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A Blockchain-Driven Stackelberg Game and MILP Algorithmic Framework for Dynamic Pricing in Multi-Agent Microgrid Networks

Min Yang[1,*], Bao Wang[1], Xiaoyu Shao[1], Fan Sun[1], Jianbin Lin[2]

[1]Institute of Economy and Technology of State Grid Anhui Electric Power Co., Ltd., Hefei 230022, China
[2]Department of Strategic Consulting, Beijing TsIntergy Technology Co. Ltd., Guangzhou 510000, China

Abstract

INTRODUCTION: Decentralized coordination and data transparency in multi-agent networks face significant computational and security bottlenecks when performing joint energy and ancillary service trading, particularly due to nonlinear optimization challenges in complex multi-domain environments. OBJECTIVES: This work aims to overcome these bottlenecks by developing an information-driven dynamic pricing framework that enables transparent, autonomous, and computationally efficient multi-agent decision-making. METHODS: The proposed framework integrates Ethereum-based smart contracts deployed on a public ledger to guarantee immutable data interactions and eliminate centralized dispatching. A Stackelberg game model is established to capture upper-lower level decision-making. To solve the resulting highly nonlinear and non-convex game exactly, the problem is transformed into a Mixed-Integer Linear Programming (MILP) model using Karush-Kuhn-Tucker (KKT) conditions and the duality theorem, ensuring exact convergence without approximation errors. RESULTS: Simulation results demonstrate the algorithm's ability to efficiently find the exact Nash equilibrium, converging to a stable state in approximately 12 iterations. The KKT-MILP framework exhibits exceptional scalability, solving a 50-agent system within just 15 seconds and significantly outperforming traditional heuristic algorithms in computational latency. CONCLUSION: The proposed algorithmic framework mathematically ensures transparent and decentralized decision-making while substantially enhancing computational accuracy and overall economic efficiency of the multi-agent system.

Keywords: blockchain technology, artificial intelligence, deep learning, smart grid, distributed energy resources

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1. Introduction

With the rapid development of the energy Internet, microgrids have become a key carrier for realizing the effective interaction and large-scale accommodation of distributed energy resources (DERs). In addition to traditional energy trading, microgrids have also demonstrated significant application potential in providing ancillary services (AS) to public distribution networks, effectively enhancing the stability and reliability of the power grid [1-5]. However, the design and implementation of AS markets in distribution networks still face numerous institutional and technical barriers [6-10]. The widespread integration and coordinated control of energy storage devices not only improve system flexibility but also bring new opportunities for the AS market [11-13]. Reasonably distributed energy storage planning and multi-energy complementary systems can significantly optimize the capability to participate in AS, thereby creating larger arbitrage spaces and economic benefits for microgrids in the joint energy and AS market [14-15].

In recent years, the mechanism design for microgrid participation in power market trading has drawn extensive attention from academia. Under the multi-agent trading architecture, a multi-market peer-to-peer (P2P) trading paradigm encompassing energy and AS has been proposed to

*Corresponding author. Email: ymin0227@163.com

facilitate direct interaction among microgrid and nanogrid prosumers [16]. To ensure the transparency of trading information and the effective management of distributed resources, energy blockchain technology has been introduced into the microgrid AS market [17]; meanwhile, DER-inverter-based reactive power AS have also been proven to effectively support P2P transactive energy trading in distribution networks [18]. Furthermore, with the popularization of multi-microgrid systems in active distribution networks, how to achieve distributed coordination among multiple microgrids to provide AS [19], and how to evaluate the AS and operational risks of networked microgrids using digital twin technology [20], have become current research hotspots for improving system operational security.

However, in the complex market environment of multi-domain microgrids, there is often a deep coupling between the dispatch of energy and AS. Existing bidding strategies and dispatch models mostly focus on the day-ahead optimization of a single microgrid in the joint energy and AS market [21], Dynamic operations are also being optimized through reinforcement learning for smart grid dispatch [22]. In recent years, increasing attention has been devoted to market-oriented flexibility valuation and storage participation mechanisms. Pricing and remuneration frameworks for electricity storage flexibility have been proposed to better integrate storage resources into market clearing processes [23]. Meanwhile, scenario-based approaches have been developed to quantify time-varying generation costs in medium- and long-term electricity markets [24]. Strategic bidding models for multi-energy market participants further improve the economic performance of integrated energy systems under market competition [25]. Furthermore, coordinated trading and scheduling frameworks that jointly consider electricity, heat, gas, and carbon markets have demonstrated significant potential for enhancing both economic efficiency and low-carbon operation [26].

Based on the above, aiming at the power market trading problem of multi-domain microgrids, this paper proposes a dynamic game pricing mechanism for multi-domain microgrids considering energy and AS trading, based on a multi-agent system architecture. First, this paper constructs a Stackelberg game model with the agent as the upper-level decision-maker and the microgrid power consumption entities as the lower-level decision-makers, comprehensively considering the coordinated dispatch of power purchasing and selling alongside AS. Second, for the solution of the game model, the Karush-Kuhn-Tucker (KKT) conditions and duality theorem are utilized to transform the nonlinear game optimization problem into a Mixed-Integer Linear Programming (MILP) problem for accurate calculation. The mechanism proposed in this paper aims to balance the competitive relationship between the microgrids and the agent, effectively improve the accuracy of users' power consumption decision-making and the economic benefits of the agent, and ultimately achieve a win-win situation for all parties in the energy and AS markets.

2. Microgrid Power Market Model

2.1. Single-Domain Microgrid Power Market Model

The distribution of common single-domain distributed generation equipment within a single-domain microgrid. The local power grid can directly supply power to microgrid users through the distribution center, while the local power grid and the agent can mutually trade electricity. The agent can not only purchase and sell electricity from and to the local power grid, but also generate power via distributed energy resources (DERs) and utilize distributed energy storage devices to alter the spatiotemporal characteristics of the electrical energy. The agent and microgrid users can mutually trade electricity through a smart centralized platform. Microgrid users can simultaneously purchase power from both the local power grid and the agent, sell surplus electricity to the agent, and utilize distributed energy storage devices (e.g., electric vehicles) to store electrical energy. In summary, various power consumption entities can achieve an effective integrated operation through the local power grid and the agent.

2.2. Multi-Domain Microgrid Power Market Model

Compared to the single-domain microgrid, the multi-domain microgrid involves an increased number of power consumption entities, leading to the emergence of multiple microgrids. These microgrids operate in an integrated manner with the local power grid and the agent, forming a multi-domain microgrid. In a multi-domain microgrid, the market primarily consists of three parts: the first part is the agent responsible for electricity trading and energy dispatch within the multi-domain microgrid; the second part is the local power grid; and the third part includes the multi-domain microgrid users.

The operational mode of the agent in the multi-domain microgrid is as follows: (1) Microgrid users can report their next-day power consumption demand to the agent, based on which the agent formulates a next-day power consumption schedule to determine the electricity demand. (2) In the day-ahead stage, the agent determines the power purchasing information for each time period based on the microgrid's electricity consumption and simultaneously publishes the next-day time-of-use (TOU) electricity prices to the users. The day-ahead market price must not exceed the real-time market price. Meanwhile, to protect the primary interests of microgrid users, an upper bound is imposed on the real-time electricity price. (3) During the real-time operation stage of the microgrid on the current day, the local power grid can supply power to the microgrid system and collect electricity fees. The agent can also sell or purchase electrical energy during this stage.

According to the aforementioned operational mode of the agent, and considering the characteristics of multi-domain microgrids, such as geographically dispersed components and random grid connection or disconnection, the agent, acting as an intermediary between the power system and the multi-domain microgrids, can collect information regarding grid electricity prices and users' power consumption periods. This information is used to formulate retail electricity prices and supply power to each microgrid, thereby implementing time-of-use (TOU) pricing. Microgrid users can connect to the power grid via smart terminals to autonomously select their power consumption strategies. In conclusion, the multi-domain microgrid market model realizes the effective management of large-scale distributed generations and loads within the microgrid, which can effectively promote the local accommodation of electrical energy and real-time trading.

2.3. Relationships Among Entities in the Multi-Domain Microgrid

Based on the multi-domain microgrid market model described above, the problem faced by the agent is how to rationally determine the electricity prices for various time periods of the next day. Within the entire trading framework, the agent's revenue primarily depends on the power consumption periods and the electricity volume of the microgrids.

The agent doesn't directly control how much power each component puts out, or how users consume electricity. But it does influence those things through the prices it sets. The average day-ahead price is actually a fixed value, basically determined by whatever microgrid data comes in that day. So the agent can’t just freely set prices. If it pushes prices too high in one period, it gets forced to drop them in others. There’s a kind of balancing act at play.

Microgrid users, of course, are going to figure this out. They see the price signals and, naturally, shift their consumption to the cheaper hours. I mean, it makes sense. What’s interesting is that this back-and-forth ends up being a Stackelberg game: the agent leads with the pricing decision, and the microgrids follow by adjusting when they use power.

In this study, the local power grid doesn’t get directly involved in selling to end users. Instead, it deals with energy dispatch after the transactions are settled. The payoff? Through the agent, the aggregated power use of all those microgrid users shows up as a big, relatively predictable load. And that helps a lot—it eases the dispatch headaches that come from users' otherwise random consumption patterns. In a way, the agent acts as a buffer, smoothing out the unpredictability.

3. Multi-Domain Microgrid Blockchain Model

3.1. Multi-Domain Microgrid Blockchain Ledger

Lately, blockchain has been popping up all over the place in microgrid research. It's easy to see why: it lets the agent and the microgrid users share things like electricity prices, consumption periods, and usage data almost instantly, all through the chain. Once real-time transaction data gets written onto the blockchain, both sides can adjust their strategies—how much power to supply, when to consume—based on that shared record. And here's the other thing: since blockchains are famously hard to tamper with, using a public ledger means the power consumption data is pretty trustworthy. That's a crucial piece. Microgrid users can, through their terminals and the public blockchain info, connect to the external grid and figure out the best consumption strategy on their own, simply by following the agent's price signals. No one needs to step in and tell them what to do—it's all automatic.

Now, Ethereum smart contracts are where this gets more interesting. They provide a Turing-complete programming environment, which is just a way of saying you can program pretty much any rule or logic you want. So, in a multi-domain microgrid setup, you can actually introduce energy blockchain smart contracts to handle the trading and dispatch. It helps to think of them in two main types:

First, there's the day-ahead scheduling contract. This one takes the next-day power demand that users submit and locks in the purchase transactions ahead of time. It also spits out a 24-hour operational plan for all the distributed generators and storage devices. Then, on top of that, you have the intraday scheduling contract—this handles real-time buying and selling as the actual demand emerges during the day, and it generates a short-term dispatch plan to keep things balanced on the fly.

What’s nice about this setup is the flexibility. Because smart contracts are Turing-complete, each multi-domain microgrid can rewrite or tweak the contract code to fit its own situation. In other words, bringing smart contracts into power trading and dispatch doesn't just automate things—it massively boosts the system's scalability. You can adapt it without tearing everything down.

There’s always the question of bad actors. To keep the microgrid stable, you can build in a penalty mechanism for malicious user nodes. Say a user lies about their next-day demand, or tries some shady power trading—well, you deduct their credit points. If their score drops too low, you might restrict their trading rights or just make buying and selling more expensive for them. The clever part: all that malicious behavior is permanently etched onto the blockchain. You can’t delete it. So the penalty system becomes genuinely enforceable, not just a theoretical threat. In a way, the immutability that makes the data reliable also makes the punishment stick.

In summary, introducing blockchain technology into the multi-domain microgrid and writing the transaction data between the agent and the microgrid into the blockchain enables the power market to be open, transparent, and immutable. It can realize effective and credible real-time interactions between the microgrid and users, helping microgrid users accurately grasp power sources, real-time electricity prices, and the credit and historical data of both trading parties, thereby more precisely adjusting their power consumption behaviors.

3.2. Microgrid User Participation Model Under Blockchain

The degree of users' power consumption selection preference in a microgrid is positively correlated with the information interaction formed by the blockchain; that is, the broader the coverage of blockchain technology and the more economic incentives there are, the more willing users are to participate in blockchain transactions. Therefore, the user's choice of the power purchaser also depends on the coverage of the blockchain and the formulation method of the electricity price. Let $s(s \in [0,1])$ be the blockchain transaction coverage rate, which is the extent to which the microgrid applies the blockchain transaction method. Assume that the agent's revenue from selling electricity increases to $\gamma_i(1<\gamma_i<1.5)$ compared with the traditional trading mode, to attract the participation of distributed generations in the microgrid; and the demand-side expenditure on purchasing electricity decreases to $\gamma_j(0.5<\gamma_j<1)$ compared with the traditional trading mode, to attract the participation of microgrid users. Considering the uncontrollability of the power grid in actual situations, the degree of economic adjustment should be restricted to less than 0.5 of the traditional mode. The larger the value of γ_i and the smaller the value of γ_j, the more inclined users are to choose the microgrid market.

The influence of various parameters on the probabilities η_{pi} and η_{pj} that power generation entities and power consumption entities choose the microgrid market can be expressed by linear functions. The probabilities η_{gi} and η_{gj} that the power generation entity i and the user choose the local power grid are as follows:

$$\begin{cases}\eta_{gi}=1-\eta_{pi}\\ \eta_{gj}=1-\eta_{pj}\end{cases} \tag{1}$$

Let Q_i and Q_j be the decision weights of the power generation entity and the user, respectively, regarding the information interaction and revenue incentives brought by the blockchain, which yields:

$$\begin{cases}\eta_{pi}=\begin{cases}Q_i s+(1-Q_i)(c(\gamma_i-1)+d), & s\neq 0\\ 0, & s=0\end{cases}\\ \eta_{pj}=\begin{cases}Q_j s+(1-Q_j)(c(1-\gamma_j)+d), & s\neq 0\\ 0, & s=0\end{cases}\end{cases} \tag{2}$$

where c and d are parameters of the linear function. Equation (2) uses linear functions to represent the probabilities of power generation entities and power consumption entities choosing to join the microgrid market under the influence of various parameters.

In the traditional trading market of a microgrid, to make better decisions regarding power purchasing and selling, user members can conduct dynamic energy trading based on the market data provided by the blockchain trading method, and the blockchain provides a full game environment for users in the microgrid. Blockchain technology enables the microgrid power market to update the electricity volume and price on the selling side, the demand on the purchasing side, and the current trading electricity price in real time, realizing the openness and transparency of information.

3.3 Dynamic Game Model Between Microgrid and Agent

3.3.1. Stackelberg Game Pricing Model Between Microgrid and Agent

In the pricing stage, the upper-level decision-maker of the Stackelberg game is the agent, and the lower-level decision-makers are the microgrid power consumption entities. Among them, to maximize profit, the upper level primarily faces three constraints: the constraint on the charging price range, the constraint on the purchased and sold electricity volume, and the constraint on the energy storage devices in the distributed microgrid. To minimize power purchase costs, the lower level is mainly constrained by the user's power consumption range and the total daily power consumption. The joint game of the above problems constitutes the formulation of the charging strategy and electricity price of the agent and the microgrid.

Specifically, the optimization problem for the agent is as follows:

$$\begin{cases}\max \sum_t \sum_i c_t p_{it}\\ +\sum_t (\pi_t^- E_t^- - \pi_t^d E_t - \pi_t^+ E_t^+)\\ \text{s.t. } c_t^l \le c_t \le c_t^u\end{cases} \tag{3}$$

where c_t is the electricity price of the microgrid at time period t; p_{it} is the power consumption of the i-th power consumption entity at time period t; E_t is the contracted electricity volume between the agent and the local power grid in the day-ahead stage at time period t; E_t^+ and E_t^- are the volume of electricity purchased and sold by the agent from and to the local power grid at time period t, respectively; π_t^+ and π_t^- are the real-time purchasing and selling electricity prices at time period t, respectively; π_t^d is the contract electricity price in the public market on the blockchain at time period t; c_t^l and c_t^u are the lower and upper bounds of the microgrid electricity price at time period t, respectively.

The objective Function (3) is the profit maximization of the agent, which consists of four parts: the revenue from selling electricity to the day-ahead microgrid market, the revenue from real-time electricity sales, the cost of purchasing electricity in the day-ahead market, and the cost of real-time electricity purchase. Furthermore, due to the openness and transparency of the blockchain, the day-ahead electricity price should be lower than the real-time electricity price.

Let r_t^+ and r_t^- be the stored and released electricity volume of the energy storage devices in the microgrid at time period t, respectively, c_{av} be the daily average electricity price in the microgrid, T be the total number of time periods, and M be the maximum allowable transaction volume between the agent and the local power grid in the real-time market. Selecting a Boolean variable z_t to represent the trading status at a time period t, the upper and lower bounds of pricing and the average price constraint can be obtained as follows:

$$\begin{cases} \sum_{t=1}^{T} c_t = Tc_{av} \\ 0 \le E_t \le M \\ 0 \le E_t^{+} \le Mz_t \\ 0 \le E_t^{-} \le M(1-z_t) \end{cases} \quad (4)$$

The volume of electricity sold by the agent to real-time power purchasing users is limited by the maximum energy storage capacity of the energy storage devices, which yields $E_t^{-} \le r_t$. In fact, the maximum power consumption of energy storage devices and microgrid users, E_t^{+} is less than the sum of the maximum power of all power-consuming equipment. Therefore, the parameter M can be set as the sum of the maximum power of all power-consuming equipment.

Let R_m^{+} and R_m^{-} be the maximum charging and discharging power of the energy storage devices in the microgrid, respectively, and the Boolean variable u_t represents the state of the energy storage devices. Then, the microgrid and the operator should satisfy the following equations:

$$\begin{cases} \sum p_{it} + r_t^{+} - r_t^{-} = E_t + E_t^{+} - E_t^{-} \\ 0 \le r_t^{+} \le u_t R_m^{+} \\ 0 \le r_t^{-} \le (1-u_t) R_m^{-} \end{cases} \quad (5)$$

Under normal circumstances, since the real-time electricity price is higher than the day-ahead electricity price for the same time period, the agent will not directly purchase electricity during the real-time trading stage. When the power consumption strategy is implemented through rolling optimization, user information will be updated via the blockchain in each time period. Therefore, the real-time power purchase and sale of the microgrid provide the local power grid with a means to cope with the randomness of power consumption, which is of certain significance for maintaining the power supply reliability of the local power grid.

Equations (4) and (5) limit the working efficiency of energy storage devices, and the variable u_t restricts that only one of r_t^{+} and r_t^{-} can be greater than 0, meaning that the energy storage device has only one working state (charging or discharging). Let η^{+} and η^{-} be the charging efficiency and discharging efficiency of the energy storage devices in the microgrid, respectively, $S_{\max}$ be the maximum storage capacity of the energy storage device, and S_0 be the initial storage capacity of the energy storage device. Then, the following equation holds:

$$\begin{cases} 0 \le S_t = S_{t-1} + \eta^{+} r_t^{+} - \dfrac{r_t^{-}}{\eta^{-}} \le S_{\max} \\ S_T = S_0 \end{cases} \quad (6)$$

The lower-level multi-domain microgrid should satisfy the following control conditions:

$$\begin{cases} (p_{it}) = \arg\min \sum_t c_t p_{it} \\ \sum_{t \in T_a} p_{it} = 0.9E_i^{m} - E_i^{0} \\ 0 \le p_{it} \le P_i^{m}, t \in T_a \\ p_{it} = 0, t \notin T_a \end{cases} \quad \mathbf{(7)}$$

where E_i^{m} is the maximum energy storage capacity of the i-th distributed generation; E_i^{0} is the initial energy storage capacity of the i-th distributed generation; P_i^{m} is the maximum energy storage power of the i-th distributed generation; and T_a is the charging period of the distributed generation.

Equation (7) indicates that, given the electricity price formulated by the agent, the microgrid should minimize its own cost and make the energy storage capacity of the microgrid, including energy storage devices, reach the corresponding State of Charge (SOC) level. The optimization conditions of the agent and the lower-level microgrid jointly constitute the Stackelberg game. Since the electricity price is already determined when the microgrid makes decisions, but the agent needs to consider the response of microgrid users to the electricity price via the blockchain, both c_t p_{it} are variables. Therefore, the game problem formed by the agent and the multi-domain microgrid is neither a linear problem nor a convex optimization problem. Equations (1) to (7) should be jointly transformed under Karush-Kuhn-Tucker (KKT) conditions and the duality theorem, to convert the original optimization problem between the microgrid and the operator under the effect of the blockchain into a Mixed-Integer Linear Programming (MILP) problem to seek the Nash equilibrium point.

3.3.2. Solution Method for Stackelberg Game Pricing Model

In the Stackelberg game, when the microgrid makes decisions, the electricity price is formulated based on public information from the blockchain. By replacing the linear programming Equation (7) with KKT conditions, the optimization problem of the lower-level microgrid can be eliminated, and the constraint relationship between variables p_{it}, c_t can be obtained. Let the dual variables be μ_i, η_{it}^{-}, η_{it}^{+}, and σ_{it}, then Equation (7) can be transformed into:

$$\begin{cases} c_t - \mu_i - \eta_{it}^{+} + \eta_{it}^{-} - \sigma_{it} = 0 \\ \sum_{t \in T_a} p_{it} = 0.9E_i^{m} - E_i^{0} \end{cases} \quad (8)$$

where μ_i is the dual variable for $\sum_{t \in T_a} p_{it} = 0.9E_i^{m} - E_i^{0}$ in Equation (7); η_{it}^{-} and η_{it}^{+} are the dual variables for $0 \le p_{it} \le P_i^{m}$ in Equation (7); and σ_{it} is the dual variable for $p_{it} = 0$ in Equation (7).

The above dual variables should simultaneously satisfy the following equations:

$$\begin{cases} 0 \le \eta_{it}^{-} \perp p_{it} \ge 0, \quad t \in T_a \\ 0 \le \eta_{it}^{+} \perp P_i^m - p_{it} \ge 0, \quad t \in T_a \\ p_{it} = 0, \quad t \notin T_a \\ \sigma_{it} = 0, \quad t \in T_a \end{cases} \tag{9}$$

The $\perp$ mentioned in Equation (9) indicates that at most one of the scalars on either side of the symbol can be greater than 0. The optimization of the lower-level microgrid can be transformed into a constraint problem. At this time, both Equation (3) and Equation (7) have been transformed into non-linear programming problems, and the game problem between the microgrid and the operator is equivalently replaced by these non-linear programming constraints.

After completing the non-linear processing of the Stackelberg game through KKT conditions, Equation (9) can be converted into linear inequalities:

$$\begin{cases} 0 \le \eta_{it}^{-} \le M\theta_{it}^{-}, \quad t \in T_a \\ 0 \le p_{it} \le M(1-\theta_{it}^{-}), \quad t \in T_a \end{cases} \tag{10}$$

By introducing Boolean logical variables θ_{it}^{-} and θ_{it}^{+}, we have:

$$\begin{cases} 0 \le P_i^m - p_{it} \le M\theta_{it}^{+}, \quad t \in T_a \\ 0 \le \eta_{it}^{+} \le M(1-\theta_{it}^{+}), \quad t \in T_a \end{cases} \tag{11}$$

In Equation (10), if $\eta_{it}^{-} > 0$, then $\theta_{it}^{-} = 1$, which implies that $p_{it} = 0$ at this time. Conversely, if $p_{it} > 0$, then $\eta_{it}^{-} = 0$. The non-linearity of the upper and lower objective functions mainly stems from the product of the electricity price provided by the upper-level service provider and the power consumption of the lower-level microgrid users, i.e., $c_t p_{it}$. According to the duality theorem:

$$\sum_t \sum_i c_t p_{it} = \sum_i \mu_i (0.9E_i^m - E_i^0) + \sum_t \sum_i \eta_{it}^{+} P_i^m \tag{12}$$

In summary, constrained by KKT conditions, the objective function is expressed as:

$$\max \sum_i \mu_i (0.9E_i^m - E_i^0) + \sum_t \sum_i \eta_{it}^{+} P_i^m + \sum_t (\pi_t^{-} E_t^{-} - \pi_t^{d} E_t - \pi_t^{+} E_t^{+}) \tag{13}$$

subject to constraints in Equations (3)-(6) and Equations (8)-(11). At this point, the decision variables are linear equations, enabling the calculation of the optimal solution in the microgrid game process. The respective variables at the optimal solution of the objective Function (13) constitute the Stackelberg equilibrium of the master-slave game model.

3.4. Microgrid Blockchain Operator Revenue Model

As the entity providing the trading service platform for the microgrid power market, the microgrid operator can meet its revenue needs by charging service fees from microgrid trading members. The revenue function can be expressed as:

$$R = \gamma \left(\sum_{i=1}^{N_1} R_i + \sum_{j=1}^{N_2} R_j \right) \tag{14}$$

where R is the operator's revenue; γ is the weight of the blockchain service fee; N_1 and N_2 are the numbers of electricity sellers and buyers in the microgrid market, respectively; and R_i and R_j are the power purchasing and selling revenues of each electricity seller and buyer, respectively.

The operator's revenue is consistent with the principal benefits of various trading participants in the microgrid, and the result of the power trading game is the operator's optimal economic revenue. In addition, the benefits obtained by electricity sellers and buyers in the microgrid market are solely related to the electricity price. However, the operator achieves maximization of economic benefits and a stable, reliable power supply by adjusting the values of γ_i and γ_j in the pricing strategy.

The overall algorithmic flow is shown in Figure 1.

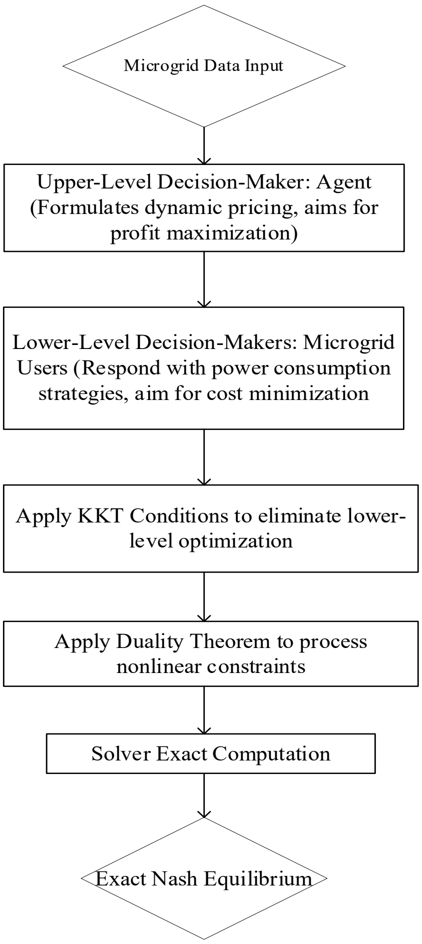

Figure 1. Algorithmic flow

4. Case Study

To effectively verify the blockchain microgrid model and the Stackelberg game solution method proposed above, and to analyze the impacts of factors such as the proportion of new energy in different microgrids, the capacity of energy storage devices, and the operator's pricing lower bound on the agent's profit and microgrid users, this paper adopts the IEEE 33-node topology circuit for experimental verification.

4.1. Scenario Simulation

To facilitate the display of calculation results, this paper assumes three groups of microgrids as representatives for computation. The three groups of microgrids in this assumption include 10, 20, and 50 users, respectively. Microgrid group A consists mainly of users who leave early and return late under normal circumstances; microgrid group B consists of users with normal routines; and microgrid group C consists of a working population that primarily works night shifts.

4.2. Analysis of Case Study Results

A Stackelberg game is formed between the microgrids and the operator to achieve multi-domain cooperative trading through the operator. Using the data from Section 4.1 to solve the mixed-integer linear programming equations (3)-(14), the maximum revenue of the agent can be obtained, along with the day-ahead electricity prices and real-time electricity prices when the Stackelberg game between the agent and the microgrids is at the optimal strategy. Since the power purchase price in the real-time market is significantly higher than that in the day-ahead market, microgrid users do not need to purchase electricity from the real-time market, thereby avoiding the uncertain factors that easily affect the local power grid if the microgrid operates off-grid after being grid-connected.

The real-time electricity prices and day-ahead electricity prices of the multi-domain microgrid are shown in Figure 2. In all periods from 0 to 24 h, the real-time electricity price is higher than the day-ahead electricity price, effectively proving that the agent can obtain more profit under these conditions.

Under the condition of satisfying the optimal electricity price game results, the energy storage strategy of the agent is shown in Figure 3. In all periods from 0 to 24 h, except for the night hours of 17 to 22 h, the energy storage devices are working for the rest of the time, and they are in a full-load working state during the period of 5 to 12 h.

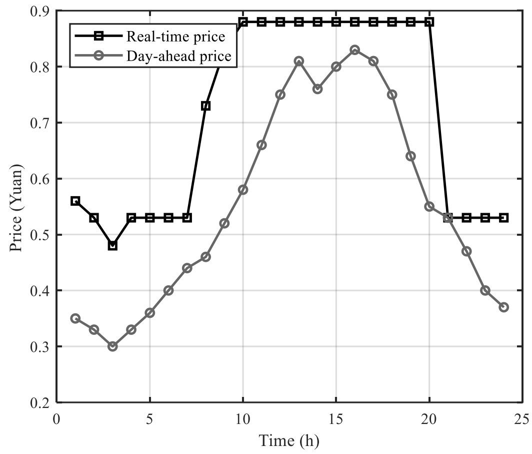

Figure 2. Real-time power prices and day-ahead power prices in a multi-domain microgrid

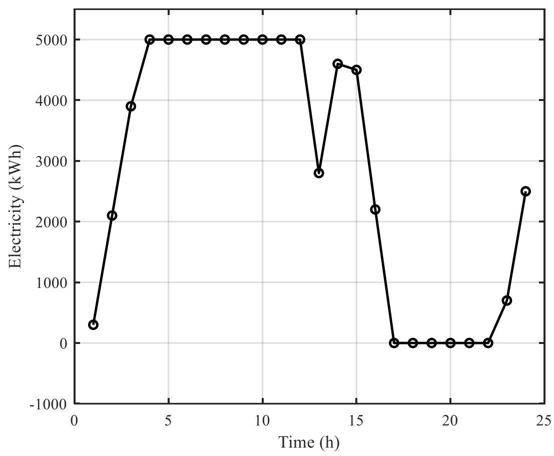

Figure 3. Schematic diagram of energy storage strategy for a multi-domain microgrid agent

Under the condition of satisfying the operator's optimal energy storage strategy and the optimal solution of the electricity price game, assuming that some users can perform load-side responses, the load response demand curves of microgrid groups B and C can be obtained as shown in Figure 4 and Figure 5. The periods and magnitudes of load response demand for both sets of users differ, which is mainly caused by the users' different power consumption periods.

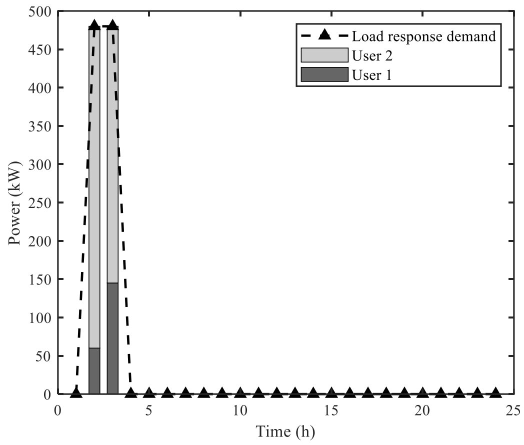

Figure 4. Load response demand curve of microgrid B

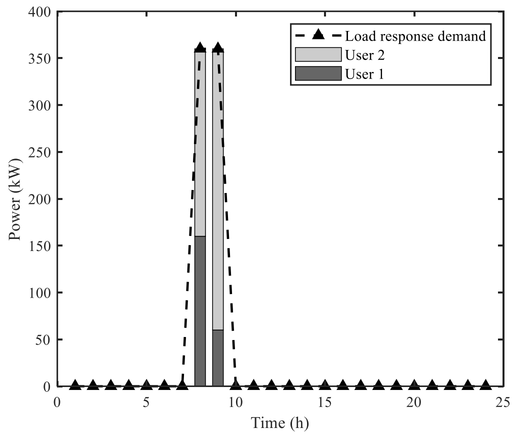

Figure 5. Load response demand curve of microgrid C

The day-ahead demand response and real-time demand response of the three groups of microgrids based on blockchain are shown in Figure 5. These two demand responses can help the operator achieve effective power market price positioning the next day, and publish the information through the blockchain. As can be seen from Figure 6, the real-time demand response is slightly higher than the day-ahead demand response, and satisfies the load demands of microgrid groups A, B, and C, realizing the economic optimal dispatch of the multi-domain microgrid.

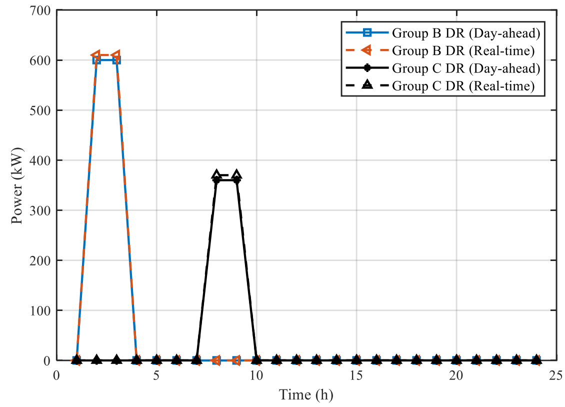

Figure 6. Day-ahead and real-time demand response curves of microgrids

Under the condition of satisfying the lower-level load-side response, the total load and day-ahead power purchase of the three groups of microgrids, as well as the microgrid power distribution of distributed units such as photovoltaics and wind power, are shown in Figure 6. Among them, the combined power of day-ahead power purchase, wind power, and photovoltaics is significantly higher than the grid load between 2 and 4 h, which is consistent with the significant increase in microgrid energy storage during this period in Figure 7.

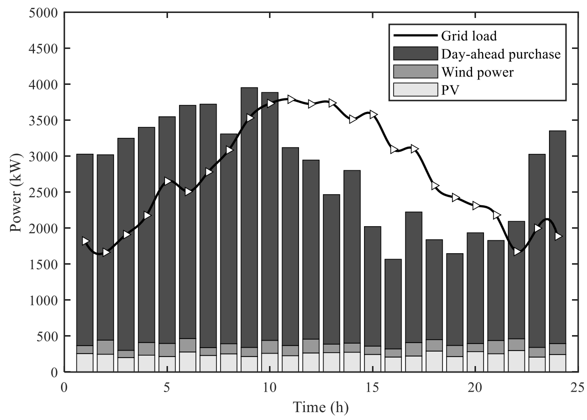

Figure 7. Comparison of the load curve and day-ahead energy storage

Under the condition of satisfying the lower-level load-side response, the real-time power purchase and sale situations and the energy storage efficacy status of the three groups of microgrids are shown in Figure 8. Energy storage and energy consumption are realized in the power consumption troughs and peaks of 0-5 h and 13-17 h, respectively, verifying the optimal dispatch effect of the operator's Stackelberg game on the microgrid portfolio.

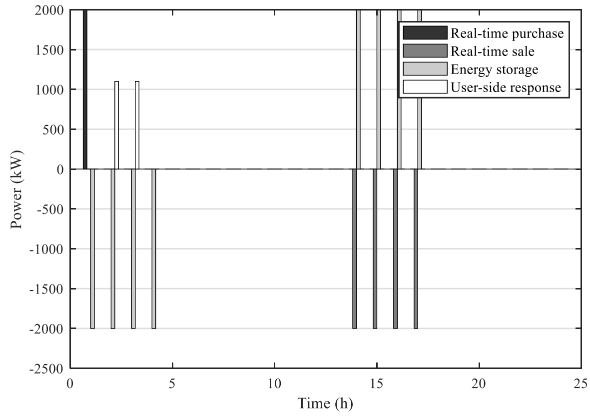

Figure 8. Distribution of power purchase and sale, and energy storage in microgrids

The upper-level comprehensive dispatching diagram of the microgrid based on blockchain is shown in Figure 9. The energy storage devices and distributed units, including wind power and photovoltaics, in the microgrid effectively respond to user demands while maximizing the operator's economic benefits, verifying the robustness of the proposed model.

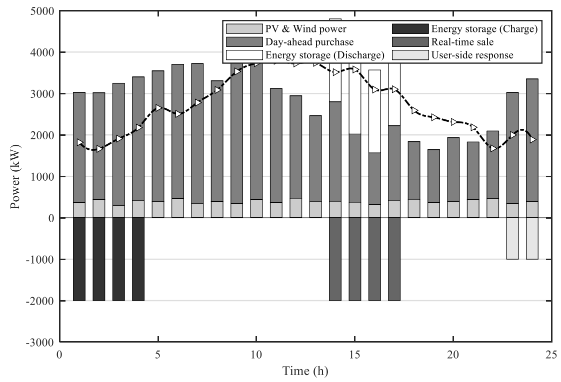

Figure 9. Upper-level comprehensive dispatching diagram of microgrids based on blockchain

Simulation experiments prove that the cooperative game solution can not only effectively improve the economic revenue of the multi-domain microgrid but also realize energy sharing among multi-domain microgrids. The case study results show that the blockchain-based microgrid market grants distributed entities sufficient choice and increases the degree of freedom in the power market. The information from the blockchain can effectively guide the choices of microgrid user groups, making the demand response more balanced and realizing the transfer of user power load on a time scale, thereby improving the load characteristics of the local power grid system and enhancing the utility of electricity commodities to maximize social benefits. The multi-domain microgrid based on blockchain not only contributes to realizing China's dual-carbon goal of "carbon neutrality and peaking carbon emissions" for energy conservation and emission reduction, but also enables the entire power system to maximize the utilization of limited resources, promotes the construction of smart grids, and realizes further interaction between information flow and energy flow.

4.3. Algorithmic Performance and Game Equilibrium Analysis

To verify the stability of the proposed Stackelberg game model, the dynamic convergence process of the upper-level agent and the lower-level microgrid users is analyzed. As shown in Figure 10, during the initial iterations, the agent continuously adjusts the pricing strategy to maximize its revenue, while users dynamically modify their demand response to minimize electricity costs. After approximately 12 iterations, both the agent's revenue and the users' comprehensive costs converge to a stable state, successfully reaching the exact Nash equilibrium. This dynamic convergence visually demonstrates the effectiveness of the decentralized decision-making mechanism driven by blockchain smart contracts.
Furthermore, to validate the computational superiority of transforming the highly nonlinear game into a Mixed-Integer Linear Programming (MILP) model via KKT conditions, the computation time of the proposed KKT-MILP framework is compared with traditional heuristic algorithms (e.g., Genetic Algorithm, GA) under varying numbers of microgrid agents.

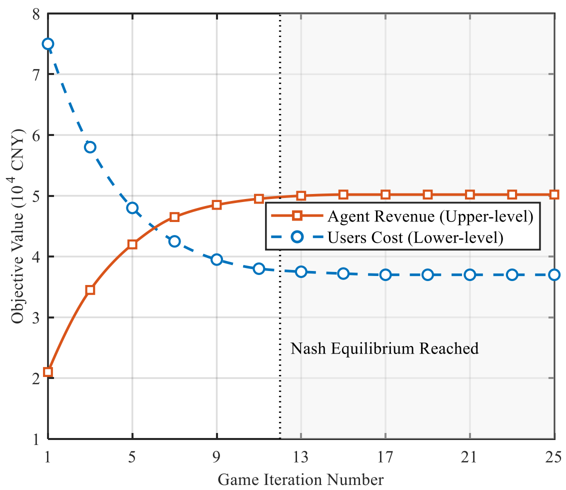

Figure 10. Dynamic convergence process of the Stackelberg game towards the Nash equilibrium

As depicted in Figure 11, traditional heuristic solvers suffer from the "curse of dimensionality," showing an exponential increase in computation time as the network scales up. In contrast, the proposed KKT-MILP algorithmic framework maintains a linear and significantly lower computational latency. It easily solves a 50-agent system within 15 seconds, proving its exceptional scalability and exact computational convergence for large-scale multi-domain microgrid trading.

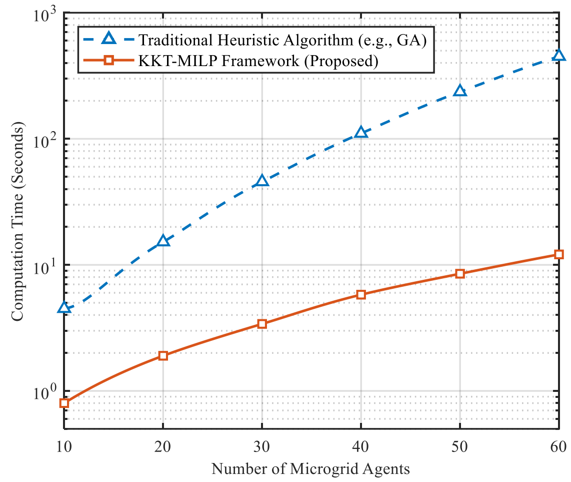

Figure 11. Comparison of computation time under different numbers of microgrid agents (Scalability analysis)

5. Conclusions

The main conclusions of this paper are as follows:
(1) This paper constructs a blockchain-based multi-domain microgrid Stackelberg game model, considers the response of microgrid users' power consumption strategies and blockchain coverage rate to electricity prices, reduces the power consumption costs of microgrid users, and achieves a win-win situation for both the agent and the multi-domain microgrid.
(2) To solve for the optimal strategy, the multi-domain microgrid game model under the effect of blockchain is transformed into a mixed-integer linear programming problem and the duality theorem of linear programming, requiring no approximation and achieving accurate calculation.
(3) The simulation examples verify the robustness of the model. The calculation results show that the real-time electricity price is significantly higher than the day-ahead electricity price; under the condition of satisfying the lower-level load-side response, changes in power demand of microgrid users at different time periods will affect the agent's revenue, and the more concentrated the power consumption is, the more power the energy storage devices output, verifying the optimal dispatch effect of the Stackelberg game between the operator and the multi-domain microgrid on the microgrid portfolio.

Author Contribution

Conceptualization, Min Yang; methodology, Bao Wang; software, Xiaoyu Shao; validation, Fan Sun and Jianbin Lin. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

No data were generated or used in this research.

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Ethics Statement

Not applicable.

Conflict of Interest Statement

The authors have no relevant financial or non-financial interests to disclose.

References

[1] Majzoobi A, Khodaei A. Application of microgrids in providing ancillary services to the utility grid. Energy. 2017; 123: 555-563.
[2] Kumar A, et al. State-of-the-art review on energy sharing and trading of resilient multi microgrids. iScience. 2024; 27(4):109549.
[3] Machele IL, et al. Interconnected smart transactive microgrids—A survey on trading, energy management systems, and optimisation approaches. J Sens Actuator Netw. 2024;13(2):20.
[4] Lei YT, et al. A renewable energy microgrids trading management platform based on permissioned blockchain. Energy Econ. 2022; 115:106375.
[5] Veerasamy V, et al. Blockchain-enabled peer-to-peer energy trading and resilient control of microgrids. Appl Energy. 2024; 353: 122107.
[6] Oureilidis K, et al. Ancillary services market design in distribution networks: Review and identification of barriers. Energies. 2020;13(4):917.
[7] Saatloo AM, Mirzaei MA, Mohammadi-Ivatloo B. A robust decentralized peer-to-peer energy trading in community of flexible microgrids. IEEE Syst J. 2022; 17(1):640-651.
[8] Gao H, et al. Green electricity trading driven low-carbon sharing for interconnected microgrids. J Clean Prod. 2023; 414:137618.
[9] Bui VH, Hussain A, Su W. A dynamic internal trading price strategy for networked microgrids: A deep reinforcement learning-based game-theoretic approach. IEEE Trans Smart Grid. 2022; 13(5):3408-3421.
[10] Zahraoui Y, et al. A competitive framework for the participation of multi-microgrids in the community energy trading market: A case study. IEEE Access. 2024; 12:68232-68248.

[11] Kumar GVB, Palanisamy K. A review of energy storage participation for ancillary services in a microgrid environment. Inventions. 2020;5(4):63.
[12] Liu S, Han S, Zhu S. Reinforcement learning-based energy trading and management of regional interconnected microgrids. IEEE Trans Smart Grid. 2022;14(3):2047-2059.
[13] Khan MHD, Imtiaz J, Islam MNU. A blockchain based secure decentralized transaction system for energy trading in microgrids. IEEE Access. 2023; 11:47236-47257.
[14] Abdeltawab H, Mohamed YARI. Energy storage planning for profitability maximization by power trading and ancillary services participation. IEEE Syst J. 2021;16(2):1909-1920.
[15] Mancarella P, Chicco G, Capuder T. Arbitrage opportunities for distributed multi-energy systems in providing power system ancillary services. Energy. 2018; 161: 381-395.
[16] Hu Q, et al. A multi-market nanogrid P2P energy and ancillary service trading paradigm: Mechanisms and implementations. Appl Energy. 2021; 293: 116938.
[17] Di Silvestre ML, et al. Ancillary services in the energy blockchain for microgrids. IEEE Trans Ind Appl. 2019;55(6):7310-7319.
[18] Zou Y, Xu Y. DER-inverter based reactive power ancillary service for supporting peer-to-peer transactive energy trading in distribution networks. IEEE Trans Power Syst. 2024;40(1):753-764.
[19] Mallick A, et al. Distributed coordination of multi-microgrids in active distribution networks for provisioning ancillary services. IEEE Syst J. 2024;18(3):1492-1503.
[20] Hong YY, Apolinario GFD. Ancillary services and risk assessment of networked microgrids using digital twin. IEEE Trans Power Syst. 2022;38(5):4542-4558.
[21] Wang J, et al. Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products. Appl Energy. 2017; 205: 294-303.
[22] Ma X, Chen M, Zhou X. Study on the probabilistic optimal capacity of energy storage in microgrid. Electric Power. 2015; 48(1):131-136.
[23] W. Zhang, P. A. Tominac, and V. M. Zavala, “Pricing and remunerating electricity storage flexibility using virtual links,” Computers & Chemical Engineering, 2022, 168: 108019.
[24] S. Huang, Y. Meng, and Z. Ye, “A scenario-based framework for measuring time-varying generation costs in medium- and long-term electricity markets,” iScience, 2026.
[25] J. Wang, Z. Shao, J. Wu, and L. Wu, “Day-ahead strategic bidding of multi-energy microgrids participating in electricity, thermal energy, and hydrogen markets: A stochastic bi-level approach,” International Journal of Electrical Power & Energy Systems, 2024, 163: 110319.
[26] D. Zhu, B. Yang, Y. Wu, H. Deng, Z. Dong, K. Ma, and X. Guan, “Joint trading and scheduling among coupled carbon-electricity-heat-gas industrial clusters.,” IEEE Transactions on Smart Grid,2024, 15(3): 3152–3164.