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V2V Energy Trading Considering User Satisfaction under Low-Carbon Objectives via Bayesian Game

Yue Yu*, **Yu Liu, Xiang Feng, Huaichao Wen**

School of Rail Transit, Hunan University of Technology, Zhuzhou, China
Email: *yuyue@hut.edu.cn, liuyu11142023@163.com, may_fx@163.com, 2822619036@qq.com

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Abstract

In response to the additional load impact caused by the integration of electric vehicles (EVs) into the grid or microgrids (MGs), as well as the issue of low responsiveness of EV users during vehicle-to-vehicle (V2V) power exchange processes, this paper explores a multi-party energy trading model considering user responsiveness under low carbon goals. The model takes into account the stochastic charging and discharging characteristics of EVs, user satisfaction, and energy exchange costs, and formulates utility functions for participating entities. This transforms the competition in multi-party energy trading into a Bayesian game problem, which is subsequently resolved. Furthermore, this paper primarily employs sensitivity analysis to evaluate the impact of multi-party energy trading on user responsiveness and green energy utilization, with the aim of promoting incentives in the electricity trading market and aligning with low-carbon requirements. Finally, through case simulations, the effectiveness of this model for the considered scenarios is demonstrated.

Keywords

Multi Electric Vehicles, Multi Microgrid, Energy Trading, Bayesian Game, Multi Party Game, Network Constraints

1. Introduction

With the transition in energy structure, distributed electricity trading methods have emerged. Due to the intermittent and stochastic nature of distributed generation, traditional energy trading methods have certain limitations in controlling and enhancing energy efficiency. Considering V2G (Vehicle-to-grid) technology, not only optimizes the charging and discharging processes of Electric Vehicles (EVs) but also mitigates the adverse effects resulting from load fluctuations and deteriorating energy quality [1] [2] [3]. Hence, against this backdrop, harnessing the economic and societal benefits of distributed energy sources through energy trading has been a recent focus of development [4] [5] [6] [7] [8].

Currently, research on the optimization of MG operation primarily focuses on considering intra-MG energy dispatch [9] [10] [11] [12] [13], while overlooking the autonomy of MGs as energy trading entities and the impact of information uncertainty in the generation process. Addressing these issues, various pricing schemes such as the Average Bidding Algorithm based on game theory [14], hybrid energy trading and dispatch strategies considering interlinked interactions between MGs [15], a decentralized market trading system for MGs employing multi-agent deep deterministic policy gradient algorithms and smart contracts [16], and the Stackelberg energy game model considering physical constraints [17] have adequately accounted for the MG's agency in trading to maximize benefits. However, these studies have yet to incorporate EVs as new participants in such MG markets. Hence, recent scholars have begun to explore the integration of EVs as new participants in MG markets and address optimization problems through game-theoretic approaches. Literature [18] [19] [20] investigates the optimization and trading models in MGs following the inclusion of EVs from the perspectives of EV state-of-charge benefits, EV stochastic characteristics, and MG load forecasting. These studies employ game equilibrium to address the MG's optimal dispatch problem but have not considered EVs as trading entities in the market and have not incorporated V2V scenarios in their models.

In the presence of a large number of EVs charging erratically and imposing stress on the grid, V2V technology is poised to alleviate this challenge by reducing power losses between transactions and providing a more convenient charging approach. Various methods, including offline and online scheduling algorithms for EV charging [21], peer-to-peer local electricity market models considering bidirectional information exchange [22], and transaction models for V2V power exchange with hierarchical control [23] [24], have adequately incorporated EVs as active market participants. However, they have yet to address network constraints within the power system. To address these concerns, J. Guerrero *et al.* [25] proposed a sensitivity analysis-based approach to assess the impact of P2P transactions on the network, ensuring that energy exchanges do not violate network constraints. This assessment includes factors such as Voltage Sensitivity Coefficients (VSC), Power Transfer Distribution Factors (PTDF), and Loss Sensitivity Factors (LSF). Yan Du *et al.* [26] introduced a cooperative game cost allocation method based on core concepts, ensuring fair cost sharing among members of MG alliances and enhancing economic stability by accounting for losses in the distribution network. These studies are comprehensive; however, they do not account for multi-user participation in transactions. B. Gao, X. *et al.* [27] explored autonomous household energy management systems that encompass multiple utility companies and residential customers, considering bidirectional energy trading. However, this approach does not consider both MGs and EVs as trading participants.

The research on user satisfaction has achieved certain outcomes. The active involvement of users in scheduling directly impacts the optimization efficacy of the scheduling process. Addressing the issues of conducting scheduling while ensuring user satisfaction and designing incentive mechanisms for user participation in the market stands as the primary concerns within the power market [28] [29]. In reference [30], a dispatch strategy for EV clustering is proposed, taking into consideration user satisfaction during the optimization scheduling. References [31] [32] establish models for user satisfaction and quantitatively calculate the overall user satisfaction. Reference [33] incorporates wind power and EV user satisfaction into an intelligent grid charging and discharging strategy. However, the aforementioned literature primarily focuses on the overall user satisfaction and neglects to consider the satisfaction level of individual EV users.

The aforementioned research has yielded valuable findings in the context of EV integration into MGs or power networks, touching upon aspects such as EVs, MGs, non-cooperative games, cooperative games, hierarchical control, stochastic characteristics of elements, network constraints, and multi-party transactions. However, there has been limited research into energy trading involving multiple MGs and EVs and only focuses on the overall user satisfaction, in addition, The impact of energy emissions has not been considered in the process of MG and EV participation in energy trading. In response, this paper introduces a multi-player Bayesian game architecture that accounts for network constraints. In response to the issue of uncoordinated charging and discharging behavior in the integration of EVs into the MG, which leads to the collapse of the microgrid scheduling system, and in order to maximize the utilization of green energy, the article makes the following contributions from three aspects: participation of electric vehicles as trading entities in the market, V2V power exchange, and consideration of user satisfaction under low-carbon standards:

1) To facilitate energy trading through V2V (Vehicle-to-Vehicle) communication, a hybrid energy trading model considering user satisfaction under low-carbon objectives is proposed in this paper. Both EVs and MGs are treated as participants in the market transactions.

2) To address the impact of stochastic factors in real-world market operations, the proposed model adopts Bayesian game theory to model the combination of participant types based on the uncertainty of information from EVs.

3) To enhance user satisfaction and align with the trend of sustainable development, this study converts user satisfaction during the electricity trading process into transaction costs for each party. Through game theory, it aims to improve the satisfaction of each user while maximizing the utilization of green

energy and meeting low-carbon requirements. Additionally, each transaction will be based on network conditions, involving physical energy exchange between MGs and EVs located in different spatial positions within the hierarchical network.

2. The Overall Framework of the Multi-Party Energy Game

In a multi-party game system, a non-cooperative game mode is employed, where each subsystem independently makes decisions. The multi-party energy game framework within a hierarchical structure is illustrated in Figure 1. The system comprises a regional distribution network, multiple MGs, multiple EVs within the MG region, and multiple aggregators. To achieve their optimal operations, MGs and several EVs in the same region enter the electricity market. The stable operation of the power trading system is influenced by factors such as cost, demand, and transmission. Consequently, the buying and selling transactions that users participate in within the entire energy trading market system are continuously adjusted dynamically. In this scenario, the power flow direction is

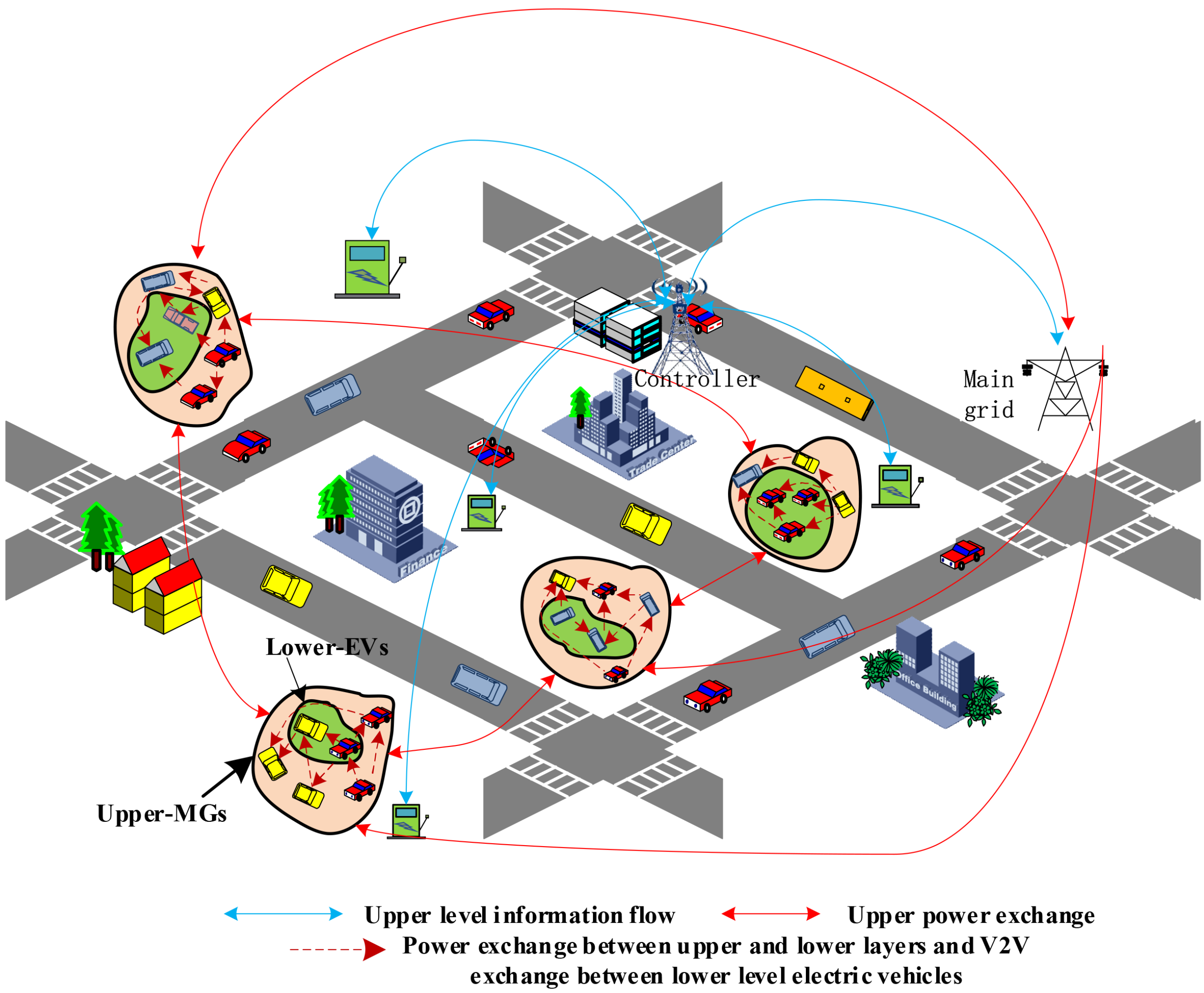

Figure 1. Multi-player game model architecture.

represented by solid lines and arrows indicating the direction. In the time optimization period, typically set to one hour ($t = 1$ hour), MG are primarily dominated by wind and photovoltaic power generation, where wind power generation and photovoltaic power generation are represented by $P_t^{\mathrm{MG}n,\mathrm{WT}}$ and $P_t^{\mathrm{MG}n,\mathrm{PV}}$, respectively. The energy storage unit's charge and discharge scheduling are denoted by $P_t^{\mathrm{MG}n,\mathrm{es}}$, and EV participation in scheduling is represented by $P_t^{n,i}$. The load of ordinary users in the MG is denoted as $L_t^{\mathrm{MG}n}$.

The multi-player game of energy transaction between EVs or MGs is shown in Figure 2. Different from V2V or V2M, the players in the multi-player game are more general, in which EV and MG are regarded as general players who play games with any other player whether the other is EV or MG. Therefore, the proposed method embodies V2V and V2M transaction mode which made VETMBG system more adaptable. MGs and EVs under hierarchical control participate in transactions obtain the maximum profit by individual energy trading. Since EVs are connected to the MGs, each MG constantly adjusts its role in the two-way game through the analysis of internal capacity, load and energy storage units, as well as the prediction of the driving and charging state of EVs. EVs make corresponding decisions according to the driving needs of drivers and the needs of their own charging state. As the MG power insufficient, it can purchase power from other MGs with sufficient power or EVs without the next day's mileage its own needs. It can be seen that the market of the whole trading system is free and completely depends on its own needs.

3. A Bayesian Game Model for Multiple MGs and EVs Considering Multiple Constraints

Participants, strategy sets, and utility functions are the three fundamental elements of a game. Additionally, player types and the probability distribution of player types are two fundamental elements of Bayesian games.

3.1. Game Participants

In a Bayesian game scenario, the game participants consist of multiple MGs and multiple EVs. Let $N = \{1,2,3,\cdots,n\}$ represent the set of all EVs and MGs in the regional distribution network. Time is divided into the set $T = \{1,2,3,\cdots\}$ ($t \in T$). Within this context, $N = J \cup I$, with the set $J = \{1,2,3,\cdots\}$ serving as

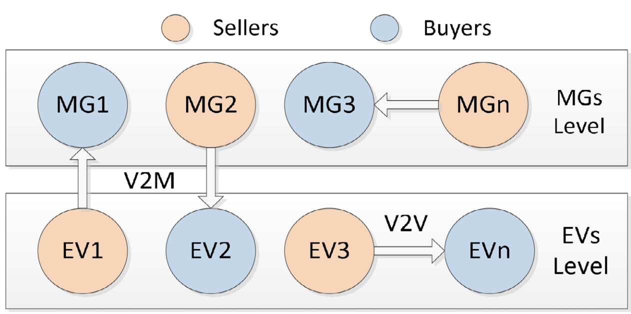

Figure 2. An example of the multi-player game.

a subset capable of selling surplus energy and the set $I = \{1, 2, 3, \cdots\}$ as a subset in need of purchasing energy due to insufficient power.

3.2. Strategy Set

Assuming that throughout the entire charging and discharging process, losses and the voltage at the energy storage unit terminal remain relatively stable. Within any given time period *t*, the strategy set for the purchasing party is represented as (1).

$$C_t^{n,j} = \left\{ C_t^{n,j} > 0 : C_t^{\mathrm{b}} < C_t^{n,j} < C_t^{\mathrm{s}}, \forall t \right\} \tag{1}$$

In Equation (1), p_i represents the purchasing price for the buyer i, and p and p_o are the buying and selling prices to the main power grid, respectively. The buyer's bid should not exceed that of the main power grid, as otherwise, the buyer would directly purchase electricity from the main power grid. Similarly, the buyer's bid should not fall below the utility company's price, or else the seller would engage in direct transactions with the utility company. If the overall discharge power of the whole system is greater than the charging power, the remaining energy will be transferred to the power grid when the multi-party transaction between MGs and EV is satisfied, that is:

$$P_{Grid} = P_t^{MG} + P_t^{EVn,j} - P_t^{EVn,i} \tag{2}$$

The strategy set of MG m and EV n as the seller respectively is expressed by (3).

$$l_t^{n,i} = \left\{ 0 < l_t^{n,i} < d_t^{j}, \forall t \right\} \tag{3}$$

The power strategies set of EV and MG n being sufficient ($n \in J$) is expressed by $P_t^{n,i}$ in (4), which represents the supplementary power sold when EV and MG n are sellers. $P_{\max}^{n}$ defined by maximum exchange power, is the maximum capacity that EV and MG can be transaction.

$$P_t^{n,i} = \left\{ 0 \le P_t^{n,i} \le P_{\max}^{n}, \forall t \right\} \tag{4}$$

In this paper, EV located at the bottom of the MG at the same bus in the hierarchical structure, where the MG is seated in the upper layer, Therefore, the system under the whole hierarchical structure must meet the power constraints in the transaction process, expressed by (7).

$$\begin{cases} P_t^{MGm,\mathrm{pv}} + P_t^{MGm,\mathrm{wT}} = P_t^{MGm,\mathrm{es}} + P_t^{MGm} + \omega_t P_t^{EV,i} + L_t^{MGm} \\ \omega_t = \begin{cases} 1, & PiT \le t \le PoT \\ 0, & \text{otherwise} \end{cases} \end{cases}, \forall t \tag{5}$$

In the above formula, we make $P_t^{\mathrm{MG}n}$ that it represents the residual energy that can be used for energy transactions under the condition that the MG meets its own requirements; $P_t^{\mathrm{MG}n,\mathrm{pv}}$ represents the energy of PV power generation, $P_t^{\mathrm{MG}n,\mathrm{wT}}$ represents the energy of wind power generation; $L_t^{\mathrm{MG}n}$ represents the load of MG m, and these parameters are derived from weather information and load prediction respectively. $P_t^{EV,i}$ represents the charging power of an EV. The departure time and arrival time of EV from MG are called PoT (Plug-out time) and PiT (Plug-in time) respectively. That EVs reach the load state of MG is called PiS. ω_t is the parameter of PiT. If the plug-in period of the EV is between PiT and PoT, the $\omega_t = 1$; otherwise, $\omega_t = 0$; At the same time, $P_t^{\mathrm{MG}n} = 0$ results that the MG achieves its own balance through the energy storage unit. If the $P_t^{\mathrm{MG}n} > 0$, the excess energy of MG can be sold through P2P energy transaction. If $P_t^{\mathrm{MG}n} < 0$, you can choose to buy it for your own use from the party with sufficient power.

3.3. Utility

In this scenario, MGs and EVs buy or sell energy based on their own energy situations, and the roles played by EVs and MGs throughout the day are time-varying parameters. Therefore, without violating network constraints, their utility function expressions are shown in (4).

$$
\begin{aligned}
&U\left(C_t^{n,j}, P_t^{n,i}\right) \\
&= \sum_{t=1}^{T} \Big[-\left(1-r_t^n\right) P_t^{j,n} C_t^{n,j} + r_t^n P_t^{n,i} C_t^{i,n} - \left(1-r_t^n\right) f_t^c \\
&\quad - \left(r_t^n \phi^n \eta P_t^{i,n} + \left(1-r_t^n\right) \phi^n \frac{P_t^{i,n}}{\eta} \right) - f_t^N \\
&\quad - \left(1-r_t^n\right) \left(a \left(\varphi_{ij}^2 \left(P_t^{n,i} + P_m\right) + \varphi_{ij} \left(P_t^{n,i} + P_m\right) \right) + \left(1-a\right) \delta P_t^{n,i} \right) \Big] - a f_t^G - \rho \\
&r_t^n = \begin{cases} 0, \text{ if } n \in I \\ 1, \text{ if } n \in J \end{cases}, \quad a = \begin{cases} 0, n \in I_1 \\ 1, n \in I_2 \end{cases}
\end{aligned}
\tag{6}
$$

In (6), r_t^n is used to distinguish whether a MG or an EV is a buyer or seller, a is used to distinguish whether the trading entity is a MG or an EV, and I_1 and I_2 represent the sets of MGs and EVs, respectively. Within the equation, φ_{ij} and δ are parameters for estimating the cost of emissions for MGs and EVs, respectively. ϕ^n and η serve as parameters to estimate the costs for MGs and EVs under stochastic conditions, primarily determined by factors such as wind power and photovoltaic generation, state of charge (SOC) when EVs are integrated into MGs, the time period of integration, and the number of buyer and seller involved in transactions. f_t^c represents the cost of losses incurred when power is transmitted through power lines in point-to-point distributed transactions, as shown in [34].

Due to the influence of the load and the working characteristics of the micro source, the exchange power between the MG and the grid may be too frequent and cause unnecessary losses when the EV is connected to the MG. In order to mitigate the impact of the exchange on the power quality, it is employed to represent the penalty cost of exchanging power with the macro power grid, where $\sigma = \sum_{t=1}^{T} \left(P_t^{n,j} - \frac{\sum_{t=1}^{T} P_t^{n,j}}{24} \right)^2$ represents the variance of power exchange.

$$f_t^G = a_1 \sum_t^T \left|P_n\right| + a_2 \sigma \tag{7}$$

a_1, a_2 is employed to represent the penalty factor of the exchange power of the macro-grid.

ρ is employed to represent the penalty cost for the deviation between the renewable energy generation capacity and the actual load in the micro energy network, where g_{re} represents the sum of power generation of renewable energy at t slot.

$$\rho = \zeta \sum_{n,m=1}^{N,M} \left(L_t^{MGm} - g_{re}\right) \tag{8}$$

In order to fully reflect the evaluation of trading users on multi-party energy transactions, the satisfaction function is established based on the actual situation of the game to quantify the users' satisfaction with the overall transaction in the paper. The satisfaction function is expressed as follows:

$$f_t^N = \alpha R_t^n + \left(1 - \alpha\right) A_t^n \tag{9}$$

A_t^n is employed to define satisfaction rate for MG is set to $A_t^n = r_t^n P_n \beta \left[\left(\frac{P_t^{n,j}}{P_n}\right)^{\alpha} - 1\right] + \left(1 - r_t^n\right) \lambda^s \ln\left(1 + C_t^{n,j}\right)$. The α, β and λ^s are satisfaction parameters ($\alpha < 1$, $\alpha\beta < 0$, $\lambda^s > 0$). R_t^n defined for EV is set to $R_t^n = \left(1 - r_t^n\right) \alpha_1 \left(1 - \frac{C_t^{n,i} - C_t^b}{C_t^s - C_t^b}\right) + r_t^n \alpha_2 \left(1 - \frac{\sum_{t=1}^{T} \left|P_t^{SOC_{\max}} - P_t^{n,j}\right|}{\sum_{t=1}^{T} \left|P_t^{SOC_{\max}} - P_t^{SOC_{\min}}\right|}\right)$, Satisfaction rate balances purchased and expected electricity, to prevent trading failures due to high electricity prices.

3.4. Bayesian Nash Equilibrium

Following the fundamental principles of Bayesian games, an incomplete game corresponds to a combination of various complete games under different conditional probabilities, influenced by the joint distribution. (6) is updated to equation (10) as shown.

$$\mathrm{E}U_n\left(r^n\right) = \sum_{r_t^n \in R_t^{-n}} U_n\left(C_t^{n,j}, P_t^{n,i}, P_t^{(J\{n\})\backslash I)}, C_t^{(J\{n\})\backslash I)}\right) \cdot p\left(r_t^{-n} \mid r_t^n\right) \tag{10}$$

The combination of $r^n = \left[r_1^n, \cdots, r_T^n\right]$ represents a particular type combination r_t^n at a specific time period t-1, where $r_t^{-n} = \left[r_t^1, \cdots, r_t^{n\text{-}1}, r_t^{n+1}, \cdots, r_t^N\right]$ represents all type combinations except r_t^n. $R_t^{-n} = R_t^1 \times R_t^2 \times \cdots \times R_t^{n-1} \times R_t^{n+1} \times \cdots \times R_t^N$ represents the type space in which the trading entity exists, and all type combinations except r_t^n. $R_t = R_t^1 \times R_t^2 \times \cdots \times R_t^N$ represents the type space of all trading entities. The symbol E denotes the expected utility $U_n\left(r^n\right)$ under other type combinations, and $p\left(r_t^{-n} \mid r_t^n\right)$ is employed to define the conditional probabilities of the trading entity given that it belongs to type combination r^n, with the other $N-1$ participants under consideration, in (10).

When $r_t \in R_t$ ($R_t = R_t^1 \times R_t^2 \times \cdots \times R_t^N$), (10) can be updated as follows in (11):

$$\mathrm{E}U_n = \sum_{r_t \in R_t} \mathrm{E}U_n\left(r^n\right) \cdot p\left(r_t^n\right) \tag{11}$$

Due to $p\left(r_t\right) = p\left(r_t^{-n} \mid r_t^n\right) \cdot p\left(r_t^n\right)$, (11) can be further updated as follows in (12).

$$\mathrm{E}U_n = \sum_{r_t \in R_t} U_n\left(r^n\right) \cdot p\left(r_t\right) \tag{12}$$

Nash equilibrium is defined as a state where every buyer and seller can achieve their best response without any motivation to change their strategies in Bayesian games, as shown in (13).

$$\mathrm{E}U_n\left(C_t^{n,j^*}, P_t^{n,i^*}, P_{I\times(j\setminus\{n\})}^{t^*}, C_{(I\setminus\{n\})\times J}^{t^*}, r_t\right) \geq \mathrm{E}U_n\left(C_t^{n,j}, P_t^{n,i}, P_{I\times(J\setminus\{n\})}^{t^*}, C_{(I\setminus\{n\})\times J)}^{t^*}, r_t\right) \tag{13}$$

Bayesian games involve trade users in various combinations of complete games, where both parties act in their self-interest. Nash equilibrium is a strategy combination where each participant's strategy is the best response to the strategies of others. Hence, it is necessary to first compute the Nash equilibrium for complete information games under all possible conditions. The conditions for the existence of equilibrium in complete games in Equation (13) are as follows:

1) For pure strategy sets, the strategy space is a non-empty compact set.

2) Under the strategy set, the utility function is continuous and quasi-concave.

Proof (1): In the strategy sets (1) and (2), the constraint conditions are linear inequalities. Thus, condition (1) is established.

Proof (2): The necessary and sufficient condition is that the Hessian matrix (14) of the utility (4) in the multi-party game is negative definite.

$$H\left(U_n\right) = \begin{vmatrix} \nabla^2_{C_t^{n,i} C_t^{n,j}} U_n & \nabla^2_{C_t^{n,j} P_t^{n,i}} U_n \\ \nabla^2_{P_t^{n,i} C_t^{n,j}} U_n & \nabla^2_{P_t^{n,i}, P_t^{n,i}} U_n \end{vmatrix} \tag{14}$$

(14) is obtained by calculating the first-order partial derivatives of (15) and (16) by simultaneously solving (6), (7),(8) and (9).

$$\begin{aligned}
\frac{\partial u\left(c_t^{n,j}, p_t^{n,i}\right)}{\partial p_t^{n,i}} = {} & r_t^n c_t^{i,n} - \left(1-r_t^n\right) c_t^{n,j} - \left(1-a\right) r_t^n \alpha\beta \left(\frac{P_t^{n,j}}{P_n}\right)^{\alpha-1} \\
& - a r_t^n \alpha_2 \left(1 - \frac{\sum_{t=1}^{T} \left| P_t^{SOC_{\max}} - 1 \right|}{\sum_{t=1}^{T} \left| P_t^{SOC_{\max}} - P_t^{SOC_{\min}} \right|}\right) \\
& - \left(1-r_t^n\right) \left(\frac{\lambda^{VSC}}{\left|V_{t-1}^k\right|} \mathrm{Re}\left(V_t^{k^*} \frac{\partial V_{t-1}^k}{\partial P_{t-1}^k}\right) + \lambda^{PTDF} \left(-\frac{\Delta P_{t-1}^{k,xy}}{P_t^{n,j^2}}\right)\right. \\
& \left. + \lambda^{LSF} \mathrm{Re}\left(V_t^{k^* T} \frac{\partial^2 V_t^k}{\partial P_t^{n,j^2}}\right)\right) - \left(a\left(\varphi_{ij}^2 + \varphi_{ij}\right) + \left(1-a\right)\delta\right)
\end{aligned} \tag{15}$$

$$\frac{\partial u\left(c_t^{n,j}, p_t^{n,i}\right)}{\partial c_t^{n,j}} = r_t^n p_t^{n,i} - \left(1-r_t^n\right)\frac{\lambda^s}{1+c_t^{i,n}} - \left(1-r_t^n\right) p_t^{j,n} - \left(1-r_t^n\right)\alpha_1\left(1-\frac{1-C_t^b}{C_t^s - C_t^b}\right) \tag{16}$$

This results in the second-order partial derivatives as shown in (17). The roles of MGs and EVs n cannot simultaneously be buyers and sellers, so, $\nabla^2_{P_t^{n,i}C_t^{n,j}}$ and $\nabla^2_{C_t^{n,j}P_t^{n,i}}$ are both equal to 0. It is observed that all diagonal elements of the (14) matrix are less than 0, and non-diagonal elements are all 0. Hence, (14) constitutes a negative definite Hessian matrix, confirming the proof for condition (2).

$$\frac{\partial u\left(c_t^{n,j}, P_t^{n,j}\right)^2}{\partial^2 P_t^{n,j}} = -2\lambda^{PTDF}\frac{\Delta P_{t-1}^{k,xy}}{P_t^{n,j}} - \lambda^{LSF}\operatorname{Re}\left[V_t^{k^*T}\frac{\partial^2 V_t^k}{\partial P_t^{n,j}}\right] - (1-a)\frac{r_t^n\alpha(\alpha-1)\beta}{P_n}\left(\frac{P_t^{n,j}}{P_n}\right) \tag{17}$$

$$\frac{\partial u\left(C_t^{n,j}, P_t^{n,i}\right)^2}{\partial^2 C_t^{n,j}} = \left(1-r_t^n\right)\frac{\lambda^s}{\left(1+C_t^{n,j}\right)^2}$$

The prerequisite for (13) is the existence of a Nash Equilibrium (NE) in complete information games. Based on the derivation of NE for complete games, (18) can be readily achieved. In conclusion, a Bayesian NE exists.

$$\begin{cases} \nabla^2_{P_t^{n,j}P_t^{n,i}} \mathrm{E}U_t^n = \nabla^2_{P_t^{n,i}P_t^{n,i}} U_t^n \sum\limits_{r_t^{-n}\in R_t^{-n}} p\left(r_t^{-n} \mid r_t^n\right) \\ \nabla^2_{C_t^{n,j}C_t^{n,j}} \mathrm{E}U_t^n = \nabla^2_{C_t^{n,j}C_t^{n,j}} U_t^n \sum\limits_{r_t^{-n}\in R_t^{-n}} p\left(r_t^{-n} \mid r_t^n\right) \\ \nabla^2_{P_t^{n,i}C_t^{n,j}} \mathrm{E}U_t^n = \nabla^2_{C_t^{n,j}P_t^{n,i}} \mathrm{E}U_t^n = 0, t \neq t' \end{cases} \tag{18}$$

The key to proving the uniqueness of Nash equilibrium lies in demonstrating that the best response functions for each seller and buyer, as defined in (4), are standard functions. As defined below, function $f(p) = \left(f_1(p), \cdots, f_N(p)\right)$, $p = \left(p_1, \cdots, p_N\right)$ is considered a standard function if it satisfies the following conditions:

1) Positive definiteness: $f(p) > 0$.

2) Monotonicity: For all p, p', if $p \geq p'$, then $f(p) \geq f(p')$.

3) Scalability: For $\mu > 1$, $\mu f(p) > f(\mu p)$.

The best response functions of trading parties at different times are standard functions of $c_t^{n,j}$ or $p_t^{n,i}$. The proof is as follows:

Since the utility functions of trading parties in different time periods are strictly concave with respect to $c_t^{n,j}$ or $p_t^{n,i}$, setting the right side of (15) to 0 yields the best response functions of trading parties.

Taking the best response function of the buying party as an example.

$$f\left(c_t^{n,j}, p_t^{n,i}\right) = p_t^{n,i}\left(1+c_t^{n,j}\right) + \lambda^s \tag{19}$$

Next, the paper sequentially proves that the function form of $f\left(c_t^{n,j}, p_t^{n,i}\right)$ as a $c_t^{n,j}$ satisfies the three properties described in the above definition of standard functions.

1) Positive definiteness: Since both $c_t^{n,j}$ $p_t^{n,i}$ and λ^s are positive numbers, $f\left(c_t^{n,j}, p_t^{n,i}\right) > 0$

2) Monotonicity: Calculating the first derivative of $f\left(c_t^{n,j}, p_t^{n,i}\right)$ with respect to $c_t^{n,j}$, we obtain $\frac{\partial f\left(c_t^{n,j}, p_t^{n,i}\right)}{\partial c_t^{n,j}} = p_t^{n,i} > 0$

3) Scalability: Based on above, $\mu f\left(c_t^{n,j}, p_t^{n,i}\right)$ and $f\left(\mu\left(c_t^{n,j}, p_t^{n,i}\right)\right)$ are calculated, yielding the following results in Equations (20) and (21).

$$\begin{aligned}\mu f\left(c_t^{n,j}, p_t^{n,i}\right) &= \mu\left(\left[p_t^{n,i} + \alpha_1\left(1 - \frac{1 - C_t^b}{C_t^s - C_t^b}\right)\right]\left(1 + c_t^{n,j}\right) + \lambda^s\right) \\ &= \mu p_t^{n,i} + \mu p_t^{n,i} c_t^{n,j} + \mu\alpha_1\left(1 - \frac{1 - C_t^b}{C_t^s - C_t^b}\right) + \mu\alpha_1\left(1 - \frac{1 - C_t^b}{C_t^s - C_t^b}\right)c_t^{n,j} + \mu\lambda^s\end{aligned} \tag{20}$$

$$\begin{aligned}f\left(\mu\left(c_t^{n,j}, p_t^{n,i}\right)\right) &= \left[p_t^{n,i} + \alpha_1\left(1 - \frac{1 - C_t^b}{C_t^s - C_t^b}\right)\right]\left(1 + \mu c_t^{n,j}\right) + \lambda^s \\ &= p_t^{n,i} + \mu p_t^{n,i} c_t^{n,j} + \alpha_1\left(1 - \frac{1 - C_t^b}{C_t^s - C_t^b}\right) + \mu c_t^{n,j}\alpha_1\left(1 - \frac{1 - C_t^b}{C_t^s - C_t^b}\right) + \lambda^s\end{aligned} \tag{21}$$

Therefore, for $\mu > 1$, $\mu f\left(c_t^{n,j}, p_t^{n,i}\right) > f\left(\mu\left(c_t^{n,j}, p_t^{n,i}\right)\right)$.

In conclusion, the uniqueness of Nash equilibrium has been established.

4. Analysis of Calculation Results

4.1. Example Parameters

To validate the feasibility of the multi-party game, this paper primarily utilized a computational platform with Python, an Intel Core i5 quad-core CPU (2.6 GHz), and 8 GB of RAM to solve the equilibrium points of the Bayesian model established in Section 2.3 using the particle swarm algorithm. Five multi-MG systems and thirteen EVs participated in the game, with the initial energy distribution determined based on weather conditions, load profiles, and the drivers' requirements. At this point, EVs were connected to various MG systems, with the configurations of each MG as shown in **Table 1**, and the total power capacity and maximum load of the EV batteries connected to the V2M were detailed in **Table 2**.

The algorithm's solving period is 24 hours. Taking V2M on the 1st of the month as an example: PV configuration is 200 kW, maximum wind turbine (WT) power generation is 200 kW, and a micro gas turbine is configured for 50 kW. The energy storage unit uses lead-acid batteries, with a total $SOC_{\max}$ of 350 kWh and a corresponding minimum $SOC_{\min}$ of 50 kWh. The maximum charge/discharge power is set to 50 kW with an efficiency of 0.95. The initial SOC is 50 kWh. The lower-level EVs connected to V2M are generally managed through Aggregator coordination, participating in scheduling. The Aggregator collects interactive information, such as the number of EVs, the initial and target SOC of EV batteries, EV charging periods, WT, PV power outputs, etc. It optimizes the V2V power exchange between EVs in this layer and the P2P energy trading between MGs and EVs, ensuring the safety of lower-level power exchanges and motivating the active participation of users. The total maximum load within the V2M system is 300 kW. In the time-optimized period, micro-source forecasts and initial SOC of EVs are shown in Figure 3, Figure 4.

4.2. Result Analysis

Using (20), the equilibrium electricity prices C_t^{n,j^*} for the purchasing party in

Table 1. Configuration of each V2M and maximum load.

No.	PV	WT	GT	DS	EV	Load
1	200 kw	200 kw	50 kw	350 kwh	80 kwh	300 kw
2	450 kw	300 kw	100 kw	400 kwh	80 kwh	350 kw
3	450 kw	200 kw	50 kw	350 kwh	85 kwh	325 kw
4	150 kw	200 kw	20 kw	250 kwh	0 kwh	250 kw
5	400 kw	300 kw	100 kw	400 kwh	160 kwh	375 kw

Table 2. Parameters of MGs No. 1.

Parameters	Symbol	Value	Unit
ES Minimum SOC	$SOC_{\min}^{es}$	15	%
ES Output	$P_{\max}^{1,DS}$	50	kW
Efficiency of ES	η^{ev}	95	%
EV Minimum SOC	$SOC_{\min}^{ev}$	10	%
EV Output	$P_{\max}^{1,EV}$	20	kW
Efficiency of EV	η^{EV}	95	%
Cost Coefficient	λ	5.3	cent/kWh

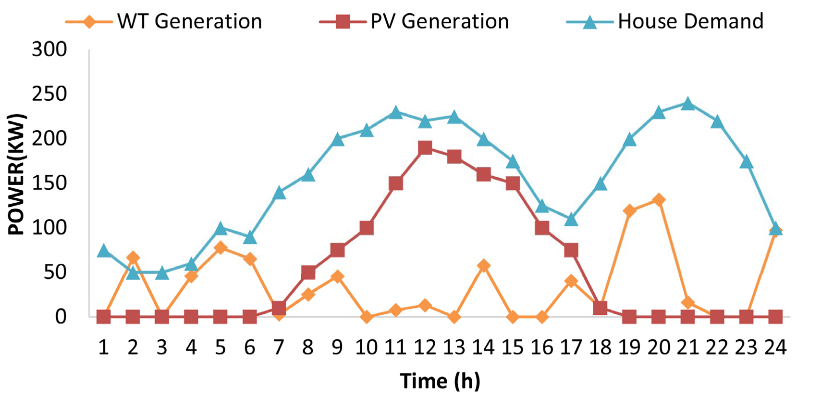

Figure 3. No.1 MG's DGs and load forecasting of power in 24 h.

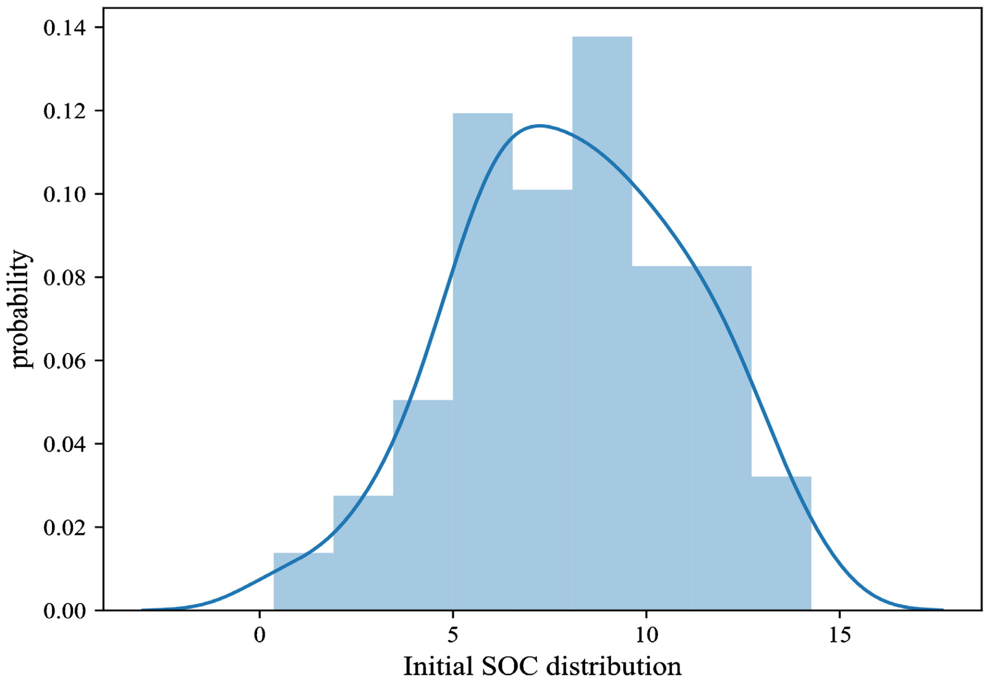

Figure 4. Initial SOC of 24-hour EV.

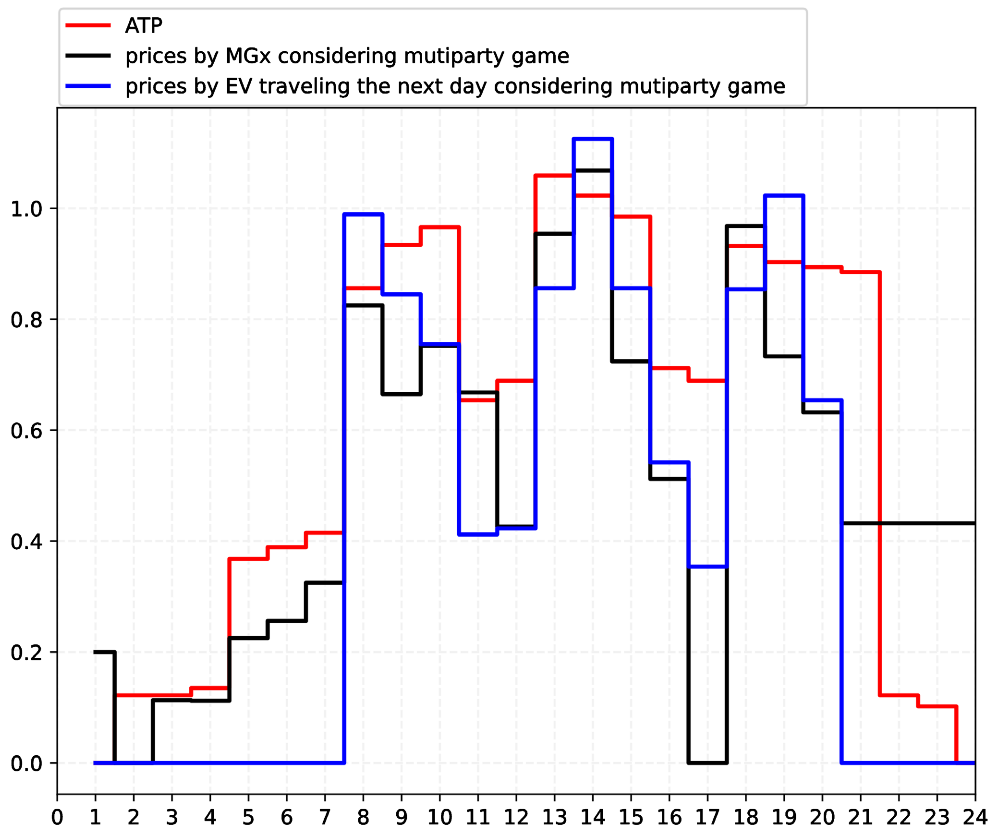

Figure 5. 24-hour price change curve.

each time period are calculated, as illustrated in Figure 5. Employing a multi-party game time-based strategy, the electricity prices are generally higher than the decision price, except during peak hours. During peak periods, MGs and EVs primarily purchase the required power to meet their own load demands. Consequently, they choose expected prices higher than the average price to procure electricity, thereby achieving stable operation and the dual objectives of acquiring more electricity at expected costs.

Under the multi-party game time-based pricing strategy, the comparison of energy sales ratios after participating in energy trading by the users is depicted in Figure 6 and Figure 7. Using the multi-party game pricing strategy, users exhibit a higher enthusiasm for participating in the market compared to traditional pricing strategies, with an increase of approximately 12%. This indicates that considering multi-party games promotes and efficiently motivates participants, resulting in increased gains.

Under the multi-party game time-based pricing strategy, the profit comparison after users participate in energy trading is presented in Figure 8. Employing the multi-party game pricing strategy results in a noticeable increase in profits. For example, the profit for MG.1 has risen from 624 yuan before optimization to the current 760 yuan, a growth of 21.79%. MG.1 and MG.2 earn more profits than other users because they have larger ES capacities and more abundant stored electricity. As a result, their electricity sales ratios are higher, attracting more trading partners and thus yielding greater profits.

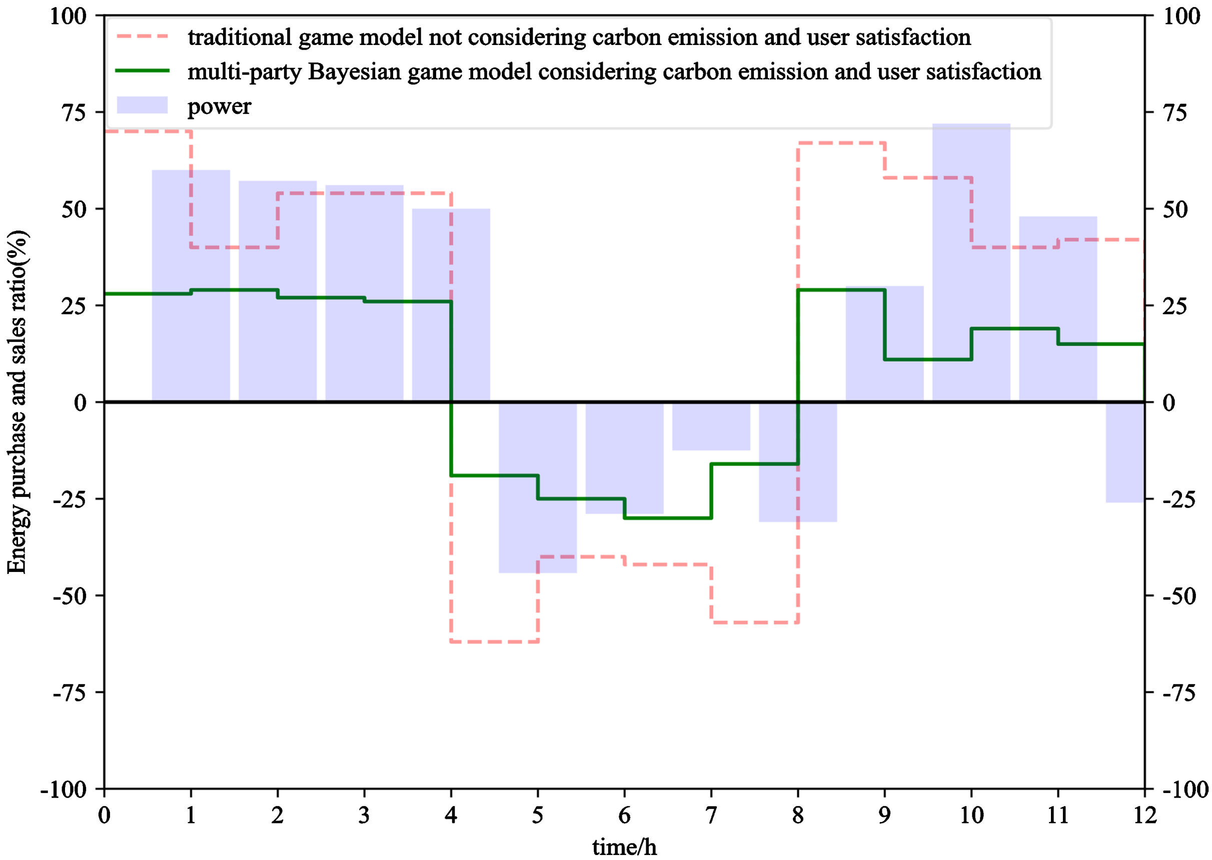

Figure 6. MGs energy transaction proportion curve within 24 h.

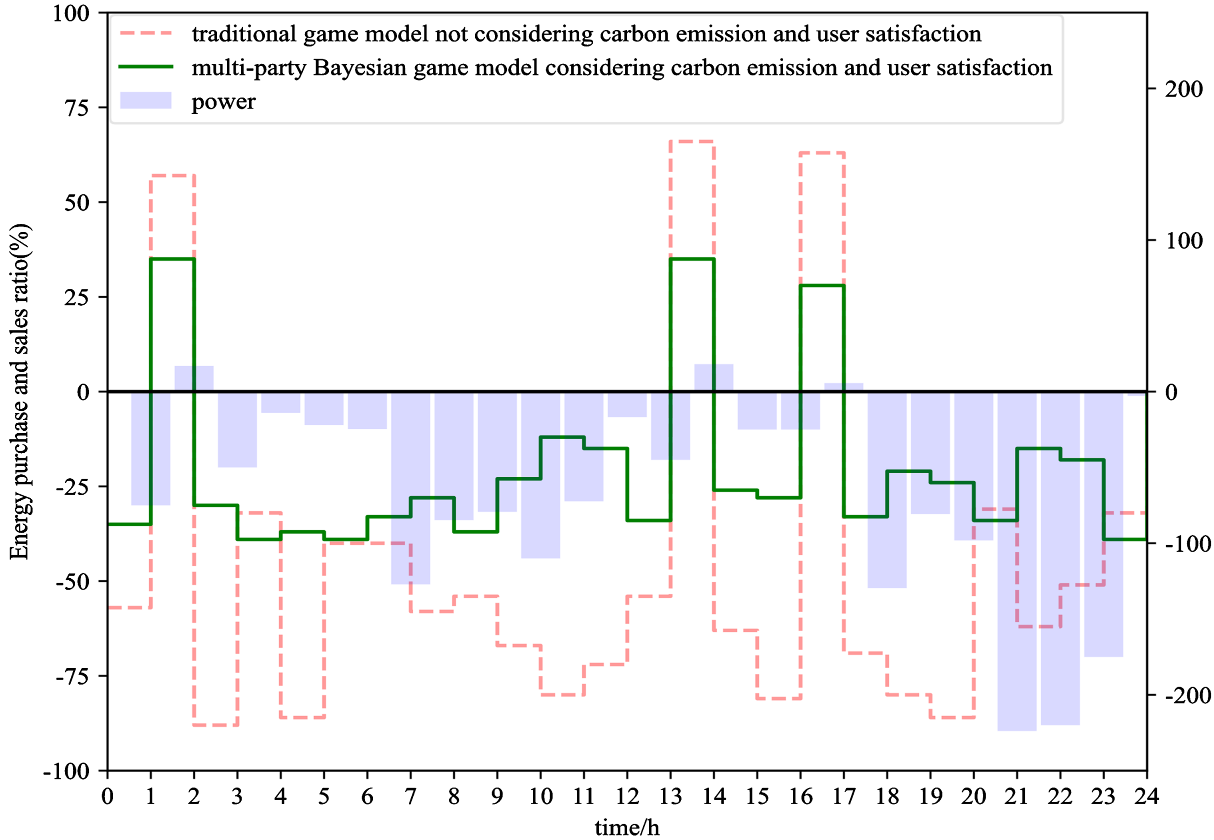

Figure 7. EVs energy transaction proportion curve within 24 h.

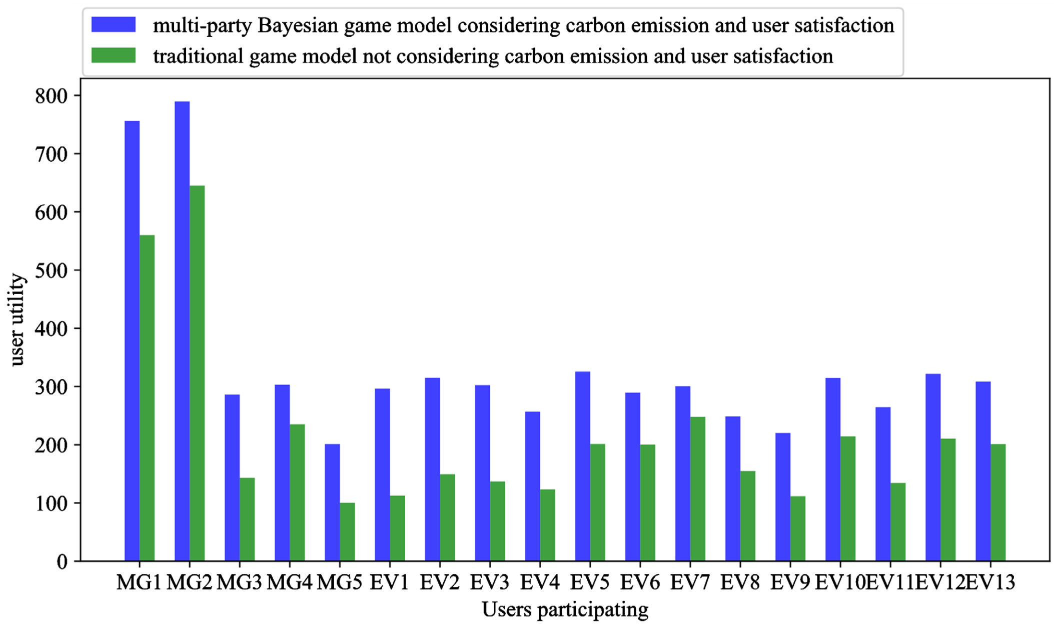

Figure 8. Comparison of transaction income of participating users.

Figure 9 show the output power comparison of micro-GT in the MG during the 24-hour multi-party energy game. It can be seen from the trend of the red curve in the figure that in order to ensure the lowest environmental consumption

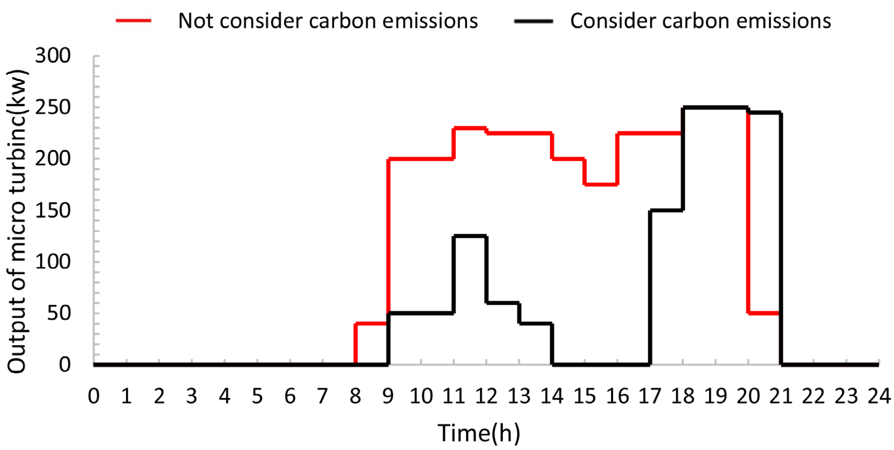

Figure 9. The output power comparison of micro-gas turbines in the MG in one day.

cost, the output of the internal steam turbine is still very high at the peak of household load demand only by increasing the participating users of MG, and it doesn't rely on energy interaction to meet the actual working conditions; From the point of view, it is also possible to purchase power from the macro grid to meet the demand, resulting in increased environmental costs and carbon emissions; a distributed energy transaction based on the multi-party game of MGs and EVs are established in the paper, which can not only improve the income, but also achieve the control goal of minimizing the environmental cost. As shown by the black curve, the output ratio of the micro-turbine in the micro grid at this node is significantly reduced, and it is in the shutdown state at 16:00, indicating that the MG can effectively withstand its internal load pressure through energy interaction and reduce the environmental cost.

In order to verify the effectiveness of the multi-party energy game optimization model proposed in this paper, the following four scenarios are set for comparative analysis: Scenario 1 is a traditional energy transaction that does not consider carbon emission costs and multi-party games; Scenario 2 considering multi-party games but the energy transaction without considering the carbon emission cost; Scenario 3 is the energy transaction considering the carbon emission cost but not considering the multi-party game; Scenario 4 is the model considering the carbon emission cost and the multi-party game.

According to the previous load forecast, we obtained the 24-hour carbon emission curves of the four scenarios as shown in **Figure 10**. After considering the emission cost, the carbon emissions of the system in scenarios 3 and 4 decreased significantly compared with the scenarios 1 and 2 in each period, which proves that the multi-party game model proposed in this paper considering the carbon emission cost can effectively reduce the carbon emissions of the system and reduce all of the cost of carbon treatment needed to achieve the economic, low-carbon goals of the model.

Comparison of Bayesian Multi-Party Game Time-of-Use Pricing considering user satisfaction with Traditional Game Pricing Methods, is shown in **Figure 11**. As the number of participating users increases, the prices after the game, using

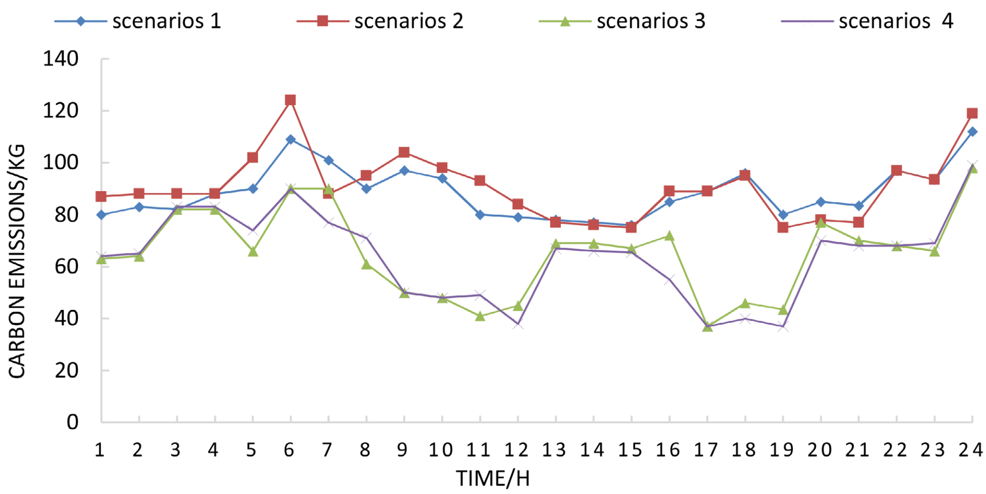

Figure 10. Comparison of 24-hour carbon emission curves under four scenarios.

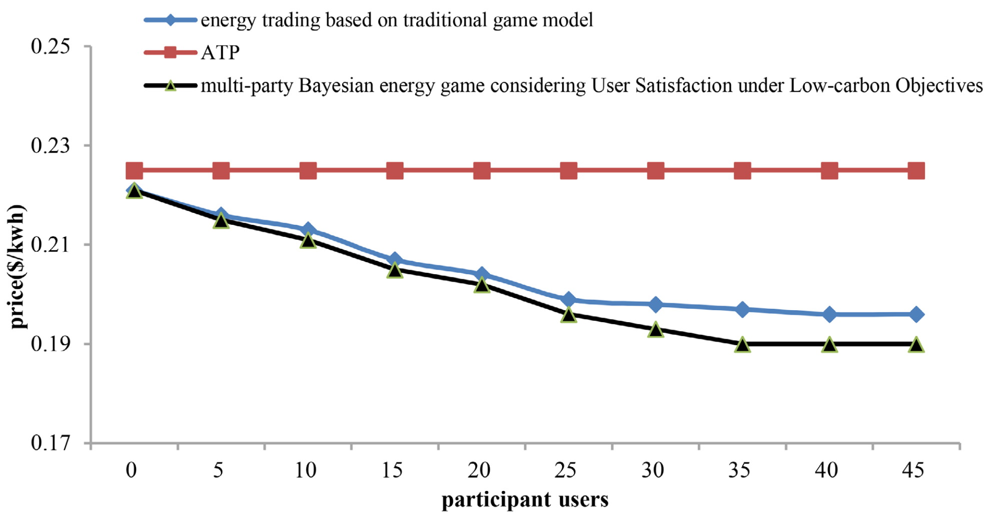

Figure 11. Optimal operation results under different algorithms.

the game pricing strategy, are lower than the average price. Furthermore, the method proposed in this paper results in lower prices compared to traditional game pricing methods. According to the calculations, the method proposed in this paper yields more significant benefits when applied to bilateral transactions, averaging 125 yuan more per time interval than the traditional methods.

Furthermore, the port load curve under Bayesian games, as shown in Figure 12, exhibits lower peak values in total port loads for the MGs compared to traditional pricing strategies, and the power distribution is more even. This indicates that for the port loads of multi-V2M systems, Bayesian game pricing strategies play a "peak-shaving" role.

Figure 13 displays the SOC changes for 13 participating EVs at different times. From the figure, it can be observed that EV NO.1 plugged into MG at 12 o'clock and left MG at 21 o'clock. During this period, assuming that EV NO.1 did not trip the next day, it acted as an energy supplier in a discharging state, using V2V exchange to sell surplus electricity and generate corresponding income.

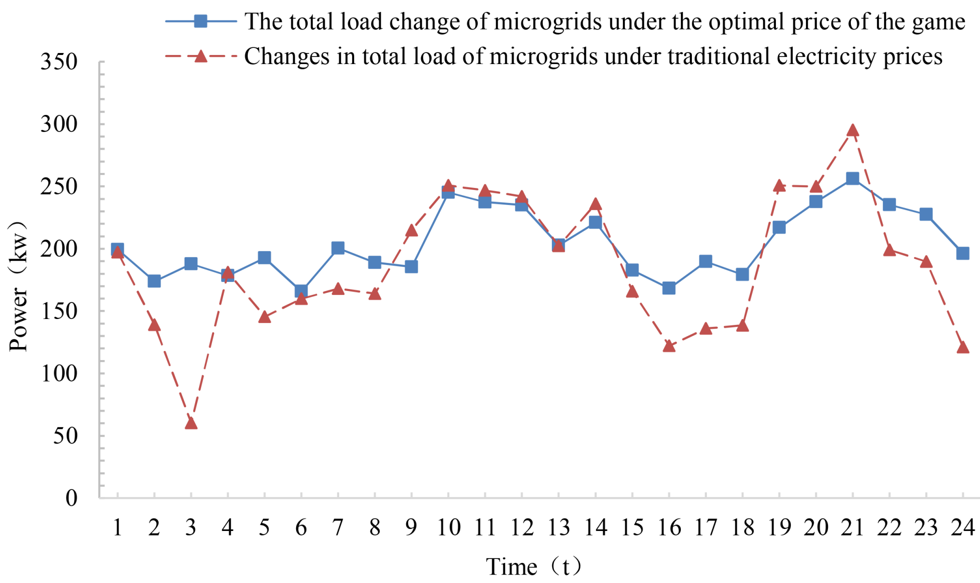

Figure 12. Comparison of MG total load peak under multi-party game.

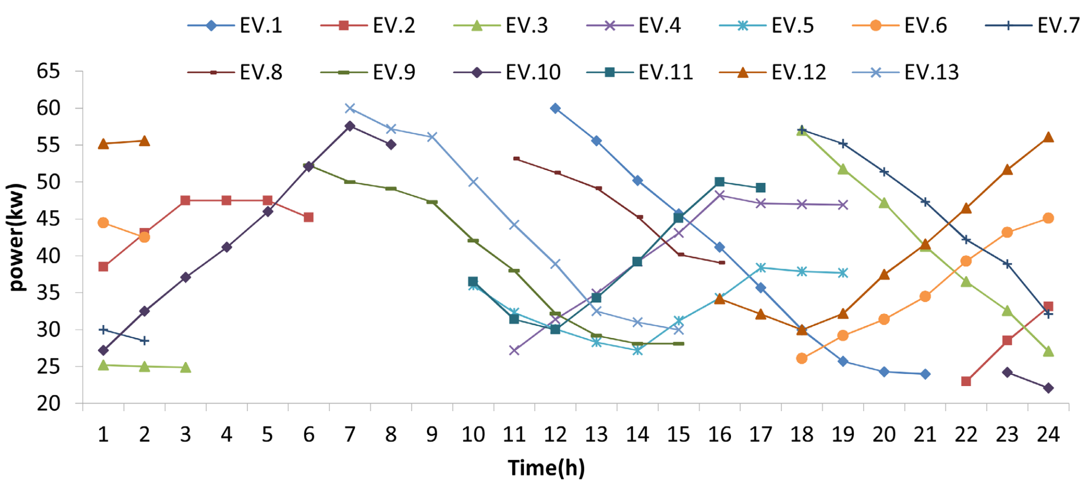

Figure 13. The SOC changes of 13 EVs participating in the transaction at different times.

5. Conclusion

For multi-party electricity trading scenarios, we have established a multi-party pricing game considering network constraints. This model takes into account the stochastic characteristics of electric vehicles (EVs) and constructs a utility function model for multi-party Bayesian games. Furthermore, it considers user responsiveness and energy exchange costs to ensure the proper functioning of incentives in the electricity trading market, cost reduction in the grid, fair energy distribution, and compliance with low carbon standards. In this game scenario, an optimal pricing strategy for multi-party energy trading considering user responsiveness under low carbon goals is proposed. Both theoretical analysis and simulations confirm the existence and uniqueness of the optimal solution. Simulations indicate that an increase in the number of trading users significantly enhances the efficiency of all parties, reduces total grid costs and energy exchange costs, ensures system stability, and encourages active user participation. This research provides valuable technical support for the development of electric vehicles. In future work, we will explore power trading in multi-party scenarios under different distribution network nodes and investigate mixed multi-party electricity trading schemes involving MGs and EVs, particularly in scenarios involving traffic and power flow coupling.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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