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A Game Theoretical Pricing Mechanism for Multi-Microgrid Energy Trading Considering Electric Vehicles Uncertainty

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ABSTRACT The electricity price mechanism based on game theory is one of the research focuses on microgrids energy trading. The complete information game is based on the certainty of the identity of roles of players and variables. However, there are many uncertain factors that cause the game in the state of incomplete information. In this paper, Microgrids Energy Trading Bayesian Game (METBG) model is proposed. The model was based on the Bayesian game, in which MGs make their decision as an agent of native users to tackle bidirectional energy trading between others. First, The Bayesian game modeled types of roles of players by the uncertainty of information including the stochastic characteristics of PEVs which result in hardness that the game participants determine whether they are sellers or buyers in the utility function that depends on the state of power surplus or lack. Moreover, the utility model of players was established by a Bayesian game with the game equilibrium derived rigorously by obligated to coordinate the sharing of energy with maximization of the players' profit. Finally, the solution of game equilibrium has been rigorously derived, and the effectiveness of the model is verified in terms of seller profit, the utilities of buyers, and the net energy usage in the microgrids. The results of the static pricing model and proposed model were compared to demonstrate the effectiveness.

INDEX TERMS Multi-microgrid, Electric vehicles, Energy trading, Bayesian game.

I. INTRODUCTION

Due to many benefits such as environment and economic cost, interests in electric vehicles (EVs) connecting to microgrids (MGs) have increased for the past few years [1]. The system not only integrates the advantages of EVs and MGs, but also initiates the newly developed research fields of MGs [2]. Moreover, compared to conventional hybrid electric vehicles (HEVs), evolved EVs, such as plug-in electric vehicles (PEVs), have enlarged battery capacities and bidirectional converters thus they can not only charge but also discharge their batteries [3].

EV batteries discharging to the microgrid have benefits which increase MGs stability and keep power balance for the randomly distributed generators (DG), such as photovoltaic (PV) and wind turbine (WT) system which do not belong to the controllable micro-source. Under this condition, EVs in MGs are similar to vehicle-to-grid (V2G) systems, could be acted as the role of energy storage (ES) for MGs [4]. However, compared with ES, EV batteries have different characteristics. First of all, the batteries of electric vehicles are not connected to MG all day. Secondly, the time of connection to MG behaves a random distribution. Thirdly, the state of charge (SOC) of EV batteries after connection also presents random distribution. Finally, the batteries of EV are essentially MG loads by charge. Based on all above conditions, the battery of EV has different characteristics compared with ES including the scheduling principle which keeps the SOC unchanged at the start and end of a scheduling cycle.

However, MGs should increase the controllable generation's output power or connect to others power grid for external power such as the macrogrid with lower SOC of ES and EV conditions which cannot keep power balance. In contrast, MG's surplus power could be stored in the ES and PEV's batteries or sold to the electricity market [5].

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Trading system should be established for MGs for the condition that surplus power is sold to the macrogrid or to other MGs. However, the static electricity pricing model in the traditional power transaction cannot satisfy the MG system with EVs [6]. At present, many research results and related literatures have been begun to seek game equilibrium methods to establish the power transaction model for MGs.

State of art literatures has presented several game equilibrium methods for electricity pricing. A game model and Nash Equilibrium (NE) were provided between the distribution network (the power company) and multiple users of the time-of-use (TOU) price, by detailed proof and equilibrium point through analysis and deduction [7]. However, the game mentioned the traditional load users only, without considering the participation of electric vehicles and multi-microgrid. A Stackelberg game model for energy trading was established under multi-microgrid and the public utility in [8], where utility function and strategies were established by ''Leader'' and ''Follower'' users. The existence and uniqueness of NE were proved. Compared with [7], it begins to study the price mechanism among multi-microgrid, yet, the sale of electricity that was selected randomly and stored in the MGs did not consider EVs' problem. Mondal *et al.* [9], [10] raised a game-theoretic ENTRANT and HoMeS scheme between the PHEVs and the micro-grids as a multi-leader and multi-follower in a Stackelberg game, in which PHEVs follow the mobility pattern of Gauss–Markov mobility model. This game model establishes the broader aspect for energy trading network in mobile smart grids. However, the ENTRANT scheme is a kind of static prediction model in which the SOC of EV for game equilibrium solving is obtained by Gauss-Markov mobility model, did not establish the influence of random variable game scenarios. A Stackelberg game for the uncertainty of PV in smart girds was established under deregulated electricity markets [11]. An effective energy-sharing management via a Stackelberg game approach was proposed for the operation. The model considers the energy transaction and price mechanism between microgrid and PV generation users under the uncertainty of PV generation. However, the influence of EVs on the model is not considered in the literature. Based on the Stackelberg game, [15] established the utility models of sellers and buyers in which include a stochastic variable model for EVs. With the proof of equilibrium and uniqueness of the Stackelberg equilibrium, the game equilibrium is solved to deal with the uncertainty of EV's energy and plugging-in time. However, the literature does not consider the role uncertainty of game players under the condition of imperfect information.

The aforementioned models based on complete information game have drawbacks where exist in MGs with the uncertainty of PEVs. Whether the surplus energy is sold or not is the fundamental reason for the uncertain role of game players. The amount of surplus energy depends on PV, WT power generation and EV's SOC. The influences of uncertain factors on game model were started from PV and WT. At present, many literatures research on PV and WT generation uncertainty. The weather forecast is used as the method to analyze the power generation uncertainty of PV and WT [12], [27]. With a large number of EVs(such as EV fleets) connected to microgrid for charging, more literatures have been focused on the random characteristics caused by the uncertainty of EV's plug-in time and initial SOC which are the issues affect players' roles in the two-level Stackelberg game model. From the perspective of game theory, the participant's profit function cannot be determined. Since much information in reality is unknown to all or many players refuse to share their private information, the complete game approach is not suitable for the situation with incomplete information. Bayesian game approach is formulated for the proposed scenario with incomplete information to reduce users' daily cost, and existence of Bayesian Nash equilibrium is proved mathematically in [13]. The scenario is proposed for DSM programs to schedule household energy consumption considering bidirectional energy trading of PEVs, in which the charging cost and discharging profit of PEVs are not public information among different communities. Although the energy exchange and price mechanism between MGs are not studied, the consideration models of EV uncertainty in the literature assisted for our research. The stochastic characteristics of PEVs and energy trading between MGs are also not considered. He *et al.* [14] presented a Bayesian Stackelberg game based paradigm to model how individual MGs make their decision with imperfect information, in which the impact of imperfect communication on the decision making in energy trading market of the privacy-preserving MGs are explored and modeled.

The above papers are all developed on basis of game theory with complete or incomplete information. However, these works were established without considering the potential information uncertainty existing in communications between MGs caused by PEV's stochastic characteristics. Liu *et al.* [14] raised a scenario for DSM programs to schedule household energy consumption considering bidirectional energy trading of PEVs with incomplete information by a Bayesian game approach. Misra *et al.* [16] proposes an incomplete information game with energy trading for the distributed smart grid architecture. Although the Bayesian game approach using for MGs in the papers, the research on PEVs with incomplete information, which is also significant for MG pricing mechanism, has not been concerned at present. Due to the PEV concerns, some MGs may not know information or share some inaccurate information, which results in action uncertainty. Focused on the time-of-use pricing system, this paper proposed Microgrid Energy Trading Bayesian Game (METBG) approach for residential MGs energy trading considering incomplete information of PEVs. Compared to the previous works in which residential MGs scheduling and EV-based energy trading were studied separately, we jointly consider the energy trading between multi-microgrid with electric vehicle, and establishes the price trading mechanism between MGs sellers and buyers. We proposed the two-level Stackelberg game as the model framework to change the previous complete information game model structure. Simultaneously, focused on the influence of the uncertainty of electric vehicles on the role of game participants, we combined the uncertain states of the game participants, and then established a price mechanism model based on Bayesian-Stackelberg game, which is used for the energy trading of MGs with EVs. Here, the agent mechanism is adopted, in which individual MGs make their decision as an agent of native users to tackle bidirectional energy trading between MGs [16]. Compared with the existing methods, we consider the stochastic combination of players' roles in energy trading. Furthermore, the uncertainty of EVs which is one of the reasons for the randomness of players' roles is further studied. In summary, our contributions in this paper are as follows.

a) A METBG model is proposed for time-of-use price based energy trading between MGs considering incomplete information caused by PEVs. The METBG model focuses on the pricing mechanism that is incorporated into residential MGs energy scheduling problem considering the EV's uncertainty, which has not been done before to the best of our knowledge.

b) The utility model of players is established by a Bayesian-Stackelberg game, which considers all combinations of different players' role states, and existence of Bayesian-Stackelberg Nash equilibrium is strictly proved by mathematical derivation.

c) The price mechanism solution has been rigorously derived. An iterative algorithm is presented to achieve the equilibrium solution. The price mechanism of multi-microgrid is established, which provides the necessary premise for energy transaction between MGs.

The remainder of this paper is organized as follows. We briefly present the system structure of METBG in next section. Section III describes the mathematical modeling of the game model. In Section IV, we formulated the stochastic variable model for dynamics PEVs by using Markov chain. The existence and uniqueness of game equilibrium are discussed in Section V. and game equilibrium solution has been rigorously derived in Section VI. Numerical results and discussion are presented in Section VII. Finally, we conclude this paper in Section VIII.

II. PROBLEM SETTING

A. METBG CONFIGURATION

Originally, ES was set up to absorb the surplus power of PV and WT. However, the energy storage unit dispatched also plays the role of load regulation, thus making the MG profitable under the condition of time-of-use price. For example, ES can be charged from the grid at a lower price and be discharged at a higher price. The amount of PEVs in MGs, being an additional scheduled energy storage unit, will play a greater role in regulation and get more profit.

As shown in Fig.1, MGs, which consists of multiple renewable energy sources such as photovoltaic (PV) and wind

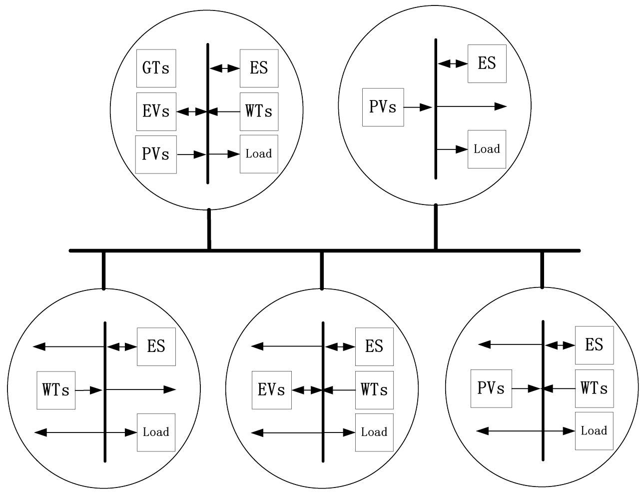

FIGURE 1. Architecture for METBG.

turbine (WT), loads, energy storage system (ES) such as large-scale battery system [10], [17], [18], are connected with each other through a common power bus which is used for energy transmission. MG has a PEV that can be regarded as shiftable load equipped with a smart meter which is employed to control center of MG. Micro-gas turbine (GT) is generally used in island operation mode, which is not discussed in this example.

III. MATHEMATICAL MODELING

The players, strategy sets, and utility functions are three basic elements in game. Furthermore, the types of player and the probability distribution of the types are the two basic elements in Bayesian game.

A. PLAYERS IN METBG

All MGs are in set N. Parts of MGs have superfluous energies to sell to the market, whereas others have not sufficient energies to support their load demands then need to buy the shortfall from the market. Based on fundamental of Stackelberg game, we define B as the set of buyers and S as the set of sellers, respectively. Because of the facts that MGs are prosumers, the elements belonging to these two sets can be time variant. Let $k = |B_t|$ denotes the number of buyers and $m = |S_t|$ be the number of sellers in time slot t. Let d_t^n denotes the total extra energy of player n, and defined by (1) in time slot t. $P_t^{n,\mathrm{pv}}$ and $P_t^{n,\mathrm{w}}$ denotes PV and WT output power respectively. L_t^n denotes loads of MG n. These parameters are obtained from weather information and load forecasting respectively. $l_t^{n,\mathrm{es}}$ represents the charging and discharging power of ES. $\hat{L}_t^{n,ev}$ denotes PEV's charging power. The time of PEV departure from MGs or arrival at MGs is called *PoT* (Plug-out Time) or *PiT* (Plug-in Time) respectively. The SOC (state of charge) of PEV arrival at MGs is called *PiS* (Plug-in SOC). ωt is the *PiT* parameter. If the PEV plugs into MG between *PiT* and *PoT*, then $\omega t = 1$ and $\omega t = 0$, respectively. $d_t^n < 0$ results in MG n acts as buyer purchasing power to satisfy the power balance when ES and PEV scheduling is still unable to fit the load demand. Conversely, if $d_t^n > 0$, it results in MG n act as seller depositing power into the ES or PEV or selling to the power market. In conclusion, the role of MG n is determined by (2).

$$\begin{cases} d_t^n = P_t^{n,\text{pv}} + P_t^{n,\text{w}} - L_t^n - l_t^{n,\text{es}} - \omega t \hat{L}_t^{n,\text{ev}} \\ \omega t = \begin{cases} 1, & PiT \le t \le PoT \\ 0, & \text{otherwise} \end{cases} \end{cases} \tag{1}$$

$$\begin{cases} n \in S_t, & \text{if } d_t^n > 0 \\ n \in B_t, & \text{if } d_t^n < 0 \end{cases} \tag{2}$$

B. STRATEGY SETS IN METBG

The strategy set of buyer i ($i \in S$) is expressed by (3), in which C_t^i represents the price bid by buyer i. C_t^{b} and C_t^{s} are the purchase price and the selling price of the macrogrid respectively. The buyer's bid should not be higher than C_t^{s} otherwise buyer will directly purchase electricity from the macrogrid. The buyers' bid should not be lower than C_t^{b} otherwise the sellers will directly trade with the power company.

$$\boldsymbol{C}_t^i = \{C_t^i > 0 : C_t^{\text{b}} < C_t^i < C_t^{\text{s}}, \forall t\} \tag{3}$$

The strategies set of seller j ($j \in B$) is expressed by (4).

$$\boldsymbol{l}_t^j = \left\{0 \le l_t^j \le d_t^j, \forall t\right\} \tag{4}$$

C. UTILITY FUNCTIONS IN COMPLETE INFORMATION GAME

The role of MG n in the game is determined by (2). Payoffs of MG n are defined as (5). $U_t^{n,j}(\cdot)$ denotes the utility function that MG n takes its role of seller j in time slot t. Let $\boldsymbol{l}_t^{-j} = \{l_t^l\} l \in J\backslash\{j\}$ be the strategy set of al1 sellers except seller j. C_t^i denotes that MG n takes its role of buyer i in time slot t. Let $\boldsymbol{C}_t^{-i} = \{C_t^l\} l \in I\backslash\{i\}$ denotes the strategy set of al1 buyers except buyer i. $U_t^{n,i}(\cdot)$ denotes the utility function that MG n takes its role of buyer i in time slot t.

$$\begin{cases} \sum_{t=0}^{T} U_t^n(l_t^j, C_t^i, \boldsymbol{l}_t^{-j}, \boldsymbol{C}_t^{-i}, r_n^t) \\ = \sum_{t=0}^{T} [r_n^t U_t^{n,j}(l_t^j, \boldsymbol{l}_t^{-j}, \boldsymbol{C}_t^i) + (1 - r_n^t) U_t^{n,i}(C_t^i, \boldsymbol{C}_t^{-i}, \boldsymbol{l}_t^j)] \\ r_t^n = \begin{cases} 1, & \text{if } n \in S_t \\ 0, & \text{if } n \in B_t \end{cases} \end{cases} \tag{5}$$

MG cannot be seller and buyer in one time slot t, therefore, r_t^n is employed to estimate the condition that $U_t^{n,j}(\cdot)$ and $U_t^{n,i}(\cdot)$ cannot exist together at the same time in (6). $U_t^{n,j}(\cdot)$ is defined by (6) in which W_t^i is the total power purchased by buyer i, which is represented by (7). $\hat{W}_t$, represented by (8), is the sum of power sales by all sellers in set J. This energy purchasing model is widely used to distribute electricity coordinating with the price offered by the seller [8]. A_t^j is a satisfaction rate function of the MG sellers.

$$U_t^{n,j}(l_t^j, \boldsymbol{l}_t^{-j}, \boldsymbol{C}_t^i) = \sum_{i \in I} W_t^i C_t^i \frac{l_t^j}{\hat{W}_t} - A_t^j - \partial(\hat{L}_t^{n,\text{ev}}) \tag{6}$$

$$W_t^i = \hat{W}_t \frac{C_t^i}{\sum_{v \in I} C_t^v} \tag{7}$$

$$\hat{W}_t = \sum_{j \in J} l_t^j \tag{8}$$

The satisfaction rate function for seller j is set to $A_t^j = d_t^j \beta \left[(l_t^j / d_t^j)^\alpha - 1\right]$. The α and β are satisfaction parameters ($\alpha < 1, \alpha\beta < 0$). Satisfaction rate balances surplus power storages and sales, to prevent over-sale of electricity through EV or ES discharge. $\partial(\hat{L}_t^{n,\text{ev}}) = \lambda \hat{L}_t^{n,\text{ev}}$ is the charge and discharge cost of EV caused by frequent charging/discharging cycles affecting the lifecycle of a battery. λ is the charge and discharge cost coefficient of EV batteries.

$U_t^{n,i}(\cdot)$ is defined by (9). $W_t^i C_t^{\text{s}}$ represents the amount of money that buyer i needs to pay if it directly obtains the amount of energy from the macrogrid. $W_t^i C_t^i$ is the amount of money that buyer i is willing to pay for buying from the sellers.

$$U_t^{n,i}(C_t^i, \boldsymbol{C}_t^{-i}, \boldsymbol{l}_t^j) = W_t^i C_t^{\text{s}} - W_t^i C_t^i - \partial(\hat{L}_t^{n,\text{ev}}) \tag{9}$$

D. UTILITY FUNCTIONS FOR BAYESIAN GAME

In Part C, each MG with the perfect information of its role in game knows their utility function completely by (2). However, it's hard to conduct the complete game in reality because much information is unknown to MGs, such as the role of players in game. For example, the role of MG n is determined by (2) in which d_t^n is an uncertain parameter caused by $\omega t \hat{L}_t^{n,\text{ev}}$ etc. Therefore, MG cannot determine its role in the game and utility function because of the lack of information for d_t^n. The modeling method on the complete game is inapplicable to this case. Then, Bayesian game is employed to describe the game behavior among MGs with incomplete information.

Based on Bayesian formula, r_t^n in (5) is defined as the type of role for MG n. Thus, combinations of $\mathbf{r}^n = [r_1^n, \ldots, r_T^n]$ is defined as one kind of r_t^n combination in all time slot 1-T. The type combination of all MG is $\mathbf{r}_t = [r_t^1, \ldots, r_t^n, \ldots, r_t^N]$ in time slot t. Accordingly, $\mathbf{r}_t^{-n} = [r_t^1, \ldots, r_t^{n-1}, r_t^{n+1}, \ldots, r_t^N]$ represents the type combination without r_t^n. $\mathbf{R}_t^n$ and $\mathbf{R}_t = \mathbf{R}_t^1 \times \mathbf{R}_t^2 \times \cdots \times \mathbf{R}_t^N$ represent the type space of MG n and every type combination of all MG respectively. Consequently, $r_t^n \in \mathbf{R}_t^n$ and $\mathbf{r}_t \in \mathbf{R}_t$ can be defined. Based on fundamental theory of Bayesian game, an incomplete game is combinations of various complete games corresponding to different type probability that are subjected to the joint distribution. Therefore, MG payoff is an expected value of all payoffs for these complete games. The utility function for MG n in (5) can be rewritten by (10).

$$U_n(\mathbf{r}^n) = \sum_{t=0}^{T} U_t^n(l_t^j, C_t^i, \boldsymbol{l}_t^{-j}, \boldsymbol{C}_t^{-i}, r_t^n) \tag{10}$$

$U_n(\mathbf{r}^n)$ denotes the utility function that MG n takes its role combination of $\mathbf{r}^n$. In the light of (10), the expected utility function (11) is achieved to MG n with $\mathbf{r}^n$. In other words, because of roles unknown to other opponents, (11) denotes that the expected utility function of MG n is the sum of combination which all other N-1 MG on different role type probability.

$$\mathrm{E}U_n(\mathbf{r}^n) = \sum_{\mathbf{r}_t^{-n} \in \mathbf{R}_t^{-n}} U_n(\mathbf{r}^n) \cdot p(\mathbf{r}_t^{-n} | r_t^n) \tag{11}$$

The E symbol represents the random expectation of $U_n(\mathbf{r}_n)$ under combinations of other N-1 MG. $p(\mathbf{r}_t^{-n}|r_t^n)$ is employed to define the conditional probability for $\mathbf{r}^{-\mathrm{n}}$ of other $N - 1$ MG under the condition when MG n belongs to r_t^n.Considering all MG n combination of $\mathbf{r}^n$ in all time slot (1 to T), (11) can be represented as (12) under $\mathbf{r}_t \in \mathbf{R}_t$.

$$\mathrm{E}U_n = \sum_{\mathbf{r}_t \in \mathbf{R}_t} EU_n(\mathbf{r}^n) \cdot p(r_t^n) \tag{12}$$

Owing to $p(\mathbf{r}_t) = p(\mathbf{r}_t^{-n}|r_t^n) \cdot p(r_t^n)$, (12) can be rewritten as (13). Obviously, (13) denotes that the expected utility function of MG n is sum of combination which all MG include itself under all possible role type combination.

$$EUn = \sum_{\mathbf{r}_t \in \mathbf{R}_t} U_n(\mathbf{r}^n) \cdot p(\mathbf{r}_t) \tag{13}$$

E. BAYESIAN NASH EQUILIBRIUM

In incomplete information, each MG calculates the expected payoffs by using a conditional probability distribution over the roles estimation for all other players (MGs). Based on (10), each MG performs the best response to the actions of others with the knowledge it gets from the market. The best response l_t^{j*} and C_t^{i*} for each MG Seller j and Buyer i, respectively, are given by (14).

$$\sum_{t=0}^{T} U_t^n(l_t^{j*}, C_t^{i*}, \boldsymbol{l}_t^{-j*}, \boldsymbol{C}_t^{-i*}, r_t^n) \geq \sum_{t=0}^{T} U_t^n(l_t^j, C_t^i, \boldsymbol{l}_t^{-j*}, \boldsymbol{C}_t^{-i*}, r_t^n) \tag{14}$$

In Bayesian game, Nash equilibrium is defined to each buyer and seller achieve its best response and have no motivation to change its strategies as described in (15).

$$\mathrm{E}Un(l_t^{j*}, C_t^{i*}, \boldsymbol{l}_t^{-j*}, \boldsymbol{C}_t^{-i*}, \mathbf{r}_t) \geq \mathrm{E}Un(l_t^j, C_t^i, \boldsymbol{l}_t^{-j*}, \boldsymbol{C}_t^{-i*}, \mathbf{r}_t) \tag{15}$$

IV. STOCHASTIC VARIABLE MODEL

The unique challenges in residential MGs with PEVs, however, are mostly in three stochastic variables: *PiT* (Plug-in Time), *PoT* (Plug-out Time), and *PiS* (Plug-in SOC).

A. DISTRIBUTION OF PLUGGING-IN AND PLUGGING-OUT TIMES

We adopted the statistical modeling method to deal with uncertainty of EV. Given statistics for these uncertain parameters, we model the PEV plug-state as a Markov chain.

A Markov chain model is a dynamic system that undergoes transitions from one state to another on a state-space. Unlike deterministic dynamical systems, the process is random and each transition is characterized by statistics. Moreover, it contains the Markov property that given the present state, the future and past states are independent.

In (1), the random characteristic of ωt has an important influence on d_t^n. Markov chain is modeled for dynamics of *PiT* and *PoT* in (16). The quantity $\varepsilon(t)$ and $\delta(t)$ are the transition probability of *PiT* and *PoT*, respectively. For example, considering the state transition Φ_{10} ($\omega t = 1$ to $\omega t + 1 = 0$), transition probability is the quantity $\varepsilon(t)$ at time t.

$$\Phi xy = \Pr[\omega_{t+1} = x | \omega_t = y, t], x, y \in \{0, 1\}$$
$$\begin{cases} \Phi_{10} = \Pr[\omega_{t+1} = 0 | \omega_t = 1, t] = \varepsilon(t) \\ \Phi_{01} = \Pr[\omega_{t+1} = 1 | \omega_t = 0, t] = \delta(t) \\ \Phi_{11} = \Pr[\omega_{t+1} = 1 | \omega_t = 1, t] = 1 - \varepsilon(t) \\ \Phi_{00} = \Pr[\omega_{t+1} = 0 | \omega_t = 0, t] = 1 - \delta(t) \end{cases} \tag{16}$$

According to the analysis of the daily driving schedules [5], the temporal distribution of vehicle transition probability is shown in Fig. 2. The PoT distribution is concentrated around 06:45-08:30.The mean value of the PoT is 7:40 AM (7.66h), and the standard deviation (std) is 0.57h. The *PiT* distribution shows the highest peak around 17:30-20:00 PM, the mean value is 6:38 PM (18.64h), and the std is 0.89h.

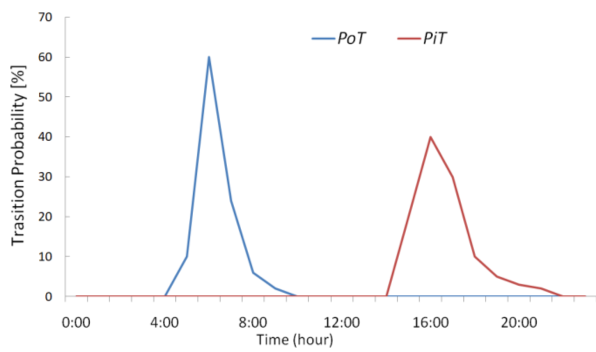

FIGURE 2. Distribution of PoT and *PiT*.

B. DISTRIBUTION OF PIS

At the beginning of working day, EV drives away from MG under a certain SOC which will be decreased with the increase of driving distance. When the EV returns to MG after the end of the day, the new SOC is defined by PoS as an important parameter to be considered in subsequent microgrid optimal operation scheduling and energy interaction. However, the *PiS* cannot be calculated directly because *PiS* is related not only to the SOC before the departure, but also to the mileage of a day. Supposed the EV leaves at full SOC, the *PiS* is related to the mileage of the day. The mileage of the day is also an uncertain variable. Therefore, the uncertainty of electric vehicles SOC in this paper focuses on the uncertainty of driving distance. The uncertainty of mileage is mainly obtained by modeling after statistical data analysis by [23].

As mentioned, PEV can act as ES after connected to MG. However, how much energy remains in the battery of the connected PEV depends on the SOC in battery. Therefore, the *PiS* is important for the subsequent scheduling. The *PiS* of PEV battery at *PiT* is mostly affected by driving distance. The driving distance D was mainly considered to compute the *PiS* in (17).

$$PiS = (PoS - \frac{D}{\mathrm{Dr}}) \geq SOC_{\mathrm{ev}}^{\min} \tag{17}$$

PoS and D_r represent the SOC at PoT and the distance that 1 kWh energies EV can drive, which is 6.7 km/kWh in [21]. $SOC_{\mathrm{ev}}^{\min}$ represents the limited of lowest SOC, which battery should not be less than with driving or discharging. Otherwise the battery will be damaged. Assume that an EV battery is $SOC_{\mathrm{ev}}^{\max}$ when it is fully charged. The uncertainty of state of charge of EV can be described by D according to the statistical daily trip length distribution in "Summary of Travel Trends 2017 U.S. National Household Travel Survey (NHTS)" [23]. Transition probability distribution of *PiS* for a given *PoS* is shown in Fig. 3. EV charging and EV battery capacity limitation should satisfy formula (18).

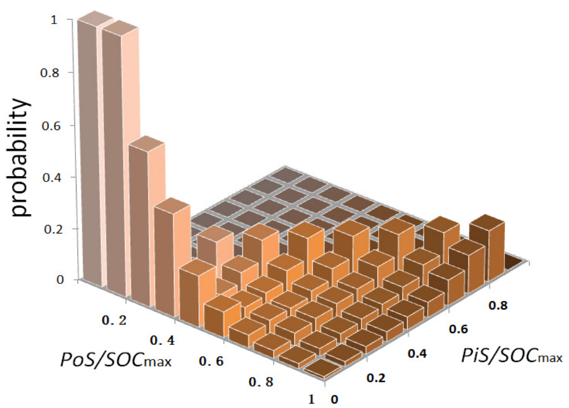

FIGURE 3. Distribution of *PiS* and *PoS*.

The η^{ev} represents efficiency of energy exchange. The quantity Ψ_{ab} is the probability that $PiS = SOC_a$, given $PoS = SOC_b$.

$$\begin{cases} \Psi_{ab} = \Pr[PiS = SOC_a | PoS = SOC_b], \\ SOC_a, SOC_b \in S \\ S = \{SOC_{t+1}^{\mathrm{ev}} = SOC_t^{\mathrm{ev}} + \Delta t \omega t \hat{L}_t^{n,\mathrm{ev}} \eta^{\mathrm{EV}}, SOC_{\mathrm{ev}}^{\min} \\ \leq SOC_t^{\mathrm{ev}} \leq SOC_{\mathrm{ev}}^{\max}\} \end{cases} \tag{18}$$

V. GAME EQUILIBRIUM ANALYSIS

A. NASH EQUILIBRIUM OF COMPLETE GAME

If the Nash Equilibrium of complete Game in (14) exists, the following conditions hold:

a. Strategy set (3) and (4) are a non-empty compact convex set in the Euclidean space.
b. Utility function (10) is continuous and quasi-concave for strategy set (3) and (4).

Proof (a): In strategy set (3) and (4), the constraint conditions are linear inequalities. Therefore condition (a) is proved.

Proof (b): If the utility function is proved to be a concave set, the necessary and sufficient condition is a negative-definite Hansen matrix of formula (20).

$$H(U^n) = \begin{vmatrix} \nabla^2_{l_t^j l_t^j} U_t^n & \nabla^2_{l_t^j C_t^i} U_t^n \\ \nabla^2_{C_t^i l_t^j} U_t^n & \nabla^2_{C_t^i C_t^i} U_t^n \end{vmatrix} \tag{19}$$

First, the first-order partial derivative of (19) is obtained by (20) after calculation of simultaneous equations (6) and (9).

$$\begin{cases} \nabla_{l_t^j} U_t^n = r_t^n [\sum_{i \in I} \frac{C_t^{i2}}{\sum_{l \in I} C_t^l} + \alpha\beta(\frac{l_t^j}{d_t^j})^{\alpha-1}] \\ \qquad + (1 - r_t^n) \frac{C_t^i}{\sum_{v \in I} C_t^v} (C_t^s - C_t^i) \\ \nabla_{C_t^i} U_t^n = r_t^n l_t^j (1 + \frac{\sum_{v \in I \backslash \{i\}} C_t^v}{\sum_{v \in I} C_t^v}) + (1 - r_t^n) \\ \qquad \times \hat{W}_t \frac{C^s \sum_{v \in I \backslash \{i\}} C_t^v - C_t^i (2 \sum_{v \in I} C_t^v - C_t^i)}{(\sum_{v \in I} C_t^v)^2} \end{cases} \tag{20}$$

Then, the second-order partial derivative (21) it yields. Note that the role of MG n cannot be both buyer and seller in the same time t, that is, $\nabla^2_{l_t^j C_{t'}^i} U_t^n$ and $\nabla^2_{C_t^i l_{t'}^j} U_t^n$ are both equal to 0 for $t \neq t'$. Observe on (21) that all the diagonal elements of the matrix are less than 0 and that the non-diagonal elements are all 0. Hence, (19) is a negative-definite Hansen matrix, with proof (b) proved.

$$\begin{cases} \nabla^2_{l_t^j l_t^j} U_t^n = -[r_t^n \alpha\beta(\alpha - 1) \frac{l_t^{j\alpha-2}}{d_t^{j\alpha-1}}] \\ \nabla^2_{C_t^i C_t^i} U_t^n = -[r_t^n l_t^j \frac{\sum_{v \in I \backslash \{i\}} C_t^v}{(\sum_{v \in I} C_t^v)^2} + 2(1 - r_t^n) \\ \qquad \times \hat{W}_t \frac{C_{\mathrm{S}} \sum_{v \in I \backslash \{i\}} C_{\mathrm{t}}^v + (\sum_{v \in I \backslash \{i\}} C_{\mathrm{t}}^v)^2}{(\sum_{v \in I} C_{\mathrm{t}}^v)^3}] \\ \nabla^2_{l_t^j C_{t'}^i} U_t^n = \nabla^2_{C_t^i l_{t'}^j} U_t^n = 0, t \neq t' \end{cases} \tag{21}$$

B. BAYESIAN NASH EQUILIBRIUM

Bayesian game is combination of various complete games whose Nash Equilibrium is proved in Part A. As long as the type combination $\mathbf{r}_{\mathrm{t}}$ among all MGs in time slot t is fixed, the equilibrium solution for (11) is also existent. Therefore, the existence of the complete game Nash Equilibrium is the necessary prerequisite for (11). According to the derivation of Nash Equilibrium of Complete Game, (22) can be

TABLE 1. The flow chart of algorithm for METBG.

Algorithm for RMTBG

Input: L_t^n loads of each MG in a week
$P_t^{n,\text{pv}}$ generation of each MG in a week
$P_t^{n,\text{w}}$ generation of each MG in a week
PiT, PoT, PiS probabilities of EV mobility
Output: C_t^{i*} the price at NE
l_t^{j*} selling power of seller j at the NE

1. **for** t=1 **to** T
2. **for** m=1 **to** N
3. Calculate d_t^n using Equation (1)
4. **if** d_t <0 **then** MG as seller j; s=s+1;
5. **else** MG as buyer i; k=k+1;
6. **next** m
7. **for** m=1 **to** N
8. Solving (23)
9. **next** m
10. Update l_t^j, C_t^i
11. **if** (15) is satisfied **then output** l_t^j, C_t^i; **go to** 13.
12. **else go to** step 7.
13. **next** t

achieved easily. Hence, the Bayesian Nash equilibrium is existent.

$$\begin{cases} \nabla^2_{l_t^j l_t^j} EU_t^n = \nabla^2_{l_t^j l_t^j} U_t^n \sum\limits_{\mathbf{r}_t^{-n} \in \mathbf{R}_t^{-n}} p(\mathbf{r}_t^{-n} | r_t^n) \\ \nabla^2_{C_t^i C_t^i} EU_t^n = \nabla^2_{C_t^i C_t^i} U_t^n \sum\limits_{\mathbf{r}_t^{-n} \in \mathbf{R}_t^{-n}} p(\mathbf{r}_t^{-n} | r_t^n) \\ \nabla^2_{l_t^j C_{t'}^i} EU_t^n = \nabla^2_{C_t^i l_{t'}^j} EU_t^n = 0, t \neq t' \end{cases} \tag{22}$$

VI. GAME EQUILIBRIUM SOLVING

To solve the Nash equilibrium of (15), the global optimal solution is generally used. Consequently, (15) can be translated into the following optimal problem:

$$\text{maximize} \left(EUn = \sum_{\mathbf{r}_t \in \mathbf{R}_t} U_n(\mathbf{r}^n) \cdot p(\mathbf{r}_t) \right)$$
$$s.t. \begin{cases} C_t^{\text{b}} < C_t^i < C_t^{\text{s}}, 0 \le l_t^j \le d_t^j, \forall t \\ d_t^n = P_t^{n,\text{pv}} + P_t^{n,\text{w}} - L_t^n - l_t^{j,\text{es}} - \omega t \hat{L}_t^{n,\text{ev}}, \\ \quad \omega t = \begin{cases} 1, & PiT \le t \le PoT \\ 0, & \text{otherwise} \end{cases}, \forall t \\ SOC_{t+1}^{\text{ev}} = SOC_t^{\text{ev}} + \Delta t \omega t \hat{L}_t^{n,\text{ev}} \eta^{\text{ev}}, SOC_{\text{ev}}^{\min} \\ \quad \le SOC_t^{\text{ev}} \le PiS \le SOC_{\text{ev}}^{\max}, \forall t \\ SOC_{t+1}^{\text{es}} = SOC_t^{\text{es}} + \Delta t l_t^{j,\text{es}} \eta^{\text{es}}, SOC_{\text{es}}^{\min} \\ \quad \le SOC_t^{\text{es}} \le SOC_{\text{es}}^{\max}, \forall t \end{cases} \tag{23}$$

The block diagram of the METBG controller is shown in Fig.4. Therefore, the algorithm for METBG contains six steps. According to the weather and load forecasts, the DG output power and the user load are determined. The second step determines the players in the game. The third step calculates d_t^j according to the (1). The fourth step solves (23). The fifth step update l_t^j and C_t^i. The sixth step goes to the fourth step, otherwise output l_t^{j*} and C_t^{i*} if all game participants no longer change their own strategies. Algorithm steps for METBG are provided in Table.1.

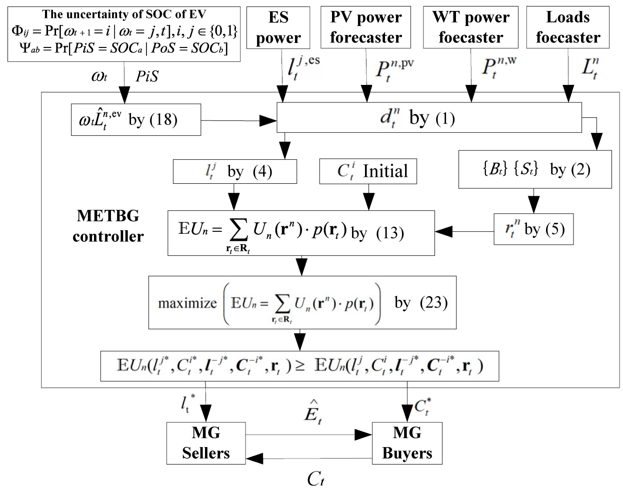

FIGURE 4. Block diagram of METBG controller.

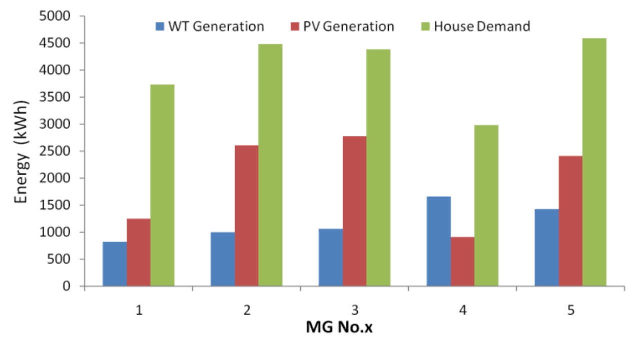

FIGURE 5. Total micro-source prediction and load forecasting on Monday.

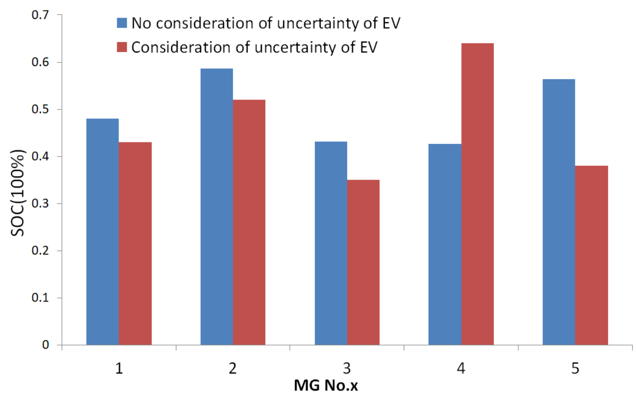

FIGURE 6. Comparison of average *PiS* for each MG in on Monday.

VII. RESULTS AND DISCUSSION

In this section, simulation results will be presented to show the performance and effectiveness of the proposed game approach for residential microgrid trading their energy by METBG pricing mechanism.

The time period is set to one working week (5 days), and the configuration of 5 MGs shown in Table 2 is set to participate in the game. The parameters of MG No.1 are provided in Table 3.

Based on forecast of weather conditions [26], [27], we adopts the weather forecast and Weibull distribution, so the DG power output [18] and household demand

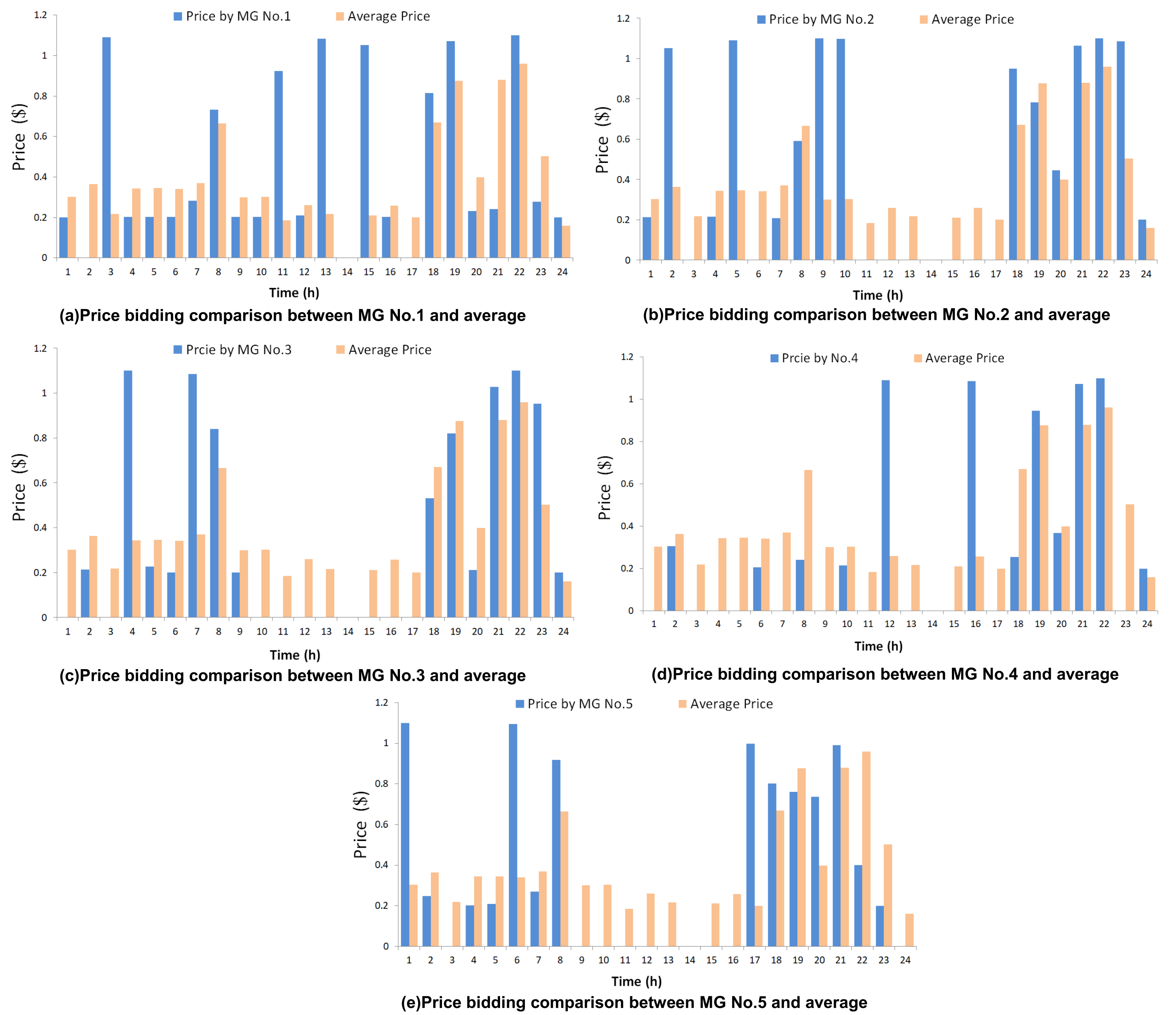

FIGURE 7. Price bidding comparison between MGs and average on Monday.

forecast [19] are shown in Fig.5. Furthermore, we use a computer with Intel Core i5-7200 CPU 2.5GHz, 8G memory, and Matlab 2010b as the testing environment for the algorithm. The average computation time is 64.642s for solving the internal prices of each time slot, compared to 1 hour time slot the computational time is negligible.

Without considering the uncertainty of EV, the existing literatures such as [28], [29] usually regard the SOC as the remaining capacity is less than 80% of the battery capacity, or as normal distribution [30], [31]. The comparisons of average *PiS* are shown in Fig.6. It can be seen from the figure that without considering the random characteristics of EVs, the average SOC is close to 50%, while the SOC with random uncertainty is closer to the actual value [23], [32]. *PoT* (*PiT*) of each of MGs is shown in Fig.2.

In the simulation, the proposed model of conditional probability distribution was estimated over the states by considering the information uncertainty of roles of METBG. The type space of any MG $i \in I$ is $r_t^n = [1, 0]$ as in (5), where type 1 and 0 are corresponding to sellers and buyers, respectively. Total micro-source predictions and load forecasting on Monday are shown in Fig.5. It can be seen from that the DG generating of Mg No.1 is much lower than its load forecast due to weather or load distribution possibly, and then it will be reflected in subsequent bids. Considering 5 MGs, there are 32 type combinations in time slot t. Fig.7(a) shows the MG No.1 decisions on the proportion of average price for all

TABLE 2. Configuration of each MG.

No.	PV	WT	GT	ES	EV	Load
1	200 kW	200 kW	50 kW	50 kWh	160 kWh	300 kWh
2	450 kW	300 kW	100 kW	100 kWh	360 kWh	350 kWh
3	450 kW	200 kW	50 kW	100 kWh	320 kWh	325 kWh
4	150 kW	200 kW	20 kW	40kWh	120 kWh	250 kWh
5	400 kW	300 kW	100 kW	100 kWh	320 kWh	375 kWh

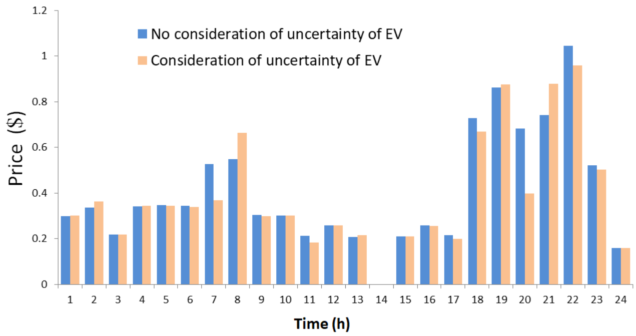

FIGURE 8. Average price comparison on Monday.

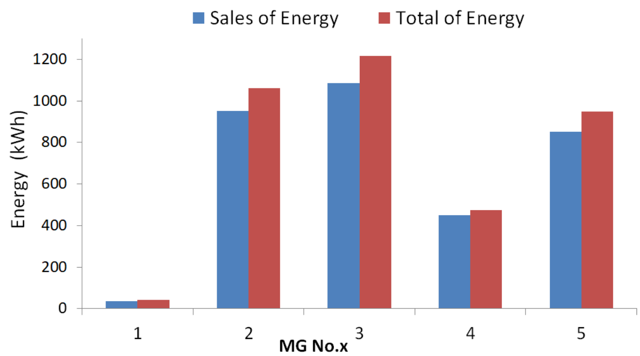

FIGURE 9. Sales of total energy by All MGs on Monday considering uncertainty of EV.

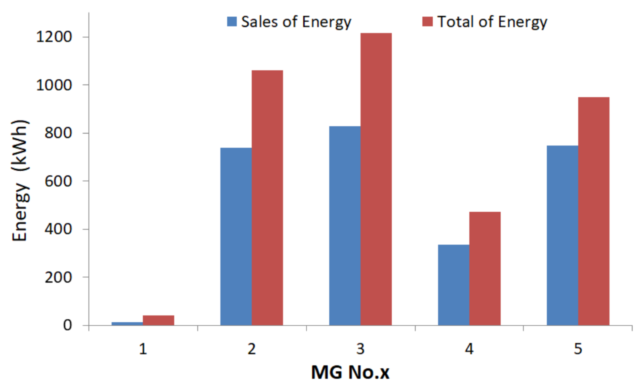

FIGURE 10. Sales of total energy by All MGs on Monday without considering uncertainty of EV.

MGs decisions on the bidding prices when they are in a buyer role. As previously speculated, MG No.1 decides to increase bidding prices is higher than average price. Considering this result, we analyze the strategies that the MG No.1 takes when DG power outputs are less than other MGs, and furthermore, as shown in Fig. 6, when its *PiS* at a low level. The impact of energy states on the decisions of others are quite obviously, which is reasonable.

Average price comparison on Monday has been show in Fig. 8 for the analysis of the influence of EV uncertainty in the case study, and compares it with that of not considering the uncertainty. It can be seen from the comparison results that the bidding price of MG without considering the uncertainty of EVs is slightly higher than that of considering the uncertainty of EVs. MGs' willingness to sell energy has been impacted on average price. From the comparison between Fig. 9 and Fig. 10, the energy sales proportion of MGs considering the uncertainty of EVs, is higher than that without considering the uncertainty. The energy trading of MGs can be increased, and the surplus energy can be more effectively mobilized to participate in power peak shaving.

TABLE 3. Parameters of MG No. 1.

Parameters	Symbol	Value	Unit
ES minimum SOC	SOC^{es}_{min}	15	%
ES output	$P^{1,DS}_{max}$	50	kW
Efficiency of ES	η^{ev}	95	%
EV minimum SOC	SOC^{ev}_{min}	10	%
EV output	$P^{1,EV}_{max}$	80	kW
Efficiency of EV	η^{EV}	95	%
cost coefficient	λ	5.3	cent/kWh

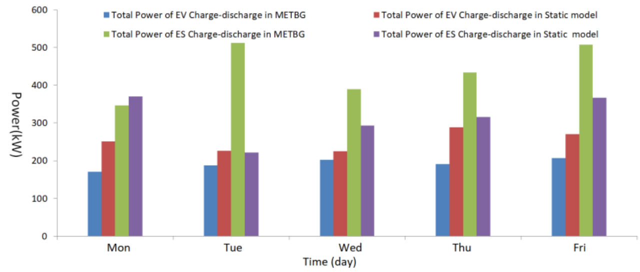

FIGURE 11. EVs and ES energy compare of MG No. 1 on the RMTBG and static models.

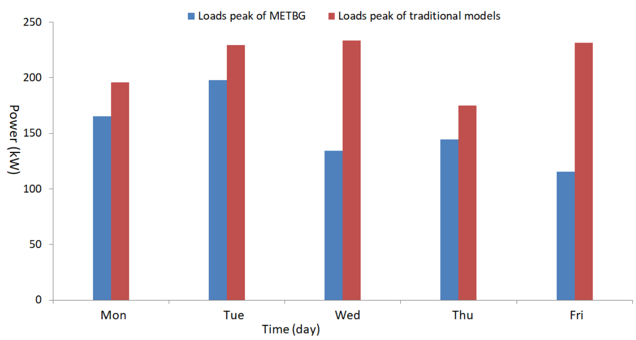

FIGURE 12. PAR compare of MG No. 1 on the METBG and static models.

Moreover, all sellers decide to sell less amount of energy than total energy, which is subject to the requirements of satisfaction, i.e. part of the energy will be stored in ES. The larger the ES, the more surplus energy can be stored, and vice versa. The MG No.4 take the strategies when its ES is less than others, so the proportion of electricity sold is higher than other MG, which is reasonable.

The daily total charge-discharge power of EV in METBG model is less than that in traditional model [23] as show in Fig.11. EV using METBG achieves battery charge and discharge energy reduction with less battery loss. Moreover, the life-time of the EV power battery will be improved and the full capacity is still guaranteed to leave the MG. In Fig. 12, the peak load is shown. The PAR using static strategy for MG No. 1 is totally higher using RMTBG. Thus, it can be seen that the power distribution is closer to the average. The METBG play the role of "cutting the peak and filling the valley." [24].

VIII. CONCLUSION

In this paper, a METBG method is proposed to trading energy for MGs considering PEV and incomplete information. Residential MGs in the game lacks the information about its role and the others. It needs to evaluate its opponents' role based on probability distribution of the type combinations. The method is mainly taken from microgrid viewpoint to coordinate the energy trading to achieve maximum profit. Moreover, this paper considers the rationality and possible multiple stochastic variables which influence on the type combinations. Based on Bayesian game, we have designed a game model consisted of the utility model of sellers and buyers. Furthermore, a TOU optimal pricing model based on METBG is proposed. The existence and uniqueness of NE for the model are proved. Finally, in order to highlight the great effect of METBG on MG energy trading. Simulation results indicate that the total cost of MGs can be reduced by coordinating the energy sharing between others compared with directly trading with utility grid under the static electricity-trading model. The internal price based on METBG exerts a positive effect on the final net energy profile of the microgrid. By analyzing the hourly deviation between static electricity price strategy and METBG total load peak value, the final load distribution is closer to the average but the effect was limited.

The following conclusions are unveiled by the studies:

1) The scheme based on the proposed METBG can guide the EVs to operate as an energy storage system by charging /discharging during off-peak/on-peak periods, which increases EV and ES participation rate.

2) The establishment of the price mechanism of METBG makes MGs willing to participate in the power exchange with more surplus energy, which is very beneficial to peak load regulation.

3) The charging and discharging capacity of ES is increased, which makes full use of the energy storage unit configuration and improves the utilization rate.

Future works will explore the following two aspects.

1) First, with the rise of P2P energy trading, the concept of block chain can be used to improve the two-level transaction model; in this paper, the METBG solution with the maximum trade quantity is selected as the optimal pricing strategy to promote energy exchange.

2) Second, the random characteristics of EVs need study, including adopting trip-chain to correlate the previous state of *PiS*, so as to predict it more accurately.

NOMENCLATURE

k, B	number of buyer and set of buyers
m, S	number of seller and set of sellers
d_t^n	the total extra energy of MG n
$P_t^{n,\mathrm{pv}}$	the PV generation by MG n
$P_t^{n,\mathrm{w}}$	the WT generation by MG n
L_t^n	load of MG n
$l_t^{n,\mathrm{es}}$	the ES scheduled energy by MG n
$\hat{L}_t^{n,ev}$	PEV's charging power in MG n
m_t^j	The ES and EV scheduled energy by seller j
PoT, PiT	Plug-out Time and Plug-in Time
ωt	PiT parameter
i,j	buyer i, seller j
$tin, tout$	EV plug-in and plug-out time
$C_t^\mathrm{b} C_t^\mathrm{s}$	purchase and selling price of the macrogrid
$\boldsymbol{C}_t^i$	The strategy set of buyer i
$\boldsymbol{l}_t^j$	The strategy set of seller j
r_t^n	condition parameter
$\hat{W}_t$	the sum of the sales of electricity by all sellers
W_t^i	the total power purchased by buyer i
A_t^j	satisfaction rate
α, β	satisfaction parameters
$\mathbf{r}^\mathrm{n}$	kind of combination
r_t^n	the type of role for MG n
D	daily trip length of EV
D_r	1 kWh energies EV can drive
λ	battery lifecycles coefficient

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