IEEE 14-bus system over a range of values $\rho \in [0.1,0.3,0.5,0.7,1,1.5,2,3,5]$. The results are shown in Figure 6.5. For all the values of ρ considered here, convergence occurs, showing the robustness of the proposed ADMM formulation in terms of choice of parameters. The welfare computed by the distributed algorithm stays almost constant, regardless of ρ, as the welfare difference from the centralized case stays consistently less than 0.02%. It can be concluded that the main effect of the penalty parameter is on convergence speed, rather than optimality.

Despite this, the convergence speed highly depends on the value of ρ chosen. When using small values of ρ, convergence will take place very slowly because of poor penalization of the consensus error, whereas too large values of ρ result in slow dual iterations and oscillations. Intermediate ρ values provide a compromise between the two processes. Considering these facts, ρ = 0.1 is chosen for all simulations, as it ensures fast convergence with stable residuals and good welfare.

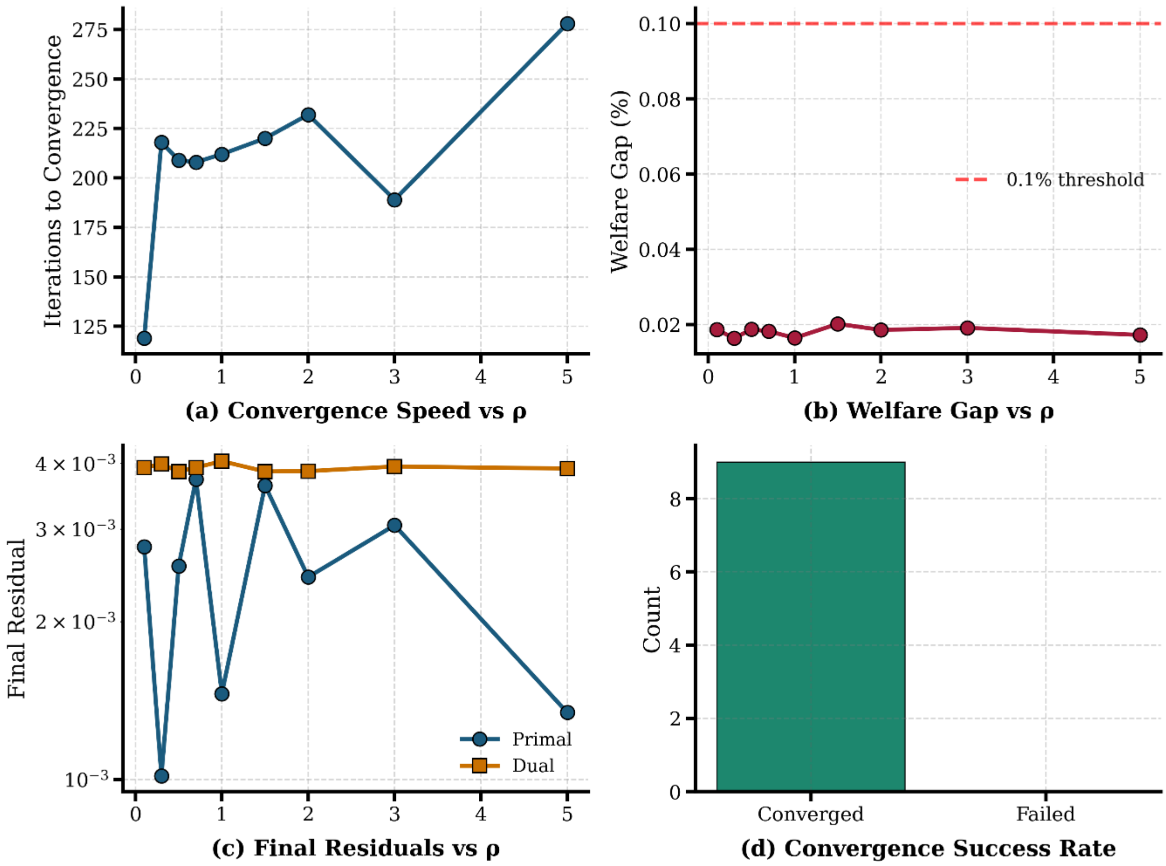


Figure 6.5 Sensitivity of ADMM performance to penalty parameter ρ.

(a) Convergence speed (iterations), (b) welfare gap relative to centralized solution, (c) final primal and dual residuals, and (d) convergence success rate across tested values of ρ.

6.6 Comparative Performance Summary

Comparison between the two methods (centralized and distributed approaches) is summarized in Table 6.6, illustrating the relationship between computing resources and practicality of solution. Figures illustrating the comparative results of both networks, namely, IEEE 14-bus and IEEE 33-bus, are shown in Figure 6.6. Distributed algorithm of ADMM generates utility levels that are close to the centralized approach, without generating any optimality gap. Simultaneously, inclusion of network constraints ensures physically realistic solutions, since the line usage is restricted by thermal limits.

While centralized optimization is solved rapidly, the distributed method requires iterative coordination, resulting in higher computation time. However, the distributed framework maintains consistent convergence behavior across both systems. The results also show that increasing system size does not degrade solution quality or convergence behavior. The IEEE 33-bus system achieves comparable welfare with fewer iterations, demonstrating the scalability of the proposed approach.

Table 6.6. Performance Comparison Across Systems

System	Method	Network Constraints	Welfare ($)	Time (s)	Iter.	Max Line Utilization
14-Bus	Centralized	No	14.11	0.413	—	211.0%
14-Bus	Centralized	Yes	13.97	0.892	—	101.0%
14-Bus	Distributed ADMM	No	14.10	72.960	84	239.1%
14-Bus	Distributed ADMM (z)	Yes	13.97	222.811	119	100.0%
33-Bus	Centralized	No	49.25	0.578	—	646.0%
33-Bus	Centralized	Yes	45.32	1.552	—	100.1%
33-Bus	Distributed ADMM	No	49.24	91.674	80	385.7%
33-Bus	Distributed ADMM (z)	Yes	45.32	124.723	49	100.0%

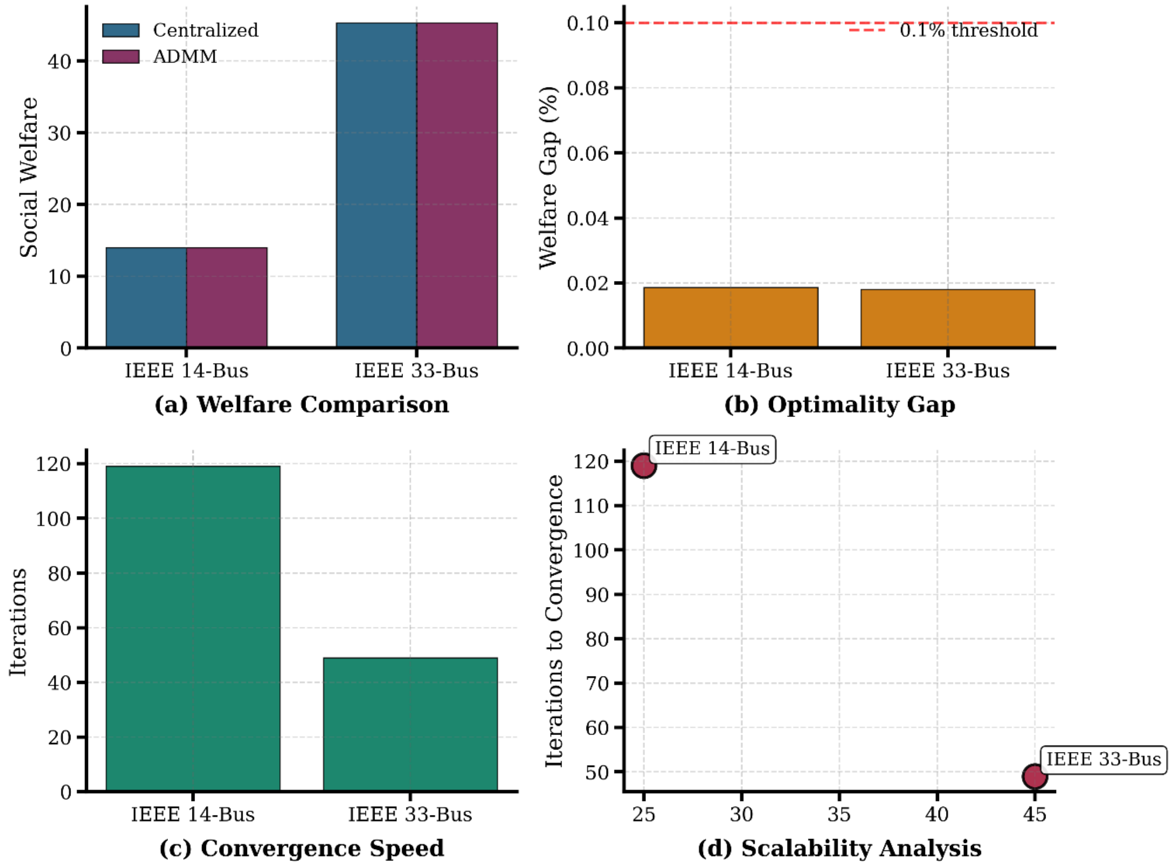


Figure 6.6 Comparative performance across IEEE 14-bus and IEEE 33-bus systems.

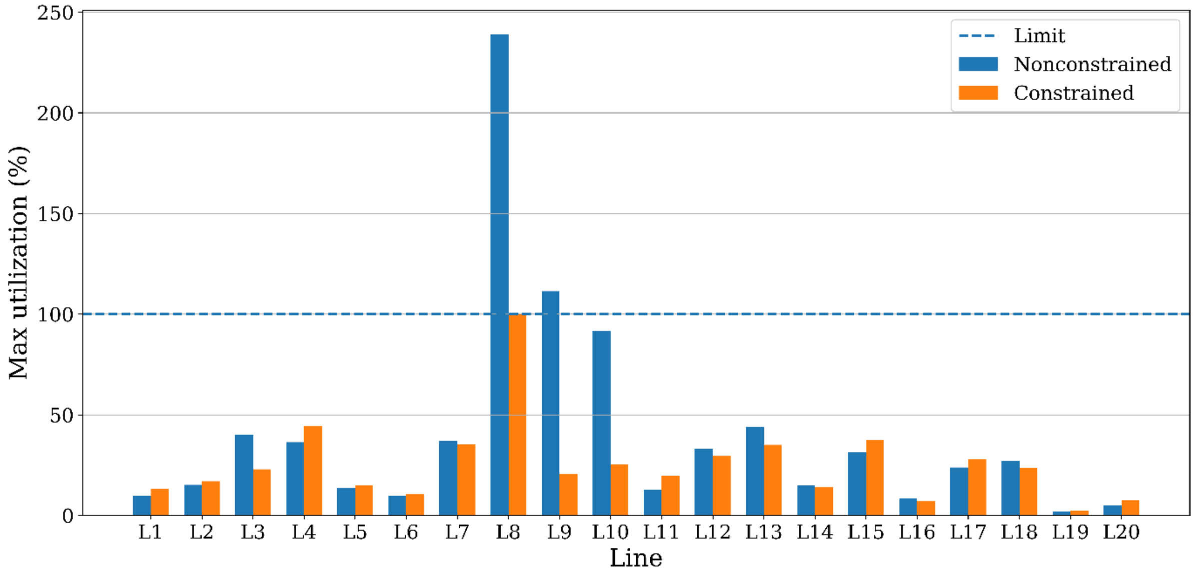
(a) Social welfare comparison between centralized and distributed methods, (b) optimality gap relative to centralized solution, (c) convergence speed in terms of iterations, and (d) scalability relationship between system size and convergence behavior.

6.7 Network Utilization and Constraint Enforcement

In the unconstrained case, the maximum utilization of the line converges above line limits both in the distributed and centralized case as shown in Table 6.7, reflecting the absence of network constraints. This results in an economically optimal yet physically infeasible power flow. It is also clear from Figure 6.7 that the majority of the overloads are concentrated on a single line. It is also clear from the results that line 8 experiences the maximum overloads. This happens because of the optimization problem's focus on economic optimality without considering line flow constraints based on PTDF. As a result, there is a concentration of flows on electrically sensitive lines. On the other hand, in the constrained formulation, network constraints based on PTDF are incorporated through the ADMM projection step and hence the feasible consensus flow variable z. As a result, line utilization remains within acceptable limits. All constraints are satisfied in the constrained case as shown in Figure 6.7 and Table 6.7. It may be noted that the marginal deterioration in social welfare arises because of the absence of infeasible high-value transactions. It may also be noted that congestion management in the network happens only through a small subset of network lines.

Table 6.7. Network Utilization and Constraint Violations

Scenario	Max Utilization	Lines > 80%	Total Lines	Violations
Unconstrained (Centralized)	≈211%	3	20	Multiple overload hours
Unconstrained (Distributed)	≈239%	1	20	Significant overload
Constrained (Distributed z)	≈100%	1	20	None



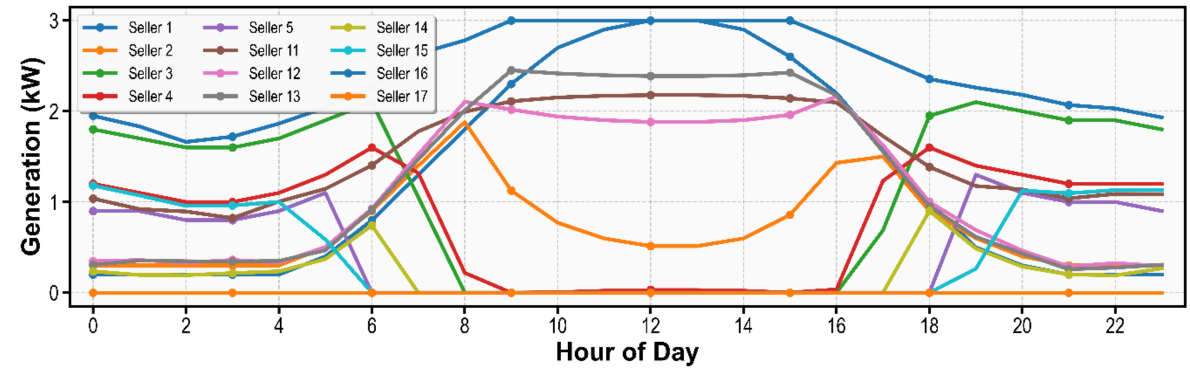
Line stress comparison: constrained vs nonconstrained

Figure 6.7 Line utilization under unconstrained and constrained market clearing.

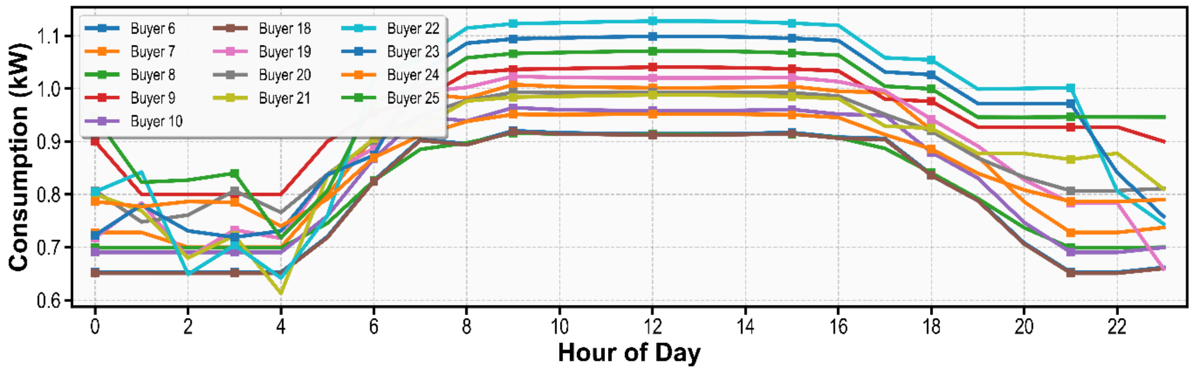
The comparison further shows that adjustments are localized: only lines near their limits change significantly, while most lines remain unaffected. Here explicit PTDF enforcement restores feasibility with minimal deviation from the economic optimum, ensuring operational compliance while preserving near-optimal welfare.

6.8 Distributed Dispatch Schedule Validation

The resulting 24-hour generation and consumption profiles for the market-clearing solution obtained with the distributed ADMM-based framework reveal a coordinated behavior of heterogeneous market participants. The generation profiles of sellers and the consumption profiles of buyers, taken together, provide insight into the evolution of decisions throughout the entire optimization horizon. Dispatch levels vary across sellers according to their respective cost functions and generation limits. Lower-cost sellers generate a higher proportion of market transactions when demands are at their peak levels, whereas higher-cost sellers are used less frequently. Sellers with storage abilities have non-monotonic behavior: they store during times of low prices due to low demands and sell during peak demands where prices are high. This reveals that the effects between periods are naturally incorporated into the model rather than resulting from any ad hoc methods. As for the demand side, consumers adjust based on the prices and utility functions of different buyers. Although the total demand profile follows a traditional diurnal profile, individual demand profiles vary in their magnitudes and timing. The smooth behavior of generation and consumption profiles confirms the stable convergence of the distributed framework and well-posedness of the resulting convex subproblems.



(a) Generation Dispatch Schedule



(b) Consumption Dispatch Schedule

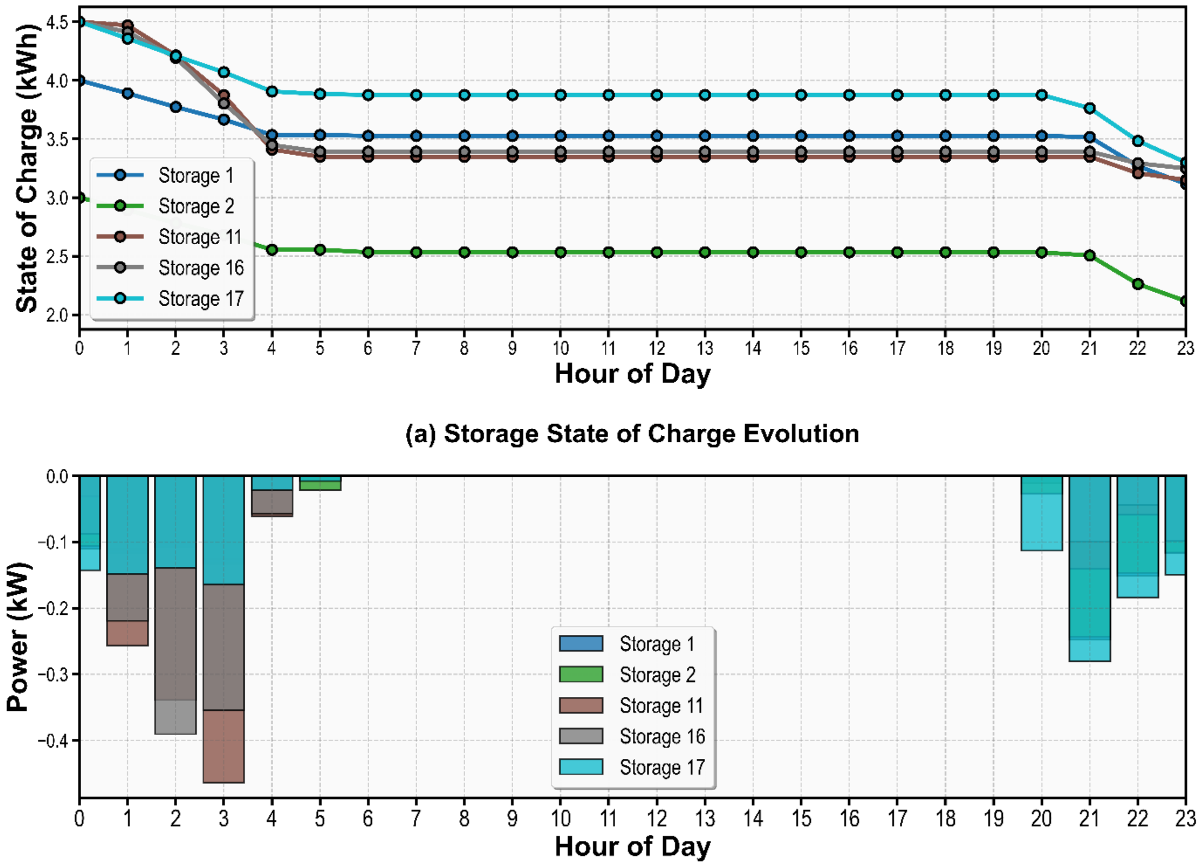
Figure 6.8 Distributed 24-hour generation and consumption dispatch schedules.

At all hours, the total generated equals the total consumed, verifying the system-wide balance. There is no infeasible dispatch, and the storage constraints are satisfied throughout the period. The similarity between the centralized and distributed schedules suggests that the economic structure and feasibility are maintained in the distributed case. Figure 6.8 demonstrates the validity of the presented distributed optimization approach, where the scheduling for all the participating entities is done in an economically rational manner while maintaining feasibility for the entire period of 24 hours.

6.9 Storage Operation and Temporal Coordination

Storage adds an intertemporal coupling effect to the market-clearing problem, considering all the decisions made during the 24-hour period. The state-of-charge (SoC) dynamics are embedded in the local optimization problem for each agent in the distributed ADMM approach, allowing for charging and discharging operations during the period. Agents with storage capacity are expected to charge during periods when the price is low and discharge during peak price periods, demonstrating an economic rationality for temporal arbitrage based on the prices generated by the endogenous market-clearing problem. As a result, the SoC dynamics are smooth, bounded, and the charging/discharging power is bounded, as depicted in Figure 6.9.

Oscillations are not observed, demonstrating the stability and convergence of the distributed algorithm, along with the satisfaction of the intertemporal constraints. The terminal SoC conditions are considered to avoid end-of-horizon bias, considering the realistic SoC dynamics, especially when the terminal equality constraint cannot be satisfied without violating other constraints. A penalty-based approach is used for the relaxation function to minimize the deviation.



(a) Storage State of Charge Evolution

(b) Storage Charging (+) / Discharging (−)

Figure 6.9: Battery State of Charge Trajectories for IEEE 14-bus constrained case.

These results confirm that the distributed framework successfully coordinates storage across time, enabling economically consistent temporal energy shifting while maintaining physical feasibility of state-of-charge, power limits, and system-wide balance constraints.

6.10 Bilateral Trading Structure and Price Formation

To clarify the manner in which the distributed market allocates energy amongst the agents over time, this sub-section simultaneously analyzes the structure of the bilateral trading architecture and the price signals generated by the market, all over the period of the 24-hour horizon. The aim is to verify whether the market indeed displays genuine peer-to-peer behavior and whether the price signals generated by the market are consistent with the temporal coordination induced by the storage component. Prior to the presentation of the evolution of the price signals generated by the market, this sub-section analyzes the way the distributed market allocates energy amongst the agents, by referring to Figure 6.10, where the total energy scheduled by each seller and each buyer is depicted for the period of the 24-hour horizon. The figure highlights the heterogeneity in the participation of the different sellers, in terms of the quantities of the generated energy related to the different values of the cost coefficients, and the different quantities of the demand related to the different values of the utility function for the buyers. There is no single seller whose contribution to the total supply is dominant, and there is no single buyer whose demand is met by a single counterparty.

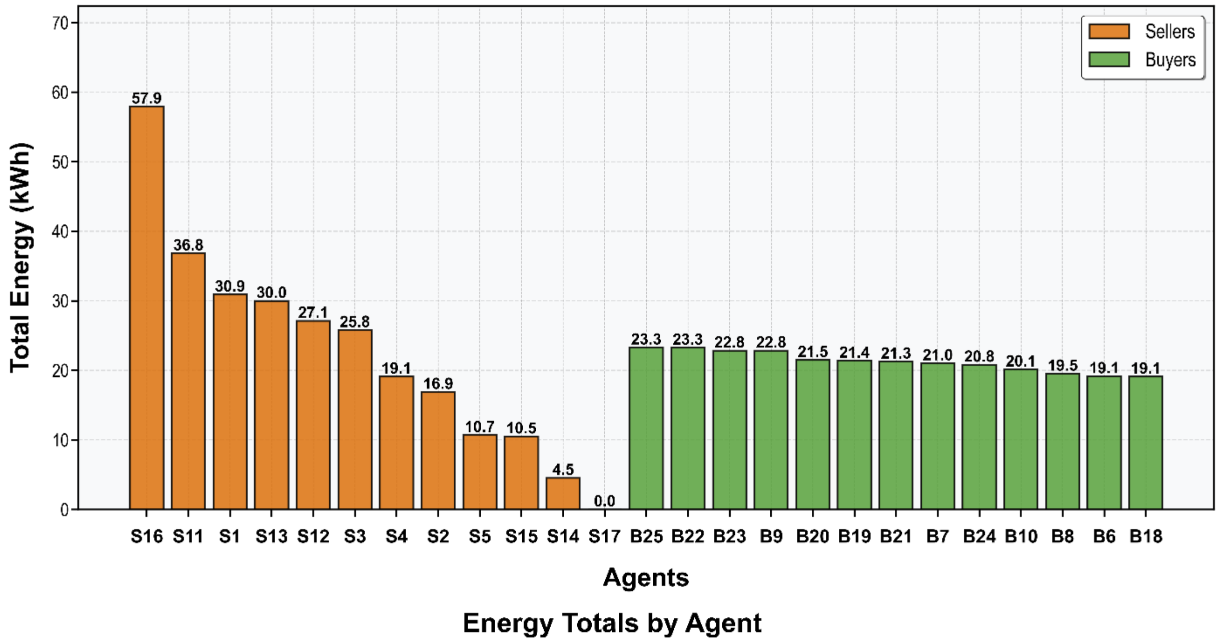


Figure 6.10: Total Energy Scheduled by Each Agent

To further understand the structure of peer-to-peer exchanges, Figure 6.11 and Figure 6.12 presents a heatmap of bilateral trading, in which each cell represents the total energy transferred between a seller-buyer pair over a 24-hour period. In total, there are 2860 bilateral transactions in the non-constrained scenario, as well as 2834 in the network-constrained scenario. From the heatmap, we observe that the trading is spread out over many pairs. The absence of a dominant trading channel implies that the ADMM-based coordination mechanism enables multi-lateral matching, as opposed to one-to-one matching, which is consistent with competitive equilibrium in decentralized networks.

Figure 6.11 Bilateral Trade Heatmap Across Agents and Time for Constrained Case

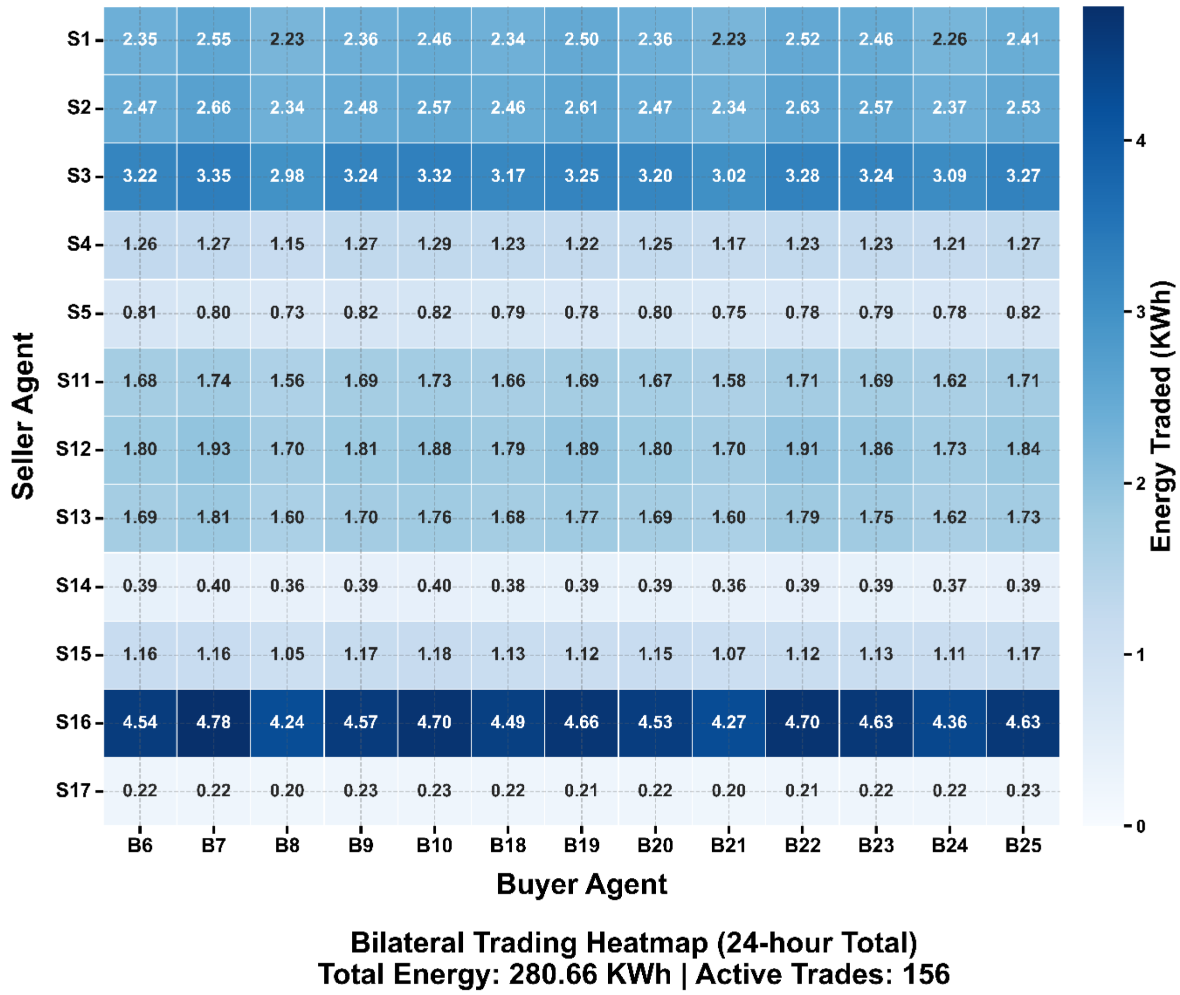


Figure 6.12 Bilateral Trade Heatmap Across Agents and Time for non-Constrained Case

The distributed nature of bilateral trades results from the constraints that the underlying network topology and storage flexibility impose. As the different agents interact with different buses, subject to PTDF-based line limits, the calculation of the optimal trades needs to account for spatial feasibility in conjunction with economic optimality. Thus, the energy allocation results from the balance between marginal cost and utility parameters, subject to congestion constraints as well as storage decisions.

Having characterized the underlying structures in energy allocation, we now consider the price dynamics that drive these energy trades. Figure 6.13 illustrates the evolution of the market-clearing price over the 24-hour horizon. The price profiles exhibit a significant diurnal pattern, with lower prices in the mid-day hours and higher prices in the evening peak hours. The spread in the price profiles encourages battery charging in the lower-priced hours and discharging in the higher-priced hours. The temporal variation in the price profiles is consistent with the earlier-presented state-of-charge profiles, thereby validating the existence of intertemporal coordination in the underlying distributed market-clearing mechanism.

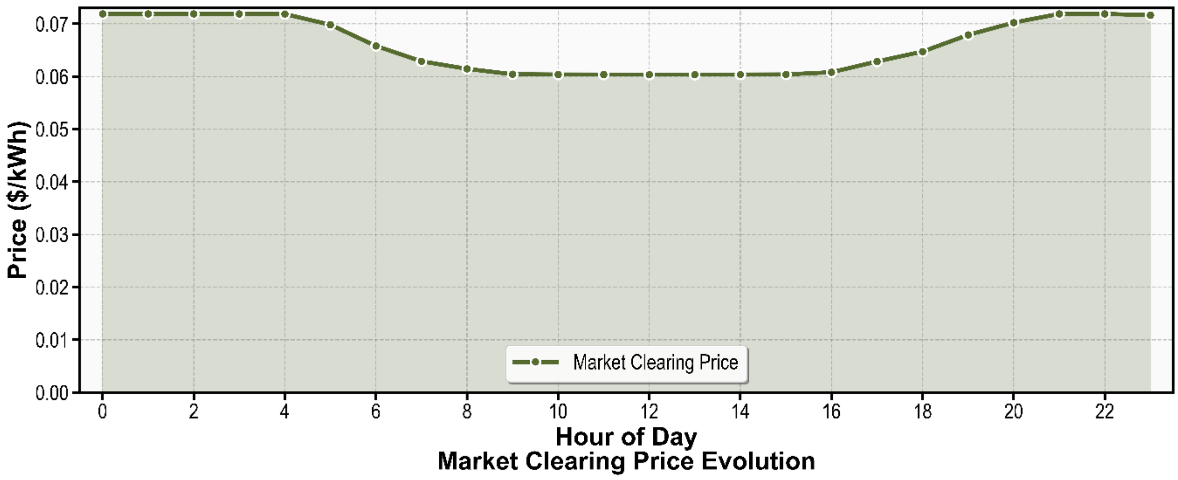


Figure 6.13: Market Clearing Price Over 24 Hour Horizon

On the other hand, the price signals are an endogenous outcome of the coordination mechanism and denote the marginal system-wide value of energy, considering the power balance and network feasibility constraints. In the absence of constraints, the price signals are mainly driven by the marginal cost of the generators and the utility gradients of the buyers. In the presence of congestion, the price signals are driven by the shadow value of the constraints introduced during the projection step. Figure 6.10 - Figure 6.13 illustrate the heterogeneous and distributed nature of the trading, the extensive peer-to-peer matching between various seller-buyer pairs, the congestion-aware and dynamic nature of the price signals, and the storage arbitrage behavior, which are all consistent with the inter-temporal optimization behavior. The above results clearly indicate the ability of the proposed decentralized ADMM mechanism to achieve the centralized welfare outcomes, while the trading structures and price signals are consistent with the decentralized energy market principles.

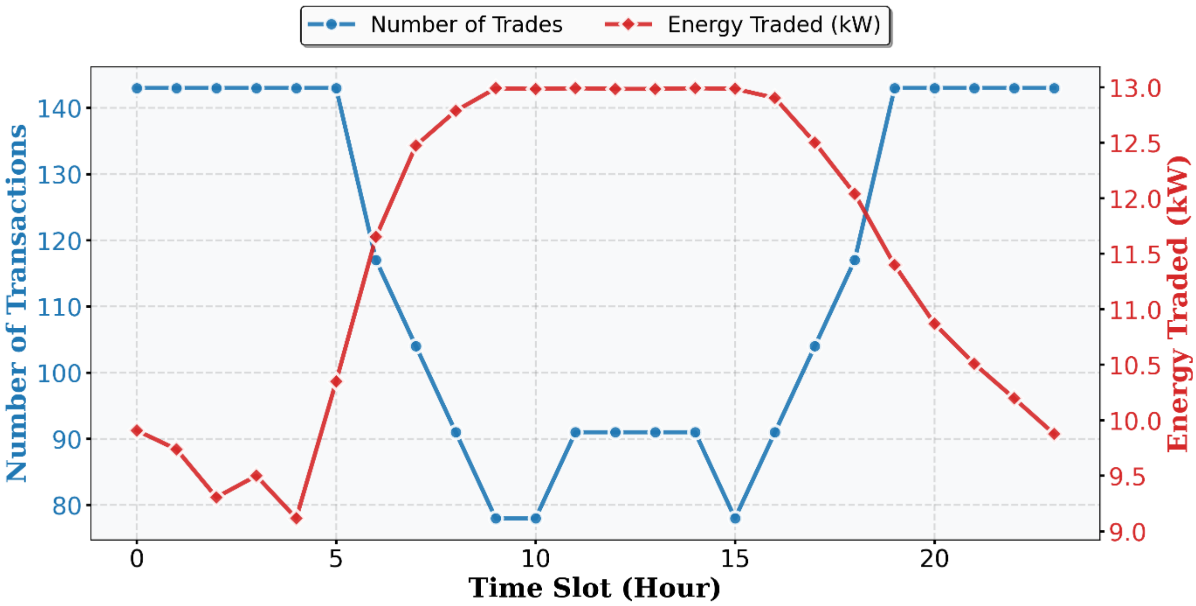
6.11 Blockchain Settlement Results

Table 6.8 shows the blockchain settlement results for the IEEE 14-bus network constrained case, indicating the total number of trades, submitted transactions, and their execution status. In 24 hours, 2,808 bilateral trades were verified and successfully batch-settled—an empirical result from the simulation environment described in Section 6.2, representing 276.05 kWh of traded energy and an aggregate transaction value of $16.56 at an average price of approximately $0.06 per kWh. After verification and filtering, all valid trades were submitted and executed correctly without failure. There were no failed or rejected transactions, which implies that the smart contract logic and verification process were consistent with the full trading volume.

Table 6.8. Blockchain Settlement Performance Metrics (Constrained Case)

Metric	Value
Total bilateral trade (market output)	2,795
Trades submitted on-chain	2,795
Transactions created	2,795
Transactions confirmed	2,795
Transactions settled	2,795
Failed transactions	0
Settlement success rate	100%

The sequence of settlements in time demonstrates the trends taking place in the blockchain layer and shows the overall market situation. As shown in Figure 6.14, the number of trades is not steady for a whole day but rather fluctuates as follows: is relatively stable in the first hours, falls during the middle hours, and rises again towards the evening hours. At the same time, the amount of energy traded demonstrates a steady trend throughout the day, rising up to noon and then falling. This difference in the trade count and the traded energy indicates that the trading activities are dominated by many transactions in the peak hours, while in the off-peak hours, the trading activities are dominated by many small transactions.



Blockchain Transaction Activity Over 24-Hour Period

Figure 6.14 Blockchain Transaction Activity Over 24 Hour Period

Figure 6.15 demonstrates the level of concordance between traded energy and value, with the hourly energy volume and transaction value plotted together. The transaction value is similar to the energy profile, with a peak occurring during the midpoint of the day and then a general decline. There are no irregularities or distortions within the value profile, indicating that prices are stable and that the value is a true reflection of the market-clearing process. This means that the total value of $16.56 is not concentrated within a particular period but rather is shared proportionally.

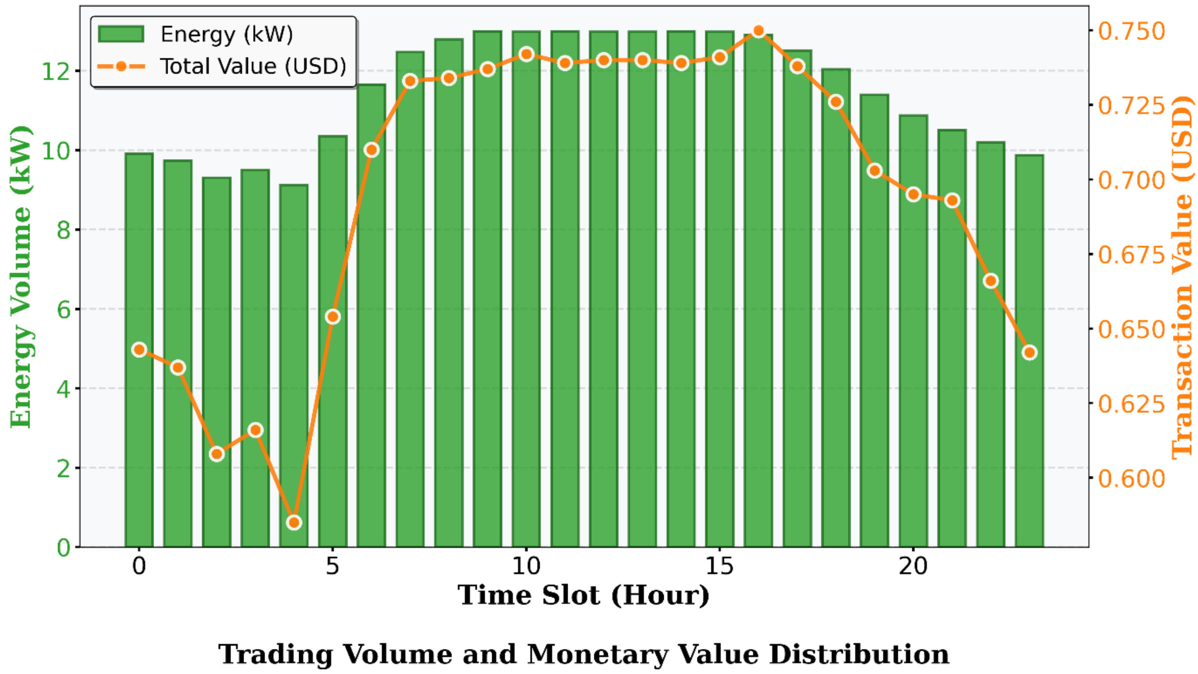


Figure 6.15 Trading Volume and Monetary Value Distribution

The spatial and temporal distribution of trades across the participants is described in Figure 6.16. The heatmap shows the distribution of trading across a large number of sellers and over time, rather than a limited subset of the agents' population. The midday hours are associated with higher trading activity, reflecting the simultaneous increase in demand and generation availability. Some agents have relatively stable outputs, while others exhibit strong temporal variation. Agents with storage capabilities exhibit strong inter-temporal behavior, with reduced trading during off-peak hours and higher trading during high-value hours, reflecting the storage effect from the optimization and confirming the presence of storage decisions in the settlement process.

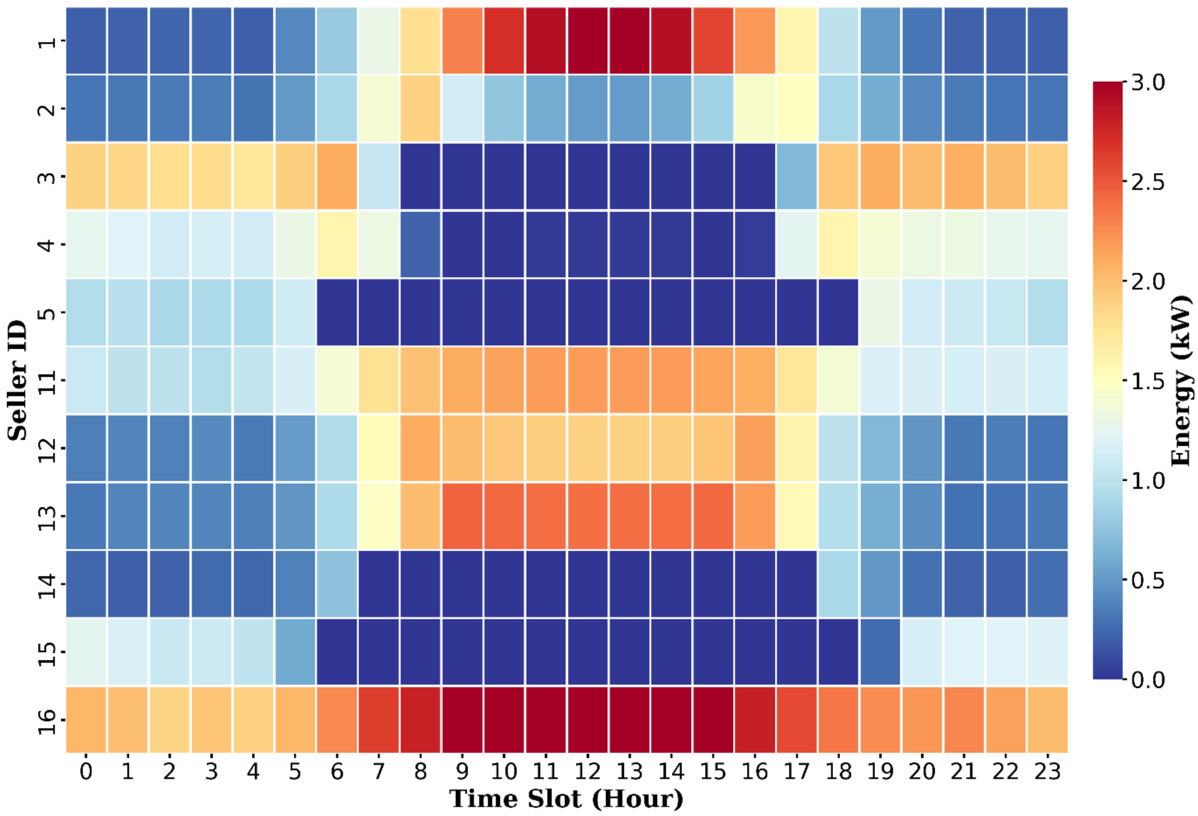


Figure 6.16 Market Activity Heatmap: Energy Trading by Seller and Time

The settlement process occurs through batch transactions, which involve the verification of multiple trades and then consolidating them into one contract call. This minimizes on-chain costs, and deterministic execution is maintained. The verification of each trade occurs before settlement, ensuring that it is done against the data from the smart meter, thereby ensuring that only actual energy consumption is settled. The successful execution of all transactions, 2,795, without any failures ensures that the settlement layer can sustain transactional throughput over the entire horizon without any execution errors or inconsistencies.

6.12 Computation Time Analysis

Table 6.9 compares the computation time of centralized optimization and the distributed ADMM coordination method, highlighting the trade-off between computational efficiency and decentralized operation. In the centralized approach, a single optimization problem is solved with full system information, resulting in low computation time while satisfying all constraints.

In the distributed ADMM formulation, the problem is decomposed across agents, each solving a local optimization problem with iterative consensus updates. Each iteration involves solving local subproblems, updating dual variables, and projecting onto power balance and PTDF-based network constraints. This increases computation time compared to the centralized case.

The inclusion of network constraints further increases computational effort due to stronger coupling among agents and the added cost of projection operations, particularly under congestion. As a result, more iterations are required to meet convergence tolerances.

Despite the higher computation time, the distributed approach achieves near-optimal performance while enabling decentralized coordination and preserving agent privacy.

Table 6.9. Computation Time Breakdown IEEE Bus 14

Phase	Time (s)	Relative to Centralized (No Network)	Relative to Centralized (With Network)
Centralized (No network)	0.41	1.0×	0.46×
Centralized (With network)	0.89	2.17×	1.0×
Distributed ADMM (No network)	72.96	178.0×	82.0×
Distributed ADMM (With network)	222.81	543.4×	250.3×

The results in this chapter demonstrate that the suggested framework is effective, i.e., it converges, remains feasible for the network, and ensures reliable settlement. In addition, based on the results obtained, chapter 7 considers the implications for decentralized energy markets, how the system operates on a day-to-day basis, and how it scales.

Chapter 7. Discussion

Chapter 7 builds on the analysis of the model proposed in Chapter 6 by considering its convergence, economic efficiency, network feasibility, and reliability of settlement. It highlights the fact that mere numbers are not enough; interpreting these numbers is key. The interpretations of the presented results consider the following: the potential for recovering welfare via distributed coordination; the impact of network effects on dispatch decisions; the implications related to computation needs; reliability of blockchain-enabled settlements; and price and trade volume impacts due to storage.

7.1 Economic Validity and Welfare Recovery

From the results obtained, it is clear that the decentralized model is able to achieve close to 99.9% of the economic efficiency compared to the centralized one despite the network limitations. The welfare gaps observed are small in terms of figures, about 0.05% and 0.02% in the absence of and presence of constraint respectively. This means that the consensus framework and local optimization problems can retain efficiency loss of no significance beyond what was caused by physical limitations. The insignificant welfare gap under constraint scenarios comes about due to the projection step done to avoid infeasible solutions in the dispatch problem. As opposed to other approaches that rely on peer-to-peer mechanisms for solving optimization problems, this framework retains privacy and network constraints enforcement capabilities. Such approaches as seen above often ignore the network constraints while some use the centralized validation of feasibility in their algorithms. This result makes decentralized energy markets viable. The close similarity in efficiency achieved to that of the centralized model makes it evident that the decentralized framework retains the economics of the model while solving local problems privately.

7.2 Role of Network Constraints and Feasibility Enforcement

The results show that while economic optimality is achieved, physical feasibility is not ensured. In the unconstrained, centralized case, the utilization of the line is 210%, indicating the presence of overloads. However, when the constraints are not considered, the economically desirable flows may be over the thermal limits, especially on the corridors that have the highest level of electrical sensitivity. The constraints based on the PTDF eliminate the overloads in the final solution. The distributed model achieves feasibility by adding a projection step on the consensus injection variable. This ensures that the flows satisfy the line constraints while satisfying the power balance. The corridor that was identified as being overloaded now becomes binding, with the flows being rerouted through alternative corridors. The reduction in welfare in the constrained case is due to the economic cost of the overloads. The infeasible flows are limited, causing the objective function to be lower, but the solution is physically realizable. This confirms that the need for network modeling is essential in realistic peer-to-peer operations, as achieved in the decentralized case.

7.3 Convergence Behavior and Computational Trade-offs

The distributed ADMM algorithm demonstrates convergence in both unconstrained and constrained scenarios, meeting the specified residual tolerances without compromising stability. The inclusion of time-coupled storage and PTDF-based constraints does not alter convergence behavior, although the constrained case requires more iterations due to increased coupling among agents. The projection step increases computation time but ensures feasibility. While decentralization increases computational cost compared to centralized optimization, it enables privacy and coordinated constraint enforcement. The penalty parameter ρ plays a key role in convergence, balancing primal feasibility and dual updates. An initial value of $\rho = 0.1$ is used based on empirical tuning. Lower values slow convergence, while higher values may cause oscillations. The results show that the consensus approach remains effective under spatial and temporal coupling, achieving convergence and near-centralized welfare recovery.

7.4 Storage Coordination and Intertemporal Effects

The inclusion of storage also adds coupling between the different time periods in the market-clearing problem through the state of charge and terminal constraints of the batteries. With respect to the Alternating Direction Method of Multipliers (ADMM) method, the optimization model for the agents with storage optimizes their charge/discharge schedules based on their energy and power constraints, where the operation is based on the dynamic price signal over the horizon, with the aim of charging during low-price periods and discharging during high-price periods, which reduces the peak demand and shifts the demand over the horizon. This is achieved solely through the optimization model and not through any external scheduling rules. Moreover, the state of charge for the batteries is maintained within given limits over the horizon, and the terminal constraints avoid any artificial effects at the end of the horizon. These results show that the decentralized approach can handle both temporal and network constraints in unison without any control over the storage resources.

7.5 Blockchain Settlement: Value Beyond Computation

As seen in the settlement results, the feasibility of the optimized market schedules can be validated and implemented separately from the clearing process. With the network constraints present, the number of generated trades remains 2,808. Settlement occurs after the clearing process. The optimization process occurs off-chain using distributed ADMM, and only the optimized trade schedules are used for verification and settlement. This approach avoids the computationally intensive process from being implemented on the blockchain while maintaining the transparency and auditability of the implemented trades. Settlement complexity depends on the number of bilateral agreements, not the optimization problem size. Trades are settled in batches after the clearing process, and there is no need for re-optimization during the execution process. This approach avoids the limitations imposed by implementing optimization on the blockchain. As seen in the settlement results, the market design is feasible for practical implementation. The optimized schedules are not theoretical but are used to validate the transactions, which are then implemented in the real world.

7.6 Comparison with Existing Literature

The results show several key differences with respect to other distributed peer-to-peer market designs. To begin with, the framework achieves a welfare gap of approximately 0.05% in the unconstrained case and 0.02% in the constrained case with respect to the centralized benchmark on the IEEE 14-bus network, even with the imposition of network constraints. This is as opposed to other distributed models, where the gap is much higher, especially if physical constraints and storage dynamics are not modeled. The negligible gap here indicates that full PTDF enforcement, as well as time-coupled models, can still be incorporated without affecting economic performance. The constrained results show that all post-clearing line violations are eliminated, as opposed to the unconstrained results, where utilization levels exceed 200%. This indicates that full network modeling is not plainly important but necessary. Several other models either abstract these distribution constraints or centrally enforce them. Here, they are ensured even with decentralization. Also, the storage results show coordinated intertemporal behavior without central scheduling, with charging and discharging aligned with price signals, state of charge, and terminal conditions.

The outcomes of the settlement show that the system can be scalable. Over 2,795 transactions can be confirmed and logged within one 24-hour window. This can be achieved without the involvement of the blockchain technology. These results prove that the model is economically viable, physically realistic, timewise coherent, and enforceable.

Chapter 8. Conclusions and Future Work

8.1 Conclusions

This thesis proposes a blockchain-based distributed solution for managing energy in microgrids that are capacity-constrained and support peer-to-peer trade. The question is: can we achieve economic efficiency, physical feasibility, and transparency without a central optimizer?

Using distributed ADMM, it decomposes a multi-period social welfare problem with hard network constraints and time-varying storage constraints. On the IEEE test case, it is observed that the distributed solution is remarkably close to the centralized solution while satisfying power balance and network constraints. The remaining optimality gap is due to the activation of network constraints, not the distributed nature of the solution. Removing network constraints from the problem makes the problem economically attractive, but physically infeasible with significant line overloads. The introduction of the NO projection step fixes these problems without affecting convergence, indicating that feasibility can indeed be achieved within a distributed framework. Time-varying storage constraints were easily incorporated into the distributed solution by letting storage respond to price signals while respecting state of charge and final state constraints. The inclusion of intertemporal storage flexibility makes the solution more realistic without affecting convergence. An end-to-end blockchain-based settlement layer was also implemented and validated with thousands of trades recorded without affecting the optimization process. The results show that with proper design, economic efficiency, physical constraints, and settlement can all be satisfied within a unified framework. At the same time, they provide a positive response to the questions raised in Chapter 1. The distributed ADMM method is guaranteed to converge and can achieve economic welfare close to what is possible with a centralized system (RQ1-RQ2). By enforcing PTDF, physical constraints are satisfied without compromising convergence stability (RQ3). Finally, using blockchain for settlement proves that smooth operation is possible even with thousands of transactions (RQ4).

8.2 Key Contributions

The main contributions of this thesis are summarized as follows:

1. The thesis presents a consensus-driven ADMM approach for multi-period peer-to-peer energy trading, and it involves the addition of explicit PTDF-based line constraints and the incorporation of time-coupled storage dynamics, with the aim of maintaining centralized welfare while ensuring power balance and thermal constraints.

2. The thesis compares the welfare recovery with centralized IEEE bus 14 benchmarks, and it achieves approximately 0.0466% welfare gap in the unconstrained scenario and 0.0187% in the constrained scenario, thus decoupling congestion from potential algorithmic inefficiency.
3. The thesis introduces a NO-based projection step, and it is incorporated into the decentralized framework to ensure satisfaction of the network constraint at convergence, thus avoiding potential post-clearing violations without the need for centralization of the objective function.
4. The thesis examines the possibility of an off-chain optimization and an on-chain settlement, and it involves the registration and verification of thousands of bilateral trades, thus proving the decoupling of settlement from computation without affecting the market outcomes.
5. The thesis presents a framework for the integration of optimization, network feasibility, storage coordination, and settlement, thus proving the consistency of the framework across the economic, physical, and execution layers.

8.3 Limitations of the Study

Despite these promising findings, however, there are several boundaries to the proposed framework. Firstly, it makes use of a PTDF-based DC power flow approximation. The latter, however, does not take voltage magnitude or reactive power flow into account. Therefore, even though it can achieve an economically optimal solution for the distribution level, it cannot guarantee full AC feasibility. The second limitation of the proposed framework lies in its assumption of accurate forecasts of both the load and the generators. This implies that it cannot account for uncertainties arising from renewable sources. The case study considers a system of 25 agents. Although it shows promise of being scalable based on the distributed nature of the solution, it may not be practical for large-scale problems because of the need for hierarchical control or faster algorithms. The proposed blockchain implementation was also validated. The meter verification was simulated instead of using actual hardware. Communication between agents was also assumed to be ideal, with no issues arising from delays, packet loss, or security risks.

8.4 Future Work

The findings and limitations of the study reveal that there are avenues that can be taken for further research. Firstly, the expansion of the model to cover alternating current power flow modeling will improve its accuracy. Secondly, the inclusion of uncertainty within the market clearing model is another area that can be considered. This will improve the model's applicability, considering that there is always uncertainty associated with the power market. Thirdly, the scalability of the model is another area that can be considered. This can be done using a hierarchical structure of ADMM. This is because, although the model is proven to work with 25 agents, there is a possibility that a much larger number of agents will be required, and the model will need to be scalable. Lastly, there is a need to study the applicability of blockchain within a real-world scenario. This can be done by assessing its performance within a public blockchain environment.

References

[1] B. Stott, J. Jardim, and O. Alsac, “DC Power Flow Revisited,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1290–1300, Aug. 2009, doi: 10.1109/TPWRS.2009.2021235.

[2] M. H. Ullah and J.-D. Park, “Network-constrained local energy market clearing for peer-to-peer trading with bilateral power losses,” *Electr. Power Syst. Res.*, vol. 245, p. 111600, Aug. 2025, doi: 10.1016/j.epsr.2025.111600.

[3] Y. Xia, Y. Huang, and J. Fang, “A generalized Nash-in-Nash bargaining solution to allocating energy loss and network usage cost of buildings in peer-to-peer trading market,” *Sustain. Energy Grids Netw.*, vol. 42, p. 101628, Jun. 2025, doi: 10.1016/j.segan.2025.101628.

[4] Z. Sun, Z. Li, Y. Li, X. Bai, J. Zhang, J. H. Zheng, and B. Deng, “Peer-to-peer energy trading with decentralized bidirectional matching of multipreference community prosumers,” *Electr. Power Syst. Res.*, vol. 238, p. 111165, Jan. 2025, doi: 10.1016/j.epsr.2024.111165.

[5] M. Andoni, V. Robu, D. Flynn, S. Abram, D. Geach, D. Jenkins, P. McCallum, and A. Peacock, “Blockchain technology in the energy sector: A systematic review of challenges and opportunities,” *Renew. Sustain. Energy Rev.*, vol. 100, pp. 143–174, Feb. 2019, doi: 10.1016/j.rser.2018.10.014.

[6] Q. Yang, H. Wang, T. Wang, S. Zhang, X. Wu, and H. Wang, “Blockchain-based decentralized energy management platform for residential distributed energy resources in a virtual power plant,” *Appl. Energy*, vol. 294, p. 117026, Jul. 2021, doi: 10.1016/j.apenergy.2021.117026.

[7] A. Umar, D. Kumar, and T. Ghose, “Blockchain-based decentralized energy intra-trading with battery storage flexibility in a community microgrid system,” *Appl. Energy*, vol. 322, p. 119544, Sep. 2022, doi: 10.1016/j.apenergy.2022.119544.

[8] J. Hong, E. Song, J. Choi, S. Song, H. Kim, H. Kang, and T. Hong, “Integrating blockchain with virtual power plants: Two-level future roadmaps for enhanced performance,” *Technol. Soc.*, vol. 84, p. 103093, Mar. 2026, doi: 10.1016/j.techsoc.2025.103093.

[9] R. Shorya and P. Jagwani, “Enhancing Digital Autonomy in Peer-to-Peer Energy Trading: A Blockchain and Predictive Analytics Approach,” *Procedia Comput. Sci.*, vol. 254, pp. 230–239, 2025, doi: 10.1016/j.procs.2025.02.082.

[10] S. Habib, S. El-Ferik, M. M. Gulzar, S. T. Chauhdary, E. M. Ahmed, and H. Alnuman, “A tri-level hierarchical optimization framework for smart homes, microgrids, and distribution networks with hydrogen integration using a distributed ADMM approach,” *Appl. Energy*, vol. 400, p. 126577, Dec. 2025, doi: 10.1016/j.apenergy.2025.126577.

[11] S. Boyd, “Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers,” *Found. Trends® Mach. Learn.*, vol. 3, no. 1, pp. 1–122, 2010, doi: 10.1561/2200000016.

[12] J. Xiong, Y. Ye, Q. Wang, X. Dong, T. Lu, and D. Ma, “A comprehensive review on distributed energy cooperative control and optimization method for energy interconnection system,” *Electr. Power Syst. Res.*, vol. 237, p. 111007, Dec. 2024, doi: 10.1016/j.epsr.2024.111007.

[13] P. Cheng, A. Basem, M. Alanazi, N. A. Othman, S. Alhumaid, R. Ghandour, M. Dahari, Z. A. B. Sinnah, Z. Bayhan, and H. E. Ali, "Multi-energy storage integration through a two-stage decentralized peer-to-peer multi-energy market in the multi-vector energy microgrid," *J. Energy Storage*, vol. 142, p. 119476, Jan. 2026, doi: 10.1016/j.est.2025.119476.

[14] Q. Wu, Q. Song, X. He, G. Chen, and T. Huang, "Distributed peer-to-peer energy trading framework with manufacturing assembly process and uncertain renewable energy plants in multi-industrial micro-grids," *Energy*, vol. 302, p. 131876, Sep. 2024, doi: 10.1016/j.energy.2024.131876.

[15] Y. Chen, L. Hao, and G. Yin, "Distributed Energy Management of the Hybrid AC/DC Microgrid with High Penetration of Distributed Energy Resources Based on ADMM," *Complexity*, vol. 2021, no. 1, p. 1863855, Jan. 2021, doi: 10.1155/2021/1863855.

[16] R. A. Mahuze, A. Amadeh, B. Yuan, and K. M. Zhang, "Collaborative optimization framework for capacity planning of a prosumer-based peer-to-peer electricity trading community," *Appl. Energy*, vol. 384, p. 125289, Apr. 2025, doi: 10.1016/j.apenergy.2025.125289.

[17] A. Schinke-Nendza, A. J. Conejo, and C. Weber, "A distributed market-clearing framework for highly interconnected electricity and gas systems," *Eur. J. Oper. Res.*, p. S0377221725008513, Oct. 2025, doi: 10.1016/j.ejor.2025.10.031.

[18] C. Shah, R. Wies, and J. King, "Consensus-Based ADMM for Distributed Optimization in Power Systems using Private Blockchain Network," Jan. 01, 2021. doi: 10.36227/techrxiv.13507176.

[19] B. Zheng and W. Wei, "Real-time peer-to-peer energy trading for networked multi-energy systems with hybrid energy storage," *J. Energy Storage*, vol. 105, p. 114530, Jan. 2025, doi: 10.1016/j.est.2024.114530.

[20] B. N. Alhasnawi, B. H. Jasim, R. Z. Homod, B. Bazooyar, M. Zanker, and V. Bureš, "A novel peer-to-peer energy trading strategy for multi-microgrid loads scheduling based on chance-constrained," *Energy Nexus*, vol. 20, p. 100536, Dec. 2025, doi: 10.1016/j.nexus.2025.100536.

[21] S. Suthar and N. M. Pindoriya, "Chance-constrained co-optimization of peer-to-peer energy trading and distribution network operations," *Sustain. Energy Grids Netw.*, vol. 38, p. 101344, Jun. 2024, doi: 10.1016/j.segan.2024.101344.

[22] H. Abdolahinia, H. Lesani, and M. Moeini-Aghtaie, "Decentralized transactive energy market framework under network constraints to deal with technical issues in a radial distribution network," *Electr. Power Syst. Res.*, vol. 223, p. 109416, Oct. 2023, doi: 10.1016/j.epsr.2023.109416.

[23] C. Zhao, Q. Liu, D. Han, P. Niu, and S. Wu, "Decentralized energy trading framework with personalized pricing for energy community embedded with shared energy storage," *Electr. Power Syst. Res.*, vol. 235, p. 110562, Oct. 2024, doi: 10.1016/j.epsr.2024.110562.

[24] A. Paudel and H. B. Gooi, "Pricing in Peer-to-Peer Energy Trading Using Distributed Optimization Approach," in *2019 IEEE Power & Energy Society General Meeting (PESGM)*, Atlanta, GA, USA: IEEE, Aug. 2019, pp. 1–5. doi: 10.1109/PESGM40551.2019.8973868.

[25] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, “Designing microgrid energy markets,” *Appl. Energy*, vol. 210, pp. 870–880, Jan. 2018, doi: 10.1016/j.apenergy.2017.06.054.

[26] X. Huo and Z. Xun, “Secure decentralized energy exchange in Networked microgrids via blockchain and multi-Agent optimization,” *Int. J. Electr. Power Energy Syst.*, vol. 172, p. 111334, Nov. 2025, doi: 10.1016/j.ijepes.2025.111334.

[27] H. Liu, T. Lu, Y. Yang, Y. Guo, Q. Wu, X. Xu, and H. Zeng, “Blockchain-based optimization of operation and trading among multiple microgrids considering market fairness,” *Int. J. Electr. Power Energy Syst.*, vol. 166, p. 110523, May 2025, doi: 10.1016/j.ijepes.2025.110523.

[28] R. Mahmud and G.-S. Seo, “Blockchain-Enabled Cyber-Secure Microgrid Control Using Consensus Algorithm,” in *2021 IEEE 22nd Workshop on Control and Modelling of Power Electronics (COMPEL)*, Cartagena, Colombia: IEEE, Nov. 2021, pp. 1–7. doi: 10.1109/COMPEL52922.2021.9645973.

[29] T. Hai, N. S. S. Singh, and F. Jamal, “Energy management of a microgrid with integration of renewable energy sources considering energy storage systems with electricity price,” *J. Energy Storage*, vol. 110, p. 115191, Feb. 2025, doi: 10.1016/j.est.2024.115191.

[30] M. Gholami, S. M. Muyeen, and S. Lin, “Optimizing microgrid efficiency: Coordinating commercial and residential demand patterns with shared battery energy storage,” *J. Energy Storage*, vol. 88, p. 111485, May 2024, doi: 10.1016/j.est.2024.111485.

[31] E. Valipour, R. Nourollahi, K. Zare, and S. G. Zadeh, “A P-robust peer-to-peer framework for multi-energy microgrids in fully renewable integrated power and gas networks,” *Electr. Power Syst. Res.*, vol. 253, p. 112525, Apr. 2026, doi: 10.1016/j.epsr.2025.112525.

[32] D. Zhang, R. Han, W. Fu, L. Ran, and J. Qin, “Bi-Level Robust Optimal Energy Management of a Community Microgrid via Stackelberg Game,” *IEEE Trans. Consum. Electron.*, vol. 71, no. 2, pp. 6889–6899, May 2025, doi: 10.1109/TCE.2024.3446611.

[33] S. M. Ahsan, A. Hussain, and P. Musilek, “Pricing and trading strategies in networked microgrid systems: A comprehensive review,” *Energy Convers. Manag. X*, vol. 28, p. 101249, Oct. 2025, doi: 10.1016/j.ecmx.2025.101249.

[34] L. Wang, C. Dou, D. Yue, H. Li, and K. Ye, “Energy Sharing Market with Dual Time Scale Coordination Considering New Energy Uncertainties and Competition Among Stakeholders,” *IEEE Trans. Energy Mark. Policy Regul.*, vol. 3, no. 3, pp. 309–323, Sep. 2025, doi: 10.1109/TEMPR.2025.3549817.

[35] H. Davoudi, F. Wang, Y. Chen, D. Shi, A. Xavier, and F. Qiu, “Market Implications of Alternative Operating Reserve Modeling in Wholesale Electricity Markets,” *IEEE Trans. Energy Mark. Policy Regul.*, vol. 3, no. 1, pp. 1–12, Mar. 2025, doi: 10.1109/TEMPR.2024.3485948.

[36] N. Saeed, F. Wen, and M. Z. Afzal, “Decentralized peer-to-peer energy trading in microgrids: Leveraging blockchain technology and smart contracts,” *Energy Rep.*, vol. 12, pp. 1753–1764, Dec. 2024, doi: 10.1016/j.egyr.2024.07.053.

[37] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, “MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education,” *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 12–19, Feb. 2011, doi: 10.1109/TPWRS.2010.2051168.

[38] T. M. Masaud, J. Warner, and E. F. El-Saadany, "A Blockchain-Enabled Decentralized Energy Trading Mechanism for Islanded Networked Microgrids," *IEEE Access*, vol. 8, pp. 211291–211302, 2020, doi: 10.1109/ACCESS.2020.3038824.

[39] H. Lou and S. Fujimura, "ADMM -Based Distributed Algorithm for Energy Management in Multi-Microgrid System," *IEEJ Trans. Electr. Electron. Eng.*, vol. 19, no. 1, pp. 79–89, Jan. 2024, doi: 10.1002/tee.23953.

[40] T. AlSkaif and G. Van Leeuwen, "Decentralized Optimal Power Flow in Distribution Networks Using Blockchain," in *2019 International Conference on Smart Energy Systems and Technologies (SEST)*, Porto, Portugal: IEEE, Sep. 2019, pp. 1–6. doi: 10.1109/SEST.2019.8849153.

[41] G. Liu, T. B. Ollis, M. F. Ferrari, A. Sundararajan, and Y. Chen, "Distributed Energy Management for Networked Microgrids Embedded Modern Distribution System Using ADMM Algorithm," *IEEE Access*, vol. 11, pp. 102589–102604, 2023, doi: 10.1109/ACCESS.2023.3316513.

[42] Z. Chen, A. M. Amani, X. Yu, and M. Jalili, "Control and Optimisation of Power Grids Using Smart Meter Data: A Review," *Sensors*, vol. 23, no. 4, p. 2118, Feb. 2023, doi: 10.3390/s23042118.

[43] N. Nasiri, S. Zeynali, S. Najafi Ravadanegh, and S. Kubler, "Moment-Based Distributionally Robust Peer-to-Peer Transactive Energy Trading Framework Between Networked Microgrids, Smart Parking Lots and Electricity Distribution Network," *IEEE Trans. Smart Grid*, vol. 15, no. 2, pp. 1965–1977, Mar. 2024, doi: 10.1109/TSG.2023.3296917.

[44] B. Han, Y. Zahraoui, M. Mubin, S. Mekhilef, T. Korõtko, and O. Alshammari, "Distributed optimal storage strategy in the ADMM-based peer-to-peer energy trading considering degradation cost," *J. Energy Storage*, vol. 96, p. 112651, Aug. 2024, doi: 10.1016/j.est.2024.112651.

[45] C. R. Baier, J. C. Hernández, and P. Wheeler, "Measurements, Predictions, and Control in Microgrids and Power Electronic Systems," *Sensors*, vol. 23, no. 8, p. 4038, Apr. 2023, doi: 10.3390/s23084038.

[46] N. A. M. Kajaan, N. H. N. Amidi, Z. Salam, and R. Z. R. M. Radzi, "Blockchain-Based Smart Contract for P2P Energy Trading in a Microgrid Environment," *J. Phys. Conf. Ser.*, vol. 2312, no. 1, p. 012020, Aug. 2022, doi: 10.1088/1742-6596/2312/1/012020.

[47] A. Aderibole, A. Aljarwan, M. H. Ur Rehman, H. H. Zeineldin, T. Mezher, K. Salah, E. Damiani, and D. Svetinovic, "Blockchain Technology for Smart Grids: Decentralized NIST Conceptual Model," *IEEE Access*, vol. 8, pp. 43177–43190, 2020, doi: 10.1109/ACCESS.2020.2977149.