IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 25 December 2024, accepted 9 January 2025, date of publication 13 January 2025, date of current version 22 January 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3529205

RESEARCH ARTICLE

Cooperative Behaviors and Multienergy Coupling Through Distributed Energy Storage in the Peer-to-Peer Market Mechanism

ZEYNEP TANIS[1,2] AND ALI DURUSU[1,3], (Member, IEEE)
[1]Department of Electrical Engineering, Yildiz Technical University, 34220 İstanbul, Türkiye
[2]Nurol Holding-Nurol Solar Energy Production Inc., 06830 Ankara, Türkiye
[3]Clean Energy Technologies Institute, Yildiz Technical University, 34220 İstanbul, Türkiye

Corresponding author: Ali Durusu (adurusu@yildiz.edu.tr)

ABSTRACT The integration of distributed energy storage systems into multienergy systems has garnered significant attention due to the increased use of renewable energy sources and the demand for improved energy management. This study explores the concept of multienergy coupling by facilitating energy storage through a peer-to-peer marketplace. An innovative peer-to-peer market structure is proposed, supported by advanced algorithms, to enable direct energy trading among prosumers. Key challenges are addressed through a systematic methodology, encompassing user registration, multienergy systems involving electricity, heat, and gas, storage cost optimization, multienergy trading, and blockchain-based transactions. A consortium blockchain-based framework ensures secure and private registration. A peer-to-peer network facilitates multienergy trading, enabling efficient energy generation and storage. A storage virtualization model is developed to minimize storage costs, and a nonlinear programming multiobjective model optimizes battery energy storage. For multienergy trading, Nash bargaining under uncertainty is introduced, allowing participants to negotiate based on their contributions. The proposed model's performance is benchmarked against conventional peer-to-peer energy trading and the Q-learning algorithm. Transactions are secured using blockchain-based payment systems. The implementation is carried out using Matlab-R2023b Network Simulator, and the results are evaluated using various performance metrics.

INDEX TERMS Distributed energy storage systems, market-based consortium blockchain, multienergy coupling, Nash bargaining, peer-to-peer, storage virtualization model.

I. INTRODUCTION

Decentralized energy management systems have become feasible due to recent advancements in energy storage technologies and the growing number of renewable energy sources. This enables peer-to-peer (P2P) energy trading networks to allow prosumers to trade electricity, heat, and gas efficiently [1], [2], [3]. Such cooperative behavior aims to maximize resource consumption to optimize system performance. Cooperation involves the interaction between energy producers, consumers, and prosumers, and P2P energy trading can drive the transition to more resilient and sustainable energy systems by utilizing dispersed energy resources and encouraging cooperation [4], [5], [6].

Distributed energy storage systems (DESS), including thermal storage units, batteries, and hydrogen storage, play a critical role in supporting P2P markets. These systems smooth out energy fluctuations, optimize consumption, and align supply with demand. Proactive management of distributed energy storage (DES) assets can enhance the value of renewable energy generation while improving overall system flexibility [6], [7], [8]. DES systems are crucial in addressing the variability of renewable energy sources and enabling multienergy integration, where excess energy can be stored and utilized when needed to stabilize and sustain the energy network.

The associate editor coordinating the review of this manuscript and approving it for publication was N. Prabaharan.

© 2025 The Authors. This work is licensed under a Creative Commons Attribution 4.0 License.
For more information, see https://creativecommons.org/licenses/by/4.0/

As new mechanisms for energy trading continue to emerge, DES becomes increasingly important in P2P markets. One such mechanism is a tri-layer multienergy day-ahead market system, allowing the trading of heat, electricity, and natural gas together [9]. However, energy trading in decentralized networks is distinct from traditional commodity trading. P2P traders must connect to the physical grid to complete their transactions. Therefore, it is vital to consider the technological limitations of the distribution network in decentralized energy trading. Ignoring these limitations could negatively impact the performance and reliability of the distribution system [10], [11].

DES also contributes to grid stability, especially in active distribution networks with high penetration of renewable energy generation (REG). Autonomous aggregators and flexible resources, such as residential energy management, are being considered to support local REG consumption. Recent studies have integrated P2P trading with optimization models, such as optimal power flow (OPF) and unit commitment (UC), to improve energy usage efficiency within the market [12], [13].

One of the major benefits of DES in P2P markets is its ability to provide ancillary services, such as voltage support and frequency regulation. By rapidly adjusting power flows in response to frequency changes, DES helps stabilize the grid and facilitates a more flexible form of energy trading among prosumers [14], [15], [16]. Additionally, the integration of various energy carriers, including heat, gas, and electricity, enhances the dependability and efficiency of the entire energy system. For example, excess renewable energy can be stored in batteries or converted to heat or gas, thereby reducing waste and increasing energy efficiency [17], [18], [19].

In this paper, a new P2P market structure is proposed that enables direct energy exchange between prosumers. This structure integrates thermal storage, gas storage, and batteries, along with advanced algorithms to manage energy exchange and storage effectively. By supporting multienergy coupling, this structure facilitates a decentralized, flexible, and efficient energy system.

A. MOTIVATION AND OBJECTIVES

The integration of renewable energy sources (RES) and decentralization of energy systems are reshaping the global energy landscape. However, previous studies have encountered several critical challenges, including issues with fixed nodal temperatures, inefficient payment mechanisms, high energy storage costs, inaccurate distributed energy resource (DER) aggregation models, and unresolved privacy concerns. The key challenges can be summarized as follows:

- Fixed Nodal Temperature: Existing methods failed to accurately address the impact of fixed nodal temperatures on dispatch and pricing. Poor selection has led to significant inaccuracies.
- Payment Methodologies: Previous systems struggled with inefficient and unreliable transaction mechanisms between users.
- High Energy Storage Costs: Previously conducted research did not consider the cost of energy storage or made it extremely high when that was brought into consideration; thereby meaning that efficient optimization strategies were needed to curtail these expenses.
- An error exists in DERs: The error in DERs arises from challenges in accurately estimating the aggregated model of heterogeneous DERs. Previous methods have failed to account for the diverse characteristics and dynamic behaviors of DERs, such as variable energy outputs and nonlinear interactions. As a result, these inaccuracies persist in energy forecasts and optimization processes, negatively impacting the overall system's efficiency and reliability.
- Privacy Preservation: Blockchain-based systems from prior research lacked comprehensive mechanisms to ensure user privacy.

To overcome these limitations, this research proposes a decentralized energy trading system. The system enables prosumers to trade energy directly using advanced algorithms for trading and storage management, maximizing both market flexibility and operational efficiency. The primary goal is to facilitate multienergy trading—including electricity, heat, and gas—within a P2P network underpinned by blockchain technology.

The specific research objectives include:

- Addressing the impact of fixed nodal temperatures by improving their selection to enhance dispatch accuracy and pricing.
- Developing equitable and reliable payment mechanisms to ensure fairness for platform users.
- Designing cost-effective energy storage solutions to reduce storage-related expenses without compromising efficiency.
- Creating accurate aggregation models for heterogeneous DERs that account for their unique operational characteristics.
- Developing robust blockchain-based privacy-preserving mechanisms to protect user data and ensure secure transactions.

This research aims to bridge existing gaps in decentralized energy systems by introducing innovative solutions. It provides a comprehensive framework to enhance sustainability, efficiency, and security in the evolving energy market.

B. RESEARCH CONTRIBUTION

By utilizing distributed power storage through a P2P marketplace, the innovative integration of multienergy coupling can address the issues of energy unpredictability and improve the system's performance and robustness. The main contributions of this study are as follows:

- A decentralized multienergy trading system combining gas, heat, and electricity has been developed. It employs blockchain-based registration for privacy, Nash bargaining for fair cooperation, and a transparent incentive structure to ensure safe transactions.

- A concept of storage virtualization has been designed, alongside a multiobjective nonlinear programming approach to optimize battery lifespan, reduce storage-related costs, and enhance resource utilization.
- Flow tracing is applied to fairly allocate costs. Blockchain technology is used to enhance security and privacy for users. Alternating direction multiplier method (ADMM) based decentralization is incorporated in the optimization technique for nodal dispatch and pricing.

C. PAPER ORGANIZATION

The remainder of the paper is organized as follows: Section II provides an overview of the current methodology and a review of the relevant literature. Section III outlines the problem statement. Section IV presents the proposed research approach, including the protocol, algorithm, mathematical formulations, and pseudocode. Section V compares the proposed approach with existing methods to present simulation results. Finally, Section VI summarizes the proposed procedure.

II. LITERATURE SURVEY

This literature review identifies several important research gaps concerning distributed energy systems (DES) and multi-energy coupling integration in peer-to-peer (P2P) market mechanisms, as highlighted in earlier publications. The study in [20] proposes a novel framework for the energy market, based on P2P agreements, to address interdependencies between various energy carriers and enable energy transactions among agents at the delivery level. Additionally, linear optimization techniques are suggested to investigate the optimal practices of market players with diverse configurations. These optimization models determine not only the best agent strategies for ''day-ahead P2P electricity, heat, and gas distribution'' networks but also the optimal operation schedules for the following day.

The proposed marketplace framework is further extended to manage energy transactions among agents at the distribution level and integrate district electricity and heating networks. For the efficient operation of multiple energy hubs (EHs), a ''market mechanism based on P2P transactions'' is introduced in [21]. Using cooperative game theory, a fair and rational payoff distribution plan is developed. The stability of the grand coalition of EHs is validated by demonstrating that several EH processes form a stable ''cooperative game.'' The issue of payoff allocation is addressed in two stages. In the first stage, the allocation is determined to minimize the worst-case excess. In the second stage, the coalition with the largest surplus is identified and reconciled with the initial problem. A column generation method under constraints is proposed to solve this two-stage problem. Additionally, the proposed P2P transaction mechanism in [21] may include other transaction types, such as natural gas trading and carbon emissions rights.

In [22], a ''shareholding-based resource sharing mechanism'' is proposed to ensure the efficient utilization of shared resources, enabling individuals to collectively manage distributed energy resource (DER) usage and act as unified prosumers. Since the proposed sharing mechanism links all energy and financial benefits to shares, a ''decision-making and shareholding transfer framework'' is developed to facilitate on-demand allocation of shares. The options for utilizing energy produced by communal DERs include P2P energy trading, participation in the local microgrid market, or self-consumption. Two models are presented based on the prosumer's ''supply-response and demand-response'' characteristics to guide production and consumption strategies. However, it should be noted that the suggested solution may significantly increase energy exchange at certain buses due to shared energy and P2P transactions, potentially causing technical issues at lower-voltage feeders.

In [23], a cooperative trading mechanism for a multienergy community (MEC) that integrates heat, natural gas, and electricity for all prosumers via an energy hub (EH) is proposed. A comparative framework for the conventional uncooperative local integrated energy system (ULIES) is also developed. A profit distribution system, based on prosumers' satisfaction and their perceptions of additional savings or profits realized in MEC compared to ULIES, is introduced. Case studies are used to evaluate the value of MEC in enhancing social welfare, considering the impact of prosumers' energy consumption patterns and buy-sell pricing strategies in the trade market. The results demonstrate that satisfaction-based profit sharing can reduce costs or increase profits for both prosumers and the EH. Strategic consumer behavior regarding satisfaction functions may also be considered. Future research could explore regulatory measures to maintain competition, equity, and prevent societal welfare losses.

To achieve social energy optimality, [24] proposes a novel cooperative framework for energy storage sharing, involving prosumers, energy storage providers (ESPs), and an intermediate agent. Within this framework, prosumers are enabled to share multiple ESPs' energy storage facilities. The optimization problem, which minimizes overall energy costs, encompasses energy storage operation, shiftable load scheduling, and energy trading with utilities. The problem is solved using the fast alternating direction multiplier method (FADMM), which converges faster than the traditional ADMM. Additionally, a clearing method, termed the profit realization ratio distribution framework, is introduced to equitably distribute net earnings among participants. Challenges such as addressing congestion and protecting confidentiality in energy storage sharing are acknowledged as potential future research topics.

In [25], a cooperative operation framework for a wind-solar-combined cooling, heating, and power (CCHP) multi-energy system is proposed. The optimal operation scheduling problem is formulated as a Nash Bargaining optimization, contrasting with the traditional noncooperative approaches. The problem is divided into two sub-problems: energy trading payment (P2) and social welfare maximization (P1). The P1 problem is solved to determine optimal energy transaction

profiles, while P2 addresses energy trading payments among photovoltaic (PV), wind turbine (WT), and CCHP agents. Both P1 and P2 are formulated as mixed-integer linear programming (MILP) problems and solved using the ADMM. However, system line losses, distributed generation uncertainties, and cooling and heating demands of end-users are not fully addressed in the study, presenting opportunities for future investigation.

Research primarily focuses on the operation of ''Wind-Hydrogen-Heat multiagent energy systems'' in [26], where Nash bargaining game theory is proposed as the cooperation planning and operation method. This approach aims to enhance the welfare of the ''Wind-Hydrogen-Heat'' system. Although the concept of a ''Wind-Hydrogen-Heat multiagent energy system'' offers a broad and extensible framework, its practical implementation in the proposed model faces challenges. To address uncertainties, a robust possibility programming method is applied in [27]. The decentralized robust problem is resolved using a fully decentralized technique based on the ADMM. This decentralized approach balances feasibility, optimality, and the average anticipated value to achieve the best possible solution.

Human factors and energy consumption behavior are examined for their effects on distribution networks. In [28], a comprehensive risk management framework is introduced to identify, categorize, evaluate, and mitigate risks faced by prosumers participating in P2P energy markets. Risk analysis identifies ten primary risks, which are categorized into three main groups. For each identified risk, potential mitigation strategies are proposed to minimize their impact on P2P electricity market participation. By managing risks from the perspectives of prosumers and integrating them into P2P power trading and microgrid scheduling, the design of an efficient market mechanism is facilitated. While numerous studies have focused on optimizing P2P community performance—addressing planning, integration, supervision, expansion, and market procedures—the associated risks have often been overlooked. Future research should address these risks comprehensively to enhance the reliability and appeal of P2P energy markets.

The features of a standard P2P energy-sharing community model are examined in [29], where the Shapley value from game theory and the ''proof of credit consensus'' mechanism in blockchain technology form the basis of the concept. A two-tier hierarchical incentive system is proposed to encourage participants to comply with energy smart contracts and engage in peak-shifting of power. The operational performance of the proposed model is evaluated using indices that consider environmental, economic, technical, and market efficiency aspects. Future work aims to develop a more realistic framework by reducing the computational time of the proposed method and incorporating the effects of various power grid regulations.

In [30], a hybrid algorithm is developed using a feed-forward neural network (FFNN) and reinforcement learning (RL) to create an analytical model and a three-tier architecture for network exploration in a blockchain-based P2P energy trading system. This architecture is analyzed to evaluate trade-offs related to latency, throughput, and safety in P2P energy trading, ultimately facilitating profitable trading among dispersed prosumers. Future research should focus on applying the proposed analytical model and algorithm in real-world scenarios.

In [31], a local energy market is introduced where prosumers trade energy without operator regulation. To support competitive trading in real-time energy markets, a two-stage energy-trade management algorithm is proposed. In the first stage, trades are managed based on prosumer offers and bids, prioritizing reasonable pricing. In the second stage, trades are facilitated for prosumers who were unable to participate initially, utilizing community energy storage managed by a reinforcement learning-based algorithm. This algorithm determines whether to buy, sell, or hold energy, charging and discharging the communal storage system accordingly. Future work involves examining actual transaction data from prosumers instead of relying on simulated data.

In [32], secure multiparty computation is applied to ensure anonymity in a P2P energy flexibility market on Ethereum. The proposed system encodes energy market orders to separate energy bids and offers, group prosumers, and create aggregated group-level orders, thereby obscuring the quantity of energy transacted. Smart contracts are used to implement an energy flexibility marketplace, ensuring privacy in activities such as order submission, bid matching, trading, and settlement. Experimental results demonstrate the system's effectiveness in facilitating peer-to-peer energy flexibility trading, reducing transaction volumes, and minimizing gas usage with low computational overhead. Future research will explore the feasibility of extending this approach to multi-energy markets, enabling the trade of other energy carriers such as gas and heat alongside electricity.

Analyzing the product differences across prosumers in [33], a novel mutual reputation index is proposed to account for their propensity to engage in bilateral trade. To accelerate the convergence rate, the traditional ADMM is replaced with the F-ADMM algorithm. The efficacy of the proposed approach is validated through software simulations. However, the study does not address network power losses, which could significantly influence energy pricing.

To address the imbalance in energy hub operations in P2P trading platforms, [34] introduces a gas-electricity integrated energy system (IES) multienergy sharing technique. Initially, the shared energy quantities of EHs participating in P2P trading are estimated, considering the characteristics of multienergy coupling and conversion. To determine more favorable energy trading prices, EHs engage in multilateral negotiations based on the Raiffa-Kalai-Smorodinsky bargaining solution. Finally, an energy trading plan is developed by producer and consumer agents for each EH. A significant challenge in this approach is the increased computational

complexity, as trade prices must be determined for every pair of EHs, limiting the scalability of one-to-one bargaining.

The work discusses risk-averse stochastic capacity planning combined with the optimization of P2P trading in multienergy microgrids under carbon emission limitations [42]. An asymmetric Nash bargaining approach is applied to allocate benefits among participants in the market. In doing so, the study aims to incorporate the complexity of multienergy systems by integrating carbon emissions and risk aversion into the benefit distribution process. While also considering multienergy systems, it distinguishes itself by including DES to manage energy fluctuations and optimize consumption, offering additional resilience and flexibility to the system. Furthermore, the focus of this paper on real-time price variations and technology-related constraints, such as network limitations, provides a more realistic view of P2P trading compared to the theoretical framework of Nash bargaining. In the context of a multienergy P2P trading system, this paper employs adaptive robust stochastic optimization to improve coordination between aggregators and networks [43]. The model integrates adaptive optimization techniques with energy trading while addressing uncertainties in both generation and consumption. This study mainly concentrates on optimization involving energy flows between aggregators and distributed energy resources. Although this concept is similar to the work in that it deals with multienergy trading, this article has a more decentralized architecture where distributed energy storage facilitates direct energy exchange between prosumers. The integration of thermal storage, gas storage, and batteries along with real-time adjustments may further enhance the flexibility and efficiency of the system, providing an innovative solution compared to the aggregator-based approaches, which are mostly centralized. Table 1 represents the summary of literature survey.

III. PROBLEM STATEMENT

The study addresses the challenge of integrating distributed energy storage into the P2P market mechanism for multienergy coupling. As renewable energy sources expand, optimizing the coordination and management of energy types such as heat, gas, and electricity becomes essential. This research aims to explore practical methods to enhance the sustainability, resilience, and efficiency of decentralized energy markets by leveraging distributed energy storage.

In [35], a Quadratic Programming model is introduced to represent a network-aware heat market. This model determines the optimal dispatch and calculates a ”set of nodal marginal prices. ” While heat networks are typically characterized by ”nonconvex constraints, ” the model achieves convexity by fixing temperature variables and neglecting pumping power. The flexibility of nodal heat injections, both in terms of sign and magnitude, is crucial for facilitating the integration of prosumers into variable flow heating networks. In this study, we incorporate explicit loss conditions into P2P transactions, forming the basis of the market. This allows us to identify the producers and consumers responsible for network losses. Using dual analysis, we reveal the nodal price components related to losses and clarify the relationship between nodal prices and buyer/seller prices. A case study compares the network-aware market mechanism with a ‘‘loss-agnostic benchmark.’’ The results demonstrate that the proposed mechanism effectively supports local heat prosumers and reduces operational costs in district heating networks.

➢ The selection of fixed nodal temperatures has a significant impact on dispatch and pricing, and should therefore be approached with care.

In [36], a revolutionary decentralized digital data marketplace platform is proposed for Internet of Things (IoT) data. The platform uses a decentralized data streaming network to ‘‘host IoT data in a dependable and fault-tolerant way.’’ It ensures fair trade, privacy-preserving data transmission and storage, and trust metric computation for network participants. An open-source library is developed based on VerneMQ’s data network layer and Hyperledger Fabric. This library is deployed on a ‘‘real-time Google Cloud platform’’ to evaluate the feasibility of the proposed system. Performance, overheads, and scalability are analyzed after testing the library.

➢ In this research, proper payment transactions between two users were not implemented.

In [37], a P2P energy trading architecture is proposed. This architecture allows for the participation of distributed PV prosumers and consumers in a cooperative distribution market organized by an energy pawn (EP), a key stakeholder. The EP is responsible for setting up, linking, overseeing, and maintaining the P2P sharing network. The EP also manages a public battery energy storage (BES) system that supports community energy sharing. A leader-follower model describes the relationships between the EP, prosumers, and consumers in a categorized P2P distribution market. The EP is responsible for two main tasks: (i) determining trade and purchase prices in the market, and (ii) improving the efficiency of the ES system’s capacity scheduling through forecasting-based rolling-horizon decision-making. Prosumers and consumers adjust their energy use based on changing sharing prices in order to optimize their utility functions and satisfaction. PV prosumers and consumers can exchange energy with the EP to balance excess solar energy production or underutilization, thus reducing their energy costs. For the EP, a dynamic pricing algorithm is proposed to simultaneously determine buying and selling prices. The proposed hierarchical decision-making issue is solved using Q-learning. An energy-sharing scenario involving ten agents is examined to evaluate the financial benefits, PV sharing improvements, and the reduction in megawatt returns to the grid. This research offers a viable win-win solution for P2P market agents, the EP, and the utility grid.

➢ However, in this study, the cost of energy storage remains high.

In [38], an aggregated operating model for heterogeneous DERs in P2P energy trading is proposed. First, an SL-aided

TABLE 1. Summary of literature survey.

References	Objective	The model used or the algorithm	Limitations
[20]	Integrated distribution energy systems	P2P electricity, heat, and gas distribution networks	• Expanded to handle energy
[21]	Multiple energy hubs with the penetration of high-level renewable energy	Payout allocation algorithm in a cooperative EH operations game	• ignores the viability of implementation
[22]	Promoting energy equity in P2P energy trading	A mechanism for sharing resources based on shareholding	• Technical problems at the lower-voltage feeders
[23]	Profit distribution in a multienergy community based on satisfaction	Uncooperative local integrated energy system (ULIES)	• Intricacy of regulations
[24]	Energy storage sharing	Alternating direction multiplier method (ADMM)	• Does not include concerns related to congestion and secrecy protection
[25]	Multienergy system based on wind, solar, and CHP using nash bargaining Solution	ADMM	• Fails to handle distributed generating uncertainty • System line losses are not taken into consideration.
[26]	Wind-hydrogen heat multiagent energy system	Nash bargaining game theory	• Not functional or implemented enough in their existing model.
[27]	Robust probabilistic programming-based P2P electricity and gas markets	Fully decentralized technique	• Does not adequately address the impact of human factors in general and energy usage by humans on distribution networks.
[28]	Framework for managing risks in peer-to-peer power marketplaces	Microgrid scheduling	• Ignores the possible dangers • Difficulties that come with P2P community optimization
[29]	P2P energy-sharing community	Proof of credit consensus in blockchain technology	• Does not examine the consequences of shortening the recommended method's duration.
[30]	An examination of networks in a peer-to-peer energy trading model	Feed-forward neural network (FFNN) and reinforcement learning (RL)	• Validate and apply the analytical model
[31]	Based on reinforcement learning P2P trade management of energy	Local energy market with a management algorithm	• Neglects to employ real energy transaction data from prosumers
[32]	Security-maintaining algorithm for distributed energy trading on an open blockchain	Multiparty computation (MPC)	• Excludes the applicability of the technique for multienergy markets
[33]	P2P energy trading in transactive markets considering physical network constraints	Fast alternating direction method of multipliers (F-ADMM)	• Failure to account for network power losses in energy price calculations
[34]	P2P trading mode-based three stage multienergy trading strategy	Gas-electricity integrated energy system (IES) multienergy sharing technique	• Computationally taxing and makes one-to-one negotiation situations less feasible

DER aggregation model is introduced to estimate the aggregated parameters of heterogeneous DERs. Next, a P2P trading mechanism is proposed for the combined DERs. To ensure privacy, aggregators can trade in a decentralized manner with each other. Finally, the iteration process among aggregators is accelerated using the F-ADMM. As a result, decisions are made more quickly, and aggregators need to communicate less, reducing communication stress. Case studies are used to validate the effectiveness of the proposed methodology.

➢ As of now, the proposed approach still estimates the combined model of heterogeneous DERs but does not allocate resources properly, which results in a margin of error.

In [39], an approach consisting of two levels is proposed: safe energy trading and authentication. To protect the suggested model against impersonation attacks, a mutual authentication process is applied at the authentication layer. A distinct consensus process is proposed at the energy trading layer to reduce the number of malicious validators. An incentive-punishment mechanism is then introduced to encourage energy prosumers to contribute more energy to the system. The dynamic contract theory is applied through a pricing mechanism based on the supply-demand ratio. The proposed price plan aims to address the issues with existing pricing schemes. It also conceals the traders' actual energy-use patterns from unwanted scrutiny. Furthermore, a consensus-based tester selection paradigm is proposed. The goal of this research is to develop a secure and efficient P2P energy trading system.

➢ In this research, the issue of privacy preservation through blockchain schemes is not fully addressed.

Although existing studies have proposed various approaches to address the challenges in decentralized energy systems, some limitations remain unresolved. This research presents a comprehensive approach to overcome these shortcomings and enhance the sustainability, efficiency, and security of

decentralized energy markets. An innovative security protocol supported by a unique public-private key mechanism has been developed for the user registration process. This method encrypts and anonymizes user authentication while ensuring the confidentiality of sensitive data. The keys generated during registration enable secure messaging and effectively prevent fraud and unauthorized access attempts. The proposed approach not only protects user privacy but also provides a security solution compatible with the fast and scalable architecture of the consortium blockchain, setting a new standard for energy trading. To address challenges related to energy storage, a storage virtualization model has been employed to reduce physical storage costs. Additionally, a multiobjective nonlinear programming model has been introduced to optimize the lifespan of battery energy storage systems while minimizing energy costs. The integration of these methods ensures cost-effectiveness and sustainability. A decentralized and parallel solution has been developed to tackle optimization challenges in multienergy systems. This solution involves a carefully designed distribution determination step, which includes time resolution selection using high-precision thermal dynamics modeling. Furthermore, an innovative node-based energy pricing method is introduced via a flow monitoring technique. This method identifies producers and consumers responsible for network losses by integrating loss conditions open to P2P transactions, thus enhancing market transparency. To further increase scalability and flexibility, an online energy control and trading algorithm has been developed. This algorithm allows prosumers to seamlessly enter and exit the system without increasing computational complexity. It also grants prosumers independent control over DERs and enables them to dynamically adjust their bids according to time-specific conditions. To address privacy concerns, a market-based consortium blockchain system is proposed. This system facilitates the secure and confidential trading of multiple energy commodities, including electricity, heat, and gas, while ensuring the protection of user data and enabling secure transactions. Finally, to address the lack of secure and efficient payment mechanisms, a blockchain-based fair incentive mechanism is proposed. This mechanism uses cryptocurrencies like Bitcoin to encourage user collaboration and ensures secure P2P payment transactions. Thus, the proposed research presents a robust framework that addresses critical gaps identified in existing studies, aiming to enhance the sustainability, resilience, and efficiency of decentralized energy systems. With innovative security protocols, advanced optimization solutions, and increased scalability, this approach sets a new milestone for the future of energy markets.

IV. PROPOSED WORK

The research conducted suggests a unique strategy centered on multienergy coupling via distributed energy storage inside the P2P market framework designed to address the growing intricacy of electrical systems. This project intends to create a workable model that enhances the dependability and efficiency of energy distribution among prosumers by combining technology related to electricity, heat, and gas storage. The goal of the proposed effort is to improve energy management techniques and investigate fresh approaches to the sustainable use of energy in decentralized marketplaces''. The following crucial actions are taken as part of this work,

- Registration
- Multienergy involving electricity, heat, and gas
- Electricity and heat storage cost
- Multienergy involving electricity, heat, and gas trading
- Blockchain-based payment methodology

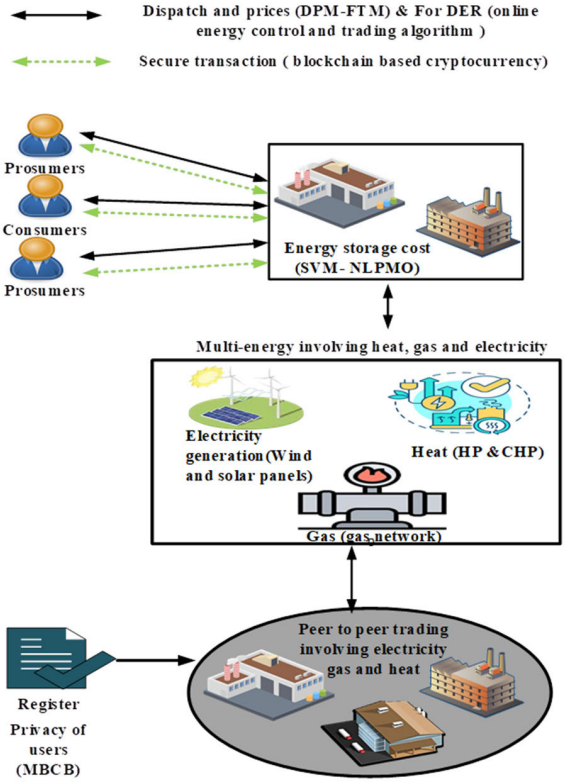


FIGURE 1. The overall proposed architecture of this research.

A. REGISTRATION

In order to participate in power exchange over the consortium blockchain, users must first register their identification information through several key components: the Trust Center (TC), the Key Generation Center (KGC), and the Registration Center (RC). This multistep registration process ensures that users are properly authenticated and that their identities are securely linked to the blockchain network. The detailed procedure is illustrated in Fig. 2, highlighting the flow of information between these entities to guarantee secure and trusted participation in the energy trading ecosystem.

$$User \rightarrow RC: .\{ID_j\}$$

The user submits their identity information, denoted as ID_j, to the RC. This identity uniquely defines the user within the system. Upon receiving ID_j, the RC validates the identity and generates a random number $N \in Z_p^* p$. Here, Z_p^*represents the

multiplicative group modulo a prime p, ensuring the randomness and security of N. This value serves as the foundation for subsequent cryptographic operations.

$$RC \rightarrow TC \rightarrow KGC: .\{N\}$$

The RC forwards the generated N to the TC. The TC selects another random number $T \in Z_p^*$ and applies a hash function $H_0(T)$. Subsequently, the TC computes $g^{H_0(T)\cdot N}$, where g is a generator of the group Z_p^*, reinforcing the cryptographic integrity of the system. The TC generates a public-private key pair for the user as follows:

$$\begin{cases} PK_{pse} = g^{H_0(ID_j)} \cdot g^{H_0(H_0(T)\cdot N)} modp \\ SK_{pse} = H_0\left(ID_j\right) + H_0(g^{H_0(T)\cdot N}) \end{cases} \quad (1)$$

The public key PK_{pse} is sent to the user, while the private key SK_{pse} is securely stored by the TC.

$$RC \rightarrow User: .\{N, PK_{pse}\}$$

After receiving PK_{pse} and N, the user selects a random number $r \in [1, p-1]$ and computes:

$$\begin{cases} u_j = g^r modp \\ u_j' = ID_j \cdot PK_{pse}^r \ modp \end{cases} \quad (2)$$

These computations yield the user's anonymous identity $ID_j' = (u_j, u_j')$, which ensures privacy during system interactions.

$$User \rightarrow KGC: .\{N, ID_j'\}$$

The user transmits ID_j' and N to the KGC. The KGC selects a random value $b_j \in Z_q^*$ and calculates:

$$\begin{aligned} B_j &= b_j P \\ d_j &= \left(b_j + h_{1,j}\right) modq \end{aligned} \quad (3)$$

Here, $h_{1,j} = H_1(ID_j', B_j, P_{pub})$ is derived using a hash function,P represents the generator point in an elliptic curve system, and P_{pub} is the public key. The user's partial private key is then defined as $D_j = (d_j, B_j)$.

$$KGC \rightarrow User: .\{D_j\}$$

The KGC sends D_j to the user, who verifies the equation $d_j P = B_j + h_{1,j} P_{pub}$. If the verification succeeds, the user selects their private random value $x_j \in Z_q^*$ and computes:

$$\begin{aligned} X_j &= x_j P \\ Q_j &= (B_j + X_j) \end{aligned} \quad (4)$$

Final key pairs are defined as:

$$\begin{aligned} PK_j &= \left(Q_j, B_j\right) \\ SK_j &= (d_j, x_j) \end{aligned} \quad (5)$$

If verification fails, the user requests a new D_j from the KGC to restart the process.

Upon successfully completing the a forementioned process, users can begin trading within the secure and efficient framework of the consortium blockchain. By leveraging pre-selected nodes for consensus, the system ensures faster transactions, reduced costs, and secure, tamper-evident data storage. These features make consortium blockchains particularly well-suited for small-scale power trading, offering a practical and scalable solution for decentralized energy markets.

This structured registration process combines detailed cryptographic operations with robust privacy measures to ensure secure and authenticated participation in the consortium blockchain. By utilizing public keys (PK_{pse}, PK_j) for user authentication and encryption, and private keys (SK_{pse}, SK_j) for signing and authorizing transactions, the system ensures that only verified participants can perform actions on the blockchain. Furthermore, the use of random values (N, r, b_j) and hash functions enhances the cryptographic integrity of the system, safeguarding against tampering or unauthorized access. The inclusion of an anonymous identity (ID_j') preserves user confidentiality during blockchain interactions, which is crucial for maintaining trust in a decentralized energy market. These features, combined with the pre-selected nodes for consensus, make consortium blockchains highly suitable for small-scale energy trading, providing faster transactions, lower costs, and secure, tamper-evident data storage. The overall system architecture ensures that every participant is securely integrated into the energy trading ecosystem while maintaining privacy and efficiency.

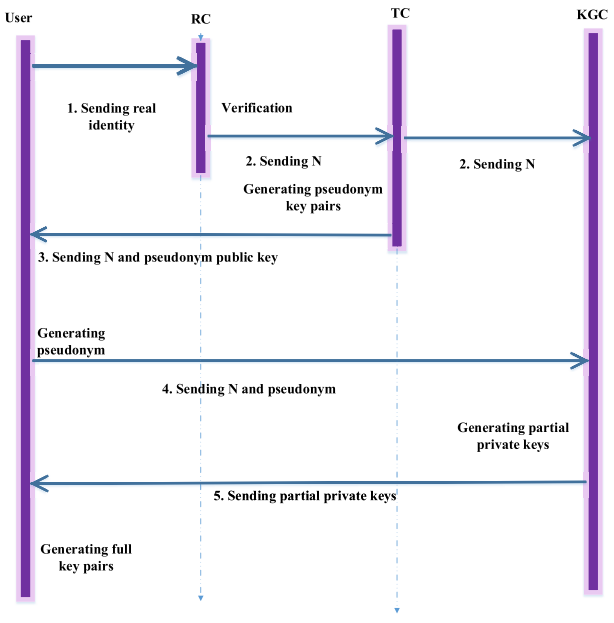


FIGURE 2. User registration process.

B. MULTİENERGY INVOLVING ELECTRICITY, HEAT, AND GAS

This multienergy trading involves and shows how it generates and stores in the P2P network.

1) ELECTRICITY GENERATION AND STORAGE

Electricity generation from WT and solar energy is inherently variable due to the fluctuations in wind speed and sunlight availability. WT transform atmospheric kinetic energy into electrical energy. When the wind blows, it causes the turbine to rotate around a rotor with blades. A generator is turned to produce electricity by use of a rotor that is fixed to the main shaft. Because wind energy is so dependent on wind supply and speed, it is a variable energy source. Solar panels, also known as solar power panels, convert direct sunlight into electricity. They are formed up of numerous solar cells produced from semiconductor components, like silicon. These cells receive solar radiation, which excites the electrons and creates an electrical current. Solar energy is dependent on sunshine availability, which varies with weather and time of day. To control the intermittent nature of wind and solar energy, power storage systems are required. Commonly used storage techniques include: Batteries store extra power created during peak production periods and release it when output drops. Lithium-ion batteries are frequently utilized due to their outstanding efficiency and high density of energy. These systems include large-scale battery banks, pumped hydro storage, and other technologies that store significant amounts of power to be used later.

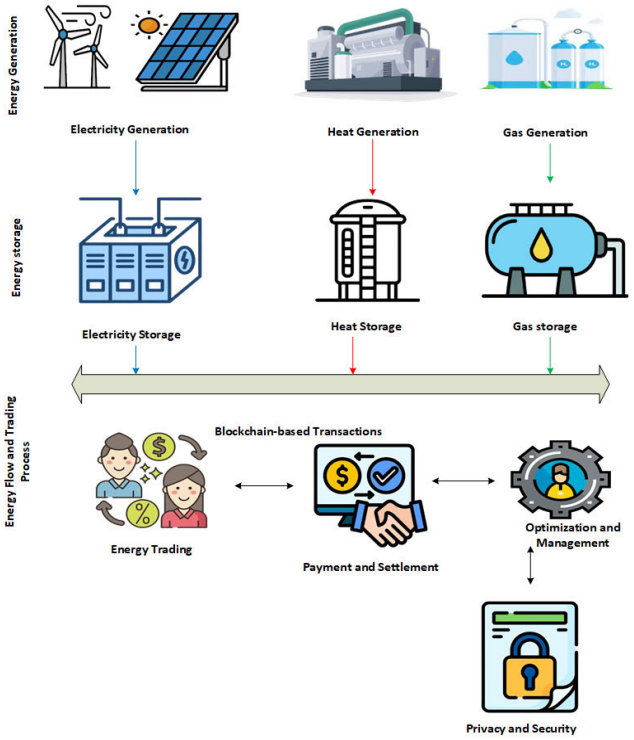


FIGURE 3. Multienergy involving electricity, heat, and gas.

2) HEAT GENERATION AND STORAGE

For the heat trading, a heat network has been established, and a heat pump and combined heat and power (CHP) model have been integrated for storage. A heat network, commonly referred to as a district heating system, distributes heat from a central source to residential and commercial buildings. This centralized approach enhances efficiency and reduces emissions compared to individual heating systems. A model with integrated heat pumps and CHP illustrates a multienergy structure involving electricity, heat, and gas, as shown in Fig. 3. Heat pumps transfer heat from a source (such as the earth, air, or water) to a destination (a building). They can also provide cooling by operating in reverse. Heat pumps are highly efficient as they move heat using electricity, rather than generating it through combustion. CHP systems generate both electricity and usable heat from the same energy source. This cogeneration technique captures and utilizes heat that would otherwise be wasted during power generation, significantly improving overall efficiency. Thermal Energy Storage (TES) systems typically store excess heat in insulated tanks filled with water or other heat-retaining materials. Phase Change Materials absorb and release thermal energy during phase transitions (e.g., from solid to liquid), providing effective heat storage solutions.

3) GAS GENERATION AND STORAGE

A P2P gas network allows for decentralized gas trade among users, increasing the flexibility and robustness of the gas supply system. This network facilitates the trade of both natural gas and renewable gases such as biogas and hydrogen. Natural gas is kept at high pressure in tanks or subterranean caves. This approach is often used for short-term storage. The gas is cooled to a liquid form at -162 °C, decreasing its volume for simpler storage and transportation. LNG storage facilities are utilized to meet both short- and long-term storage requirements. Large amounts of gas are held in depleted oil and gas fields, aquifers, and salt caverns. These facilities offer seasonal storage, maintaining a steady supply throughout peak demand seasons. In a P2P energy trading system, users may swap electricity, heat, and gas directly, negating the need for traditional utility suppliers.

C. ELECTRICITY AND HEAT STORAGE COST

After establishing the networks, it becomes critical to reduce physical energy storage costs to ensure an effective system. To address this issue, a storage virtualization model has been developed to eliminate the disadvantages associated with physical storage. Additionally, a nonlinear programming multiobjective model (NLPMO) has been implemented to extend the lifespan of battery energy storage systems and reduce overall energy costs. The integration of the storage virtualization approach with NLPMO has successfully maximized battery lifespan and minimized energy costs. This combined strategy provides an effective solution for overcoming the limitations of physical storage while enhancing cost-efficiency in decentralized energy systems.

1) STORAGE VIRTUALIZATION MODEL

The storage virtualization technology, which abstracts and consolidates physical storage resources into a unified,

flexible system, is transforming energy storage economics. This approach integrates various storage systems, including thermal storage, batteries, and other storage units, into a virtual platform capable of dynamically allocating and optimizing storage capacity based on real-time demand and supply conditions. By pooling resources, the infrastructure achieves greater efficiency, significantly reducing capital costs and minimizing the need for excess physical storage.

A key advantage of storage virtualization is its ability to dynamically allocate resources. In conventional storage setups, individual units operate independently, often leading to low utilization rates and inefficiencies. Virtualization, however, enables centralized control of storage resources, allowing energy to be distributed to the areas where it is needed most, exactly when it is required. This dynamic load distribution enhances system reliability by preventing specific units from becoming overburdened, safeguarding the security of other units, reducing energy losses, and lowering operational expenses.

Another notable benefit of virtual storage systems is their integrated management capability, which streamlines monitoring and maintenance processes. This integrated approach extends the lifespan of storage devices by reducing strain on components. Maintenance tasks, such as optimizing charging and discharging cycles and maintaining optimal operational conditions, help alleviate stress on batteries. Consequently, these measures reduce wear and tear, extend battery life, and yield significant cost savings over time.

Storage virtualization also plays a critical role in scalability. Without requiring substantial upfront investments in physical storage assets, virtualization systems can seamlessly incorporate new storage technologies and scale up to meet growing demands. This flexibility allows the system to adapt over time, integrating advancements rapidly without necessitating significant financial outlays. Furthermore, it supports incremental growth, reducing the need for expensive and disruptive overhauls while enabling more practical, smaller expansions of storage capacity.

2) COST AND ENERGY MANAGEMENT FOR BESS OPERATIONS

The multiobjective model in Non-linear programming (NLP) serves as a proactive approach aimed at optimizing the efficiency and reducing costs of battery energy storage system (BESS) operations. This method addresses multiple objectives simultaneously, such as minimizing overall energy costs and maximizing battery lifespan. By integrating these optimization techniques with conventional energy management systems, the BESS provides a highly efficient and cost-effective solution for energy storage.

The financial framework of BESS encompasses both revenue and investment expenses. These are divided into capital investment costs and monthly operational and maintenance (O&M) costs. The main components consist of capital investment costs, which include the power conversion equipment costs (expressed in \$/kW) and the energy storage capacity costs (C_{cap}, in \$/kWh), as well as community grid costs, encompassing the energy price ($\lambda^{grid}(t)$,cost per kWh at time t) and the maximum demand charges (C_{md}).

The decision variables for optimization include the power conversion rating E^b, the energy storage capacity E^{con}, and the battery charge/discharge schedule $P^{bat}(t)$.

The operational constraints are defined as follows:

1. Energy cost is defined based on whether the grid is buying or selling energy:

$$\lambda^{grid}(t) = \begin{cases} \lambda^{buy}(t), & P^{grid}(t) \geq 0 \\ \lambda^{sell}, & P^{grid}(t) < 0 \end{cases} \tag{6}$$

2. The internal pricing for battery charging and discharging is determined by:

$$Pr_b(t) = \begin{cases} Pr^{sell}(t), & P^{bat}(t) \geq 0 \\ Pr^{buy}(t), & P^{bat}(t) \geq 0 \end{cases} \tag{7}$$

3. Battery power is constrained to remain within predefined operational limits.

$$P^{bat}_{min} \leq P^{bat}(t) \leq P^{bat}_{max} \tag{8}$$

4. Battery energy levels are maintained within operational boundaries:

$$E^{bat}_{min} \leq E^{bat}(t) \leq E^{bat}_{max} \tag{9}$$

5. Energy balance is enforced over the operational horizon:

$$E^{bat}(T) = E^{bat}(0) \tag{10}$$

6. Financial feasibility is ensured by guaranteeing a positive Net Present Value (NPV):

$$BESS_{NPV} > 0 \tag{11}$$

The optimization goal is to minimize the total cost C_{total} while adhering to the operational constraints. The detailed objective function is defined as:

$$\min f = \min \{\sum\nolimits_t [\lambda_{grid}(t) P_{grid}(t) + P_{OM} + E_{OM}] + C_{cap} + C_{md}\} \tag{12}$$

The variables used in the objective function are defined as follows:$\lambda_{grid}(t)$ represents the grid energy price at time t; $P_{grid}(t)$ denotes the power exchanged with the grid; P_{OM} indicates the monthly operational costs for power conversion; E_{OM} refers to the monthly energy operational costs. The purpose of the objective function is to minimize C_{total} by optimizing the battery's operation, which includes determining the charge and discharge schedule, size, and energy rating. This optimization aims to reduce energy purchase costs, maximize revenues from energy sales, and ensure operational costs remain manageable.

Battery lifespan L_{bat} is influenced by factors such as depth of discharge (DoD), charge/discharge cycles, and temperature

conditions. To incorporate battery lifespan into the optimization model, a lifespan function is introduced:

$$maxL_{bat} = f(DoD, P_{bat}(t)) \tag{13}$$

This ensures that the depth of discharge E_{bat} remains within safe operational limits to minimize degradation and that the charge/discharge cycles P_{bat} are optimized to extend battery life.

To balance cost minimization and lifespan maximization, a weighted multiobjective function is used:

$$minF = C_{total} - wE_{bat} \tag{14}$$

w represents a weighting factor that determines the balance between minimizing costs and maximizing battery lifespan.

For accurate cost predictions, future energy price fluctuations are taken into account using the present value factor (PVF), which adjusts future costs for the time value of money. The energy price for charging or discharging at time t, $P_{r_b}(t)$, is defined as:

$$Pr_i(t) = f\left(p_i^{net}(t)\right) = \begin{cases} Pr^{sell}(t), p_i^{net}(t) < 0 \\ Pr^{buy}(t), p_i^{net}(t) \geq 0 \end{cases} \tag{15}$$

The Present Value Factor (PVF) is used to account for future energy increases:

$$PVF = \frac{(1+n')^d - 1}{n'(1+n')^d} \tag{16}$$

where d is the number of years, and n is the comparable discount rate. The rate n' is calculated as:

$$n' = \frac{n-e}{1+e} \tag{17}$$

D. MULTİENERGY INVOLVING ELECTRICITY, HEAT, AND GAS TRADING

Subsequently, energy trading was conducted based on the demands of prosumers and consumers. For the purpose of energy trading, Nash bargaining under uncertainty conditions was proposed, where negotiations were carried out among participants based on their energy contributions within the cooperation. Finally, the model was aggregated.

E. INDIVIDUAL DER

Employing the ''online energy control and trading algorithm'' enables prosumers to seamlessly enter or exit the proposed scalable energy trading system without incurring additional computational overhead. This provides each prosumer with the autonomy to independently control their DER and set their energy bid for each time slot. The Lyapunov-based approach handles time-coupling constraints effectively by leveraging a look-ahead queue for a single time slot. This approach progressively relaxes and transforms the optimization problem, enabling efficient system improvement.

The optimization system does not require statistical data on each prosumer's renewable energy generation or load demand. Instead, the control vectors $Y_i(t)$ and $X_i(t)$ are determined solely by the state of each prosumer's energy supply at each specific time slot. Applying Lyapunov optimization theory to this system involves transforming time-averaged constraints into queue safety constraints for dynamic systems and developing real-time algorithms based on virtual queues. However, the standard Lyapunov optimization approach cannot be directly applied to Problem P1 due to the time-dependence of charging and discharging decisions across multiple time slots. To overcome this time-coupling, we relax the constraint into a soft constraint as follows:

$$\lim_{T\to\infty} \frac{1}{T} \sum_{i=0}^{T-1} \mathrm{E} \left\{ \begin{matrix} \eta_i^{ch} g_i^{ch}(t) + \eta_i^s g_i^s(t) \\ -\eta_i^{dis} g_i^{dis}(t) \end{matrix} \right\} = 0 \tag{18}$$

The charging efficiency factor for prosumer i at time t is represented by η_i^{ch}, while $g_i^{ch}(t)$ denotes the amount of energy charged by prosumer i at time t. The storage efficiency factor for prosumer i is given by η_i^s, and $g_i^s(t)$ represents the amount of energy stored by prosumer i at time t. Finally, the discharging efficiency factor for prosumer i is denoted by η_i^{dis}, with $g_i^{dis}(t)$ representing the amount of energy discharged by prosumer i at time t.

Rather than limiting the state of energy $S_i(t)$, (19) ensures the constancy of the average rate of total effective charging and discharging amounts. The calculation of (19) is provided in our earlier work and is done within the context of Lyapunov maximization of efficiency. The application of typical Lyapunov optimization techniques is made possible by eliminating the dependence of per-time-slot control choices on the battery condition to address P2. By converting the time-averaged constraints (19) in P2 into constraints with queue stability, we introduce a virtual energy line $E_i(t)$ and a QoS-control queue of load $Q_i(t)$.

P2:

$$\min_{Y_i(t)} \lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} E\{C_i(t)\} \tag{19}$$

where $C_i(t)$ represents the cost incurred by prosumer i at time t.

The definition of the virtual energy queue is $E_i(t) = S_i(t) - \theta_i$ where θ_i is a fluctuation parameter that may be created to make sure the lower bound on the energy state is met. The dynamics of $E_i(t)$are given by:

$$E_i(t) = E_i(t-1) + (\eta_i^{ch} g_i^{ch}(t) + \eta_i^s g_i^s(t) - \eta_i^{dis} g_i^{dis}(t)) \tag{20}$$

It is defined as the QoS-control queue of load as,

$$Q_i(t-1) = \max\{Q_i(t) - \epsilon_i, 0\} + \frac{\bar{D}_i(t) - D_i(t)}{\bar{D}_i(t) - \underline{D_i}(t)} \tag{21}$$

The QoS-control queue of load for prosumer i at time t is represented by $Q_i(t)$, while ϵ_i denotes the departure rate for prosumer i. $\bar{D}_i(t)$ and $D_i(t)$ represent the maximum and actual load demand of prosumer i at time t, respectively. Additionally, $\underline{D_i}(t)$ is the minimum load demand of prosumer i at time t.

If the departure rate is ϵ_i and the percentage of shedding is the arrival rate, the stability of the load queue is ensured. It is

necessary for the time-averaged load shedding percentage to be less than or equal to i for $Q_i(t)$ to remain stable. Therefore, satisfying the constraint is equivalent to ensuring the stability of $Q_i(t)$.

An array of virtual queues is thus defined as $\{E_i(t), Q_i(t)\}$, and a Lyapunov function related to $E_i(t)$ is defined as:

$$L_i(t) = \frac{1}{2}[E_i(t)^2 + Q_i(t)^2] \tag{22}$$

By minimizing the quadratic Lyapunov function, a decision-making procedure that minimizes the drift of $E_i(t)$ drives $S_i(t)$ towards θ_i. Thus, ensuring that the battery queue always resides in the viable range requires careful selection of the perturbation parameter.

Give the following definition for the predicted change in the Lyapunov function from one-time slot to the next is shown by the conditional one-slot Lyapunov drift:

$$\Delta L_i(t)\, E\{L_i(t+1) - L_i(t) | F_i(t)\} \tag{23}$$

Prior to making assumptions about the random process connected to the energy supply state $[g_i^R(t), \bar{D}_i(t), \underline{D_i}(t), S_i(t)]$ the virtual queue states $E_i(t)$ and $Q_i(t)$virtual queue states at the moment.

This gives the drift-plus-penalty expression:

$$\Delta L_i(t) + V_i E\{C_i(t)\} \tag{24}$$

where V_i is a tuning parameter that controls the trade-off between minimizing energy cost and minimizing queue delay.

The virtual energy queue's stability is represented by the Lyapunov drift in the first term, and V_i controls the performance trade-off between minimizing the energy cost and minimizing the queueing delay in the second term. Next, we apply a weighted Lyapunov drift using the time-averaged energy cost. A larger V_i indicates a greater emphasis on reducing energy expenses at the expense of a larger virtual energy queue, and vice versa.

The control choices are selected to minimize the upper bound of the drift-plus-penalty expression, as provided in (25), in order to simultaneously decrease the prosumer's time-averaged energy expenditure and ensure the reliability of the virtual energy queue. This strategy is based on minimizing the drift-plus-cost:

$$\begin{aligned}
&\Delta L_i(t) + V_i E[C_i(t)] \\
&\le B_i + E_i(t)\, E\left[\eta_i^{ch}\left(g_i^{ch}(t) + g_i^s(t) - \eta_i^{dis} g_i^{dis}(t)\right)\right] \\
&\quad + Q_i(t)\, E\left[\frac{\bar{D}_i(t) - D_i(t)}{\bar{D}_i(t) - \underline{D_i}(t)} - \epsilon_i\right] + V_i E[C_i(t)]
\end{aligned} \tag{25}$$

Next, the algorithm for trading and controlling energy is built: for every time slot t, each prosumer i control decision $Y_i(t)$ is established by solving for its current virtual queue state $[E_i(t), Q_i(t)]$ and energy state $X_i(t)$. The subsequent issue is formulated as the linear programming problem:

$$\begin{aligned}
\min_{Y_i(t)} E\Big[&E_i(t)\left(\eta_i^{ch} g_i^{ch}(t) + \eta_i^{ch} g_i^s(t) - \eta_i^{dis} g_i^{dis}(t)\right) \\
&+ Q_i(t)\frac{\bar{D}_i(t) - D_i(t)}{\bar{D}_i(t) - \underline{D_i}(t)} + V_i\{C_i(t)\}\Big]
\end{aligned} \tag{26}$$

Energy trading allows prosumers to reduce their immediate energy costs within a time window by selling energy. Nonetheless, the best possible (23) solution can result in a scenario where prosumer forces itself to eventually purchase more energy from the utility supplier in order to fulfill its own load need because it sells too much energy to other prosumers at relatively lower energy trading prices. The over-selling problem is addressed by limiting the total energy difference between prosumer i's stored energy available for trading and the discharged energy for load maintenance.

$$EG_i(t) = \sum_{t=1}^{t-1} \eta_i^{ch}[g_i^{ch}(\tau) + g_i^s(\tau)] - \eta_i^{dis} g_i^{dis-D}(\tau) \ge \emptyset_i \tag{27}$$

When prosumer i trades energy, it will not sell its stored energy in time slot t if $EG_i(t) < \emptyset_i$, that is, $g_i^{es} - E(t) = 0$.

1) NODAL TEMPERATURE DISPATCH AND PRICE

Comprehensive ways to optimize are required for the management of energy systems, especially when it comes to nodal temperature dispatch and pricing. This paper describes a decentralized parallel solution technique that properly models heat dynamics while optimizing dispatch methods. The technique is based on the ADMM. A unique nodal energy pricing plan based on the flow-tracing technique is also suggested.

2) DECENTRALISED PARALLEL SOLUTION METHOD

For decentralized and parallel processing, ADMM is used in the suggested approach. Large-scale optimization issues may be effectively solved with the ADMM framework by breaking them down into more manageable subproblems. An example of a formulation of the core optimization issue is as follows:

Let's use the energy trading system to define the decision variables:

x_i : Prosumer i's energy storage choice variable. This represents the amount of energy that prosumers have stored (e.g., thermal storage, batteries, etc.).

z_i : An auxiliary variable that represents the energy flow for prosumer i, such as the amount of heat, gas, or electricity transferred across the network.

y_i : For prosumers, the dual variable (also referred to as the Lagrange multiplier) represents limitations concerning the energy price or trading of energy for prosumer i.

In general, the objective is the optimization of energy trading and consumption, for example, cutting costs of energy storage or making multienergy trade more effective. The

objective function can be expressed as:

$$min \sum_{i=1}^{N} (c_i x_i + d_i z_i) \tag{28}$$

where c_i represents the cost associated with storing energy for prosumer i, and d_i is the cost or reward related to energy flow z_i for prosumer i.

The objective function aims to minimize the combined cost of energy storage (c_i) and energy flow (d_i), ensuring optimal trading and storage decisions for each prosumer. We may encounter a number of limitations in the decentralized energy system, such as:

Energy balance: The amount of energy produced must equal the amount of energy used and stored. This may be shown as follows for each prosumer i:

$$x_i - z_i = e_i \tag{29}$$

where e_i symbolizes the energy surplus (if positive) or demand (if negative) for prosumer i.

Energy storage capacity: The energy should be kept within the greatest amount of space that is available:

$$0 \leq x_i \leq x_{max,i} \tag{30}$$

Transmission restrictions: The capacity of the network restricts how much energy can be sent from prosumer$i$ to other users. This could be shown as:

$$0 \leq z_i \leq z_{max,i} \tag{31}$$

Market price constraints: The price at which each prosumer exchanges energy is determined by the state of the market:

$$p_i \leq p_{max,i} \tag{32}$$

where p_i is the trading price of energy for prosumer i.

There are three primary phases in the ADMM framework:

Step 1: Local optimization (Prosumers)

Every prosumer i solves the local optimization problem involving their market price, energy stored, and energy flowing through. This enforces global energy balance using the dual variables y_i presented to update x_i and z_i. Now, the goal for each prosumer will be to satisfy:

$$\min_{x_i z_i} (c_i.x_i + d_i z_i + y_i^T (x_i - z_i - e_i)) \tag{33}$$

where y_i are the two variables connected to the limitation on energy balance.

Step 2: Global coordination (Energy flow)

After optimizing the local goal of each prosumer, the system has to ensure that global coordination, like energy exchange between prosumers, is preserved. This is achieved by changing the dual variables y_i and ensuring that the energy balance constraint applies to the entire network:

$$y_i^{(k+1)} = y_i^{(k)} + \rho(x_i^{(k)} - y_i^{(k)} - e_i) \tag{34}$$

where ρ is the step size (a hyperparameter).

Step 3: Global updates

Finally, based on all prosumer's summed-up results, the globally declared variables that represent market price as well as total energy intake are updated. This, in turn, ensures that all decisions of prosumers based on energy flow and storage are aligned with the multienergy system's maximization.

Initialize decision variables x_i, z_i and dual variables y_i. Using their objective function, each prosumer maximizes their local energy storage and trading choices. Make adjustments for energy balance and pricing limitations by computing global dual variables y_i. Iterate the process, refining x_i, z_i and y_i until convergence.

After a few iterations of rounds, the algorithm converges, and each prosumer finds the best option under local cost minimization while satisfying global constraints. ADMM's distributed architecture empowers prosumers to make choices that are optimal for them independently while keeping the pricing as well as energy flow into equilibrium.

The x, y, and u represent the optimized energy storage decisions, trading prices, and dual variables for the system, respectively, ensuring equilibrium between prosumer actions and global constraints.

Algorithm 1 ADMM – Based Decentralized and Parallel Processing Technique

Require: A, B, c, step size ρ, tolerance tol, and maximum iterations $max - itera$
Ensure: x, y, u
Step 1: Initialize parameters
Step 2: **For** each iteration k from 1 to max_itera **do**
Step 3: Update x by solving its subproblem, (30) minimizing the augmented Lagrangian with regard to x
Step 4: Update y by solving its subproblem, (31) minimizing the augmented Lagrangian with regard to y
Step 5: By utilizing the primal residual, update the dual variable u (32).
Step 6: Determine the primal residual r (33)
Step 7: Determine the dual residual (34)
Step 8: Verify convergence
If $||r^{k+1}||_2 < tol$ and $||s^{(k+1)}||_2 < tol$,
break the loop
Step 9: **End For**
Step 10: **Return** x, y, u

F. DISPATCHING DETERMINATION STEP

It is the responsibility of the dispatching decision phase to select a temporal resolution that is suitable for the dispatch model. To achieve a balance between the quantitative simplicity and the time step granularity, this step is necessary. It is crucial to ensure that the temporal resolution, denoted by the symbol Δt, is both small enough to allow for precise thermal dynamics and large enough to capture the fundamental dynamics of the system.

The dispatch system can be resolved using the ADMM framework, and its results have been verified through intensive thermal dynamics simulations. This verification involves

solving the heat equation:

$$\frac{\partial T}{\partial t} = \alpha \nabla^2 T + Q \tag{35}$$

where T is the temperature, t is the time, α is the thermal diffusivity, and Q is the amount of heat generated internally.

1) FLOW TRACING METHOD

A new nodal energy pricing model is developed using the flow-tracing approach. This approach enables precise cost allocation by tracking the energy flow from generation nodes to consumption nodes. The flow-tracing algorithm is described as follows:

$$F_{ij} = P_i \frac{d_{ij}}{\sum_j d_{ij}} \tag{36}$$

where: F_{ij} represents the flow of energy from node i to node j, P_i denotes the power generated at node i, and d_{ij} represents the demand at node j attributed to the power generated at node i.

The cost at node j, denoted C_j, is calculated by summing up the expenses associated with the energy flows from each generation node i to the consumption node j:

$$C_j = \sum\nolimits_i F_{ij} \lambda_i \tag{37}$$

where: λ_i is the marginal cost of generation at node i. This pricing structure accurately reflects the true cost of delivering energy to each node. It ensures that charges are allocated fairly and in proportion to the actual energy flows within the network.

G. BLOCKCHAIN-BASED PAYMENT METHODOLOGY

After the trading of multienergy resources, such as electricity, gas, and heat, transactions between prosumers and end-users are facilitated through a blockchain-based truthful incentive mechanism. Cryptocurrencies like Bitcoin are employed to ensure secure payments and incentivize user cooperation. Encouraging cooperation among intermediary nodes in a dynamic and decentralized environment is essential. In this context, while the recipient is known to the sender, the specific transmission path remains unidentified.

Intermediary nodes are categorized based on their contribution to data transmission: positive cooperative nodes ensure successful delivery to the recipient, whereas negative cooperative nodes transmit data but fail to achieve successful delivery. Within this framework, only positive cooperative nodes are reimbursed, and these reimbursements are facilitated through a blockchain-based P2P system. The process begins with the sender declaring a transmission task and depositing funds to guarantee that, should the relay node successfully deliver the data to the recipient, it will be reimbursed. Subsequently, data is transmitted to the recipient using opportunistic connections, and finally, positive cooperative nodes are rewarded upon the successful completion of their tasks. Initially, the process is simplified by considering a single positive cooperative node. Later, the scheme is generalized to accommodate multiple cooperative nodes.

Algorithm 2 Blockchain-Based Truthful Incentive Mechanism

Phase: One positive cooperative node

Step 1: Setup the variables

- Generate two random numbers,R_1 and R_2
- Compute:
  $h_1 = E_{PK_A}(R_1)$ and $h_2 = H(R_2)$

Step 2: Disseminating a transmission task

- Node A makes a deposit transaction:
  $Deposit_A$

Step 3: Data transmission

- Node A prepares and transmits the message m.
- Relay node B receives the data and broadcasts the payment transaction $Payment_{B\to E}$.
- Upon receiving the information, recipient E sends a signed acknowledgment to node B using $B's$ public key:
  $ACK_E = Sig_{SK_E}(\text{“}ACK\text{”})$

Step 4: Obtaining Payments

- Relay node B and recipient E provide the necessary information to miners:
  $E_{PK_B}(ACK_E)$, $E_{PK_B}(R_1)$, $\{R_2, E_{PK_E}(ACK_E)\}$
- Miners validate the transactions, ensuring all conditions are met. If validated, miners process the payment transactions:
  $Payment_{A\to B}$, $Payment_{B\to E}$

1) ONE POSITIVE COOPERATIVE NODE

Assume that a message m is sent from sender A to recipient E. Between the sender A and the recipient E, there is only one relay node B. Let the public/private key pair for node $i$be denoted as PK_i, SK_i where PK_i is the public key and SK_i is the private key. The function E() represents encryption,. $H()$ represents a hash function, and $Sig()$ denotes a signing function. The payment process is described as follows:

a: PUBLISHING A TRANSMISSION TASK

Node A publishes the encrypted value:

$$h_1 = E_{PK_A}(R_1),$$

where R_1 is a random number (nonce) generated by sender A. The random number R_1 ensures that each transmission is unique and prevents replay attacks. By encrypting R_1 with A 's public key, this step ensures that only the intended recipient (or an authorized intermediary) can later access the actual value of R_1.

Node A also publishes the hash of another random number R_2:

$$h_2 = H(R_2),$$

where R_2 is kept confidential. The hash function $H()$ ensures the integrity of R_2; any tampering with R_2 would result in a different hash, making the alteration detectable. This step ensures that R_2 remains confidential but can be verified by the relevant parties.

Node A then deposits funds in a transaction called $Deposit_A$, ensuring that, should node B successfully deliver the data to recipient E, the payment to node B will be made.

b: DATA TRANSMISSION

Node A transmits the message m along with the encrypted random number R_2 to node B:

$$m \,||E_{PK_E}(R_2)||\, \sigma \,||Sig_{SK_A}(R_1)$$

where:

- m is the message being transmitted,
- $E_{PK_E}(R_2)$ is the encryption of R_2 with the public key of recipient E, ensuring only E can decrypt it,
- σ is a digital signature on the hash of the message and R_2, verifying the integrity of the transmitted data,
- $Sig_{SK_A}(R_1)$ is the signature of R_1 by sender A, confirming the authenticity of the message.

The purpose of this encryption and signing process is to ensure that both the message and the random values are not tampered with during transmission, and to prove that the data originates from sender A and is directed to recipient E.

Node A also broadcasts the transaction $Payment_{B\to E}$ to the blockchain network for validation. This step ensures that the transaction is logged and validated on the blockchain, confirming the agreement to pay relay node B for successful data delivery.

Once recipient E receives the message, node B creates and broadcasts the transaction $Payment_{A\to B}$ to the blockchain network. This confirms that node B has successfully delivered the message to E.

Upon receiving the message, recipient E checks the validity of the signature σ and sends a signed acknowledgment back to node B using node B 's public key:

$$E_{PK_E}(Sig_{SK_E}(ACK_E)$$

where ACK_E is the acknowledgment message confirming successful receipt of the data. This acknowledgment is encrypted using B 's public key to ensure its confidentiality and authenticity. The blockchain ensures that the transactions $Payment_{A\to B}$ and $Payment_{B\to E}$ are not executed until they are confirmed by miners, thus preventing fraud or premature payments.

c: OBTAINING THE PAYMENTS

For miners to redeem the prizes, B and E provide the following information to the miners:

$$E_{PK_B}(ACK_E)\,, E_{PK_B}(R_1), \left\{R_2, E_{PK_E}(ACK_E)\right\}$$

The miners then validate the transactions by verifying the following conditions:

1) $H(R_2) = h_2$, which ensures that the random number R_2 has been correctly transmitted and matches the published hash value. This validation confirms the integrity of R_2 without exposing it.
2) $E_{PK_B}(h_1) = E_{PK_A}(E_{PK_B}(R_1))$, which ensures that node B has received and forwarded R_1 correctly. This verifies the secure transmission of R_1 between sender A and relay node B.
3) $E_{PK_B}\left(E_{PK_E}(ACK_E)\right) = E_{PK_E}\left(E_{PK_B}(ACK_E)\right)$, which confirms the authenticity and integrity of the acknowledgment message, ensuring that recipient E successfully received the data.

If all conditions are met, the miners process the transactions $Payment_{A\to B}$ and $Payment_{B\to E}$.

2) MULTIPLE POSITIVE COOPERATIVE NODES

Assume that positive cooperative nodes B, C, and D assist sender A in sending the data to recipient E when A sends message $mtoE$. The payment process is explained in more detail below,

3) PUBLISHING A TRANSMISSION TASK

Sender A declares a transmission task to recipient$E$, denoted as $A \to E : m$, and generates two arbitrary quantities, R_1 and R_2, which must remain confidential. These random numbers serve crucial roles in encryption and authentication processes. The purpose of R_1 is to provide a signature for A's request, ensuring data integrity and preventing tampering. Similarly, R_2 is used by E for verifying the authenticity of the received data and ensuring that no unauthorized modifications have been made.

Next, A creates a deposit to guarantee that, should the message be successfully delivered to recipient E, incentives will be awarded to the cooperative nodes (B, C, and D) that positively assist in the data transmission. If the message is not successfully delivered, A will receive the deposit back.

a: DATA TRANSMISSION

The data transmission process from A to E is described as follows.

A first sends the message $m|\left|E_{PK_E}(R_2)\right||\sigma Sig_{SK_A}(R_1)$ to B, generating the transaction $Payment_{A\to B}$. The message includes the encrypted random number R_2 and the signature of A 's random number R_1 using SK_A, ensuring data integrity and authenticity. B, C, and D then help A in forwarding the message to recipient E and create the corresponding transactions $Payment_{B\to C}$, $Payment_{C\to D}$ and $Payment_{D\to E}$. A signed encrypted acknowledgment is subsequently returned to B, C, and E in that order. It is important to note that the following transactions indicate a promise: funds will not be transferred until the miners validate them:

$$Payment_{A\to B}, Payment_{B\to C}, Payment_{C\to D}, \text{and } Payment_{D\to E}.$$

b: OBTAINING THE PAYMENTS

Once recipient E has successfully received the data, miners must be provided with proof of participation by each cooperative node to reward them for their positive assistance in the data transmission. Each node provides the following data for verification:

- Node B supplies:

$$\left\{E_{PK_B}(R_1), E_{PK_B}(ACK_c), PK_A, PK_C\right\}$$

- Node C supplies:

$$\{E_{PK_C}(ACK_c), E_{PK_C}(ACK_D), PK_D\}$$

- Node D supplies:

$$\{E_{PK_D}(ACK_D), E_{PK_D}(ACK_E), PK_E\}$$

- Node E supplies:

$$\{R_2, E_{PK_E}(ACK_E)\}$$

For the transactions to be considered legitimate, the following conditions must be met:

1) Verification of R_2 by E:

$$H(R_2) = h_2$$

The random number R_2, supplied by E, must match the hash h_2, ensuring the authenticity and integrity of the message.

2) Route discovery from A to E:

The transaction chain from A to E can be traced to discover the route from A to E, verifying the path of the message.

3) Verification of R_1 by B:

$$E_{PK_B}(h_1) = E_{PK_A}(E_{PK_B}(R_1))$$

Node B verifies the correctness of R_1 using this equation, ensuring that the random number R_1 provided by A was valid and correctly transmitted.

4) Signed Acknowledgments:

For Node$B$, the signed acknowledgment from C is verified as:

$$E_{PK_B}\left(E_{PK_C}(ACK_C)\right) = E_{PK_C}\left(E_{PK_B}(ACK_C)\right)$$

For Node C, the signed acknowledgment from D is verified as:

$$E_{PK_C}\left(E_{PK_D}(ACK_D)\right) = E_{PK_D}\left(E_{PK_D}(ACK_D)\right)$$

For Node D, the signed acknowledgment from E is verified as:

$$E_{PK_D}\left(E_{PK_E}(ACK_E)\right) = E_{PK_E}(E_{PK_D}(ACK_E))$$

Each of these verifications ensures that the signed acknowledgments are authentic and that the data was successfully transmitted by each cooperative node.

V. EXPERIMENTAL RESULTS

This section presents the performance assessment and experimental analysis of the proposed study plan. It is structured into three subsections: a simulation study, a comparative analysis, and a research summary.

A. SIMULATION STUDY

The proposed study technique is simulated using the network simulator Matlab R2023b. This tool offers an efficient network topology and provides all the necessary specifications for implementing the proposed technique. The system specifications are presented in Table 2.

TABLE 2. System specifications.

Software Specifications	OS	Windows-10 (64-bit)
	Network Simulator	Matlab-R2023b
Hardware Specifications	RAM	4GB
	Hard Disk	500GB

B. COMPARATIVE ANALYSIS

This subsection compares the proposed technique with several existing approaches, including the P2P market model [40], the P2P multi-energy market method [41], and energy trading [11], to evaluate its performance. The validation process involves assessing performance metrics such as time (h), heating power (kW), electricity demand (MWh), storage cost (CNY), energy storage (kWh), energy trading volume, total energy (kWh), and the total cost calculated per millisecond (ms).

1) TIME VS. HEATING POWER

Equation (38) models the relationship between time (t), representing hours in a day, and heating power (kW), which corresponds to the energy consumed for heating purposes. Heating demand peaks in the morning and evening, while renewable energy sources such as solar power reach their peak during midday. The equation is expressed as:

$$\begin{aligned} P_{net}(t) &= \left(A\sin\left(\frac{2\pi}{24}(t-t_0)+B\right)\right. \\ &\quad \left.-\left(C\sin\left(\frac{2\pi}{24}(t-t_1)\right)\max(0,\cos\left(\frac{2\pi}{24}(t-t_2)\right)\right)\right) \end{aligned} \tag{38}$$

The parameters A, B, and C characterize the magnitude of heating demand variations throughout the day, with A representing the amplitude of fluctuations, B accounting for base demand during peak morning and evening periods, and C modeling daily energy consumption patterns. The time shifts t_0, t_1, and t_2 represent the start of morning demand, evening peak demand, and nighttime low demand, respectively. The expression $\max(0, \cos\left(\frac{2\pi}{24}(t-t_2)\right))$ ensures that

TABLE 3. Representation of the relationship between time and heating power.

Time(h)	Heating power (kW)		
	P2P market model	Q-learning algorithm	Proposed
4	7	8	10
8	20	24	25
12	6	7	6
16	16	18	20
20	19	20	21
24	8	10	12

only positive heating demand is considered, eliminating any possibility of negative energy consumption. This model captures the cyclical nature of energy demand, enabling systems to respond flexibly and efficiently to fluctuations in heating needs.

The proposed model demonstrates superior performance in energy distribution compared to the P2P market model and the Q-learning algorithm, as shown in the graph. It provides a more balanced and efficient heating power distribution during peak demand hours, such as at 8:00 and 20:00, effectively meeting users' energy needs. Its ability to adapt to peak loads and optimize the demand-supply balance reduces energy losses and enhances the system's cost efficiency. Additionally, the proposed model responds better to demand fluctuations and minimizes unequal energy distribution compared to other models, increasing user satisfaction and supporting system sustainability. These features clearly highlight the proposed model as a superior solution in real-time applications of P2P energy trading, advancing beyond existing approaches.

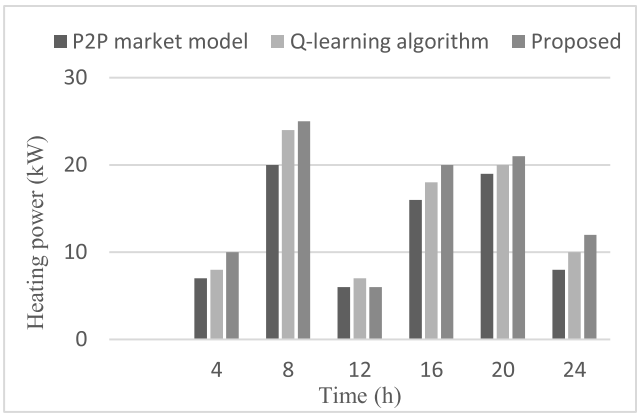


FIGURE 4. Time vs. heating power.

2) TIME VS. ELECTRICITY DEMANDS

Equation (39) models the relationship between Time (h), representing the number of hours in a day, and Energy Demand (MWh), the amount of power required at a specific time. Typically, electricity demand fluctuates throughout the day, with peaks occurring in the morning and evening due to consumption patterns. The equation is expressed as:

$$D(t) = A\sin\left(\frac{2\pi}{24}(t - t_0)\right) + B \tag{39}$$

where $D(t)$ represents the energy demand at time t (in MWh), t is the time of day in hours, A is the amplitude determining the magnitude of variations in energy demand, t_0 is the time shift representing when demand peaks (e.g., during morning or evening hours), and B is the baseline level of energy demand. This equation demonstrates that electricity demand varies periodically throughout the day, with higher demands in the morning and evening, and helps to understand fluctuations in energy usage to optimize energy distribution.

TABLE 4. Representation of the relationship between time and electricity demand.

Time(h)	Electricity demands (MWh)		
	P2P market model	Q-learning algorithm	Proposed
4	5	4	3
8	8.2	9	9.9
12	3.9	4	4.2
16	6.6	7	7.5
20	7.9	8	8.5
24	1	2	2.5

The graph clearly demonstrates the superior performance of the proposed model in managing electricity demand compared to the P2P market model and Q-learning algorithm. The proposed model excels in balancing energy distribution during peak demand hours, such as at 8:00 and 20:00, ensuring consistent and reliable energy delivery even under high-demand conditions. Unlike the other models, it maintains efficiency during low-demand hours, such as at 4:00 and 24:00, minimizing energy losses and enhancing overall system performance. Its ability to swiftly adapt to fluctuating demand, particularly between 16:00 and 20:00, highlights its advanced demand-supply balancing capabilities. Furthermore, the proposed model offers a more precise alignment with user energy needs, which not only enhances system reliability but also boosts user satisfaction and sustainability. These attributes underscore the technological and economic superiority of the proposed model, establishing it as a highly effective solution for real-time and large-scale applications in P2P energy trading systems.

3) TIME VS. STORAGE PRICE

Equation (40) models the relationship between time and storage price, where Time (h) represents the hour of the day (ranging from 0 to 23, covering a 24-hour cycle), and Storage Price (CNY) denotes the cost of energy storage per unit. The equation accounts for daily fluctuations in storage costs due to supply and demand dynamics:

$$P(t) = A\sin\left(\frac{2\pi}{24}(t - t_0)\right) + B \tag{40}$$

TABLE 5. Representation of the relationship between time and storage price.

Time(h)	Storage price (CNY)		
	P2P market model	Q-learning algorithm	Proposed
4	6.3	6.46	7.5
8	11	11.29	12.5
12	14.83	14.83	15
16	11.29	12	12.5
20	6.46	7	7.5
24	5.17	5.10	5

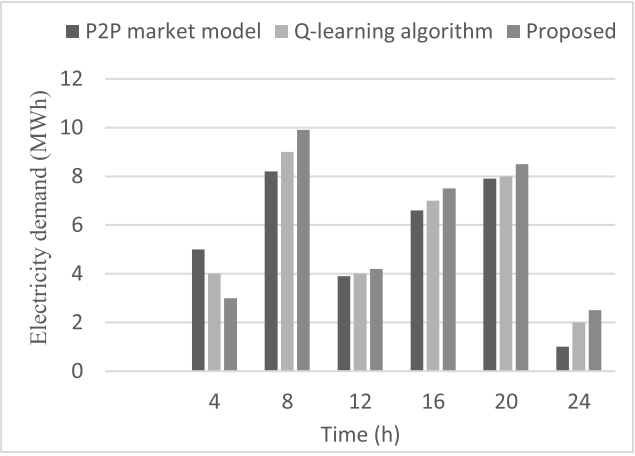


FIGURE 5. Time vs. electricity demands.

Here, A represents the amplitude of price variation, t_0 indicates the time of peak storage price, and B defines the average baseline price. This formulation effectively captures periodic variations, providing insights into optimizing cost management strategies within energy systems.

Considering the relationship between energy storage capacity and storage prices, the superiority of the proposed model becomes evident. The increase in storage capacity is accompanied by a rise in storage prices. However, the proposed model not only optimizes storage capacity but also manages storage prices more effectively. While storage prices fluctuate over time, the proposed model consistently provides higher storage capacity compared to the P2P market model and the Q-learning algorithm. For instance, at 04:00 AM, the storage price is 6.3 CNY in the P2P market model, 6.46 CNY in the Q-learning algorithm, and 7.5 CNY in the proposed model. During later hours, particularly in low-demand periods (e.g., 8:00 PM), storage prices decrease across all models, but in the proposed model, the price remains slightly higher than the other two models. Nevertheless, the proposed model excels in managing storage prices while optimizing storage capacity. Despite the increase in storage capacity, the dynamic pricing mechanism of the proposed model ensures that storage prices are steadily controlled, contributing to the sustainability of the system. This feature helps maintain cost control even in energy systems with high storage capacity.

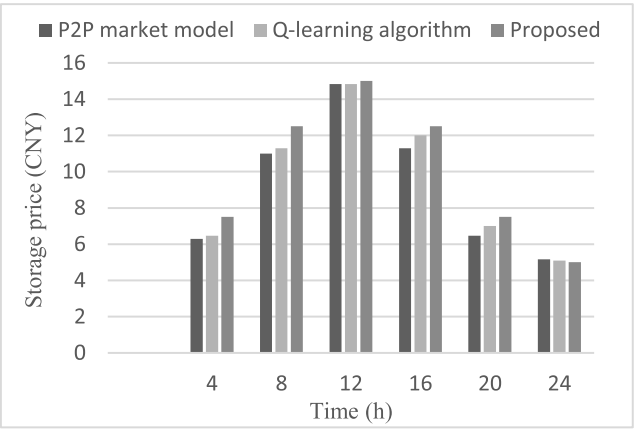


FIGURE 6. Time vs. storage price.

TABLE 6. Representation of the relationship between number of prosumers and energy storage.

Number of prosumers	Energy storage (kWh)		
	P2P market model	Q-learning algorithm	Proposed
5	794	945	1146
10	1376	1629	1875
15	2327	2585	2746
20	2986	3176	3376
25	3768	4086	4387

TABLE 7. Representation of the relationship between energy trading and energy.

Energy trading	Energy (kWh)		
	P2P market model	Q-learning algorithm	Proposed
20	11	14	17
40	20	25	28
60	31	34	37
80	42	46	50
100	56	61	65
120	71	76	80

The proposed model offers a flexible and scalable solution, effectively managing both energy storage and price control, while ensuring cost efficiency, even for larger prosumer groups.

4) NUMBER OF PROSUMERS VS. ENERGY STORAGE

The number of prosumers in an energy system affects the overall energy storage capacity, which is typically measured in kilowatt-hours (kWh). As the number of prosumers increases, the total energy storage capacity also increases, demonstrating a clear scaling relationship. This relationship can be expressed numerically as in (41):

$$E = NE_{per\ prosumer} \tag{41}$$

where E represents the total energy storage capacity, N is the number of prosumers, and $E_{per\ prosumer}$ is the energy storage capacity per prosumer."

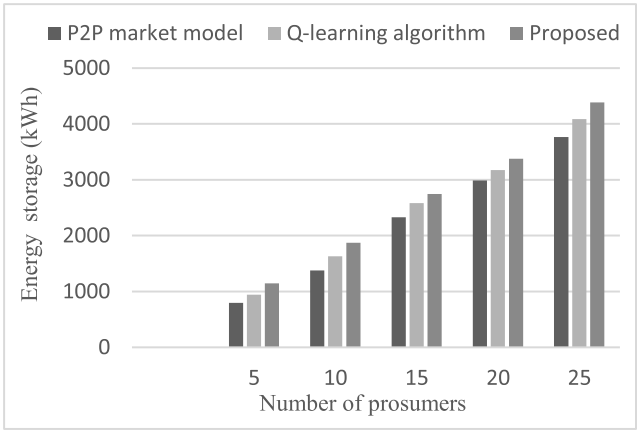


FIGURE 7. Number of prosumers vs. energy storage.

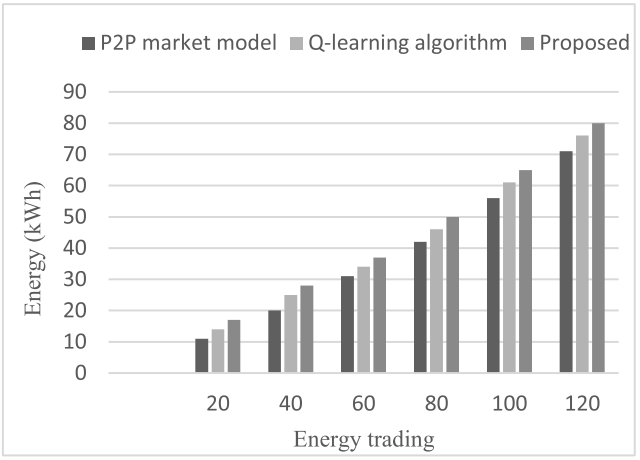


FIGURE 8. Energy trading vs. energy.

The graph clearly demonstrates the superior energy storage performance of the proposed model compared to the P2P market model and the Q-learning algorithm. While energy storage capacity increases with the number of prosumers across all models, the proposed model significantly outperforms, reaching approximately 4500 kWh for 25 prosumers. This superiority stems from the model's ability to swiftly adapt to dynamic changes in demand and supply, effectively manage system imbalances by prioritizing energy storage, and intelligently allocate storage resources. Furthermore, the model's capability to maintain minimal transaction costs while delivering stable performance across large-scale user groups highlights its advanced flexibility and scalability. By optimizing storage capacity despite the growing number of prosumers, the proposed model not only ensures system sustainability but also establishes itself as a robust solution for broader applications in future energy systems.

5) ENERGY TRADING VS. ENERGY

The distribution and use of energy within a market or system are directly influenced by energy trading, which involves purchasing and selling energy units, expressed in kilowatt-hours (kWh). This activity optimizes the distribution of energy to enhance grid stability and efficiency, based on the current dynamics of supply and demand.

A basic (42) can be used to express the relationship between energy traded and the total energy consumption over a specific time period:

$$E_{traded} - \int_{t1}^{t_2} P(t)dt \tag{42}$$

Here, E_{traded} represents the total energy traded in kWh, while the integral term $\int_{t1}^{t2} P(t)\,dt$ represents the total energy consumption or distribution within the time interval from t_1 to t_2, where $P(t)$denotes the power at any given time t. The equation captures the balance between traded energy and the total energy consumed or distributed during this period.

The graph clearly demonstrates the superiority of the proposed model in energy trading. While all models show an increase in energy transfer as trading volume grows, the proposed model stands out, particularly at higher trading levels (80-120 units). The traditional P2P market model struggles to adapt to rising trade demands, and the Q-learning algorithm shows limited improvements in efficiency. In contrast, the proposed model exhibits exceptional responsiveness to fluctuations and peak demand periods, enabled by its optimized energy management and innovative trading strategies. Even under high trading volumes, the system maintains maximum energy transfer, ensuring both scalability and reliability. This performance highlights not only the technical efficiency of the proposed system but also its ability to set a new benchmark for sustainability, trust, and trading effectiveness in the energy market.

TABLE 8. Representation of the relationship between the number of users and total calculated cost/ms.

Number of users	Total calculated cost/ms		
	P2P market model	Q-learning algorithm	Proposed
10	500	577	658
20	715	832	951
30	1145	1323	1487
40	1652	1758	1876
50	2176	2394	2500

6) NUMBER OF USERS VS. TOTAL CALCULATED COST

Equation (43) assumes that the number of people using a system or service N can impact the overall cost per millisecond C. Here, $C_{peruser}$ represents the cost associated with each individual user. This relationship illustrates how the cost increases as the number of users grows. engagement.

$$C = NC_{per\ user} \tag{43}$$

The graph illustrates the total calculated cost per millisecond as the number of users in the system increases, representing the computational and operational expenses associated with energy trading processes. While all models

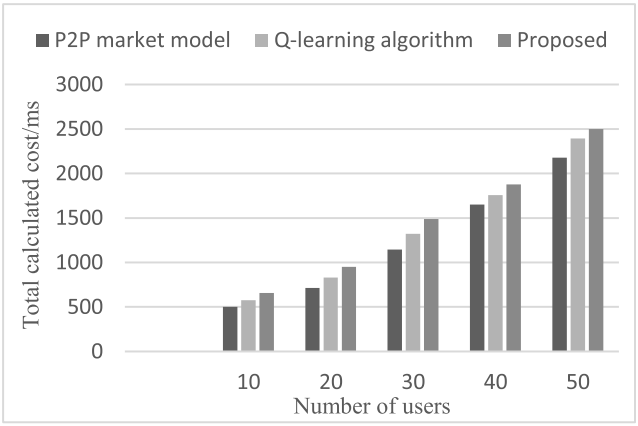


FIGURE 9. Number of users vs. total calculated cost/ms.

show rising costs with additional users, the proposed model demonstrates a clear advantage by maintaining significantly lower costs compared to both the P2P market model and the Q-learning algorithm, particularly in scenarios with higher user counts (40)-50 users). The P2P market model exhibits the highest costs, indicating inefficiencies in handling large-scale networks, while the Q-learning algorithm offers moderate improvements but fails to match the efficiency of the proposed model. By optimizing computational resources and streamlining energy trading operations, the proposed model ensures cost-effectiveness and scalability even in high-demand, multi-user environments. This highlights its ability to support larger networks while minimizing operational expenses, establishing it as a superior solution for sustainable and efficient energy trading.

VI. CONCLUSION

This study proposed a novel approach for integrating DESS into a P2P market structure for multi-energy sources, enabling the efficient management and trading of electricity, gas, and heat. The system leverages advanced blockchain technology to establish a decentralized, transparent, and secure marketplace that not only optimizes energy management but also ensures privacy and fraud prevention. The adoption of a storage virtualization model combined with a nonlinear programming multi-objective approach resulted in an 18% reduction in energy storage costs and a 15–20% improvement in battery life compared to traditional methods. Additionally, the incorporation of the Nash bargaining model within the decentralized network improved energy trading efficiency by approximately 15%, particularly during peak demand periods, by ensuring responsiveness to energy flow fluctuations and optimizing energy transfer. Simulation results using MATLAB-R2023b demonstrated the stability and scalability of the proposed system, even with an increasing number of prosumers. The system maintained constant transaction costs and ensured optimal energy distribution for up to fifty prosumers, highlighting its robustness in accommodating market growth. The blockchain-based payment mechanism further bolstered market confidence by ensuring transaction integrity, anonymity, and transparency, aligning individual incentives with broader market objectives. By minimizing transaction costs and enhancing energy exchange success rates, the proposed approach significantly improved overall market efficiency. This research underscores the potential of multienergy coupling in distributed systems and establishes a foundation for the broader integration of renewable energy sources into decentralized energy markets. The proposed P2P trading paradigm demonstrates considerable promise in enhancing energy resilience and sustainability by promoting the effective utilization of DERs and reducing dependency on centralized energy suppliers. Future work will focus on scaling the model to larger networks, incorporating additional renewable energy sources, and refining real-time pricing models to better adapt to market dynamics and the variability of renewable generation. Furthermore, the economic and environmental implications of global implementation will be explored, with particular emphasis on reducing operational costs and improving system flexibility.

REFERENCES

[1] Y. Wu, Y. Wu, H. Cimen, J. C. Vasquez, and J. M. Guerrero, "Towards collective energy community: Potential roles of microgrid and blockchain to go beyond P2P energy trading," *Appl. Energy*, vol. 314, May 15, 2022, Art. no. 119003, doi: 10.1016/j.apenergy.2022.119003.

[2] D. Xu, B. Zhou, N. Liu, Q. Wu, N. Voropai, C. Li, and E. Barakhtenko, "Peer-to-peer multienergy and communication resource trading for interconnected microgrids," *IEEE Trans. Ind. Informat.*, vol. 17, no. 4, pp. 2522–2533, Apr. 2021, doi: 10.1109/TII.2020.3000906.

[3] L. P. M. I. Sampath, A. Paudel, H. D. Nguyen, E. Y. S. Foo, and H. B. Gooi, "Peer-to-peer energy trading enabled optimal decentralized operation of smart distribution grids," *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 654–666, Jan. 2022, doi: 10.1109/TSG.2021.3110889.

[4] M. Shi, H. Wang, P. Xie, C. Lyu, L. Jian, and Y. Jia, "Distributed energy scheduling for integrated energy system clusters with peer-to-peer energy transaction," *IEEE Trans. Smart Grid*, vol. 14, no. 1, pp. 142–156, Jan. 2023, doi: 10.1109/TSG.2022.3197435.

[5] S. Ghaemi and A. Anvari-Moghaddam, "Local energy communities with strategic behavior of multi-energy players for peer-to-peer trading: A techno-economic assessment," *Sustain. Energy, Grids Netw.*, vol. 34, Jun. 2023, Art. no. 101059, doi: 10.1016/j.segan.2023.101059.

[6] T. Chen, S. Bu, X. Liu, J. Kang, F. R. Yu, and Z. Han, "Peer-to-peer energy trading and energy conversion in interconnected multi-energy microgrids using multi-agent deep reinforcement learning," *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 715–727, Jan. 2022, doi: 10.1109/TSG.2021.3124465.

[7] G. Sun, J. Sun, S. Chen, Z. Wei, and H. Zang, "Market-based coordination of regional electric and natural gas systems: A peer-to-peer energy trading model," *CSEE J. Power Energy Syst.*, early access, May 6, 2022, doi: 10.17775/CSEEJPES.2021.03970.

[8] Y. Xia, Q. Xu, Y. Ding, L. Shi, and F. Wu, "Generalized Nash equilibrium analysis for peer-to-peer transactive energy market considering coupling distribution network constraints," *IEEE Trans. Ind. Informat.*, vol. 20, no. 6, pp. 8125–8137, Jun. 2024, doi: 10.1109/TII.2024.3366995.

[9] L. Chen, Q. Xu, Y. Yang, H. Gao, and W. Xiong, "Community integrated energy system trading: A comprehensive review," *J. Modern Power Syst. Clean Energy*, vol. 10, no. 6, pp. 1445–1458, Nov. 2022, doi: 10.35833/MPCE.2022.000044.

[10] Y. Zhou, J. Wang, Y. Zhang, J. Wei, W. Sun, and J. Wang, "A fully-decentralized transactive energy management under distribution network constraints via peer-to-peer energy trading," *IEEE Trans. Energy Markets, Policy Regulation*, vol. 1, no. 4, pp. 297–309, Mar. 2023, doi: 10.1109/TEMPR.2023.3263685.

[11] T. Huang, Y. Sun, J. Hao, C. Sun, and C. Liu, "A distributed peer-to-peer energy trading model in integrated electric–thermal system," *IET Renew. Power Gener.*, vol. 18, no. 15, pp. 3188–3203, Nov. 2024, doi: 10.1049/rpg2.12918.

[12] Y. Jia, C. Wan, W. Cui, Y. Song, and P. Ju, "Peer-to-peer energy trading using prediction intervals of renewable energy generation," *IEEE Trans. Smart Grid*, vol. 14, no. 2, pp. 1454–1465, Mar. 2023, doi: 10.1109/TSG.2022.3168150.

[13] H. Hou, Z. Wang, B. Zhao, L. Zhang, Y. Shi, C. Xie, Z. Dong, and K. Yu, "Distributed optimization for joint peer-to-peer electricity and carbon trading among multi-energy microgrids considering renewable generation uncertainty," *Energy Convers. Econ.*, vol. 5, no. 2, pp. 116–131, Apr. 2024, doi: 10.1049/enc2.12110.

[14] L. Wang, Y. Xie, D. Zhang, J. Liu, S. Jiang, Y. Zhang, and M. Li, "Credible peer-to-peer trading with double-layer energy blockchain network in distributed electricity markets," *Electronics*, vol. 10, no. 15, p. 1815, Jul. 2021, doi: 10.3390/electronics10151815.

[15] F. Gulotta, E. Daccò, A. Bosisio, and D. Falabretti, "Opening of ancillary service markets to distributed energy resources: A review," *Energies*, vol. 16, no. 6, p. 2814, Mar. 2023, doi: 10.3390/en16062814.

[16] M. Khojasteh, P. Faria, L. Gomes, and Z. Vale, "Energy trading strategy of community shared energy storage," *Electr. Eng.*, vol. 106, no. 3, pp. 3415–3426, Jun. 2024, doi: 10.1007/s00202-023-02163-0.

[17] D. Wang, D. Huang, H. Jia, B. Liu, and Y. Lei, "Electricity-heat-based integrated demand response considering double auction energy market with multi-energy storage for interconnected areas," *CSEE J. Power Energy Syst.*, vol. 10, no. 4, pp. 1688–1700, Jul. 2024, doi: 10.17775/CSEEJPES.2022.02140.

[18] G. H. Krishna, K. V. S. M. Babu, D. Dwivedi, P. Chakraborty, P. K. Yemula, and M. Pal, "Energy sharing among resources within electrical distribution systems: A systematic review," 2024, *arXiv:2401.01597*.

[19] Z. Ye, Y. Wang, K. Han, C. Zhao, J. Han, and Y. Zhu, "Bi-objective optimization and emergy analysis of multi-distributed energy system considering shared energy storage," *Sustainability*, vol. 15, no. 2, p. 1011, Jan. 2023, doi: 10.3390/su15021011.

[20] M. Davoudi and M. Moeini-Aghtaie, "Local energy markets design for integrated distribution energy systems based on the concept of transactive peer-to-peer market," *IET Gener., Transmiss. Distrib.*, vol. 16, no. 1, pp. 41–56, Jan. 2022, doi: 10.1049/gtd2.12274.

[21] W. Gan, M. Yan, W. Yao, and J. Wen, "Peer to peer transactive energy for multiple energy hub with the penetration of high-level renewable energy," *Appl. Energy*, vol. 295, Aug. 2021, Art. no. 117027, doi: 10.1016/j.apenergy.2021.117027.

[22] J. Lei, S. Gao, X. Wei, J. Shi, T. Huang, N. D. Hatziargyriou, and C. Y. Chung, "A shareholding-based resource sharing mechanism for promoting energy equity in peer-to-peer energy trading," *IEEE Trans. Power Syst.*, vol. 38, no. 6, pp. 5113–5127, Nov. 2023, doi: 10.1109/TPWRS.2022.3225656.

[23] J. Wang, N. Xie, V. Ilea, C. Bovo, H. Xin, and Y. Wang, "Cooperative trading mechanism and satisfaction-based profit distribution in a multi-energy community," *Frontiers Energy Res.*, vol. 9, Nov. 2021, Art. no. 723192, doi: 10.3389/fenrg.2021.723192.

[24] X. He, J.-W. Xiao, S.-C. Cui, X.-K. Liu, and Y.-W. Wang, "A new cooperation framework with a fair clearing scheme for energy storage sharing," *IEEE Trans. Ind. Informat.*, vol. 18, no. 9, pp. 5893–5904, Sep. 2022, doi: 10.1109/TII.2021.3137823.

[25] M. Yunshou, W. Jiekang, C. Zhihong, W. Ruidong, Z. Ran, and C. Lingmin, "Cooperative operation framework for a wind-solar-CCHP multi-energy system based on Nash bargaining solution," *IEEE Access*, vol. 9, pp. 119987–120000, 2021, doi: 10.1109/ACCESS.2021.3107156.

[26] T. Ma, W. Pei, W. Deng, H. Xiao, Y. Yang, and C. Tang, "A Nash bargaining-based cooperative planning and operation method for wind-hydrogen-heat multi-agent energy system," *Energy*, vol. 239, Jan. 2022, Art. no. 122435, doi: 10.1016/j.energy.2021.122435.

[27] S. A. Sedgh, H. Aghamohammadloo, H. Khazaei, M. Mehdinejad, and S. Asadi, "A new design for the peer-to-peer electricity and gas markets based on robust probabilistic programming," *Energies*, vol. 16, no. 8, p. 3464, Apr. 2023, doi: 10.3390/en16083464.

[28] S. S. Seyedhossein and M. Moeini-Aghtaie, "Risk management framework of peer-to-peer electricity markets," *Energy*, vol. 261, Dec. 2022, Art. no. 125264, doi: 10.1016/j.energy.2022.125264.

[29] Y. Wang, Y. Cao, Y. Li, L. Jiang, Y. Long, Y. Deng, Y. Zhou, and Y. Nakanishi, "Modelling and analysis of a two-level incentive mechanism based peer-to-peer energy sharing community," *Int. J. Electr. Power Energy Syst.*, vol. 133, Dec. 2021, Art. no. 107202, doi: 10.1016/j.ijepes.2021.107202.

[30] S. Shukla, S. Hussain, R. R. Irshad, A. A. Alattab, S. Thakur, J. G. Breslin, M. F. Hassan, S. Abimannan, S. Husain, and S. M. Jameel, "Network analysis in a peer-to-peer energy trading model using blockchain and machine learning," *Comput. Standards Interfaces*, vol. 88, Mar. 2024, Art. no. 103799, doi: 10.1016/j.csi.2023.103799.

[31] H. Zang and J. Kim, "Reinforcement learning based peer-to-peer energy trade management using community energy storage in local energy market," *Energies*, vol. 14, no. 14, p. 4131, Jul. 2021, doi: 10.3390/en14144131.

[32] D. Mitrea, T. Cioara, and I. Anghel, "Privacy-preserving computation for peer-to-peer energy trading on a public blockchain," *Sensors*, vol. 23, no. 10, p. 4640, May 2023, doi: 10.3390/s23104640.

[33] M. H. Ullah and J.-D. Park, "Peer-to-peer energy trading in transactive markets considering physical network constraints," *IEEE Trans. Smart Grid*, vol. 12, no. 4, pp. 3390–3403, Jul. 2021, doi: 10.1109/TSG.2021.3063960.

[34] J. Yang, W. Xu, K. Ma, and C. Li, "A three-stage multi-energy trading strategy based on P2P trading mode," *IEEE Trans. Sustain. Energy*, vol. 14, no. 1, pp. 233–241, Jan. 2023, doi: 10.1109/TSTE.2022.3208369.

[35] L. Frölke, T. Sousa, and P. Pinson, "A network-aware market mechanism for decentralized district heating systems," *Appl. Energy*, vol. 306, Jan. 2022, Art. no. 117956, doi: 10.1016/j.apenergy.2021.117956.

[36] A. Dixit, A. Singh, Y. Rahulamathavan, and M. Rajarajan, "FAST DATA: A fair, secure, and trusted decentralized IIoT data marketplace enabled by blockchain," *IEEE Internet Things J.*, vol. 10, no. 4, pp. 2934–2944, Feb. 2023, doi: 10.1109/JIOT.2021.3120640.

[37] L. He, Y. Liu, and J. Zhang, "Peer-to-peer energy sharing with battery storage: Energy pawn in the smart grid," *Appl. Energy*, vol. 297, Sep. 2021, Art. no. 117129, doi: 10.1016/j.apenergy.2021.117129.

[38] X. Zhao, L. Li, Y. Tao, S. Lai, X. Zhou, and J. Qiu, "Aggregated operation of heterogeneous small-capacity distributed energy resources in peer-to-peer energy trading," *Int. J. Electr. Power Energy Syst.*, vol. 141, Oct. 2022, Art. no. 108162, doi: 10.1016/j.ijepes.2022.108162.

[39] A. S. Yahaya, N. Javaid, A. Almogren, A. Ahmed, S. M. Gulfam, and A. Radwan, "A two-stage privacy preservation and secure peer-to-peer energy trading model using blockchain and cloud-based aggregator," *IEEE Access*, vol. 9, pp. 143121–143137, 2021, doi: 10.1109/ACCESS.2021.3120737.

[40] N. Wang, Z. Liu, P. Heijnen, and M. Warnier, "A peer-to-peer market mechanism incorporating multi-energy coupling and cooperative behaviors," *Appl. Energy*, vol. 311, Apr. 2022, Art. no. 118572, doi: 10.1016/j.apenergy.2022.118572.

[41] C. García-Santacruz, P. J. Gómez, J. M. Carrasco, and E. Galván, "Multi P2P energy trading market, integrating energy storage systems and used for optimal scheduling," *IEEE Access*, vol. 10, pp. 64302–64315, 2022, doi: 10.1109/ACCESS.2022.3182698.

[42] Z. Wang, H. Hou, B. Zhao, L. Zhang, Y. Shi, and C. Xie, "Risk-averse stochastic capacity planning and P2P trading collaborative optimization for multi-energy microgrids considering carbon emission limitations: An asymmetric Nash bargaining approach," *Appl. Energy*, vol. 357, Mar. 2024, Art. no. 122505, doi: 10.1016/j.apenergy.2023.122505.

[43] Y. Zou, Y. Xu, and J. Li, "Aggregator-network coordinated peer-to-peer multi-energy trading via adaptive robust stochastic optimization," *IEEE Trans. Power Syst.*, vol. 39, no. 6, pp. 7124–7137, Nov. 2024, doi: 10.1109/TPWRS.2024.3376808.



ZEYNEP TANIS received the bachelor's degree in electrical and electronics engineering (English) from Marmara University, in 2015, and the master's degree in electrical machines and power electronics from Yildiz Technical University, in 2019, where she is currently pursuing the Ph.D. degree. During this time, she was a Project Engineer with Solvo Solar Energy, until 2019. In addition, she is a Project Engineer with Nurol Solar Energy.



ALI DURUSU (Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from Yildiz Technical University, Türkiye, in 2009, 2011, and 2016, respectively. He moved to Vienna, Austria, to perform the Ph.D. Researcher with Vienna University of Technology, from April 2015 to December 2015. He is currently with the Department of Electrical Engineering, Yildiz Technical University. He has published refereed manuscripts in various reputable international journals. His industry and research interests include PV power plant design and optimization, power system modeling and control, and renewable energy. He is certificated energy manager, certificated energy auditor and certificated measurement, and verification professional. He received the Scientific and Technological Research Council of Türkiye (TÜBİTAK) Ph.D. Research Fellowship, in 2015, the TÜBİTAK Primary Subject Fellowship, in 2014, the Best Paper Award at the IEEE Conference on Systems, Process, and Control, in 2019, and the Best Paper Award at the European Conference on Science, Art and Culture, in 2018. He is a Guest Editor for a Special Issue in *International Transactions on Electrical Energy Systems* journal. He is also acting as a reviewer for various reputed journals.