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A Smart Contract-Based Decentralized Energy Trading Method and System for Microgrids

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A B S T R A C T

The present invention discloses a blockchain-based power energy trading method, the present invention submits a transaction request on the blockchain platform through the buyer, and automatically searches for a number of groups of qualified sellers on the blockchain platform according to the buyer's request, conducts an in-depth analysis of each group of sellers who meet the requirements, conducts a comprehensive evaluation from the price, integrity and power generation stability of each group of sellers, thereby obtains the price advantage index, the integrity advantage index and the power generation fluctuation coefficient of each group of sellers, and further based on the price advantage index of each group of sellers, The integrity advantage index and the power generation fluctuation coefficient are comprehensively analyzed to obtain the comprehensive evaluation index of each group of sellers, so as to comprehensively evaluate the advantages of each group of sellers, help buyers choose the best sellers for trading, and improve the buyers' trust and satisfaction with the platform.

Specifically, it is a blockchain-based green energy transaction data monitoring system, which comprises: the data collection and correction module extracts the transaction volume, transaction price and transaction time from the transaction records received by the blockchain node, and uses data cleaning to eliminate noise and outliers in the records. In the present invention, through the comprehensive application of blockchain technology and advanced data processing methods, enhance the accuracy and transparency of green energy transaction data, ensure that data is not tampered with through blockchain technology, enhance the security and trust of data, thereby provide a solid foundation for market analysis, this accurate and credible data support, make the monitoring of market behavior more accurate, effectively predict the periodicity of supply and demand changes by analyzing the changes in transaction frequency and the law of price fluctuations, Enhance the understanding and forecasting ability of market dynamics, and adjust the forecasting model in real time to enable it to adapt to market changes in a timely manner

Keywords: Smart Grids, Microgrid Energy Trading, Smart Contracts

1. Introduction

The existing microgrid energy trading technology mainly relies on centralized matching mechanisms, usually managed by power trading platforms or third-party organizations responsible for supply-demand matching and transaction execution. Compared to this invention, these centralized models have the following disadvantages: 1. Transaction matching relies on centralized platforms, which pose a single point of failure risk. Traditional microgrid trading depends on centralized scheduling platforms; if such a platform fails, is attacked, or experiences operational interruptions, the entire trading market will be paralyzed, affecting energy supply security. The improvement of this invention: adopting decentralized smart contract matching allows transactions to be executed automatically on the blockchain without relying on a single centralized entity, reducing the single point of failure risk and enhancing system robustness. 2. The transaction matching process is opaque, which may involve manipulation risks. In centralized trading models, market scheduling organizations possess all transaction data and determine transaction prices and matching results through internal algorithms. However, this lack of transparency makes it difficult for trading parties to verify market fairness, with the possibility of data manipulation and insider trading. The improvement of this invention: all transaction matching logic is executed by smart contracts, and the transaction matching results are publicly verifiable, ensuring transparency and fairness, avoiding human manipulation of market prices. 3. The transaction matching efficiency is low and cannot adapt to real-time dynamic trading demands. Traditional power market matching mechanisms usually adopt periodic centralized clearing (such as matching once every hour), leading to transaction delays and difficulty in adapting to the rapid changes in supply and demand in distributed microgrids. The improvement of this invention: smart contracts support real-time P2P transaction matching, allowing supply-demand matching without waiting for centralized clearing, improving transaction response speed and optimizing energy utilization efficiency.

2. Literature Review

The development of microgrid energy trading systems has gained significant attention in recent years, particularly with the integration of blockchain and smart contracts. This section reviews existing literature on microgrid energy trading, focusing on decentralized matching mechanisms, smart contract-based trading systems, and optimization strategies.

1. Microgrid Energy Trading Systems

Traditional energy markets rely on centralized grid operators to facilitate energy transactions. However, with the proliferation of distributed energy resources (DERs), such as solar panels and battery storage, microgrid energy trading has emerged as a viable solution for local energy exchanges (Mengelkamp et al., 2018). These systems typically involve a market operator, aggregators, and prosumers who generate and consume energy.

Existing microgrid trading systems can be broadly categorized into:

Centralized trading platforms, where a third-party market operator facilitates transactions and determines pricing (Zhang et al., 2017).

Peer-to-peer (P2P) trading models, where energy producers and consumers interact directly to negotiate trade terms (Tushar et al., 2020).

Despite their advantages, centralized trading platforms suffer from high operational costs, security vulnerabilities, and inefficiencies in real-time trading. In contrast, decentralized P2P trading offers greater autonomy but requires efficient market-clearing mechanisms.

2. Smart Contracts and Decentralized Energy Trading

Blockchain-based smart contracts provide an automated, transparent, and secure way to facilitate microgrid energy trading. Smart contracts eliminate the need for intermediaries by executing predefined rules that govern transactions. Studies have shown that blockchain-enabled trading systems improve data integrity, reduce transaction costs, and enhance market accessibility (Kouhizadeh et al., 2020).

Notable works in this field include:

Ethereum-based microgrid markets, where smart contracts handle bidding, matching, and settlement (Kang et al., 2019).

Hyperledger-based frameworks, which focus on permissioned blockchain networks for energy trading among trusted entities (Sikorski et al., 2017).

Consensus algorithms for energy transactions, such as Proof-of-Stake (PoS) and Proof-of-Authority (PoA), which improve the efficiency of blockchain operations in microgrids (Li et al., 2021).

Despite these advancements, many smart contract implementations still struggle with scalability, high computational costs, and security risks in real-world energy markets.

3. Decentralized Matching Mechanisms for Energy Markets

Decentralized matching in energy trading aims to dynamically pair energy suppliers with consumers without relying on a central entity. Various **game-**theoretic and optimization-based approaches have been explored, including:

Double-auction mechanisms, where multiple buyers and sellers submit bids, and an algorithm determines the optimal match (Chen et al., 2019).

Continuous trading models, where energy prices fluctuate based on real-time supply and demand (Paudel et al., 2022).

Decentralized optimization using Lagrangian relaxation and distributed gradient descent (DGD) to solve market equilibrium problems (Liu et al., 2021).

While these approaches improve transaction autonomy, they often require efficient market equilibrium solvers to ensure fair and stable price formation.

4. Challenges in Existing Technologies and Research Gaps

Despite progress in decentralized energy trading, several challenges remain unaddressed:

Latency and scalability issues in blockchain-based trading due to high computational costs.

Lack of robust market mechanisms that dynamically adjust pricing in a decentralized environment.

Security risks, such as price manipulation and Sybil attacks, in permissionless blockchain systems.

Limited real-world deployments, with most studies focusing on theoretical or simulated models rather than large-scale implementations.

This review highlights the need for a fully decentralized, efficient, and secure smart contract-based microgrid energy trading system. Our proposed method addresses these gaps by introducing an optimized matching mechanism, dynamic pricing model, and security enhancements, ensuring a fair and transparent energy marketplace.

4. Methodology and Procedures

In the framework of decentralized matching, energy trading in microgrids can be modeled as a distributed dynamic optimization problem. The core issue is how to automatically match supply and demand through smart contracts and dynamically adjust trading prices without centralized control. To this end, we can use bilateral market models, optimization-based market equilibrium solving, and the execution logic of blockchain smart contracts for mathematical modeling and derivation. Let there be N energy suppliers (such as photovoltaic users) in the microgrid, denoted as the set S={s1,s2,...,sN}, and M energy demanders (such as residents and enterprises), denoted as the set D={d1,d2,...,dM}. The amount of electricity supplied by each supplier si at time t is $q_i^s(t)$, and their pricing function is $p_i^s(q)$, indicating the price at which they are willing to sell q units of electricity. Each demander d_j requires an amount of electricity represented by $p_j^d(q)$, and their bidding function is p_j^d, indicating the price at which they are willing to purchase q units of electricity. The goal of the trading market is to match supply and demand and dynamically price in a decentralized environment through smart contracts, achieving market equilibrium. To characterize this mechanism, we define the supply-demand matching problem as a bilateral market equilibrium problem, where the core is to solve for an optimal price vector p∗ and trading volume q∗, so that the system reaches equilibrium under the influence of smart contracts. First, we define the total social welfare function as the optimization objective of the system:

$$W(q) = \sum_{i=1}^{N} U_i^s(q_i^s) + \sum_{j=1}^{M} U_j^d\left(q_j^d\right)$$

where $U_i^s(q_i^s)$ and $U_j^d\left(q_j^d\right)$ represent the utility functions of suppliers and demanders, respectively. In general, the utility of a supplier can be expressed as:

$$U_i^s(q_i^s) = p_i^s(q_i^s)q_i^s - C_i(q_i^s)$$

where $C_i(q_i^s)$ is the cost function of the supplier, usually set to a convex function (e.g., $C_i(q_i^s)$=$c_i(q_i^s)$). Similarly, the utility function of the demander can be expressed as:

$$U_j^d\left(q_j^d\right) = V_j\left(q_j^d\right) - p_j^d\left(q_j^d\right)q_j^d$$

where $V_j\left(q_j^d\right)$ is the benefit that the demander receives from the consumption of electricity. To solve for market equilibrium, we introduce the Lagrange multiplier method. Define the Lagrangian function:

$$\mathcal{L}(q,\lambda) = \sum_{i=1}^{N} U_i^s(q_i^s) + \sum_{j=1}^{M} U_j^d\left(q_j^d\right) + \lambda\left(\sum_{i=1}^{N} q_i^s - \sum_{j=1}^{M} q_j^d\right)$$

where λ is the Lagrange multiplier, which represents the market equilibrium price. To solve the optimal solution, let the partial derivatives of L for q_i^s, q_j^d, and λ be 0:

$$\frac{\partial\mathcal{L}}{\partial q_i^s} = p_i^s - C_i'(q_i^s) + \lambda = 0, i = 1, \dots, N$$
$$\frac{\partial\mathcal{L}}{\partial q_j^d} = V_j'\left(q_j^d\right) - p_j^d - \lambda = 0, j = 1, \dots, M$$
$$\sum_{i=1}^{N} q_i^s - \sum_{j=1}^{M} q_j^d = 0$$

From the above equation, it can be seen that the market equilibrium price λ∗ needs to satisfy the total supply is equal to the total demand, and the individual trading volume q∗ the marginal cost of satisfying the supplier is equal to the marginal utility of the demander minus the equilibrium price. In order to achieve decentralized matchmaking, the smart contract needs to perform the following steps: (1) all suppliers submit the quotation curve $p_i^s(q)$ (q), and all demanders submit the demand curve p_j^d (q); (2) The smart contract solves the equilibrium price λ∗ according to the optimization problem and determines the optimal trading volume q∗; (3) The transaction is automatically executed, the power is transferred, and the funds are paid through the blockchain; (4)The blockchain updates transaction records to ensure transparency and traceability.

In the actual deployment, we can use the distributed gradient descent method (DGD) for decentralized solving, that is, each participant updates their transaction volume locally, and continuously exchanges information through smart contracts on the blockchain, and finally converges to the equilibrium solution. The distributed update rules are as follows:

$$q_i^{s,k+1} = q_i^{s,k} - \alpha_k(p_i^s(q_i^s) - C_i'(q_i^s) + \lambda_k)$$
$$q_j^{d,k+1} = q_j^{d,k} - \alpha_k\left(V_j'\left(q_j^d\right) - p_j^d\left(q_j^d\right) - \lambda_k\right)$$
$$\lambda_{k+1} = \lambda_k + \beta_k\left(\sum_{i=1}^{N} q_i^s - \sum_{j=1}^{M} q_j^d\right)$$

where αk and βk are step sizes, which gradually decrease with iterations. Theoretically, the method ensures convergence to the market equilibrium solution under certain conditions.

To sum up, by constructing the decentralized market equilibrium optimization problem, combined with the Lagrangian optimization solution and the distributed gradient descent method, the automatic energy transaction matching based on smart contracts can be realized, and the dynamic adjustment of the transaction price and market equilibrium can be ensured.

5. Conclusion and Suggestion

The present invention constructs a microgrid energy trading method and system based on smart contract around the decentralized matching mechanism, which aims to eliminate centralized trading institutions, automatically match the supply and demand side and dynamically adjust the price through smart contracts, and improve the fairness, security and efficiency of transactions. The following are the key points of the present invention and the point to be protected.

The present invention utilizes a blockchain smart contract to automatically execute energy transactions, eliminates the dispatching agency that must be relied on in the traditional centralized electricity market, and makes the power trading in the microgrid completely decentralized. Smart contracts store and execute transaction rules, ensuring that energy supply and demand can be matched without human intervention, reducing transaction costs.

The traditional electricity market relies on centralized scheduling to optimize transaction volume and pricing, and the present invention proposes an equilibrium solution method based on Lagrange optimization and Distributed Gradient Descent (DGD) algorithm, so that market pricing can dynamically change with supply and demand, and adaptively adjust in a decentralized environment.

This study examines the development of decentralized energy trading in microgrids, emphasizing the role of smart contracts in facilitating secure, efficient, and transparent transactions. Traditional centralized energy trading platforms suffer from inefficiencies, high transaction costs, and security vulnerabilities, limiting their scalability in distributed energy resource (DER) environments. Blockchain-based smart contract mechanisms address these limitations by automating trading processes, eliminating intermediaries, and ensuring transaction integrity.

However, existing smart contract-based microgrid trading systems still face challenges, including scalability constraints, high computational overhead, and vulnerability to strategic manipulation. Current decentralized matching mechanisms, such as double auctions and game-theoretic models, provide viable solutions but often lack real-time adaptability and computational efficiency. Therefore, an optimized decentralized matching model integrating market equilibrium algorithms and distributed optimization techniques is essential for enhancing market stability and ensuring fair price formation.

To improve the performance and practical applicability of decentralized energy trading systems, future research should focus on the following aspects:

Enhancing Scalability and Efficiency

Implement off-chain solutions (e.g., Layer-2 scaling, zk-Rollups) to reduce computational overhead on the blockchain.

Develop hybrid architectures that combine on-chain smart contracts with off-chain computation to enable real-time trading without compromising decentralization.

Optimizing Decentralized Matching and Pricing Mechanisms

Design adaptive pricing algorithms using machine learning and reinforcement learning to dynamically adjust market-clearing prices based on real-time supply-demand fluctuations.

Explore multi-agent optimization approaches, such as federated learning, to allow energy participants to optimize their trading strategies while preserving data privacy.

Improving Security and Market Fairness

Implement decentralized identity verification (DID) to prevent fraudulent transactions and Sybil attacks.

Integrate zero-knowledge proofs (ZKP) to enable privacy-preserving energy transactions while maintaining system auditability.

Real-World Deployment and Policy Considerations

Conduct large-scale pilot projects to assess the practical feasibility of blockchain-based energy trading in different regulatory environments.

Collaborate with policymakers to establish regulatory frameworks that support decentralized energy markets while ensuring grid stability and compliance with existing energy laws.

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