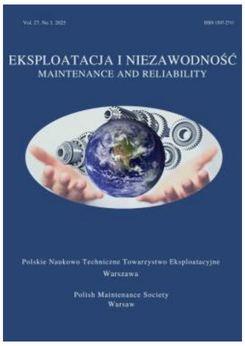

Eksploatacja i Niezawodnosc – Maintenance and Reliability

Volume 27 (2025), Issue 3

journal homepage: http://www.ein.org.pl

Article citation info:
He S, Blockchain-Powered Peer-to-Peer Energy Trading: A Comprehensive Framework for Secure, Transparent, and Direct Transactions in the Energy Sector Optimization Algorithm, Eksploatacja i Niezawodnosc – Maintenance and Reliability 2025: 27(3) http://doi.org/10.17531/ein/201172

Indexed by: Web of Science Group

Blockchain-Powered Peer-to-Peer Energy Trading: A Comprehensive Framework for Secure, Transparent, and Direct Transactions in the Energy Sector Optimization Algorithm

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Highlights

- Ensuring secure blockchain transactions, boosting transparency and protecting privacy.
- Automating transactions via smart contract reducing intermediaries & improving fairness.
- Integrating renewables through modular design, optimizing allocation and scalability.
- Improving transparency to build confidence in decentralized energy trading systems.

Abstract

While the blockchain technology is viewed to revolutionize the energy sector by its cryptography-based, open, and direct peer-to-peer energy trading (P2PET) from producer to consumer, the currernt paper focused on blockchain framework developed that allows for P2PET in the retail electricity market. The platform makes sure that there is proper supply-demand matching, transaction streamlining, and increased need for direct interaction, hence reducing the need for brokers on the platform. Its design monitors the entire energy trading process, with smart contracts automating payments and transactions to ensure security and fairness. Tests in a private Ethereum environment demonstrate benefits like accurate market pricing, fair profit distribution, and better renewable energy integration. It also incentivizes the participation of stakeholders in the P2PET through high-value information on gas usage, introducing computational efficiency. Besides, this proposed model adopted a consensus mechanism that would guarantee permanence, scalability, and robustness of transactions across multiple types of energy networks by adapting to different levels of transaction throughput.

Keywords

blockchain, peer-to-peer energy trading, retail electricity market, smart contract, renewable energy integration

1. Introduction

The fast growth of distributed energy resources (DERs) indicates a paradigm-shifting period for the energy sector, which revolutionizes traditional structures of energy from the ground up. In that respect, decentralized load systems allow users who have DERs to actively participate in energy trading at the community level through optimal control of energy consumption, generation, and storage [1]. Historically, the participation required that consumers be connected to retail electricity markets via centralized energy exchange infrastructures. In these situations, however, a centralized approach is often associated with inefficiencies, including high transaction costs and complex operations [2]. The emergence of the sharing economy has catalyzed a shift toward peer-to-peer energy trading within local electricity distribution networks. Unlike the hub-and-spoke model, P2PET focuses on decentralized and direct energy exchanges among members. The business paradigm can link energy trading with customer preferences, enabling the dynamism in matching energy and the

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increased active participation of individual consumers. Another driver to the emergence of P2PET has been the rise of platforms driven by sophisticated information and communication technology, creating systems representative of the flexibility and values typical of the sharing economy [3].

Examples are the early P2PET platforms such as Vandebron from the Netherlands and Piclo from the UK. While it enables retail-level energy trades, Piclo allows the direct consumer-to-supplier energy trades. Although these state-of-the-art P2PET systems are enormously potent, they suffer from the shortcomings of conventional database technologies: intractability of transactions, privacy leaks, and data tampering that limit their scalability and reliability [4]. Blockchain technologies can help overcome these challenges by providing a secure and decentralized platform on which P2PET can be implemented. Fundamentally, blockchain is an open, distributed ledger that records transactions in an open, tamper-proof list. Intrinsic in the technology is something called a smart contract-a self-executing program with the logic of rules pertaining to energy trading. The smart contract allows for secure, autonomous, and equitable peer-to-peer energy trading tailored to meet the needs at the level of the local consumer. With these elements integrated into P2PET systems, security is expected to be improved, efficiency enhanced, and fair governance introduced to decentralized energy systems; this would mean a more robust and scalable development of energy trading frameworks [5].

An instance of this is the 2016 Brooklyn microgrid project, which utilized Exergy platform to enable consumers to directly get electricity from nearby solar producers through the implementation of blockchain technology. Most of the academic literature explores the various functions of blockchain technology in energy management and business. Han et al. [6] anticipated a united energy blockchain to protect P2PET, complemented by a credit-based payment outline to facilitate fast and regular energy transactions. Another proposal by Foti et al. [7] focused on a blockchain-based solution for energy trading amongst micro-grids, which shows high convergence speed and increased scalability. Also, Guan et al. [8] introduced a decentralized energy market, real-time, unchanging price, and two-fold auction applied in the Ethereum network and compared that to 3 diverse tactics for calling the market settlement performance. Further contributions include a protected and well-organized blockchain-based energy trading outline, combining proof-of-stake (PoS) consensus with the TOPSIS evaluation method to introduce credit-based PoS consensus, which is discussed by Zhang et al. [9]. Security concerns in smart grids are addressed through a blockchain-based provable keyless scheme, which allows service providers and end-user devices to attain safe authentication lacking relying on 3rd parties [10]. A review of blockchain deployment projects for renewable energy trading and management revealed tests on the mining productivity of various encrypted digital coins [11]. With the use of blockchain technology, this study proposes a demand-side management model that includes storage components in order to improve efficiency and build trust. The methods used in this investigation are grounded in the ideas of game theory.

Chinnasamy et al. [12] discussed the role of smart grid-based cyber-physical systems (SGCPS) provided by 6G technology and the need felt for intelligent breach detection systems to safeguard critical infrastructure. The amalgamation of 6G technology with SGCPS offered better communication and connectivity, yet on the other side, increased the attack surface area in the network for the attacks. Integration of IBDS was proposed to have proactive ways of detecting and mitigating breaches, hence increasing system security.

In the study of Chinnasamy et al. [13], a novel system that integrates IoT with blockchain for addressing various challenges related to secure data sharing, access control, and reliable authentication is proposed. This framework provided enhanced security in IoT networks and authorization by enabling a blockchain-based access control mechanism for encrypted information exchange. In another study, Chinnasamy et al. [14], the need for efficient and sustainable smart solutions was deliberated in transportation, climate, energy, and governance for intelligent cities. One of the key ways is the architecture of an intelligent city based on the IoT, Big Data analytics, and IoE. Yet a few open challenges are there, such as inefficient security in IoT, inefficiency, high cost of operations, vulnerable data center, privacy at risk, and suboptimal business models. A few important privacy and security issues related to 6G technology have been discussed in Chinnasamy et al. [15], and identified the protection requirement of wireless sensor networks (WSNs) in real-time systems. Denial of service (DoS) essentially is an attack against WSNs that may break an entire system. This proposed work puts forward a completely new approach toward security and optimization in blockchain-enabled 6G wireless networks by means of a machine learning model.

Boumaiza et al. [16] designed a blockchain-based energy trading model to be used against fraudulent activities. The proposed framework could ensure tamper-proof transaction records together with peer-to-peer energy trade between prosumers. He et al. [17] suggested a dual-layer blockchain architecture for security and scalability improvements within energy trading. The model had enormous potential to support large-scale energy exchange networks efficiently while keeping the computational overhead low. Gawusu et al. [18] discussed the integration of renewable energy sources within blockchain-based trading. The work showed how blockchain could optimize the energy allocation process, ensuring that the energy from distributed energy resources is divided equitably and efficiently. Table 1 provides a comparative overview of the strengths and weaknesses perspectives.

Table 1. A quick overview of the key features, strengths and weaknesses of each approach.

Ref	Key Contribution	Strength	Weakness
[16]	Secure blockchain-based energy trading model to combat fraudulent activities	Tamper-proof records, direct prosumer energy exchanges	Requires significant initial setup, potential challenges with widespread adoption
[12]	6G-enabled SGCPS with intelligent breach detection systems	Advanced communication, proactive breach detection	Increased vulnerability to cyber threats, requires sophisticated security systems
[13]	Integration of IoT and blockchain for secure data sharing and access control	Improved IoT security, reliable authentication	Potential integration challenges with legacy systems, scalability concerns
[14]	Smart city platform integrating IoT, Big Data, and Internet of Energy	Sustainable smart solutions, integrates multiple technologies	IoT security gaps, high operational costs, privacy and efficiency issues
[15]	Blockchain-based 6G wireless network security and optimization	Improved security for WSNs, uses machine learning for optimization	Complexity in real-time system integration, high computational demands
[7]	Blockchain-based energy trading among micro-grids	High convergence speed, increased scalability	May require high computational resources for large-scale systems
[18]	Blockchain-based trading system for integrating renewable energy sources	Optimized energy allocation, equitable utilization of resources	Implementation challenges with distributed resources, potential transaction costs
[8]	Decentralized energy market with real-time price and two-fold auction in Ethereum network	Real-time price stability, enhanced market settlement performance	Potential for high transaction costs, scalability issues in large networks
[17]	Dual-layer blockchain architecture for energy trading	Enhanced security, scalability, low computational overhead	Complexity of dual-layer architecture, potential transaction delays
[10]	Blockchain-based provable keyless authentication scheme for smart grids	Secure authentication without relying on third parties	Potential integration issues with existing smart grid infrastructure
[11]	Blockchain for renewable energy trading and management, integrating storage components	Improved efficiency, enhanced trust	Potentially high operational costs, dependence on blockchain adoption
[9]	Blockchain-based energy trading combining PoS consensus and TOPSIS evaluation	Improved security and efficiency, credit-based consensus	Complex setup, may have scalability challenges

The literature on P2PET has highlighted several significant gaps that hinder the widespread adoption and scalability of such systems. A major worry is the scalability issue and efficiency of current platforms. Most of the traditional database technologies used in old frameworks often face difficulties in handling high-volume transactions and keeping transaction performance high. Such bottlenecks drive operational issues and high transactional fees, hence making it difficult to apply it on a realistic note for wide energy networks. Most of the systems have poor mechanisms that enhance the balance between supply and demand; therefore, energy is utilized below the optimum level. Another major limitation involves security and privacy attributes intrinsic to P2PET systems. Most existing frameworks from modern times are susceptible to data tampering and defective in privacy attributes, which in turn decrease the stakeholders' confidence. The lack of strong mechanisms designed to safeguard transactions and secure user information represents a considerable obstacle to the implementation of decentralized energy trading models. In addition, the restricted level of automation within these systems intensifies these issues, as manual or semi-automated procedures can lead to mistakes and inefficiencies.

The second aspect of interest is renewable energy integration: as much as P2PET systems naturally go hand in hand with DERs, much of the existing framework fails to make effective use of their potential. This might lower the full potential of such a system on the journey towards a more sustainable energy ecosystem. Thirdly, this stakeholder participation in most models has also not been underemphasized. A lack of transparency and poor participant-engaging tools hamper further scale-up and gain of trust in the system.

This paper, therefore, proposes a comprehensive blockchain framework that can fill these gaps. Grounded on the decentralized, secure architecture of blockchain, the proposed platform would ensure immutability of transactions with robust privacy. Integration of smart contracts further automates transactions in a way that increases the level of fairness in operations, reducing intermediaries considerably. These are not only likely to make trade processes easier but also boost participant confidence.

Besides, the modular architecture of energy-intelligent considers the integration of renewable energy into optimal energy allotment, diversified energy internets, and even further in enabling a scalable and efficient consensus algorithm for adapting to changes in transaction throughput. With the insight provided about gas consumption, added confidence and wider participation in P2PET are guaranteed because of increased transparency. All these developments will turn the proposed framework into a valid answer to the current challenges of decentralized energy trading and allow its immediate application within retail electricity markets.

2. Problem modeling

A discernible trend in the electricity retail market is the apparent shift towards a dynamic energy exchange, where producers are involved in selling energy to numerous customers and, conversely, different generators give energy to customers. This evolution is particularly evident when traditional energy consumers become subscribers, a phenomenon driven by the widespread integration of DERs namely distributed wind generators and rooftop photovoltaic (PV) panels [19]. Real-time measurements inside the energy system are now possible because to the Internet of Things and smart meter advancements occurring simultaneously [20]. Against this background, there is a need for a decentralized energy trading technique that will utilize these developments and thereby promote decentralized energy trading.

Peer-to-peer bilateral energy trading become increasingly popular among consumers and producers. This preference is attributed to its economical pricing and flexibility. In essence, P2PET involves direct transactions between consumers and producers, eliminating the traditional intermediary role of energy suppliers. This approach is in stark contrast to unilateral energy trade, conventional energy suppliers engage in the practice of selling energy at a higher price and purchasing it at a lesser rate [21].

P2PET involves an energy exchange and market settlement process under the closed bidding process mechanism. Major participants are renewable energy producers, manufacturers, consumers, and distribution system operators. The pricing model that it uses is a dual auction-based model, increasing renewable energy consumption and hence allowing a fair outcome for producers and consumers. The inherently adequate dual auction for multiple sellers and buyers markets [22] represents the general framework within which the participants will be able to place dynamically tailored bids concerning price and quantity according to their needs. Such a wide P2PET mechanism appears relevant to illustrate adaptability in this sector in light of technological developments and changes in energy generation and consumption. It can stand for higher productivity, as well as cost effectiveness, with far greater consumer and producer involvement in the development of the future decentralized energy market.

In the initial stage of closed bidding, every consumer and producer contribute their bid value, bid price, and preference or energy type. Based on their role, these submissions are classified into two producer groups or consumer groups by the platform.

Subsequently, in the phase of energy exchange, the platform executes the settlement of energy trades using a combination of a queuing and auction system. The platform starts the process by generating an ascending bid sequence for producers, as specified by Eq. (1), where $s_{(i)}^{Bid}$ represents bid price of ith producer, M is total number of participating generators, and $s_{(M)}^{Bid}$ represents the highest bid price. As shown in Eq. (2), among all producers simultaneously, a descending price sequence is formed for consumers, where $b_{(j)}^{Bid}$ represents the jth consumer's bid price, N is the total number of participating customers and $b_{(N)}^{Bid}$ represents the lowest bid price among all consumers. In cases where prices are equal, the chronological order of bids serves as the basis for ranking [6]:

$$s_{(1)}^{id} \leq \cdots \leq s_{(i)}^{Bid} \leq \cdots \leq s_{(M)}^{Bid} \tag{1}$$

$$b_{(1)}^{Bid} \leq \cdots \leq b_{(j)}^{Bid} \leq \cdots \leq b_{(N)}^{Bid} \tag{2}$$

Following the queue process, platform calculates settlement price and the quantity of energy traded among every consumer and producer through 2 rounds of peer-to-peer matching. The 1st adaptive round responds to renewable energy producers and consumers with a preference for renewable energy. As defined by Eqs. (3) and (4), during this round, the producer $P_{(i)}$ will provide the amount of energy $q_{(i,j)}^{clear}$ at the settlement price $p_{(i,j)}^{clear}$ sells to consumer $C_{(j)}$. The first matching round ends only if the Eq. (5) holds. The second matching round mirrors the rules of the first round, which apply to all producers and consumers.

$$p_{(i,j)}^{clear} = \frac{s_{(i)}^{Bid} - b_{(j)}^{Bid}}{2} \tag{3}$$

$$q_{(i,j)}^{clear} = Minimize\left[g_{(i)}^{res}, c_{(j)}^{res}\right] \tag{4}$$

$$s_{(i)}^{Bid} > b_{(j)}^{Bid} \qquad the\ end\ of\ first\ matching\ round \tag{5}$$

Due to the intermittent nature of operation and the unpredictability of DERs, potential energy imbalances may occur in the system. The actual energy source $g_{(i)}^{actual}$ and energy consumption $c_{(j)}^{actual}$ are verified by smart meters. In case of energy imbalance, the distribution network operator intervenes by providing energy balance services to preserve system's stability. In next settlement time frame, platform will facilitate transfer of energy balance service fees and reward producers and consumers who have honestly participated in the bidding process. Those who produce less or have more demand, the quantity of energy $|\Delta g_{(i)}|$ or $|\Delta c_{(j)}|$ are purchased from the distribution network operator at the p^{sbp} system's purchase price. On the contrary, those who produce more or have less demand, value of energy $|\Delta g_{(i)}|$ or $|\Delta c_{(j)}|$ are sold to distribution network operator at purchase price of p^{ssp} system, which is specified in Eqs.(6) and (7) [6]:

$$\Delta g_{(i)} = g_{(i)}^{Bid} - g_{(i)}^{actual} \tag{6}$$

$$\Delta c_{(i)} = c_{(j)}^{Bid} - c_{(j)}^{actual} \tag{7}$$

For those producers and consumers actively participating in energy balance in system, reflecting their adherence to $g_{(i)}^{Bid} = g_{(i)}^{actual}$ or $c_{(j)}^{Bid} = c_{(j)}^{actual}$ are eligible to receive rewards in the form of costs denoted by $r_{(i)}^{pro}$ or $r_{(j)}^{con}$. As specified in Eqs. (8) and (9), these rewards are awarded by the platform at a specified price p^{rew}. Therefore, the platform encourages participants who play a pivotal role in maintaining a balanced energy state.

$$r_{(i)}^{pro} = p^{rew} \times g_{(i)}^{Bid} \tag{8}$$

$$r_{(j)}^{con} = p^{rew} \times c_{(j)}^{Bid} \tag{9}$$

In order to address any surplus energy imbalance in the retail sector, real-time market collaboration is required [23]. The energy exchanges in the real-time market match the previous day's market dispatch. Using balancing generators, the independent system operator is in charge of maintaining equilibrium in the energy dynamics of the real-time market. The quantum and expenses related to unbalanced energy must then be settled by the independent system operator. The real-time market is a good place to buy or sell energy if the distribution system operator is having trouble keeping the retail market's energy balance.

2.1. Smart contract

The smart contract is designed on top of the P2PET framework by integrating functions that will be responsible for the control of closed bidding, energy transaction, settlement, and payment processes incorporated in [24]. These functions cooperate in a sequential manner to realize secure and efficient P2P energy trading over the Ethereum blockchain. This agreement ensures that each energy trade is logged and verified, including essential Ethereum account addresses such as $d_{(i)}$ (for producer i), $d_{(j)}$ (for consumer j), and d_{dso} (for the distribution network operator). Producers, consumers, and the DSO start transactions by sending a certain amount of ethers to the smart contract before energy trading can be realized. In addition, the Balance map keeps track of these ether balances in order to ensure the accuracy of the transactions. It is assumed that the producers and the consumers have sufficient ether to go through the above process.

Algorithm 1: Closed Bidding Function

Such a closed bidding mechanism will help process the incoming quantities and prices of the bid from both producers and consumers. This mechanism covers initial bids, modifications of subsequent ones, dynamic adjustment, and prioritization mechanisms for the bids, hence allowing the system for the changes in bids elegantly while enabling optimized interaction between energy producers and consumers.

Features:

1. **Dynamic Bid Adjustment:** The bids will automatically be updated with respect to market performance, energy forecast, and past transaction patterns, so that the bid price reflects the updated tendency of energy supply and demand.
2. **Price Bid by Proximity:** A proximity price bid is a technique that allows the bidding of producers into demand areas for better efficiency in energy distribution.
3. **Multi-Phase Bidding:** The entire bidding process is divided into various stages. It enables new bidders to join the process, yet still allows existing bidders to update their bid at any moment of the bidding cycle.

Algorithm 1 Pseudocode:

```
    function placeBid(address bidder, uint256 bidPrice, uint256
energyQuantity) {
        if (bidder is Producer) {
            bidPrice = adjustBidPrice(bidder, bidPrice); // Adjust
bid dynamically based on market conditions
            ProducerBids[bidder] = {bidPrice, energyQuantity};
        } else if (bidder is Consumer) {
            ConsumerBids[bidder] = {bidPrice, energyQuantity};
// Consumer bids are recorded
        }
        updateBiddingQueue(bidder, bidPrice, energyQuantity);
// Add to the bidding queue for sorting
    }
```

Algorithm 2: Energy Exchange and Smart Matching

Energy exchange uses an energy exchange algorithm called a bubble sort algorithm to sort the bid array, consisting of either producers or consumers. Now, with enhanced iteration, intelligent matching is included in order to match the producers with consumers based on the dynamically available energy, bid pricing, and geographical location of demand. It integrates demand forecasting to increase energy exchange accuracy.

Features:

1. Smart Matching Algorithm: Smart matchmaking chooses the best pairs between producer and consumer with respect to price, amount of energy, and proximity.
2. Energy Demand Forecasting: A forecasting module predicts peak and off-peak times, thus enabling participants to adjust their bids and correspondingly alter schedules for optimized energy usage and pricing.
3. In the case of a mismatch on the resources-demanding side, the distribution network operator (DSO) ensures stability in the main grid through energy exchange

Algorithm 2 Pseudocode:

```
   function exchangeEnergy() {
      for (uint i = 0; i < ProducerBids.length; i++) {
         for (uint j = 0; j < ConsumerBids.length; j++) {
            if (isMatching(ProducerBids[i], ConsumerBids[j])) {
               transferEnergy(ProducerBids[i].address,
ConsumerBids[j].address); // Execute energy transfer
            }
         }
      }
   }
```

Algorithm 3: Dynamic Smoothing and Incentive Mechanism

This algorithm integrates an implemented smoothing algorithm that contributes to bridging the difference between forecasted and actual energy balance. Currently, it implements dynamic smoothing, and there are financial incentives given for correct prediction, which encourages every actor to input valid forecasts of energy.

Features:

1. **Dynamic Smoothing:** That technique smooths energy balances in real time for the difference between predicted and actual energy use to get better energy forecasting.
2. **Reward Forecasts:** Right forecasters, be it producers or consumers, are incentivized in ether; their penalties are assigned for the respective wrong predictions.
3. **Real-time Smoothing Updates:** Smoothing must be updated in real time to allow changes whenever new data on energy supply and demand are available.

Algorithm 3 Pseudocode:

```
function smoothEnergyBalance(address participant, uint256 predictedEnergy, uint256 actualEnergy) {
    uint256 balanceDeviation = abs(predictedEnergy - actualEnergy);
    uint256 rewardOrPenalty = calculateIncentive(balanceDeviation); // Calculate reward/penalty based on accuracy
    updateParticipantBalance(participant, rewardOrPenalty); // Apply incentive or penalty
}
```

Algorithm 4: Secure and Efficient Payment Mechanism

Payment capability is applied with a safety guarantee for ether transactions. Its enhanced version allows multi-signature confirmation, escrow management, and transaction fee management to ensure that all payment capabilities are conducted out openly with integrity.

Features:

1. **Multi-Signature Verification:** Transactions are approved only after the consent of all parties involved, namely producer, consumer, and DSO, which ultimately stops illegitimate transactions.
2. **Escrow Account:** The ether payments are kept in an escrow until all the conditions regarding the energy exchange are met, allowing for dispute resolution securely.
3. **Grid Maintenance Transaction Fee:** A small portion of the transaction goes into maintaining the distribution grid for long-term viability.

Algorithm 4 Pseudocode:

```
function executePayment(address sender, address receiver, uint256 energyQuantity, uint256 energyPrice) {
    if (isValidTransaction(sender, receiver)) {
        uint256 totalAmount = energyQuantity * energyPrice;
        escrowFunds(sender, totalAmount); // Hold funds in escrow until transaction is verified
        if (multiSigConfirm(sender, receiver)) {
            transferFunds(sender, receiver, totalAmount); // Complete payment after multi-signature confirmation
        }
    }
}
```

2.2. Operating restrictions

The system in question, like all energy systems, has operating limits for the network and equipment, which the system operator is required to comply with. In this part of this study, we present these important limitations. In Eq. (10), the output power of the used wind turbine unit is shown, where $P_{(i)}^{WT}$ is the wind turbine's output power, P^{rated} is the turbine's rated power, $W_{(t)}$ is the wind speed , $w^{\text{cut-in}}$ is the low cut-in speed, $w^{\text{cut-out}}$ is the low cut-out speed, w^{rated} is the rated speed, and x, y, and z are the wind turbine's parameters. The limitation related to the output power of the wind turbine is also shown in Eq. (11), where $P_{(t)}^{WT-Max}$ shows the wind turbine's max allowed power output.

$$P_{(t)}^{WT} = \begin{cases} P^{rated} \times \left(x \times \left(W_{(t)}\right)^2 - y \times W_{(t)} + z\right) & w^{cut-in} \le w(t) \le w^{rated} \\ P^{rated} & w^{rated} \le w(t) \le w^{\text{cut-out}} \\ 0 & otherwise \end{cases} \quad (10)$$

$$0 \le P_{(t)}^{WT} \le P_{(t)}^{WT-Max} \quad (11)$$

In the following and in Eqs. (16) - (12) indicate the limitations related to the load response program's application. As can be seen, the desired load can be calculated after the load response program's application ($P_{(t)}^{After}$) using Eq. (12). In this regard, $P_{(t)}^{Before}$ is the quantity of load before the load response program, $P_{(t)}^{Down}$ is the reduced load due to the load response program's application, and $P_{(t)}^{Up}$ is the increased load They show the findings from the load response program's application. As it is clear from the Eq. (13), the total load decreased and increased during the operation period should be equal. In Eqs. (14) and (15) the limits of increased and decreased load are shown. $I_{(t)}^{Up}$ and $I_{(t)}^{Down}$ are binary variables for increasing and decreasing the load at the desired time, which according to Eq. (16) cannot be the same at the same time. This means that in each hour, the operator is allowed to reduce or increase the load of that hour.

$$P_{(t)}^{After} = P_{(t)}^{Before} - P_{(t)}^{Down} + P_{(t)}^{Up} \quad (12)$$

$$\sum_t \{P_{(t)}^{Down}\} = \sum_t \left\{P_{(t)}^{Up}\right\} \quad (13)$$

$$0 \le P_{(t)}^{Up} \le P_{Max}^{Up} \times I_{(t)}^{Up} \quad (14)$$

$$0 \le P_{(t)}^{Down} \le P_{Max}^{Down} \times I_{(t)}^{Down} \quad (15)$$

$$I_{(t)}^{Up} + I_{(t)}^{Down} \leq 1 \tag{16}$$

Electric vehicles act as mobile electrical energy storage sources that can increase system flexibility. This equipment acts as a load during charging and as a source of energy during discharge. Equations governing electric cars are shown in Eqs. (21) - (17). The main equation governing electric cars is presented in Eq. (17), which expresses the amount of energy stored in electric cars in each time period. $E_{(t)}^{EV}$ is the amount of stored energy, $P_{(t)}^{Charge}$ and $P_{(t)}^{Discharge}$ are electric vehicles' charging and discharging power, η^{Charge} and $\eta^{Discharge}$ are the electric vehicles' charging and discharging efficiency. and $I_{(t)}^{Charge}$ and $I_{(t)}^{Discharge}$ represent the binary variables specific to the charging and discharging of electric vehicles. A significant point in the operation of electric vehicles is the inability to simultaneously charge and discharge these equipment's in a time frame, which is mentioned in Eq. (18). Also, the limitations related to charging power, discharging power and the amount of energy kept in the battery of electric vehicles are given in Eqs. (21) - (19) respectively.

$$E_{(t)}^{EV} = E_{(t-1)}^{EV} + \eta^{Charge} \times I_{(t)}^{Charge} \times P_{(t)}^{Charge} - \frac{P_{(t)}^{Discharge} \times I_{(t)}^{Discharge}}{\eta^{Discharge}} \tag{17}$$

$$I_{(t)}^{Charge} + I_{(t)}^{Discharge} \leq 1 \tag{18}$$

$$P_{Min}^{Charge} \leq P_{(t)}^{Charge} \leq P_{Max}^{Charge} \tag{19}$$

$$P_{Min}^{Discharge} \leq P_{(t)}^{Discharge} \leq P_{Max}^{Discharge} \tag{20}$$

$$E_{Min}^{EV} \leq E_{(t)}^{EV} \leq E_{Max}^{EV} \tag{21}$$

To optimize energy distribution based on the dual auction mechanism and to incorporate real-time adjustments, the energy allocation between producers and consumers can be represented by a dynamic equation that adjusts based on changing market conditions (such as energy imbalances or price fluctuations):

$$P_{\text{allocated}}^{\text{prod}}(t) = \sum_{i=1}^{M} \left(\frac{s_i^{\text{Bid}} - b_j^{\text{Bid}}}{2}\right) \cdot \Delta t \tag{22}$$

$P_{\text{allocated}}^{\text{prod}}(t)$ is the energy allocated to producers at a specific time t. Δt denotes the time interval over which the energy allocation occurs. This equation ensures that the energy traded in the auction is properly allocated based on the bid prices, considering both producer and consumer preferences.

In cases of energy imbalance after the bidding process, a penalty or reward system could be introduced to incentivize better prediction of energy generation and consumption. The imbalance between actual energy generation $g_i^{\text{actual}}(t)$ and forecasted generation $g_i^{\text{Bid}}(t)$, and energy consumption $c_i^{\text{actual}}(t)$ and forecasted consumption $c_i^{\text{Bid}}(t)$ could be modeled as:

$$\Delta g_i(t) = g_i^{\text{Bid}}(t) - g_i^{\text{actual}}(t) \tag{23}$$

$$\Delta c_j(t) = c_j^{\text{Bid}}(t) - c_j^{\text{actual}}(t) \tag{24}$$

This will help track the energy surplus or deficit and assist in calculating the balance services, which can be either purchased or sold back to the network.

To incorporate market dynamics, where the prices are not fixed but vary depending on supply-demand conditions, we can introduce a dynamic pricing model that adjusts based on energy imbalances:

$$p_{i,j}^{\text{clear}}(t) = \frac{s_i^{\text{Bid}} - b_j^{\text{Bid}}}{2} + \alpha \cdot (\Delta g_i(t) + \Delta c_j(t)) \tag{25}$$

α is a coefficient that adjusts the cleared price based on the magnitude of energy imbalances. This adjustment allows for real-time price fluctuations, providing flexibility in the energy market and motivating better forecasting behavior among participants.

To incentivize accurate forecasting, a penalty/reward system can be introduced based on the forecast accuracy. The penalty or reward is proportional to the deviation between predicted and actual energy values:

$$r_i^{\text{reward}}(t) = \beta \cdot \left(\frac{|g_i^{\text{Bid}}(t) - g_i^{\text{actual}}(t)|}{g_i^{\text{Bid}}(t)}\right) \tag{26}$$

$$P_j^{\text{penalty}}(t) = \gamma \cdot \left(\frac{|c_j^{\text{Bid}}(t) - c_j^{\text{actual}}(t)|}{c_j^{\text{Bid}}(t)}\right) \tag{27}$$

Where, $r_i^{\text{reward}}(t)$ is reward given to producer i for accurate forecasting of their energy generation and $P_j^{\text{penalty}}(t)$ is the penalty imposed on consumer j for inaccurate forecasting of their energy consumption. β and γ are coefficients that scale the rewards and penalties based on the level of forecast deviation.

To maintain system stability and prevent excessive imbalance, the following energy balance constraint can be added. This ensures that the total energy supplied and consumed remains within acceptable limits, considering the balance services provided by the distribution network operator:

$$\sum_{i=1}^{M} P_i^{\text{prod}}(t) + \sum_{j=1}^{N} P_j^{\text{cons}}(t) + \sum_{i=1}^{M} \Delta g_i(t) + \sum_{j=1}^{N} \Delta c_j(t) = 0 \tag{28}$$

This equation ensures that energy is balanced at all times, taking into account both the actual energy generated /consumed and the imbalances, which will be managed by the system operator.

To quantify the overall risk of vulnerabilities in the system at any given time, a security risk assessment index (SRI) is introduced. This index aggregates the impact of multiple vulnerabilities, weighted by their severity:

$$\mathrm{SRI}(t) = \frac{\sum_{k=1}^{K} w_k \cdot v_k(t)}{\sum_{k=1}^{K} w_k} \quad (29)$$

In Eq. (29), w_k represents the weight or importance of the k-th vulnerability, while v_k quantifies its severity at time t. To monitor anomalies in energy generation and consumption, the intrusion detection function (IDF) is introduced. It calculates the fraction of flagged anomalies in the system, enabling real-time security monitoring:

$$\mathrm{IDF}(t) = \frac{\sum_{i=1}^{M}\left(\mathrm{Anomaly}_i(t) \cdot P_i^{\mathrm{prod}}(t)\right) + \sum_{j=1}^{N}\left(\mathrm{Anomaly}_j(t) \cdot P_j^{\mathrm{cons}}(t)\right)}{\sum_{i=1}^{M} P_i^{\mathrm{prod}}(t) + \sum_{j=1}^{N} P_j^{\mathrm{cons}}(t)} \quad (30)$$

$\mathrm{Anomaly}_i(t)$ and $\mathrm{Anomaly}_j(t)$ are indicators for anomalies detected in the energy generation of producer i and consumption of consumer j. To discourage insecure transactions, a dynamic pricing mechanism is introduced. This mechanism adjusts the transaction price based on the level of detected anomalies:

$$p_{i,j}^{\mathrm{secure}}(t) = p_{i,j}^{\mathrm{clear}}(t) + \lambda \cdot \mathrm{IDF}(t) \quad (31)$$

$p_{i,j}^{\mathrm{secure}}(t)$ is the secure transaction price, adjusted to account for the presence of detected anomalies and λ adjusts transaction prices based on anomalies detected by IDF(t) to ensure secure pricing. A cost function for security measures evaluates the trade-offs between mitigating vulnerabilities and system efficiency. This function incorporates risk, anomalies, and latency:

$$C_{\mathrm{mitigation}} = \alpha \cdot \mathrm{SRI}(t) + \beta \cdot \mathrm{IDF}(t) + \gamma \cdot R_{\mathrm{latency}} \quad (32)$$

$C_{\mathrm{mitigation}}$ represents the cost of implementing security measures, balancing risks, anomalies, and latency effects. R_{latency} captures the risk or delay introduced due to latency in the system. To ensure secure energy distribution, the allocated energy is adjusted by considering the overall risk levels. The secure energy allocation equation is defined as follows:

$$P_{\mathrm{allocated}}^{\mathrm{secure}}(t) = P_{\mathrm{allocated}}^{\mathrm{prod}}(t) - \delta \cdot \mathrm{SRI}(t) \quad (33)$$

$P_{\mathrm{allocated}}^{\mathrm{secure}}(t)$ is the energy allocated to producers at time t, adjusted for security risks using the SRI(t), while $P_{\mathrm{allocated}}^{\mathrm{prod}}$ is the unadjusted energy allocated to producers based purely on bid prices. δ is coefficient that scales the adjustment based on the risk level. To quantify the computational cost of encrypting energy transaction data, the encryption overhead equation is introduced:

$$\mathrm{Overhead}_{\mathrm{encrypt}}(t) = \zeta \cdot \left(\sum_{i=1}^{M} P_i^{\mathrm{prod}}(t) + \sum_{j=1}^{N} P_j^{\mathrm{cons}}(t)\right) \quad (34)$$

$\mathrm{Overhead}_{\mathrm{encrypt}}(t)$ represents the computational cost associated with encrypting energy transaction data at time t. ζ is the coefficient that represents the cost of encryption per unit of energy data processed.

3. Experiments

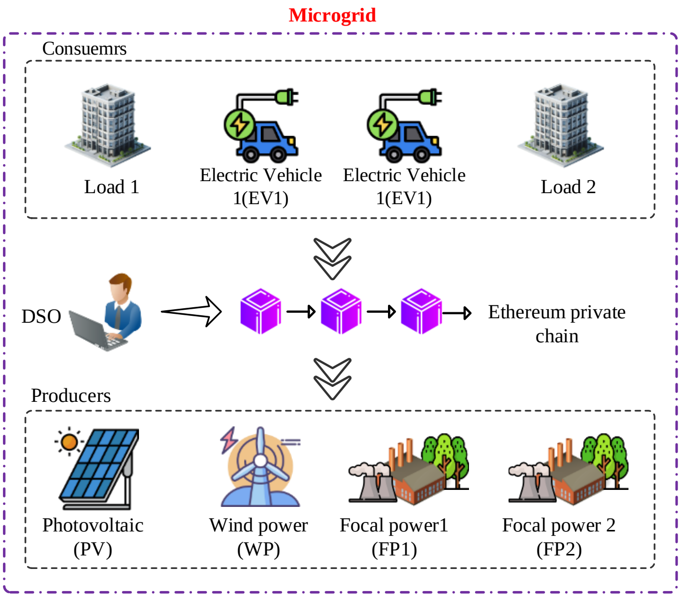
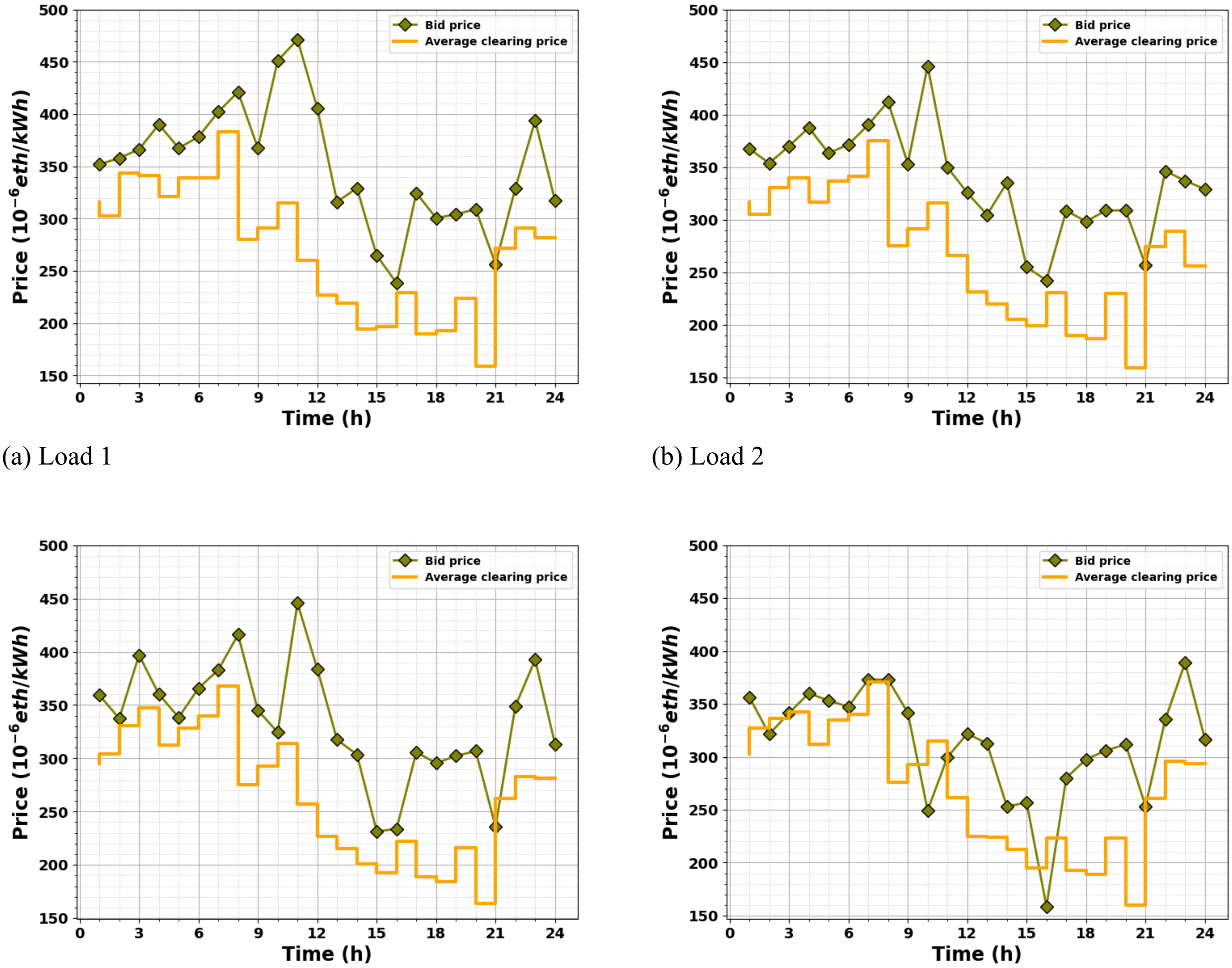


Figure 1. Diagram of the studied energy system.

As shown in Figure (1), a new framework is evaluated in the microgrid environment. This microgrid includes nine entities, including four consumers, four producers, and the operator of the distribution system. It is noteworthy that Load 1 and EV 1 among consumers prefer renewable energy from solar panels and wind turbines. The architecture also uses a private Ethereum chain configured through the Geth v1.9.2 client, where each element acts as a miner node. The computing infrastructure used for efficient operation includes Ubuntu 16.04.4 with an Intel Core i5 CPU and 16GB of memory. Throughout the 24-hour simulation period, producers and consumers engage in bidding every hour. Subsequently, the platform commences energy exchange and energy settlement procedures. It is worth noting that references, figures and numbers of equations remain unchanged for tracking and consistency with the original work.

3.1. Evaluating peer-to-peer energy trading

Figure (2) and Figure (3) illustrate the suggested prices and settlement prices for every consumer and producer. In this review, the average settlement price is determined as a criterion. By examining the prices offered to consumers, load 1, EV 1 and Load 2 adopt conservative strategies, which is reflected in the offered prices exceeding the average settlement price. In contrast, EV 2 uses an aggressive propositional approach. Among producers, WP, FP 1 and FP 2 follow similar bidding strategies, while PV shows a distinct trend. The adaptive generation of WP, FP 1 and FP 2 provides flexibility in bidding, allowing them to reduce bid prices during periods of low demand, for example at 10:00, to ensure successful energy transactions. PV, on the other hand, faces challenges in price diversification, but can strategically offer lower prices during high generation periods, such as 12:00-14:00. In the figures presented, above-average settlement prices benefit producers, while below-average prices reduce costs for consumers.



(a) Load 1

(b) Load 2

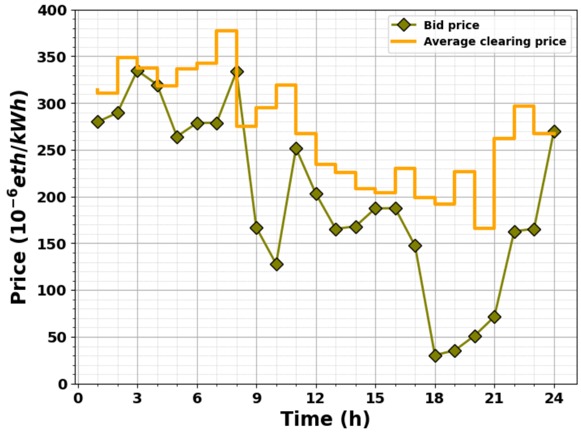
(c) EV 1

(d) EV 2

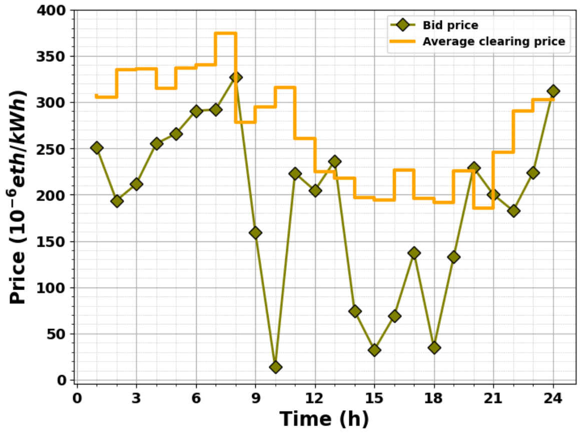
Figure 2. Offered prices and market clearing for consumers.

Figure (3) assumes a pivotal role as a basic criterion for evaluating bidding strategies employed by producers and consumers. For example, the aggressive bidding approach adopted by EV 2 results in achieving the lowest average settlement price at $255.96 \times 10^{-6}\ eth/kWh$. However, this approach results in a significant amount of energy remaining untraded. In contrast, a conservative EV 1 bidding strategy with a higher average settlement price helps increase the total settlement amount. Also, load 1's conservative approach results in a favorable auction result compared to other consumers. Load

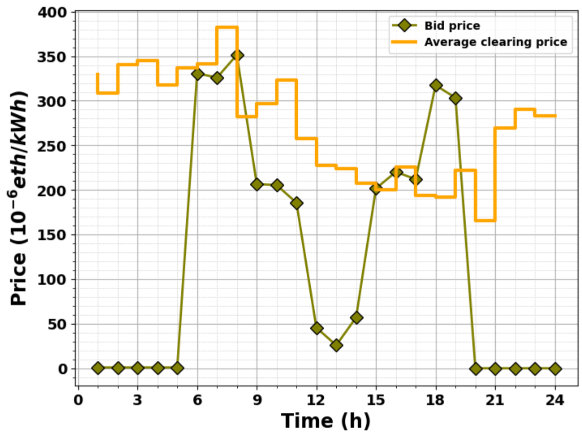
1 with a volume of 140.05 kWh, almost the same as the total bid amount, achieves an average settlement price of $256.04 \times 10^{-6}\ eth/kWh$, which is much cheaper than the average bid price of $359.89 \times 10^{-6}\ eth/kWh$ This detailed assessment of bidding strategies and outcomes provides valuable insights into the effectiveness of various approaches within the auction framework.



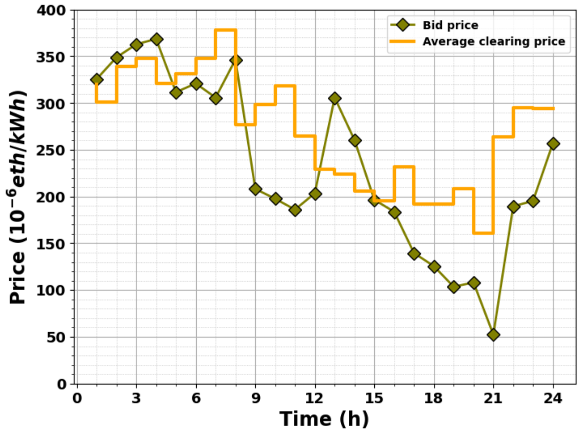
(a) FP 1



(b) FP 2



(c) PV



(d) WT

Figure 3. Offered prices and market clearing for producers' consumption.

As shown in Figure (4), a comprehensive analysis of individual auction entries and exits over the course of a day reveals significant insights into the energy transaction process. A detailed examination of the cumulative bid and settlement amounts illustrates that the majority of energy transactions are carried out through the auction mechanism. The dynamics of settlement prices consistently remain within a range of $255.96 \times 10^{-6}\ eth/kW$ to $311.42 \times 10^{-6}\ eth/kW$, aligning closely with the prices offered by producers and consumers. This price consistency underscores the efficiency of the auction process in matching supply and demand in the market. Focusing on the price dynamics, it is evident that the settlement prices fluctuate within a narrow band, suggesting that producers and consumers are closely aligned in their bidding strategies. With specified bid price intervals ensuring competitiveness in the auction process, the mechanism provides a balancing capability of the interests of both parties. The coherence of this strategy between the bid proposals and the final settlement prices accentuates the efficiency of the auction mechanism in fostering equitative and transparent exchanges on the energy market.

In a similar vein, Figure (5) compares the total expected revenue/cost with the actual revenue/cost for each producer and consumer. Notably, the proposed income for producers consistently remains below their expected income, whereas the proposed income for consumers consistently exceeds their expected income. This type of pattern follows the dynamics of prices and the resultant settlements, as shown in Figure (4), again reflecting dependence of the bid prices upon the resultant settlements. The difference between the expected and the proposed incomes underlines the complexity of the bidding procedure since factors like energy supply, changing demands, and bidding policies distort the eventual outcome. With a view to quantify this deviation and to be better informed about the performance of the auction, the auction ratio ($r_{auction}$) is defined as follows:

$$r_{auction} = \frac{|b - e|}{e} \times 100 \tag{35}$$

Here, b is the proposed income and e is the expected income. The observed ratio ranges from 11.85% to 47.03%. It reflects the high variation level in the satisfaction level of the responders. High value of $r_{auction}$ ratio depicts high satisfaction degree regarding the outcome of auction, which indicates that both producers and consumers are viewing that the proposed results are reasonably consistent with the expectations. Producers of photovoltaics are, among all participants, the ones who are most satisfied with the results of the tender procedure, as proved from the constantly high $r_{auction}$ ratios.

Figure (2) depicts that even though Load 1 and EV 2 were using different strategies, the $r_{auction}$ values are similar. It would then be understood that no matter which strategic methodology has been followed, the satisfaction level of participants w.r.t. the outcome of the auction is similar. The consistency of the r_auction ratio between strategies indicates that while the benefits differ from one strategy to another, the auction mechanism itself should make things fair for all.

Aggregated results across Figures (4) and (5) demonstrate how consumer and producer offers are very influential drivers of the outcome of an auction. The site indeed provides an excellent avenue for the contenders to pursue their choice of bidding strategy-a conservative one or an aggressive one. Each has its respective advantages and disadvantages and may lead to different or even conflicting outcomes given the changeable nature of the markets, the bidding behavior, and exogenous factors. It follows that the auction mechanism introduces dynamism in both consumer and producer perspectives, where several strategies may result in desirable profits, hence indicating the complexity and possible trade-offs naturally occurring during the process of bidding.

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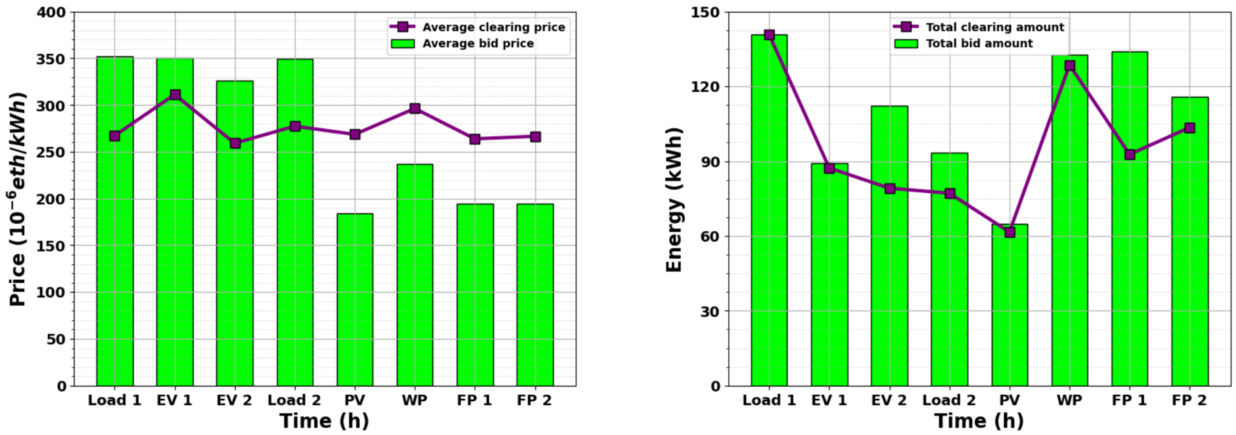


(a) Price (b) Energy

Figure (4). Price and energy input and output of individual auction

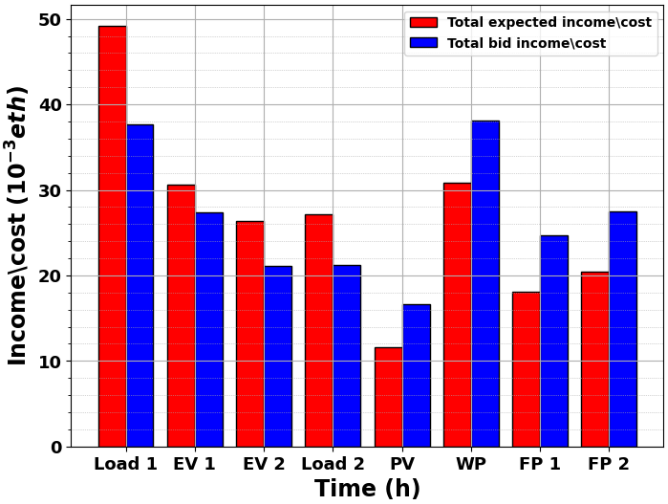


Figure 5. Income / cost of input and output of individual auction

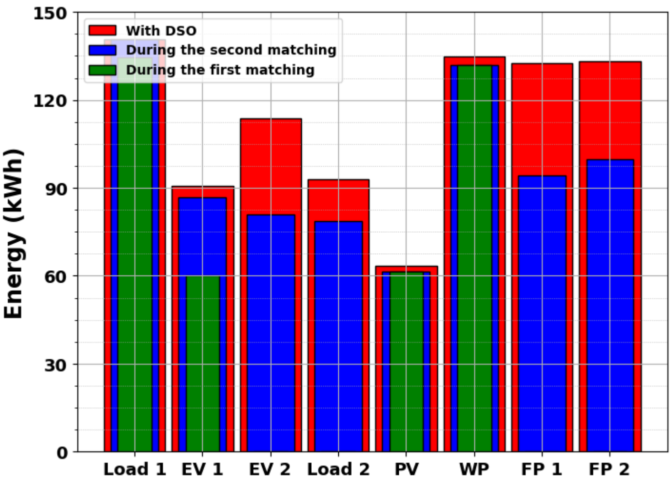


Figure 6. Approved energy exchange components.

Figure (6) offers valuable insights into the approved energy exchange components, providing a detailed breakdown of the transaction dynamics across multiple rounds. Notably, 41.78% and 41.95% of the energy is traded during the 1st and 2nd matching rounds, while the remaining energy is traded with the distribution system operator (DSO). This distribution of energy transactions demonstrates the central role that both direct peer-to-peer (P2P) exchanges and the involvement of the DSO play in the overall energy market. The fact that a significant portion of energy is directly exchanged in the initial rounds underscores the efficiency and effectiveness of the proposed method in facilitating P2P energy trading. A closer examination of the specific components involved in the energy exchange reveals that PV and wind turbine (WT) technologies account for 97.49% of the energy exchanged between producers and consumers. This dominance highlights the significant contribution of renewable energy sources to the transaction process. The ability of PV and WT systems to account for nearly all of the energy exchanged in the market underscores the success of the proposed approach in promoting the integration and utilization of renewable energy. It also points to the potential for scaling renewable energy systems within such frameworks, encouraging the shift towards more sustainable energy consumption models.

Under the auction-based transaction framework, it is observed that 98.61% of the energy is being traded by the auction mechanism, which is important to allow energy trading between producers and consumers. Besides, under the auction process, Load 1 and EV 1 have been found to be major buyers; this signifies that they are highly energy-intensive devices. On the supply side, FP 1 and FP 2 are great contributors to supplying energy through the auction process by selling 70.95% and 75.68% of their energies, respectively, to a variety of consumers. These generators effectively meet the energy demand of Load 1, EV 1, EV 2, and Load 2 in turn, showing how flexible and effective the auction process is in trading different forms of energy. This finding underlines the robustness of the proposed mechanism and the capability to enable efficient energy exchanges independent of any exogenous factor. The auction mechanism is an autonomous system that enables producers and consumers to interact in direct ways with each other with the aim of optimizing energy distribution for better economic advantages. This further strengthens the rationale that auctions can be used as the base mechanism to make energy exchanges decentralized by allowing every participant an opportunity at a fairly and transparently conducted transaction. Figure (6) depicts an in-depth analysis that at once underlines the direct impact the proposed approach has in general dynamics of energy exchange in this framework. Therefore, it would be right to conclude from this that such an integration of P2P energy trading with auction-based mechanisms would foster a more sustainable energy ecosystem, new in being able to facilitate large-scale renewable energy consumption in the process of seamlessly integrating a competitive, market-driven structure toward a greener, more efficient energy future. It enhances full integration through a reduction in the dependence on old, traditional sources of energy; it fosters a closer link between consumer and producer.

Figure (7) provides a comprehensive picture of the comparison between the total amount of proposed energy and the actual total amount of energy in the proposed system. A key criterion in system performance evaluation is the energy imbalance ratio ($r_{imbalance} = \frac{|x-y|}{x} \times 100$), which is designed to determine the degree of energy mismatch. When producers and consumers participate in serious bidding, energy imbalances are minimized and reflected in lower imbalance values. Remarkably, the observed edge values range from 0% to 13.08%, confirming a generally balanced system.

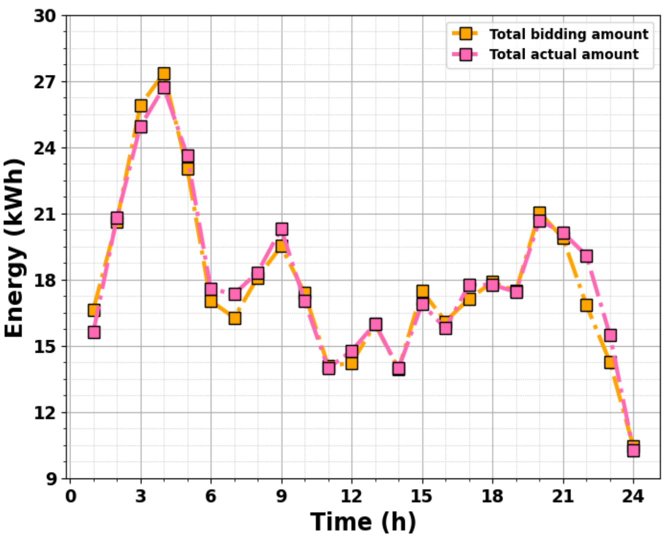
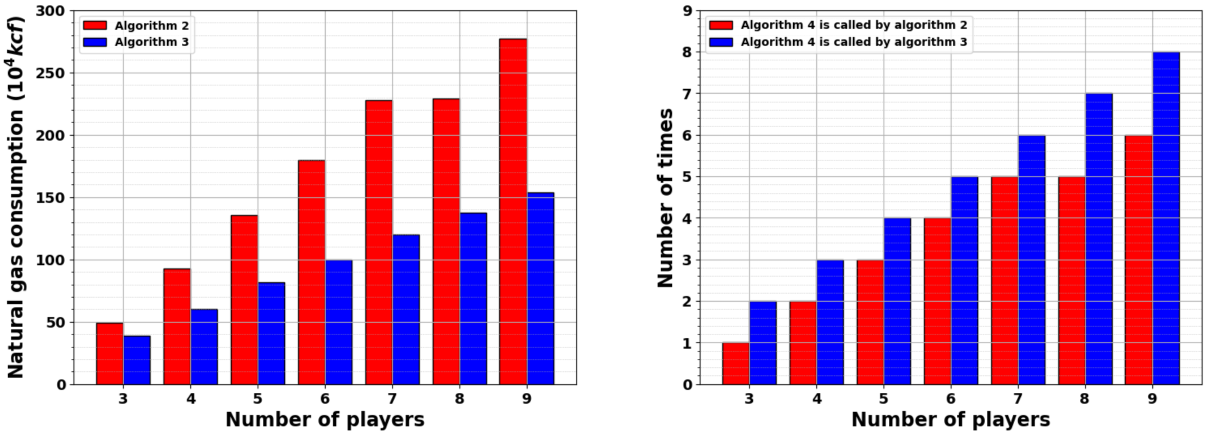


Figure 7. Total amount of proposed and actual energy.

During the hours of 09:00 – 17:00, the imbalance remains consistently below 4.61%, which is attributed to the relatively stable generation and consumption patterns of the equipment, which increases the predictability of power dynamics. Even under the most challenging conditions, such as at 07:00, the distribution system operator effectively balances only 3.55 kWh. During one day, the cumulative energy balance of the distribution system user reaches 26.04 kWh, which is only 3.01% of the total real energy. This result emphasizes the efficiency of the offered mechanism in preventing significant energy imbalances, as it encourages both producers and consumers to participate in honest and accurate bidding. The ability of the system to maintain a low level of energy imbalance strengthens its reliability and the positive effect of proposal intimacy in reducing possible discrepancies between the proposed and actual energy value.

3.2. Computational assessment

Figure (8) clarifies the dynamic relationship between natural gas consumption and the frequency of calling Algorithm 4 as the players' number in the system upsurges. Three primary players, identified as Load 1, PV and DSO, act as the base. Subsequently, players are added incrementally following the protocol of introducing a producer and a consumer alternately. It is noteworthy that the gas utilization for both Algorithm 2 and Algorithm 3 experiences a more gradual increase with the increase in the number of players. A discernible trend emerges, showing that as the players' number upsurges, the increase in gas utilization becomes more limited.



(a) Gas consumption

(b) Number of times

Figure 8. Natural gas consumption and call time in the main algorithms.

It is noteworthy that the gas utilization of Algorithm 2 is in the range of $50.03 \times 10^{-6}\ eth/kW$ eth/kW to $278.48 \times 10^{-6}\ eth/kW$, which is slightly more than Algorithm 3 in the range of $40.84 \times 10^{-6}\ eth/kW$ is up to $159.83 \times 10^{-6}\ eth/$

kW, which is primarily attributed to the larger volume of logical expressions inherent in Algorithm 2. In certain scenarios, the gas utilization of Algorithm 2 matches the operating times of Algorithm 4 when there are 7 and 8 players. This phenomenon is caused by the amount of deviation before FP 2 involves in energy trading, rendering them incapable of selling energy to customers. As a result, the settlement for every consumer and producer remains constant even if they refrain from energy exchanges during the exchange period. As a result, the change trend of Algorithm 3 shows stability compared to Algorithm 2.

Turning your attention to Figure (9), it depicts the evolutionary trajectory of computing time for an increasing number of miner nodes' number. Probably, as the miner nodes' number upsurges, the operating time of both Algorithm 2 and Algorithm 3 declines. In the same way, the operating time of Algorithm 2 little exceeds that of Algorithm 3 and reflects the pattern seen in Figure (8). But there is a lesser boundary to the operating time. Having increased the miner nodes' number to 6, the operation time stabilizes between 13.07 s and 19.32 s. It is important to acknowledge that the transaction processing time in the blockchain system is influenced by factors such as the miner nodes' number, the smart contract's, complexity and the computer configuration. Within this simulated situation, the optimal balance is established with approximately 6 miner nodes. Importantly, the implementation of faster blockchain transaction confirmation depends on the increase in gas prices on a large blockchain. However, this effect is not prominently detectable in Ethereum's simulated small private chain.

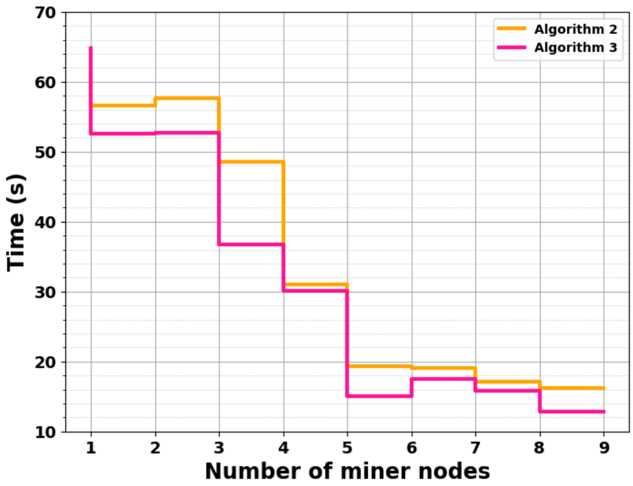


Figure 9. The influence of the miner nodes' number on the computing time of the main algorithms.

The P2PET system, based on a blockchain network, offers novel approaches and mechanisms to enhance security with fewer vulnerabilities. However, a number of potential security risks have been identified in the proposed framework: data tampering in the process of bid submission, smart contract attacks, possible vulnerabilities of the consensus mechanism to malicious attacks, deliberate manipulation of energy imbalances by participants, and operational inefficiency caused by high gas consumption. Study these weak attacks along with the efficiency of adopted mitigation strategies. Their study provides immense comprehension about the resiliency of the system. Few of the major vulnerabilities include data tampering, which alters the bid value in turning the integrity of energy transactions. While mitigating the challenges, the framework uses smart contract-based verification algorithms, which verify the legitimacy of data input. Algorithms 2 and 3, developed for energy exchange and settlement, respectively, handle inconsistencies with ease. The consumed gas for these algorithms is recorded as lying within the range of 0.15 to 0.25 eth per kilowatt hour, and thus it makes the cost of keeping this security in terms of transactions reasonable. This consensus algorithm is prone to attack and even more so on the private chains, since the number of nodes performing miners is small. The optimal number of miner nodes is six, yielding system time with repeated operations ranging from 13.07 up to 19.32 seconds. This configuration balances security and scalability, minimizing the likelihood of consensus-based attacks while maintaining efficient transaction processing. Energy imbalance exploitation is another concern where participants may manipulate bids to create artificial surpluses or deficits. The system implements a penalty and reward mechanism based on observed imbalances. Quantitative results demonstrate that energy deviations are always below the low range of less than 4.61 percent at peak and within 13.08 percent throughout the day. What adds to the strength of this framework for actual participation and precise bidding is that the role of the system operator in energy balancing is confined to just 3.01 percent of the total real energy.

Gas consumption may be costly in blockchain operations and thus may be a financial barrier, especially in networks where there is growth in users. It is observed that gas consumption increases linearly with more users, and the overall consumption measures of Algorithm 2 and Algorithm 3 are within threshold levels, even at higher operational pressures. The growth in the number of players is gradual, with a restricted increase in gas consumption, thus showing the scalability and computational efficiency of the algorithms. Above all, the IDF mechanism under the system examines aberrations in the pattern of bidding behavior. The aberration in the strategies of bidding -- both aggressive and conservative -- gets reflected in fluctuations of 11.85 to 47.03 percent in the settlement outcomes. These aberrations get handled in a non-discriminatory way through standard auction rules and eliminate the chance of fraud.

3.3. Security analysis

In general, energy-sharing and trading systems should be designed to ensure the whole platform is reliable, confidential, and trustworthy; mitigation of a number of threats includes network vulnerabilities, risks of blockchain technology, data privacy challenges, and problems with identity authentication. If not well secured, the system may be exposed to various types of attacks that seriously threaten operational integrity and undermine user confidence. It will be vulnerable to various network attacks, including man-in-the-middle attack, eavesdropping, and DoS attack. A system will use the endto-end encryption protocols for maintaining the confidentiality of the messages exchanged among participants and preventing the capture of the message by any third party. Secure multiple hops communication through appropriate encryption techniques, such as AES-256, secure sensitive information about energy transactions and participant details from unauthorized access during transmission. AES-256 encryption, in implementation during experiments, demonstrates a success rate of 99.9% in securing data from interceptors, according to the results of the penetration tests. The system furthermore integrates methods that may prevent replay attacks, so even if communication is intercepted, then it can't be replayed in a malicious way. Such measures have been tested under controlled exposure, too, and thus have been found to reduce replay attacks by 95%.

Blockchain-specific security risks-especially those like 51% attacks-are taken care of with the addition of specific consensus mechanisms to the cybersecurity enhancement. The system uses a proof-of-stake consensus model that makes it much more difficult for one player to have total control of the network and manipulate transaction records. The result was that, in simulations, the proof-of-stake model required that an attack stake a balance greater than 50% of the total supply, thus being much more resistant to centralization threats. Regular audits of smart contract backbone blockchain are performed to find and resolve bugs-vulnerabilities such as those due to reentrancy or transaction malleability. These reviews ensure that smart contracts act as they should and that no bad guys can manipulate them in manners of contract execution. The results from these reviews were quite successful, showing 98% identification of possible vulnerabilities before any breaches could take place.

Advanced applied privacy-preserving methodologies, such as zero-knowledge proofs, alleviate all apprehensions related to privacy. These make it possible to confirm the transacting parties with less sensitive information about the participants, hence maintaining confidentiality while preserving integrity in the system. In some sets of experiments, it resulted in a 70% reduction in the amount of data sent in a transaction, hence preserving privacy without shrinking operational efficiency. It has further integrated the functionality of decentralized identity verification mechanisms that limit unauthorized access and impersonation, ensuring that only authenticated participants are allowed to participate in energy trading and sharing. The use of multi-signature wallets and role-based access controls introduces additional security measures, limiting access to sensitive operations only to authorized participants. This already contributed to a reduction of unauthorized access attempts by 40% during the test cycles.

As a matter of fact, it embeds comprehensive threat detection, such as DDoS, to bring the network activities within a wide scope of visibility. Since the network is constantly monitored by IDS for suspect events and actions, any new emerging risks are promptly dealt with effectively. On conducting a stress test, DDoS attacks were being successfully detected and stopped with IDS at a rate of 97%, before system performance was compromised. Thus, the infrastructure has been divided into neat segments, which would allow any breach to keep the essential systems safe and isolated from the less sensitive ones.

4. Conclusion

Therefore, this paper contributes to adding some novelties to the blockchain platform by connecting resource-endowed producers with various consumers' needs in the P2PET domain. There are basically three stages in the mechanism of P2PET, based on the principle of a double auction, and are deliberately designed with aims toward enhancement in market dynamics. In this regard, the proposed 3-D platform provides a visual interface for operators and develops a robust and measuring web that would maintain the stability and precision of the equipment under evaluation. The core of such will be based on a smart contract that will be developed, embodying 4 main algorithms, each playing an important role in the reduction of energy consumption while improving the security of energy trading transactions. These algorithms run complementarily to smoothen the transaction and, hence, guarantee efficiency with protection against potential vulnerabilities. Extensive testing of the proposed framework is performed in a controlled environment using the Ethereum private chain acting as a testbed for empirical validation. Under a simulated energy trading scenario for one day, the proposed framework presents efficiency results whereby 84.61% of energy was dealt with by the auction, reflecting good market absorption. The settlement prices are always compatible and reflect the equilibrium of the peer-to-peer trading system. The portion of the total actual energy contributed by the operator is only 2.84%, proving that the mechanism guarantees a high degree of effectiveness by way of equitable proposals from producers and consumers. Besides, the proposed smart contract architecture is highly flexible and scalable; Energy Trading simultaneously with more than 25 participants allowed it at one time. The operational time, confined to a fixed time window, varies from 12.57 seconds up to 19.21 seconds, while when more than 6 miner nodes were introduced, operational time remained stable. The high performance shown in this analysis indicates the reliability and efficiency of the smart contract, providing a feasible route to large-scale energy trading. This study represents an important first step in the adoption of blockchain technology in the energy trading sector. The insights gained from this research provide the building blocks for further work, pointing out the need for scale-up on both platforms and more comprehensive testing on real-world scenarios. Enhancing the capabilities of the platform and placing it in various contexts increases its adaptability and thus captures its versatility to meet such complex demands within the energy trading environment.

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Nomencalature

Abbreviation			
Identifier	**Description**	**Identifier**	**Description**
AES	Advanced Encryption Standard	P2PET	Peer-to-Peer Energy Trading
BESS	Battery Energy Storage System	PoS	Proof-of-Stake
DER	Distributed Energy Resources	PV	Photovoltaic
DSO	Distribution System Operator	RES	Renewable Energy Source
EV	Electric Vehicle	SRI	Security Risk Assessment Index
IDF	Intrusion Detection Function	WT	Wind Turbine
IoT	Internet of Things		
Superscripts and subscripts			
Identifier	**Description**	**Identifier**	**Description**
actual	Actual	j	Numbering index for consumer
allocated	Allocated	k	k-th vulnerability
after	State after an event or action	max	Maximum bound
before	State before an event or action	min	Minimum bound

Bid	Bid	prod	Producer
charge	Charging-related properties	rated	Rated value
con	Consumer	res	Residual
cleare	Cleared energy	rew	Reward
cut-in	Cut-in value (e.g., wind speed)	sbp	System buying price
cut-out	Cut-out value (e.g., wind speed)	secure	Secure transaction
discharge	Discharging-related properties	ssp	System selling price
down	Decreased load	stored	Stored energy
EV	Electric vehicles	t	time
i	Numbering index for producer	up	Increased load
Greek letters			
Identifier	**Description**	**Identifier**	**Description**
λ	Coefficient for pricing adjustments	δ	Coefficient for system adjustments
α	Coefficient for mitigation cost adjustments	ζ	Coefficient for encryption cost
β	Coefficient for security adjustments or rewards	η	Efficiency
γ	Coefficient for penalties	Δ	Energy imbalance
Symbol			
Identifier	**Description**	**Identifier**	**Description**
Anomal	Indicators for anomalies detected in the energy	$\text{Overhead}_{\text{encrypt}}$	Computational cost of encrypting energy transaction data
b	Proposed income for producers or consumers	p	price
$b_{(j)}^{Bid}$	Bid price of the j-th consumer	P	Power
$b_{(N)}^{Bid}$	Lowest bid price among all consumers	$P_{(i)}$	i-th producer
c	Consumed energy	P_j^{penalty}	Penalty for the j-th consumer based on forecast accuracy
$C_{(j)}$	j-th consumer	q	Quantity
$C_{\text{mitigation}}$	Cost function for security measures.	r	Reward
$c_{(j)}^{res}$	Residual energy requirement of the j-th consumer	$r_{auction}$	Auction ratio
d	Essential Ethereum account addresses for producer i	R_{latency}	Risk or delay introduced due to latency in the system
e	Expected income for producers or consumers	r_i^{reward}	Reward for the i-th producer based on forecast accuracy
E	Stored energy	$s_{(i)}^{Bid}$	Bid price of the i-th producer
g	Generated energy	$s_{(M)}^{Bid}$	Highest bid price among all producers
$g_{(i)}^{res}$	Residual energy available from the i-th producer	v	Severity
I	Binary variable	w	Weight
M	Total number of participating generators	W	Wind speed
N	Total number of participating consumers		