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Incentive-Driven Energy Trading in the Smart Grid

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ABSTRACT The smart grid is widely considered as an efficient and intelligent power system. With the aid of communication technologies, the smart grid can enhance the efficiency and reliability of the grid system through intelligent energy management. However, with the development of new energy sources, storage and transmission technologies together with the heterogeneous architecture of the grid network, several new features have been incorporated into the smart grid. These features make the energy trading more complex and pose a significant challenge on designing efficient trading schemes. Based on this motivation, in this paper, we present a comprehensive review of several typical economic incentive approaches adopted in the energy-trading control mechanisms. We focus on the technologies that address the challenges specific to the new features of the smart grid. Furthermore, we investigate the energy trading in a new cloud-based vehicle-to-vehicle energy exchange scenario. We propose an optimal contract-based electricity trading scheme, which efficiently increases the generated profit.

INDEX TERMS Energy trading, economic incentive, smart grid.

I. INTRODUCTION

Internet of Things (IoT) is regarded as an indispensable part of smart cities for improving the power management by providing timely and efficient information and communications [1], [2]. With the aid of IoT technologies, in the smart grid, power generation, storage, transmission, distribution and consumption are interconnected through a communication network [3]–[9]. Thus, the smart grid can make use of the two-way flows of electricity and information to deliver power efficiently and reliably [10]–[13].

Energy management plays a critical role in balancing and shaping the electricity demand and supply. Among energy management mechanisms, energy trading is an effective mechanism that accounts the interest of both the supply and the demand sides. In energy trading, the electricity providers aim to schedule power generation among generators according to the power demand obeying the physical constraints of the power system [14]. On the consumers side, they reshape their demand profiles in response to the supply conditions. As both sides are rational, thereby aiming to maximize their own profits, incentive-based schemes naturally offer great potential for efficient and effective energy trading.

Among incentive-based energy trading schemes, pricing is one of the most common tools for energy flow control and energy management. The power demand from the consumers is a function of the unit price, which will in turn influence the supply strategies of the providers. To model the electricity market mechanisms, game theory, a powerful economic tool to analyze the rational interactions between two or more individuals, is a natural choice for modeling a wide range of scenarios. Besides pricing and game theoretic approaches, there are some other incentive-based approaches to improve the efficiency of the electricity dispatch and consumption, such as auction, bargain and contract theories, which are able to depict the behaviors of self-serving energy trading participants.

Fig. 1 shows an architecture of the smart grid. Recently, with the development of IoT, power technologies

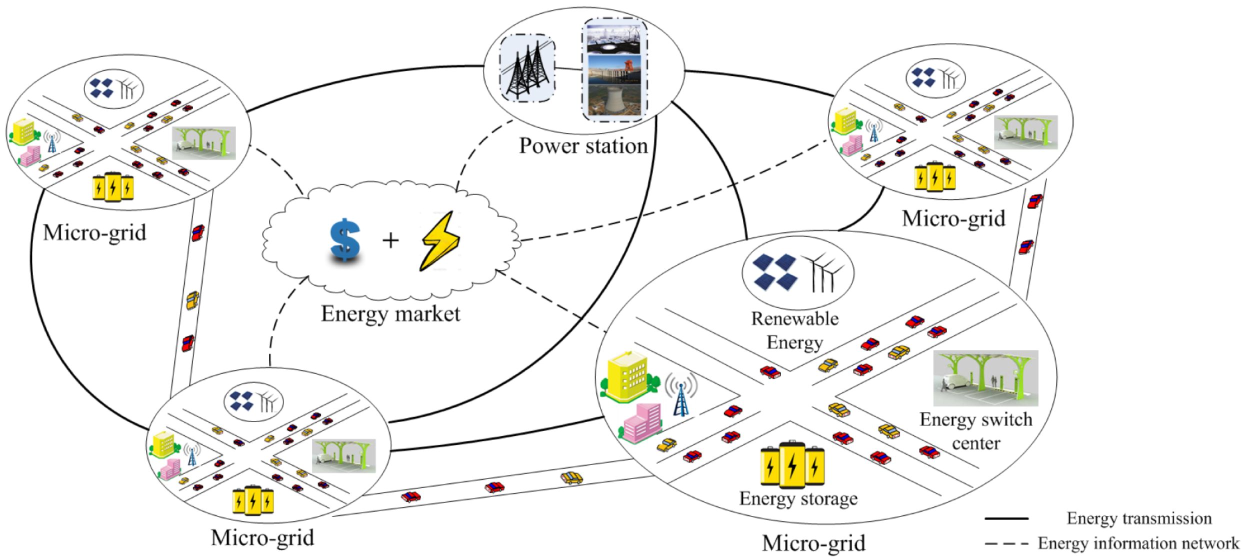

FIGURE 1. The smart grid network architecture with new features.

and smart transportation, several important features have been integrated into the smart grid. The new features are described as below.

- *Distributed Architecture:* The smart grid can be modeled as a hierarchical architecture with some interactive micro-grids [15]. The variation of load balancing of each micro-grid together with the interconnections between those micro-grids make the energy management of the smart grid even more complex.
- *Heterogeneous Renewable Energy Sources:* Large-scale integration of heterogeneous distributed Renewable Energy Sources (RESs), which include solar, wind and hydroelectric power sources, etc., has a great impact on power grid operation [16].
- *Distributed Energy Storage:* To mitigate the variability and intermittency of RESs, distributed energy storage can be exploited to shift energy consumption in time, where the coordination of supply, demand and storage should be investigated [17].
- *Widespread Electric Vehicles (EVs):* With the widespread adoption of EVs, their flexible mobile energy storage functionality should be effectively utilized. The bidirectional energy flow between EVs and the grid can help to archive demand balance in local area. Furthermore, as EVs always travel among different areas, their function of the energy transportation from one place to another may improve the energy reliability among different areas [18].

The features above increase the scale of the energy management. In addition, the heterogeneous energy sources, consumers and transmission technologies may vary in time, space and energy trading preference. Taking into account these essential characteristics of the energy management, the power trading mechanism becomes complicated, and it is challenged to improve the social welfare of the transaction parties as well as to make the power system more reliable. Thus, we are motivated to investigate the incentive approaches for the smart grid energy trading.

In this paper, we present the requirements and challenges of energy trading mechanisms, review existing economic incentive based approaches, and propose an optimal contract theoretic energy trading scheme in a new cloud-based Vehicle-to-Vehicle (V2V) power exchange scenario. Specifically, we will discuss the following topics in this paper.

- *Incentive-Based Economic Theories:* Due to their high potential of modeling the strategies and decisions of rational transaction parties, incentive-based economic theories are widely adopted in the designing of energy trading control schemes. Thus, we first present a review of these theories, providing the sketch and some essential information of them.
- *Incentive-Based Energy Trading Schemes:* To incorporate the features in the smart grid, several schemes have been proposed for energy trading. We focus on the schemes of Demand Response Management (DRM), where some technical components, e.g., RESs, energy storage and Vehicle-to-Grid (V2G), may be integrated into the energy trading process. We present some discussions on the incentive-based approaches adopted in these mechanisms, including the advantages and limitations of the existing solutions.
- *A New Energy Exchange Scheme:* The charging demand of a large EV population is inhomogeneous in space and time. This inhomogeneity may result in unprecedented challenges in the already strained grid. Although traditional energy management schemes can mitigate load-imbalance of the grid, they may cause power transmission cost. To address the problem, we propose a new cloud-based V2V energy trading framework, where the electricity trading takes place at a local level and the

process is modeled and solved by a contract theoretic approach. We also conduct a simulation study to illustrate the efficiency of the proposed schemes.

The rest of the paper is organized as follows. In Section II, we introduce the theoretic concepts and methodologies of the incentive-based approaches associated with the energy trading in the smart grid. Some efficient incentive-based energy trading schemes are presented and discussed in Section III. In Section IV, we provide a case study where a new contract-based energy trading scheme and its performance evaluation are presented. Finally, we conclude our work in Section V.

II. INCENTIVE-BASED ECONOMIC THEORIES

In this section, some theoretic issues of the incentive-based economic approaches are presented, with the focus on pricing, game theory, bargain, auction and contract theories.

A. PRICING

Pricing is a powerful tool to stimulate consumers to behave in an economically optimal way. In other words, when electricity prices are high, users naturally reschedule their energy consumption or curtail it, and consequently, the demand at peak times decreases.

As the load of the smart grid varies with time, the corresponding electricity prices are different at different times. According to the characteristics of their variation, the pricing schemes can be classified into following three types [19].

1) REAL-TIME PRICING (RTP)

The RTP is time-varying according to the current energy load conditions. By using RTP, the current cost of electric consumption can be informed to consumers accurately and timely. Thus, it has been taken as one of the most efficient approaches to improve the performance of the energy market [20].

2) TIME OF USE (ToU) PRICING

Unlike RTP changing frequently, the determination of ToU pricing is based on the energy load levels in a relatively long time period, such as an hour, daytime and night-time. Furthermore, ToU pricing is released in advance and is constant for a long period. Based on the basic rate structure of ToU pricing, when the grid is facing a critical jeopardy, Critical Peak Pricing (CPP) can be employed to shave the peak load.

3) INCLINING BLOCK RATE (IBR) PRICING

The IBR pricing is designed with multi-level rate structures where various prices correspond to different electricity consumption levels. These levels are determined by the average electricity consumption in a period with the fixed thresholds.

By using these pricing schemes, the change of the energy usage patterns induced by the varying prices can be feedback to the providers timely, which will in turn affect the generation level of the supply side. In economics literature, this feedback information is called consumer's price elasticity ε which can be shown as

$$\varepsilon = \frac{\Delta L/L}{\Delta P/P}, \tag{1}$$

where ΔL and ΔP are the changes of consumer's load and the change of price, respectively. P is the forecasted energy price, and L is the consumer's base load [21]. This equation indicates that the larger ε means the higher sensitivity of the consumers to the price. In the case where the price elasticity is negative, the load will decrease as the price grows.

B. GAME THEORY

In the smart grid, both supply and demand sides are rational and self-interested. For efficient energy management, while energy providers need to adjust their generations, dispatch strategies and electricity prices under different operating conditions, consumers respond to the changes of the provider by rescheduling their demands to maximize their own utilities. Since both sides are participating in the energy market, and the changes of one side can impact the strategies of the other, game theory is a natural choice to model and analyze the trading strategies and decisions [22].

In a game-theoretic framework, there are three main components: the set of players denoted as $\mathcal{N}$, the player i's action set $\mathcal{A}_i$, and its corresponding utility function u_i, $i \in \mathcal{N}$. In a game, each player i chooses an action $a_i \in \mathcal{A}_i$ to maximize its utility function $u_i(a_i, a_{-i})$, which not only depends on its own action a_i but also on the actions taken by the players other than i, denoted as $\{a_{-i}\}$.

The objective of the players is to optimize their utilities by adjusting their strategies. One of the most important strategy concepts for game theory is called Nash equilibrium. The Nash equilibrium is a state where no player can improve its utility by changing its action unilaterally, given the actions of the other players. For a static game, the Nash equilibrium with pure strategies can be formally defined as a vector of actions $a^* \in \mathcal{A}$, provided $u_i(a_i^*, a_{-i}^*) \geq u_i(a_i, a_{-i}^*)$ holds, $\forall a_i \in \mathcal{A}_i$, $i \in \mathcal{N}$ [23].

According to whether players coordinate or compete with each other, games can be classified into two types, namely noncooperative games and cooperative games. In the smart grid, noncooperative games can be used to model the distributed energy trading between the competitive providers and consumers. Cooperative games are instead suitable for the scenarios where energy trading participants cooperate with the aid of communication networks, so as to improve the social welfare or efficiency of the collaborators.

C. AUCTION THEORY

Auction is a market mechanism used for trading the commodity from a number of sellers to several buyers who want to improve their utilities by obtaining these goods. There are four basic types of auctions, namely the ascending-bid auction, the descending-bid auction, the first-price sealed-bid auction and the second-price sealed-bid auction [24].

The outcome of the auction is the final price and the amount of good of the trade.

In auction, different bidders value the objects for sale with various evaluation criteria. For example, for buying the same amount of electricity, the micro-grid can obtain a higher profit during peak hours compared to that during off-peak hours. As the evaluation information is private for each bidder, there is asymmetric information in the auction process. In the asymmetric information scenario, to get more profit, self-interested bidders may misrepresent their valuations by bidding untruthfully. This cheating, which may harm the efficiency and fairness of the trade, can be implemented individually or collusively. The classic Vickrey-Clarke-Groves (VCG) auction mechanism is proved truthful and is thus widely deployed [24].

The hierarchical architecture of the smart grid together with the proliferation of distributed energy resources make an open market where energy can be exchanged at local and regional levels. To improve the efficiency of electricity distribution, an autonomous and distributed energy management is imperatively needed. In this context, the distributed auction scheme, which incentivizes energy trading between small scale energy providers and local customers, is suitable for the autonomous management. By employing this scheme, bidding information is shared among local nodes, and electricity is dispatched within adjacent areas, which greatly improve the transmission efficiency of the communication network and the power network. However, considering the integrity of the smart grid, an auction scheme, which only concerns power optimization within a local area, may cause energy imbalances between different districts and degrade the grid reliability. Hence, adaptive hierarchical auction based energy trading schemes are necessary for the electricity management.

Due to the limited capacity of the distributed generations and the ever-increasing demands, one consumer may purchase electricity from several providers, where a multi-item energy auction scheme is required. Furthermore, with the proliferation of the RESs, the Renewable Energy (RE) generators can also participate in the energy trade. The intermittent nature of RESs makes the trading of RE stochastic. Thus, the risk of shortfall from contracted amounts of RE should be taken into consideration in the design of the auction schemes.

D. BARGAIN THEORY

In the smart grid, the consumers can reschedule electricity consumption and strive for their preferred payment by a bargain mechanism. The bargaining process starts with the initial bids of both sides, and is terminated by the successful deals [25]. Unlike auction theory, which concentrates on the utility maximization of auctioneers and bidders, bargain theory aims at achieving a fair, and thus self-enforcing, gain or cost allocation.

To enhance the winning chances and the revenues in a bargain, the participants in the same side always form some coalitions. Nash Bargaining Solution (NBS) concept, which develops in the realm of the game theory and bases on a cooperative game-theoretical framework, can be used in this scenario to distribute bidding goods and bidding cost among these collaborators.

For a bargaining taking place among a set of players denoted as $\mathcal{N}$, the Nash bargaining problem can be formally expressed as

$$\max_{\{B_i^*\}} \Pi_{n\in\mathcal{N}}(U_n^c - U_n^d)$$
$$s.t.\ U_n^c \geq U_n^d, \quad \forall n \in \mathcal{N}, \tag{2}$$

where U_n^c and U_n^d are the utilities of player n gained with and without collaboration, respectively. $\{B_i^*\}$ is the NBS, which determines a fare and Pareto optimal sharing strategies for dividing the jointly archived profit or cost among the collaborative players.

The energy trading in the smart grid usually involves massive participants, such as distributed electricity generators, EVs and a wide variety of electric devices. Taking all of these players directly into a centralized bargaining process will heavily increase the complexity in obtaining the NBS. We can resort to a distributed algorithm, where energy trading participants bargain with the others in a limited area. Thus, some local optimal bargaining solutions can be obtained with limited information exchange.

To make distributed bargain schemes scalable and efficient, a number of trading participants can be classified into groups according to their correlation in the trading process. In this scenario, a representative scheme, which treats groups of individuals as single bargainers, can be utilized in the bargaining process. Thus, the operation complexity of bargaining process can be greatly reduced. However, the mechanism of grouping individuals efficiently in the context of the smart grid, and the determination of a fair welfare allocation between and within groups make the bargain scheme design a challenge [26].

E. CONTRACT THEORY

The participants of the energy trading process can be classified into several types according to their characteristics, such as energy generation and consumption preferences. Intuitively, different reward or cost should be implemented to these participants according to their trading features. However, due to their rational and selfish nature, each participant may attempt to gain more profit by disguising its type, which brings difficulty to the trading scheme design. Furthermore, this problem may be exacerbated by the information asymmetry in the energy market, where one side can not be aware of the actual types of the participants belonging to the other side.

To address the problem, contract theory, which is a powerful tool from microeconomics, can be adopted to incentivize the trading participants based on their true types under information asymmetry [27]. Considering N types of participants, the trading contract for each type can be presented as (a_i, q_i), where $i \in \mathcal{N}$, $\mathcal{N} = \{1, 2, \ldots, N\}$. Here a_i is the reward

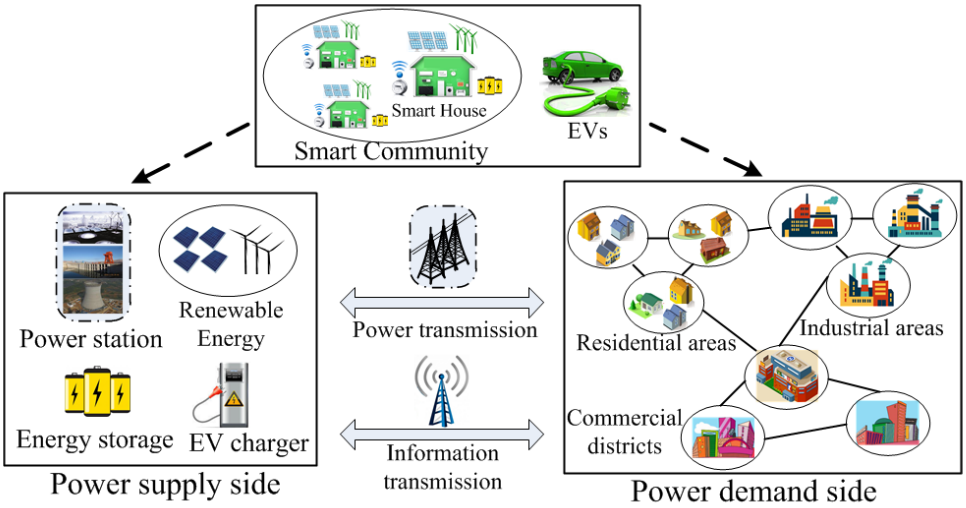

FIGURE 2. Demand response in the smart grid.

or payment for the type-i participant trading electricity of amount q_i.

To be a feasible scheme, the designed contracts should satisfy the Individual Rationality (IR) constraint and the Incentive Compatibility (IC) constraint, which are defined as follows.

Definition 1: IR constraint: A contract satisfies the individual rationality constraint if the utility of each type of participants is guaranteed to be nonnegative, i.e.,

$$U_i(a_i, q_i) \geq 0, \quad i \in \mathcal{N}, \tag{3}$$

where, U_i is the utility of type-i participants.

The IR constraint motivates the trading of the self-interested participants, since positive profit can be gained from the trading.

Definition 2: IC constraint: A contract satisfies the incentive compatible constraint if the contract (a_i, q_i) chosen by the participants of type-i attains the highest utility they could obtain, i.e.,

$$U_i(a_i, q_i) \geq U_i(a_j, q_j), \quad i, j \in \mathcal{N}, \ i \neq j. \tag{4}$$

The IC constraint makes the participants of type-i prefer the contract (a_i, q_i) over all other options.

As the contracts are made by the dominant side in the trade, a well-designed contract mechanism can be utilized to maximize the profit of the dominant side by making other participants to behave in the desired way.

III. INCENTIVE-BASED APPROACHES IN DEMAND RESPONSE MANAGEMENT

DRM is a key component in the smart grid, which can effectively reduce consumer payments and electricity generation costs [28]. Fig. 2 illustrates the interaction between the power supply and demand sides, where RESs, energy storage and EVs are incorporated into the interaction. As they are applicable to stimulate both consumers and power utilities to adaptively reschedule load and supply profiles, incentive-based approaches are widely used in DRM. In the following, we present some typical incentive-based approaches implemented in the design of DRM schemes. Specifically, the energy trading schemes for DRM incorporating with technical components, such as RESs, energy storage and V2G, are illustrated. Table 1 shows the taxonomy of these schemes.

There are several incentive-based approaches focusing on optimizing DRM. One of the typical examples of these approaches is the pricing scheme. In [21], the authors proposed an agent-based model that simulates the deregulated electricity markets. The relationship between energy load L and electricity price P can be written as

$$L = a \cdot P^{\varepsilon}, \tag{5}$$

where a is a constant, and ε is the price elasticity defined in (1). In [29], in order to optimize the energy providers' benefit as well as to satisfy consumers, a real time pricing based DRM scheme was proposed.

In energy trading management, as it is hard to obtain accurate price elasticity in practice, many studies resort to game theory, which is an effective way of modeling the rational interaction between two or more individuals. The game theory based schemes incentivize the demand and supply sides to adapt their trading strategies, which may lead to optimal profits to these trading participants. With the expansion of participants in the energy trading, the interaction among them becomes complicated, thus hierarchical games shall be leveraged to solve the demand response problem. For instance, the studies in [30] modeled the DRM interaction as a two-level game, where the competition between utility companies is formulated as a non-cooperative game, and the interaction among residential users forms an evolutionary game. In [31], the authors presented a hierarchical system model consisting of power generation units, utility companies and electricity end users. A Stackelberg game between these three parts,

TABLE 1. A taxonomy of typical incentive-based energy trading schemes.

	DRM	DRM with renewable energy sources	DRM with energy storage	DRM with V2G
Price theoretic approaches	Price elasticity in the agent-based market model [21]; Real-time pricing-based income maximization for smart grid [29];	Household-based energy management [37];	Electricity price structure for households' storage batteries [42];	Evaluating the reaction of EVs to electricity price [46];
Game theoretic approaches	A two-level game-based DRM scheme with multiple utility companies [30]; DRM for the grid with multiple providers and a large number of consumers [31];	Consumption tradeoff between renewable and non-renewable energy [38];	Demand side management with energy storage devices [43];	EV charging and discharging processes coordination [47];
Bargain theory based approaches	Energy trade between micro-grids [32]; Distributed reactive power compensation [33]; Group bargaining-based energy allocation [26];	Distributed resource allocation for multi-zone buildings in the smart grid [39];	Energy storage utilization and cost sharing between users [45];	Bargain strategies for scheduling the EV charging loads [25];
Auction theory based approaches	Modeling and design of demand response auction [34]; Cheat-proof energy trade [35]; Non-convex power dispatch problem [36];	Wind power dispatch in a deregulated market [40]; Reverse auction model for micro-grid market [41];	Trading interactions between energy storage units [44];	Group-selling V2G scheme [48];
Contract theory based approaches				Coordinate ancillary services to the grid by a large number of heterogeneous EVs [49];

where the energy providers behave as leaders and end users act as the followers, was proposed.

Considering the fairness of the profit in the DRM, several bargain theory based approaches have been proposed in the energy trading management. In [32], the authors studied the energy trading among multiple connected micro-grids and proposed a bargain theory based energy trading scheme, where the interconnected micro-grids cooperatively decide the amount of energy trade and the associated costs. The work in [33] focused on a distributed reactive power compensation problem where distributed generation units can contribute to the local voltage control. The interaction between one electric utility company and multiple users is modeled and analyzed by using Nash bargaining theory. In order to cope with the complex energy management which incorporates numerous devices, the authors in [26] designed an algorithm that employs the group bargaining concept of game theory. In this algorithm, each representative, who represents on behalf of the group it belongs to, bargains with each other. By distinguishing between inter- and intra-group bargaining processes, the complexity of energy distribution is greatly reduced, and energy can be efficiently allocated to various devices according to their actual requirements.

As an important part of economic theory, auction provides an efficient way to carry out demand response between energy trading participants of different sides. The work in [34] explored the modeling and design of demand response auctions, with the focus on adjustable power, information truthfulness, computational efficiency, and economic profits. Due to their rationality, consumers may cheat in the energy demand request for obtaining more profit, which may cause extra cost for the energy providers. To prevent users' cheating in the energy trading, the authors in [35] proposed an efficient auction method, where users' payment is related to their consumption credit records. Low credit records will bring extra pay to the cheating users. In the case where the DRM optimization problem has several complex constraints, auction can be employed to solve the problem. In [36], an auction-based distributed algorithm and consensus protocols were proposed to solve a non-convex economic power dispatch problem in the smart grid, where the generation cost is minimized.

A. DEMAND RESPONSE MANAGEMENT WITH RENEWABLE ENERGY SOURCES

As it is environmentally friendly and cost effective, integrating RESs into the power grid is one of the highly emphasized features of the smart grid. However, the inherent intermittence of RESs heavily impact their utilization, which makes energy trade more sophisticated. To address the RE intermittence issue, in [37], the authors focused on the pricing scheme employed in the household-based energy management. To keep the consumption below a pre-defined acceptable level, optimal energy price signals, which incentivize households to adaptively schedule their consumption, are estimated and broadcast in advance. The authors in [38] considered both renewable and nonrenewable energy sources, and attempted to optimize the tradeoff between the two types of energy sources. Based on an analytic model of a multi-leader and multi-follower Stackelberg game approach, a bi-level hybrid evolutionary algorithm was proposed to leverage affordable electric power while minimizing carbon emissions.

Besides these studies, auction theory is commonly used in the RE management. The authors in [40] studied the participation of wind power producers in a deregulated electricity market, and proposed an auction paradigm where RE suppliers bid probability distributions of generation. In [41], a reverse auction model for micro-grid market operations was presented. The model is utilized to obtain an efficient power supply, by scheduling the electricity commitment of conventional and distributed RESs in an hour-ahead market.

B. DEMAND RESPONSE MANAGEMENT WITH ENERGY STORAGE

Energy storage constitutes a key element in the smart grid, which can help flatten the power load and counter the intermittence of RESs by bidirectional energy exchange. In [42], the authors proposed a decentralized charging scheme of households' storage batteries, where the households' electricity consumption is reduced by using an appropriate electricity price structure. To utilize the energy storage units efficiently, the authors in [43] studied the demand side management problem in the scenario where energy consumers are equipped with energy storage devices. A non-cooperative game between residential energy consumers, and a Stackelberg game between utility providers and energy consumers were proposed. The paper [44] analyzed the complex interactions between energy storage units that want to sell part of their stored energy to grid elements. In this energy exchange market, the energy trading price is determined via a double auction mechanism.

Due to the high cost of energy storage systems' deployment, the storage users should deploy and share these devices collaboratively. However, the utilization of these devices depends on the energy distribution losses, electricity prices and users' various profiles. The studies in [45] focused on the RESs aided houses' charging and discharging of the deployed energy storage devices, as well as the corresponding cost each house should pay. By employing Nash bargaining framework, a fair and self-enforcing cost sharing scheme between these houses was proposed, which incentivizes the collaborative utilization of storage devices to save significant energy.

C. DEMAND RESPONSE MANAGEMENT WITH VEHICLE-TO-GRID

V2G is a promising technology to balance the load level of the smart grid through bidirectional energy flow between EVs and the smart grid. The key problem in V2G is the determination of the amount and the time of the energy exchange between EVs and the grid. To address this issue, the authors in [46] presented a mathematical model for evaluating the reaction of EVs in response to electricity price. In [47], a hierarchical game approach was adopted to coordinate the charging and discharging processes of EVs in a decentralized fashion. In the designed hierarchical game, the V2G capacity of each EV was obtained through an evolutionary game in the upper level, while the charging sequence of the EVs was determined by a noncooperative game at the lower level. In [25], the authors designed a bargaining mechanism for EV aggregators and power system dispatchers scheduling the EV charging and discharging behaviors.

Considering the huge electricity demands and the limited electricity capacity of an EV, the authors in [48] proposed an incentivized auction-based group-selling V2G scheme, which consists of a two-level auction process. In the first level, the auction takes place between a group of EVs and an aggregator, and in the second level, the auction is between aggregators and the smart grid. This hierarchical auction scheme efficiently reduces the complexity of the auction process between a large number of participants, and benefits the load balance management.

As EVs are selfish and have various preferences towards energy switching based on their own constraints, the authors in [49] proposed a contract-based mechanism to manage the V2G process. Different types of EVs rationally choose the corresponding contracts, that specifies the EVs' charging/discharging rates and the payments. Through the optimally designed contracts, EVs are stimulated to provide ancillary services to the grid and help match the service request of the grid.

IV. OPTIMAL ENERGY EXCHANGE SCHEMES

EVs' charging management is an important part of grid DRM. The aggregation of charging demands from a large population of EVs in an area may cause heavy-load of the grid. In traditional DRM schemes, this burden can be alleviated by energy dispatching between different areas. However, long distance energy transmission results in high costs. To manage EVs' charging more efficiently, in this section, we present a cloud-based Vehicle-to-Vehicle (V2V) energy exchange framework. In the framework, the energy for EV charging can be acquired from two sources, namely the discharging EVs or RESs. In addition, the discharging and the corresponding charging processes are carried out at the same Energy Switch Center (ESC), without long distance energy transmission in the grid. Here the energy trading process is modeled in a contract theoretic approach. We derive the optimal feasible contracts which maximize the profit generated from the ESC. Furthermore, taking into account the intermittence of RESs, we propose an optimal contract-based electricity trading scheme.

A. SCENARIO DESCRIPTION

Although V2G technology has the potential to efficiently alleviate the load during peak hours, the electricity fed back to the grid always needs to be delivered and distributed through the transmission and distribution networks, which may result in

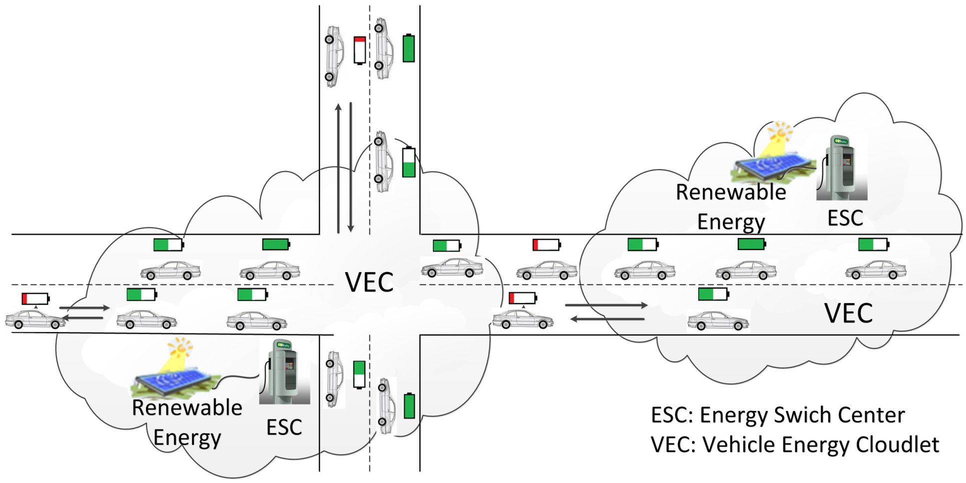

FIGURE 3. V2V electricity exchange via VEC in the smart grid networks.

high dispatch costs and eventually may challenge the stability of the grid. These negative factors are likely to lower the profits of electricity utilities, and consequently may hinder the development and deployment of V2G technology.

To cope with this problem, several studies have focused on the utilization of EVs for energy transmission. For instance, the authors in [50] proposed a renewable energy transfer scheme by operating electrical buses between two locations. In [18], the authors studied the impact of EVs, which act as energy transporters between different districts, on the DRM of the smart grid. In [51], an EV energy network, where moving EVs are adopted for energy transmission and distribution was proposed. However, few studies have considered the V2V charging mechanism, which can be achieved with the aid of aggregator devices [52]. Furthermore, various characteristics of the discharging EVs, such as State of Charge (SoC) and discharging cost, which play an important role in the energy trade, have not been taken into account.

In this paper, we propose a new cloud-based V2V energy exchange framework. As the batteries equipped on EVs have limited capacities, to satisfy the charging demand, the V2V energy switching needs to be realized through a large number of discharging EVs. Considering discharging EVs may have various discharging capacities and characteristics, these EVs are categorized into multiple types based on the defined Range Anxiety Levels (RAL) concept. We design a contract scheme to maximize the profit generated from the ESC, and meanwhile enhance the satisfactions of the discharging EVs of different types. Unlike the contract-based schemes in previous studies, the contracts in our scheme are made by the buying side, which is dominant in this trade. Furthermore, RE has been recognized as an environmentally and economically beneficial solution for the smart grid [53]. With the incorporated RESs, the cost reduction together with the intermittence feature are inherently brought to the energy trade process. Considering the fluctuation of RESs, which may make the total supply capacity exceed the charging demand, we design a contract theoretic mechanism for the optimal trading energy under the stochastic nature of the charging demand and RE supply.

B. SYSTEM MODEL

Fig. 3 shows a V2G smart grid network with Vehicle Energy Cloudlets (VECs) to realize V2V energy exchange. Each VEC has an ESC aided with an RE generator. The ESCs are operated by electric utility companies. Each ESC acts as a broker in the energy exchange process, which obtains electricity from the discharging EVs or RES, and then resells it to the charging EVs. The power availability of the RESs is modeled as a Discrete Time Markov Chain (DTMC) [54]. The highest amount of the electricity which can be obtained from the renewable generator is M units. Thus, the harvested RE is represented as an M states DTMC. The steady state probability of the RE generator is given as π_i for the state i, i.e., the generated RE is at i units, $0 \leq i \leq M$, $\sum_{i=0}^{M} \pi_i = 1$. Compared to the electricity drawn from the discharging EVs, the cost of the energy obtained from the RE source is much cheaper. Here, we consider the harvested RE is free to be used by the ESC. To reduce its operation cost, the ESC is more inclined to use RE. However, in the case where the RE is inadequate for charging, some extra electricity needs to be bought from the discharging EVs.

In order to concentrate on the study of the discharging scheme, we consider a fixed price c for selling unit electricity to the charging EVs, and model the charging demand at the ESC as a Poisson process with arrival rate λ_d. The probability of the charging demand d at n units electricity is given as

$$P_d(n) = \frac{e^{-\lambda_d} {\lambda_d}^n}{n!}, \quad n \geq 0. \tag{6}$$

As the SoCs and the distance to reach the ESC are different for the discharging EVs, we classify the EVs into different types. The types are distinguished by the concept of RAL of discharging EVs, which are heterogeneous in terms of the

EVs' SoCs and the electricity consumption to reach the ESC. Let S_i^{ini}, l_i and r_i denote the initial SoC of discharging EV i before discharging, the distance for EV i to reach the ESC, and the electricity consumption per unit distance, respectively. The definition of RAL of EV i can be given as

$$\theta_i = f(S_i^{ini} - r_i l_i), \tag{7}$$

where $f(\cdot)$ is the range anxiety function, $f'(\cdot) > 0$ and $f''(\cdot) < 0$.

Considering the cost of energy for EV traveling to the ESC, we assume that each discharging EV has at most one chance to accomplish a discharging task. Given the profit incentive, the discharging EVs with higher RAL prefer to sell more electricity to the ESC. We consider there are a finite number of RAL types with indices $\theta_1, \theta_2, \ldots, \theta_N$. Without loss of generality, we assume that $\theta_1 < \theta_2 < \ldots < \theta_N$. β_i is the proportion of discharging EVs of type-θ_i in all the discharging EVs, and $\sum_{i=1}^{N} \beta_i = 1$. Each discharging EV knows perfectly which type it belongs to. However, as the type is private information for each EV, the ESC may not be well aware of that, i.e., there is information asymmetry between the ESC and discharging EVs. However, we assume that the ESC has the knowledge of the probability distribution of discharging EV types based on statistical information.

To provide reliable charging service while maximizing its revenue, the ESC derives the amount of the electricity required to buy from the discharging EVs according to the difference between the energy demand and the RE supply. Then the ESC broadcasts the demand information to the discharging EVs in contract forms by using wireless communications technologies [55]–[57]. We consider the number of discharging EVs in each VEC area is W. These discharging EVs are rational and self-interested. They count their utilities for discharging and choose whether to sell the electricity to the ESC.

C. CONTRACT THEORETIC APPROACH FOR ENERGY TRADING

In this subsection, we consider a scenario where the charging electricity demand is higher than the sum of discharging and RE supply, and propose a contract theoretic approach for the cloud-based V2V electricity trading. In practice, however, it is more reasonable that the total demand is comparable to the sum of supply. For instance, the sum of supply may higher than the demand due to the high energy generation of photovoltaic panels at noon. This motivates us to propose a trading scheme in a more practical scenario, which will be discussed in the following subsection.

As there are N types of discharging EVs according to their RAL, the ESC provides N different contracts. The contract designed for type-θ_i discharging EVs is given as (a_i, q_i), where q_i is the amount of electricity that a type-θ_i discharging EV sells to the ESC, and a_i is the corresponding reward to the EV.

With the offered contracts, each discharging EV can choose to accept one contract or decline all of them based on its utility of this energy trade. Here, the utility function of a type-θ_i EV, selling electricity based on the contract (a_i, q_i) is defined as

$$U_{EV}^{i} = \theta_i v(a_i) - e q_i, \quad i \in \mathcal{N}, \tag{8}$$

where $v(0) = 0$, $v'(a_i) > 0$, and $v''(a_i) < 0$ for all a_i. $\mathcal{N} = \{1, 2, \ldots, N\}$. e is the cost of per unit electricity for the discharging EVs before they arrive in the VEC area.

Due to the rationality of the discharging EVs, they will not accept a contract that results in negative utility. Thus, the IR constraint should be satisfied in these contracts, which can be expressed as

$$U_{EV}^{i} \geq 0, \quad i \in \mathcal{N}. \tag{9}$$

Besides the IR constraint, a feasible contract should also satisfy the IC constraint, which incentivizes type-θ_i EVs to prefer the contracts designed for their own type. Formally, in this case, the IC constraint can be written as

$$\theta_i v(a_i) - e q_i \geq \theta_i v(a_j) - e q_j, \quad i \neq j, \quad i, j \in \mathcal{N}. \tag{10}$$

In this scenario, the total utility generated from the ESC is given as

$$U_{ESC}^{total} = cm + \sum_{i=1}^{N} w_i (c q_i - a_i), \tag{11}$$

where c is the price for selling unit electricity to the charging EVs, and m is the amount of electricity obtained from the RES. $w_i = \beta_i W$ is the number of type-θ_i discharging EVs in this trading. Note that, as the charging demand is higher than the total supply, the improvement of U_{ESC}^{total} mainly depends on the participation of EVs to discharge electricity. Thus, we focus our study on the optimization of the second part of (11).

Given above definitions and the IR and IC constraints, the contract-based optimization problem for maximizing the revenue generated from the ESC can be formulated as

$$\begin{aligned} &\max_{\{q_i, a_i\}} U_{ESC} = \sum_{i=1}^{N} w_i (c q_i - a_i) \\ &s.t.\ \theta_i v(a_i) - e q_i \geq 0, \quad i \in \mathcal{N}, \\ &\quad \theta_i v(a_i) - e q_i \geq \theta_i v(a_j) - e q_j, \quad i \neq j,\ i, j \in \mathcal{N}. \end{aligned} \tag{12}$$

In (12), the total number of the constraints is N^2. The computational complexity of solving the optimization problem grows rapidly as N increases. To get a solution with higher practical use, the constraints should be reduced. Here, we derive the necessary and sufficient conditions for simplifying the problem, and propose an efficient algorithm to obtain the optimal contracts.

Lemma 1: Monotonicity: Both the monetary reward $\{a_i\}$ and the amount of trading electricity $\{q_i\}$ are monotonically increasing in $\{\theta_i\}$, $i \in \mathcal{N}$, i.e., for any feasible contract items, $a_i \geq a_j$ and $q_i \geq q_j$ if and only if $\theta_i > \theta_j$.

Proof: See Appendix A. □

Lemma 2: IR Constraints Reduction: Under the condition that the IR constraint of type-θ_1 is satisfied, the other IR constraints automatically hold.

Proof: See Appendix B. □

Here, we give the definitions of some special IC constraints as follows [27]. The IC constraints between type-θ_i and θ_j, $j \in \{1, \ldots, i-1\}$ are defined as Downward Incentive Constraints (DICs). Especially, the IC constraints between θ_i and θ_{i-1}, $1 < i \leq N$, are Local Downward Incentive Constraints (LDICs), which can be represented as

$$\theta_i v(a_i) - eq_i \geq \theta_i v(a_{i-1}) - eq_{i-1}. \tag{13}$$

Similarly, the IC constraints between type-θ_i and $\theta_j, j \in \{i+1, \ldots, N\}$ are Upward Incentive Constraints (UICs), and the IC constraints between θ_i and θ_{i+1}, $1 \leq i < N$, are Local Upward Incentive Constraints (LUICs). It can be proved that with the LDICs, all the DICs hold, and with the LUICs, all the UICs hold. Further more, according to the monotonicity condition $a_{i-1} < a_i, 1 < i \leq N$, the LUIC can be easily drawn from LDIC [58]. Thus, we get the conclusion that with LDIC, both DICs and UICs can be reduced.

Lemma 3: LDICs are binding for the contract-based optimization problem.

Proof: See Appendix C. □

Given the condition that all the LDICs are binding, together with the monotonicity proved in Lemma 1, the optimization problem in (12) can be rewritten as

$$\begin{aligned}
&\max_{\{q_i, a_i\}} U_{ESC} = \sum_{i=1}^{N} w_i(cq_i - a_i) \\
&\text{s.t. } \theta_1 v(a_1) - eq_1 = 0, \\
&\quad \theta_i v(a_i) - eq_i = \theta_i v(a_{i-1}) - eq_{i-1}, \quad 1 < i \leq N, \\
&\quad 0 \leq a_1 \leq a_2 \leq \ldots \leq a_N, \\
&\quad q_i \geq 0, \quad i \in \mathcal{N}.
\end{aligned} \tag{14}$$

Let $\Delta_k = \theta_k(v(a_k) - v(a_{k-1})), 1 < i \leq N$ and $\Delta_1 = 0$ [49]. According to the first two constraints of (14), we have

$$q_i = (\theta_1 v(a_1) + \sum_{k=1}^{i} \Delta_k)/e, \quad i \in \mathcal{N}. \tag{15}$$

By substituting (15) into the object function of (14), the optimization problem of (14) can be equally changed to a problem only with variables $\{a_i\}$, which is shown as

$$\begin{aligned}
&\max_{\{a_i\}} U_{ESC} \\
&= \sum_{i=1}^{N} \{v(a_i)(\theta_i \sum_{k=i}^{N} w_k - \theta_{i+1} \sum_{j=i+1}^{N} w_j)c/e - w_i a_i\} \\
&\text{s.t. } 0 \leq a_1 \leq a_2 \leq \ldots \leq a_N.
\end{aligned} \tag{16}$$

Let $G_i = v(a_i)(\theta_i \sum_{k=i}^{N} w_k - \theta_{i+1} \sum_{j=i+1}^{N} w_j)c/e - w_i a_i$, then we get $U_{ESC} = \sum_{i=1}^{N} G_i$. Since G_i is only related to the discharging reward assigned to type-θ_i EVs, the optimal rewards $\{a_i^*\}$ which maximize U_{ESC} can be computed separately by setting $\hat{a}_i = \arg\max_{a_i} G_i$, $i \in \mathcal{N}$. Noting that $\mathrm{d}^2 G_i/\mathrm{d}a_i^2 = v''(a_i)(\theta_i \sum_{k=i}^{N} w_k - \theta_{i+1} \sum_{j=i+1}^{N} w_j)c/e$, as $v''(a_i) < 0$ for all a_i, G_i is a concave function on a_i under the condition that $\theta_i/(\theta_{i+1} - \theta_i) > \sum_{j=i+1}^{N} w_j/w_i$. In the following sections, we consider the case that $\{\theta_i\}$ satisfy this condition. Then, according to Fermat's theorem, $\hat{a}_i$ can be obtained by setting $\mathrm{d}G_i/\mathrm{d}a_i = 0$. If the obtained $\hat{a}_i$ is a negative, set $\hat{a}_i = 0$ due to the boundary condition. Then the corresponding contract item is $\{0, \mathtt{Na}\}$ which means that the ESC will not buy any electricity from type-θ_i EVs.

As each $\hat{a}_i$ is obtained separately, the set $\{\hat{a}_i\}$ may not follow the constraint in (16), in other words, there may be some sub-sequences which are not in the increasing order. This type of sub-sequence is called as an infeasible sub-sequence [49]. For example, given $\hat{a}_i > \hat{a}_j$, $\{\hat{a}_i, \hat{a}_{i+1}, \ldots, \hat{a}_j\}$ is an infeasible sub-sequence, if $\hat{a}_i \geq \hat{a}_{i+1} \geq \ldots \geq \hat{a}_j$. Considering that $\{G_i\}$ are concave functions, these infeasible sub-sequences of $\{\hat{a}_i\}$ can be replaced by feasible sub-sequences iteratively [49].

Based on the obtained feasible set $\{\hat{a}_i\}$, the corresponding set $\{\hat{q}_i\}$ is easy to get according to (15). Thus, we can derive the optimal contracts $\{\hat{a}_i, \hat{q}_i\}$, which maximize the profit generated from the ESC.

D. OPTIMAL CONTRACT-BASED ENERGY TRADING SCHEME

In a practical scenario, due to the variability of the charging demand and renewable energy supply, the charging demand may be less than the sum of the RE generation and discharging EVs' supply capacity. Under this condition, to maximize its profit, the ESC will set the purchase amount of the electricity equal to the difference between the charging demand d and the renewable energy supply m. However, since both d and m are stochastic variables, it is hard to accurately obtain the optimal purchase amount. Thus, the expected utility generated from the ESC in a practical scenario can be expressed as

$$\bar{U}_{ESC}(q) = c \cdot \mathbb{E}[\min(d, m+q)] - \sum_{i=1}^{N} w_i a_i, \tag{17}$$

where $q = \sum_{i=1}^{N} w_i q_i$, and $\mathbb{E}$ represents expectation over d and m.

As a rational broker, the ESC sets the selling price c higher than the buying price a_i, $i \in \mathcal{N}$. According to (17), under the condition that $d < m + q$, the most economical purchase electricity of the ESC may be less than the amount which the discharging EVs can supply. Due to various supply capacities of these discharging EVs and the corresponding payments, the purchase priority among these different types will impact the profit generated from the ESC.

Considering there are N types of discharging EVs, we denote the utility that the ESC achieves from the electricity trading with a type-θ_i EV as

$$R_i = c\hat{q}_i - \hat{a}_i. \tag{18}$$

Then we have the following theorem:

Theorem 1: Adopting the optimal contract $\{\hat{a}_i, \hat{q}_i\}$, the ESC achieves higher utility from a higher type discharging EV than from a lower one, i.e., $R_i < R_{i+1}$.

Proof: See Appendix D. □

Algorithm 1 The Contract-Based Electricity Trading Algorithm

Initialization: The total supply capacity of the discharging EVs q, expectations of RE $\bar{m}$ and charging demand $\bar{d}$

1: **if** $\bar{d} \geq \bar{m} + q$ **then**
2: Derive the optimal contracts $\{\hat{a}_i, \hat{q}_i\}$ as described in subsection IV. C.;
3: **else**
4: Get the optimal contracts $\{\hat{a}_i, \hat{q}_i\}$ similarly as that in step 2;
5: Compute the index of the critical type of the discharging EVs, denoted as N_0, which satisfies that $\sum_{i=N_0+1}^{N} w_i\hat{q}_i < \bar{m} + q - \bar{d}$ and $\sum_{i=N_0}^{N} w_i\hat{q}_i \geq \bar{m} + q - \bar{d}$;
6: For type $\{\theta_1, \theta_2, ..., \theta_{N_0-1}\}$ discharging EVs, the contracts turns to $\{0, \mathtt{Na}\}$;
7: For type-θ_{N_0} discharging EVs, the contract is changed to $\{\hat{a}_{N_0}, \hat{q}_{N_0}\}$, where $\hat{q}_{N_0} = (\bar{m} + q - \bar{d} - \sum_{i=N_0+1}^{N} w_i\hat{q}_i)/w_{N_0}$;
8: Set $\hat{a}_{N_0} = e^{\hat{q}_{N_0} e/\theta_{N_0}} - 1$;
9: **end if**
10: ESC sends the contracts $\{\hat{a}_i, \hat{q}_i\}$, $i \in \mathcal{N}$, to the discharging EVs and purchases energy from them.

Based on theorem 1, we propose the optimal contract-based electricity trading algorithm as follows.

E. NUMERICAL RESULTS

In this section, we evaluate the performance of our proposed contract-based electricity purchase schemes through the presented simulations. We consider there are $W = 30$ discharging EVs in the proximity area of the ESC, which are classified into $N = 5$ types with $\theta = \{1.2, 1.3, 1.5, 1.8, 2.0\}$. Correspondingly, the discharging EVs belong to these types with the probabilities $\{0.17, 0.22, 0.28, 0.18, 0.15\}$. The cost of unit electricity obtained by discharging EVs is set $e = 0.5$. The highest renewable energy the ESC can get is given as $M = 9$.

Fig. 4 compares the profit generated from the ESC adopting the contract-based electricity trading scheme with that adopting the Real-time Pricing (RTP) scheme. Considering the charging demand is different in a day, the unit electricity selling price varies with time [59]. In the RTP-based scheme, the unit electricity purchase price for the discharging EVs only depends on the various selling prices, but ignores the different characteristics of discharging EVs. It can be seen from the figure that the contract-based scheme makes the ESC gain more profit than the other one does. The reason is that in the contract approach, each contract is designed for the corresponding EV type, and the profit generated from the ESC could be improved by binding the LDICs as described in Lemma 3. However, in the RTP-based scheme, only the reward for unit discharging electricity is specified by the ESC, and each EV determines the discharging amount according to its own utility. Thus, the ESC can not improve its profit.

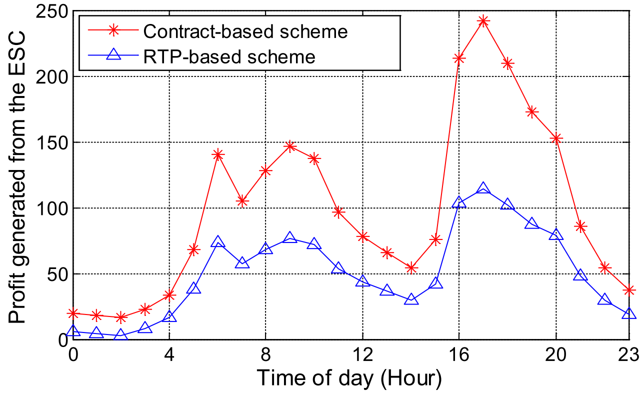

FIGURE 4. Profit generated from the ESC with different schemes.

Fig. 5 shows the ESC profit gained from one discharging EV of different types. We can see that an EV of a higher type provides more profit for the ESC, which proves Theorem 1 of this paper. The difference between the profit gained from various types of EVs at a given selling price is affected by both the optimal amount of electricity and the corresponding reward to an EV. Furthermore, it can be seen from this figure that the profit gained from each type of EV increases as the selling price grows up. The explanation is that more profit can be gained by the contract binding with the increase of the selling price.

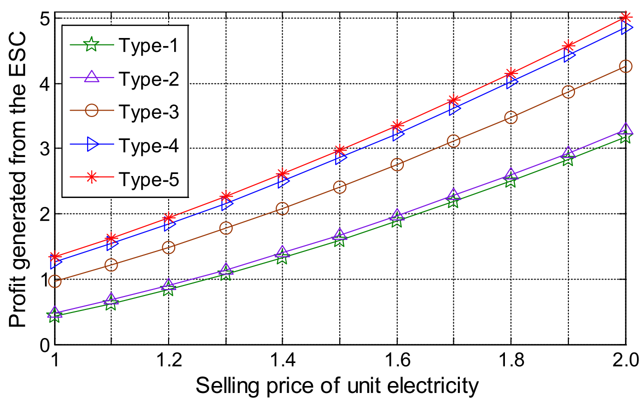

FIGURE 5. Profit gained from one discharging EV of different types.

Fig. 6 shows the amount of the electricity in the optimal contracts for different types of discharging EVs, in the scenario where the charging electricity demand is less than the total supply. It is clearly seen that as the average charging demand increases, more lower types discharging EVs are included in the contracts to provide more discharging electricity.

Fig. 7 evaluates the performance of the proposed optimal electricity trading scheme with different average charging demand. In this scheme, the discharging EVs' type selection is employed. The electricity of the discharging EVs that belong to the more profitable types, are purchased by the ESC with higher priority. In contrast, the other contract-based scheme does not consider the difference of the profits

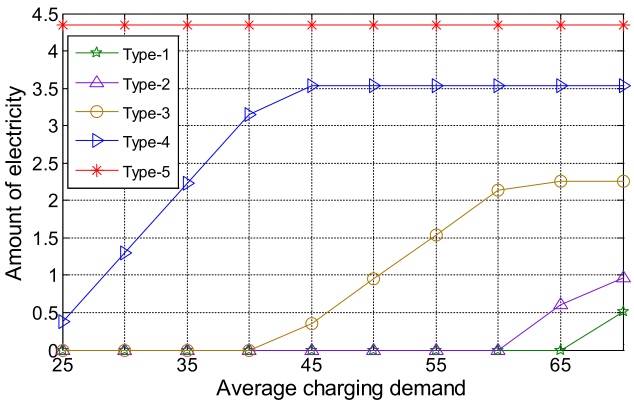

FIGURE 6. Amount of the electricity in the optimal contracts for different types of discharging EVs.

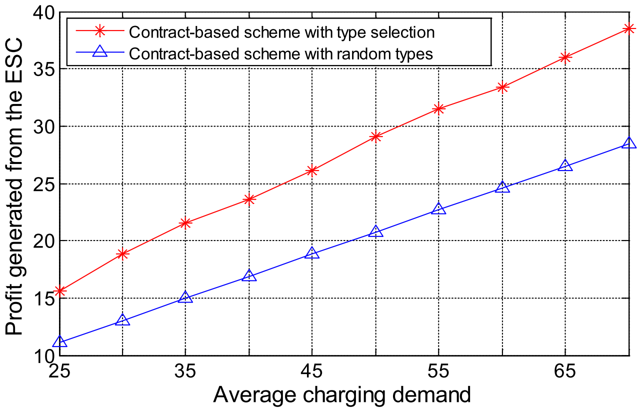

FIGURE 7. Profit generated from the ESC by using different contract-based schemes.

obtained from various of EV types, and purchases electricity from random types. We can find that the scheme with type selection brings more profit to the ESC compared with the other one.

V. CONCLUSION

In this paper, we investigated incentive-based energy trading mechanisms in the smart grid. We started with the introduction of some economic theories that provide guidelines for the design of efficient energy trading schemes. Then we reviewed several typical incentive-based trading schemes. Specifically, we focused on the schemes adopted in the DRM with some technical components, which pose challenges on the scheme design. To reduce electricity transmission cost and provide efficient EV charging service, we proposed a cloud-based V2V energy exchange framework. An optimal contract-based electricity purchase scheme, which takes into account the profit of ESC as well as various characteristics of discharging EVs, has been designed. In addition, we conducted a simulation study, which corroborates our theoretical analysis and clearly displays the profit enhancement in our proposed scheme.

APPENDIX A
PROOF OF LEMMA 1

From the IC constraints of type-θ_i and θ_j discharging EVs, $i \neq j$, $i, j \in \mathcal{N}$, we get $\theta_i v(a_i) - eq_i \geq \theta_i v(a_j) - eq_j$, and $\theta_j v(a_j) - eq_j \geq \theta_j v(a_i) - eq_i$. Adding these two inequalities, we have $(\theta_i - \theta_j)[v(a_i) - v(a_j)] \geq 0$. In addition, we have $v'(a) > 0$, so we come to the conclusion that $a_i > a_j$ must hold whenever $\theta_i > \theta_j$ in a contract satisfying IC constraint. Given $a_i \geq a_j$, according to the IC constraint, we get $\theta_j(v(a_j) - v(a_i)) \geq e(q_j - q_i)$. As $v'(\cdot) > 0$, we have $q_i \geq q_j$. Similarly, under the condition that $q_i \geq q_j$, due to $\theta_i(v(a_i) - v(a_j)) \geq e(q_i - q_j) \geq 0$. Thus, we get $a_i \geq a_j$.

APPENDIX B
PROOF OF LEMMA 2

We have $\theta_i v(a_i) - eq_i \geq \theta_i v(a_1) - eq_1 \geq \theta_1 v(a_1) - eq_1 \geq 0$, $1 < i \leq N$, where the first inequality follows from the IC constraints and the second inequality is obtained through the definition of θ_i, $i \in \mathcal{N}$. Thus, we only need to keep the IR constraint of type-θ_1 in the constraints of the optimization problem.

APPENDIX C
PROOF OF LEMMA 3

If the type-θ_i discharging EVs's LDIC is not binding, that is, $\theta_i v(a_i) - eq_i > \theta_i v(a_{i-1}) - eq_{i-1}$, $1 < i \leq N$. In this case, all q_j for $j \geq i$ in the contract items can be raised by the ESC to make the LDIC binding. Using this method, the maximum utility generated from the ESC can be improved without affecting all the LDICs of the other types of discharging EVs.

APPENDIX D
PROOF OF THEOREM 1

Based on (18), the difference between the ESC's utility got from type-θ_{i+1} and θ_i EVs is shown as

$$\begin{aligned} R_{i+1} - R_i &= c(\hat{q}_{i+1} - \hat{q}_i) + (\hat{a}_i - \hat{a}_{i+1}) \\ &= \theta_{i+1}(v(\hat{a}_{i+1}) - v(\hat{a}_i))c/e + (\hat{a}_i - \hat{a}_{i+1}). \end{aligned} \tag{19}$$

Let $Q(\theta_{i+1}, a) = \theta_{i+1} v(a)c/e - a$, then $R_{i+1} - R_i = Q(\theta_{i+1}, \hat{a}_{i+1}) - Q(\theta_{i+1}, \hat{a}_i)$. We have $\partial Q(\theta_{i+1}, a)/\partial a = \theta_{i+1} v'(a)c/e - 1$ and $\partial^2 Q(\theta_{i+1}, a)/\partial a^2 = \theta_{i+1} v''(a)c/e$. As $v''(\cdot) < 0$, it is clear that $Q(\theta_{i+1}, a)$ is a concave function and it gets maximum at a^* which satisfies $\partial Q(\theta_{i+1}, a)/\partial a|_{a=a^*} = 0$. Recall that $dG_{i+1}/da_{i+1}|_{a_{i+1}=\hat{a}_{i+1}} = 0$. Then, we have

$$\begin{aligned} &\partial Q(\theta_{i+1}, a)/\partial a|_{a=\hat{a}_{i+1}} \\ &\quad = \frac{\theta_{i+1} w_{i+1}}{\theta_{i+1} \sum_{k=i+1}^{N} w_k - \theta_{i+2} \sum_{j=i+2}^{N} w_j} - 1 \\ &\quad > \frac{\theta_{i+1} w_{i+1}}{\theta_{i+1} \sum_{k=i+1}^{N} w_k - \theta_{i+1} \sum_{j=i+2}^{N} w_j} - 1 \\ &\quad = 0. \end{aligned} \tag{20}$$

Considering the concave function $Q(\theta_{i+1}, a)$ increases with a if $a < a^*$, we have the inequalities $\hat{a}_i < \hat{a}_{i+1} < a^*$ and get the conclusion that $R_{i+1} > R_i$.

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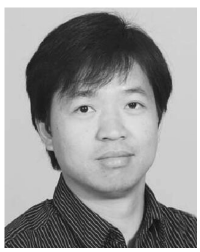

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