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# Blockchain-Driven Peer-to-Peer Smart Energy Trading for Decentralized Power Networks

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**ABSTRACT**

Renewable sources of energy distributed across the electrical grid have a growing influence on energy transactions. This rise of distributed or decentralized energy systems requires innovative, fast, and secure methods for enabling energy trading. This paper presents a Privacy-preserving Blockchain-enabled Energy Trading Chain (PBET-Chain). It is a privacy-preserving blockchain-enabled platform designed for decentralized peer-to-peer (P2P) energy trading through community microgrids. The proposed framework incorporates a dual-layer blockchain architecture, reinforcement-learning-based dynamic price determination, trust-aware partnering processes, and zero-knowledge proof-based smart-meter verification. The feasibility of PBET-Chain is demonstrated through experimental simulations using a modified IEEE 34-bus distribution feeder that contains 50 prosumers and 60 consumers of energy. Experimental outcomes reveal that PBET-Chain provides market efficiency of 92.4%, energy usage of 88.7%, and trust accuracy of 94.8% that substantially surpass traditional blockchain-based and traditional learning-enabled P2P trading models. Moreover, the dual-layer settlement design provides trading latency of 0.41 s for trading protocols and execution time of smart contracts (56 ms) with a transaction throughput of 142 transactions/sec. There is great potential for large-scale and highly unpredictable applications, and currently working to further establish the viability of the framework.

## 1. INTRODUCTION

The most recent trends in the operation and design of a power grid include an influx of distributed energy resources (DERs) from rooftop solar panels, wind turbines, and home battery systems; as the number of DERs continues to grow, so too does the spectrum of risk and reward for both consumers and utilities. This development has allowed those who produce their own electricity (prosumers) to participate in local energy markets and therefore decrease their reliance on large centralized electricity suppliers. Another benefit of allowing prosumers to directly sell surplus energy generated by their DER is that grid operators have greater capabilities to enhance grid resilience and flexibility [1]. Conversely, establishing a market structure that meets the needs of all participants while simultaneously providing adequate security and privacy for distributed energy generation and storage [2].

Peer-to-peer (P2P) energy trading allows for transactions between prosumers and avoids the costs of relying on a centralized third party for these transactions [3]. Prosumer-to-prosumer transactions improve the local utilization of renewable energy generation and minimize the amount of energy lost during the long-distance transmission of electricity, as well as provide opportunities for a more competitive and consumer-centric pricing model. Therefore, to create an efficient, automated, trustworthy P2P energy market, a reliable e-transaction platform must also possess transparency, low latency, privacy, and auditability simultaneously. No currently available e-Transaction platforms possess all of the features outlined above [4]. Blockchain technology provides the foundational building blocks for P2P energy trading markets with capabilities such as decentralization, immutability, automated instructions through smart contracts, etc. The results of proof-of-concept projects and pilot programs demonstrate blockchain technology's ability to alleviate specific trust issues while allowing bid/offer matching automation, settlements, and reputation accounting to be implemented automatically [5]. Nevertheless, Blockchain Technology faces many real-life challenges when it comes to implementing successful deployments. Public Blockchains are characterized by high latency and cost per transaction, which serve as hurdles to successful implementations. Second, purely singular layered blockchains will encounter challenges due to throughput and privacy concerns. Lastly, many proposed schemes do not address regulatory compliance and long-term auditing [6].

There have been many recent publications regarding the various challenges mentioned above. Specifically, cryptographic primitives such as commitments and zero-knowledge proofs are now being incorporated into privacy-enhancing technologies utilizing sufficiently secure meter-level consumption data, bid information, and verifiable settlement capabilities [7]. By using advanced forecasting techniques based on artificial intelligence (AI) and advanced time series models (e.g., LSTM and Transformer), traders can take advantage of better-informed decisions in order to increase their pre-emptive trades. In addition, through the use of machine learning algorithms, energy companies and blockchain transaction network (graph) service providers have successfully detected fraudulent and abnormal activities occurring through their energy and blockchain networks [8]. Additionally, machine-learning algorithms have been utilized to provide energy companies with a means to identify thefts, tampering, and manipulation of transactions that occur on their blockchain transaction network [9].

While advances have been made in developing P2P trading technology for urban microgrid energy systems, this research identifies three significant gaps: Many research efforts have focused on one primary component without developing a cohesive architecture to satisfy all three components of latency, scalability, and regulatory auditing. There is a lack of available solutions that include the integration of predictive analytics into smart contracts, enabling preemptive matching and grid-aware trading that is based on short-term forecast data and actual network constraints. And comprehensive countermeasures that combine methods for cryptographic privacy, reputation/incentive design, and machine learning-based fraud detection in a unified and operational framework are extremely limited [10-12].

The above-mentioned issues ultimately result in a barrier for the practical use of P2P trading technology within the scope of urban microgrids/community energy systems. Also, due to these identified barriers, this paper is proposing the PBET-Chain, a new architecture that simultaneously addresses the following five critical objectives: latency, privacy, auditability, predictive optimization, and security. The PBET-Chain architecture has an additional layer that separates the functions of the above objectives into two complementary layers of blockchain. One layer is the Fast-Trading Layer (FTL), which is a lightweight, fast, and low-latency second-consortium-chain architecture designed for higher-frequency microtransactions; and the other layer is the Settlement & Audit Layer (SAL), which provides a more secure, immutable ledger to ensure that transactions can be audited, reported to regulatory authorities, and provide an avenue for resolving disputes. An AI-Enhanced Energy Prediction Engine (AI-EPE) works closely together with a Multi-Criteria Energy Matching Algorithm (MCEMA) for the purpose of pairing energy buyers and sellers based on their locations on a grid while using a cost-sensitive approach. Privacy-preserving metering using Zero Knowledge Proofs (ZKP) and a mixed cyber-fraud detection and incentive structure contributes towards the protection of participant data and the integrity of the system.

The three main contributions of this research include the following:

- The PBET-Chain dual-layer blockchain design that combines low latency, auditability, and regulatory compliance;
- An AI-enabled integrated multi-criteria matching methodology that takes into consideration short-term forecasts, grid limitations and trade partners' reputations;
- A layered security and privacy toolkit that includes a zero-knowledge proof system for meter verification combined with ML techniques for fraud detection and a token-based mechanism for reporting and rewarding good behavior;
- Implemented PBET-Chain in tandem with smart meter readings and carried out simulations of microgrids measuring the performance of PBET-Chain against that of single-layered blockchain systems.

The remainder of this paper consists of the following sections: In Section 2, the literature surrounding the topic, Section 3 provides a complete overview of PBET-Chain's architecture and its associated threat model. Section 4 outlines the experimental infrastructure on which PBET-Chain's performance was evaluated. Finally, Section 5 provides a conclusive statement about what was learned from this study and the possible directions for additional research.

## 2. RELATED WORK

The current trend of examining blockchain-based P2P energy trading has included an evaluation of the potential benefits to power distribution systems of using blockchain technology along with the use of smart contracts and intelligent pricing structures to improve efficiency, transparency, and security on a decentralized basis, as described in the literature. This review section contains a summary of the findings from the literature on the topic of decentralized energy exchange markets. The contribution of those published studies is identified, as well as the research gaps they did not address. The proposed PBET-Chain prototype will fill these gaps. Pradhan et al. [13] have designed a lightweight P2P system for community energy trading based on the IOTA Tangle. The system uses Masked Authentication Messaging (MAM) channels on the IOTA Tangle to publish producers' data and to settle transactions at little cost. The authors show that the IOTA DAG solution has much lower operating costs and lower energy footprints than typical blockchains. Nevertheless, it does not offer a combined privacy-preserving settlement mechanism for IOTA/DAG-based applications, nor does it provide a mechanism for adversarial fraud detection at large scale.

Aoun et al. [14] have studied P2P trading based on blockchain and compared it with net-metering and feed-in tariff schemes in providing economic key performance indicators (KPIs) for rural/isolated microgrids. The report presents an analysis of the economic benefits of P2P designs and the trade-offs with regard to market clearing decisions; however, the study is primarily a com-clearing study and simulation-based analysis. The report does not provide a complete end-to-end architecture for P2P energy trading that considers the needs for low latency, privacy protection and regulatory auditability. The approach taken by the researchers

Mitrea et al. [15] for privacy in P2P flexibility energy markets is a multi-party computation (MPC) approach. The authors describe how their MPC system allows for the preservation of meter privacy while enabling settlement and that, therefore, the use of secure computing off-chain can enhance the current methods of logic, which are based on Ethereum (blockchain) and therefore ready to be applied in the P2P energy trading market. Nevertheless, the obstacle to low-latency trading associated with this paper is the increase in computational and communication overhead associated with the MPC process, and the paper does not provide any combination of off-chain secure computation in a lightweight real-time (RT) chain.

Khan et al. [16] have conducted a study that reviewed blockchain solutions for Vehicle-to-Grid (V2G) and P2P energy trading between electric vehicles (EVs), concluding that V2G presents unique challenges requiring smart contract logic and incentivization strategies tailored for this type of market. Furthermore, they identified the lack of generalizable reputation/fraud detection mechanisms applicable to the highly distributed nature of EV market participants as a significant barrier to adoption. Zedan et al. [17] have summarized current developments in P2P energy trading and highlighted several barriers to successful implementation, including scalability, privacy issues, regulatory acceptance, and integration with distribution network constraints. They also point out how fragmented the current body of research is and describe the importance of developing comprehensive, multi-layered solutions that incorporate prediction analytics, privacy protection, and audit trails.

RETINA has been developed by Bolgouras et al. [18]; it is a distributed trust management architecture for smart grids that fuses public key infrastructure (PKI) and Web of Trust (WoT) models with blockchain-based solutions for trading. With respect to pricing, RETINA takes both proximity and trust into consideration while also validating the proposed platform's performance in a simulated environment with 500 nodes. However, while RETINA is strong in Trust Modelling, it does not address the use of Private/Public Key Infrastructure (PPKI) based on Zero-Knowledge Proofs (ZKPs) for Meter Validation, nor does it propose a Dual Ledger Accounting Model for Settlement. Nikbakht et al. [19] have introduced a Decentralized Energy Marketplace (DEM) that utilizes non-fungible tokens (NFTs) to create profiles for energy use and federated deep reinforcement learning (FDRL) agents to evaluate trading options. Although DEM appears to scale well and adapt agent behaviors, the cryptographic protection of NFTs raises privacy issues, and there is no similar verification method for meter readings.

Nadella et al. [20] have proposed blockchain-related fraud detection unsupervised clustering methodologies used to identify anomalous activities within blockchain transaction records. This work demonstrates the potential of using off-chain machine-learning assessments on blockchain graphs to identify behaviors and includes no connection between detection results and actions taken to correct behavior on the blockchain, limiting its utility in the (distributed) energy sector. Palaiokrassas et al. [21] have done a systematic review of ML applied to blockchain records that covers the application of Classification, Clustering, and Graph-ML techniques to identify anomalies/fraudulently placed orders as well as classify contracts. Tlabeledew identifies challenges related to the scarcity of labeled training data and the use of streaming data analyses, creating opportunities to combine online ML with reputation systems, providing rapid remediation in a P2P energy transaction environment.

Zhang et al. [22] developed a design using blockchain technology and zero-knowledge proof (ZKP) to allow the verification of aggregated demand-response certificates on-chain without disclosing any raw meter data, as shown in their prototype for energy applications, although there are still unresolved issues regarding the cost of producing the proof and the ability to connect low-latency trading systems to the generation of proof. Ashfaq et al. [23] proposed a blockchain structure designed for hybrid microgrid systems that combines droop control without synchronous control with an on-chain bidding approach. The approach integrates physical control rules and the bidding rules of market places to allow for grid stability. While this structure provides a good foundation for grid-aware market design, it does not provide privacy assurances or a layered ledger to separate audit trails from fast trading transactions.

Shuaib et al. [24] described a framework using IoT and blockchain technologies to integrate lightweight sensors, convolutional neural networks (CNN), and blockchain logs for various applications in energy consumption. The authors focus on analysis using edge devices for anomaly detection within their framework; however, at this time, they do not provide any formal privacy proofs or multi-objective matching algorithms in their work. Sindi et al. [25] have investigated numerous applied architecture explorations implementing machine learning (ML) and blockchain for fraud detection and incentives alignment (recent engineering and whitepapers), demonstrating actual benefits of hybrid on-chain/off-chain designs for monitoring and remediation; however, many of these applications are prototypes with limited peer-reviewed testing in realistic microgrids. Therefore, many studies developed motivation for PBET-Chain's integrated on-chain ZKP, ML-based detection, and reputation system.

Muhsen et al. [26], along with other business layer analyses, researched business models and incentive structures for P2P platforms and defined numerous methods of clearing auctions (game theory-based) and created catalogs of auction and game theory clearing mechanisms. While these studies provide ample evidence supporting the necessity of robust incentive structures and reputation systems for sustaining prosumer participation, they generally do not provide cryptographic privacy or utilize ML-based fraud mitigation systems to enhance their functionality, providing motivation for PBET-Chain's Hybrid Incentive Creation and Technological Fraud Detection Approach.

Davda [27] has proposed a new hash algorithm with the goal of enhancing blockchain security through the development of better collision-resistant and efficient methods for processing data in distributed ledger systems. This research demonstrates an increase in the need for cryptographically secure hash functions to prevent tampering or unauthorized changes to the data contained in blockchain transactions. Joshi et al. [28] proposed the use of a hashed-based method to improve the quality and reliability of image datasets, particularly for applications that utilize artificial intelligence (AI). Using both perceptual hashing and cryptographic hashing, this research aimed to identify and eliminate duplicate, corrupted images. Using blockchain technology, Madhu et al. [29] have designed a smart bot-enabled and e-commerce platform that relies on Internet of Things (IoT) devices to provide a more transparent and autonomous means of conducting online transactions.

The works we surveyed have all made strides in creating the building blocks for P2P energy trading by developing things like DAG alternatives (IOTA), consortium blockchains, multi-party computation/zero-knowledge proof (MPC/ZKP) privacy schemes, machine learning (ML)-based fraud detection, grid-aware bidding, and incentive/reputation models, but almost all focus on addressing only one dimension of this issue and do not create a solution that encompasses all four goals of achieving (1) at least sub-second or low-latency trading; (2) meter privacy guaranteed by cryptographic proof; (3) long-term auditability of settlement for regulators; and (4) a fraud detection system that is based on machine learning and integrated with incentives and a reputation system, etc. This creates an existing gap that is what motivates the design of our model D-BET.

## 3. PROPOSED MODEL

Hierarchical levels establish the way that components interact with each other while performing their designated tasks in the architecture of the PBET-Chain, which is made up of five layers. These five layers' purpose is to provide the P2P energy exchange, or trading, necessary to securely, autonomously, and privately trade energy between both users and providers in an open and decentralized manner. In addition, the four layers provide a modular approach for scaling, interoperability, and robustness against uncertainties resulting from their operation. The next section will explain each of the five layers in detail.

### 3.1 Architectural overview

At the bottom level of the PBET-Chain is a smart meter, which provides the means for measuring DERs such as photovoltaic systems, batteries, and controllable loads. The smart meter continuously measures and records three key criteria: 1. real-time production and consumption, 2. voltage, and 3. frequency. A cryptographic hash of the information contained in each data packet is created using SHA-3 prior to the data packet being sent to the edge device. Edge devices perform specific preprocessing functions. Examples of preprocessing functions include anomaly filtering, timing synchronization, and local aggregation. The results are passed through a communication channel to allow edge devices to interact with one another virtually instantaneously with minimal delays.

The consortium blockchain layer consists of a secure and tamper-proof ledger for all trading transactions. The validation of blocks occurs using a DPoA method. Here, a limited number of trustworthy validators, typically utility operators and community hubs, come to consensus, achieving high throughput and low levels of energy consumption. Every block contains a hashed version of smart meter data, proof of the transaction performed, a trust score, and a timestamp, providing for transparency and auditability. Links between blocks throughout the blockchain are achieved using cryptographic hashes, making it virtually impossible to manipulate energy tokens or double spend them, as it is immutable.

The smart contract execution layer allows for the automation of market operation through a collection of smart contracts. The Energy Offer Contract (EOC) allows a prosumer to register the surplus energy they have available for sale. Energy Demand Contracts (EDC) allow consumers to request energy. The Matching and Settlement Contract (MSC) automatically pairs up buyers and sellers based on price, trust score, and availability. Smart contracts allow trades to occur autonomously, without the need for a centralized intermediary, because they carry out the terms and conditions of trading. A trade can only take place when the offered price meets the purchased price and when the prosumer meets the minimum trust requirement. Contracts control how token-based micro-payments and meter validation are performed, ensuring a fair, transparent, and tamper-resistant process.

PBET-Chain has an energy market optimizer layer as the intelligence behind its price, energy routing, and trust management system, as well as combining reinforcement learning (RL), graph optimizations, and behavioral analytics to continually adjust market prices, direct energy locally via RL algorithms, and assess trustworthiness based on evaluation metrics related to participant productivity.

The PBET-Chain utilizes various forms of cryptographic protection to enhance the confidentiality of energy trade transacted by individuals. The zero-knowledge meter proofs system allows a single user/consumer to validate that their usage/generation of energy was accurately tracked, but does not require the user to reveal actual values for both meter readings. Utility providers take additional steps to protect device anonymity by producing hashed versions of their identifier when communicating with the utility provider and associating them to eliminate the risk of user profiling. All interaction between all participants on the PBET-Chain is protected by end-to-end encryption, and access to sensitive information is restricted. This combination of methods provides safeguards for the integrity of the data, protection against impersonation attacks, mitigation of meter tampering, and maintenance of confidentiality and security for the operation of the decentralized energy trading markets.

### 3.2 Mathematical model

The smart meter's layer serves as the metering and sensing backbone of the PBET-Chain and is responsible for providing an honest view of energy measurements so that trustworthy energy transactions can occur between peers. The surplus for the seller $i$ is shown in Eq. (1).

$$s_i(t) = \{0,\ g_i(t) - c_i(t) - u_i^{reserve}(t)\} \tag{1}$$

Here, $i$ denotes an index that represents an energy producer selling electricity through a P2P electricity trading network, and j denotes an index representing the consumer of electricity from the network. $t$ denotes a discrete time index. $s_i(t)$ represents the excess energy available for sale by prosumer i at time $t$, and $g_i(t)$ represents the total amount of energy that prosumer i produces at time $t$. $c_i(t)$ represents the quantity of energy consumed directly by prosumer $i$ at time $t$ and $u_i^{reserve}(t)$ refers to any quantity of energy that prosumer i has set aside for use in contingency situations or as a backup energy source. The overall balance between supply and demand in the entire system, and they ultimately have an effect on how prices, matches, and congestion management function in the PBET-Chain energy trading system as shown in Eq. (2).

$$S(t) = \sum_{i \in P_s} s_i(t), D(t) = \sum_{j \in P_b} d_j(t) \tag{2}$$

Here, $P_s$ denotes the collection of prosumers that take part in an energy exchange network. $P_b$ denotes the collection of consumers that take part in an energy exchange network. S(t) denotes and represents the total quantity of energy supplied to the energy exchange marketplace at time $t$. $d_J(t)$ represents the amount of energy requested by buyer $j$.

The blockchain provides a basis for the distributed trust found in the exchange of data and from the trading participants. Consensus latency model for fast-time ledger (FTL) settlement as shown in Eq. (3).

$$\tau_{FTL}(t) = \tau_0^{FTL} + \beta_{FTL}\, n_{tx}(t) \quad (3)$$

Here, $\tau_{FTL}(t)$ denotes an average consensus latency and $\tau_0^{FTL}$ denotes the latency of the FTL mechanism when no transactions are present, capturing fixed overhead such as block proposal and validation delays. $\beta_{FTL}$ denotes scaling coefficient that represents the incremental latency added per transaction processed under FTL settlement. And $n_{tx}(t)$ denotes the number of individual energy trading transactions submitted for settlement at a time. The consensus latency model for slow aggregated ledger (SAL) settlement is computed in Eq. (4).

$$\tau_{SAL}(t) = \tau_0^{SAL} + \beta_{SAL}\, n_{batch}(t) \quad (4)$$

Here, $\tau_{SAL(t)}$ denotes average consensus latency for the SAL settlement on time t, used for processing groups of transactions. $\tau_0^{SAL}$ denotes the baseline ACL latency associated with SAL settlement, which includes the latencies associated with batching, aggregating, and delayed confirmations. $\beta_{SAL}$ denotes the ACL Latency Scaling Factor (LSF) for SAL settlement based on the impact that the size of the transaction batch has on the ACL of the settlement. And $n_{batch(t)}$ denotes the total number of transaction batches that were processed in the SAL ledger on time t. The transaction cost model is given as shown in Eq. (5).

$$C_{tx}(t) = c_{FTL}\, n_{tx}^{FTL}(t) + c_{SAL}\, n_{tx}^{SAL}(t) \quad (5)$$

Here, $C_{tx}$ denotes the transaction processing cost incurred by the blockchain network at time T, $c_{FTL}$ denotes the unit cost to process one transaction in the FTL method, $c_{SAL}$ denotes the unit cost to process one transaction in the SAL method, $n_{tx}^{FTL}$ denotes the number of all transactions recorded on the FTL's ledger as of Time T, $n_{tx}^{SAL}$ denotes the number of all transactions recorded on the SAL's ledger as of time T. A latency penalty may be included in the system objective as shown in Eq. (6).

$$J_{lat}(t) = \lambda \cdot \tau_{FTL}(t) \quad (6)$$

Here, $J_{lat(t)}$ denotes the latency penalty incorporated into the total system objective function of the system as of time t. λ represents a weighting factor signifying the magnitude by which minimizing latency is relative to the importance of other optimization objectives like cost, trust, or energy usage.

Energy matching variables are represented as energy traded from seller i to buyer j. Multi-objective matching optimization with the scalarized objective function is given as Eq. (7).

$$J(t)_{\,x_{ij}(t)} = \sum_{i,j} (\alpha p_{ij}(t) + \beta l_{ij} - \gamma \rho_i(t)) x_{ij}(t) + n_{trades} C_{tx} \quad (7)$$

Here, the objective combines three competing goals: minimizing the total payment made by buyers, reducing network-related energy losses, and maximizing trust in the trading process. The weighting coefficients $\alpha$, $\beta$, and $\gamma$ allow system operators to tune the relative importance of economic efficiency, physical network performance, and participant trustworthiness. The term $n_{trades}C_{tx}$ accounts for blockchain transaction overhead, encouraging efficient batching and reduced ledger load. The first supply constraint is represented as Eq. (8).

$$\sum_j x_{ij}(t) \le s_i(t), \forall i \in P_s \quad (8)$$

Here, $P_s$ denotes all prosumers in the marketplace, $x_{ij}(t)$ denotes the volume of electricity sold by prosumer i to consumer j at time t, and $s_i(t)$ denotes Surplus electricity of prosumer i available at time t. Demand constraint is shown in Eq. (9).

$$\sum_i x_{ij}(t) \le d_j(t), \forall j \in P_b \quad (9)$$

Here, $P_b$ denoted as all consumers in the marketplace, $d_j(t)$ denotes the demand for electricity requested by consumer j at time t. The transmission capacity must be as Eq. (10).

$$x_{ij}(t) \le T_{ij} \quad (10)$$

Here, $T_{ij}$ denoted as the maximum amount of electricity that can be transferred from prosumer i to consumer j due to limitations of the electrical power distribution network. ZKP enforcement must be as shown in Eq. (11).

$$x_{ij}(t) \le M \cdot \epsilon_{ZK,i}(t) \quad (11)$$

Here, $\epsilon_{(ZK,i)}(t)$ indicates whether a zero-knowledge proof has been validated at time t for seller i. M denotes a value intended to restrict energy trades through a ZKP-based methodology using a big-M approach. The budget constraint is considered as Eq. (12).

$$\sum_i p_{ij}(t) x_{ij}(t) \le B_j(t) \quad (12)$$

Here, $B_j(t)$ refers to the largest potential monetary amount that buyer j has access to when acquiring energy at time t. It $p_{ij}(t)$ denotes the price (in dollars) of electricity prosumer i sells to consumer j at time t. This formulation results in a linear program (LP) or mixed-integer LP (MILP). As the next layer benefits from continual reinforcement learning (RL-based) and ongoing graph optimizations, it maintains market stability by curbing volatility and increasing fairness; it also removes the potential for fraudulent activity. The trust update rule is shown in Eq. (13).

$$\rho_i(t+1) = clip\,(\rho_i(t) + \eta \Delta\rho_i(t),\ 0,\ 1) \quad (13)$$

Here, $\rho_i(t)$ is the trust or reputation score of seller i at time t. This score will be between 0 and 1. $\rho_i(t+1)$ is the updated trust score for seller i, at a future time slot. $clip(\cdot, 0,1)$ is a bounding function that limits the trust score to be between 0 and 1. η is the trust learning rate that controls the responsiveness of trust updates due to seller actions. $\Delta\rho_i(t)$ is the incremental increase or decrease in trust for seller i, based on actions taken by seller i, at time t.

$$\Delta\rho_i(t) = w_1 1_{ontime} + w_2 \epsilon_{ZK,i}(t) - w_3 1_{anomaly} \quad (14)$$

Here , $w_1, w_2, and\ w_3$ are weighting parameters used to denote how much weighting to give to positive and negative seller actions. $1_{ontime}$ is the indicator function and is 1 if the seller delivered and settled the energy on time and 0 if they did not. $\epsilon_{(ZK,i)}(t)$ is an indicator function that is the outcome of zero-knowledge proof validation for seller i at time t. $1_{anomaly}$ is the indicator function and is 1 if there is an anomalous or fraudulent action detected from seller i and 0 otherwise. $m_i(t)$ is the actual meter reading (metered consumption or generated) of seller i at time t. The smart meter records the reading and generates a random nonce; a cryptographic commitment is computed using Eq. (15).

$$h_i(t) = H(m_i(t) \parallel r_i(t)) \quad (15)$$

Here, Hash( · ) denotes the cryptographic hash function SHA-3, used so that no two data sets can produce the same hash value. $h_{i(t)}$ denotes the hashed commitment of the meter reading broadcast to the blockchain. R denotes the range of valid meter readings, defined by the system or regulatory authorities. The seller improves in zero knowledge without revealing $m_i(t)$ as shown in Eq. (16).

$$m_i(t) \in RandH(m_i(t) \parallel r_i(t)) = h_i(t) \quad (16)$$

This is implemented using a range-proof ZKP protocol as shown in Eq. (17).

$$\pi_i(t) = ZKProve(m_i(t), r_i(t), h_i(t)) \quad (17)$$

Then the blockchain validators check the committed reading and approve using Eq. (18).

$$Verify(\pi_i(t), h_i(t)) \rightarrow \epsilon_{ZK,i}(t) \in \{0,1\} \quad (18)$$

Here, $\epsilon_{ZK,i}(t)$ zero shows the proof rejected, and $\epsilon_{ZK,i}(t)$ one shows the proof accepted. The result is stored on-chain and used in the trust update model. The dynamic pricing model is given as Eq. (19).

$$p_{ij}(t) = p^{base}(t) + \kappa\, Cong_{ij}(t) - \delta\, \rho_i(t) + \phi\left(\frac{D(t) - S(t)}{S(t) + \varepsilon}\right) \quad (19)$$

Here, $p^{base}$ denote the base price, $\kappa$ denote the congestion price scaling coefficient, $\delta$ denote the trust-based price adjustment coefficient, and $\phi$ denote the surge pricing sensitivity coefficient. S(t) is the total energy supply in the market, $\varepsilon$ let the small constant, and D(t) is the total energy demand in the market. The reinforcement learning reward is computed using the various factors as shown in Eq. (20).

$$R(t) = \omega_1 UG(t) - \omega_2 APV(t) + \omega_3 NR(t) - \omega_4 VP(t) \quad (20)$$

Here, $\omega_1, \omega_2, \omega_3, \omega_4$ denotes the weighing coefficients balancing the objectives, $UG(t)$ denotes the ratio of successfully traded energy, APV(t) denotes the average deviation of prices from the mean price across buyers, $NR(t)$ denotes the net economic revenue generated by the market over time. $VP(t)$ denotes the penalty term for constraint violations, instability, and unfair behavior. The RL agent's maximums are given as Eq. (21).

$$\sum_t \gamma^t R(t) \quad (21)$$

Here, $\gamma$ denotes the discount factor, R(t) is the immediate reward received by the RL agent. The fairness penalty is the quadratic penalty measuring unmet demand to promote the energy distribution, computed using Eq. (22).

$$FPen(t) = \zeta \sum_j \left(\left(0, d_j(t) - \sum_i x_{ij}(t)\right)\right)^2 \quad (22)$$

Here, $\zeta$ denotes the fairness weighting coefficient, $d_j(t)$ denotes an energy demand requested by the buyer, and denotes an energy allocated from the seller to the buyer.

The framework of PBET-Chain uses mathematical formulations to develop models to support decentralized P2P energy trading, blockchain-based settlement, estimation of trust, and price optimization. As part of the PBET-Chain architecture, this section outlines the symbols used to illustrate the PBET-Chain equations that govern the behavior of energy price flows through the network, how transactions are verified on the blockchain, and how the PBET-Chain determines what will be sold by the seller to buyers in the market. The PBET-Chain framework for trading distributed energy incorporates all elements necessary for providing a secure, efficient, and accountable marketplace for users and buyers to exchange energy. Each of the five functional layers supports and integrates with the others. Smart meters provide accurate data; the blockchain establishes secure transactions; the smart contract enables automated trades; the AI-driven optimizer improves trading efficiency; and the privacy & security components maintain confidentiality and safeguard the integrity of the marketplace. PBET-Chain is built on the foundation of being able to grow, evolve, and achieve maximum transparency while supporting a decentralized P2P trading experience for all users.

## 4. RESULTS

The proposed PBET-Chain framework experimentation is conducted by utilizing a hybrid simulation environment consisting of a power system model, a blockchain infrastructure, and a set of intelligent pricing mechanisms. In order to provide a full picture of all aspects of system operation, scalability, and security overhead associated with the various supply-demand conditions, we designed our experiment to replicate realistic scenarios for decentralized energy trading by creating a community microgrid with the following characteristics:

We developed a microgrid that was structured to accommodate 50 prosumers and 60 consumers in the microgrid. All prosumers had rooftop photovoltaic generation units as well as optional battery storage units in terms of electrical loads. Consumers were represented as residential loads that exhibited dynamic consumption behavior. Our electric network configuration followed a modified version of the IEEE 34 Bus Test Feeder configuration to accurately simulate realistic power flow constraints and localized congestion effects. Additionally, the generation capacity of each of the generation units represented in the microgrid ranged from 1KW to 5KW. And while the consumption patterns of the consumer nodes have a strong temporal component, their respective consumption profiles can vary dramatically. Particularly due to stochastic demand fluctuations caused by peak and off-peak conditions.

The consortium blockchain network uses a Delegated Proof-of-Authority to facilitate decentralized transaction management. This platform consists of five validator nodes that maintain both the ledger and validate blocks on behalf of each trusted community representative, such as utility companies and neighborhood energy groups. To store information associated with energy offers, demand registrations, trade matching, and settlements, smart contracts were created on the blockchain. Every smart-metered building submits hourly hashed readings generated using the SHA-3 algorithm to secure the integrity of each meter reading before it is entered into the blockchain.

Pricing and matching intelligence of PBET-Chain were built upon a dynamic pricing agent using reinforcement-learning techniques. This agent continuously analyzed current market conditions such as supply vs. demand, intensity of depreciation, and prior transaction history to reprice energy according to maximizing the efficiency and maximizing the utility of the prosumer. The agent went through a series of training simulations to achieve a convergence of agent simulations for stable pricing policies/price convergence. A trust assessment module operated concurrently, creating trust levels for each prosumer per successful transaction percentage, meter accuracy, and behavioral consistency.

The experimental conditions for the current research utilized three sets of data: Pecan Street data for actual home energy use and solar power production. Standard profiles for residential and commercial customers. A demand simulation model that created the system stress tests through artificially high demand peaks. To prevent any loss of privacy or security during these experiments, a zero-knowledge proof was utilized to verify energy consumption readings without actually revealing what the amount was. Also, all data exchanged between participants was secured through encryption. In addition, in order to evaluate the model's performance, the simulated trading period for each experiment was a full 24 hours long and was repeated several times to ensure statistical reliability. For each experiment, the following metrics were evaluated: Blockchain throughput, price stability, trustworthiness, accuracy of energy utilization, efficiency in market transactions, trading speed, and level of security overhead. All of this data allowed for a better understanding of how well the prorl-based.

Figure 1 provides an extensive comparison of the market. Efficiency of the proposed PBET-Chain framework with that of three other current P2P energy trading models. This includes examining various types of metrics: market efficiency, energy utilization, transaction latency, blockchain throughput, smart contract execution time, pricing stability, and trust accuracy. The results show that PBET-Chain has the highest performance on all of these metrics compared to existing P2P energy trading models. For example, PBET-Chain's market efficiency score was 92.4%, which was considerably higher than the baseline P2P blockchain model [30] (74.2%), A-reinforcement learning (RL)-based trading model [31] (82.4%), and smart contract exchange models [32] (85.7%). This demonstrates the benefits of combining reinforcement-learning-based dynamic pricing and trust-aware matching strategies; together, these improve supply-demand balance and reduce energy mismatches between buyers and sellers.

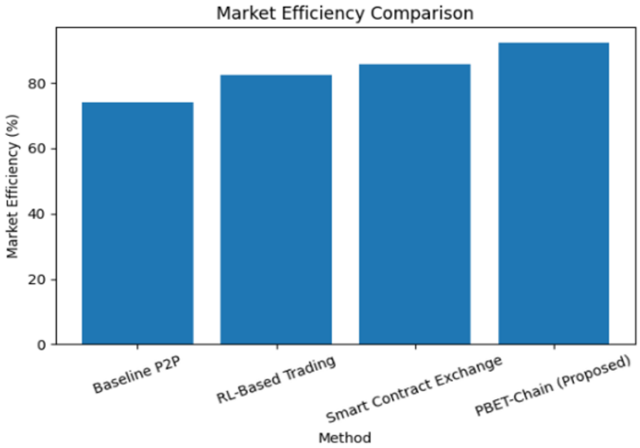


**Figure 1.** Market efficiency comparison of Privacy-preserving Blockchain-enabled Energy Trading Chain (PBET-Chain)

To ensure replicability, an experimental evaluation was performed utilizing a modified IEEE 34-Bus distribution feeder. The addition of residential loads was made based on supporting P2P trading participants by extending the use of 50 buses as prosumers through the inclusion of distributed solar photovoltaics (PV) and smart meters, and the remaining 60 buses were modeled as consumers with no load added. To validate the original benchmark, the feeder configuration and parameters were preserved. PBET-Chain smart contracts were implemented on a private, permissioned, Ethereum-compatible blockchain utilizing Proof-of-Authority consensus, with a reported execution time of 56 ms being the time taken to process the smart contracts and to confirm each transaction locally within this environment. For market optimization, a reinforcement learning-based agent was used for the state space to consider aggregate supply/demand, trust scores, congestion indicators, and recent price signals. The agent controlled pricing adjustments, settlement selection, and threshold for accepting trades as its action space. The reward function was developed to incorporate the gain from utilization, the increase in revenue, stability of price, and penalties for violating constraints in order for the agent to learn efficient and stable policies for trading.

PBET-Chain also achieved a significant increase in energy utilization (88.7%), thus allowing for more of the locally generated renewable energy to be traded within the microgrid and thereby reducing waste and reliance on centralized grids. Additionally, the proposed research achieved a low average trading latency of 0.41 sec, allowing for near-real-time energy transactions as opposed to existing models that exhibit longer trade delays. PBET-Chain provides a very high level of scalability in terms of the performance of the blockchain with a maximum throughput of 142 TPS and a smart contract execution speed of just 56.0 ms. Improving this scalability was achieved through the adoption of Delegated Proof-of-Authority as the preferred consensus mechanism for accurate and timely validation of transactions coupled with the implementation of optimized contract logic. PBET-Chain also has the lowest level of price volatility measured by the price stability index, allowing energy to be offered at a predictable and fair price. The Trusted Engine also helps to improve the reliability of the PBET-Chain system through its achieved trust accuracy of 94.8%. The Trusted Engine can therefore reduce instances of fraud and/or failure of transaction validation.

**Table 1.** Economic impact analysis

| Parameter | Without PBET-Chain | With PBET-Chain |
|---|---|---|
| Average Consumer Energy Cost Reduction (%) | – | 16.7 |
| Average Prosumer Revenue Increase (%) | – | 22.4 |
| Unsold Surplus Energy (%) | 21.5 | 7.6 |
| Price Volatility | High | Low |

Note: PBET-Chain: Privacy-preserving Blockchain-enabled Energy Trading Chain.

Table 1 displays the economic impact of implementing the PBET-Chain framework by comparing the results from energy trading before implementing PBET-Chain and the results after implementing PBET-Chain. The results demonstrate the extent to which the PBET Chain has improved the economic efficiency for both consumers and prosumers of the decentralized energy market. Prior to PBET Chain's launch, many consumers had no way to take advantage of the lower cost of electricity because they were limited to fixed-rate pricing and could only use their locally supplied electricity. Since implementing PBET Chain, consumers have experienced a 16.7% decrease in their average energy expenditure. The majority of this savings can be attributed to the use of dynamic reinforcement learning-based pricing, which created opportunities for local P2P energy transactions, thereby decreasing the need to purchase electricity from the external power grid.

Prosumers have also benefited from the increased efficiency of their surplus electricity trades, seeing a 22.4% increase in the revenue generated from their surplus energy sales. This increase in revenue has been attributed to the application of trust-enabling smart contracts and adaptive pricing models. The implementation of PBET-Chain has created a new opportunity for distributed renewable energy producers to become more involved in the market as a driving force towards increased development of sustainable energy production systems. Along with this incentive, the amount of surplus energy that is not sold has decreased significantly since the implementation of this new system, i.e., from 21.5% to 7.6%. This remarkable drop in the level of unsold surplus energy suggests that there is now a much greater degree of use of the energy created from the source. It demonstrates the capability of this system to create an optimized balance between supply and demand by greatly reducing the level of renewable energy that is not used. Overall results from these types of economic analysis provide evidence of the fact that PBET-Chain is a win-win situation for both consumers, since consumers would be able to purchase the same amount of energy at a lower cost through this type of system, and prosumers would be able to sell their excess energy for greater financial benefit than they were previously able to achieve.

The PBET-Chain performance has been compared against other security and blockchain technologies; Table 2 illustrates this comparison. The comparison indicates that the PBET-Chain was able to provide real-time P2P energy trading due to the use of DPoA for fast block confirmation (0.41 seconds) and minimal power consumption. Therefore, a fast block confirmation time and low latency are vital in executing timely energy transactions in a microgrid application. The computational overhead of performing cryptographic operations using SHA-3 hashing for the meter record on average per record is only 1.8 milliseconds. Furthermore, the average time to generate a zero-knowledge proof is 5.4 milliseconds. With these average times, a secure and private system has the ability to offer the same level of service as less secure systems. The PBET-Chain demonstrated a 100% success rate in its ability to detect tampering; there was no indication that personal information related to a customer's generation or consumption was disclosed during trading.

**Table 2.** Blockchain and security performance

| Security / Blockchain Metric | Observed Value |
|---|---|
| Consensus Mechanism | DPoA |
| Block Validation Time (s) | 0.41 |
| Hash Computation Overhead (ms) | 1.8 |
| Zero-Knowledge Proof Time (ms) | 5.4 |
| Tamper Detection Accuracy (%) | 100 |
| Privacy Leakage | None Detected |

The assessment of the performance of the integrated trust engine of the PBET-Chain Framework is outlined in Table 3. A 96.1% success ratio demonstrates that most initiated trades were executed successfully without disputes or failures. Thus, the trust-aware participant selection method demonstrates the reliability of trust-based participant selection. This high success ratio confirms the effectiveness of including historical trade performances and meter verification accuracies into the trust calculation process. A 94.8% trust accuracy confirms that the proposed trust engine's model effectively identifies trustworthy prosumers, thus decreasing the risk of unfair/untrustworthy participants affecting the market.

**Table 3.** Trust engine evaluation

| Trust Metric | Value |
|---|---|
| Successful Trade Ratio (%) | 96.1 |
| False Trust Assignment (%) | 3.1 |
| Fairness Improvement over Random Matching (%) | 17.0 |
| Reliable Prosumer Identification Accuracy (%) | 94.8 |

Table 3 further indicate a 17% improvement in fairness in relation to random matching approaches, signifying that trust-based participant selection produces an equitable allocation of energy in the P2P trading environment. It is particularly important to improve on fairness because there is a high level of competition in P2P markets where numerous suppliers compete for the same limited level of demand. The very low false allocation ratio of 3.1% indicates that there are very few cases where untrustworthy suppliers were elevated to a trusted status. This proves that the measures we are using to assess the trust level of all participants in these networks are highly effective. Therefore, all of our findings indicate that the trust engine that we have proposed will greatly enhance transaction reliability, fairness, and trust in the P2P market and in a decentralized marketing model.

## 5. CONCLUSION

PBET-Chain is an innovative framework built on a blockchain to facilitate P2P energy trading. It uses reinforcement learning to develop dynamic pricing structures, find trusted traders, and verify electricity usage. Experimental testing of PBET-Chain on a modified IEEE 34 bus microgrid. It indicates PBET-Chain's dual-layer blockchain architecture and intelligent market coordination enable significant improvements in efficiency and economic performance. The findings of this study show that PBET-Chain achieved 92.4% market efficiency and 88.7% renewable energy use efficiency, outperforming traditional blockchain and RL-based trading methodologies. The DPoA used in PBET-Chain ensures low latency time for processing transactions, supports high transaction throughput, and facilitates fast contract execution. This allows for near-real-time transaction processing in the decentralized energy trading market. The use of RL-driven pricing agents has demonstrated that PBET-Chain's pricing structure is stable while enabling an increase in supply and demand proximity and that the use of an integrated trust engine increased the reliability of prosumer identification by 94.8%, thus reducing fraudulent participation and increasing fairness by 17% when compared to random matching methods.

The continued development will include research into resilience to adversarial attacks as well as future development opportunities related to predictive analysis and anomaly detection using enhanced machine learning models. Energy is being traded and exchanged between microgrids. There is potential for microgrids to work together by connecting through an integrated energy network that can be connected to a national marketplace. Also allowing the application of privacy-preserving federated learning techniques to assist with decentralized pricing intelligence. Future research will enable PBET-Chain to be developed from a successful high-quality research prototype into a comprehensive, market-ready solution for decentralized energy distribution.

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## NOMENCLATURE

| Symbol | Meaning |
|---|---|
| $i, j$ | Seller and buyer indices |
| $t$ | Discrete trading time slot |
| $g_i(t)$ | Energy generated by seller $i$ |
| $c_i(t)$ | Local consumption of seller $i$ |
| $u_i^{reserve}(t)$ | Reserved backup energy |
| $s_i(t)$ | Seller surplus energy available for trading |
| $d_j(t)$ | Demand requested by buyer $j$ |
| $S(t)$ | Total available supply in the network |
| $D(t)$ | Total demand in the network |
| $x_{ij}(t)$ | Energy traded from seller $i$to buyer $j$ |
| $p_{ij}(t)$ | Unit trading price |
| $l_{ij}$ | Transmission loss coefficient |
| $\rho_i(t)$ | Trust score of seller $i$ |
| $T_{ij}$ | Transmission capacity limit |
| $B_j(t)$ | Buyer budget |
| $C_{tx}$ | Blockchain transaction cost |
| $n_{trades}$ | Number of executed trades |
| $\epsilon_{ZK,i}(t)$ | ZKP verification indicator |
| $\kappa, \delta, \phi$ | Pricing adjustment parameters |
| $\eta$ | Trust learning rate |
| $w_1, w_2, w_3$ | Trust update weights |
| $\lambda$ | Latency penalty coefficient |
| $\gamma$ | RL discount factor |
| $\omega_1 .. \omega_4$ | RL reward weights |
| $\zeta$ | Fairness penalty weight |