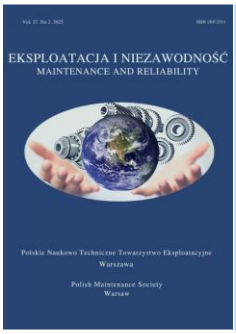


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# Dynamic Modeling and Optimization of Energy Storage in Peer-to-Peer Energy Trading Systems

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## Highlights

- Two-stage optimization manages P2P energy sharing, ensuring fair benefit distribution.
- Nash bargaining theory ensures fairness in energy trading between prosumers and consumers.
- Real-time pricing adapts to demand, improving economic efficiency and energy management.
- Consumer-side storage optimizes trading and storage based on load and renewable energy.
- System reduces external power use by optimizing local renewable energy during peak times.



## Abstract

The power system landscape has evolved from isolated end-users to interactive communities due to advances in information and communication technologies. This paper explores peer-to-peer energy (P2PE) trading and sharing within a community, where customer incentives for energy exchange enhance collective profits. A two-stage optimization (TSO) framework is proposed: the first stage determines customer participation in P2PE, balancing individual and collective benefits, while the second stage optimizes economic aspects of P2P trading using a payment bargaining model. A case study demonstrates significant cost reductions and improved renewable energy utilization, with notable profit increments for participants. The study highlights the effectiveness of Nash bargaining theory and privacy-preserving algorithms in optimizing social welfare and economic interactions. Limitations include a focus on wind energy and simplified assumptions about energy storage. Future research should incorporate diverse renewable sources, dynamic modeling, and multi-community interactions.

**Keywords**
community energy trading, Peer-to-Peer energy sharing, privacy-preserving algorithms, renewable energy utilization, two-stage optimization

## 1. Introduction

### 1.1. Background and motivations

The energy sector is undergoing a transformative shift from centralized systems, which traditionally rely on large-scale power plants and extensive transmission networks, to decentralized models that emphasize local generation and consumption [1]. This shift is driven by the growing need for sustainable energy solutions, increased energy efficiency, and the resilience of power systems [2]. Peer-to-Peer Energy Sharing (P2PES) systems have emerged as a promising approach to address these needs by enabling direct energy exchanges between individuals within a community, thereby reducing reliance on centralized utilities and enhancing local energy security [3]. Wind energy has become a focal point in this transition due to its substantial potential as a renewable resource. With advancements in wind turbine technology and the decreasing costs of wind energy production, wind power has demonstrated significant potential for contributing to sustainable energy systems [4]. Its integration into decentralized energy networks offers several advantages, including the reduction of greenhouse gas emissions, the mitigation of energy

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supply vulnerabilities, and the promotion of energy independence for local communities [5]. The motivation for focusing on wind energy within the context of P2PES systems is multifaceted. Wind power is not only a well-established and reliable technology but also aligns with the broader goals of reducing carbon emissions and fostering the use of renewable resources [6]. Its variability and intermittent nature present both challenges and opportunities for energy management, making it a critical component for exploring and optimizing decentralized energy systems [7]. By integrating wind energy into P2PES frameworks, researchers and practitioners can address these challenges and leverage the benefits of distributed renewable resources to create more resilient, efficient, and sustainable energy systems [8].

### 1.2. Literature review

The shift towards decentralized energy systems, driven by sustainability and efficiency goals, is transforming energy generation and consumption. Peer-to-Peer Energy Sharing (P2PES) is a key innovation in this transition, enabling local energy exchanges and reducing reliance on traditional utilities. This review examines recent advancements and challenges in decentralized energy systems and P2PES, offering insights into current research and future directions. In [9] presented a decentralized energy trading model that integrates blockchain technology to enhance the security and transparency of Peer-to-Peer (P2P) energy transactions. Their approach ensures immutability in transaction records, thereby minimizing potential errors and improving trust between participants in decentralized energy systems. In [10] developed an optimization framework for P2P energy management, focusing on real-time balancing of energy supply and demand among distributed entities. Their model incorporates dynamic adjustments based on real-time consumption data and renewable energy generation. This work provides insights into the application of adaptive optimization techniques, offering improvements in system performance and energy distribution efficiency under fluctuating conditions. In [11] explored a hybrid pricing model for P2P energy markets, combining dynamic pricing with fixed tariffs. Their analysis demonstrates how this hybrid approach can mitigate price volatility and provide equitable compensation for both energy producers and consumers. The research contributes to the field by offering an effective mechanism to manage price fluctuations while maintaining market stability, particularly in systems with diverse energy contributors. In [12] investigated the role of energy storage systems in P2P energy exchanges, specifically examining how batteries can stabilize energy supply and improve distribution efficiency. Their model evaluates the interplay between storage management and energy trading, revealing strategies to optimize storage utilization and reduce costs. This study enhances the understanding of energy storage's potential to support distributed energy networks, particularly under varying demand and supply conditions.

In [13] conducted a comprehensive analysis of renewable energy sources, focusing on solar and wind power in the context of P2P energy markets. Their simulation framework evaluates the influence of different renewable energy profiles on market dynamics and participant outcomes. The study sheds light on the interaction between renewable energy variability and the economic stability of P2P energy trading, offering valuable insights for systems with high renewable energy penetration. In [14] developed a decentralized control strategy for managing P2P energy systems, utilizing machine learning algorithms to predict fluctuations in energy demand and supply. Their integration of predictive analytics enhances the accuracy of energy distribution, reducing the system's dependency on external energy sources. The research demonstrates how advanced computational techniques can improve the adaptability and efficiency of decentralized energy systems. In [15] proposed a multi-agent system for P2P energy exchanges, where each participant operates as an autonomous agent capable of making decentralized decisions. Their work highlights the advantages of agent-based models in terms of system scalability and resilience. By focusing on decentralized decision-making processes, the study provides a framework that can accommodate a growing number of participants while maintaining system flexibility and efficiency.

Erol and Filik [1]studied energy sharing management in a microgrid with photovoltaic and wind turbine prosumers, energy storage systems, and EV charging stations. They used a single-leader, multi-follower Stackelberg game model, with the microgrid operator (MGO) as the leader and prosumers and charging stations as followers. Unlike previous approaches where prosumer roles were fixed, their model allowed prosumers to dynamically switch between buyers and sellers based on the MGO's pricing policy. Prosumers could also shape their energy consumption strategies using specified decision parameters. A real-like microgrid simulation showed that this method nearly doubled the MGO's total profit compared to utility grid prices and reduced the microgrid's dependency on the utility grid by enhancing prosumer flexibility. Shen et al. [2] studied the strategic behavior of distributed energy resources (DERs) aggregators in electricity markets, focusing on their impact on distribution system security. They used a single-leader, multi-follower Stackelberg game model, with the DER aggregator as the leader and the system operators as followers. To ensure operational security, they addressed security check problems in three scenarios, linearized using a mixed-integer linear power flow model. The model was converted into a bi-level mixed-integer linear programming (BMILP) model using the strong duality theorem. An accelerated relaxation-based bi-level reformulation and decomposition algorithm was proposed to solve the BMILP problem. Case studies on constructed and practical integrated transmission and distribution (T&D) systems verified the model's effectiveness. Results showed that the DER aggregator's available downward reserve decreased with distribution system security limitations. Kosucki et al. conducted a numerical investigation of an overhead crane's energy consumption using a hybrid model of drive mechanisms and experimentally measured power consumption. The model was verified on a real crane. The study analyzed energy consumption relative to traveled distance and lifting/lowering heights, focusing on the hoist for energy efficiency improvements. Various transported mass magnitudes were assessed. Mahdavi-Meymand et al. [3], [4] developed and employed integrative machine learning models with the firefly algorithm (FA) to predict energy dissipation on block ramps. Models included MLPNN, adaptive network-based fuzzy inference system (ANFIS), GMDH, SVR, LE, and NE. The study showed that machine learning models and NE outperformed LE, and FA improved all models' performance. ANFIS-FA was the most stable integrative model, while GMDH and SVR were the most stable techniques overall. LE-FA had relatively low accuracy (RMSE=0.091), while SVR-FA had the highest accuracy (RMSE=0.034). Świder and Zbilski [5]investigated power losses as a factor affecting the energy effectiveness of production processes. They focused on low working conditions of a robot electric motor, examining how power losses changed from driving mode to stand-still mode. This study not only determined power map components but also addressed managing technical limitations in measuring industrial robot electrical states under conditions of high disturbances, noise, and limited robot axis angle range. Belgana et al. [6] introduced an approach leveraging microsources to reduce carbon emissions and exploit renewable energy sources to meet growing global electrical demand. Despite potential benefits, challenges, such as optimizing the tradeoff between renewable and nonrenewable energy sources for affordable, low-carbon power, persisted. Game theoretic approaches and evolutionary paradigms have been extensively applied to smart grids. Belgana et al. combined these methods within open energy markets, developing an analytic model using a multileader and multifollower Stackelberg game approach. They proposed a bi-level hybrid multiobjective evolutionary algorithm to maximize utility profits and minimize carbon emissions among interconnected microsources. Tushar et al. [7] investigated a three-party energy management problem in a smart community with residential units (RUs) having distributed energy resources (DERs), a shared facility controller (SFC), and the main grid. They formulated a Stackelberg game benefiting both the SFC and RUs in terms of cost and utility from energy trading. The study demonstrated the existence of a unique Stackelberg equilibrium (SE) and proposed a novel algorithm for RUs and the SFC to reach the SE in a distributed manner. The algorithm's convergence was proven, and numerical examples validated the scheme's properties and effectiveness. Wang et al. [8] examined the use of renewable energy resources (RESs) in microgrids, proposing a heuristic method for load demand management based on produced power and forecasted market clearing prices. They considered uncertainties in resources and load demand, with a forecasting unit informing operators of power levels for the next 24 hours. They added an energy storage system (ESS) to manage operation costs. Using a new decision-making criterion and particle swarm optimization (PSO), they optimized the generation schedule and economic dispatch to reduce consumer costs. The model ensured voltage stability and basic load support. Simulations with and without price-based demand response showed that demand management reduced system costs by 20–30%, improved voltage dip (max 1.4%), and power deviation (max 1.25%). Huang and Abedinia [9] addressed the increasing use of renewable resources, such as wind turbines (WT) and photovoltaic (PV) systems, in microgrids (MG). They proposed a planning model considering renewable energy uncertainty, demand response, and electric vehicles (EVs) to minimize electricity market costs. To manage power flow and ensure load support and voltage stability, they employed energy storage systems (ESS) and time-of-use (TOU) demand response programs. Price-based demand response (DR) for various loads was also considered. A modified virus colony search (VCS) algorithm based on chaos theory solved the optimization problem. Their approach, tested on an MG system with various scenarios, showed that DR significantly reduced total costs by 20–26%, improved voltage dip (max 1.4%), and enhanced power deviation (max 1.2%). Liu et al. [10] investigated energy policies that promote local PV energy consumption, finding energy sharing among neighboring PV prosumers more effective than independent operations. To facilitate this sharing, they proposed an energy storage-equipped energy-sharing provider (ESP). The ESP enabled PV prosumers to form a network, allowing direct and buffered energy sharing. Liu et al. created a day-ahead scheduling model for the ESP to boost profits and improve the net power profile, taking into account uncertainties in PV energy, electricity prices, and prosumer load. They also introduced a real-time demand response model based on a Stackelberg game to coordinate energy consumption using internal prices. A practical case study verified the method's effectiveness, showing significant improvements in economic benefits and PV energy sharing. Fan et al. [11] looked into how flexible demand response aggregators (DRAs) and a distribution company (Disco) with its own generators trade energy. They suggested a bargaining-based cooperative model instead of the usual non-cooperative game approach. In this model, Disco and DRAs collaboratively decided on energy trade amounts and payments, benefiting both by reducing peak demand and increasing cost savings. Benefits were fairly allocated using Nash's bargaining theory. The decentralized solution addressed privacy and autonomy concerns with minimal information exchange. Numerical studies demonstrated the framework's effectiveness, revealing significant improvements in system benefits. Devi et al. [12] propose a model for energy trading in smart grids using a game-theory-based multi-stage Nash Bargaining Solution (NBS). The model enables participants, including utilities, private parties, and prosumers, to negotiate mutually acceptable prices, promoting participation and reducing greenhouse gas emissions. By balancing the benefits for consumers and producers, the model ensures fairness in the final agreed price. Comparative analysis with feed-in-tariff (FiT) techniques shows that the proposed model reduces consumers' energy bills by an average of 32.8% and increases producers' revenue by 64.83%. Additionally, the model demonstrates superior performance with an increase in the number of participants. Carbon emission reduction analysis indicates significant reductions, with approximately 28.48 kg/kWh for 10 participants and 342.397 kg/kWh for 100 participants. Alizadeh et al. [13] introduce a Prosumer-Based Multi-Carrier Energy System (PB-MCES) framework for scheduling Multi-Carrier Energy Systems (MCESs) and forming an Energy Hub (EH) with Transactive Energy Control (TEC). Addressing challenges such as network constraints and uncertainty of Renewable Energy Sources (RESs), they employ Nash Bargaining Game Theory to develop a cooperative TEC prioritizing peer-to-peer (P2P) energy trade. PB-MCESs estimate uncertainty using stochastic programming, allocating reserve capacity for managing uncertainty through P2P reserve trading and internal reserves. Risk control is facilitated by adjusting the risk-taking factor based on the Conditional Value-at-Risk (CVAR) index. Implementation results demonstrate a 17.14% reduction in total costs with the cooperative TEC and a 16.32% reduction with P2P reserve trading. In a power distribution system made up of many microgrids, some agent-based hierarchical power management models were proposed to solve the power management issues [14], [15], [16], [17]. A fair cost-sharing mechanism based on Nash bargaining was created by [18] to encourage cooperative planning amongst several microgrids. References [11], [19] focused on energy trading among aggregators, exploring economic interactions between distribution companies and aggregators, while not considering buyers in their models.

### 1.3. Literature Gap and Research Contribution

A detailed review of the literature has revealed several research gaps that merit further exploration. As consumer-side renewable energy technologies, particularly solar and wind, continue to evolve, their adoption is expected to rise significantly. However, many studies currently focus on the interactions between distribution operators and aggregators, often overlooking the critical role of individual purchasers in decentralized energy markets. While much attention has been given to peer-to-peer energy sharing (P2PES) price mechanisms, the potential of these pricing strategies to optimize social welfare remains uncertain. Various methods, including the average market rate mechanism, supply-demand ratio mechanism, and supply-demand ratio with compensatory pricing, have been proposed, yet their ability to ensure optimal outcomes is still under scrutiny. Nash bargaining theory, which stems from cooperative game theory, has been frequently employed to model economic interactions between energy buyers and sellers due to its emphasis on collective rationality. This research addresses the complexities of supply-demand dynamics in P2PES by introducing an incentive-based system to improve economic exchanges between community members. Through this framework, participants collaboratively plan energy exchanges, accounting for fluctuating electricity demand and renewable energy generation. By encouraging consumers to trade energy directly, the system aims to enhance overall satisfaction and create more efficient and economically beneficial energy-sharing environments.

This paper addresses the identified research gaps by introducing a comprehensive framework that enhances peer-to-peer energy sharing (P2PES) through an innovative two-stage optimization process. Unlike previous studies that often overlook the role of purchasers or focus narrowly on pricing mechanisms, this work directly incorporates the dynamics of both prosumers and consumers into the decision-making process. By using a combination of Nash bargaining theory and advanced distributed algorithms, the paper ensures that participants' energy exchanges are optimized for both social welfare and individual benefits. The main contributions and key innovations of this paper can be summarized as follows:

1. A novel two-stage optimization approach is proposed to manage peer-to-peer energy sharing (P2PES), enabling both efficient energy exchange and equitable benefit distribution among community members.
2. The study leverages Nash bargaining theory to address energy trading interactions between prosumers and consumers, ensuring fairness in energy distribution and maximizing community-wide social welfare.
3. A flexible, real-time pricing mechanism is introduced, which adapts to fluctuations in electricity demand and renewable energy output, improving both economic efficiency and energy management within the community.
4. The framework takes into account the role of consumer-side energy storage systems, optimizing energy trading and storage decisions in response to changing load profiles and renewable energy availability.
5. The proposed system significantly reduces reliance on external power sources, especially during peak periods, by optimizing the use of locally generated renewable energy within the community.
6. An incentive mechanism is developed to enhance economic interactions between buyers and sellers in the energy-sharing network, encouraging active participation and increasing the overall profitability of energy trading.
7. The framework is validated through detailed case studies that demonstrate its effectiveness in improving community-level energy sharing, with clear benefits for both prosumers and consumers.

## 2. Problem modeling

### 2.1. Recommended system

The Peer-to-Peer (P2P) sharing community is divided into two distinct groups: Customers and Prosumers. Customers are individuals or entities that exclusively use electricity within the community, without generating their own. In contrast, Prosumers are distinguished by owning their personal renewable energy systems, allowing them to both produce and consume electricity. For this study, we specifically focus on wind energy as the primary renewable resource. This focus can be due to the advantages that wind energy has.

1. Abundant and Sustainable Resource: Wind energy is

pure and endless, hence forming a very key component in driving sustainable energy solutions. In turn, this has allowed wind energy to be integrated into a study that tries to leverage a renewable source in order to meet global goals with regard to low dependence on fossil fuels and reduction of greenhouse gas emissions.

2. Cost-Effectiveness: The production of wind energy is much cheaper by comparison, at least in the longer term, considering the advancement in the field of turbine technology. This could even be economically feasible for communities that needed to generate and share renewable energy locally. Lower production costs mean higher economic viability of wind energy in decentralized systems.
3. Energy Independence: Wind energy enables a community to produce energy on their own instead of relying on centralized power grids and external supplies. This turns out to be particularly important in the P2PES system described in this paper, in which energy will be traded directly between community members. In this way, by generating excess energy via wind turbines, prosumers can contribute to and be actively involved in the local energy market.
4. Environmental Impact: In a wider perspective of zero carbon dioxide emission or any other sort of polluting material released, wind energy production presents an active means towards eradicating the carbon footprint from energy production. This may be important in the context of decentralized energy systems that promote clean energy practices with minimum environmental impact of energy use.
5. Variability and Flexibility: Wind energy is an intermittent energy source that may be a challenge but also a great opportunity regarding energy management. Management of the intermittent nature of wind power in the P2PES system is helpful for optimizing energy distribution or storage. Indeed, by balancing wind energy production against the ESS, communities can better cope with fluctuations in power generation and demand, raising overall system resilience and efficiency.

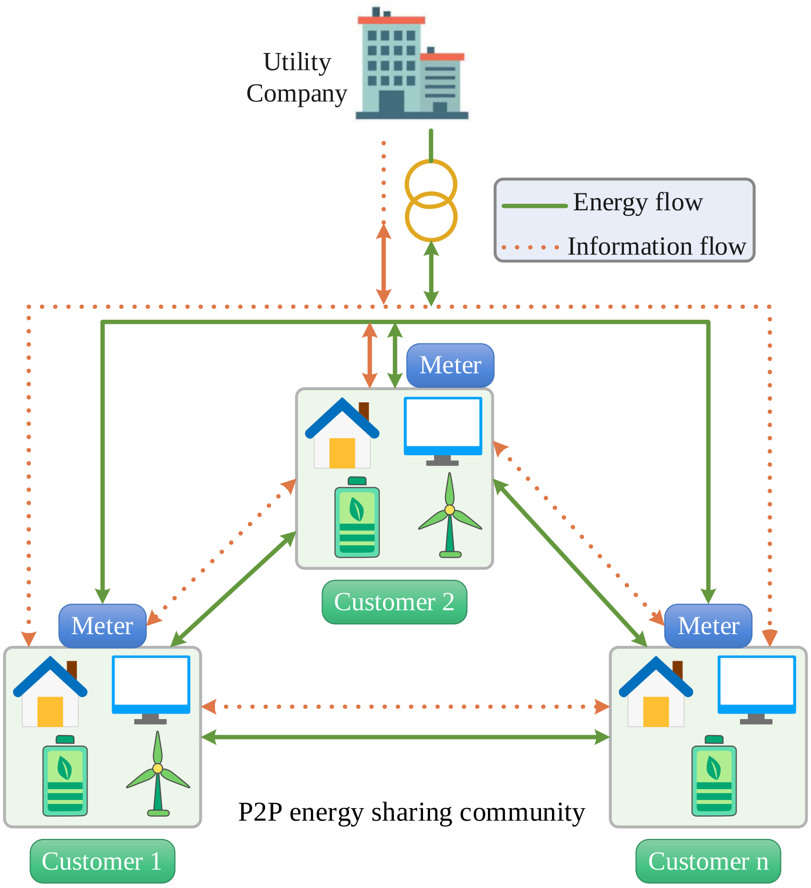


Fig. 1. The overview of peer-to-peer energy sharing system.

In a P2P Energy Sharing (P2PES) community, buyers, or Customers, have the ability to share their wind-generated electricity with other community members. This sharing is facilitated by Prosumers who often have a surplus of generated electricity. Prosumers need to procure additional electricity to meet their needs due to variations in electricity demand and the status of their Energy Storage Systems (ESSs). The power output of wind turbines within the community may show similarities, but the net energy needs of Prosumers differ. These differences arise from varying electricity demands and the operational status of their ESSs. Typically, the extra electricity generated by renewable energy sources is first used to power nearby high-energy buildings. Any remaining surplus energy can then be stored in batteries or sold to the electricity provider. P2PES provides a platform for Customers to engage in the local energy market, which is a crucial component of the community energy system. This system not only enhances the efficient use of distributed energy resources but also promotes local energy trading among community members, ensuring that surplus energy is effectively utilized within the community. This collaborative approach supports the viability of the local economy by retaining financial activities within the community and enhancing overall energy efficiency. This process supports the viability of the local economy by ensuring that financial activities continue within the community [20]. In this work, we envision a peer-to-peer (P2P) sharing community of subscribers who can trade and exchange energy resources with one another, as depicted in Fig. 1. A two-way communication and energy flow system connects these consumers, facilitating efficient and sustainable energy distribution within the community.

### 2.2. Energy storage

Every member of the P2PES community has batteries, as was stated in the introductory section. We make the assumption that throughout time, the charge and discharge power won't change. Assume that at the conclusion of each period, a subscriber's energy storage status vector, $S_{(i)} = \{S_{(i,1)}, \dots, S_{(i,t)}, \dots, S_{(i,T)}\}$, displays i. Therefore, electricity level in common ESS i can be expressed as shown in Eq. (1), where $\eta_{(i)}^{Loss}$ represents its discharge rate in a time interval gives, while $\eta_{(i)}^{C}$ and $\eta_{(i)}^{D}$ related to the efficiency of charging and discharging (CDC) in each cycle and $R_{(i,t)}^{C}$ and $R_{(i,t)}^{D}$ represent the CDC rates of electricity in period t. In this study, Δt is set equal to 1 [5]:

$$S_{(i,t)} = S_{(i,t-\Delta t)}\left(1 - \eta_{(i)}^{Loss}\right) + \Delta t\left(R_{(i,t)}^{C} \cdot \eta_{(i)}^{C} - \frac{R_{(i,t)}^{D}}{\eta_{(i)}^{D}}\right) \quad (1)$$

Because the depth of discharge has a significant impact on battery life, in practical applications, the energy level in the battery is often controlled to prevent overcharging and overdischarging. Let $C_{(i)}^{Min}$ and $C_{(i)}^{Max}$ represent each battery's min/max capacity for storage. Eq. (2) thus sets a limit on the battery's energy level. Furthermore, the CDC power in the period t must also meet Eq. (3) and Eq. (4) since the rate of CDC, which is restricted by the size of the inverter, also affects the battery's lifetime, where $R_{(i)}^{C-Min}$ and $R_{(i)}^{C-Max}$ are the minimum and maximum charging rates in each period and $R_{(i)}^{D-Min}$ and $R_{(i)}^{D-Max}$ show the minimum and maximum discharge rate in each period [5]:

$$C_{(i)}^{Min} \le S_{(i,t)} \le C_{(i)}^{Max} \quad (2)$$

$$R_{(i)}^{C-Min} \le R_{(i,t)}^{C} \le R_{(i)}^{C-Max} \quad (3)$$

$$R_{(i)}^{D-Min} \le R_{(i,t)}^{D} \le R_{(i)}^{D-Max} \quad (4)$$

In addition, each subscriber must consider the costs associated with the destruction of energy storage. We use the method in Eq. (5) to determine the deterioration that occurs while charging or discharging an energy unit, and we include a cost parameter υ to account for this degradation as repeated cycles of charging and discharging might cause some degree of degradation in the storage device. The number of CDC cycles and the battery price p define the amount of υ, which is the cost suffered by each customer due to storage deterioration [21].

$$C_{(i)}^{CD}\left(R_{(i,t)}^{C}, R_{(i,t)}^{D}\right) = \upsilon\left(\sum_{t=1}^{T} R_{(i,t)}^{C} \cdot \Delta t + \sum_{t=1}^{T} R_{(i,t)}^{D} \cdot \Delta t\right), \quad i \in N \quad (5)$$

### 2.3. Energy interaction

The shared power source i represents a combination of wind energy and electricity provided by the power company. We show the actual use of wind energy by subscribers as $W_{(i)} = \{W_{(i,1)}, \dots, W_{(i,t)}, \dots, W_{(i,T)}\}$ we give, a set that satisfies the constraint (6). In this case, $W_{(i,t)}^{Max}$ denotes the wind turbine's maximum allowable output power for period t. Eq. (7) explains the use of renewable energy data to estimate the power produced by a wind turbine. The air density and wind speed that subscriber i experienced in period t are represented by $D_{(i,t)}$ and $V_{(i,t)}$ respectively, in this equation. A denotes the turbine's swept area, while K stands for the turbine's power factor. It is worth noting that subscribers who have no wind energy sources and only have ESSs show zero actual wind energy output [22].

$$0 \leq W_{(i,t)} \leq W_{(i,t)}^{Max} \tag{6}$$

$$W_{(i,t)}^{Max} = \frac{1}{2}.A.K.D_{(i,t)}.\left(V_{(i,t)}\right)^3 \tag{7}$$

When a customer's demands exceed the amount of renewable energy available, the client may require power from the utility in addition to renewable energy. Conversely, customers who have excess electricity have the opportunity to sell it to the utility. We show the amounts of energy that subscribers may buy and sell to the power company in different periods as relations (8) and (9), respectively. The selling price of electricity $P_{(i)}^{S}$ and the purchase price $P_{(i)}^{P}$ provided by the electricity company during each time interval can be described as Eq. (10) and Eq. (11). As a result, the costs incurred by each subscriber i to receive electricity from the power company are calculated as shown in Eq. (12) [22].

$$B_{(i)}^{P} = \left\{B_{(i,1)}^{P}, \dots, B_{(i,t)}^{P}, \dots, B_{(i,T)}^{P}\right\} \tag{8}$$

$$B_{(i)}^{S} = \left\{B_{(i,1)}^{S}, \dots, B_{(i,t)}^{S}, \dots, B_{(i,T)}^{S}\right\} \tag{9}$$

$$P_{(i)}^{S} = \left\{P_{(i,1)}^{S}, \dots, P_{(i,t)}^{S}, \dots, P_{(i,T)}^{S}\right\} \tag{10}$$

$$P_{(i)}^{P} = \left\{P_{(i,1)}^{P}, \dots, P_{(i,t)}^{P}, \dots, P_{(i,T)}^{P}\right\} \tag{11}$$

$$C_{(i)}^{Grid}\left(B_{(i,t)}^{P}, B_{(i,t)}^{S}\right) = \sum_{t=1}^{T}\left(P_{(i,t)}^{S} \cdot B_{(i,t)}^{P} - P_{(i,t)}^{P} \cdot B_{(i,t)}^{S}\right) \quad \forall i \in N \tag{12}$$

Fixed loads and detachable loads are the two general categories into which electric load profiles for subscribers may be divided [22]. In our analysis, a certain percentage of detachable loads are made up of both consumers and customers. Customers can modify service durations or power usage with switchable loads in response to variable factors like energy pricing, informational signals, or individual preferences. These removable power load profiles for subscriber i in fixed duration $d_{(i)}$ can be shown as Eq. (13). For each $d_{(i,t)}$, the system loads must obey the conditions expressed in Eq. (14) and Eq. (15), where $d_{(i,t)}^{Min}$ and $d_{(i,t)}^{Max}$ represents min/max bounds for electricity of subscriber i at time t and $D_{(i,t)}^{Min}$ represents the minimum cumulative demand [22].

$$d_{(i)} = \left\{d_{(i,1)}, \dots, d_{(i,t)}, \dots, d_{(i,T)}\right\} \tag{13}$$

$$d_{(i,t)}^{Min} \leq d_{(i,t)} \leq d_{(i,t)}^{Max} \tag{14}$$

$$\sum_{t=1}^{24} d_{(i,t)} \geq D_{(i,t)}^{Min} \tag{15}$$

To provide more clarity, consider that the ideal demand profile for subscriber i at time t is represented by $d_{(i)}^{IDE}$ in Eq. (16). Eq. (17) may be used to calculate the cost of discontent incurred by each subscriber using sources [11], [19]. In this case, the priority coefficient given to each subscriber i in the subscriber set N is denoted by $\beta_{(i)}$. A larger value of $\beta_{(i)}$ indicates a stronger joint aversion to deviation from ideal power demand levels. To ensure joint comfort, it becomes necessary to adhere to the relation between $d_{(i,t)}$ and $d_{(i,t)}^{IDE}$, as defined in Eq. (18) [11], [19].

$$d_{(i)}^{IDE} = \left\{d_{(i,1)}^{IDE}, \dots, d_{(i,t)}^{IDE}, \dots, d_{(i,T)}^{IDE}\right\} \tag{16}$$

$$C_{(i)}^{Dis}\left(d_{(i,t)}\right) = d_{(i,t)}^{IDE} \cdot \beta_{(i)} \cdot ln\left[\frac{sin\left(\frac{d_{(i,t)}}{d_{(i,t)}^{Ide}} - 2 + \frac{\pi}{2}\right)}{sin\left(-1 + \frac{\pi}{2}\right)}\right] \tag{17}$$

$$0.5 \leq \frac{d_{(i,t)}}{d_{(i,t)}^{IDE}} \leq 2 \tag{18}$$

Considering those subscribers, especially in commercial and industrial areas, get tangible benefits from energy consumption instead of just billing, our optimal performance takes this into account. The utility achieved by subscriber i through energy consumption $d_{(i,t)}$ is enclosed in Eq. (19). Here, $k_{(i,t)}$ represents a composite expression that integrates weight coefficients and preference parameters [10], and as a reflection of the importance attributed to the utility of energy consumption and the preferences of subscribers regarding energy consumption. it works [10].

$$U_{(i)}\left(d_{(i,t)}\right) = k_{(i,t)}.ln\left(1 + d_{(i,t)}\right) \tag{19}$$

## 3. Cooperative bargaining

In this section, we provide a brief overview of the basic tenets of Nash bargaining game theory to set the stage for investigating cooperative interactions between customers in a society. In the framework of cooperative bargaining games, participants representing customers in the community provide incentives to each other to encourage cooperation. Members of the community can work together to maximize their advantages to one another. The simulation of situations in which players coordinate their activities to arrive at a win-win solution is the fundamental component of cooperative game theory in attaining an ideal social result.

Within the framework of the game, N = {1, 2, …, i, …, n} is the set of players, with i standing for each participant. Every player has a utility, referred to as UI, and if an agreement cannot be reached, the player is awarded a disagreement point. Players are obligated by the terms of any agreements once they are struck. If not, they behave irrationally. The formulation of the Nash bargaining model is given in reference [23]. The Nash bargaining model's solution complies with the following five essential requirements: Pareto optimality, independence from unrelated alternatives, independence from dependent transformations, and individual rationality [23].

$$Max \prod_{i=1}^{n}\left[u_{(i)} - D_{(i)}\right] \tag{20}$$

$$u_{(i)} \geq D_{(i)} \tag{21}$$

As mentioned earlier, subscribers are willing to provide incentives to encourage energy exchange in the P2PES community and explore collaborative relationships to maximize their benefits. This begs the following questions: What is the best choice for the subscriber, in terms of the ideal quantity of energy exchanged? What constitutes the ideal profit margin for a subscriber engaged in a P2PES business? These questions will be investigated in the next section through a TSO approach.

### 3.1. First level optimization

Considering the analysis above, a subscriber's ability to raise the total social utility determines whether or not they are eligible to play the bargaining game. The advantage that all members of society receive collectively is referred to in this study as social utility.

**I. Social desirability model**

$P^{E}_{(ij,t)}$ represents the energy received by subscriber i from subscriber j in a certain period, and $P^{E}_{(ji,t)}$ represents the electricity sold by subscriber j to subscriber i in the same period is when they must satisfy the constraint (22), which leads to an energy balance constraint described in Eq. (23). Specifically, $\sum_{j\in N, j\neq i} P^{E}_{(ij,t)}$ represents the net electricity traded between subscriber i and other subscribers in a certain time interval. When $\sum_{j\in N, j\neq i} P^{E}_{(ij,t)} > 0$ , it means that subscriber i is receiving energy from other subscribers to meet its electricity demand and vice versa. , when $\sum_{j\in N, j\neq i} P^{E}_{(ij,t)} < 0$ , it means that subscriber i is supplying energy to other subscribers in the community.

As mentioned earlier, joint competence to participate in the bargaining game is conditional on their ability to increase social welfare. As shown in Eq. (24), to illustrate this, we define the social welfare maximization model, where $U_{sw}$ represents the collective utility of all subscribers in the society. Also, at this stage of optimization, our objective function is in the form of Eq. (25) [5]:

$$P^{E}_{(ij,t)} = -P^{E}_{(ji,t)} \qquad \forall i \in N, j \in N, j \neq i \tag{22}$$

$$B^{P}_{(i,t)} + W_{(i,t)} + \sum_{j\in N, j\neq i} P^{E}_{(ij,t)} + R^{D}_{(i,t)} = d_{(i,t)} + R^{C}_{(i,t)} + B^{S}_{(i,t)} \qquad \forall t \in T^{Ime}, \forall i \in N \tag{23}$$

$$\begin{aligned} U_{sw} = {} & \sum_{i=1}^{n}\sum_{t=1}^{24}\left\{k_{(i,t)}.ln\left(1 + d_{(i,t)}\right)\right\} + v\sum_{i=1}^{n}\left\{\sum_{t=1}^{T} R^{C}_{(i,t)} \cdot \Delta t + \sum_{t=1}^{T} R^{D}_{(i,t)} \cdot \Delta t\right\} - \sum_{i=1}^{n}\sum_{t=1}^{24}\left\{P^{S}_{(i,t)} \cdot B^{P}_{(i,t)} - P^{P}_{(i,t)} \cdot B^{S}_{(i,t)}\right\} \\ & - \sum_{i=1}^{n}\sum_{t=1}^{24}\left\{d^{IDE}_{(i,t)} \cdot \beta_{(i)} \cdot ln\left[\frac{sin\left(\frac{d_{(i,t)}}{d^{Ide}_{(i,t)}} - 2 + \frac{\pi}{2}\right)}{sin\left(-1 + \frac{\pi}{2}\right)}\right]\right\} \end{aligned} \tag{24}$$

$$Max \sum_{i=1}^{n} U^{Con}_{(i)}\left(W_{(i,t)}, d_{(i,t)}, B^{S}_{(i,t)}, B^{P}_{(i,t)}, R^{C}_{(i,t)}, R^{D}_{(i,t)}\right) \tag{25}$$

**II. Distributed solution of social utility**

To solve the issue indicated in relations (26) and (27), we provide in this part a distributed algorithm based on the approach of alternating direction of coefficients. Convex optimization issues can be solved by breaking them down into smaller, more manageable components using the method of alternating direction of coefficients. Auxiliary variables are introduced as shown in Eq. (26) and Eq. (27). $P^{E}_{(ij,t)}$ in these relationships denotes the energy transferred in a given time interval between joint i and joint j, while $\hat{P}^{E}_{(ij,t)}$ for each auxiliary variable denotes the recommended quantity of electricity. Eq. (28) expresses the augmented Lagrangian function for the issue in Eq. (25) where ρ > 0 is a penalty parameter connected to constraints (26) and (27). $\lambda_{(ij,t)}$ is introduced as the Lagrangian coefficient. Relationships between optimization problems with fixed dual variables and auxiliary variables are provided in relation (29) [5]:

$$\hat{P}^{E}_{(ij,t)} = P^{E}_{(ij,t)} \tag{26}$$
$$\hat{P}^{E}_{(ij,t)} = -\hat{P}^{E}_{(ji,t)} \tag{27}$$
$$L = \sum_{i=1}^{n}\sum_{t=1}^{T}\left[U_{(i)}\left(d_{(i,t)}\right) - C^{Grid}_{(i)}\left(B^{P}_{(i,t)}, B^{S}_{(i,t)}\right) - C^{Dis}_{(i)}\left(d_{(i,t)}\right)\right] - \sum_{i=1}^{n} C^{CD}_{(i)}\left(R^{C}_{(i,t)}, R^{D}_{(i,t)}\right) + \frac{\rho_1}{2}\sum_{j\in N/i}\sum_{t=1}^{T}\left(\hat{P}^{E}_{(ij,t)} - P^{E}_{(ij,t)}\right)^2 + \sum_{j\in N/i}\sum_{t=1}^{T}\lambda_{(ij,t)}\left(\hat{P}^{E}_{(ij,t)} - P^{E}_{(ij,t)}\right) \tag{28}$$
$$Max\sum_{t=1}^{T}\left[U_{(i)}\left(d_{(i,t)}\right) - C^{Grid}_{(i)}\left(B^{P}_{(i,t)}, B^{S}_{(i,t)}\right) - C^{Dis}_{(i)}\left(d_{(i,t)}\right)\right] - C^{CD}_{(i)}\left(R^{C}_{(i,t)}, R^{D}_{(i,t)}\right) + \frac{\rho_1}{2}\sum_{j\in N/i}\sum_{t=1}^{T}\left(\hat{P}^{E}_{(ij,t)} - P^{E}_{(ij,t)}\right)^2 + \sum_{j\in N/i}\sum_{t=1}^{T}\lambda_{(ij,t)}\left(\hat{P}^{E}_{(ij,t)} - P^{E}_{(ij,t)}\right) \tag{29}$$

**III. Iterative algorithm for solving social utility problem**

As the name suggests, the basic concept of alternating direction of coefficients method involves modifying one variable, updating another variable, and repeating this process repeatedly until a predefined level of accuracy is reached. At first, the optimization problem is solved in relation (30) to get the optimal solution. Subsequently, based on the values of $P^{E}_{(ij,t)}(k+1)$ and $P^{E}_{(ji,t)}(k+1)$ , auxiliary variables and binary variables according to expressions (32) - (30) are updated [5].

$$\hat{P}^{E}_{(ij,t)}(k+1) = \left[\rho_1 \cdot P^{E}_{(ij,t)}(k+1) - P^{E}_{(ij,t)}(k+1) + \lambda_{(ji,t)}(k) - \lambda_{(ij,t)}(k)\right]/(2\cdot\rho_1) \tag{30}$$
$$\lambda_{(ji,t)}(k+1) = \lambda_{(ji,t)}(k) + \rho_1 \cdot P^{E}_{(ij,t)}(k+1) - P^{E}_{(ij,t)}(k+1) \tag{31}$$
$$\hat{P}^{E}_{(ij,t)}(k) = -\hat{P}^{E}_{(ji,t)}(k) \tag{32}$$

### 3.2. Second level optimization

Herein, applying principles derived from Nash Bargaining Theory, we address the dynamics of the customer segment in P2PET. To establish the context of our exploration, it begins by examining the utility of individual subscribers in society, which is called the point of difference in bargaining theory.

**I. The point of difference in the bargaining model**

In order to guarantee that the overall power supply during a period is equal to the total consumption, each subscriber must first abide by the energy relationship, which is outlined in Eq. (33). Furthermore, the power company's purchase of electricity during time t must to meet the inequality (34). The difference between the wind turbine's maximum allowed output power in period t and the actual wind energy consumption is taken into account by this inequality, where $W^{Max}_{(i,t)}$ represents the surplus wind energy in period t and $S_{(i,t)}$ represents the battery level. The objective utility function of the subscribers in the instances illustrated in connection (35) comprises elements like utility from energy usage, discontent costs, power purchase costs, and storage costs [5].

$$B^{P}_{(i,t)} + W_{(i,t)} + R^{D}_{(i,t)} = d_{(i,t)} + R^{C}_{(i,t)} + B^{S}_{(i,t)} \quad \forall t \in T^{Ime}, \forall i \in N \tag{33}$$
$$B^{S}_{(i,t)} \le W^{Max}_{(i,t)} - W_{(i,t)} + S_{(i,t)} \tag{34}$$
$$Max\sum_{t=1}^{T}\left[U_{(i)}\left(d_{(i,t)}\right) - C^{Dis}_{(i)}\left(d_{(i,t)}\right) - C^{Grid}_{(i)}\left(B^{P}_{(i,t)}, B^{S}_{(i,t)}\right)\right] - C^{CD}_{(i)}\left(R^{C}_{(i,t)}, R^{D}_{(i,t)}\right) \tag{35}$$

**I. Payment bargaining problem for P2PES business**

With Eq. (25), we identify the set of subscribers in the amount of P2PES. For each subscriber i ∈ M, the energy trade-off $P^{E}_{(ij,t)}$ can be determined. $P^{E}_{(ij,t)}$ is considered a specific parameter in the bargaining issue, and $f^{E}_{(ij,t)}$ represents the corresponding payoff. A positive value indicates that subscriber i receives a payment from subscriber j, while a negative value indicates that subscriber i provides a payment to subscriber j. Payments among all subscribers in set M must obey constraint (36). In practice, the subscriber in set M engages in P2PET and bargaining game only when the total utility ($U^{Con}_{(i)} + U^{f}_{(i)}$) of the otherwise optimized profit subscription ($U^{Non}_{(i)}$) exceeds. As a result, for each subscriber participating in the P2PES trade, bound (37) must be calculated. Therefore, the payment bargaining problem for subscribers involved in P2PE can be formulated in detail in Eq. (38). In Eq. (38), the term $-U_{(i)}^{Non} + U_{(i)}^{Con} + U_{(i)}^{f}$ represents the improved utility that the subscriber receives when participating in the P2PES trade. The peer bargains using theoretical experience. The utility value when participating in P2PES business ($U_{(i)}^{Con}$) and the desirable value individually ($U_{(i)}^{Non}$) are among the influential items in this equation [5].

$$f_{(ij,t)}^{E} = -f_{(ji,t)}^{E} \qquad \forall t \in T^{Ime}, \forall i \in M, j \in M, j \neq i \tag{36}$$

$$U_{(i)}^{Non} \leq U_{(i)}^{Con} + U_{(i)}^{f} \tag{37}$$

$$Max \prod_{i=1}^{n} \left[-U_{(i)}^{Non} + U_{(i)}^{Con} + U_{(i)}^{f}\right] \tag{38}$$

## II. An iterative algorithm for solving the payment bargaining problem

Similar to Eq. (25), Eq. (38) includes a distributed algorithm. Auxiliary variables presented in Eq. (39) and Eq. (40) are introduced. The variation $f_{(ij,t)}^{E}$ represents the payment related to the energy trade between subscriber i and subscriber j in a certain time interval, while each contribution $\hat{f}_{(ij,t)}^{E}$ represents the cost issued by the subscriber. We introduce $\alpha_{(ji,t)}$ to represent the Lagrange coefficients, which is the full Lagrange equation of the second level of optimization shown in Eq. (41). Further updates for covariates and binomial variables can be done according to equationss (42) - (44) [5]:

$$\hat{f}_{(ij,t)}^{E} = f_{(ij,t)}^{E} \qquad \forall t \in T^{Ime}, \forall i \in N, j \in M, j \neq i \tag{39}$$

$$\hat{f}_{(ij,t)}^{E} = -\hat{f}_{(ji,t)}^{E} \qquad \forall t \in T^{Ime}, \forall i \in M, j \in M, j \neq i \tag{40}$$

$$\dot{L} = -\sum_{i \in M} ln\left(u_{(i)}^{Con} + u_{(i)}^{F} - u_{(i)}^{Non}\right) + \frac{\rho_2}{2} \sum_{j \in M/i} \sum_{t=1}^{T} \left(\hat{f}_{(ij,t)}^{E} - f_{(ij,t)}^{E}\right)^2 + \sum_{j \in M/i} \sum_{t=1}^{T} \alpha_{(ij,t)} \left(\hat{f}_{(ij,t)}^{E} - f_{(ij,t)}^{E}\right) \tag{41}$$

$$\hat{f}_{(ij,t)}^{E}(k+1) = \left[\rho_2 \cdot f_{(ij,t)}^{E}(k+1) - f_{(ij,t)}^{E}(k+1) + \alpha_{(ji,t)}(k) - \alpha_{(ij,t)}(k)\right] / (2 \cdot \rho_2) \tag{42}$$

$$\hat{f}_{(ij,t)}^{E}(k) = -\hat{f}_{(ji,t)}^{E}(k) \tag{43}$$

$$\alpha_{(ji,t)}(k+1) = \alpha_{(ji,t)}(k) + \rho_2 \cdot f_{(ij,t)}^{E}(k+1) - f_{(ij,t)}^{E}(k+1) \tag{44}$$

## III. Incorporating Dynamic Pricing for Energy Exchange

The model can be updated to account for dynamic pricing based on real-time supply-demand conditions within the P2P community. This helps to reflect market conditions better, and participants will benefit from more flexible trading prices [24]:

$$\text{Minimize} \sum_{t=1}^{T} \left( \sum_{i=1}^{N} C_i\,(t) \cdot \left(P_{\text{import}}(t) + P_{\text{export}}(t)\right) \right) \tag{45}$$

where, Ci(t) is the cost coefficient for participant i at time t, $P_{import}(t)$ and $P_{export}(t)$ are the power imported from and exported to the grid, respectively, N is the number of participants, and T is the total time period. The dynamic price Ci(t) can be calculated based on [24]:

$$C_i(t) = C_{\text{base}}(t) \cdot f\left(\frac{P_{\text{total, demand}}(t)}{P_{\text{total, supply}}(t)}\right) \tag{46}$$

where, $C_{base}(t)$ is the base price at time t, $P_{total,\ demand}(t)$ is the total demand in the community at time t, $P_{total,\ supply}(t)$ is the total supply from Prosumers at time t. The original formulation can be enhanced by considering battery degradation costs over time. This would add realism to the model, as batteries are not infinitely durable [24]:

$$\text{Minimize} \sum_{i=1}^{N} \left( C_{\text{battery}}(i) \cdot \left(E_{\text{stored}}(i,t) - E_{\text{discharged}}(i,t)\right) \right) \tag{47}$$

where, Cbattery(i) is the degradation cost coefficient for the ESS of participant i, Estored(i,t) and Edischarged(i,t) are the energy stored and discharged from the battery for participant i at time t. In other side, Demand Response (DR) allows prosumers and consumers to adjust their electricity usage in response to external signals (like price or grid conditions). The total demand, Pdemand(i,t), for prosumer/consumer i at time t is split into two parts: base demand and flexible demand [24]:

$$P_{\text{demand}}(i,t) = P_{\text{base}}(i,t) + P_{\text{flex}}(i,t) \tag{48}$$

where, Pbase(i,t) is the base (non-flexible) demand. Pflex(i,t) is the flexible portion of the demand that can be adjusted in response to DR signals.

The flexible demand can be shifted or reduced. Let, Pshift (i,t) represent the amount of demand shifted to another time period. Preduced(i,t) represent the amount of demand reduced.

The flexible demand is thus [24]:

$$P_{\text{flex}}(i,t) = P_{\text{shift}}(i,t) + P_{\text{reduced}}(i,t) \quad (49)$$

Additionally, limits are imposed on the amount of demand that can be shifted or reduced [24]:

$$0 \le P_{\text{shift}}(i,t) \le P_{\text{shift, max}}(i) \quad (50)$$

$$0 \le P_{\text{reduced}}(i,t) \le P_{\text{reduced, max}}(i) \quad (51)$$

where, Pshift, max(i) is the maximum amount of demand that can be shifted. Preduced, max(i) is the maximum amount of demand that can be reduced. Incentives are provided to consumers for participating in DR. The incentive function, DR(i,t), rewards consumers for reducing or shifting their demand [24]:

$$DR(i,t) = \alpha_i \cdot P_{\text{reduced}}(i,t) + \beta_i \cdot P_{\text{shift}}(i,t) \quad (52)$$

where, αi is the reward per unit of reduced demand. βi is the reward per unit of shifted demand.

## IV. Optimizing Energy Storage with Battery Degradation Considerations

In practical scenarios, battery degradation is not only influenced by the charge and discharge rates but also by the cumulative number of charge-discharge cycles. This degradation can impact the overall efficiency and capacity of the battery, which in turn affects the operational costs and performance of the energy storage system. To capture the effect of cumulative degradation over multiple periods, consider the following equation [25]:

$$\text{Degradation}_i(t) = \text{Degradation}_i(t-1) + \left(\frac{R_{i,t}^C + R_{i,t}^D}{\text{Cycle Capacity}_i}\right) \cdot \Delta t \cdot \text{Degradation Rate}_i \quad (53)$$

where, Degradationi(t) represents the cumulative degradation of the battery for subscriber i at time t. Degradationi(t−1) is the cumulative degradation at the previous period. $R_{i,t}^C$ and $R_{i,t}^D$ are the charging and discharging rates of the battery at time t, respectively. Cycle Capacityi is the maximum number of cycles the battery can handle before significant degradation occurs. Δt is the time interval (which is set to 1 in your case). Degradation Ratei is a parameter representing the rate at which the battery degrades per cycle. Modify the existing equation (1) to account for the effects of degradation [25]:

$$S_{i,t} = S_{i,t-\Delta t} \cdot (1-\eta_i^{\text{Loss}}) + \Delta t \cdot \left(\frac{R_{i,t}^C \cdot \eta_i^C - R_{i,t}^D}{\text{Capacity Factor}_i}\right) \quad (54)$$

where, Capacity Factori adjusts the effective capacity of the battery based on the cumulative degradation. Incorporate degradation into the cost function [25]:

$$C_i^{\text{CD}}(R_{i,t}^C, R_{i,t}^D) = \nu\left(\sum_{t=1}^{T}\left(R_{i,t}^C + R_{i,t}^D\right) \cdot \Delta t\right) + \text{Degradation Cost}_i(t) \quad (55)$$

where, Degradation Cost(i)(t) is calculated based on the cumulative degradation.

## 4. Case studies and presentation of results

In this section, we present a series of numerical case studies aimed at demonstrating the characteristics and effectiveness of the P2PE approach. The simulated P2PES community consists of five participants, including two consumers and three prosumers equipped with wind turbines. The 24-hour simulation is divided into hourly intervals to depict changes in electricity demand. To align with established practices and reflect real-world dynamics, the day is divided into three distinct periods: peak hours (15:00-23:00), mid-peak hours (10:00-15:00, 23:00-02:00), and off-peak hours (02:00-10:00). The cost of power varies according to these periods, with peak load times costing 2.98 ¥/kWh, off-peak times costing 0.83 ¥/kWh, and mid-peak times costing 1.91 ¥/kWh. It is essential to note that, as seen in Fig. 1, the current regulations controlling surplus electricity in distributed power systems dictate that the price at which electricity is purchased is fixed for the entire day.

Fig. 2 presents the ideal load of customers, creating a daily power load profile. We have calculated the expected wind turbine output based on the reference [26], providing a realistic representation of the contribution of renewable energy. Fig. 3 depicts individual and cumulative hourly wind energy production for consumers with wind turbines. The weight coefficient ω varies across different time intervals, with values of 1.5, 1.75, and 1.95 for peak load, medium load, and low load periods, respectively. Additionally, each of the five customers in the community is equipped with a battery with capacities of 12 kWh, 16 kWh, 4 kWh, 4 kWh, and 8 kWh.

These case studies will help illustrate the effectiveness of the P2PE approach in managing energy distribution and costs within the community, taking into account varying demand, production, and storage capacities.

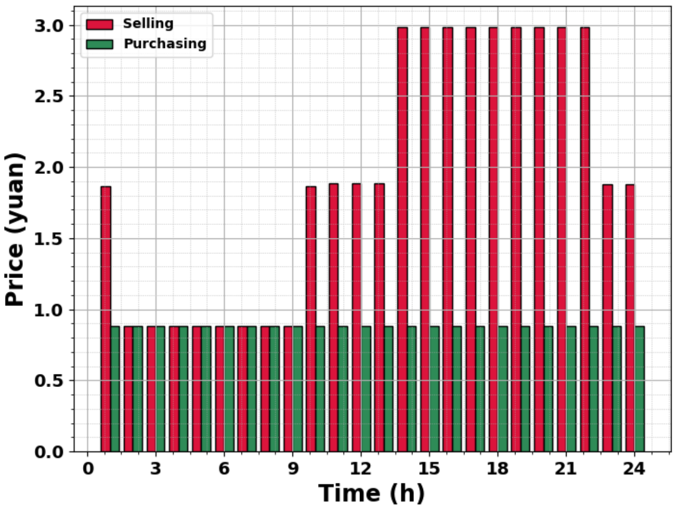


Fig. 2. The price of buying and selling electric energy of the power grid.

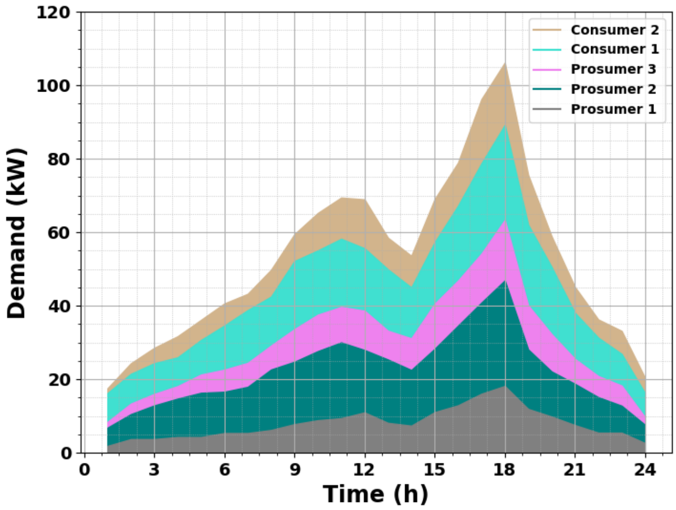


Fig. 3. The singular and aggregate hourly wind energy production for users with wind turbines.

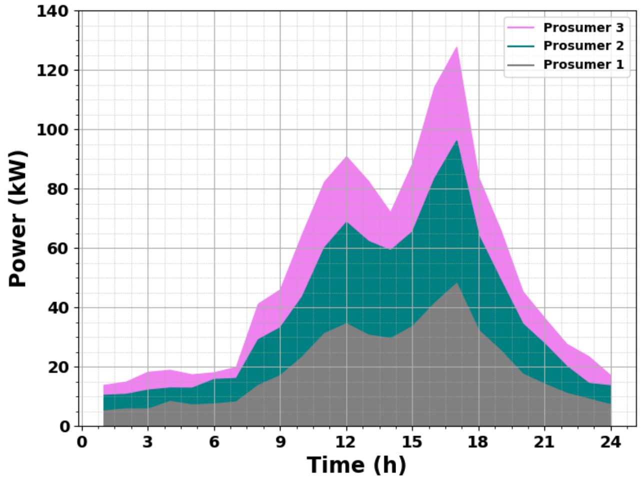


Fig. 4. The electrical power generated by the wind turbines of each User.

### 4.1. First level optimization results

Figure 4 provides an overview of the energy exchange dynamics within the community, highlighting the periods of energy trade among the five customers. The data reveals distinct patterns that underscore the efficiency and operational characteristics of the P2PES system. During the early morning hours (01:00 to 07:00), as depicted in Figure 4, all five customers exhibit zero traded energy. This observation can be attributed to the fact that the wind energy produced during these hours is sufficient only to meet the customers' own demands. Consequently, there is no surplus energy available for trading within the community, forcing customers to rely on the utility provider for additional energy needs. Figure 5 reinforces this point, as it shows no difference in electricity purchase levels between the P2P and P2PES systems during this time. This period effectively demonstrates the limits of energy availability from renewable sources alone and the necessity of relying on external utility supplies during low production periods.

In the late morning (08:00 to 09:00) and evening to night hours (18:00 to 23:00), Figure 4 shows that Prosumers begin to generate a modest surplus of energy. Despite this, customers still need to purchase electricity from the utility provider. Figure 5 illustrates a marginal reduction in power system purchases with the P2PES trading method compared to a scenario without P2PES. This reduction, though relatively small, highlights the beginning of a more efficient energy distribution system where surplus energy can start to contribute to reducing reliance on the utility grid.

A more pronounced shift occurs between 11:00 and 17:00, as shown in Figure 4. During this period, Prosumers experience a significant increase in energy production, creating a surplus despite high local energy consumption. Figure 5 reveals that power system purchases decrease substantially when P2PES trading is implemented, eventually reaching zero. This finding illustrates the effectiveness of the P2PES system in utilizing surplus renewable energy to fully meet the local demand, thereby eliminating the need for additional power from the utility.

An in-depth analysis reveals that despite the similar ideal power loads of Prosumer 1 and Prosumer 2, Prosumer 1 consistently shows lower ideal power loads during peak periods when utility prices are highest. This is evident in Figure 4. In scenarios where Prosumer 1 and Prosumer 3 have different wind energy efficiencies but similar ideal electricity usage, Prosumer 1 is able to outsell Prosumer 3, as illustrated by their higher energy sales figures. This results in customers such as Customer 1 and Customer 2 opting to purchase power at more favorable rates from Prosumers 1 and 2 during high load periods.

Figure 6 provides a comprehensive view of the battery storage profiles for each subscriber. The figures illustrate the energy levels maintained in Prosumers' and Customers' batteries, reflecting the dynamic trends in energy storage and usage throughout the day. The data highlights the variability in battery storage and its impact on energy availability and trading dynamics. Effective battery management allows Prosumers to maximize their surplus energy and offers customers the flexibility to benefit from energy savings when trading within the P2PES system.

The figures collectively demonstrate that the P2PES system enhances energy distribution efficiency by enabling effective trading of surplus energy. It reduces reliance on the utility grid during periods of high local production, balances energy supply and demand, and provides economic benefits to both Prosumers and Customers. The observed patterns and financial benefits underscore the potential of the P2PES system to optimize energy utilization and promote sustainable energy practices within the community.

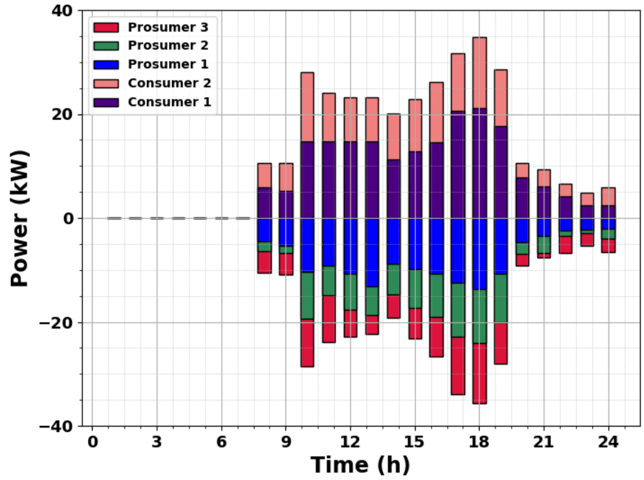


Fig. 5. Electric energy transacted among customers inside the system throughout a 24-hour duration.

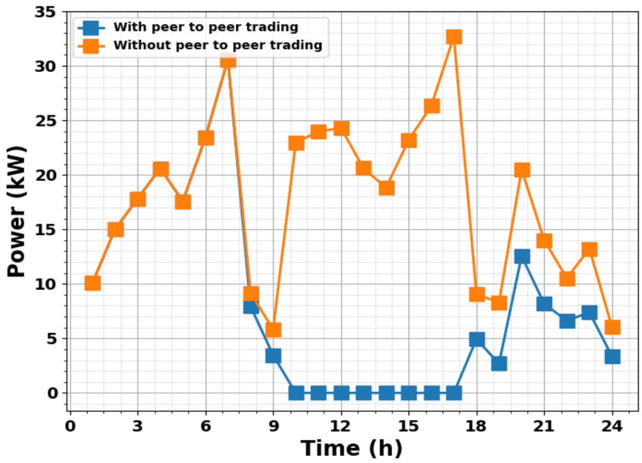


Fig. 6. The influence of the peer-to-peer mechanism on the electrical energy acquired by the system throughout a 24-hour duration.

### 4.2. Second-level optimization results

Table 1 provides a comprehensive overview of the payments and benefits experienced by subscribers within the P2PES community. It illustrates that Prosumers consistently record positive payoff values, indicating that they receive payments for the energy they provide to Customers. This is a direct result of their ability to generate surplus energy and sell it within the community, highlighting the financial advantages of being a Prosumer. Conversely, Customers show negative payoff values, reflecting their role as net energy consumers who pay Prosumers for the energy they receive. Notably, Prosumer 1 has the highest absolute payment value among the Prosumers, which aligns with their greater energy production capacity compared to others. This significant payoff for Prosumer 1 underscores their higher production capabilities and the economic benefits gained from supplying energy, reinforcing the value of participating in the P2PES system. The data presented in Table 1 reveals insightful trends regarding the financial impacts of the P2PES system on various subscribers. The profit increments and associated payments underscore the economic dynamics of the peer-to-peer energy trading system.

Table. 1. Paid cost and profit of subscribers using P2PES

| Items | Associated payments (¥) | Profit increment (¥) |
|---|---|---|
| **Costumer 1** | -72.54 | 199.04 |
| **Costumer 2** | -61.72 | 118.87 |
| **Prosumer 1** | 96.89 | 73.98 |
| **Prosumer 2** | 34.67 | 55.54 |
| **Prosumer 3** | 38.03 | 65.36 |
| **System** | - | 510.73 |

Customer 1 and Customer 2 exhibit significant profit increments of ¥199.04 and ¥118.87, respectively, while incurring associated payments of ¥72.54 and ¥61.72. This translates to profit percentages of approximately 73.98% and 65.00%, respectively. These values highlight that both customers benefit substantially from the P2PES system. The higher profit for Customer 1 can be attributed to the larger volume of energy received from Prosumers, coupled with the reduced costs compared to traditional utility purchases. On the other hand, the Prosumers show varying profit margins and payment structures. Prosumer 1 records a profit increment of ¥73.98 with an associated payment of ¥96.89, reflecting a net gain and a profit margin of approximately 43.22%. Prosumer 2 and Prosumer 3 follow with profit increments of ¥55.54 and ¥65.36 and associated payments of ¥34.67 and ¥38.03, respectively. Their profit margins are approximately 61.60% and 63.12%. These figures illustrate that while Prosumers do incur costs related to energy trading, they also benefit financially from selling surplus energy. The variance in profit margins among Prosumers indicates differing levels of efficiency and energy production capacities. Overall, the cumulative system benefit amounts to ¥510.73, with the system effectively redistributing costs and benefits among participants. This collective gain illustrates the overall efficiency and attractiveness of the P2PES framework. The system not only enhances the profitability for customers and Prosumers but also optimizes energy utilization and distribution within the community.

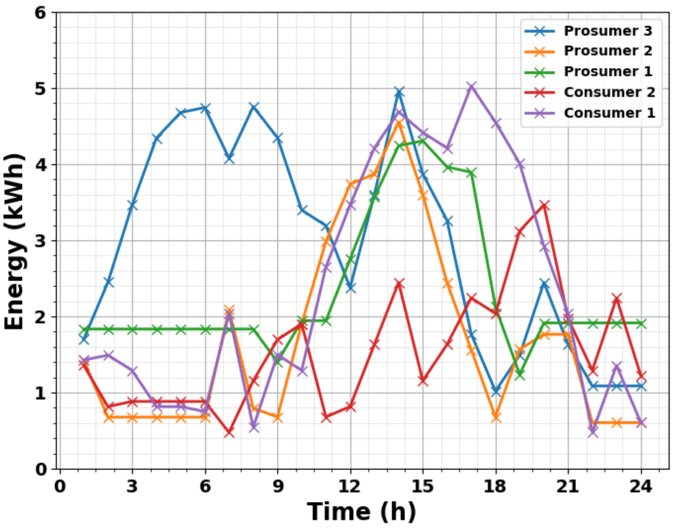


Fig. 7. The quantity of energy retained in the battery memory for every user throughout a 24-hour duration.

Fig. 7 outlines the tangible benefits subscribers gain through the implementation of the proposed P2PE framework. This demonstration highlights the profit differences experienced by customers when engaging in P2PE versus scenarios without such trading. In the absence of P2PE, Prosumers sell their excess energy to the utility, while Customers obtain their electricity directly from the utility and do not interact with Prosumers. The results in Fig. 8 emphasize the varying degrees of benefit improvement experienced by different subscriber segments. Prosumer 1, Prosumer 2, and Prosumer 3 show relatively small profit increases of 73.98 ¥, 55.54 ¥, and 65.36 ¥, respectively. In contrast, Customer 1 and Customer 2 experience significantly higher profit increases of 199.04 ¥ and 118.87 ¥, respectively. This disparity in advantages can be attributed to different customer battery capacities, variations in Prosumer energy output during the day, and shifts in power consumption.

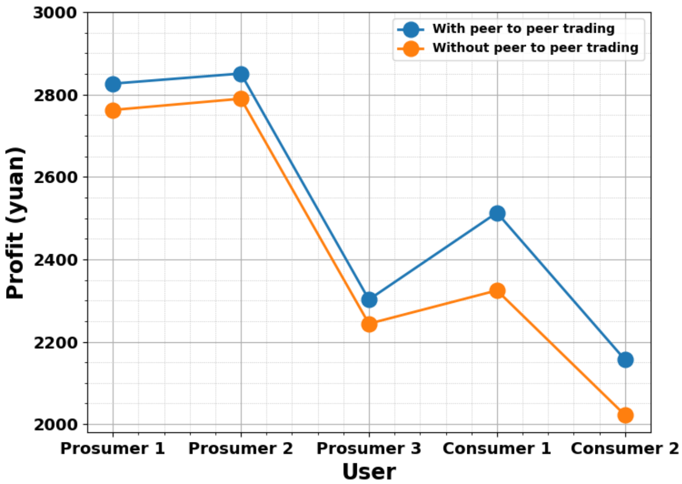


Fig. 8. Comparison of subscriber earnings in two scenarios: with and without the inclusion of a peer-to-peer energy system.

These dynamic factors lead to varying levels of desirability among different subscriber segments. It is crucial to emphasize that the P2PE trading framework is continuously beneficial to all subscribers at different times of the day, enhancing incentives for active participation in P2PE throughout the community. This framework not only ensures a fair distribution of energy but also acts as a catalyst for improved consumer benefits and increases the attractiveness of P2PE. These results indicate that the P2PES system successfully incentivizes energy trading, balancing the interests of both energy producers and consumers. By allowing Prosumers to profit from their surplus energy and Customers to achieve cost savings, the system promotes a more efficient and collaborative energy environment. The substantial profit increments for Customers, in particular, underscore the system's potential to offer significant financial benefits compared to traditional energy procurement methods.

### 4.3. Discusion

The results obtained from the case studies provide valuable insights into the practical implications of implementing the P2PE approach for energy management in a community setting. The analysis highlights several key aspects that are crucial for understanding how P2PE can be effectively applied in real-world scenarios. Firstly, the observation that all five customers show zero traded energy between 01:00 and 07:00 underscores the limitation of wind energy production during these hours. This finding indicates that in practical applications, reliance on wind energy alone may not suffice to meet energy demands during low production periods. Consequently, incorporating additional energy sources or storage solutions could be essential to bridge the gap and ensure a consistent energy supply. For example, integrating battery storage systems with advanced scheduling algorithms could mitigate periods of low renewable energy output and enhance overall system reliability. During the peak periods (08:00 to 09:00 and 18:00 to 23:00), the results reveal a small surplus of energy available for sale by Prosumers, yet Customers still purchase electricity from the utility. This suggests that the current pricing structure and the fixed rate for surplus electricity might not fully incentivize energy trading within the community. Adjusting the regulatory framework to offer dynamic pricing or incentives for surplus energy could further stimulate internal energy trading and reduce dependence on external utility providers. The significant increase in energy production between 11:00 and 17:00, coupled with a reduction in power system purchases, highlights the effectiveness of the P2PE system in utilizing local renewable resources. This indicates that P2PE can significantly enhance the efficiency of energy distribution by leveraging surplus production and reducing reliance on external sources. In practical terms, this could lead to reduced energy costs and lower carbon footprints for both consumers and Prosumers. The ability of the system to achieve zero power purchases during this period demonstrates the potential for optimizing local energy use and improving sustainability. The observed variations in profitability among different subscribers, with Prosumers generally recording positive payoffs and Customers experiencing negative payoffs, reflect the economic dynamics of energy trading. The higher profit increments for Customers, particularly those with lower battery capacities, suggest that they benefit more from participating in the P2PE system compared to Prosumers. This disparity emphasizes the need for balanced incentives to encourage active participation from all community members. For practical implementation, developing a fair and transparent pricing mechanism that aligns the benefits of energy trading with the contributions of each participant could enhance overall system performance and equity.

## 5. Conclusion

This study presents a detailed analysis of the Peer-to-Peer Energy Sharing (P2PES) approach within a simulated community of five participants, including both consumers and prosumers equipped with wind turbines. The findings demonstrate the effectiveness of the P2PE approach in optimizing energy distribution and minimizing costs within the community.

1. **Energy Exchange Dynamics:** The analysis reveals that during off-peak hours (01:00-07:00), all participants rely on the utility provider for energy, as the wind energy produced is insufficient to meet the demand. During peak periods, Prosumers, particularly Prosumers 1 and 2, show a surplus of energy which is sold to consumers. However, Prosumers and Consumers alike benefit from the P2PES system, as it reduces reliance on the utility provider and enables more efficient energy use.
2. **Optimization Benefits:** The first-level optimization results indicate that the P2PES approach leads to significant reductions in overall power system purchases, particularly between 11:00 and 17:00 when local renewable energy production is high. Prosumers with higher energy production capacities, such as Prosumers 1 and 2, play a crucial role in meeting consumer needs during peak periods, demonstrating the effectiveness of localized energy trading.
3. **Economic Impact:** The second-level optimization results, summarized in Table 1, highlight the economic

benefits for all participants. Prosumers receive positive payments for their energy contributions, while consumers experience reduced costs. Notably, Consumer 1 and Consumer 2 benefit more significantly from the P2PES framework, with increased profits compared to scenarios without P2PES trading. This disparity underscores the impact of varying battery capacities and energy production levels on economic outcomes.

4. **Enhanced Community Benefits:** The P2PES framework not only ensures a fair distribution of energy but also enhances overall community benefits. The results, illustrated in Fig. 7 and Fig. 8, indicate that the implementation of the P2PE approach leads to improved consumer satisfaction and incentivizes active participation in energy sharing.

In summary, the P2PES approach proves to be a valuable tool for optimizing energy distribution and reducing costs in a simulated community. The study's findings emphasize the importance of integrating local energy production with trading mechanisms to enhance both economic and operational efficiencies. Future work should explore the scalability of this approach in larger communities and its potential impact on broader energy systems.

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**Nomenclature**

| **Abbreviations** | | $R_{(i)}^{D-Max}$ | Maximum discharging rate of battery i |
|---|---|---|---|
| ANFIS | Adaptive Network-based Fuzzy Inference System | $S_{(i,t)}$ | Energy storage level of subscriber i at time t |
| BMILP | Bi-level Mixed-Integer Linear Programming | $W_{(i,t)}$ | Wind energy produced by subscriber i at time t |
| CDC | Charging and Discharging | $W_{(i,t)}^{Max}$ | Maximum allowable wind power output from the turbine for subscriber i at time t |
| CVAR | Conditional Value-at-Risk | $D_{(i,t)}$ | Air density for subscriber i at time t |

| | | | |
|---|---|---|---|
| DER | Distributed Energy Resources | $V_{(i,t)}$ | Wind speed for subscriber i at time t |
| DR | Demand Response | $B_{(i,t)}^{P}$ | Amount of power purchased by subscriber i at time t |
| DRA | Demand Response Aggregator | $B_{(i,t)}^{S}$ | Amount of power sold by subscriber i at time t |
| EH | Energy Hub | $P_{(i,t)}^{S}$ | Selling price of electricity for subscriber i at time t |
| ESP | Energy-Sharing Provider | $P_{(i,t)}^{P}$ | Purchase price of electricity for subscriber i at time t |
| ESS | Energy Storage System | $d_{(i)}$ | Load profile of subscriber |
| EV | Electrical Vehicle | $d_{(i,t)}$ | Load profile of subscriber i at time t |
| MGO | Microgrid Operator | $d_{(i,t)}^{Min}$ | Minimum load for subscriber i at time t |
| NBS | Nash Bargaining Solution | $d_{(i,t)}^{Max}$ | Maximum load for subscriber i at time t |
| P2P | Peer-to-Peer | $D_{(i,t)}^{Min}$ | Minimum cumulative demand for subscriber i at time t |
| P2PES | Peer-to-Peer Energy Sharing | $d(_{i,t})^{IDE}$ | Ideal demand profile for subscriber i at time t |
| PSO | Particle Swarm Optimization | $U_{(i)(}{}^{d(i,t))}$ | Utility of energy consumption for subscriber i at time t |
| PV | Photovoltaic | $k_{(i,t)}$ | Composite expression of weight coefficients and preference parameters for subscriber i at time t |
| RU | Residential Units | $R_{(i,t)}^{C}$ | Charging rate of energy storage system i at time t |
| T&D | Transmission and Distribution | $u_{(i)}$ | Utility of player i |
| TEC | Transactive Energy Control | $D_{(i)}$ | Disagreement points for player i |
| TOU | Time-of-Use | $P_{(ij,t)}^{E}$ | Energy received by subscriber i from subscriber j at time t |
| VCS | Virus Colony Search | $P_{(ji,t)}^{E}$ | Energy sold by subscriber j to subscriber i at time t |
| WT | Wind Turbine | Usw | Collective utility of all subscribers. |
| **Symbols** | | $f_{(ij,t)}^{E}$ | Payoff related to energy trade between subscriber iii and subscriber j at time t |
| A | Swept area of the wind turbine | $P_{import}(t)$ | Power imported from the grid at time t |
| ν | Cost parameter associated with the deterioration of energy storage | $P_{export}(t)$ | Power exported to the grid at time t |
| L | Augmented Lagrangian function | $P_{total, demand}(t)$ | Total demand in the community at time t |
| L′ | Full Lagrange equation of the second level of optimization. | $R_{(i,t)}^{D}$ | Discharging rate of energy storage system i at time t |
| N | Set of players in the bargaining game | | **Greek Symbols** |
| p | Price of the battery | ρ | Penalty parameter associated with constraints |
| K | Power factor of the wind turbine | $\eta_{(i)}^{Loss}$ | Discharge loss efficiency of energy storage system i |
| $C_{(i)}^{Max}$ | Maximum storage capacity of battery i | $\eta_{(i)}^{D}$ | Discharging efficiency of energy storage system i |
| $C_{(i)}^{Min}$ | Minimum storage capacity of battery i | $\alpha_{(ji,t)}(k)$ | Lagrange coefficient updated at iteration kkk. |
| $C_i(t)$ | Cost coefficient for participant i at time t | $\alpha_{(ji,t)}$ | Lagrange coefficient for payment bargaining |
| $C_{base}(t)$ | Base price at time t | $\eta_{(i)}^{C}$ | Charging efficiency of energy storage system i |
| $C_{(i)}^{Dis}(d(i,t))$ | Cost of discontent for subscriber iii due to deviation from ideal demand. | $\lambda_{(ij,t)}$ | Lagrangian coefficient for energy trade between subscriber iii and subscriber j at time t |
| $R_{(i)}^{C-Min}$ | Minimum charging rate of battery i | $\beta_{(i)}$ | Priority coefficient for subscriber i |
| $R_{(i)}^{C-Max}$ | Maximum charging rate of battery i | | |
| $R_{(i)}^{D-Min}$ | Minimum discharging rate of battery i | | |