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Game and Contract Theory-Based Energy Transaction Management for Internet of Electric Vehicle

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ABSTRACT With the development and expansion of smart grid systems, vehicle-to-grid (V2G) has become a new type of energy interaction based on Internet of Electric Vehicles (IoEVs). By leveraging the charging/discharging capabilities of EVs, V2G can be implemented in smart grid to enable intelligent energy transactions and reduce the unbalance of supply and demand. However, the implementation of interaction between the existing V2G technology and IoEVs faces the problems of high-complexity energy transaction management, insufficient computing capability, poor scalability, and lack of incentive mechanisms. The three-tier bi-directional energy transaction management strategies based on game and contract theory have been proposed. Firstly, the optimal pricing and EV discharging strategy is obtained based on the non-cooperative Stackelberg game and the energy-price equilibrium. Secondly, in order to optimize the utility of EAG, the information asymmetry incentive mechanism based on contract theory is proposed. This mechanism can effectively stimulate EVs to contribute to V2G energy transaction and further improve social benefits considering the energy transmission loss and battery life cycle degradation. To reduce the communication as well as processing latency and improve the efficiency of energy transaction management, edge computing has been incorporated. Simulation results show that the performance of the proposed scheme significantly outperforms other existing schemes under various scenarios.

INDEX TERMS Smart grid, V2G energy management optimization, Stackelberg game, contract theory, edge computing.

I. INTRODUCTION

Energy has been playing an increasing function in the technological development and growth of human beings. The world-wide electrical energy demand is observed to be growing and evolving in recent years, and it is anticipated to double in the coming 20 years [1]. In addition, with the development of smart grid and the popularity of renewable energy generation, the demand for power storage has also increased. Smart energy management is an active, equipped, and systematic coordination of power generation, transformation, distribution, and consumption to meet the balance of supply and demand, taking into account environmental and monetary objectives [2], [3]. Vehicle-to-grid (V2G) has evolved into a feasible smart energy management technology by leveraging the bi-directional energy transaction capacity of Internet of electric vehicles (IoEVs) [4]. In V2G, electric vehicles (EVs) contribute to the demand-supply balance by charging as well as storing the excessive energy during the off-peak time as energy consumers, and discharging during the peak time as energy providers [5], [6]. The bi-directional energy flow between EVs and the grid copes with the time-varying storage and supply requirements, while avoiding the overhead associated with the extra infrastructure deployment.

Despite the above mentioned advantages, the extensive application of V2G technology in smart grid still faces severe challenges. First, the energy management based on the interaction between V2G and IoEVs is extremely complex due

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to the participation of multiple entities as well as the game and decision coupling among them, such as the grid, energy aggregator (EAG), and EVs. Second, considering the battery consumption and other costs caused by discharging behaviors, EVs are reluctant to participate in energy transaction without adequate compensation. On the other hand, paying excessive rewards for EVs will lead to a loss of the EAG's utility. In addition, the EV-side information is unknown to EAG due to the signaling overhead and privacy concern. Last but not least, a large number of computational-intensive tasks are generated during the bi-directional energy transaction management process. However, the traditional cloud computing architecture results in high latency and low network scalability due to the remote nature and lack of spectrum resources. Therefore, it is urgent to design the low-complex energy transaction strategy and efficient incentive mechanism for the energy management in V2G.

The studies on energy management in smart grid have received considerable attentions from academia. In [7], Wu *et al.* considered the energy transaction between the energy consumers and local trading centers (LTC), and proposed the optimal pricing and energy scheduling strategies for both nonprofit-oriented LTC and profit-oriented LTC by analyzing the properties of the formulated optimization problem. In [8], considering the volatility of the grid caused by the dynamic nature of renewable generation and EV charging behaviors, Zhou *et al.* proposed a robust energy scheduling scheme to adjustably cope with the over-conservatism problem by leveraging chance-constrained methods. In [9], Sun *et al.* considered a fog-computing based real-time energy transaction system for plug-in hybrid EVs, and proposed the charging/discharging optimization solutions by leveraging and improving the non-dominated sorting genetic algorithm. However, the above mentioned works have assumed that the global information is available to the energy transaction entities, and do not take into account the unequal status and information asymmetry between every providers and consumers. They cannot directly applied to the energy management in V2G, where the EAG has a dominate energy transaction status over EVs, and the private information of EVs is unknown to EAG.

Motivated by the above challenges, we propose a three-tier bi-directional V2G competitive energy transaction management model, which consists of three key components: energy grid as an energy supplier, EAG as an energy distributer, and EVs as energy providers. Two V2G energy transaction management strategies are proposed. First, considering the conflicting objectives and unequal status of EVs and EAG, we formulated a Stackelberg game to solve the optimal pricing and EV discharging problem by achieving energy-price game-equilibrium. Second, under the scenarios with and without information asymmetry, contract-theory based incentive mechanisms are proposed to motivate the EVs to participate in the energy transaction and discharge electricity during peak time, while maximizing the utility of EAG. In addition,

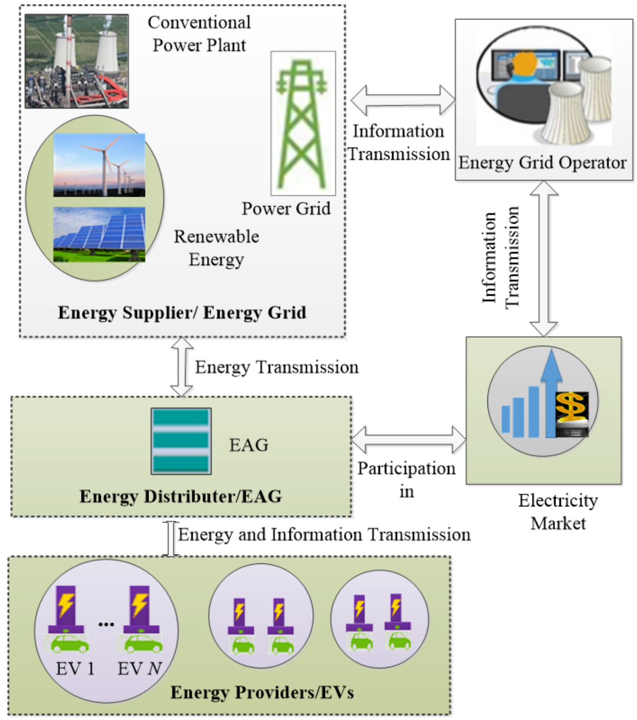

FIGURE 1. The architecture of the proposed three-tier bi-directional V2G energy transaction management.

edge severs are deployed with the EAG to provide sufficient computing resources and improve the efficiency of the energy transaction management.

The reminder of this paper is organized as follows. The proposed three-tier bi-directional V2G system model is presented in section II. The optimal pricing and EV discharging strategy based on Stackelberg game is provided in section III. Section IV elaborates the incentive mechanisms based on contract theory. The simulation result is illustrated in section V. Finally, this paper is concluded in section VI.

II. SYSTEM MODEL

The system model of the proposed three-tier bi-directional V2G energy transaction management is shown in Fig. 1, which consists of three key components: the energy grid as an energy supplier, EAG as an energy distributor, and several EVs as energy providers. The specific capability and functionality of each component are elaborated as follows.

A. ENERGY GRID (ENERGY SUPPLIER)

The energy grid is responsible for generating electricity and supplying it to the energy customers. As energy supplier, the energy grid integrates the computation, communication, and storage resources to provide energy services to EAGs. In addition, the overloaded energy grid needs to obtain electricity from the EAG during peak time, which is the focus of this paper. The details of how to design the optimal price strategy for the energy grid and how to model and formulate the interactions between the energy grid and EVs based on game theory and contract theory are illustrated in section III and IV, respectively.

B. EAG (ENERGY DISTRIBUTER)

EAG can coordinate the energy flow and energy transaction process between EVs and the energy grid with integration of IoEVs, including information collection, status monitoring, and discharging scheduling. Specifically, as shown in Fig. 1, the EAG plays an important role in solving the urgent energy demand of the energy grid by purchasing electricity from EVs and selling it back to the energy grid. In addition, EAG is equipped with edge servers to provide sufficient computation resources, relieve network burden and reduce transmission delay. The strategy optimization and decision making can be performed at the network edge, which improves the efficiency of energy transaction management.

C. EVs (ENERGY PROVIDERS)

In the bi-directional V2G energy transaction, EVs can act as energy providers to supply electricity for the overloaded energy grid by discharging its battery during the peak time, while they can also act as energy consumers by charging its battery with cheaper electricity and help to absorb the extra energy during the off-peak time.

III. V2G ENERGY TRANSACTION MANAGEMENT STRATEGY BASED ON GAME-THEORY

In this section, we use Stackelberg game to solve the optimal pricing and EV discharging problem considering the dominate position of EAG over EVs.

A. GAME DESCRIPTION

Stackelberg game involves players with unequal status which are classified into leader and follower. The leader first makes a decision, and then the follower chooses a policy based on the leader's decision to optimize its goal. The leader estimates the optimal policy of the follower and chooses the corresponding possible optimal strategy [10].

The V2G energy transaction management can be modeled as a Stackelberg game, which includes four inputs:

Players: The entities who interact in the game are regarded as players, where EAG acts as a leader and all EVs act as followers.

Players' Strategy: The leader's strategy is defined as a series of price vectors and each follower's strategy is considered as the discharging policy under certain constraints.

Utility Functions: The utility functions are defined for both leader and followers, to quantify the cost that the leader/EAG spends on purchasing electricity from the followers/EVs (cost minimization) and the benefit of each follower that sells its surplus electricity to the leader (benefit maximization).

Information: The information includes what players know about the situation and each other, and what actions they would follow before making a decision.

Stackelberg equilibrium (SE) is defined as a game-theoretic solution for this type of game. At the SE, the leader minimizes its cost function based on the identified best response strategies of all the followers. Subsequently, each follower maximizes its benefit by selecting the optimal-response strategy. Thus, the SE can be expressed as a profile of equilibrium strategies over which each player will not benefit more individually by deviating from this SE [11]. Non-cooperative game-equilibrium (GE) in the concept of game theory is a solution to the game involving two or more players [12]. The formulated non-cooperative Stackelberg game consists of one leader/EAG and N followers/EVs. The leader/EAG sends a price signal to the followers/EVs, which response by selecting the optimal discharging strategy.

In order to undergo a successful collision, there must have a total energy demand, which is determined by the minimum energy threshold of the energy grid and the backup energy stored in EAG. Denote the total energy demands of the energy grid as E_{grid}, which satisfies

$$E_{grid} \leq e_{EAG}, \tag{1}$$

where e_{EAG} is energy requested from the energy grid to EAG, i.e., the energy demand of EAG. Hence, the energy discharging required from all EVs should be greater or equal to the energy demand of EAG to satisfy the ancillary service, which is given by

$$\sum_{n=1}^{N} d_n \geq e_{EAG}, \forall n \in \mathcal{N}, \tag{2}$$

where $\mathcal{N} = \{1, \cdots, n, \cdots, N\}$ represents the index set of EVs, and d_n is the energy discharging requirement for EV n.

In the following, we derive the threshold of d_n by introducing the state of charge (SoC) [13]–[15]. SoC and battery capacity estimation are key issues in the EV battery management systems. For EV n, SoC_n is defined as the ratio of its available battery energy E_n to the maximum battery capacity $C_{n,max}$, i.e.,

$$SoC_n = \frac{E_n}{C_{n,max}}. \tag{3}$$

After discharging, the remaining SoC_n should satisfy the minimum energy requirement for traveling, which is given by

$$\frac{E_n - d_n}{C_{n,max}} \geq X(D_n), \tag{4}$$

where D_n is the distance that has to be traveled before the next charging. $X(D_n)$ is the required SoC to travel the distance D_n after discharging, which is a monotonically increasing function of D_n. Combining (3) and (4), we can derive the threshold of d_n, which is given by

$$d_n \leq C_{n,max}[SoC_n - X(D_n)]. \tag{5}$$

B. OPTIMAL DISCHARGING STRATEGY OF EVs

As energy providers, the utility of followers/EVs are strongly correlated with the pricing strategy of EAG. Once the price provided by EAG is received, each EV reacts to it by selecting the optimal discharging strategy. Specifically, the discharging strategy of the EV n is equivalent to d_n, $\forall n \in \mathcal{N}$.

Let $\bar{\boldsymbol{p}} = [p_1, \cdots, p_n, \cdots, p_N]$ be the pricing strategy of the EAG, where each element p_n corresponds to the price determined for the EV n. When the EAG announces its strategy $\bar{\boldsymbol{p}}$, each EV will react based on the specified price p_n and generate its best response strategy. The utility of EVs is determined by the following three measures.

1) MONETARY REVENUE

The EVs earn the monetary revenue by selling their surplus electricity to the EAG, which is calculated as the price times the amount of the discharging electricity, i.e., $p_n d_n$.

2) DISSATISFACTION REVENUE

Dissatisfaction revenue of EVs assesses the dissatisfaction level towards the remaining SoC. The discharging behavior conducts a negative impact on the dissatisfaction level of EVs. Specifically, the more energy discharged, the less satisfaction EVs will have. Therefore, we define the dissatisfaction parameter for EV n as a function which decreases with SoC_n [16], i.e.,

$$Dr_n(d_n) = \frac{\frac{1}{SoC_n}}{\sum_{n=1}^{N}(\frac{1}{SoC_n})}, SoC_n > 0, \tag{6}$$

EV n with a smaller SoC_n has a larger Dr_n, indicating a high dissatisfaction. In the contract, a larger SoC_n implies that EV n can discharge more surplus energy. In fact, EV n with a larger Dr_n is in a static status, which means a long idle period, while EV n with a smaller Dr_n is more active and more willing to discharge [16]. In addition, we model the dissatisfaction revenue as $-\frac{1}{2}Dr_n(d_n)^2$, which is negative and decreases with the dissatisfaction parameter and discharge, implying more cost.

3) CONTRIBUTION REVENUE

Contribution revenue evaluates the contribution of an EV compared with that of all the other EVs. Here, the contribution revenue is defined to be proportional to the difference between d_n and the average discharge of all EVs $(\frac{1}{N})\sum_{n=1}^{N} d_n$, i.e., $d_n - (\frac{1}{N})\sum_{n=1}^{N} d_n$. Basically, the average discharge shows the overall performance of all EVs. As the difference between d_n and $(\frac{1}{N})\sum_{n=1}^{N} d_n$ changes from a positive number to a negative one, the contribution level of EV n drops and affects its overall utility. The consideration of contribution revenue effectively mitigates the selfish behavior. As a matter of fact, one with less contribution cannot take any advantage from others that contribute more [16].

Based on the EAG's pricing strategy $\bar{\boldsymbol{p}}$, the utility function of EV n is defined as

$$U_n(\bar{\boldsymbol{p}}, d_n) = p_n d_n + \frac{1}{2}p_n(d_n - \frac{1}{N}\sum_{n=1}^{N} d_n) - \frac{1}{2}Dr_n(d_n)^2. \tag{7}$$

Here, the three terms on the right hand side represent the monetary revenue, the contribution revenue, and the dissatisfaction revenue, respectively. Among them, the second and third terms indicate the effect of all the other followers, and show the impact of a particular EV on overall performance. Taking the second term for example, if d_n is larger than $(\frac{1}{N})\sum_{n=1}^{N} d_n$, more discharge is achieved, which can improve overall performance.

The utility optimization problem **P1** for each EV is formulated as

$$\begin{aligned} P1: \ & \max U_n(\bar{\boldsymbol{p}}, d_n) \\ & \text{s.t. } C_1: \ d_n^{\min} \le d_n \le d_n^{\max}, \\ & \quad C_2: \ \sum_{n=1}^{N} d_n \ge e_{EAG}, \\ & \quad C_3: \ d_n \le C_{n,max}[SoC_n - X(D_n)], \end{aligned} \tag{8}$$

where C_1 indicates the lower and upper bound of energy discharging strategy for EV n. C_2 indicates that the total discharged energy should be greater or equal to the energy demand of EAG. C_3 is the threshold of d_n.

The optimization objective, i.e., each EV's utility function is a convex function of d_n. By deriving the first-order derivative of $U_n(\bar{\boldsymbol{p}}, d_n)$, i.e.,

$$\frac{\partial U_n(\bar{\boldsymbol{p}}, d_n)}{\partial d_n} = p_n + \frac{1}{2}p_n(1 - \frac{1}{N}) - Dr_n d_n. \tag{9}$$

we can directly get the optimal response discharging strategy as

$$d_n^* = \frac{1}{Dr_n}(\frac{3}{2} - \frac{1}{2N})p_n. \tag{10}$$

C. OPTIMAL PRICING STRATEGY OF EAG

The EAG can make a profit by buying surplus energy from EVs and selling it back to the energy grid. The utility of EAG is defined as

$$\begin{aligned} U_{EAG}(\bar{\boldsymbol{p}}, \bar{\boldsymbol{d}}) = & \beta \ln(\sum_{n=1}^{N} d_n + \sum_{n=1}^{N}(d_n)^2) - \sum_{n=1}^{N}(p_n d_n + \\ & p_n(d_n - \frac{1}{N}\sum_{n=1}^{N} d_n)) - P_{loss}\sum_{n-1}^{N} d_n - B_{de}\sum_{n=1}^{N} d_n, \end{aligned} \tag{11}$$

where the first term represents the sum of virtual revenue based on the energy it receives and β is the discharging range constraint for each EV. The second term shows the total cost for purchasing electricity. The third term represents the cost of power loss P_{loss} and the last term represents the compensation cost caused by the battery degradation B_{de}.

The EAG updates its strategy based on the follower's strategies denoted as $\bar{\boldsymbol{d}} = [d_1, d_n, \cdots, d_N]$. The pricing strategy optimization problem is formulated as

$$P2: \max\ U_{EAG}(\bar{\boldsymbol{p}}, \bar{\boldsymbol{d}})$$
$$\text{s.t. } C_4: \ 0 \leq \sum_{n=1}^{N} d_n \leq (\frac{1}{N})\sum_{n=1}^{N} d_n$$
$$C_5: \ \beta_n \ln(\sum_{n=1}^{N} d_n + \sum_{n=1}^{N}(d_n)^2) \geq \sum_{n=1}^{N} p_n d_n$$
$$+ P_{loss}\sum\nolimits_{n-1}^{N} d_n + B_{de}\sum\nolimits_{n=1}^{N} d_n. \tag{12}$$

Then, the EAG needs to adaptively provide the optimum price vector $\bar{\boldsymbol{p}}$ for those connected EVs based on their optimal discharging response d_n^*. Similarly, we leverage the partial derivative to calculate the optimal price p_n^*. Given

$$\frac{\partial U_{EAG}(\bar{\boldsymbol{p}}, \bar{\boldsymbol{d}})}{\partial p_n} = \beta \ln(1 + 2\sum_{n=1}^{N} d_n) - \sum_{n=1}^{N}(2 - \frac{1}{N})p_n, \tag{13}$$

the optimal pricing strategy is calculated as

$$p_n^* = \frac{\beta \ln(1 + 2\sum_{n=1}^{N} d_n)}{\sum_{n=1}^{N}(2 + \frac{1}{N})}. \tag{14}$$

The optimal pricing and discharging strategies of EAG and EVs $(\bar{\boldsymbol{p}}^*, \bar{\boldsymbol{d}}^*)$ is an SE for the one-leader and N-followers game if it corresponds to the solution of the following optimization problem.

$$(\bar{\boldsymbol{p}}^*, \bar{\boldsymbol{d}}^*) = \arg\max_{\boldsymbol{p},\boldsymbol{d}} U_{EAG}(\bar{\boldsymbol{p}}, \bar{\boldsymbol{d}}^*),$$
$$\text{s.t. } d_n^* = \arg\max_{d_n} U_n(\bar{\boldsymbol{p}}, d_n). \tag{15}$$

IV. V2G ENERGY TRANSACTION MANAGEMENT BASED ON CONTRACT-THEORY

In this section, we propose contract theory-based incentive mechanisms to motivate EVs to participate in energy transaction and to optimize the utility of EAG under the scenarios with and without information asymmetry.

A. EV TYPE MODELING

EVs are interested in contributing to support the energy demand of the energy grid by discharging their batteries if an adequate compensation is provided. EAG can design and sign a contract, which specifies the required electricity and the corresponding reward, with EVs to obtain the surplus electricity of EVs and supplement to the overloaded energy grid [17]. Based on the battery capacity and preference towards discharging, the considered N EVs can be sorted in an ascending order and classified into N types, the set of which is denoted as Θ, $\Theta = [\theta_1, \ldots -, \theta_n, \ldots, \theta_N]$. Then we have

$$\theta_1 \leq \ldots \leq \theta_n \leq \ldots \leq \theta_N, \quad n = 1, \cdots, N. \tag{16}$$

For the sake of simplicity, Θ is assumed to be a discrete and finite space. Numerically, θ_n is equal to the maximum electricity that can be discharged by the corresponding EV. The specific type of an EV is only known by itself and is unavailable to the EAG.

Algorithm 1 Algorithm to Reach Non-Cooperative SE

1: **Initialization**: $N, SoC_{n,int}, p_{int}, d_n^{min}, d_n, d_n^{max}, C_{n,max}, \beta_n, P_{loss}, B_{de}$.
2: For each EV in $\mathcal{N}$, calculate $Dr_n(d_n)$.
3: EAG first generates its strategy:
For each EV in $\mathcal{N}$, EAG initiates $\bar{\boldsymbol{p}} = [p_1, p_2, \cdots, p_N]$.
4: EVs determine their best-response strategy:
For each EV in $\mathcal{N}$, the best response strategy $d_n(\bar{\boldsymbol{p}})$ corresponding to $\bar{\boldsymbol{p}}$ can be obtained by solving (8). Update $Dr_n(d_n)$ as equation (6), and take the first-order derivative of (7) with d_n and set it to zero as $\frac{\partial U_n(\bar{\boldsymbol{p}}, d_n)}{\partial d_n} = 0$. Then $d_n(\bar{p}) = \arg\max_{d_n} U_n(\bar{\boldsymbol{p}}, d_n)$ as equation (15).
5: EAG then upgrades and re-generates its optimal strategy:
Update $d_n(\bar{\boldsymbol{p}})$ as the input of equation (11). Solve (11) by taking the partial derivative with each p_n in $\bar{\boldsymbol{p}}$ to be zero as $\frac{\partial U_{EAG}(\bar{\boldsymbol{p}}, \bar{\boldsymbol{d}})}{\partial [p_1, p_2, \ldots, p_N]} = 0$. Then, $\bar{\boldsymbol{p}} = \arg\max_{\bar{\boldsymbol{p}}^*} U_{EAG}(\bar{\boldsymbol{p}}, d_1(\bar{\boldsymbol{p}}), \ldots, d_N(\bar{\boldsymbol{p}}))$
Record $d_n^*(\bar{\boldsymbol{p}})$ and $\bar{\boldsymbol{p}}^*$ as the optimal strategy
6: Repeat 3-5 to obtain the optimal solution until the SE is satisfied.

B. CONTRACT FORMULATION

A contract which consists of N contract items is designed for N types of EVs, i.e., one contract item for each type of EV [17], [18]. The contract item designed for type θ_n EV is denoted as (d_n, R_n), where R_n is the dedicated reward in terms of energy coins for type θ_n EV and d_n is the required electricity as defined before. The contract is denoted as $\{(d_n, R_n), \forall n \in \mathcal{N}\}$.With information asymmetry, EAG does not know the specific type of each EV, but only has the knowledge of the total number of EV types and the probability distribution. Denoting the probability that an EV belongs to type θ_n as λ_n, we have $\sum_{n=1}^{N} \lambda_n = 1$.

In this scenario, considering a total of N EV types as well as the battery degradation and power loss, the estimated utility of the EAG, U_{EAG}, is calculated as [19]

$$U_{EAG}(\{d_n\}, \{R_n\}) = N\sum_{n=1}^{N} \lambda_n(\gamma_{EAG} d_n - R_n)$$
$$-P_{loss}\sum_{n=1}^{N} d_n - B_{de}\sum_{n=1}^{N} d_n, \tag{17}$$

where the γ_{EAG} is the unit value of obtained electricity for the EAG. The EAG will benefit from the contract item designed for type θ_n EVs only if $\gamma_{EAG} d_n - R_n \geq 0$, otherwise, the EAG has no incentive to purchase electricity from type θ_n EVs.

The utility function of type θ_n EV which accepts the contract item (d_n, R_n) is the offered reward minus the cost of discharged electricity, which is given by

$$U_n(d_n, R_n) = \theta_n m(R_n) - \gamma d_n, \forall n \in \mathcal{N}, \tag{18}$$

where γ is the unit cost of discharged electricity. $\theta_n m(R_n)$ represents the value of R_n for type θ_n EV, and $m(R_n)$ is the evaluation function of the reward, which satisfies $m(0) = 0$, $m'(R_n) > 0$, and $m''(R_n) < 0$ for all R_n. Without loss of generality, $m(R_n)$ can be calculated as a logarithmic function, i.e.,

$$m(R_n) = \log_e(R_n) = \ln(R_n). \tag{19}$$

Therefore, the expected social welfare (SW) is the sum utility of the EAG and the N EVs, which is given by

$$SW(d_n, R_n) = \sum_{n=1}^{N} U_n(d_n, R_n) + U_{EAG}(\{d_n\}, \{R_n\}). \tag{20}$$

Three constraints should be satisfied for the feasibility and effectiveness of the contract. First, an EV will not accept the corresponding contract item if it results in a negative utility considering the rationality of energy transaction. In other words, the **individual rationality (IR) constraints** should be satisfied, which can be given by

$$U_n(d_n, R_n) \geq 0 \Rightarrow \theta_n m(R_n) - \gamma d_n \geq 0, \forall n \in \mathcal{N}. \tag{21}$$

Besides, a feasible contract has to consistently satisfy the **incentive compatibility (IC) constraints**, which motivates type θ_n EV to select the contract item intended for its own type. In other words, when the EV selects the contract items which are not designed for its type, no more utility will be obtained. The IC constraints can be formulated as

$$\theta_n m(R_n) - \gamma d_n \geq \theta_n m(R_j) - \gamma d_j, j \neq n, \forall n, j \in \mathcal{N}. \tag{22}$$

In addition, the reward of higher type EVs should also be higher than that of the lower type EVs considering the superior discharging capability, which is known as **monotonicity constraints** and given by $0 \leq R_1 < \cdots < R_n < \cdots < R_N$.

Therefore, the expected social welfare (SW) is the sum utility of the EAG and the N EVs, which is given by

$$SW(d_n, R_n) = \sum_{n=1}^{N} U_n(d_n, R_n) + U_{EAG}(\{d_n\}, \{R_n\}). \tag{23}$$

The objective of the contract theory-based incentive mechanism is to maximize the utility of EAG, which is formulated as

$$\begin{aligned}
P3: \quad & \max_{\{d_n\},\{R_n\}} U_{EAG}\left(\{d_n\}, \{R_n\}\right) \\
\text{s.t. } & C_1: \theta_n m\left(R_n\right) - \gamma d_n \geq 0, \text{(IR)} \\
& C_2: \theta_n m\left(R_n\right) - \gamma d_n \geq \theta_n m\left(R_j\right) - \gamma d_j, \text{(IC)} \\
& C_3: 0 \leq R_1 < \cdots < R_n < \cdots < R_N, \\
& C_4: d_n \leq \theta_n, \\
& C_5: \sum_{n=1}^{N} d_n \geq e_{EAG}, \\
& \forall n, j \in \mathcal{N},
\end{aligned} \tag{24}$$

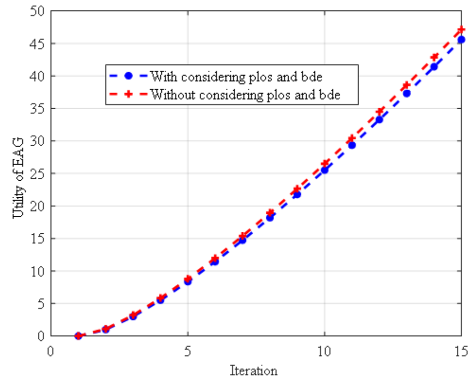

FIGURE 2. Utility of EAG with and without power losses (plos) and battery degradation (bde).

where C_1, C_2, and C_3 represent the IR, IC and monotonicity constraints, respectively. C_4 is the upper bound of d_n. C_5 represents the total electricity obtained from EVs should satisfy the requirements of EAG.

Based on the IR, IC, and monotonicity constraints, the following properties can be derived [20].

Proposition 1: For any $n \neq j, n, j \in N$, if $\theta_n > \theta_j$, then $R_n > R_j$, and $R_n = R_j$ if and only if $\theta_n = \theta_j$.

Proposition 2: For any d_n, R_n, the inequalities must be hold as

$$\begin{aligned}
&0 \leq d_1 \leq \cdots \leq d_n \leq \cdots \leq d_N, \\
&0 \leq R_1 \leq \cdots \leq R_n \leq \cdots \leq R_N, \\
&0 \leq U_1 \leq \cdots \leq U_n \leq \cdots \leq U_N.
\end{aligned} \tag{25}$$

C. CONTRACT OPTIMIZATION WITH INFORMATION ASYMMETRY

First, the sufficient and necessary conditions for contract feasibility are defined.

Theorem 1: The contract $\{(d_n, R_n), \forall n \in \mathcal{N}\}$ is feasible and achievable if and only if the following conditions are satisfied [22].

- $0 \leq R_1 \leq \cdots \leq R_n \leq \cdots \leq R_N$,
- $0 \leq d_1 \leq \cdots \leq d_n \leq \cdots \leq d_N$,
- $\theta_1 m(R_1) - \gamma d_1 \geq 0$,
- $\gamma d_{n-1} + \theta n - 1[m(R_n - R_{n-1})] \leq \gamma d_n \leq \gamma d_{n-1} + \theta_n[m(R_n - R_{n-1})], n \in \{2, \cdots, N\}$.

Proof: The detailed proof of Theorem 1 is omitted here due to space limitation. A similar proof can be found in [21]. □

The N IR constraints and $N(N-1)$ IC constraints can be reduced to 1 and $N-1$, respectively [21], [22], and **P3** can be rewritten as

$$\begin{aligned}
P4: \quad & \max_{\{d_n\},\{R_n\}} U_{EAG}\left(\{d_n\}, \{R_n\}\right) \\
\text{s.t. } & C_1: \theta_1 m\left(R_1\right) - \gamma d_1 \geq 0,
\end{aligned}$$

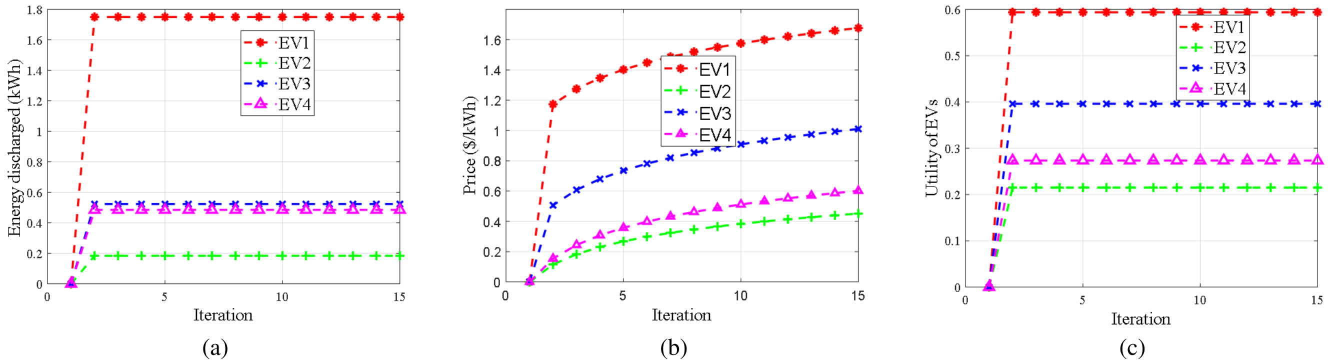

FIGURE 3. **The convergence of (a) energy discharged, (b) deal prices, and (c) utility of EVs.**

$$C_2:\ \theta_n m\left(R_{n-1}\right) - \gamma d_{n-1} \le \theta_n m\left(R_n\right) - \gamma d_n,$$
$$n \in \{2, \cdots, N\}$$
$$C_3, C_4, C_5, \forall n \in \mathcal{N}. \tag{26}$$

By checking the Hessian matrix, we can prove that the objective of **P3** is a concave function and the concave-convex procedure (CCP) algorithm proposed in [23] is adopted to solve **P4**. The proposed CCP-based algorithm is summarized in Algorithm 2 and performed in an iterative mode. At iteration τ, a feasible initial point $R_{n,\tau}$ is selected and the non-linear function $m(R_n)$ can be approximated by using its first-order Taylor series expansion with regards to $R_{n,\tau}$ as

$$\begin{aligned} m(R_n) &\approx m(R_{n,\tau}) + \nabla m(R_{n,\tau})(R_{n,\tau}) \\ &= \ln(R_{n,\tau}) + \frac{R_n - R_n, \tau}{R_{n,\tau}}. \end{aligned} \tag{27}$$

Then, the constraint C_2 with the difference of two concave functions is transformed as

$$\tilde{C}_2:\ \theta_n[\ln(R_{n,\tau}) + \frac{R_n - R_{n,\tau}}{R_{n,\tau}}] - \gamma d_n \ge \theta_n m(R_{n-1}) - \gamma d_{n-1}. \tag{28}$$

By replacing C_2 with $\tilde{C}_2$, **P4** is transformed into a convex programming problem and the optimal solutions for each iteration, $d^*_{n,\tau}$ and $R^*_{n,\tau}$, are achieved by solving the transformed convex problem. Then, the initial point for Taylor series expansion at iteration $\tau + 1$ is defined as $R_{n,\tau+1} = R^*_{n,\tau}$. The iterative process terminates until the improvement in the utility of EAG is lower than or equal to some positive threshold μ, i.e.,

$$U_{EAG}(\{d^*_{n,\tau+1}\}, \{R^*_{n,\tau+1}\}) - U_{EAG}(\{d^*_{n,\tau}\}, \{R^*_{n,\tau}\}) \le \mu. \tag{29}$$

Theorem 2: Convergence: At any iteration, the obtained $d^*_{n,\tau}$ and $R^*_{n,\tau}$ are feasible. Assume $d^*_{n,\tau}$ and $R^*_{n,\tau}$ are feasible points for (21) and the sub-problem (28). Then $d^*_{n,\tau+1}$ and $R^*_{n,\tau+1}$ can be existent to (29), and the objective value converges [23], i.e.,

$$U_{EAG}(\{d^*_{n,\tau}\}, \{R^*_{n,\tau}\}) \le U_{EAG}(\{d^*_{n,\tau+1}\}, \{R^*_{n,\tau+1}\}). \tag{30}$$

Algorithm 2 CCP-Based Contract Optimization Algorithm

Initialization: $R_{n,\tau}$, Θ, γd_n, γ_{EAG}, P_{loss}, B_{de}.
Output: $d^*_{n,\tau}$ and $R^*_{n,\tau}$, $\forall n \in \mathcal{N}$.
$\tau = 0$
Repeat
Transform the concave function $m(R_n)$, into logarithm function by using (27).
Transform **P4** into a convex programming problem.
Obtain $d^*_{n,\tau}$ and $R^*_{n,\tau}$ by using Karush-Kuh-Tucker (KKT) conditions.
Update: $\tau = \tau + 1$, $R_{n,\tau+1} = R^*_{n,\tau}$.
Until satisfying the stopping criterion (29) .

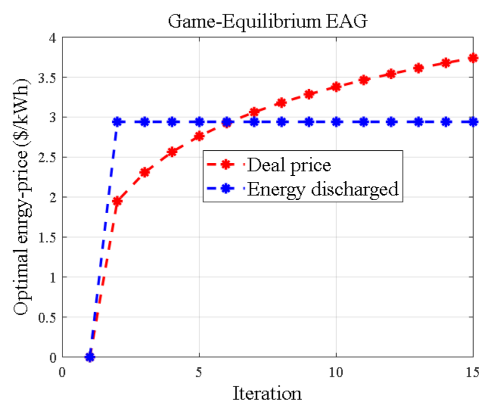

FIGURE 4. **The optimal energy-price convergence of the EAG game equilibrium.**

D. CONTRACT OPTIMIZATION WITHOUT INFORMATION ASYMMETRY

Without information asymmetry, there exists a selfish EAG which is accurately aware of each EV's type. The EAG can further increase its utility as long as each EV only accepts the contract item designed for its type and the utility of each EV is non-negative. Otherwise, the EVs have no incentive to sign the contract item and discharge electricity.

Proposition 3: Without information asymmetry, any contract item (d_n, R_n) should satisfy $\theta_n m(R_n) = \gamma d_n$, i.e., the utility for any EV is zero. If the contract item (R_n, d_n)

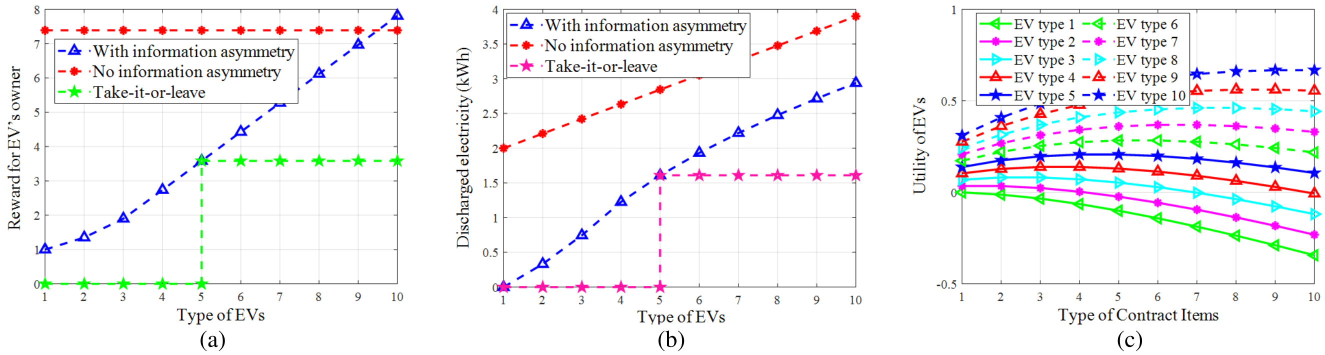

FIGURE 5. Contract feasibility of (a) reward for EV's owner, (b) discharged electricity, and (c) utility of EVs.

TABLE 1. The Parameter Setting of EV1-4.

Number of EV	Battery Capacity (kWh)	Initial SoC	Discharging Constrain	β_n	Initial Price (cent/kWh)
1	28	88	[0, 20]	0.5	0.5
2	24	74	[0, 14]	0.5	0.2
3	24	80	[0, 18]	0.5	0.35
4	22	77	[0, 16]	0.5	0.25

satisfies $\theta_n m(R_n) - \gamma d_n > 0$, the EAG can increase its utility by increasing d_n or decreasing R_n until $\theta_n m(R_n) - \gamma d_n = 0$. The SW is equivalent to the utility of the EAG while the utility of each EV is zero. The optimization problem is expressed as

$$\begin{aligned} P5: \quad & \max_{\{d_n\},\{R_n\}} U_{EAG}(\{d_n\},\{R_n\}) \\ & s.t.\ C_1: \theta_n m(R_n) - \gamma d_n = 0, \forall n \in \mathcal{N}, \\ & \quad C_2: \theta_n m(R_n) - \gamma d_n = \theta_n m(R_{n-1}) - \gamma d_{n-1}, \\ & \quad n \in \{2, \cdots, N\}, \\ & \quad C_3, C_4, C_5, \forall n \in \mathcal{N}. \end{aligned} \tag{31}$$

Proposition 4: In the contract design without information asymmetry, for any EV of type θ_n, R_n is fixed regardless of θ_n. Substituting $\theta_n m(R_n) - \gamma d_n = 0$ into (23), it can be verified that the SW increases monotonically with $\sum_{n=1}^{N} d_n$. Hence, EAG can increase d_n until $d_n = \theta_n$. Substituting $d_n = \theta_n$ into $\theta_n m(R_n) - \gamma d_n = 0$, we have $m(R_n) = \gamma$.

V. RESULT AND ANALYSIS

In this section, we validate the proposed energy transaction management strategies via simulations.

A. NUMERICAL RESULTS OF NON-COOPERATIVE STAKELBERG-GE

The numerical results validate that the performance and operation of the proposed Stackelberg-GE energy discharging strategies and energy-price GE are investigated. Assume a number of EVs are connected to the EAG during peak hours, where each of the EVs initial SoC upon arrival is randomly selected among its capacity. Consequently, the corresponding dissatisfaction parameter Dr_n can obtained. Set the power losses P_{loss} as 0.04 and battery degradation B_{de} as 0.15.

Fig. 2 shows the utility of EAG, with and without power loss and EVs' battery degradation. Fig. 3 (a), (b), and (c) show that the convergence process of the discharged electricity, price, and utility of EV1 to EV4. In the follower's perspective, they are willing to earn a profit by selling as much surplus energy to EAG and the sold energy is different for all EVs because of the different SoC and discharging constraints. Therefore the prices increase as the discharged energy increases. The corresponding utility for each EV takes into account the dissatisfaction parameters, and different EVs, utilities, and their relationships with the relative energy loss during different SoC and discharged constraints.

Fig. 4 represents the convergence of the total optimal energy-price that the EAG purchased and collected from all participating EVs. Therefore, when EAG buys more energy, the higher price is made.

B. NUMERICAL RESULTS OF CONTRACT FEASIBILITY

We considre a parking lot with one EAG and $N = 10$ EVs. For any EV, the battery capacity is 24 kWh, and the unit discharging cost is 2 cents/kWh, i.e.,$\gamma = 2$. The unit revenue of electricity for the EAG is 4 cents/kWh. Assume the power loss $P_{loss} = 0.035$ and battery degradation $B_{de} = 0.019$. The proposed schemes under the scenarios with and without information asymmetry as well as the take-it-or-leave contract [22] are compared to evaluate the optimization performance. In the take-it-or-leave contract, the EAG cannot distinguish EVs by their types. EV with higher types, i.e., more than θ_j,will accept the contract, while others will reject the contract.

Fig. 5 (a) and (b) show the contract feasibility of the EV owner's reward and discharge power relative to the EVs' type, respectively. In the case of information asymmetric, both EV owner's reward and discharged electricity increase monotonically with the EVs type, which follows the proposition 2. In the case of information symmetry, the energy demands require much higher amounts of electricity from EVs compared with the case of information asymmetry and offer each EV with the same R_n, which is consistent with proposition 4.

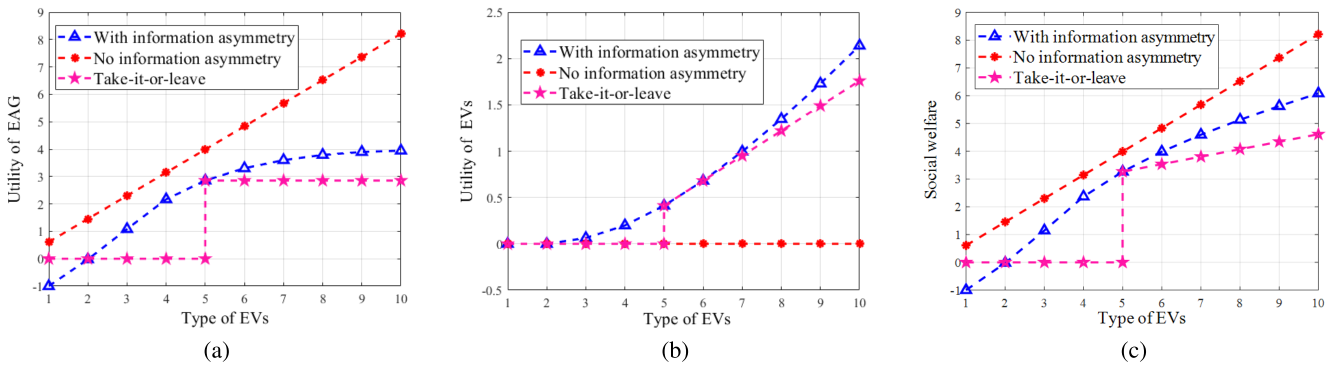

FIGURE 6. System performance of (a) utility of EAG, (b) utility of EV, and (c) social welfare.

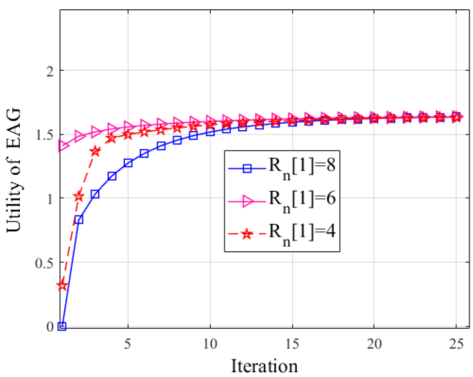

FIGURE 7. The convergence performance of the proposed CCP-based solution.

In the take-it-or-leave contract, only EVs whose types are no less than θ_j will have non-zero discharged electricity and rewards. Fig. 4(c) shows the relationships between the utilities of different types of EVs versus different types of contract items. It is verified that the proposed contract is incentive compatible. Hence, if and only if it takes the contract, with item committed to its type, EV can achieve its maximum utility. In addition, it can be seen that the utility of EV U_n increases with the increase of EV type, which is consistent with preposition 2.

Figs. 6 (a) and (b) show the performance of the utility of EAG and EVs, respectively. It can be seen that, the EAG can achieve a much higher utility, while the utility of any EV remains zero in the case of information symmetry, which is consistent with proposition 3. In the case of information asymmetry, EVs can get many benefits from the existence of information asymmetry, because the EAG cannot extract all the available electricity from EV due to information asymmetry. Fig. 6 (c) shows the relationship between social welfare and EV types. The contract without information asymmetry outperforms the contract with information asymmetry. The reason is that the social welfare is equal to the utility of EAG and the utility of each EV is zero when the contract without information asymmetry, which follows the proposition 3. In take-it-or-leave contract, only EVs whose types are no less than θ_j will have non-zero utilities.

Fig. 7 shows the convergence performance of the proposed CCP-based contract optimization algorithm with three different initial points, i.e., $R_n[1] = 8$, 6, and 4. With the number of iteration increases, all three cases converge to optimal utility.

VI. CONCLUSION

In this paper, we first proposed the three-tier bi-directional V2G energy transaction management system model consisting of energy grid, EAG, and EVs. The edge computing was introduced to assist in decision making and strategy optimization. A game-theory based optimal pricing and EV discharging strategy and a contract-theory based incentive mechanism were proposed to cope with the unequal positions and information asymmetry between EVs and EAG. Simulation results show the superior performance of the proposed algorithms in terms of energy-price equilibrium, utility of EVs and EAG, as well as convergence. In the future, we will take into account the security of energy transaction and joint energy scheduling among multiple EAGs.

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