

Received February 3, 2019, accepted February 17, 2019, date of publication February 21, 2019, date of current version March 8, 2019. Digital Object Identifier 10.1109/ACCESS.2019.2900356

Game-Theoretic Approaches Applied to **Transactions in the Open and Ever-Growing Electricity Markets From the Perspective of Power Demand Response: An Overview**

LEFENG CHENG^(D), **(Student Member, IEEE), AND TAO YU**^(D), **(Member, IEEE)** School of Electric Power, South China University of Technology, Guangzhou 510641, China

Guangdong Key Laboratory of Clean Energy Technology, Guangzhou 510641, China

Corresponding authors: Lefeng Cheng (chenglf_scut@163.com) and Tao Yu (taoyu1@scut.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 51777078 and Grant 51477055, in part by the Key Science and Technology Project of China Southern Power Grid Co., Ltd. under Grant GZKJQQ00000419, and in part by the Science and Technology Project of China Southern Power Grid Co., Ltd. under Grant GDKJXM20180576.

ABSTRACT This paper conducts a detailed overview on game-theoretic approaches for power demand response (DR) in the open and ever-growing electricity market (EM) in terms of three major categories of games, including non-cooperative game, cooperative game, and evolutionary game. In addition, we also separately review the Stackelberg game and Bayesian game in power DR. First, we briefly describe the main contents of game theory and the game behaviors of the electricity sellers, electricity suppliers, and electricity users in EM. Second, we comprehensively introduce the principle of the above-mentioned five categories of games and thoroughly review their applications in power DR in the context of open EMs, considering the transactions such as electricity pricing and electricity capacity trading among the electricity supplier side, electricity seller side, and electricity user side in the perfect open EMs, such as retail market, spot market, wholesale market, and ancillary service market. In this survey, aiming at each type of game mentioned above, we try to summarize the advantages and shortcomings of their application in EM in terms of power DR, as well as the issues that need to be solved currently or in the future. Finally, we offer some prospects on the scenario application and future development of game-theoretic approaches for power DR in an open EM. The biggest innovation of this paper lies in conducting a comprehensive survey on game-theoretic approaches applied to transactions in the open and ever-growing EMs from the perspective of power DR in terms of five major categories of games. We conduct this survey intended to arouse the interest and excitement of experts and scholars in the energy and electric power system industry and to look ahead to efforts that jointly promote the rapid development of game theory in the perfect open EM field.

INDEX TERMS Power system, smart grid, game theory, game-theoretic approaches, power demand response, electricity market, non-cooperative game theory, cooperative game theory, Stackelberg game theory, Bayesian game theory, evolutionary game theory, review.

I. INTRODUCTION

The non-renewability of fossil energy and the environmental pollution issues caused by its production and consumption have slowly and severely affected the rapid development of human economy and society. In 2011, the famous American economist Rifkin [1] first proposed the concept of Energy

Internet and made a concrete definition of it: People can produce and share renewable energy resources in a decentralized and free manner, and the existing power grid will become a shared peer-to-peer energy network. The technical basis for the development of the Energy Internet is smart grid. Compared with traditional power grid, the smart grid has the characteristics of bidirectional interaction of power flow and information flow [2]. It builds a highly intelligent energy exchange network through high-speed and real-time

2169-3536 © 2019 IEEE. Translations and content mining are permitted for academic research only. Personal use is also permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

The associate editor coordinating the review of this manuscript and approving it for publication was Yanbo Chen.

communication technology and advanced data measurement and acquisition technologies.

With the bidirectional interaction capability of information and power of smart grids, the role of demand-side users in the power grid is gradually emerging. For power generation corporations (which are collectively refer to electricity suppliers), how to effectively improve its profitability and user's electricity use satisfaction through effective userfriendly interactions is an important issue that needs to be solved urgently. For power grid companies and power sales companies (which are called electricity sellers), how to enrich their profit models by interacting with grid companies and power consumers to effectively participate in electricity market (EM) transactions is very important. For power consumption users (which are collectively called electricity users), small and medium electricity users with low energy consumption such as residential and commercial users mainly interact with power grid through demand-responsive market means to achieve load flexibility and improve terminal power efficiency; large electricity users with high energy consumption such as industrial users mainly interact with the power generation side through the power retail market to balance the supply and demand of source and load, and improve the reliability of power supply; and users with distributed renewable energy resources can participate in the market as the stakeholders of the purchase of electricity, and can also sell electricity to the grid as the stakeholders of the electricity sales, called prosumers. For these above-mentioned types of electricity users, how to effectively interact with electricity suppliers and electricity and electricity sellers to improve the comfort of electricity consumption and reduce the cost of electricity is the primary concern for them.

Therefore, demand-side users are increasingly pursuing the development of smart electricity utilization (SEU) [2]. The core feature of SEU is to realize flexible interaction between power grid and user energy flow, information flow and service flow. As the core business that can best reflect flexible interactive features in SEU, the power demand response is currently developing in the direction of integrated demand response (IDR) [3], [4] and automated demand response (ADR) [5]–[8]. Among these, IDR targets the multi-energy users in Energy Internet or smart energy hub, and ADR targets the demand-side users in the smart grid. The main characteristics of power demand response (DR) are standardization of information interaction, intelligent decision making and automation of execution.

In this context, the EM under the smart grid has also been open and ever-growing, and the participants in the EM have become more and more complex and diverse [9], [10], including traditional power grid enterprises and power consumers. In addition, a large number of distributed generations, energy storage, controllable loads, and electric vehicles (EVs) have emerged in the power grid, making EM more open, complex and diverse. Not only traditional power grid enterprises, power producers and power consumers affect the development of EM, but also new power supply entities (NPSEs) such as emerging power sales service providers and load aggregators are influencing the development of EM to varying degrees, making the economic behavior of power trading very complicated. Therefore, due to the large number of users on the DR and the variety of loads, especially the widespread use of distributed power sources and EVs, and the diversification of the stakeholders of electricity sales and trading modes in an open EM, the determination of the optimal strategy is very challenging for the demand-side decision-making stakeholders. Actually, the optimal theoretical system of traditional single stakeholder-based decision-making has gradually been unable to satisfy the strategy optimization among multiple decision-making stakeholders [10].

In view of this, to investigate the complex economic behaviors of different stakeholders, as a solution to the optimization of multi-stakeholder decision-making, game theory is expected to become a powerful tool to solve the issues existing in power DR in a fair environment [11]. For instance, in the EM, game theory is heavily used to analyze power producer bidding strategies and establish EM models, such as Cournot model [12], [13] and Bertrand model [14], [15]. Specifically, when the power producers in the EM make quotations, they need to consider the quotation strategies of other power producers when the information is not enough (i.e., the information is limited for available). At this point, the incomplete information-based static game theory [16] in game theory can provide a good theoretical guidance for the determination of quotation strategies.

It is foreseeable that as the DR becomes more prominent in the smart grid, good decision-making tools for demandside users are of great significance for the construction of a strong smart grid [17]. Therefore, the application research of game theory on the power DR also has important theoretical and practical significance. To this end, this paper conducts a detailed survey on game-theoretic approaches for power DR in the EM in terms of three categories of games, including non-cooperative game [18], cooperative game [19], and evolutionary game [9], [20], [21]. In particular, we separately select Stackelberg game [22] and Bayesian game [23] from non-cooperative games to review their applications in power DR. In summary, this paper contributes in the following aspects:

1) We briefly describe the main contents of game theory and game behaviors of the EM among electricity suppliers, electricity sellers and electricity users in terms of power DR.

2) We comprehensively introduce the principle of abovementioned three categories of games as well as Stackelberg game and Bayesian game, and then thoroughly review their applications in power DR in the context of open EMs such as retail market, spot market, wholesale market and ancillary service market, considering the EM competitions such as electricity pricing and electricity trading among electricity supplier side, electricity seller side and electricity user side.

3) We offer some prospects on the application scenarios development and corresponding research directions for the

above-mentioned five game-theoretic approaches in the field of EM from the perspective of power DR.

On the whole, the biggest innovation of this paper lies in conducting a comprehensive survey on the major gametheoretic approaches applied to competitive transactions in the open and ever-growing EMs from the perspective of power DR. We conduct this survey on relevant achievements of game theory obtained recently in EMs such as retail market, spot market, wholesale market and auxiliary service market from aspect of power DR, with the goal of hoping to arouse the interest and excitement of experts and scholars in the energy and electric power system industry and looking ahead to efforts that jointly promote the rapid development of game theory in the perfect open EM field.

The rest of the paper is organized as follows: Section II briefly introduces the main contents of game theory and the game behaviors in EM on electricity supplier, electricity seller and electricity user sides. Based on the introduction of non-cooperative game, cooperative game and evolutionary game, Sections III, IV and V thoroughly review their applications in power DR in the context of open and evergrowing EM, respectively. In addition, we also separately review Stackelberg game and Bayesian game in EMs in terms of power DR in Sections VI and VII, respectively. Moreover, in Section VIII, we offer some prospects on the application of game-theoretic approaches in power DR in the future. Finally, Section IX concludes this paper. In addition, a nomenclature is contained in the end of this paper.

II. GAME THEORY AND GAME BEHAVIORS IN THE EM

As stated previously, more and more new stakeholders on electricity supplier side, electricity seller side and electricity user side participate in EM trading, thus making the transaction behaviors in EM become increasingly complex and diverse. In this context, how to solve the issue of multistakeholder decision-making in EM become crucial, which can be summarized into a class of multi-agent and multiobjective optimization decision problems of complex systems. To overcome such EM optimization decision-making problems, game theory has become a powerful tool in recent years [17], [24]. To this end, this section introduces the basic principle of game theory and general game behaviors appear in EM among electricity supplier side, electricity seller side and electricity user side.

A. GAME THEORY

1) INTRODUCTION

Game theory is a branch of modern mathematics. It is mainly used to investigate how a stakeholder or player can make a decision that is conducive to can make a decision that is conducive to the maker's own decision according to the maker's own capability and the information the maker has mastered when there are conflicts of interest between multiple decision-making stakeholders [25]. The evolution of game theory is demonstrated in Figure 1.



FIGURE 1. Illustration of the evolution of game theory.

Timeline

Further, game theory can also be considered as a theory of policy interaction, that is, each decision-making stakeholder must consider how other decision-makers act and how such actions will affect their own interests. In a word, game theory is a theory of investigating the mutual influence of strategies. In a game problem, each participant must consider how other participants act when making decisions. Since its birth, game theory has had far-reaching influence on many fields such as economics, sociology, military science, political science and engineering science [9]. It has become an indispensable analytical and auxiliary design tool in the field of control and decision-making.

Generally speaking, game theory is mainly composed of cooperative game, non-cooperative game and evolutionary game. Among these, the cooperative game theory is founded by Neumann and Morgenstern [26], and the non-cooperative game is represented by Nash's work [27]-[30]. He proved the existence of non-cooperative game solution, that is, the existence of Nash equilibrium, thus laying the theoretical foundation of modern non-cooperative game. As for the evolutionary game, it is generally recognized that it was officially founded by Maynard Smith and Price [31]. This theory can be regarded as an organic combination of general game theory and dynamic evolution process [32]. Among these, the former focuses on the game problem within the framework of bounded rationality rather than complete rationality, while the latter draws on the biological evolution theory in biology field. In short, the decision-making stakeholders (i.e., players or participants) in an evolutionary game constantly adjust their own strategies according to environmental changes and the strategies of other decision-making stakeholders in order to adapt to the game environment under the conditions of limited knowledge, information and reasoning ability [9], [33].

For a standard game model [9], it includes at least three elements: participants, strategy, and payment or income.

Among these, we assume that $N = \{1, 2, \dots, n\}$ represents a set of participants in an *n*-player game; S_i denotes the strategy set of participant $i \in N$; $S = \{S_1, S_2, \dots, S_n\}$ refers to the strategy set of all participants in an *n*-player game; $s = \{s_1, s_2, \dots, s_n\}$ represents the strategy combination of all participants; and $u = \{u_1, u_2, \dots, u_n\}$ means payment or income, which is used to quantify the benefits of participants in the game, and denotes the payment or income vector of all participants. In an *n*-player game, the goal of the participants is usually to minimize payments or maximize incomes. Based on this, a typical *n*-player game [9] can be expressed as

$$G = \{N; S_1, S_2, \cdots, S_n; u_1, u_2, \cdots, u_n\}.$$
 (1)

which shows a standard game model. For example, as shown in equation (1), the Nash equilibrium is such a combination of strategies that allows each participant's strategy to be optimally responsive to other participants' strategies at the same time [27]–[30].

2) CLASSIFICATION

As mentioned previously, game theory is mainly divided into three branches: cooperative game, non-cooperative game and evolutionary game. Generally speaking, the games can be divided into classic game and evolutionary game according to the degree of rationality of the participants. Among these, the classic game requires participants to be completely rational, while the evolutionary game only requires participants to have bounded rationality [9]. In addition, the classic game can be divided into cooperative game and non-cooperative game according to whether the participants cooperate or not. At this point, according to the degree of understanding of the participants' information on other participants, the game can be divided into a complete information game and a Bayesian game with incomplete information; and according to the order in which the participants take actions, the game can be divided into static games and dynamic games. Overall, there are many classification methods for game theory, as demonstrated Figure 2, which illustrates a detailed game classification from seven aspects, including the behavioral logic, the game process, the degree of understanding of the players, the number of players, different types of strategies, the payoff, the rationality of the players, and the structure of the game process information. Actually, since 1994, a total of seven times of Nobel Prize in economics have been awarded for game theory research.

B. GAME BEHAVIORS IN EM

In an open and ever-growing EM, there is a fierce game relationship between power generation companies, power grid companies, power sales companies, and power consumers [9]. Actually, on one hand, the electricity sellers and trading models in the EM are developing in a diversified direction. Thus, the opening of the electricity sales market makes demand-side resources no longer only concentrated on the user loads, and it also includes distributed energy such



FIGURE 2. Illustration of the game classification.

as distributed generation, distributed energy storage and EVs [34], [35]. On the other hand, power consumers are not only given the right to freely choose the electricity sellers, but also can directly conduct power transactions with the power generation companies, such as the high energy consumption users (e.g., big industrial users). In addition, the users with distributed energy resources such as solar energy and wind energy gradually become prosumers [36], that is, they are both consuming energy and have the option of trading superfluous energy with the electricity sales companies. Therefore, the development of multi-agent and diversified transactions in the open and ever-growing EM will inevitably have complex and intricate game behaviors [9], [37].

On the whole, these above-mentioned participants can be divided into electricity suppliers such as power generation companies, electricity sellers such as power sales companies and power grid companies, and electricity users (i.e., power consumers) such as residential, commercial and industrial users, and users with distributed energy resources. Accordingly, they are called electricity supplier side, electricity seller side and electricity user side, respectively. Therefore, the game relationship between above participants can be summarized as game relationships between electricity supplier side and electricity seller side, game relationships between electricity seller side and electricity user side, game relationships between electricity user side and electricity supplier side, and game relationships among electricity supplier side, electricity seller side and electricity user side. These game behavior relationships in EM are demonstrated in Figure 3, and they are introduced as follows. Based on Figure 3, Zeng et al. [38] construct a concrete application structure of an EM containing generation side,



FIGURE 3. Game behavior relationships in an open and ever-growing EM.

transmission and distribution side, and electricity utilization side in Sichuan Province of China under the new situation, as demonstrated in Figure 4.



FIGURE 4. Illustration of a concrete application structure of an EM containing generation side, transmission and distribution side, and electricity utilization side in Sichuan Province of China under the new situation.

1) GAME RELATIONSHIPS BETWEEN ELECTRICITY SUPPLIER SIDE AND ELECTRICITY SELLER SIDE

In a traditional EM, the game relationships between electricity supplier side and electricity seller side are very common, and there is often a fierce game relationship between them. However, under such an EM trading mechanism, since the EM is not yet open, the power consumers on the DR often only passively accept the sales prices released by the grid companies. At this time, there is no direct competition between electricity users and between grid companies.

2) GAME RELATIONSHIPS BETWEEN ELECTRICITY SELLER SIDE AND ELECTRICITY USER SIDE

In an open and ever-growing EM, the game relationships between electricity seller side and electricity user side are always reflected in two cases. One is the game relationship between the small and medium users with a level of low energy consumption (e.g., the residential and commercial users) and the power grid companies and power sales companies. At this point, such users are an important part in power DR, and they will change the way of electricity use to reduce their electricity bills under the incentive of the electricity price mechanism [39]. During the process of power DR, the user's electricity demand will affect the electricity price through the market. As a result, because each electricity user has a goal of minimizing the cost of electricity use, there will be a game relationship between these users. Moreover, in an open EM, the electricity seller side is also open for all electricity users, thus these small and medium users can freely choose the electricity sellers from the EM with the goal of minimizing the cost of electricity use. At this point, power sales companies and power grid companies both want to attract more users to maximize their own benefits, thus there will be a fierce game relationship between users and power sales companies and power grid companies.

In addition, there is also a special type of power consumers on the electricity user side, and they are both energy consumers and energy producers, called energy prosumers [40]. Such electricity users have some distributed energy resources such as roof photovoltaic, EVs and wind generation, thus they can use distributed energy or energy storage equipment and EVs to finish discharging and they can also implement transactions in the EM as an electricity seller. In order to minimize the cost of electricity users as prosumers will need to play games with other electricity sellers (i.e., other prosumers), power grid companies and power sales companies.

3) GAME RELATIONSHIPS BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SUPPLIER SIDE

Apart from above-mentioned small and medium electricity users with low energy consumption, for the electricity users with high energy consumption (who are called large electricity users) such as large industrial users, they will also need to participate in electricity trading in an open and evergrowing EM. At this point, in order to reduce their production costs, they are bound to prefer to conduct direct electricity purchase transactions with power generation companies [41], [42]. Accordingly, there will be a game relationship between the electricity supplier side and electricity user side. In this type of game, the electricity supplier side as sellers and the electricity user side as buyers will both try to get the most benefit from the transaction, which results in a direct purchase game between them. At this point, such games may occur between a single large industrial user and a single power generation company, or between multiple large industrial users and multiple power generation companies.

4) GAME RELATIONSHIPS AMONG ELECTRICITY SUPPLIER SIDE, ELECTRICITY SELLER SIDE, AND ELECTRICITY USER SIDE

In an open and ever-growing EM, as various stakeholders are free to participate in EM transactions, we need to simultaneously consider the game relationships among electricity supplier side, electricity seller side and electricity user side. This means that we need to extend the convergence domain of the game system from a two-dimensional plane to a three-dimensional space [9], [17].

Specifically, we take the aforementioned power grid companies (here we divide the power grid companies into the electricity supplier side), NPSEs (which denotes the electricity seller side) and power consumers (which represents the electricity user side) as an example, who participate in EM trading in aspects of time-of-use (TOU) electricity pricing and electricity sales trading, as demonstrated in Figure 5. At this point, according to the idea of non-cooperative game, there is no mutually binding agreement between the participants in the game, which means that they all have individual rationality, and both of them aim at maximizing their own interests for power trading. Based on this, if we assume that the power grid companies are treated as the dominant player of the game, who first set the price of electricity for each time period; then, the NPSEs refer to the grid companies' electricity prices, consider their own conditions and needs, and give their own electricity prices; and finally, the power consumers will select the power suppliers according to their own power demands and the price given by each power supplier, and make power arrangements at each moment. In this example, there is a complex game relationship among electricity supplier side, electricity seller side and electricity user side, and in which they all participate in the EM game with the goal of maximizing their own interests [9].



FIGURE 5. A complex market transaction network among electricity suppliers, electricity sellers and electricity users in an open and ever-growing EM.

III. NON-COOPERATIVE GAME-THEORETIC APPROACH AND ITS APPLICATIONS IN EM

In a non-cooperative game, there is no binding agreement between the participants or players. This type of game can be divided into static game and dynamic game (see Figure 2). As stated previously, non-cooperative game theory is represented by Nash's work [27]–[30]. He first proved the existence of the non-cooperative game solution under certain conditions, that is, the existence of the famous Nash equilibrium, thus laying the theoretical foundation for the modern non-cooperative game. Nash equilibrium is a core concept in non-cooperative game theory. It means that no participant can get more benefits by unilaterally changing its strategy when all participants are in a Nash equilibrium state. This concept has been widely used in multi-party non-cooperative games in an EM. To this end, this section first introduces the basic concepts of non-cooperative game theory, and then focuses on the application of non-cooperative games in multi-party game-based power DR in the EM.

A. NON-COOPERATIVE GAME THEORY 1) BASIC CONCEPTION

The non-cooperative game is completely different from the cooperative game. The difference between them is whether there is a binding agreement between the parties (i.e., the stakeholders or players) in a game. If there is, the game is a cooperative game. Otherwise, it is a non-cooperative game. Generally speaking, non-cooperative games can be divided into static games and dynamic games. In a static game, all participants select actions at the same time, or although they are not at the same time, but the players in the post-action are not aware of the actions taken by the players who act first; hence, static non-cooperative games are also commonly referred to as strategic games. In contrast, in a dynamic game, the participants' actions are taken in order, and the participants can obtain the historical information of the game, and optimize their actions according to all the information currently available before making a decision. From the perspective of the characteristics of non-cooperative games, most of the control and decision problems in smart grid belong to the category of non-cooperative games, such as robust optimization and robust control. Certainly, in the EM, non-cooperative games are also widely used, especially for multi-objective optimization problems. Different targets in such problems are often competitive, and the optimization goal of one party is often at the expense of the other party's interests.

2) NASH EQUILIBRIUM

Nash equilibrium is a very important concept in noncooperative game theory, which means that no player can achieve more benefits by unilaterally changing its own strategy when all players in a Nash equilibrium status. As shown in Figure 2, non-cooperative games can be subdivided into four categories of games based on the game process and the degree of information understanding by participants: complete information-based static game, complete informationbased dynamic game, incomplete information-based static game, and incomplete information-based dynamic game. Nash equilibrium has different expressions in these four game forms, and the corresponding equilibrium concepts are Nash equilibrium, subgame perfect Nash equilibrium, Bayesian Nash equilibrium, and perfect Bayesian Nash equilibrium (see Figure 2). Specifically, the basic conception of Nash equilibrium is given as follows.

We call a mixed strategy combination σ_i^* is a Nash equilibrium when it satisfies the following inequality [43]:

$$u_i(\sigma_i^*, \sigma_{-i}^*) \ge u_i(s_i, \sigma_{-i}^*), \quad \forall s_i \in S_i, \ \forall i, \tag{2}$$

when the above strategy σ_i^* is a pure strategy, we call it as a pure strategy Nash equilibrium s^* . Obviously, the definition of mixed strategy Nash equilibrium in (2) is a more general definition, thus pure strategy can be seen as a special form of mixed strategy. Nash equilibrium has characteristics of strategically stable and self-reinforcement [43]. In fact, only Nash equilibrium allows each participant to recognize this outcome and has no incentive to deviate from this outcome, and all participants know that other participants also accept this outcome.

3) SOLUTION METHODS

For the non-cooperative games, generally, it is difficult to solve the Nash equilibrium and prove its existence due to the diversification of practical problems and their complexity and variability, especially when there are many participants in a non-cooperative game. Actually, researchers usually prove the existence of equilibrium by proving the existence of a solution to a fixed point problem [44]. However, this will be a complex mathematical issue that is not conducive to promotion to practical applications. To this end, for some game models with specific behavioral space and income function with special structural properties, many scholars have proposed a series of methods to prove the existence of Nash equilibriumin these models. Among these, one of the classic methods for existence proof is given by Nash, Jr. [28]. Among these methods, the commonly used methods for solving non-cooperative game Nash equilibrium are the best response and fictitious play strategies [45], [46], in which each player chooses the action that maximizes its payoff given the actions of the other players. Recently, the distributed optimization game algorithms have been widely concerned [47]. In addition, the algorithms based on learning theory for Nash equilibrium solving have also been widely used [48].

B. A SURVEY

As stated previously, non-cooperative games are one of the most common types of games in practical multi-stakeholder game issues. The power DR in the open EM is more reflected in the electricity user side, which is treated as one party of the stakeholders participating in the EM electricity pricing and electricity purchasing. This is mainly due to the diversification of power consumers on the electricity utilization side. Actually, with the rapid development of EM in the smart grid and Energy Internet, compared with traditional power consumers, the electricity user side includes both small and medium users with low energy consumption, such as common residential users and building commercial users, as well as large users with high energy consumption, such as large industrial users. Certainly, in addition to these types of users, the electricity user side also includes prosumers who can both consume energy and produce energy. For these prosumers, they can conduct two-way energy trading with the electricity seller side (e.g., power grid companies and power generation companies) through various distributed energy devices such as distributed energy storage systems, distributed generation and EVs. In the process of this electric energy transaction, the prosumers can freely sell electricity to the stakeholders on the electricity seller side based on the above-mentioned distributed energy devices. Here, the electricity seller side includes power grid companies, emerging electricity sellers, load aggregators, and so on. Therefore, the application of game theory in this two-way transaction process can provide a new way for the prosumers to make optimal decisions. In fact, game theory has been widely used in the power DR between the electricity user side and electricity seller side, especially the non-cooperative game theory and the cooperative game theory. In this section, we mainly review the application of non-cooperative games.

1) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SELLER SIDE IN EM

In the aspect of EM trading between the electricity user side and electricity seller side, Geerli et al. [18] consider the pricing structure between an electric utility on electricity seller side and independent power producers on electricity user side via constructing a market model based on noncooperative game. In this model, the non-cooperative game rules developed for the two types of stakeholders can be seen as an extension of the conventional equalizing incremental cost method for the deregulated power systems. Moreover, a Nash equilibrium of the non-cooperative game is used to analyze the negotiation between the two stakeholders, and it shows that the Nash equilibrium and the Stackelberg strategy have different solutions when the purchased electric energy is assumed to depend on its price or a function of the price. Marzband et al. [49] construct an EM structure with high penetration of distributed energy resources (DERs) based on non-cooperative game theory. In addition, the electricity users in this market structure are able to participate in the market as producer and consumer at the same time (i.e., prosumers). Based on a full consideration of related uncertainties, the DERs can take the price bidding strategies to maximize their expected payoff or profit at a Nash equilibrium in the market structure. Moreover, the effectiveness and accuracy of this market framework are verified via a case study. Su and Huang [10] construct an *n*-person noncooperative game-theoretic framework for a next-generation retail EM with high penetration of distributed residential electricity suppliers. The effectiveness of this framework is verified via an IEEE 13-bus simulation case, and the simulation results demonstrate that as a seller participating in power DR, the residential users can play a vital role in the operation and management of distributed generation and energy storage. Researchers in [50] design a new energy cost function to apply to the scenario of electricity trading between

the electricity user side and electricity seller side, where the electricity user as a prosumer can use the energy storage to sell electricity to the grid. Specifically, the non-cooperative game model is employed to minimize the energy costs of users via optimizing the load schedule of users at various times.

In addition, based on non-cooperative game theory, researchers in [51] adopt a non-cooperative game approach to investigate the game behavior of residents and the grid when conducting bilateral transactions. In this trading scenario, users can supply power to their loads through distributed generation and energy storage devices, and can also sell electricity to the grid when they have superfluous energy supply. Certainly, in addition to the above research work, scholars also investigate how to promote the use of EVs by the power consumers to participate in power DR between electricity user side and electricity seller side. For instance, researchers in [52] and [56] investigate how to use EVs as a medium for trading between the electricity user side and electricity seller side (e.g., power grid companies, emerging electricity sales companies, EV aggregators, load aggregators), and use the multi-agent game mechanism to obtain the Nash equilibrium of electricity users participating in the EM transaction through the EV charging and discharging strategies. However, although the researchers in [55] adopt the noncooperative game method to optimize the trading strategy, they do not consider the transferability and uncertainty of user's other loads.

Apart from prosumers discussed above, the general power consumers on electricity user side often conduct electricity trading with power sales companies on electricity seller side. Specifically, the electricity sales companies release the electricity price for each time period, and accordingly, the electricity user give a strategy for electricity purchasing. In this process of trading, non-cooperative game theory is mainly applied in TOU mechanism-based electricity trading and real-time pricing (RTP) mechanism-based electricity trading between electricity user side and electricity seller side. For example, Jalali and Kazemi [57] establish a non-cooperative game model on the electricity user side and the electricity seller side (i.e., the power sales company) respectively, and conduct simulation verification with three power sales companies and 1000 users as a case study in the simulation analysis. The simulation results show that this proposed noncooperative game model can reduce the user's energy consumption cost and the peak-to-valley difference of the power grid, and can also be applied to the power system with largescale residential users. Maharjan et al. [58] develop a Stackelberg model combining with a non-cooperative model to analyze the electricity pricing decision between the electricity sales company and the electricity user side. In this proposed model, the Lagrange multiplier method is used to derive the optimal power purchase combination from different power sales companies, so as to maximize the utility of user's power consumption. Based on TOU mechanism, Yang et al. [59] introduce the non-cooperative game mechanism to the energy trading between the electricity sales company side and the electricity user side. During the energy trading process, on one hand, the electricity sales companies can effectively increase their profitability via optimizing the price of electricity sold in each time period, and on the other hand, in order to improve the electricity consumption satisfaction and simultaneously reduce the energy consumption cost, the electricity user side will reasonably arrange and optimize their loads in each time period under the premise of passively accepting the TOU prices.

In addition, non-cooperative game theory also has been applied in RTP-based power DR between users, or between the electricity seller side and electricity user side from the perspective of optimizing the electricity cost of individual user. For example, Samadi et al. [60] use the difference between utility and electricity cost as the target of user participating in simulation modeling of a non-cooperative game. In this model, the researchers assume that the utility generated by the user's electricity utilization is a quadratic function of the electricity consumption amount, and the electricity price is a linear function of the electricity consumption amount. Chen et al. [61] develop a power function type electricity price model for autonomous demand side management based on energy consumption scheduling and instantaneous load billing. In this model, researchers use the theory of variational inequality to solve the power range in the case of the existence of Nash equilibrium in a non-cooperative game, and thereby establishing a non-cooperative game model between the electricity users regarding the electricity cost. In addition, researchers in [62] use non-cooperative game theory to establish a two-layer game model on the electricity sales company side and residential user side, which can effectively reduce the peak-to-valley difference of load and the energy costs.

2) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

In the aspect of EM trading between the electricity user side and electricity supplier side (e.g., power generation companies), the non-cooperative game theory has also been applied initially, especially for direct electricity purchasing transactions between large industrial users with high energy consumption and the power generation companies. In fact, most of the research work in this aspect has been conducted in a trading mechanism similar to direct power purchasing. Specifically, based on such face-to-face direct power purchasing mechanism, the electricity supplier side and the large power users (i.e., the electricity user side) conduct a bilateral transaction through face-to-face direct negotiations, and during which both parties involved in the transaction hope to optimize their utility functions through the formulation of their own strategies. For this reason, based on non-cooperative game theory, under the bilateral transaction mode that takes into account the direct transactions between multiple power producers (i.e., the electricity supplier side) and multiple large users (i.e., the electricity user side), Wu [63] investigates the issues of large users' optimal power

purchasing combination and power suppliers' optimal bidding strategy considering the willingness of the two parties involved in the transaction. Specifically, on one hand, the power producers obtain more contract shares through the competition of contract quotation, and on the other hand, according to the quotation of each power producer and the predicted electricity price of the spot market at each time of the contract period, the large users will formulate the power purchase strategy within the contract period, that is, the contracted electricity capacity of each power producer and the purchase of electricity in the spot market. According to the above game behavior, and under the condition of complete information, Wu [63] establishes a master-slave game model including the non-cooperative game between the upper power producers and the optimization of the power purchasing cost of the lower-level large users. The existence of Nash equilibrium of the non-cooperative game has been proved and the effectiveness of the entire game model has been verified. In addition, researchers in [64] build a complete information non-cooperation bi-level programming model considering that the electricity pricing and the products price for large customers both affect the benefits of all participants in the course of the direct power purchasing, with the goal of finding the best pricing status and achieving the equilibrium of all participants in the system based on game theory. In the case study in [64], researchers analyze the different effects of cooperative games and non-cooperative games in direct power purchasing, and the results show that the global equilibrium pricing strategy generated by the established game model can ensure the balance between the electricity user side and electricity supplier side, and can guarantee the stability of the transaction. In this bi-level non-cooperative game model established in [64], the game process of selecting the electricity pricing models in the upper-level is demonstrated in Figure 6.



FIGURE 6. The game process of selecting the electricity pricing models in the upper-level developed by researchers in [64].

3) POWER DR BETWEEN ELECTRICITY SELLER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

In aspect of power DR between electricity seller side and electricity supplier side in EM, non-cooperative game theory

has been preliminarily applied to solve the EM equilibrium. For instance, Zhao et al. [65] construct an equilibrium model of EM based on non-cooperative game for the electricity supplier side containing wind farms and thermal power plants and the power grid companies as the electricity seller side. This Nash equilibrium-based three-party non-cooperative game model is used to analyze the main factors influencing utility of each player. Moreover, the dispersed point pattern and chain net model are proposed in the non-cooperative game model. A case study conducted for this game model shows that the transaction service fee charged by power grid companies, surplus electricity price and penalty paid by thermal power plants may change the transaction mode. Moreover, some factors have been found that can directly affect the utility value of the players in this non-cooperative game, but they make no effects on distribution of Nash equilibrium dots. These influencing factors include the government subsidies for wind power, the power generation cost of wind farms and thermal power plants, and the average electricity purchasing cost of power grid companies. This Nash equilibrium-based three-party non-cooperative game model involving wind farms, thermal farms and power grid companies is demonstrated in Figure 7.



FIGURE 7. Illustration of the Nash equilibrium-based three-party non-cooperative game model involving wind farms, thermal farms and power grid companies developed in [65].

In addition, researchers in [66] investigate the gaming equilibrium among the electricity supplier side (which contains fossil-fueled generation companies and wind generation companies), the electricity seller side (which refers to the grid company) and the electricity user side (i.e., the customers) participating in an emission trading market and the day-ahead EM, and finally propose a complementarity method to obtain the Nash equilibrium; and in [67] develop a bi-level model to find the equilibria in the short-term EM with large-scale wind power penetration, and finally the Nash equilibria of the EM containing the electricity supplier side and electricity seller side are obtained by solving the equilibrium problem with equilibrium constraints using game theory and the diagonalization algorithm, and the case studies verify the effectiveness of the proposed non-cooperative model.

4) A BRIEF SUMMARY

Overall, non-cooperative games in game theory are the most widely used in power DR of EM. However, due to the diversification of practical multi-party game problems and their complexity and variability, especially when the game issue involves numerous participants from different parties, there are some difficulties in proving the existence and solving of Nash equilibrium. For this reason, researchers have put forward some effective methods, such as [45]–[48], best response, fictitious play strategies, distributed optimization game algorithms, and the algorithms based on learning theory.

IV. COOPERATIVE GAME-THEORETIC APPROACH AND ITS APPLICATIONS IN EM

In an open and ever-growing EM, the power sales stakeholders on the electricity seller side such as wind farms and photovoltaic stations generally belong to different parties or players in an EM game. Moreover, the natural complementarity of wind and photovoltaic resources makes it possible for the cooperation between the two to achieve more benefits in the EM transactions. Therefore, cooperative game theory can be used as an effective analytical tool to reasonably determine the cooperation mode and income distribution mechanism of the two types of stakeholders. To this end, aiming at the power DR in the EM among electricity supplier, seller and user sides, we first briefly introduce the basic principle of cooperative game in this section, and then comprehensively summarize the application of cooperative game theory in power DR of EM.

A. COOPERATIVE GAME THEORY

1) BASIC CONCEPTION

Cooperative game theory was first founded by Neumann and Morgenstern [26]. In a cooperative game, there is a binding agreement between the participants, and the participants are no longer completely confrontational, but present a cooperative status. Cooperative game theory aims at how to achieve cooperation for participants and how to allocate the additional incomes produced from interactions for each participant. Therefore, cooperative game issues are generally solved based on Nash bargaining game theory [27], [30] and the Shapley value-based methods [68]. For instance, the Shapley value is defined as follows. For a cooperative game $G = \langle N, v \rangle$, |N| = n, the Shapley value of the participant *i* is defined as

$$\varphi_i(G) = \frac{1}{n!} \sum_{\pi \in P(N)} \delta_i(S_\pi(i)), \tag{3}$$

where $\delta_i(S_{\pi}(i))$ is the marginal contribution of the participant *i* under the given permutation π ; P(N) is the set of all permutations under the set $N = \{1, 2, \dots, n\}$, and then the number of potential permutations in the set N equals to the permutation of $\{1, 2, \dots, n\}$, and which is n!; $\varphi_i(G)$ is the average of the marginal contribution under possible orders. In addition, the π refers to a change in order, and it is defined as a one-to-one mapping of the sequence number set to itself, namely $\pi : \{1, 2, \dots, n\} \rightarrow \{1, 2, \dots, n\}$. For the element *i* and permutation $\pi \in P(N)$ selected in the set $N = \{1, 2, \dots, n\}$, all the elements before the element *i* in the set after a permutation π form a collection and it refers to $S_{\pi}(i)$. For the $C \subseteq N$, which means any subset of $N = \{1, 2, \dots, n\}$, the definition of $\delta_i(C)$ is given as $\delta_i(C) = v(C \cup \{i\}) - v(C)$. Overall, from a computational point of view, the calculation of the Shapley value can also be regarded as a sampling of the participant set permutation π .

2) CLASSIFICATION

In a cooperative game, if the additional income from players' cooperation can be distributed among the participants, the game is called a transferable utility cooperative game, and it is usually a coalitional game; otherwise, the game is called a non-transferable utility cooperative game, and this kind of game can be further divided into two categories: the nontransferable coalitional game and the negotiation problemtype game. Certainly, according to the factors affecting the benefits of the alliance, the transferable utility cooperative game can further be divided into partition function game and characteristic function game. The former refers to the fact that when all the players in the game form a number of alliances, the income of each alliance depends on their own actions, and also depends on the actions of other alliances. This is also the most common situation in a transferable utility cooperative game. The latter is a relatively special kind of cooperative game. In this game, the benefits of the alliance depend only on the actions of the alliance itself, and have nothing to do with the actions of other alliances. Therefore, in this type of cooperative game, each alliance can be identified by the benefits determined by its own best actions. At this point, the feature function is the benefit of the alliance.

In addition, from the perspective of game structure, the cooperative game can also be divided into two-person cooperative game and multi-player cooperative game. The former is also called the two-person bargaining problem.

3) SOLUTION METHODS

There are three basic problems in the field of cooperative game theory, and they are cooperative game solutions, structural stability of cooperative game solutions, and formation mechanisms of cooperative game solutions [69]. As stated previously, the cooperative game can be divided into a two-person cooperative game and multi-player cooperative game. For the former, it is generally solved via the Nash bargaining equilibrium method [27], [30], [70], [71]. For the latter, it is also known as the coalitional game, and its solutions mainly include the core-based dominant solution [72], and the Shapley value-based valuation method [68], [73], [74].

B. A SURVEY

Cooperative game theory belongs to classical game theory, which has been widely used in power DR among electricity supplier side, electricity seller side and electricity user side. In this section, we conduct a detailed review on application of cooperative game theory in above electricity sides.

1) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SELLER SIDE IN EM

As elaborated previously, the users on electricity user side can be divided into small and medium users, large users, and users with distributed energy resources.

First, for the users with distributed energy resources, called distributed energy users, who are playing an important role in power DR of EM, especially in electricity trading between electricity sellers and electricity users. Here, the electricity seller side includes power grid companies and power sales companies. The distributed energy users are able to use the distributed energy equipment such as energy storage, distributed generation and EVs as a medium to conduct bidirectional transactions with the electricity seller side. During this electricity trading, with the goal of achieving high returns, distributed energy users need to consider many factors such as grid load level, electricity price released in the market and load matching when they are scheduling their distributed energy outputs. Here, the factors such as load level and market electricity price are closely related to the market behavior of other stakeholders. Therefore, in the process of this trading, the application of cooperative games can provide some new ways for distributed energy users to develop strategies. For example, the distributed energy users can use their EVs as a medium for trading between users and the power grid. Here, EVs have the capabilities of storing electrical energy during off-peak hours and supplying the stored energy to the power grid during peak hours. Hence, during this process, we can use some cooperative game mechanisms to investigate the charging and discharging strategies of EVs. To this end, Kim et al. [54] consider a power system with an aggregator on the electricity seller side and multiple customers with EVs on the electricity user side and proposes a cooperative and a non-cooperative approach for the customers to determine how much energy to purchase or to sell to the aggregator while taking into consideration of the load demands of their residential appliances and the associated electricity bill. Specifically, in the proposed cooperative game model, an optimal distributed load scheduling algorithm considering the uncertainty in the load demands is developed to maximize the social welfare of the power system. Moreover, in this model, a worst-case-uncertainty approach is used and some distributed load scheduling algorithms are developed to investigate the impact of the uncertainty. The simulation results show that the energy stored in the EV under the two game modes can both meet the user's energy demand during the peak load period, and can reduce the power supply pressure of the grid and increase the social welfare of the power system.

In addition, aiming at the electricity trading between small and medium users on the electricity user side and the electricity seller side such as power grid companies, power sales companies, and retail market, cooperative game theory has been preliminarily used by scholars. For example, Prete and Hobbs [75] introduce a microgrid that can provide energy, ancillary services, heat and enhanced reliability to its customers to a regulated electricity network and uses the framework of cooperative game theory to assess the interactions among market participants. In this cooperative game framework, based on an assumption of exchangeable utility and full public information, they quantify how microgrid development affects prices, costs and benefits for parties in the network under alternative sets of assumptions. The case study shows that the proposed cooperative game framework is useful to regulators and policy makers for identifying the beneficiaries of microgrid promotion policies, and for correcting the market failures in utility pricing that can distort incentives for microgrid investment. Wang et al. [76] propose a Shapley value determined incentives apportioning method for end-users when wholesale pricing rises. In the proposed model, the Shapley value in cooperative game theory achieves maximal profits equilibrium for each participant in grand coalition game. A case study is conducted to examine the effects of Shapley value-based DR with two IEEE benchmark distribution networks, and the proposed Shapley value-DR program can help retailers assure profitability, and enhance customers' initiatives.

In addition, Peng and Tao [19] thoroughly investigate the electricity retailers in China's spot EM by applying the cooperative game theory and Shapley value to allocate benefit in a deregulated market. Specifically, researchers in [19] introduce a cooperative game under different coalitions to improve electricity retailers' competitiveness, and use the Shapley value, which is one of the well-known solutions to a cooperative game, to distribute profits among multiple participants in an EM and calculate benefit allocation in different provinces of China. Researchers also find that various coalitions may be formed in a cooperative game and cooperation with other participants is an effective measure to improve the competitiveness of retailers in a restructured EM. Srinivasan et al. [77] develop an evolutionary algorithm to generate cooperative strategies for the individual buyers in a competitive power market. Specifically, the buyers cooperate with each other to lower their costs by using an evolutionary algorithm that evolves the group sizes and memberships. The methods developed in [77] also suitable for bigger networks and a larger number of sellers and buyers, and can encourage power buyers to cooperate and mitigate the market power of wholesale sellers. Wang et al. [78] propose a microgrid operation strategy that implements TOU when the demand-side user appropriately transfers the load, which is used to maximize the microgrid revenue and optimize reliability. Specifically, based on the cooperative game theory, researchers use the cooperative game method to jointly optimize the configuration of the three parties, including users who transfer loads, users with load response under TOU tariffs, and energy storage systems, and then adopt an iterative algorithm to find a three-party joint optimization Nash equilibrium point (i.e., the optimal configuration scheme). Based on this, the system joint optimization operation strategies are finally proposed and verified via an actual photovoltaic microgrid system.

Moreover, Zhang *et al.* [79] develop a power purchasing strategy model for electricity sellers in the EM mode based on cooperative game theory. In this model, researchers discuss the changes in the interests of various electricity retailers under the case of alliance formation, and construct a sale equilibrium model of cooperation profit among electricity supplier alliance by using Shapley value method. In addition, researchers perform additional investigations on profit allocation among different electricity suppliers.

Overall, for the small and medium users such as commercial and residential users on the electricity user side, although whose individual energy demand of residential users is not large, there is still a large DR potential due to the large number of users. Currently, in an open EM, the electricity sellers mainly focus on adjusting the electricity price structure to attract small and medium energy users to actively participate in the power DR. Specifically, more effective electricity price mechanisms include TOU mechanism and RTP mechanism. At present, game theory has relatively mature research achievements in these two aspects. However, the existing research is mainly aimed at residential users, and there are fewer applications for commercial users. For example, aiming at investigations on RTP game, the game forms are mainly cooperative game [80]-[82] and non-cooperative game [60]–[62]. Among these, the cooperative game is mainly used to optimize the user' collective electricity cost. For instance, Mohsenian-Rad et al. [80] assume that the power generation cost of the traditional generator sets is a quadratic function form of power generation capacity. Based on this, they establish a one-day total power cost optimization model for all users. Further, they allocate the power consumption cost of each user according to the calculation result that is obtained by multiplying the proportion of daily electricity consumption of each user in total electricity consumption by the cost of all users, and then establish an optimization model of the user game. However, since the proportion of daily electricity consumption of each user in [80] is a constant, each user still takes the minimum collective cost as the goal in the cooperative game, that is, the established game belongs to the category of typical cooperative game. In addition, Baharlouei et al. [81] set a similar game mechanism as developed in [80]. The difference between them is that the user fee in [81] is settled according to each time period; in contrast, it is settled according to the total daily fee in [80]. Researchers in [81] find that the user fee after the load is reduced during the peak period is lower than the cost after the same load is reduced during the flat period based on a comparative case study, and the user in [80] has the same fee in these two cases.

2) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

In aspect of power DR between electricity user side and electricity supplier side in EM, where the electricity user side mainly refers to large power consumers with high energy consumption, such as large industrial users, who can directly conduct transactions with the electricity supplier side, such as the power generation companies, called direct power purchasing model. During this process, cooperative game theory can also play a certain role in the power transactions between a single industrial user and a single power generation company or multiple power generation companies, or between multiple industrial users and multiple power generation companies.

For example, Taheri et al. [83] investigate the power generation companies' bidding strategies in a pool-based EM simultaneously using cooperative game and non-cooperative game theory. Specifically, in the non-cooperative case, a Nash equilibrium can be achieved as an optimal bidding strategy for each competitive generation company. In addition, based on cooperative game theory, researchers propose that the generation companies can make alliances with each other in order to propose their coordinated bids, called coalition condition. They argue that the coalition's optimal bidding strategy can be calculated via cooperative game theory, and the obtained profit from such coalition can be allocated among its members based upon Shapely value. The numerical results show that the cooperative game theory-based alliance proposed in [83] is efficient and has impressive impact on generation companies' profits. Researchers in [84] use the cooperative game model for energy supply system planning in the market environment. In the proposed model, they also consider the possibilities of forming coalitions between companies. A case study shows that the proposed cooperative coalition model is rational and efficient in energy supply system planning in the market environment.

In addition, Wang et al. [85] consider the wind power supplier on the electricity supplier side and the EV aggregator on the electricity user side as stakeholders participating in day-ahead EM trading. In this study, researchers thoroughly investigate the impacts of a virtual power plant (VPP) formed by wind power producer (WPP) and EV aggregator on EM equilibrium outcomes. Specifically, they apply the Shapley value conception in cooperative game theory to allocate the VPP profits between WPP and EV aggregator, which is verified reasonableness and effectiveness via numerical examples. Moreover, they argue that when WPP and EV aggregator bid in a VPP mode, the bid error will be lowered and both profits of WPP and EV aggregator will increase. This means that the WPP and EV aggregator have incentives to voluntarily form a VPP to participate in the EM. The schematic diagram of VPP participating in the day-ahead EM proposed in [85] is demonstrated in Figure 8.

3) POWER DR BETWEEN ELECTRICITY SELLER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

Actually, with the rapid develop of renewables in the smart grid, more and more new energy producers participate in EM trading with power grid companies, or power consumers, or even emerging power sales companies. Among these, the cooperative game theory is very suitable for the power DR between the new energy suppliers such as wind farms and photovoltaic farms and the electricity sellers such



FIGURE 8. Illustration of the VPP participating in the day-ahead EM proposed in [65], where the joint operation of wind power with EVs is helpful to alleviate the negative effects of wind power integration on power systems. x_i here means the power generation output of the *i*th power generation company.

as power grid company, power sales company and EV aggregator. This is because the natural complementarity of wind power and photovoltaic resources can make the cooperation of the two have the potential to benefit. Therefore, the cooperative game as an analytical tool can provide a new way to reasonably determine the cooperation mode and income allocation for the two.

To this end, aiming at the fact that the phenomenon of wind curtailment is getting worse in China due to the serious shortage of power peaking capacity of regional power grid, Li et al. [86] introduce an idea of cooperative game of wind and thermal power and consider a principle that maximizes benefits of wind power and thermal power enterprises, and finally compare the benefits of power generation companies gained in the situations of wind and thermal power participating in market transactions with that in the situations of companies independently participating in market transactions. The comparative results show that the joint operations of wind and thermal power companies are better than single operation. In this study, the cooperative game theory is used to build a symbiotic model of wind farm and thermal power plant, which can provide the most optimal solution to the allocation of increased interests, and provide a theoretical basis for promoting cooperation and joint market transaction of wind power and thermal power.

In addition, researchers in [87] investigate the energy trading among flexible DR aggregators and a distribution company with self-owned generators. Specifically, they model the economic interaction between distribution company and DR aggregator as a bargaining-based cooperative game, where the distribution company and DR aggregators collaboratively decide the amounts of energy trade and the associated payments. The results show that such a bargaining-based cooperative interaction is beneficial to both distribution company and DR aggregators. Based on the Nash bargaining theory in cooperative game theory, the increased benefits from cooperation between the distribution company and DR aggregators can be fairly allocated among these participants. Overall, compared with a non-cooperative game, the bargaining-based cooperative game proposed in [87] can further improve the benefits of the distribution company and DR aggregators, and simultaneously the bargaining outcome can maximize the social welfare of the system. Aiming at such bargaining problem, the researchers in [87] propose a decentralized solution with minimum information exchange, which is verified to be effective in this proposed bargaining-based cooperative game framework. In addition, researchers in [88] also design a cooperative game mechanism based on the side payment for the thermal power plant to participate in wind power heating in EMs, which is proven to be effective in promoting the participants' enthusiasm to the transaction.

4) A BRIEF SUMMARY

Overall, for the power DR in an open EM, cooperative game theory is mainly applied in two aspects. One is how to achieve cooperation for multiple stakeholders on electricity supplier, seller and user sides. The other is how each participant allocates additional benefits from interactions. Therefore, compared with non-cooperative games reviewed in the previous section, the overall benefit of a cooperative alliance in a cooperative game is generally greater than the sum of the benefits of individuals when they conduct a non-cooperative game, that is, the so-called cooperative surplus. At this point, participants form an alliance to cooperate with each other to obtain additional overall benefits, and to stabilize the alliance through a reasonable allocation mechanism, thereby changing the inefficient equilibrium achieved in a non-cooperative game.

That is also an important reason why the cooperative game can continue in stakeholders. However, considering the selfinterested characteristics of individuals participating in the game, once the inequality phenomenon appears, it is very likely to lead to the collapse of the alliance when the interests of the alliance are redistributed. Therefore, the design of the benefit distribution mechanism in the actual scenario is a difficult issue. To this end, axiomatic approaches are the most basic research measure in a cooperative game, which require that the formulation of the allocation strategies in a cooperative game adopts an axiomatic design mechanism. On the whole, related representative research achievements include Nash bargaining game theory [27], [30] and Shapley value [68].

V. EVOLUTIONARY GAME-THEORETIC APPROACH AND ITS APPLICATIONS IN EM

As discussed previously, game theory can be divided into three categories, i.e., non-cooperative game, cooperative game and evolutionary game. Among these, evolutionary game theory (EGT) was originally proposed by Maynard Smith and Price [31] during the study of biological evolution in 1973. Unlike traditional game theory, EGT adopts natural selection mechanisms, and it does not require strict rational assumptions (i.e., bounded rationality). Thus, its application scenarios are closer to the reality. However, how to choose the selection and mutation mechanisms in an evolutionary game and make them closer to actual issues is very challenging [9]. Currently, EGT is mainly used in EM's quotation strategy research and long-term equilibrium analysis, and most of these investigations are aimed at two-group or two-party evolutionary game problems. For example, researchers in [21] simulate and analyze the behavior of generation companies in the EM based on the EGT, in [89] use the competitive co-evolutionary game to model the equilibrium calculation in EM as a two-stage stochastic game problem, and in [90] conduct an evolutionary game analysis of the EM bidding strategy on the power generation side, and argue that the adoption of EGT to analyze the EM formed in the early stage is of great value for market policy research. On the whole, EGT has been gradually adopted by scholars to investigate the issues in an EM in recent years. To this end, this section first briefly introduces the basic idea of EGT, and then thoroughly reviews its application in a perfect open EM in terms of power DR among the electricity supplier side, electricity seller side and electricity user side.

A. EVOLUTIONARY GAME THEORY

1) INTRODUCTION

Generally speaking, classical game theory has the following three defects: i) the complete rational hypothesis is too far from the reality, ii) there are flaws in the way to handle incomplete information, and the assumptions set do not match the reality, and iii) it requires each participant to know exactly how other participants will choose. However, where does this knowledge come from? To obstacle these issues, EGT is proposed by researchers. As mentioned above, EGT was firstly proposed by Maynard Smith and Price [31]. Compared with classic game theory, the EGT takes the population as the research object, and believes that the game individual is bounded rational, and the strategy of the individual game may change due to the variation. Thus, EGT is more in line with the realistic game situation because it adopts the mechanism of natural selection and does not require strict rational assumptions. There are some most important concepts involved in EGT and they are: multi-group evolutionary stability strategy (MESS), replicator dynamics (RD), and asymptotically stable equilibrium point (ASEP). According to [19], they are defined as follows.

MESS: We assume that the number of individuals in a population is *n*, and then we call the strategy combination $X = \{X_1, X_2, \dots, X_n\} \in \Omega$ is an evolutionary stable strategy combination, i.e., an MESS, where Ω is the strategy space. At this point, for any mutation strategy denoted by $Y = \{Y_1, Y_2, \dots, Y_m\} \in \Omega$, there will be an ω meeting $0 < \omega < 1$ when $Y \neq X$; and moreover, for any ϖ meeting $0 < \varpi < \omega$ and any strategy combination *S* meeting $S = \varpi Y + (1 - \varpi)X$

 $(\forall S \neq X, \forall S \neq Y)$, there will be an *i* meeting i = 1, 2, ..., *n*, thus making the expected revenue meet the following inequality when the *i*th population adopts the strategy X_i and Y_i respectively, while other populations adopt the strategy combination $S_{-i}(S_{-i} \in S, \forall S_{-i} \neq X)$.

$$E(X_i, S_{-i}) > E(Y_i, S_{-i}), \quad i = 1, 2, \cdots, n,$$
 (4)

where, if the strategy X is an MESS, then it is definitely a Nash equilibrium strategy according to the mathematical definition of Nash equilibrium elaborated in previous sections. Moreover, its evolutionary stable equilibrium must be a Nash equilibrium. From this, we can find that evolutionary stable equilibrium is a refined Nash equilibrium. In contrast, a weak Nash equilibrium strategy is not necessarily an MESS. Thus, MESS is an equilibrium concept that can describe the general characteristics of evolutionary games and is much more complex than Nash equilibrium.

RD: This concept is used to simulate the dynamic adjustment process of the strategy to characterize the response speed of the population to adjust its scale through imitation and learning. It reveals the evolution law of the population number or proportion, which can be expressed by a dynamic differential equation of the probability or frequency x_i of a particular pure strategy X_i , adopted in a population, that is, we can use a replicator dynamics system (RDS) equation to describe the evolution law. At this point, its value is proportional to the ratio x_i of groups who select this pure strategy X_i , and is proportional to the difference between the its expected revenue $E(X_i)$ and the group mean revenue $E_{av}(X_i)$, namely

$$\frac{\mathrm{d}x_i}{\mathrm{d}t} = x_i \cdot [E(X_i) - E_{\mathrm{av}}(X_i)],\tag{5}$$

ASEP: We assume that ϑ , $\vartheta^* \in \Omega$ are both hybrid strategies of an evolutionary game, and ϑ^* is an MESS. Thus, if this MESS meets the following two conditions: a) equilibrium condition (that is, for any $\vartheta \in \Omega$, there will be $E(\vartheta, \vartheta^*) \leq E(\vartheta^*, \vartheta^*)$), and b) stability condition (that is, if $E(\vartheta, \vartheta^*) = E(\vartheta^*, \vartheta^*)$, then for any $\vartheta \neq \vartheta^*$, there will be $E(\vartheta, \vartheta) < E(\vartheta^*, \vartheta)$), then the group state $p^* = \vartheta^*$ is an ASEP of the RDS model presented in (5). From condition b), it can be further concluded that the weak Nash equilibrium is not necessarily an MESS.

Overall, there are four most important components in EGT, including a game framework, fitness function, RD model, and evolutionary stable equilibrium (ESE) or evolutionary stable strategy, which are described as shown in Figure 9.

2) EVOLUTIONARY GAME EQUILIBRIUM

The equilibrium form of an evolutionary game is called ESE or evolutionary equilibrium, as elaborated previously, which is a refined Nash equilibrium. Based on (4) and (5), and according to [9] and [43], we give the definition of evolutionary stable strategy and ESE as follows.

Evolutionary stable strategy: In a game denoted by G, we call a behavioral strategy $s \in S$ an evolutionary stable



FIGURE 9. Illustration of the four most important components involved in an evolutionary game issue.

strategy when it meets

$$\begin{cases} 1): f(s', s) \le f(s, s), & \forall s' \in S \\ 2): f(s', s') < f(s, s'), & \forall s' \ne S, \text{ if } f(s', s) = f(s, s), \end{cases}$$
(6)

ESE: We assume that $\sigma, \sigma^* \in \Sigma$ are hybrid strategy of a game, and then we call σ^* an ESE when it meets

$$\begin{cases} 1): f(\sigma, \sigma^*) \le f(\sigma^*, \sigma^*), & \forall \sigma \in \Sigma \\ 2): f(\sigma, \sigma) < f(\sigma^*, \sigma), & \forall \sigma \ne \sigma^*, \\ & \text{if } f(\sigma, \sigma^*) = f(\sigma^*, \sigma^*), \end{cases}$$
(7)

In addition, according to (7), if we assume that σ^* is an ESE of an evolutionary game *G*, then the group state $p^* = \sigma^*$ shift the asymptotically stable equilibrium point of the RD model presented in (5) [9], [43].

3) SOLUTION METHODS

Overall, according to the introduction of EGT above, the difference between EGT and classic game theory (such as cooperative game and non-cooperative game) is obvious, and according to [43], this difference is demonstrated in Table 1.

Therefore, we often use some evolution mechanisms to solve a specific evolutionary game issue, such as the aforementioned RD mechanism [9], [43], [91]. Specifically, there are some commonly used rules to update the individual behavioral action strategies in an evolutionary game, including pairwise comparison process [91], Fermi process [92], [93], Moran process [94] and Wright-Fisher process [95]. Now we take the Fermi process as an example, under this rule, the PDR will be able to imitate or directly copy the behavioral action strategy taken by the neighboring PDR, i.e., among the group PDRs, the individual *i* imitates the strategy of individual *j* with probability *p* as

$$p(P_i \leftarrow P_j) = \frac{1}{1 + \exp\left[-(U_j - U_i)/\kappa\right]},\tag{8}$$

TABLE 1. The difference between EGT and classic game theory.

Game issue	Classic game theory	EGT		
Rationality assumption	Perfect rationality	Bounded rationality		
Research objective	The individual	The group formed by individuals		
Dynamics concept	This concept does not involve the adjustment process to achieve equilibrium and the impact of external factors on equilibrium.	This concept focuses on the adjustment process of group behavior to achieve equilibrium.		
Equilibrium concept	Any participant who will not be able to increase its revenue via unilaterally deviating from the equilibrium strategy.	The group can eliminate small mutations (i.e., mutation strategy) when the ESE is reached in the entire group.		
Methods to refine equilibrium	The refinement thought comes from the backward induction method, which is premised on sequential rationality.	The refinement thought comes from forward induction method, that is, the genetic method or learning method.		
Process of reaching equilibrium	The system is often in an equilibrium state, and no time is needed for the system from non- equilibrium to equilibrium.	The equilibrium of the group is temporary or even impossible, and the system needs a long-term evolution process to achieve equilibrium.		

where P_i and P_j are the probability of selecting a strategy for individual *i* and *j*, respectively. U_i and U_j are the cumulative earnings of the current round for individual *i* and *j*, respectively. κ is the noise parameter, and when $\kappa > 0$, representing the possibility of irrational behavior caused by a decision error or external influence, at this point it is generally very small; when $\kappa \to \infty$, representing all the information is drowned out by the noise, at the moment the strategies are updated in a completely random way; when $\kappa \to 0$, representing a definite rule of imitation, that is, when the cumulative income of individual *j* is higher than individual *i*, the latter will adopts the strategy of the former.

B. A SURVEY

As elaborated previously, in a perfect open and ever-growing EM, participants will become more diverse, the competition will become more intense, and the economic behavior of power trading will also become very complicated. To study the complex economic behavior of different stakeholders, game theory is undoubtedly an effective mathematical tool. The market competition involving multi-stakeholders in EM will be a complex process of dynamic evolution will be a complex process of dynamic evolution, and accompanied by more complex market economic behavior characteristics. Therefore, it is necessary to combine the theoretical analysis of multi-group game behavior with its complex dynamic evolution process, and EGT is an important and powerful tool to study the long-term game behavior characteristics of multigroup. Overall, the EGT abandons the assumption that the players must be completely rational, so that their application scenarios are closer to the reality. Actually, at present, EGT is mainly used for EM's quotation strategy research [90] and long-term equilibrium analysis [9], [17], and most evolutionary game scenarios are aimed at the two-group bilateral evolutionary game issues. To this end, next, we will conduct a detailed review on the application of EGT in a perfect open and ever-growing EM in terms of power DR among the electricity supplier side, electricity seller side and electricity user side.

1) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SELLER SIDE IN EM

As discussed previously, the power DR between electricity user side and electricity seller side mainly focuses on electricity pricing and electricity capacity transactions among residential and commercial users, power sales companies, NPSEs, load aggregators, and power grid companies. For example, aiming at electricity pricing games in terms of TOU pricing, the electricity sellers announce the electricity prices for each time period, and then the electricity users will make responses to them based on their own electricity purchasing strategies. This is similar to the direct power purchasing transaction between large consumers and power generation entities. In terms of TOU price-based games, EGT has been preliminarily adopted by scholars considering bounded rationality and incomplete information. To this end, researchers in [96] and [97] model the interactive relationship between power grid companies (i.e., the utility companies) and residential users as a two-level game model considering the DR management (DRM) with multiple utility companies. Specifically, the competition among utility companies is formulated as a non-cooperative game, while the interaction among the residential users is formulated as an evolutionary game. In this evolutionary game, the household users living in the same community are considered to be a group, and each residential user in the group adjusts its own electricity demand according to the electricity price announced by the entity companies. The evolutionary game model developed in [96] and [97] can be used to analyze the evolution process of residential user's behavior strategies. For these residential users involved in this evolutionary game, their main goal is to purchase electricity at low electricity prices to achieve more user utilities, while the entity companies expect to sell electricity to the users at higher electricity prices to achieve more utilities. Ultimately, researchers in [96] and [97] develop a distributed algorithm to make these two parties to converge to their respective equilibrium points, and design appropriate strategies to maintain the balance between supply and demand for power companies and residential users. Further, Sun et al. [98] investigate the power consumers' choices of electricity retailers in an electricity selling market, where the EGT is used to analyze user selection process, and a dynamic evolutionary model of different types of users choosing retailers is established based on logic revision protocol. Numerical simulation shows that this evolutionary game model can effectively analyze the influence of various factors on user selection. Overall, researchers in above investigations [96]–[98] all use evolutionary games to study the decision-making behavior of incomplete rational user groups purchasing electricity from different power-selling utility companies under the influence of other users, and establish an evolutionary game model to describe the behavior of users' choices of electricity selling companies. In these studies, they find that the electricity prices and electricity sales capacity given by the electricity seller side will directly affect the evolution trend of the user group's electricity purchase, and these trends can provide some reference for the electricity seller side to formulate the electricity price strategies. Use Zhang [99] uses the dynamic evolutionary game to analyze the innovation value-added services of electricity sales enterprise under the new power system reform. The results show that the innovative value-added services motivation of two types of electricity sales providers are mainly driven by their market share, the degree of difference between the innovative value-added service level and the market demand, and the elasticity coefficient that innovation value-added service costs affecting service gap. In addition, researchers of [100] use EGT to investigate the RTP issues in smart grid with multiple power retailers combining with the Stackelberg game. Wang et al. [101] evaluate the impact of the social network on the diffusion of RTP using evolutionary game theoretical analysis, and conclude that the higher degree of the consumers social network, the slower the diffusion of RTP.

Moreover, researchers in [17] discuss how to apply the equilibrium stability of multi-group asymmetric evolutionary game in some typical scenarios of an ever-growing and open EM in the context of Energy Internet. In this study, an asymmetric evolutionary game containing three different parties (i.e., power grid enterprises, NPSEs and electricity consumers) participating in electricity trading of demandside EM is developed, which shows that through the government's policy interventions, the final evolution of the threeparty evolutionary game system can be rationalized to meet the economic laws of EM development.

2) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

In terms of power DR, EGT has also been gradually adopted by researchers to model the competitive relationship between the electricity user side (e.g., the large consumers) and electricity supplier side (e.g., the power generation companies). For example, the bidding strategies formulation of power generation company and direct power purchasing transaction. To this end, Wang *et al.* [20] use an evolutionary imperfect information game approach to analyze bidding strategies in EMs with price-elastic demand. In this study, the evolutionary game approach is used to model the generation companies' dynamic and adaptive behavior to meet an elastic demand, thus the proposed adaptive and learning agents can dynamically update their beliefs about opponent generation companies' bidding strategies during the simulation. In addition, researchers in [21] and [90] simulate the bidding behavior of power generation companies based on EGT. Among these, researchers in [90] conduct an evolutionary game analysis of the EM bidding strategy on the power generation side, and believe that using the evolutionary game method to analyze the power generation-side EM formed in the initial stage is very valuable for policy research. Moreover, researchers of [17] use EGT to investigate the evolutionary stability of two types of power generation company groups (e.g., small-sized and large-sized power generation company groups) in bidding strategy formulation in a bilateral EM. In this study, the authors provide the dynamic adjustment process of pricing strategy for the two types of generation enterprise groups, as demonstrated in Figure 10.



FIGURE 10. The dynamic adjustment process of pricing strategy for the two types of generation enterprise groups proposed in [17]. In this figure, the subgraphs (a)~(d) show different evolutionary game situations, where (p_s , q_s) is a saddle point, the blue and purple solid arrows refer to the dynamic adjust the directions of the strategy within the convergence domain (i.e., the evolutionary convergence direction), the green imaginary arrow represents the dynamic adjustment direction of the convergence domain, the blue point, red point and green point represent the unstable equilibrium node point, asymptotically stable equilibrium point, and saddle point, respectively. and two convergence domains are formed by i) and ii), iii) and iv), respectively.

In terms of direct power purchasing between large consumers and power generation companies, researchers also adopt evolutionary game approaches to analyze the power purchasing behavior of large consumers. For example, Shi [102] uses the equilibrium analysis method of EGT to investigate the purchase and sale price issues and power balance between large consumers and generators. In this study, the DR equation of group strategy is established to analyze the evolution state of equilibrium solution using numerical analysis methods. Huang and Wang [103] simulate and analyze the power generation companies' bidding strategies based on EGT. In this study, the results demonstrate that the multi-population RD model can well describe the dynamic process of generation companies' bidding. Researchers in [103] also suggest that reasonable price competition rules must be constituted to ensure and promote the healthy development of the generation side power market. In addition, researchers in [104]-[109] also use EGT to simulate and analyze the strategic bidding behavior of power producers in competitive EMs or renewable portfolio standard. Moreover, researchers use EGT to model the electricity selling competition among multiple power producers [110], to model the peak-shaving behavior of thermal power plants [111] and the behavior of renewable energy power plants under the incentive mechanism [112], to model the supply-demand interaction (e.g., supplier-consumer interaction in an EM) of power systems [113]–[115], and to investigate the generation expansion planning under the background of EM [116].

Overall, aiming at the power DR between the electricity supplier side and electricity user side, the EGT is mostly applied to analyze and simulate the bidding behavior of power generation companies (e.g., power producers) [117] on the electricity supplier side and the electricity purchasing behavior of consumers on the electricity user side. With high-penetrate renewables connecting to the smart grid, EGT will be able to play an important role in analyzing and simulating the behavior of new energy producers when participating in EM transactions in a competitive environment.

3) POWER DR BETWEEN ELECTRICITY SELLER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

As more and more renewable energy producers participating in EM trading, the power DR between the electricity supplier side (e.g., renewable energy generation companies) and electricity seller side (e.g., power grid companies) has been investigated by more and more scholars. Among these, many researchers attempt to use EGT to analyze and simulate the behavior of electricity suppliers during the EM trading. For example, researchers of [9] use RD model in EGT to analyze the equilibrium stability of multi-group asymmetric evolutionary games in a perfect open EM, where the NPSEs and power grid companies on the electricity seller side play games with the power generation companies on the electricity supplier side in terms of TOU electricity pricing and electricity selling. In addition, researchers in [118] use evolutionary game to analyze the interest coordination of gridconnected renewable energy power generation, and believe that the formulation process of such interest coordination is a dynamic and gradually evolutionary process. In [119], researchers use evolutionary game to analyze and simulate the tripartite behaviors and interest relationship among wind power enterprises, thermal power enterprises and power grid enterprises (who behave as players with bounded rationality), and results obtained can offer some reference for the formulation of EM structure and competition rules. Aiming at the bidding strategies of regional EMs, Zhang et al. [120] consider the actual situation of EM in southern region of China, and then use the multi-group competition method in EGT to establish a market equilibrium model of joint bidding between the power generation companies on the electricity supplier side and the power grid companies on the electricity seller side, and finally obtain the stable strategy point of the market from the perspective of profit distribution. Moreover, Liu and Yu [121] use an evolutionary game model to investigate the motivation strategy between generation and retail power companies under the incomplete contract. In this study, the evolutionary game model of the cooperation between the generator and the seller is constructed based on incomplete contract. Based on a discussion on the local equilibrium point and the dynamic evolution process of the game and the simulation results, researchers believe that the proposed incentive strategy of promoting cooperation between the two parties under the condition of incomplete contract will provide some reference for the cooperation of the power producers and the sellers under the situation of the reform of the new electric power and the reform of the state-owned enterprises.

4) A BRIEF SUMMARY

Compared with the classical game theory which assumes that individuals are very rational and their goals are all to pursue their own maximum benefits, and they also know that other players are completely rational, the EGT takes the population as the research object, abandons the assumption that the players must be completely rational, and believes that the players are bounded rational and their strategies may change due to mutations, so that the characteristics of EGT are more consistent with the actual networks, making the EGT in the EM has attracted more and more attentions. Overall, the application scenarios of EGT are closer to the reality. For the application of EGT in EM in terms of power DR, on one hand, EGT is very suitable to model the competition among the electricity users (especially residential users) while considering the private information of the power retailers and entity companies on the electricity seller side and the residential users on the electricity user side. By combining the EGT with classical game theory (such as non-cooperative game), the evolution trend of electricity user groups in electricity purchasing can be clearly depicted. These trends (i.e., the DR behaviors based on price between power retailers and residential users) are helpful to realize power supply and demand balance, so as to maintain the safe operation of the power systems. On the other hand, EGT is very suitable to model the purchase and sale prices issues and power balance between large consumers and power suppliers (e.g., power producers) in direct power purchasing transactions. Besides, certainly, EGT can also be used to analyze the interest coordination mechanism between the electricity supplier side (e.g., the renewable energy power generation companies) and the electricity seller side (e.g., the power grid enterprises). Based on EGT, the formation process of such interest balance is a dynamic and gradual evolution process. Overall, EGT is founded based on individuals with bounded rationality, in which the group behaviors are achieved through some dynamic interaction processes between individuals such as imitation, learning and communication, such that this theory can well describe the trends of group behavior and accurately predict the group behavior of an individual. Currently, EGT has been gradually adopted by more and more scholars in addressing actual power DR issues in the context of a perfect open and ever-growing EM. However, for these actual game issues, how to choose and establish the selection and mutation mechanisms in an evolutionary game to make them closer to an actual problem will be challenging and need to be addressed immediately in the future.

VI. STACKELBERG GAME-THEORETIC APPROACH

AND ITS APPLICATIONS IN EM

Stackelberg game (sometimes we also call it as leaderfollower game or master-slave game) is a very important branch in non-cooperative game theory. For this reason, we use a separate section to summarize the application of the Stackelberg game in power DR of EM. In fact, Stackelberg game theory has been widely used in the EM, such as retail market, wholesale market and auxiliary service market, and related scientific research achievements are also becoming more and more abundant. The research history of the Stackelberg game can be traced back to 1934. It was first proposed by the German economist Stackelberg [122], so the leaderfollower game or Stackelberg game is also called Stackelberg equilibrium. Currently, Stackelberg game occupies a very important position in economics, management science and social science. Actually, there are some master-slave relationships in the EM. For example, we usually assume that the power grid company is a leader in a Stackelberg game who first sets the price of electricity for each time period, and the NPSEs such as emerging electricity sellers and load aggregators as the followers of the game, who refer to the electricity price released by the power grid company, and provide their electricity price strategies considering their own conditions and the demands of electricity users. To this end, this section first briefly introduces the basic principle of Stackelberg game, and then provides a detailed survey on the application of Stackelberg game in power DR of EM.

A. STACKELBERG GAME THEORY

1) INTRODUCTION

Since Stackelberg game was proposed, it has evolved from the original single-leader-single-follower to the current multi-leader-multi-follower multi-objective game and leaderfollower differential game. In a Stackelberg game, the leader has a leadership advantage, occupying a favorable position in the game; and the follower follows the leader's decisions. In reality there are many such examples, such as the price competition between large companies and small companies, the game between central government and local government, and the relationship between central bank and commercial banks, and so on. For a Stackelberg game with only one leader and multiple followers, which is short for N-Stackelberg game, the leader first makes the decision that is most beneficial to him. After observing the leader's decision, the multiple followers make the decision to maximize their own benefits without knowing each other. For this case, the mathematical expression is as follows [33], [123], [124]:

$$\begin{cases} \left(\bar{\boldsymbol{x}}_{g}^{*}, \bar{\boldsymbol{x}}^{*}\right) = \arg \max_{\boldsymbol{x}_{g} \in \boldsymbol{A}_{\text{leader}}} U_{\text{leader}}\left(\boldsymbol{x}_{g}, \bar{\boldsymbol{x}}^{*}\right), \\ \text{for the leader} \\ \bar{\boldsymbol{x}}_{m}^{*} = \arg \max_{\boldsymbol{x}_{m} \in \boldsymbol{A}_{m}} U_{m}\left(\bar{\boldsymbol{x}}_{g}^{*}, \boldsymbol{x}_{m}\right), \\ \text{for the follower } m, \end{cases}$$
(9)

subject to $\bar{\mathbf{x}}^* = \left(\bar{\mathbf{x}}_1^*, \cdots, \bar{\mathbf{x}}_m^*, \cdots, \bar{\mathbf{x}}_M^*\right)$ (10)

where *m* represents the *m*th follower in a Stackelberg game, and $m = 1, 2, \dots, M$; *M* is the total number of followers; \bar{x}_g^* is the current optimal strategy of the leader; \bar{x}^* is the joint optimal strategy of all followers; \bar{x}_m^* is the current optimal strategy of the *m*th follower; U_{leader} and U_m are the payoff functions of the leader and the *m*th follower, respectively; A_{leader} and A_m are the decision-searching space of the leader and the *m*th follower, respectively.

For example, researchers of [125] provide the architecture for a Stackelberg game, in which the upper-level decisionmakers of this pricing Stackelberg game are agents, and the lower-level decision-makers are EV owners, as demonstrated in Figure 11.



FIGURE 11. Illustration of an architecture for the pricing Stackelberg game proposed in [125].

2) CLASSIFICATION

According to the number of leaders and followers in a Stackelberg game, which can be divided into i) the game with one leader and one follower, ii) the game with one leader and multiple followers, and iii) the game with multiple leaders and multiple followers. Actually, Basar and Olsder [126] define the two-person Stackelberg game and multi-leader-multi-follower Stackelberg game, and prove the existence of their equilibria. Pang and Fukushima [127] introduce the concept of multi-leader-follower games. Based on this, Yu and Wang [128] give a general existence theorem for equilibrium points for multi-leader-follower games.

3) SOLUTION METHODS

There are many solutions to solve the Stackelberg game. In fact, the existence proof and solution of the Nash equilibrium for the Stackelberg game is very hard in actual issues. Generally speaking, when the issue of the Follower satisfies a certain constraint specification, its optimal solution can be expressed by the Karush-Kuhn-Tucker (KKT) optimality condition [43]. Therefore, the two-level optimization problem of Stackelberg game can be transformed into an optimization problem with KKT condition as the constraint. It should be noted that because the KKT condition contains complementary relaxation constraints, the transformed nonlinear programming is non-convex, and violates common constraint specifications. Actually, in actual engineering decision problems, researchers [43] often generalize the Nash game and the Stackelberg game into a kind of game issue, called Nash-Stackelberg-Nash type leader-follower game (i.e., N-S-N game). Such N-S-N games are generally used to solve the multi-agent decision problem in engineering practice. The characteristics of this game are that [43], the strategy of the upper-level participants is the parameter of the lowerlevel game problem, and the lower-level game problem is the constraint of the upper-level game problem; and in the case where the lower-level participant's optimal strategy is unique, the upper-level participants can predict the reaction of the lower-level participants to their own strategies. Researchers in [43] argue that the structure of N-S-N game is similar to the equilibrium problem with equilibrium constraint, and the researcher in [129] proposes two representative methods to solve the N-S-N game issue. One is stationary point method, also called ALLKKT method, in which we need to first replace the lower-level Nash game with the equivalent KKT system, and then list the KKT conditions of each leader's equivalent nonlinear programming, and then join them together to solve. The other is fixed point type iterative algorithm, in which we need to first replace the lowerlevel Nash game with the equivalent KKT system, and then alternately solve the equivalent nonlinear programming of each upper-level problem until it converges to the fixed point; thus, such algorithms can be divided into Jacobi type iteration and Gauss-Seidel type iteration.

In addition, researchers in [33] use the methods of group Q-learning and transfer learning to form a fast Stackelberg equilibrium learning (FSEL) based group intelligent decision-making approach. In this approach, the Q-learning expression is presented as follows:

$$\begin{cases} \boldsymbol{Q}_{mt}^{q,k+1}\left(s_{mt}^{qp,k}, a_{mt}^{qp,k}\right) = \boldsymbol{Q}_{mt}^{q,k}\left(s_{mt}^{qp,k}, a_{mt}^{qp,k}\right) + \alpha \cdot \Delta \boldsymbol{Q}_{mt}^{q,k} \\ \Delta \boldsymbol{Q}_{mt}^{q,k} = R_{mt}^{qp}\left(s_{mt}^{qp,k}, s_{mt}^{qp,k+1}, a_{mt}^{qp,k}\right) \\ + \gamma \cdot \max_{a_{mt}^{q} \in A_{mt}^{q}} \boldsymbol{Q}_{mt}^{q,k}\left(s_{mt}^{qp,k+1}, a_{mt}^{q}\right) - \boldsymbol{Q}_{mt}^{q,k}\left(s_{mt}^{qp,k}, a_{mt}^{qp,k}\right) \end{cases}$$
(11)

$$a_{mt}^{qp,k} = \begin{cases} \arg \max_{a_{mt}^{q} \in A_{mt}^{q}} \mathcal{Q}_{mt}^{qp,k}(s_{mt}^{qp,k}, a_{mt}^{q}), & \text{if } q_{0}' \leq \varepsilon \\ a_{rand}, & \text{otherwise} \end{cases}$$
(12)

where $m = 1, 2, \dots, M$; $t = 1, 2, \dots, M_m$, and M_m is the total number of followers who have interaction with follower m; $q = 1, 2, \dots, Q_L$, and Q_L is the total number of real code for transfer learning of follower m; $p = 1, 2, \dots, P_S$, and P_S is the total number of searching of follower m; Q_l^k is the knowledge matrix of the *l*th decision agent at the *k*th iteration, which represents the knowledge values of stateaction pairs; s_k is the state of the multi-agent system at the *k*th iteration; $\vec{a} = [a_1, \dots, a_l, \dots, a_L]$ is the joint action of all the decision agents; a_l is the action of the *l*th decision agent; *L* is the number of the agents; \vec{a}_{-l} is the joint action of all the decision agents except the *l*th decision agent; α is the knowledge learning factor; γ is the discount factor; $R_l(s_k, \vec{a})$ is the feedback reward after implementing a joint decision-making action \vec{a} under state s_k ; and the relevant symbols have been defined in (9) and (10). It should be added that the superscripts q, p and k represent the qth real code for transfer learning, the pth searching, and the kth iteration, respectively; R_{mt}^{qp} is an immediate feedback reward, which can generally be transformed from the optimal objective; Q_{mt}^q and ΔQ_{mt}^q are the knowledge matrix and its increment, respectively; q'_0 is a random value in the unified probability distribution; ε is a parameter of local greedy searching; a_{rand} represents the global random searching action.

B. A SURVEY

Actually, Stackelberg games, as a very important part of non-cooperative game theory, have been widely used in the smart grid field, including real-time supply-demand interaction [123], parameters tuning of nonlinear robust power system stabilizer [130], retail energy market pricing issue [131], EV charging and discharging management [125], coordinated optimization of TOU price and dispatching model combining wind power and energy storage [132], and direct power purchasing in EM [133], and so on. This section mainly reviews the application of Stackelberg game in the EM from the perspective of power DR. we still conduct the survey from three aspects: power DR between electricity user side and electricity seller side, power DR between electricity user side and electricity supplier side, and power DR electricity seller side and electricity supplier side, which are presented as follows.

1) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SELLER SIDE IN EM

As stated previously, the user types on the electricity user side are becoming more and more diverse, which not only include traditional small and medium commercial and residential users, but also include large industrial users with high energy consumption, and even include distributed new energy users. These users have different market statuses in the process of EM trading. Therefore, Stackelberg game will play an important role in addressing multi-party games with different statuses.

First, for the traditional small and medium users on the electricity user side such as commercial and residential users, they have a large number in the smart grid with greater DR potential. As stated previously, researchers are mainly concerned with studying the adjustment of electricity price structures to attract small and medium users with low energy consumption to actively participate in the DR of the EM. Currently, TOU mechanism and RTP mechanism are two major effective electricity pricing mechanisms in EM trading, where the Stackelberg game theory has been preliminarily used in transactions between small and medium users and the electricity seller side containing NPSEs, traditional electricity sellers and the power grid companies. For example, based on TOU mechanism, the electricity sellers generally release the electricity price for each period, and the electricity

users formulate the power purchasing strategies according to these released electricity prices. Such TOU mechanism-based games can be constructed as Stackelberg game. To this end, aiming at the DRM in the smart grid applied to reduce power generation costs and user bills, Maharjan et al. [58] develop a model for transactions between the electricity utility companies (who play a non-cooperative game with each other and act as the leaders) on the electricity seller side and the end-users (who behave as the followers to accept the prices announced by the leader(s)) on the electricity user side to maximize the revenue of each utility company and the payoff of each user based on a Stackelberg game approach. In this model, researchers prove the existence of a unique Stackelberg equilibrium of the game, design a distributed algorithm which can converge to the Stackelberg equilibrium with only local information available for these two types of game players, and propose a novel conception of shared reserve power used to improve the grid reliability and ensure its dependability. As a result, analytical and numerical results have proved the validity of these concepts proposed in [58]. In addition, the model of communication between these two parties in the proposed Stackelberg game model is provided in [58], as illustrated in Figure 12.



FIGURE 12. Illustration of the model of communication between the entity companies and end-users, where the entity companies as the leaders in the Stackelberg game announce electricity prices to the end-users who are treated as the followers in the game.

Moreover, researchers in [100] and [134]-[137] all use the Stackelberg game theory to investigate the RTP scheme for the transactions between electricity sellers such as retailers and electricity users such as residential users. Among these, researchers in [136] use the Stackelberg game theory to achieve the power scheduling scheme between a service provider on the electricity seller side and the residential users with similar objectives on the electricity user side. Researchers in [138] and [139] design or propose Stackelberg game scheme or scenario for EMs, wherein the retailers aim to reduce the comfort losses of consumers and costs of purchasing electricity, or aim to maximize their profits. In addition, Yang et al. [140] consider the DR problem for a retailer and multiple residential consumers in smart grid with a one-leader N-follower Stackelberg game, which can effectively model the interactions among the retailer and consumers. Moreover, when the user side involves com-

mercial users such as building users, Stackelberg game can also be used to model the power DR interactions between such type of consumers and the electricity seller side. For example, researchers in [141] treat the microgrid operator consisting of combined heat and power (CHP) as the leader and the consumers as the followers to construct a one-leader N-follower Stackelberg game to investigate the thermal and electricity demand problems in a microgrid. In this study, an optimization profit model considering multiple objectives is formulated for the leader, and an optimization model is formulated for the building energy consumers (i.e., the followers) considering multiple objectives, too, such as the utility of electricity consumption. Based on an existence proof of the Stackelberg equilibrium, the Stackelberg game model proposed in [141] shows effective via the case study of a CHP-microgrid system containing six building energy consumers.

Second, the Stackelberg game theory has also been applied by researchers to the electricity trading between the distributed new energy users on the electricity user side and the electricity seller side. Specifically, the new energy users can use their distributed new energy generation to participate in electricity trading with the electricity sellers such as the retailers, NPSEs and power grid companies. Generally, the new energy users and electricity sellers are treated as the followers and leaders in a Stackelberg game, respectively. For example, based on the energy storage and distributed generation on the electricity user side, researchers in [50] investigate the DRM problem based on two games, i.e., a non-cooperative game between the residential energy consumers equipped with energy storage devices, and a Stackelberg game between the utility provider and the energy consumers. In this study, researchers propose a new cost function for the energy consumers who can sell back stored energy. In the non-cooperative game, the users schedule their energy production can achieve the minimum energy cost at a unique Nash equilibrium. In the Stackelberg game, the utility provider is treated as a leader who sets the prices with the goal of maximizing its revenue knowing that will respond by minimizing their energy cost. In addition, researchers in [142] propose to investigate the energy management in smart distribution systems based on a Stackelberg game scenario, where the utility companies and microgrids are treated as game leaders, and customers are game followers. The leaders formulate the electricity pricing strategies and the followers adjust their electricity procurement amounts based on the leaders' prices. In this two-stage Stackelberg game, a Nash equilibrium is obtained by a distributed energy management algorithm, and the computer simulations verify the relationships among utility functions, electricity prices, electricity demands, electricity procurement amounts, and pollutant parameters. Certainly, researchers in [143] and [144] also use the Stackelberg game to model the electricity trading between the electricity sellers and new energy users equipped with distributed energy storage, EVs, distributed generation, and so on.

2) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

As elaborated previously, the power DR between electricity user side and electricity supplier side mainly refers to the electricity transaction between large consumers (e.g., industrial users with high energy consumption) and power generation companies. To this end, Stackelberg game theory can be used to model the interactions between the two parties from the perspective of direct power purchasing. Specifically, the large consumers directly purchase electricity from the power generation companies with the goal of minimizing their energy cost, while the latter party formulates strategies to maximize their profit. Currently, such direct power purchasing models can be divided into one-leader N-follower trading and N-leader N-follower trading. In these two models, the leader is generally the power generation company and the followers are large consumers such as industrial users. For example, Xia et al. [64] investigate the bilateral electricity pricing in direct power purchase based on a Stackelberg game model, in which the Stackelberg issue is transformed into a bi-level optimization one. This Stackelberg equilibrium of this model is proved to be more suitable for development needs of the power plants, the leader, in the course of direct power purchase. Moreover, Kebriaei et al. [145] construct a Stackelberg game model for the bilateral contracts of energy, in which the consumer behaves as a leader, and the power generation companies act as the followers. Such Stackelberg game model is used to match the seller and buyer agents. Specifically, the followers announce their electricity purchase amounts and electricity prices to the leader, and then each leader provides the corresponding price. During this bilateral trading, the leaders and followers negotiate and match the price and amounts of electricity sold with the goal of maximizing their own profits.

In addition, researchers in [133] and [146] both propose a Stackelberg game to investigate the bilateral contract transaction for the generation companies and large consumers; and in this game model, the generation companies and large consumers are the leaders and followers, respectively. Concretely, the goal of the leader in [133] and [146] is to determine the optimal bidding price through an incooperative game and a Bayesian game with other power suppliers to maximize its bilateral trading profit, respectively; while the large consumers decide their personal purchase strategy to minimize their cost and based on the contract price provided by generation companies and the forecast of the spot price. In the two studies, researchers prove the existence of the Nash equilibrium for the game model and present its solution. Numerical simulations both show that each participant can benefit from the proposed game. Moreover, researchers in [146] present a decision relationship framework for the Stackelberg game among power generation companies and large consumers, as demonstrated in Figure 13. In this figure, as explained in [146], $a_i =$ $(a_{i,1}, a_{i,2}, \cdots, a_{i,J})$ denotes the bidding price set of the *i*th generation company for all large consumers, a_{-i} represents

other companies' bidding price except company i, $a_{-i,j} = (a_{1,j}, a_{2,j}, \dots, a_{i-1,j}, a_{i+1,j}, \dots, a_{i,J})$ represents other companies' bidding price for large consumer j except company i, $a_{i,-j} = (a_{i,1}, a_{i,2}, \dots, a_{i,j-1}, a_{i,j+1}, \dots, a_{i,J})$ represents the bidding price of company i for all large consumers except consumer j, $q_{i,j} = [q_{i,j}^1, q_{i,j}^2, \dots, q_{i,j}^H]^T$ represents contract quantity purchased by large consumer j from company i in H time slots, and $q_{S,j} = [q_{S,j}^1, q_{S,j}^2, \dots, q_{S,j}^H]^T$ represents the energy quantity purchased by large consumer j in spot market in H time slots.



FIGURE 13. Illustration of the decision relationship for the Stackelberg game proposed in [146], where the power generation companies behave as leaders and play with each other in a Bayesian game with the goal of obtaining the optimal bidding price, while the large consumers behave as followers in the Stackelberg game with an aim of minimizing their cost of electricity purchase based on the bidding price provided by the leaders and the predicted spot price.

Apart from above research work, researchers in [147] also establish a Stackelberg game between multiple providers and end users in the smart grid. In this model, the electricity provides behave as leaders with the goal of maximizing their profit and the end users act as the followers aiming at maximizing their individual welfare. Zhang et al. [148] develop a deep transfer Q-learning model with virtual leaderfollower for the supply-demand Stackelberg game of smart grid. In this model, each power generation company on the electricity supplier side behaves as a leader and each load on the electricity user side acts as a follower, thus forming a supplier-demander Stackelberg game. Moreover, a deep belief network is used in this model for knowledge transfer, which can help to rapidly obtain an optimal solution of a new task. A 94-agent system and a practical grid study verify the effectiveness of the Stackelberg game model. In addition, researchers in [149] also construct a Stackelberg game model to investigate multiple energies trading among a number of distributed energy stations (who behave as the leaders) and multiple energy users (who act as the followers) in integrated energy systems, based on a best response algorithm. Numerical studies demonstrate the convergence of this algorithm, corroborate the jointly effects of market scale and exogenous parameter on the unique Stackelberg equilibrium and verify the practicability of the proposed model.

3) POWER DR BETWEEN ELECTRICITY SELLER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

With the opening of the electricity sales side, the electricity sales business will gradually open to social capital. As the major representatives in the electricity sales side, the electricity sales companies will participant in games under the market-oriented market model and formulate their own power purchase and sales strategies to maximize the revenue [150]. In this paper, the emerging power sales companies and traditional electricity sellers, load aggregators, and the power grid companies are included in the electricity seller side. Among these, the power DR here mainly focuses on the electricity trading between electricity sellers and the power generation company. To this end, we find that the Stackelberg game theory is rarely applied to such type of electricity trading. Based on a detailed survey, we argue that Nash game and cooperative game have been preliminarily used in this aspect. From the perspective of Stackelberg game, researchers in [151] construct a new two-stage game framework for power demand/response management in smart grids, which aims to model and analyze efficiently issues in DRM and the issue of huge waste in power production due to separate solving of the power generation and consumption optimization problems. Specifically, in the first stage of the game framework, researchers establish a Stackelberg game framework for power generation companies on the electricity supplier side and utility companies on the electricity seller side, in order to solve the cost optimization problem for power generation. For this purpose, researchers in [151] obtain a unique Nash equilibrium in this proposed Stackelberg game, which means that the utility company obtains the optimized power outputs with the first-mover advantage. In the second stage, researchers propose an infinite repeated game framework. Finally, the numerical results demonstrate that this two-stage framework proposed in [151] can raise the profit for the utility company up to 8% while reduce the summation of the customers' costs up to 10%. In addition, Asimakopoulou et al. [152] establish a Stackelberg game model for the energy management of multiple microgrids. In this model, the central production unit in upper-level behaves as a leader either the goal of minimizing the production cost based on the decision variable of profit margin, and the energy services provider in lower-level representing several microgrids act as followers with an aim of maximizing the net profit based on decision variables of retail price and production mix for serving the load. In this study, the comparative results highlight the benefits of applying the proposed leader-follower structure in the simulated interaction.

4) A BRIEF SUMMARY

On the whole, Stackelberg games have been widely used in the EM as a type of special non-cooperative games for the hierarchical decision-making processes of multiple decision makers, especially in the design of energy management schemes. It is more common used in the some scenarios with

the goal of minimizing the electricity users' daily payments while maximizing the electricity suppliers' or electricity sellers' profits by optimizing electricity prices, such as the bilateral contract transactions between power producers and large users, the interactive transactions between suppliers and buyers (i.e., supply-demand interaction), the electricity price and electricity capacity transactions between electricity sellers (e.g., the retailers) or grid companies and small and medium users (e.g., the residential users), and the power generation transactions between power grid companies and new energy power generation companies. In fact, the Stackelberg game is a dynamic game behavior of successive decision-making due to the unequal position of the two sides in the EM. In this game process, one of the two sides is in a leader position, while the other is in the status of follower. Therefore, this type of non-cooperative game is more common in power transactions between the two sides with unequal status in the EM. For example, the direct power purchasing between power producers and large users such as the large industrial users with high energy consumption. However, in a Stackelberg game, the process of solving the Stackelberg equilibrium solution is usually cumbersome, due to that the leader needs to fully consider the follower's response model when formulating the strategy. Furthermore, it is often difficult to prove the existence of the Nash equilibrium of the Stackelberg game. Therefore, researchers have proposed some effective methods to solve and prove the Nash equilibrium of a Stackelberg game issue. For example, researchers have proposed the stationary point method and fixed point type iterative algorithm [129]. What these two methods have in common is that they all need to first replace the lower-level Nash game with the equivalent KKT system. In this case, the KKT condition contains complementary relaxation constraints, resulting in that the transformed nonlinear programming is non-convex, and it violates common constraint specifications. To this end, researchers in [33] propose an FSEL algorithm-based group intelligent decision-making approach using the methods of group Q-learning and transfer learning, which has been proved to be very effective via numerical simulations in [33].

VII. BAYESIAN GAME-THEORETIC APPROACH AND ITS APPLICATIONS IN EM

As stated previously, game theory can be divided into game with complete information and incomplete information (see Figure 2). Among these, Bayesian game is a typical game with incomplete information, which can be further divided into static Bayesian game with incomplete information and dynamic Bayesian game with incomplete information. Their equilibrium forms are Bayesian-Nash equilibrium and perfect Bayesian-Nash equilibrium (see Figure 2), respectively. For the two categories of Bayesian games, one of the main application aspects of the static Bayesian game with incomplete information is the auction, which is a common method of allocating goods with different valuations among auction participants [43]. In contrast, one of the main application aspects of the dynamic Bayesian game with incomplete information is signaling game [153], such as enterprise investment game and employment market signal game [43]. In terms of power DR in the EM, Bayesian game theory has been preliminarily applied by scholars in following aspects: DRM, real-time DR and energy trading in the smart grid or microgrid [52], [110], [154]-[157], bidding strategy formulation of generation companies [133], [146], [158]–[163], incentive mechanism in electricity auction market [153], [164], [165], contract negotiation [166], [167], electric power bidding under uncertain demand [168]. For this reason, we separately choose Bayesian game from the noncooperative game theory and conduct a survey on its application in the EM from the perspective of power DR among electricity supplier side (e.g., power generation companies), electricity seller side (e.g., power grid companies, power sales companies, load aggregator), and electricity user side (e.g., small and medium users, large users, distributed new energy users) in this section. First, we briefly introduce the Bayesian game theory, and then we conduct a detailed overview on its application in the EM in terms of power DR.

A. BAYESIAN GAME THEORY

1) INTRODUCTION

As explained previously, Bayesian game is a typical noncooperative game and also known as an incompleteinformation game. The Bayesian game model is a kind of incomplete information strategy game applied to model the situation in which a part of participants do not know exactly the characteristics of another part of participants. It has two basic elements of strategic game: player set and action set [163]. Researchers in [43] give the definition static incomplete-information Bayesian game and incomplete-information Bayesian game as follows. First, for a static incomplete-information Bayesian game problem, it is described as

$$\Gamma = \langle N, S, \Theta, p, u \rangle \tag{13}$$

where N is the player set, and $i \in N$ means player i. S is the strategy space, and S_i means the strategy set of player *i*. Generally speaking, we use type to define the player's private information in game theory, and the type of player i is denoted by $\theta_i \in \Theta_i$, where Θ_i is the set of all possible types of player *i*. Further, $\Theta = \prod_{i \in N} \Theta_i$ refers to a space composed of a combination of types of all participants, called a type space, and any type combination of these types in the type space is denoted as $\theta = (\theta_i, \theta_{-i})$, where θ_{-i} and Θ_{-i} represent a combination of the types of all players except player *i*, and a set of all such type combinations θ_{-i} , $\forall i$, respectively. p is the joint probability distribution, wherein it is assumed that the type of player *i*, $\{\theta_i\}_{i=1}^n$, comes from a joint probability distribution $p(\theta_1, \theta_2, \dots, \theta_n)$ on one type, with an aim of describing the participant's common information about the type. This joint probability distribution $p(\theta_1, \theta_2, \dots, \theta_n)$ is public knowledge for all players. u is an expected payoff function. In addition, the strategy of player i is a mapping

from Θ_i to S_i , i.e., $\phi_i : \Theta_i \to S_i$. This mapping means that player *i* formulates a strategy $s_i \in S_i$ for each possible type $\theta_i \in \Theta_i$. As researchers put forward in [43], in an incompleteinformation game, the strategies can be divided into two categories: the separating strategy and the pooling strategy. The former refers to that each type $\theta_i \in \Theta_i$ selects different action a_i from the action set A_i , and the latter means that all the types in Θ_i choose the same action. In addition, the payoff function, possible type and the joint probability distribution are all public knowledge for all players in a Bayesian game. Therefore, the Bayes rule, $p_i(\theta_{-i}|\theta_i)$, and the expected payoff of player *i* in type θ_i , $u_i(s_i, s_{-i}, \theta_i)$, are expressed respectively as

$$p_i(\theta_{-i}|\theta_i) = \frac{p_i(\theta_{-i}, \theta_i)}{\sum_{\theta_{-i} \in \Theta_{-i}} p_i(\theta_{-i}, \theta_i)}$$
(14)

$$u_i(s_i, s_{-i}, \theta_i) = \sum_{\theta_{-i} \in \Theta_{-i}} p(\theta_{-i}|\theta_i) u_i(s_i, s_{-i}(\theta_{-i}), \theta_i, \theta_{-i}) \quad (15)$$

or

$$u_i(s_i, s_{-i}, \theta_i) = \int u_i(s_i, s_{-i}(\theta_{-i}), \theta_i, \theta_{-i}) dP(\theta_{-i}|\theta_i)$$
(16)

In addition, the definition of a dynamic incompleteinformation Bayesian game can also be referred in [43], which is not repeated here.

2) NASH EQUILIBRIUM CONCEPTS IN BAYESIAN GAME

As elaborated previously, the Nash equilibrium of Bayesian game can be divided into Bayes-Nash equilibrium and perfect Bayes-Nash equilibrium (see Figure 2), which are corresponding to a static incomplete-information Bayesian game and a dynamic incomplete-information Bayesian game, respectively. At this point, based on (13), and referring to [43], the definition of Bayes-Nash equilibrium is given as follows. For a static incomplete-information Bayes game problem shown in (13), we call the strategy combination $(\phi_i^*(\theta_i), \phi_{-i}^*; \theta_i)$ as a Bayes-Nash equilibrium when it meets

$$E[u_i(\phi_i^*(\theta_i), \phi_{-i}^*; \theta_i)] \ge E[u_i(s_i, \phi_{-i}^*; \theta_i)]$$

$$\forall s_i \in S_i, \quad \forall \theta_i \in \Theta_i, \ \forall i \in N$$
(17)

where $E[u_i]$ is the expected utility of player *i*. Besides, researchers in [43] also give another definition of Bayes-Nash equilibrium as follows. We call the strategy combination $s^* = (s_i^*, s_{-i}^*)$ is a (pure-strategy) Bayes-Nash equilibrium when it meets

$$\begin{cases} s_i^*(\theta_i) \in \underset{s_i \in S_i}{\operatorname{arg max}} \sum_{\substack{\theta_{-i} \in \Theta_{-i} \\ \theta_{-i} \in \Theta_{-i}}} p(\theta_{-i}|\theta_i) u_i(s_i, s_{-i}(\theta_{-i}), \theta_i, \theta_{-i}) \\ \forall \theta_i \in \Theta_i, \quad \forall i \in N \end{cases}$$
(18)

In addition, the definition of hybrid-strategy Bayes-Nash equilibrium for a finite incomplete-information static Bayesian game and perfect Bayes-Nash equilibrium for a finite incomplete-information dynamic Bayesian game can also be referred to [43].

3) SOLUTION METHODS

As introduced previously, since Bayesian game is a kind of typical non-cooperative game in classical game theory, the solutions to solve the non-cooperative game introduced previously can also be suitable for solving Bayesian game. Hence, we do not repeat again here. Specific solutions to solve the Bayesian games can also refer to [43], [153], [156], and [169]–[175].

B. A SURVEY

1) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SELLER SIDE IN EM

As discussed previously, the power DR between electricity user side and electricity seller side mainly involve the electricity pricing and electricity capacity transactions between the electricity users who are small and medium such as general residential and commercial users or new energy users equipped with distributed energy equipment, and the power sales companies or power grid companies. To this end, we review the application of Bayesian game in power DR between the above two parties from two aspects: one is small and medium users, and the other is new energy users.

First, for the traditional small and medium users on the electricity user side such as building commercial users and home residential users, who have a large number in EM, as well as a large DR potential. At present, the electricity seller side mainly attracts these users via adjusting the electricity price structure released by them, such as TOU mechanism and RTP mechanism. For example, based on TOU mechanism, the Bayesian game-based transaction between power sales company and electricity users is implemented via directly purchasing electricity from the electricity seller side by users. At this point, the power sales companies on the electricity seller side will formulate and announce their TOU prices to maximize their profits, while the corresponding electricity users formulate their power purchasing strategies to minimize their costs. Specifically, Misra et al. [154] investigate the energy trading scenario for the distributed smart grid architecture based on an incomplete information game, where they design a real-time energy management scheme with incomplete information as a Bayesian game model. In this model, the incomplete information is considered as the real-time demand and price to grid and customers, respectively. The customers and grid are treated as customer-gents (behave as players in the game) and grid-agent (acts as one player in the game) in the proposed scheme, respectively. Among these, the former can estimate adequately the realtime price decided by the grid, and on the contrary, the latter deployed at the service provider' end can estimate adequate real-time energy demand from the customers. These two types of intelligent agents can take real-time decisions for cost-effective energy management under incompleteinformation conditions. In this study, researchers provide a proof for the existence of the Bayesian Nash equilibrium point of the proposed game, at which the utility of customers

and grid is maximized. Moreover, simulation results show that the Bayesian game approach proposed in [154] is wellenough to predict the real-time demand and price to the grid and the customers, respectively. Specifically, by introducing the proposed Bayesian game model, the utility of the grid increases approximately 40% over that of the existing ones under the scenario of information incompleteness.

Second, we find that Bayesian games have been widely used by scholars for the electricity trading between the new energy users, who are equipped with distributed energy equipment such as EVs, energy storage devices, and distributed generation, and electricity sellers. Specifically, Sola and Vitetta [155] and [156] investigate the demand-side management among users in a smart low-voltage microgrid based on distributed approach using Bayesian game theory. Researchers here model the energy consumption scheduling of the shiftable loads such as plug-in EVs (PEVs) that belong to a given user as a non-cooperative two-layer game of incomplete information (i.e., Bayesian game), in which each user is endowed with statistical information about its behavior and that of its opponent with the goal of choosing actions to maximize its expected utility. On the whole, the Bayesian game strategies reported in [155] and [156] are effective in managing the charging of EVs in a microgrid. In addition, researchers also report a Bayesian game model in [157]. Specifically, they investigate the energy consumption scheduling of residential users with PEVs based on an incomplete-information Bayesian game model. In this model, PEV users cannot acquire the PEV types of other users (as incomplete information). This Bayesian model helps users to evaluate other users' types with probability distribution of the types before scheduling their energy consumption, and it finally can shift loads from peak hours and minimize the cost of residential users.

Certainly, Bayesian game theory has also been employed by researchers in [110] aiming at modeling the competition between DR aggregators on the electricity seller side to sell aggregated energy stored in storage devices directly to other aggregators in an EM which is cleared in each time interval of a day using a repeated game-theoretic framework. At this point, the RTP in each time interval of a day with updating demand and supply and the TOU with demand price-based scheduling through dynamic programming are considered in the proposed market framework. On the whole, researchers in this study use the public statistical data and a Bayesian approach to derive probability distributions for DR aggregators' types. By introducing a repeated incompleteinformation game, the customers in light of the utility's optimal price can minimize their electricity cost and optimally schedule their power consumption in order to participate in the DR market.

2) POWER DR BETWEEN ELECTRICITY USER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

For the power DR between electricity user side and electricity supplier side in EM, we find that the Bayesian game theory is mainly employed for contract negotiation or bidding under uncertain demand after a detailed survey. At this point, the electricity user side is represented by large consumers with high energy consumption, such as large industrial users, who will directly buy electricity from power generation companies on the electricity supplier side in a perfect open bilateral EM, called direct power purchasing transaction. In this trading scenario, Bayesian game theory can be employed to build effective bidding strategies for the power generation companies and large consumers to carry out a one-for-one transaction and determine the price of electricity. For example, Fang and Wang [158] build a Bayesian game model with incomplete information for the double auction between generation company and large customer in a perfect open bilateral EM. They solve the Bayesian Nash equilibrium of the game and finally obtain the equilibrium bidding strategies for the generation company and large customer. However, this Bayesian game model is only suitable for a single-stage game. Actually, there are often multiple rounds of negotiations between power generation companies and large users to reach an agreement. For this reason, researchers in [159] use a bilateral auction and a sequential game model to design a negotiation model for a single large electric power user and a single power producer. In this model, they study the bidding strategies of power producers and large users for static games and dynamic games with non-complete information. Although the sequential game model is closer to the actual situation of large users participating in direct power purchasing games, it does not consider how the two sides use the transaction information to adjust the game strategy in the dynamic game. To obstacle this issue, Tan et al. [160] introduce the Bayesian learning-based dynamic game model to improve the learning ability of power producers and large users. In this study, during the trading process, the generator and the large consumer take turns to quote their price, which enables both of them to gradually revise their awareness of the reserved price of the other side and to forecast the price more precisely. In addition, Fang et al. [161] also develop the Bayesian Nash equilibrium bidding strategies for the generation companies. Further, researchers in [162] establish a Bayesian-Cournot Nash game model to formulate bidding strategies with incomplete information among non-cooperative generation companies. Aiming at how the power supplier and demander to build their own bidding strategies in a bilateral EM, Fang et al. [163] construct a double auction Bayesian model in which all power generation companies are regarded as the supplier and all the purchase agents of power are regarded as the demander. Based on the transaction rule of the auction and a consideration that the production cost of power supplier and the estimated price of the demander are private information, this proposed Bayesian game between the power supplier and demander can achieve a Bayesian Nash equilibrium, where the optimal bidding strategies for power supplier and demander are given by researchers. In addition, researchers in [133] and [146] combine the aforementioned Stackelberg game with Bayesian

game to investigate the direct power purchasing transactions among electricity suppliers and big electricity users. In these studies, the Stackelberg game is used to model the transaction between the power generation company (behaves as a leader) and large consumers (act as the followers), and the Bayesian game theory is employed to form a non-cooperative game among the power generation companies (see Figure 13).

In addition, aiming at the incentive mechanism in an electricity auction market, Liu et al. [153] use Bayesian game theory to design a proper bidding mechanism to decrease the generators' market power, with the goal of deepening the reform of the EM. They select the signaling game theory in Bayesian game to analyze the main electricity bidding mechanisms in the electricity auction markets considering the degree of information disturbance as an important factor for evaluating bidding mechanisms. Further, they propose an incentive electricity bidding mechanism, called the Generator Semi-randomized Matching (GSM) mechanism. Such GSM bidding mechanism can effectively decrease the clearing price, increase the total transaction volume, decrease the profits of electricity generators, and increase the overall benefits of purchasers. In addition, researchers in [164] and [165] both use the Bayesian game theory to investigate the incentive mechanisms in the auction market. For example, Yue et al. [165] apply the method of Bayesian game to analyze the pricing method in electricity distribution market, which indicates that the recommended method is not only a valid method for EM extension, but also has important reference value for electricity distribution pricing.

Moreover, researchers gradually use the Bayesian game theory to formulate strategies for the contract negotiation in the EM. For example, Zhang et al. [166] investigate the negotiation strategy of discharging price of EV among EV agents and power companies based on fuzzy Bayesian learning. In this study, they use the fuzzy probability calculation method to estimate and calculate the uncertain parameter of the function of EV agents and power companies. On the whole, the negotiation strategy is verified to be effective in a practical case study. In addition, Wang et al. [167] use the Bayesian game theory for a power generation market, where the long-term contract is one of the common and important choices of power generation company and transaction center to purchase benefits and evade risks. In this study, they adopt the Bayesian equilibrium of non-cooperative game theory to analyze the rational conditions of contract price formation. Apart from above investigations, aiming at the electric power bidding under uncertain demand, Zhang and Ye [168] model the power bidding behaviors of power plant company on the electricity supplier side under certain and uncertain electricity power demand as a two-generator game. In this study, they deduce the Bayesian Nash equilibrium of the game model and argue that the equilibrium bid of power plants is close to the upper or lower limit permitted under certain electricity power demand generally, but the optimal bid fluctuates between lower limit and the middle point of bid interval permitted for a power company under uncertain electricity power demand.

wer com

25752

In addition, they also find that the middle point bid will be chosen when the maximal supply of the rival is close to zero, and the lower limit will be chosen possibly if the generation power cost is close to zero.

3) POWER DR BETWEEN ELECTRICITY SELLER SIDE AND ELECTRICITY SUPPLIER SIDE IN EM

We find that Bayesian game theory is rarely used in power DR between electricity sellers and electricity suppliers. This is because Bayesian game is a non-cooperative game with incomplete information, which is more suitable for the game in which the players' private information is very important in a non-cooperative game. On the whole, the Bayesian game as an incomplete information game has been used by the researchers in [110] for a real-time DR market among the aggregators (behave as energy suppliers), power grid, and consumers. In this study, the proposed method minimizes the fuel consumption and operation costs and optimally schedules the generation in grid's supply side, and it also presents optimal prices during different periods simultaneously.

4) A BRIEF SUMMARY

On the whole, as a special type of non-cooperative game in classic game theory, the Bayesian game known as an incomplete information-game has been preliminarily used in EM in terms of power DR. In this section, we conduct a detailed overview on the application of Bayesian game theory in power DR under an open and ever-growing EM, from the perspective of games among electricity supplier side, electricity seller side and electricity user side. Generally speaking, Bayesian game theory has been applied by researchers to some scenarios of power DR in the EM, including electricity auction market, electric power bidding under uncertain demand, DRM and real-time DR, contract negotiation, and bidding strategy formulation of generation companies. It can be said that since the Bayesian game abandons the assumption that the game information must be completely known, thereby its application scenarios are closer to the reality. However, how to choose and establish a probabilistic model for the incomplete information in a Bayesian game to make which more in line with actual issues is still difficult for researchers in EM application scenarios. As elaborated previously, the equilibrium form of dynamic incomplete information-Bayesian game refers to a perfect Bayesian-Nash equilibrium, which is the most perfect equilibrium form in Nash equilibrium forms. However, such type of Nash equilibrium is still not guaranteed to be completely reasonable. To this end, scholars successively propose equilibrium concepts of trembling-hand perfect equilibrium and proper equilibrium to further perfect the above-mentioned perfect Bayesian-Nash equilibrium form [43], [169], [170].

VIII. PROSPECTS

A. A BRIEF SUMMARY

As the EM becomes more open and new energy entities join in EM, the stakeholders involved in the EM are becoming more diverse, which makes the power competition among stakeholders in the EM become complex multi-stakeholder game issues. Therefore, we argue that game theory will become a more and more important mathematical tool for addressing such issues. Overall, in this paper, we conduct a comprehensive overview on the application of game-theoretic approaches in EM trading in terms of power DR from the aspect of five categories of games.

On the whole, in this section, we conduct a detailed comparative analysis and summarization for the major game theoretic-approaches investigated in this paper from nine aspects, including the founder(s), major application scenarios in EM, major application scenarios in other fields, model features, solution methods, concrete subdivision, equilibrium concept(s), main academic references, and application level in EM, as demonstrated in Table 2.

B. PROSPECTS

Along with the rapid development of the EM, various emerging power sales entities (i.e., NPSEs) begin to participate in the EM transactions, which have changed the structure and operation mode of the EM to some extent. As a result, the past one-way load management has evolved into today's interactive DR, which is also one of the important features of the smart grid. Actually, with a large number of smart homes, distributed generation devices, energy storage devices, and EVs participating in the power system operation, they bring convenience to the power DR, but also make the game models in the context of EM more complicated. Due to the existence of multiple decision-making agents and various interest relationships such as competition and cooperation, in fact, the electricity trading decision-making process in the EM has gradually evolved into a multi-agent game issue with complete information or incomplete information. To this end, as a theoretical tool for studying multi-agent market conflicts of interest and trading decisions, game theory has been widely used in EM competition among electricity supplier side (e.g., power generation companies), electricity seller side (e.g., power grid companies, power sales companies, load aggregators), and electricity user side (e.g., residential users, commercial users, industrial users, distributed new energy users or prosumers).

1) ON THE ELECTRICITY SUPPLIER SIDE

It refers to the power generation side, where game theory is mainly used to study the bidding games between power generation entities [20], [103]–[106], that is, how various power generation entities formulate bidding strategies to participate in EM transactions. These bidding strategies are effective measures for them to achieve the best interests of their respective economic entities. In traditional generationside games, the Cournot game (i.e., production competition model) and Bertrand model (i.e., price competition model) are generally used to analyze the behavior of power generation companies. Besides, among the types of games in which power generation entities participate in EM transactions, one of the most important games is the direct power purchasing between the power generation side and the large electricity user side. Among them, the electricity user side mainly refers to large industrial consumers with high energy consumption. At this point, such types of large consumers are more sensitive to electricity price and can effectively participate in grid load dispatching. They can purchase electricity through some market transactions such as forward contracts (i.e., longterm power purchasing contracts), options method, and spot trading. Among these, the Cournot model [176] is suitable for analyzing the long-term behavior of the EM, while the Bertrand model [15] is more suitable for analyzing the shortterm behavior of the EM.

In addition, taking large consumers to participate in direct power purchasing in the EM as an example, this kind of game issue can be addressed by a master-slave game-theoretic approach, i.e., the Stackelberg game-theoretic approach. In this solution process, the goal of large consumers is to achieve the lowest cost of purchasing electricity by formulating the optimal power purchasing strategy, while the goal of the power generation company is to develop an optimal bidding strategy to attract more users to maximize its revenue. This type of game issue is a typical master-slave game, in which the upper-level problem is a type of noncooperative games (such as classic non-cooperative game, Bayesian game) between power generation companies; and the lower-layer users together with upper-level power generation company constitutes a master-slave game. Based on the power purchase strategy model of the lower-level users, the upper-level power generation company constructs a quotation strategy model. In this solution process, the Nash equilibrium algorithms based on parallel and distributed computing are the focus of future research. They are often used to solve the master-slave game equilibrium. At this point, as an important technical means to improve computational efficiency, parallel and distributed computing methods are necessary to be deeply investigated in terms of efficient solving of Nash equilibrium, such as sequence linearization methods, and decentralized iterative methods. In addition, the research on the multi-Nash equilibrium algorithm based on learning theory can also be carried out in the future.

In the above-mentioned actual direct power purchasing of large consumers, since there are much unknown private information on both sides, the Bayesian game or evolutionary game can be used to solve such a kind of game issues with limited information or bounded rationality. This proved to be very effective for direct power purchasing transaction between large consumers and power generation companies. In this solution process, the Bayesian game abandons the assumption that the game information must be completely known; and the EGT adopts the mechanism of natural selection, which does not require strict rational assumptions, and is closer to the reality, making it more reflective of the spontaneous evolution process (which is a dynamic process) of different interest groups. Therefore, in the future, how to select and establish the probability models with incomplete

TABLE 2. A comparative analysis and summarization for the major game-theoretic approaches investigated in this paper.

	Comparative items								
Game- theoretic approaches	Founder(s)	Major application scenarios in EM	Major application scenarios in other fields	Model features	Solution methods	Concrete subdivision	Equilibrium concept(s)	Main academic references	Application level in EM (five stars means highest level)
Non- cooperative game- theoretic approach	John Forbes Nash Jr	 Pricing and operation in deregulated EM Optimization of EV charging under demand uncertainty Equilibrium model development of the EM Generation companies' bidding strategies formulation Microgrid electricity pricing strategies formulation 	 Robust optimization Robust control Game planning model considering wind and photovoltaic output uncertainty 	 Perfect rationality There is no binding agreement between the participants Any participant who will not be able to increase its revenue via unilaterally deviating from the equilibrium strategy The research objective is the individuals Does not involve the adjustment process to achieve equilibrium and the impact of external factors on equilibrium The refinement thought comes from the backward induction method, which is premised on sequential rationality The system is often in an equilibrium state, and no time is needed for the system from non- equilibrium to equilibrium 	 Nash solution method Best response Ficitious play strategies Distributed game algorithms Learning theory based algorithms 	 Static games with complete information Static games with incomplete information Dynamic games with complete information Dynamic games with incomplete information 	 Nash equilibrium Subgame perfect Nash equilibrium Bayesian Nash equilibrium Perfect Bayesian Nash equilibrium 	[10], [18], [27]-[30], [43]-[67]	****
Cooperative game- theoretic approach	von Neumann	 Electricity price problem of grid- connected wind power Power sales entities such as wind farms and photovoltaic power plants participate in EM transactions Achieve cooperation for multiple stakeholders on electricity supplier, seller and user sides Help participant allocates additional benefits from interactions Incentives for microgrids in regulated ems 	 Dynamic cooperative game modeling of microgrid group Microgrid pricing strategy based on dynamic cooperative game 	 Perfect rationality There is a binding agreement between the participants The participants are no longer completely confrontational, but present a cooperative status Aims at how to achieve cooperation for participants and how to allocate the additional incomes produced from interactions for each participant It is generally solved based on Nash bargaining game theory and the Shapley value-based methods The research objective is the individuals 	 Nash bargaining equilibrium method Core-based dominant solution Shapley value-based valuation method 	 Transferable utility cooperative game (coalitional game) Non- transferable utility cooperative game (including non-transferable coalitional game and negotiation problem-type game) 	 Nash bargaining equilibrium Shapley value 	[19], [26], [27], [30], [68]-[88]	****
Evolutionary game- theoretic approach	Maynard Smith	 Model the competition among the residential users while considering the private information Direct power purchasing transactions Analyze the interest coordination mechanism between the electricity supplier side and the electricity seller side Power generation companies bidding Evolutionary stability analysis and equilibrium calculation 	Communication network evolution analysis, including construction of fitness function and design of selection and mutation mechanisms in power grid evolution Long-term equilibrium analysis	 Bounded rationality The research objective is the group formed by individuals Focuses on the adjustment process of group behavior to achieve equilibrium The group can eliminate small mutations (i.e., mutation strategy) when the ESE is reached in the entire group The refinement thought comes from forward induction method, that is, the genetic method or learning method The equilibrium of the group is temporary or even impossible, and the system needs a long-term evolution process to achieve equilibrium 	 RD equation pairwise comparison process Fermi process Moran process Wright- Fisher process Machine learning methods such as Q-learning algorithm 	 Monomorphic population model Polymorphic population model 	 Evolutionary stable equilibrium (evolutionary stable strategy) 	[9], [19], [21], [31], [89]-[121]	***

Stackelberg game- theoretic approach	Heinrich Von Stackelberg	 Charge and discharge management of EVs Bilateral contract transactions Supply-demand interaction Electricity price and electricity capacity transactions between electricity sellers or grid companies and small and medium users Power generation transactions direct power purchasing 	 The game between central government and local government The game between central banks and commercial banks Price competition between large companies and small companies 	 Perfect rationality The research objective is the individuals Does not involve the adjustment process to achieve equilibrium and the impact of external factors on equilibrium A dynamic game behavior of successive decision-making due to the unequal position of the two sides 	 Stationary point method Fixed point type iterative algorithm (including Jacobi type iteration and Gauss-Seidel type iteration) Other intelligent algorithms 	 Two-person Stackelberg game One-leader- multi-follower Stackelberg game Multi-leader- multi-follower Stackelberg game 	• Stackelberg Nash equilibrium	[33], [43], [50], [58], [64], [100], [122]-[152]	***
Bayesian game- theoretic approach	JohnC.Harsanyi	 Demand response based on incomplete- information game Direct power purchasing Electricity auction market Electric power bidding under uncertain demand DRM and real- time DR Contract negotiation Bidding strategy formulation of generation companies 	 Auction market Competition in the product market Signaling game, such as enterprise investment game and employment market signal game 	 Perfect rationality The research objective is the individuals Does not involve the adjustment process to achieve equilibrium and the impact of external factors on equilibrium A kind of incomplete-information strategy game 	 Nash solution method Best response Ficitious play strategies Distributed game algorithms Learning theory based algorithms 	 Incomplete- information static Bayes game Incomplete- information dynamic Bayes game 	 Bayes-Nash equilibrium Perfect Bayes-Nash equilibrium 	[43], [52], [110], [133], [146], [153]-[170]	***

TABLE 2. (Continued.) A comparative analysis and summarization for the major game-theoretic approaches investigated in this paper.

information in Bayesian game and the selection and mutation mechanisms in evolutionary game to make them closer to the actual game issues under limited information and bounded rationality conditions will be one of the research highlights in such type of game issues.

2) ON THE ELECTRICITY USER SIDE

It refers to the power consumer side, where game theory is mainly used to investigate the game issues of users participating in EM transactions, i.e., the formulation of game strategies used to analyze the power purchasing, electricity selling and electricity consumption of users, who have excess power capacity, participating in EM transactions after the distributed power generations are widely used among users. In addition, game theory is also used to study the joint game issues among power generation side, distribution side and power consumption side. For example, we can achieve the market-sharing distribution of peak load shaving benefits in all aspects of the system through the dynamic game linkage equilibrium of the power generation-side and demandside TOU electricity pricing. In general, as more and more users have own distributed energy equipment, they are both energy consumers and energy producers, called prosumers. They will participate in the EM trading as an independent NPSE. When a large number of prosumers participate in use game theory to develop effective power consumption and power sales strategies for such users is an important issue. If addressed, they will be able to fully mobilize the distributed power supply, energy storage devices, EVs, and other distributed energy devices to participate in the grid frequency adjustment, thereby optimally configuring the users' distributed energy devices. In this process, cooperative games and non-cooperative games can play an important role. For example, based on a typical type of non-cooperative game, i.e., the master-slave game, we can realize the charge and discharge management of EVs based on master-slave game, and fully play the role of EV's peak shaving and load leveling through appropriate regulation. In addition, by establishing a non-cooperative game model between users, we can also obtain the Nash Equilibrium to achieve the optimal configuration of distributed generation, energy storage and EVs for each user, so that they can maximize the sales profit while minimizing the investment and operation and maintenance costs and meanwhile, the safe and stable operation of the grid can be effectively guaranteed.

the EM trading as an NPSE, they will inevitably affect the

security and stability of the power grid. Therefore, how to

In addition, when the user-side residential users participate in the EM transactions in terms of power DR, the method of game modeling is not unique due to the differences in power usage, load types, and consumption attitudes. Therefore, in the future, when residents participate in the EM transaction, we should fully consider the user's electricity usage behavior, living habits and other factors that affect the user's electricity consumption, and further establish a specific game model based on the user's electricity usage behavior. For example, we can conduct deep investigations on how to use evolutionary games to simulate the power consumption behavior between users. Here, these behaviors include personal electricity use privacy information. At this point, the power transaction between the seller side and the user side can be modeled as a two-level master-slave game problem. In this problem, the price competition between the upperlevel sellers is modeled as a non-cooperative game model. In this way, when the residential users with limited rationality and incomplete information compete for power consumption, we can construct an evolutionary game process between residential users, so that we can gradually realize the evolutionary equilibrium of user groups by designing appropriate RD factors. Here, each user chooses the strategy of the electricity seller to purchase electricity as a hybrid strategy. At this time, a dynamic pricing-based power DR behavior is formed between the electricity seller and the user, and the supplydemand balance can be finally achieved. In general, for the user side, due to the large number of loads, it is difficult to obtain the information of the full load, and part of the load information may belong to user privacy. In this case, the Bayesian game based on incomplete information and the evolutionary game based on bounded rationality are expected to be a powerful mathematical tool for solving such problem of massive load DR in smart grid.

Certainly, the improvement of communication network is very important for users to participate in power market transactions. Therefore, how to improve the quality of service to users and the efficiency of decision-making by all parties can be solved by relying on game theory in the research of information network topology. In addition, in the future, we can also use game theory to deal with network attack activities in the power grid, and provide theoretical analysis tools for the safe operation of communication networks.

3) ON THE ELECTRICITY SELLER SIDE

It refers to the power grid company (the distribution side) and power-selling sides, where game theory is mainly used to analyze the distribution and quotation of power distribution companies according to market demand, as well as the competitive transactions of electricity prices and electricity purchase among electricity sellers, grid companies and users. With the in-depth development of the EM, there are more and more new types of power supply entities as agents participating in EM transactions, including new types of prosumers, load aggregators, large/small-scale power retail companies, and distributed power supplier groups, large-scale power generation company's direct electricity seller group, micro-gridtype electricity sellers, public service industry, energy-saving service companies, and so on. Among these, the addition become more complicated and diversified. Taking NPSE as an example, there will be more and more influencing factors affecting the game between the NPSE on power-selling side and the user side, including the level of the fee setting between the grid company and the NPSE, the number of NPSEs, and each NPSE individual's own capacity limit and its own cost coefficient, the way the fee is paid, the rules of power trading, the user's mastery of the transaction information and the degree of participation, and so on. Under this circumstance, the conflict of interest between different stakeholders of the power grid dispatching department and various types of electricity sellers and load agents will be effectively analyzed through different game models. For example, when different load agents compete for market share, for the strategic quotation of load reduction, the reduction of bidding and other issues, a reasonable solution can be given by solving the game model such as non-cooperative game. In addition, taking the microgrid-type service providers as an example, when they participate in electricity distribution and selling businesses, how to use game theory to develop a reasonable quotation strategy for them to attract more users deserve a further study in the future. Moreover, whether there is a need to form alliances among multiple microgrid-selling vendors, and how the chargeable and discharge facilities such as energy storage and EVs play a role in the profitability of microgrid-selling vendors are also worthy of further study.

of some NPSEs has made the competitive games in EM

In general, for the participation of multi-stakeholders in the EM, game theory is very suitable for modeling and analyzing the power trading competition relationship between the electricity supplier side, electricity seller side and electricity user side. In the future, game theory will play a more important role in the power DR in the context of a perfect open and evergrowing EM. The combination of game theory and intelligent algorithms can produce a model that is more in line with the real environment of the EM for different stakeholders to participate in the EM competition. Of course, there are some key scientific issues that need to be studied in the application of game theoretic-approaches to the EM in terms of power DR.

The key to solving these issues is to further combine game theory with various intelligent algorithms and artificial intelligence techniques such as machine learning algorithms and heuristic swarm intelligence algorithms [177]-[180], so as to develop more advanced intelligent algorithms for solving the game equilibrium of different actual game issues. For example, we can use stagnation method, variational inequality method, variable-scale feedback linearization method, and other methods to solve the equilibrium solution of a noncooperative game [131], [181], [182]; we can use the eigenfunction to construct the kernel of the game or the Shapley value method and Nash bargaining to solve the equilibrium of a cooperative game [27], [68]; and we can use artificial intelligence techniques, such as Q-learning and other machine learning algorithms [34] to solve the equilibrium of an evolutionary game. Therefore, on the whole, in the future,

the combination of game theory and various intelligent algorithms for solving different types of actual game problems will be one of the research hotspots.

IX. CONCLUSION

The characteristics of the intelligent distribution network determine that its operation, scheduling, control and other forms are significantly different from the traditional distribution network. How to determine the optimal strategy for each decision-making agent in the intelligent distribution network system in order to balance and optimize the interests of all parties is a challenging topic. However, the traditional optimization theory system with single-agent decisionmaking as the main feature is difficult to overcome this difficulty. In contrast, the game theory for complex multiagent multi-objective optimization is expected to become a powerful mathematical tool to overcome many problems in smart distribution networks. To this end, this paper conducts a detailed survey on game-theoretic approaches applied to the perfect open and ever-growing EM in terms of power DR from the perspective of three categories of games, including non-cooperative game, cooperative game, and evolutionary game. Particularly, we separately select Stackelberg game and Bayesian game from non-cooperative games and review their applications in power DR. Overall, the main contributions of this paper are summarized as follows:

1) We completely introduce the main contents of game theory and the major game behaviors of stakeholders participating in EM competitions in terms of power DR. These stakeholders are classified as three categories in this paper, including electricity supplier side, electricity seller side, and electricity user side.

2) Based on above classification, considering the EM competitions such as electricity pricing and electricity trading among electricity suppliers, electricity sellers and electricity users, we comprehensively introduce the principle of abovementioned three categories of games as well as Stackelberg game and Bayesian game, and then thoroughly review their applications in power DR in the context of perfect open and ever-growing EMs such as retail market, spot market, wholesale market and ancillary service market.

3) We offer some prospects on the application scenarios development and corresponding research directions for the above-mentioned five game-theoretic approaches in the field of EM from the perspective of power DR.

Overall, the biggest innovation of this paper lies in conducting a comprehensive survey on the major game-theoretic approaches applied to competitive transactions in the perfect open and ever-growing EMs from the perspective of power DR. We conduct this survey on relevant achievements of game theory obtained recently in EMs, with the goal of hoping to arouse the interest and excitement of experts and scholars in the energy and electric power system industry and looking ahead to efforts that jointly promote the rapid development of game-theoretic approaches in the field of perfect open EM.

NOMENC	LATURE
ASEP	asymptotically stable equilibrium point
ADR	automated demand response
CHP	combined heat and power
DR	demand response
DER	distributed energy resource
DRM	DR management
EM	electricity market
EV	electric vehicle
EGT	evolutionary game theory
ESE	evolutionary stable equilibrium
FSEL	fast Stackelberg equilibrium learning
GSM	generator semi-randomized matching
IDR	integrated demand response
KKT	Karush-Kuhn-Tucker
MESS	multi-group evolutionary stability strategy
NPSE	new power supply entity
N-S-N	Nash-Stackelberg-Nash
PEV	plug-in EV
RTP	real-time pricing
RD	replicator dynamics
RDS	replicator dynamics system
SEU	smart electricity utilization
TOU	time-of-use

- VPP virtual power plant
- WPP wind power producer

REFERENCES

- J. Rifkin, *The Third Industrial Revolution: How Lateral Power is Trans*forming Energy, the Economy, and the World. New York, NY, USA: Palgrave MacMillan, 2011, pp. 24–71.
- [2] L. Cheng *et al.*, "Local energy management and optimization: A novel energy universal service bus system based on energy Internet technologies," *Energies*, vol. 11, no. 5, p. 1160, May 2018. doi: 10.3390/ en11051160.
- [3] S. Bahrami and A. Sheikhi, "From demand response in smart grid toward integrated demand response in smart energy hub," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 650–658, Mar. 2016. doi: 10.1109/ TSG.2015.2464374.
- [4] P. Faria, J. Soares, Z. Vale, H. Morais, and T. Sousa, "Modified particle swarm optimization applied to integrated demand response and DG resources scheduling," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 606–616, Mar. 2013.
- [5] S. Althaher, P. Mancarella, and J. Mutale, "Automated demand response from home energy management system under dynamic pricing and power and comfort constraints," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1874–1883, Jul. 2015.
- [6] K. Vanthournout, B. Dupont, W. Foubert, C. Stuckens, and S. Claessens, "An automated residential demand response pilot experiment, based on day-ahead dynamic pricing," *Appl. Energy*, vol. 155, pp. 195–203, Oct. 2015. doi: 10.1016/j.apenergy.2015.05.100.
- [7] D. F. Lincoln, "Automated demand response applied to a set of commercial facilities," Ph.D dissertation, Univ. New Mexico, Albuquerque, NM, USA, Dec. 2009, pp. 1–12. [Online]. Available: https://search. proquest.com/docview/304951023
- [8] K.-M. Im, "Automated demand response system in lighting for optimization of electricity cost," *Energy Efficient*, vol. 10, no. 6, pp. 1329–1341, Dec. 2017. doi: 10.1007/s12053-017-9519-2.
- [9] L. F. Cheng and T. Yu, "Nash equilibrium-based asymptotic stability analysis of multi-group asymmetric evolutionary games in typical scenario of electricity market," *IEEE Access*, vol. 6, pp. 32064–32086, Dec. 2018. doi: 10.1109/ACCESS.2018.2842469.

- [10] W. C. Su and A. Q. Huang, "A game theoretic framework for a nextgeneration retail electricity market with high penetration of distributed residential electricity suppliers," *Appl. Energy*, vol. 119, pp. 341–350, Apr. 2014. doi: 10.1016/j.apenergy.2014.01.003.
- [11] S. Pal, S. Thakur, R. Kumar, and B. K. Panigrahi, "A strategical game theoretic based demand response model for residential consumers in a fair environment," *Int. J. Elect. Power Energy Syst.*, vol. 97, pp. 201–210, Apr. 2018. doi: 10.1016/j.ijepes.2017.10.036.
- [12] M. Mazadi, W. D. Rosehart, H. Zareipour, O. P. Malik, and M. Oloomi, "Impact of wind integration on electricity markets: A chance-constrained Nash Cournot model," *Int. Trans. Elect. Energ. Syst.*, vol. 23, pp. 83–96, Jan. 2013. doi: 10.1002/etep.650.
- [13] J. Yan and K. Folly, "Investigation of the impact of demand elasticity on electricity market using extended Cournot approach," *Int. J. Elect. Power Energy Syst.*, vol. 60, pp. 347–356, Sep. 2014. doi: 10.1016/j.ijepes.2014.03.037.
- [14] L. Z. Wang, M. Mazumdar, M. D. Bailey, and J. Valenzuela, "Oligopoly models for market price of electricity under demand uncertainty and unit reliability," *Eur. J. Oper. Res.*, vol. 181, vol. 3, pp. 1309–1321, Sep. 2007. doi: 10.1016/j.ejor.2005.07.027.
- [15] J. Yao, S. S. Oren, and B. F. Hobbs, *Restructured Electric Power Systems:* Analysis of Electricity Markets With Equilibrium Models, Hoboken, NJ, USA: Wiley, 2010, pp. 167–192. doi: 10.1002/9780470608555.ch5.
- [16] C. Wang, W. S. Tang, and R. Q. Zhao, "Static Bayesian games with finite fuzzy types and the existence of equilibrium," *Inf. Sci.*, vol. 178, no. 24, pp. 4688–4698, Dec. 2008. doi: 10.1016/j.ins.2008.08.007.
- [17] L. F. Cheng and T. Yu, "Typical scenario analysis of equilibrium stability of multi-group asymmetric evolutionary games in the open and evergrowing electricity market," *Proc. Chin. Soc. Electr. Eng.*, vol. 38, no. 19, pp. 5687–5703, Oct. 2018. doi: 10.13334/j.0258-8013.pcsee.172219.
- [18] L. Geerli, L. Chen, and R. Yokoyama, "Pricing and operation in deregulated electricity market by noncooperative game," *Electr. Power Syst. Res.*, vol. 57, no. 2, pp. 133–139, Mar. 2001. doi: 10.1016/S0378-7796(01)00094-3.
- [19] X. Peng and X. Tao, "Cooperative game of electricity retailers in China's spot electricity market," *Energy*, vol. 145, pp. 152–170, Feb. 2018. doi: 10.1016/j.energy.2017.12.122.
- [20] J. H. Wang, Z. Zhou, and A. Botterud, "An evolutionary game approach to analyzing bidding strategies in electricity markets with elastic demand," *Energy*, vol. 36, no. 5, pp. 3459–3467, May 2011. doi: 10.1016/j.energy.2011.03.050.
- [21] D. Menniti, A. Pinnarelli, and N. Sorrentino, "Simulation of producers behaviour in the electricity market by evolutionary games," *Electr. Power Syst. Res.*, vol. 78, no. 3, pp. 475–483, Mar. 2008. doi: 10.1016/j.epsr.2007.04.005.
- [22] M. M. Yu and S. H. Hong, "Incentive-based demand response considering hierarchical electricity market: A Stackelberg game approach," *Appl. Energy*, vol. 203, pp. 267–279, Oct. 2017. doi: 10.1016/ j.apenergy.2017.06.010.
- [23] P. Zou, Q. X. Chen, Q. Xia, C. He, and C. Kang, "Incentive compatible pool-based electricity market design and implementation: A Bayesian mechanism design approach," *Appl. Energy*, vol. 158, pp. 508–518, Nov. 2015. doi: 10.1016/j.apenergy.2015.08.099.
- [24] A. Yassine, A. A. N. Shirehjini, and S. Shirmohammadi, "Smart meters big data: Game theoretic model for fair data sharing in deregulated smart grids," *IEEE Access*, vol. 3, pp. 2169–3536, Dec. 2015. doi: 10.1109/ACCESS.2015.2504503.
- [25] J. G. Tisdell and S. R. Harrison, *Game Theory and Economic Modelling*. Oxford, U.K.: Clarendon Press, 1990.
- [26] J. von Neumann and O. Morgenstern, *Theory of Games and Economic Behavior*. Princeton, NJ, USA: Princeton Univ. Press, 1944.
- [27] J. F. Nash, Jr., "The bargaining problem," *Econometrica*, vol. 18, no. 2, pp. 155–162, 1950.
- [28] J. F. Nash, Jr., "Equilibrium points in n-person games," Proc. Nat. Acad. Sci. USA, vol. 36, no. 1, pp. 48–49, 1950.
- [29] J. Nash, "Non-cooperative games," Ann. Math., vol. 54, no. 2, pp. 286–295, 1951.
- [30] J. Nash, Jr., "Two-person cooperative games," *Econometrica*, vol. 21, no. 1, pp. 128–140, Feb. 1953. doi: 10.2307/1906951.
- [31] J. M. Smith and G. R. Price, "The logic of animal conflict," *Nature*, vol. 246, no. 5427, pp. 15–18, Jan. 1973. doi: 10.1038/246015a0.
- [32] P. D. Taylor and L. B. Jonker, "Evolutionary stable strategies and game dynamics," *Math. Biosci.*, vol. 40, nos. 1–2, pp. 145–156, Jul. 1978. doi: 10.1016/0025-5564(78)90077-9.

- [33] L. F. Cheng and T. Yu, "Exploration and exploitation of new knowledge emergence to improve the collective intelligent decision-making level of Web-of-cells with cyber-physical-social systems based on complex network modeling," *IEEE Access*, vol. 6, pp. 74204–74239, Oct. 2018. doi: 10.1109/ACCESS.2018.2879025.
- [34] L. F. Cheng and T. Yu, "A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems," *Int. J. Energy Res.*, to be published. doi: 10.1002/er.4333.
- [35] L. F. Cheng, T. Yu, X. S. Zhang, and B. Yang, "Parallel cyber-physicalsocial systems based smart energy robotic dispatcher and knowledge automation: Concepts, architectures and challenges," *IEEE Intell. Syst.*, to be published. doi: 10.1109/MIS.2018.2882360.
- [36] S. Ottesen, A. Tomasgard, and S.-E. Fleten, "Prosumer bidding and scheduling in electricity markets," *Energy*, vol. 94, pp. 828–843, Jan. 2016. doi: 10.1016/j.energy.2015.11.047.
- [37] Z. Y. Zhou *et al.*, "Game-theoretical energy management for energy Internet with big data-based renewable power forecasting," *IEEE Access*, vol. 5, pp. 5731–5746, Feb. 2017. doi: 10.1109/ACCESS.2017.2658952.
- [38] J. Z. Zeng, X. F. Zhao, J. Li, G. Li, K. J. Li, and Z. B. Wei, "Game among multiple entities in electricity market with liberalization of power demand side market," *Autom. Electr. Power Syst.*, vol. 41, no. 24, pp. 129–136, Dec. 2017. doi: 10.7500/AEPS20170616005.
- [39] M. Bae, H. Kim, E. Kim, A. Y. Chung, H. Kim, and J. H. Roh, "Toward electricity retail competition: Survey and case study on technical infrastructure for advanced electricity market system," *Appl. Energy*, vol. 133, pp. 252–273, Nov. 2014. doi: 10.1016/j.apenergy.2014.07.044.
- [40] N. Liu, X. H. Yu, C. Wang, C. J. Li, L. Ma, and J. Y. Lei, "Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3569–3583, Sep. 2017. doi: 10.1109/TPWRS.2017.2649558.
- [41] Y. Zheng, G. Li, M. Zhou, and X. Liu, "An integrated approach on allocating the congestion management cost under large consumers electricity direct purchase mode," in *Proc. 3rd Int. Conf. Deregulation Restruct. Power Technol. (DRPT)*, Nanjing, China, May 2008, pp. 539–544. doi: 10.1109/DRPT.2008.4523465.
- [42] Y. B. Liu, J. Y. Liu, L. F. Tian, and K. Zhu, "Pareto improvement of large customer direct power-purchase by use of multi-objective optimization," in *Proc. Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Wuhan, China, May 2009, p. 5. doi: 10.1109/APPEEC.2009.4918586.
- [43] S. W. Mei, F. Liu, and W. Wei, *Engineering Game Theory Foundation* and Power System Application. Beijing, China: Science Press, 2016, pp. 56–190.
- [44] K. C. Border, Fixed Point Theorems With Applications to Economics and Game Theory. Cambridge, U.K.: Cambridge Univ. Press, 1985, pp. 22–50.
- [45] P. Frihauf, M. Krstić, and T. Başar, "Nash equilibrium seeking in noncooperative games," *IEEE Trans. Autom. Control*, vol. 57, no. 5, pp. 1192–1207, May 2012.
- [46] E. Hopkins, "A note on best response dynamics," Games Econ. Behav., vol. 29, nos. 1–2, pp. 138–150, Oct. 1999. doi: 10.1006/game.1997.0636.
- [47] W. Tushar, W. Saad, H. V. Poor, and D. B. Smith, "Economics of electric vehicle charging: A game theoretic approach," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1767–1778, Dec. 2012.
- [48] R. Sharma and M. Gopal, "Synergizing reinforcement learning and game theoryâĂŤA new direction for control," *Appl. Soft Comput.*, vol. 10, no. 3, pp. 675–688, Jun. 2010. doi: 10.1016/j.asoc.2009.10.020.
- [49] M. Marzband, M. Javadi, J. L. Dominguez-Garcia, and M. M. Moghaddam, "Non-cooperative game theory based energy management systems for energy district in the retail market considering DER uncertainties," *IET Gener. Transmiss. Distrib.*, vol. 10, no. 12, pp. 2999–3009, Aug. 2016. doi: 10.1049/iet-gtd.2016.0024.
- [50] H. M. Soliman and A. Leon-Garcia, "Game-theoretic demand-side management with storage devices for the future smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1475–1485, May 2014.
- [51] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Demand-side management via distributed energy generation and storage optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 866–876, Jun. 2013.
- [52] X. Liu, B. Gao, C. Wu, and Y. Tang, "Demand-side management with household plug-in electric vehicles: A Bayesian game-theoretic approach," *IEEE Syst. J.*, vol. 12, no. 3, pp. 2894–2904, Sep. 2018. doi: 10.1109/JSYST.2017.2741719.

- [53] H. Yang, X. Xie, and A. Vasilakos, "Noncooperative and cooperative optimization of electric vehicle charging under demand uncertainty: A robust Stackelberg game," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1043–1058, Mar. 2016. doi: 10.1109/TVT.2015.2490280.
- [54] B.-G. Kim, S. Ren, M. van der Schaar, and J.-W. Lee, "Bidirectional energy trading and residential load scheduling with electric vehicles in the smart grid," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1219–1234, Jul. 2013.
- [55] C. Wu, H. Mohsenian-Rad, and J. Huang, "Vehicle-to-aggregator interaction game," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 434–442, Mar. 2012.
- [56] M. Pantos, "Exploitation of electric-drive vehicles in electricity markets," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 682–694, May 2012.
- [57] M. M. Jalali and A. Kazemi, "Demand side management in a smart grid with multiple electricity suppliers," *Energy*, vol. 81, pp. 766–776, Mar. 2015. doi: 10.1016/j.energy.2015.01.027.
- [58] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Dependable demand response management in the smart grid: A Stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 120–132, Mar. 2013.
- [59] P. Yang, G. Tang, and A. Nehorai, "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 884–892, May 2013.
- [60] P. Samadi, H. Mohsenian-Rad, R. Schober, and V. W. S. Wong, "Advanced demand side management for the future smart grid using mechanism design," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1170–1180, Sep. 2012.
- [61] H. Chen, Y. Li, R. H. Y. Louie, and B. Vucetic, "Autonomous demand side management based on energy consumption scheduling and instantaneous load billing: An aggregative game approach," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1744–1754, Jul. 2014.
- [62] Z. M. Fadlullah, D. M. Quan, N. Kato, and I. Stojmenovic, "GTES: An optimized game-theoretic demand-side management scheme for smart grid," *IEEE Syst. J.*, vol. 8, no. 2, pp. 588–597, Jun. 2014.
- [63] C. Wu, "Research on bilateral decision making of large consumers direct power purchasing based on game theory," Ph.D. dissertation, School Electr. Eng., Southeast Univ., Nanjing, China, Jun. 2017, pp. 27–33.
- [64] W. Xia, L. Lv, and P. Liu, "Economic game theory research on bilateral electricity pricing direct power purchase," *Mod. Electr. Power*, vol. 32, no. 3, pp. 71–75, Jun. 2015. doi: 10.19725/j.cnki.1007-2322.2015.03.012.
- [65] W. H. Zhao, H. N. Yan, and W. He, "Equilibrium model of electricity market based on non-cooperative game of wind farms, thermal power plants and power grid company," *Power Syst. Technol.*, vol. 42, no. 1, pp. 103–109, Jan. 2018. doi: 10.13335/j.1000-3673.pst.2017.1337.
- [66] B. Xun, F. Wen, and S. Tong, "Electricity market equilibrium of thermal and wind generating plants in emission trading environment," *Int. J. Energy Sector Manage.*, vol. 5, no. 3, pp. 416–435, 2011. doi: 10.1108/ 17506221111169908.
- [67] T. Dai and W. Qiao, "Finding equilibria in the pool-based electricity market with strategic wind power producers and network constraints," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 389–399, Jan. 2017. doi: 10.1109/ TPWRS.2016.2549003.
- [68] L. S. Shapley, "A value for N-person games," RAND, Santa Monica, CA, USA, Tech. Rep. P-295, 1952. [Online]. Available: https://www. rand.org/pubs/papers/P0295.html
- [69] T. W. Li, "The study on game alliance formation and distribution for multiple agent system," Ph.D. dissertation, School Inf. Sci. Eng., Yunnan Univ., Kunming, China, Dec. 2013.
- [70] N. P. Yu, L. Tesfatsion, and C. C. Liu, "Financial bilateral contract negotiation in wholesale electricity markets using Nash bargaining theory," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 251–267, Feb. 2012. doi: 10.1109/TPWRS.2011.2162637.
- [71] Z. Zhang, J. Shi, H. H. Chen, M. Guizani, and P. Qiu, "A cooperation strategy based on Nash bargaining solution in cooperative relay networks," *IEEE Trans. Veh. Technol.*, vol. 57, no. 4, pp. 2570–2577, Jul. 2008.
- [72] A. Kimms and I. Kozeletskyi, "Core-based cost allocation in the cooperative traveling salesman problem," *Eur. J. Oper. Res.*, vol. 248, no. 3, pp. 910–916, 2016. doi: 10.1016/j.ejor.2015.08.002.
- [73] E. Faria, L. A. Barroso, R. Kelman, S. Granville, and M. V. Pereira, "Allocation of firm-energy rights among hydro plants: An Aumann– Shapley approach," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 541–551, May 2009. doi: 10.1109/TPWRS.2009.2016376.

- [74] Y. P. Molina, R. B. Prada, and O. R. Saavedra, "Complex losses allocation to generators and loads based on circuit theory and Aumann-Shapley method," *IEEE Trans. Power Syst.*, vol. 25, no. 4, pp. 1928–1936, Nov. 2010. doi: 10.1109/TPWRS.2010.2044425.
- [75] C. L. Prete and B. F. Hobbs, "A cooperative game theoretic analysis of incentives for microgrids in regulated electricity markets," *Appl. Energy*, vol. 169, pp. 524–541, May 2016. doi: 10.1016/j.apenergy.2016.01.099.
- [76] J. Wang et al., "Ensuring profitability of retailers via Shapley value based demand response," Int. J. Electr. Power Energy Syst., vol. 108, pp. 72–85, Jan. 2019. doi: 10.1016/j.ijepes.2018.12.031.
- [77] D. Srinivasan and D. Woo, "Evolving cooperative bidding strategies in a power market," *Appl. Intell.*, vol. 29, no. 2, pp. 162–173, Oct. 2008. doi: 10.1007/s10489-007-0050-6.
- [78] S. D. Wang, W. Du, L. Lin, J. H. Li, W. Q. Chen, and X. Gao, "Optimal allocation of photovoltaic energy storage microgrid under the demand side response based on cooperative game," *Power Syst. Prot. Control*, vol. 46, no. 1, pp. 129–137, Jan. 2018. doi: 10.7667/PSPC162051.
- [79] C. Zhang, X. Y. Han, C. F. Bai, B. Hu, Y. F. Chai, and J. Q. Zhou, "Purchasing strategy model for power supplier based on the cooperative game theory in an open electricity market," *Electr. Power*, vol. 50, no. 6, pp. 177–184, Jun. 2017. doi: 10.11930/j.issn.1004-9649.2017.06.177.08.
- [80] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.
- [81] Z. Baharlouei, M. Hashemi, H. Narimani, and H. Mohsenian-Rad, "Achieving optimality and fairness in autonomous demand response: Benchmarks and billing mechanisms," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 968–975, Jun. 2013.
- [82] B. Gao, X. Liu, W. Zhang, and Y. Tang, "Autonomous household energy management based on a double cooperative game approach in the smart grid," *Energies*, vol. 8, pp. 7326–7343, Jul. 2015. doi: 10.3390/en8077326.
- [83] I. Taheri, M. Rashidinejad, A. Badri, and A. Abdollahi, "The study of GENCOs' bidding strategies in a pool-based electricity market using cooperative and non-cooperative game theory," *J. Elect. Syst. Signals*, vol. 1, no. 1, pp. 19–28, Mar. 2013.
- [84] V. Neimane, A. Sauhats, G. Vempers, I. Tereskina, and G. Bockarjova, "Approach for energy supply system planning based on cooperative game theory," in *Proc. 5th Int. Conf. Eur. Elect. Market (EEM)*, Lisboa, Portugal, Jul. 2008, p. 6. doi: 10.1109/EEM.2008.4579032.
- [85] X. Wang, H. J. Zhang, and S. H. Zhang, "Game model of electric power market involving virtual power plants composed of wind power and electric vehicles," *Autom. Electr. Power Syst.*, vol. 43, no. 3, pp. 155–162, Feb. 2019. doi: 10.7500/AEPS20180211004.
- [86] W. Li, Q. Yang, H. Zhang, and Q. Wang, "Incentive mechanism research on accommodation of wind power in regional electricity market based on cooperative game," *Renew. Energy Resour.*, vol. 32, no. 4, pp. 475–480, Apr. 2014. doi: 10.13941/j.cnki.21-1469/tk.2014.04.018.
- [87] S. Fan, Q. Ai, and L. Piao, "Bargaining-based cooperative energy trading for distribution company and demand response," *Appl. Energy*, vol. 226, pp. 469–482, Sep. 2018. doi: 10.1016/j.apenergy.2018.05.095.
- [88] L. Li, B. Duan, Y. Xu, and Y. Su, "A game theory mechanism for thermal power plant to participate in wind power heating in electricity markets," in *Proc. China Int. Conf. Electr. Distrib. (CICED)*, Xi'an, China, Sep. 2016, pp. 1–5. doi: 10.1109/CICED.2016.7576299.
- [89] A. A. Ladjici, A. Tiguercha, and M. Boudour, "Equilibrium calculation in electricity market modeled as a two-stage stochastic game using competitive coevolutionary algorithms," in *Proc. 8th Power Plant Power Syst. Control Symp. (PPPSC)*, Toulouse, France, Sep. 2012, pp. 524–529.
- [90] J. Gao and Z. H. Sheng, "Evolutionary game analysis of price competition strategy for power generation-side market," *J. Ind. Eng. Eng. Manag.*, vol. 18, no. 3, pp. 91–95, Mar. 2004. doi: 10.13587/ j.cnki.jieem.2004.03.020.
- [91] A. Traulsen, J. C. Claussen, and C. Hauert, "Coevolutionary dynamics: From finite to infinite populations," *Phys. Rev. Lett.*, vol. 95, no. 23, Jan. 2006, Art. no. 238701. doi: 10.1103/PhysRevLett.95.238701.
- [92] A. Traulsen, M. A. Nowak, and J. M. Pacheco, "Stochastic dynamics of invasion and fixation," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 74, no. 1, Aug. 2006, Art. no. 011909. doi: 10.1103/physreve.74.011909.
- [93] A. Traulsen, and C. Hauert, "Stochastic evolutionary game dynamics," in *Reviews of Nonlinear Dynamics and Complexity*, vol. 2, H. G. Schuster, Ed. Weinheim, Germany: Wiley, 2010, pp. 25–61.

- [94] M. A. Nowak, A. Sasaki, C. Taylor, and D. Fudenberg, "Emergence of cooperation and evolutionary stability in finite populations," *Nature*, vol. 428, no. 6983, pp. 646–650, Apr. 2004. doi: 10.1038/nature02414.
- [95] L. A. Imhof and M. A. Nowak, "Evolutionary game dynamics in a Wright-Fisher process," *J. Math. Biol.*, vol. 52, no. 5, pp. 667–681, May 2006. doi: 10.1007/s00285-005-0369-8.
- [96] B. Chai, J. Chen, Z. Yang, and Y. Zhang, "Demand response management with multiple utility companies: A two-level game approach," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 722–731, Mar. 2014.
- [97] B. Chai, "Energy management optimization in smart distribution grid," Ph.D. dissertation, College Control Sci. Eng., Zhejiang Univ., Hangzhou, China, Jun. 2015, pp. 59–68.
- [98] Y. T. Sun, Y. Q. Song, L. Z. Yao, and Z. Yan, "Study on power consumers' choices of electricity retailers in the electric selling market," *Power Syst. Technol.*, vol. 42, no. 4, pp. 1124–1131, Apr. 2018. doi: 10.13335/j.1000-3673.pst.2017.2338.
- [99] J. J. Zhang, "Dynamic evolutionary game analysis on innovation valueadded services of electricity sales enterprise under the new power system reform," *Coal Econ. Res.*, vol. 36, no. 9, pp. 59–65, Sep. 2016. doi: 10.13202/j.cnki.cer.2016.09.012.
- [100] Y. Dai, Y. Gao, H. Gao, and H. Zhu, "Real-time pricing scheme based on Stackelberg game in smart grid with multiple power retailers," *Neurocomputing*, vol. 260, pp. 149–156, Oct. 2017. doi: 10.1016/j.neucom.2017.04.027.
- [101] G. Wang, Q. Zhang, H. L. Li, Y. Li, and S. Y. Chen, "The impact of social network on the adoption of real-time electricity pricing mechanism," *Energy Proceedia*, vol. 142, pp. 3154–3159, Dec. 2017. doi: 10.1016/j.egypro.2017.12.383.
- [102] C. H. Shi, "The research on large consumer's direct buying based on evolutionary game theory," Ph.D. dissertation, Nanjing Univ. Sci. Technol., Nanjing, China, Jun. 2006, pp. 26–34.
- [103] X. Huang and Z. H. Wang, "Simulation and analysis of generation companies' bidding strategies based on evolutionary game theory," *Mod. Electr. Power*, vol. 26, no. 3, pp. 91–94, Jun. 2009.
- [104] F. Zaman, S. M. Elsayed, T. Ray, and R. A. Sarker, "Co-evolutionary approach for strategic bidding in competitive electricity markets," *Appl. Soft Comput.*, vol. 51, pp. 1–22, Feb. 2017. doi: 10.1016/ j.asoc.2016.11.049.
- [105] X.-G. Zhao, L.-Z. Ren, Y.-Z. Zhang, and G. Wan, "Evolutionary game analysis on the behavior strategies of power producers in renewable portfolio standard," *Energy*, vol. 162, pp. 505–516, Nov. 2018. doi: 10.1016/j.energy.2018.07.209.
- [106] K. Qian, "Research on differential evolution game bidding strategy for power generation side in the smart grid," Ph.D. dissertation, School Electr. Autom. Eng., East China Jiaotong Univ., Nanchang, China, Jun. 2018, pp. 12–24.
- [107] R. Y. Chen, "Evolutionary game of electricity market based on different behavioral decision-making and its chaos control," Ph.D. dissertation, School Electr. Inf. Eng., Changsha Univ. Sci. Technol., Changsha, China, Apr. 2010, pp. 19–38.
- [108] Y. Yuan, F.-Y. Wang, and D. Zeng, "Developing a cooperative bidding framework for sponsored search markets—An evolutionary perspective," *Inf. Sci.*, vol. 369, pp. 674–689, Nov. 2016. doi: 10.1016/ j.ins.2016.07.041.
- [109] Y. Zuo, X.-G. Zhao, Y.-Z. Zhang, and Y. Zhou, "From feed-in tariff to renewable portfolio standards: An evolutionary game theory perspective," *J. Clean. Prod.*, vol. 213, pp. 1274–1289, Mar. 2019. doi: 10.1016/ j.jclepro.2018.12.170.
- [110] M. Motalleb, A. Annaswamy, and R. Ghorbani, "A real-time demand response market through a repeated incomplete-information game," *Energy*, vol. 143, pp. 424–438, Jan. 2018. doi: 10.1016/ j.energy.2017.10.129.
- [111] Y. Zhang, "Evolutionary game theory on thermal power peaking under large scale of wind power integration," Ph.D. dissertation, School Econ. Manage., North China Electr. Power Univ., Baoding, China, Mar. 2017, pp. 8–49.
- [112] S. W. Liu, "Research on incentive mechanisms of renewable energy generation based on game theory," Ph.D. dissertation, School Econ. Manag., North China Electr. Power Univ., Baoding, China, Mar. 2017, pp. 17–58.
- [113] T. Bao, "Multi-agent game solving method of supply-demand interaction in power system," Ph.D. dissertation, School Electr. Power, South China Univ. Technol., Guangzhou, China, Apr. 2018, pp. 33–54.

- [114] A. A. Ladjici, A. Tiguercha, and M. Boudour, "Nash Equilibrium in a two-settlement electricity market using competitive coevolutionary algorithms," *Int. J. Elect. Power Energy Syst.*, vol. 57, pp. 148–155, May 2014. doi: 10.1016/j.ijepes.2013.11.045.
- [115] A. G. Azar, M. Afsharchi, M. Davoodi, and B. S. Bigham, "A multiobjective market-driven framework for power matching in the smart grid," *Eng. Appl. Artif. Intell.*, vol. 70, pp. 199–215, Apr. 2018. doi: 10.1016/j.engappai.2018.02.003.
- [116] P. Xu, "Research on generation expansion planning under the background of electricity market based on evolutionary game," Ph.D. dissertation, School Control Sci. Eng., North China Electr. Power Univ., Baoding, China, Mar. 2017, pp. 13–19.
- [117] X. Huang and Z. H. Wang, "Analysis of bidding strategies of generation companies by evolutionary game theory," in *Proc. 2nd Int. Conf. Inf. Comput. Sci.*, Manchester, U.K., Jul. 2009, pp. 62–65. doi: 10.1109/ICIC.2009.221.
- [118] X. T. Wang, H. F. Xue, and Q. Zhang, "Evolutionary game analysis on the interest coordination of grid-connected renewable energy power generation," *Syst. Eng.*, vol. 30, no. 4, pp. 94–99, Apr. 2012.
- [119] L. Liu, H. Liu, Z. Liu, and W. Chen, "Analysis of tripartite asymmetric evolutionary game among wind power enterprises, thermal power enterprises and power grid enterprises under new energy resources integrated," *Sci. Sinica Technol.*, Vol. 45, no. 12, pp. 1297–1303, Dec. 2015. doi: 10.1360/N092015-00244.
- [120] C. Zhang, S. H. Du, and J. Su, "Study on bidding strategies of regional electricity markets based on evolutionary game theory," *Mod. Electr. Power*, vol. 27, no. 2, pp. 87–90, Apr. 2010.
- [121] J. C. Liu and J. Yu, "Research on evolutionary game model and motivation strategy between generation and retail power companies: Under incomplete contract," *Sci. Technol. Manage. Res.*, vol. 38, no. 15, pp. 246–252, Aug. 2018. doi: 10.3969/j.issn.1000-7695.2018.15.035.
- [122] H. V. Stackelberg, The Theory of the Market Economy. Oxford, U.K.: Oxford Univ. Press, 1952, pp. 97–105. doi: 10.2307/3502458.
- [123] T. Bao, X. S. Zhang, T. Yu, X. Z. Liu, and D. Z. Wang, "A Stackelberg game model of real-time supply-demand interaction and the solving method via reinforcement learning," *Proc. Chin. Soc. Electr. Eng.*, vol. 38, no. 10, pp. 2947–2955, May 2018. doi: 10.13334/j.0258-8013.pcsee.162388.
- [124] M. J. Osbome and A. Rubinstein, A Course in Game Theory. Cambridge, MA, USA: MIT Press, 1944, pp. 5–25.
- [125] W. Wei, Y. Chen, F. Liu, S. W. Mei, F. Tian, and X. Zhang, "Stackelberg game based retailer pricing scheme and EV charging management in smart residential area," *Power Syst. Technol.*, vol. 39, no. 4, pp. 939–945, Apr. 2015. doi: 10.13335/j.1000-3673.pst.2015.04.010.
- [126] T. Basar and G. J. Olsder, *Dynamic Noncooperative Game Theory*. New York, NY, USA: Academic, 1995, pp. 25–37.
- [127] J. S. Pang and M. Fukushima, "Quasi-variational inequalities, generalized Nash equilibria, and multi-leader-follower games," *Comput. Manage. Sci.*, vol. 2, no. 1, pp. 21–56, Jan. 2005. doi: 10.1007/s10287-004-0010-0.
- [128] J. Yu and H. L. Wang, "An existence theorem for equilibrium points for multi-leader-follower games," *Nonlinear Anal. Theory, Method. Appl.*, vol. 69, nos. 5–6, pp. 1775–1777, Sep. 2008. doi: 10.1016/ j.na.2007.07.022.
- [129] X. Hu, "Mathematical programs with complementary constraints and game theory models in electricity markets," Ph.D. dissertation, Univ. Melbourne, Melbourne, VIC, Australia, 2003.
- [130] H. Wang, W. Wei, Y. F. Pan, X. M. Zhang, and S. W. Mei, "A bilevel programming based method for tuning parameters of nonlinear robust power system stabilizer," *Autom. Electr. Power Syst.*, vol. 38, no. 14, pp. 42–48, Jul. 2014. doi: 10.7500/AEPS20130905006.
- [131] S. W. Mei and W. Wei, "Hierarchal game and its applications in the smart grid," J. Syst. Sci. Math. Scis., vol. 34, no. 11, pp. 1331–1344, Nov. 2014.
- [132] R. Li, L. Dang, Z. Dong, and H. H. Zhou, "Coordinated optimization of time-of-use price and dispatching model combining wind power and energy storage under guidance of master-slave game," *Power Syst. Technol.*, vol. 39, no. 11, pp. 3247–3253, Nov. 2015. doi: 10.13335/j.1000-3673.pst.2015.11.035.
- [133] C. Wu, B. T. Gao, Y. Tang, and Q. Wang, "Master-slave game based bilateral contract transaction model for generation companies and large consumers," *Autom. Electr. Syst.*, vol. 40, no. 22, pp. 56–62, Nov. 2016. doi: 10.7500/AEPS20151110003.

- [134] M. M. Yu and S. H. Hong, "A real-time demand-response algorithm for smart grids: A Stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 879–888, Mar. 2016. doi: 10.1109/TSG.2015.2413813.
- [135] F. L. Meng and X. J. Zeng, "An optimal real-time pricing for demandside management: A Stackelberg game and genetic algorithm approach," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Beijing, China, Sep. 2014, pp. 1703–1710. doi: 10.1109/IJCNN.2014.6889608.
- [136] M. Latifi, A. Khalili, A. Rastegarnia, and S. Sanei, "Fully distributed demand response using the adaptive diffusion–Stackelberg algorithm," *IEEE Trans. Ind. Informat.*, vol. 13, no. 5, pp. 2291–2301, Oct. 2017. doi: 10.1109/TII.2017.2703132.
- [137] M. Yu and S. H. Hong, "Supply-demand balancing for power management in smart grid: A Stackelberg game approach," *Appl. Energy*, vol. 164, pp. 702–710, Feb. 2016. doi: 10.1016/j.apenergy.2015.12.039.
- [138] M. Zugno, J. M. Morales, P. Pinson, and H. Madsen, "Modeling demand response in electricity retail markets as a Stackelberg game," in *Proc. 12th IAEE Eur. Energy Conf. Energy Challenge Environ. Sustain.*, Venice, Italy, Sep. 2012, pp. 1–10.
- [139] O. Kilkki, A. Alahäivälä, and I. Seilonen, "Optimized control of price-based demand response with electric storage space heating," *IEEE Trans. Ind. Informat.*, vol. 11, no. 1, pp. 281–288, Feb. 2015. doi: 10.1109/TII.2014.2342032.
- [140] J. Yang, G. S. Zhang, and K. Ma, "Demand response based on stackelberg game in smart grid," in *Proc. 32nd Chin. Control Conf.*, Xi'an, China, Oct. 2013, pp. 8820–8824.
- [141] N. Liu, L. He, X. H. Yu, and L. Ma, "Multiparty energy management for grid-connected microgrids with heat- and electricity-coupled demand response," *IEEE Trans. Ind. Informat.*, vol. 14, no. 5, pp. 1887–1897, May 2018. doi: 10.1109/TII.2017.2757443.
- [142] Z. Y. Zhou, J. F. Bai, and S. Zhou, "A Stackelberg game approach for energy management in smart distribution systems with multiple microgrids," in *Proc. IEEE 12th Int. Symp. Auton. Decentralized Syst.*, Taiwan, China, Apr. 2015, pp. 248–253. doi: 10.1109/ ISADS.2015.15.
- [143] K. Alshehri, J. Liu, X. D. Chen, and T. Basar, "A Stackelberg game for multi-period demand response management in the smart grid," in *Proc.* 54th IEEE Conf. Decis. Control, Osaka, Japan, Feb. 2016, pp. 5889–5894. doi: 10.1109/CDC.2015.7403145.
- [144] S.-G. Yoon, Y.-J. Choi, J.-K. Park, and S. Bahk, "Stackelberg-gamebased demand response for at-home electric vehicle charging," *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4172–4184, Jun. 2015. doi: 10.1109/TVT.2015.2440471.
- [145] H. Kebriaei, A. Rahimi-Kian, and V. J. Majd, "An agent-based system for bilateral contracts of energy," *Expert Syst. Appl.*, vol. 39, no. 9, pp. 11369–11376, Sep. 2011. doi: 10.1016/j.eswa.2011.03.005.
- [146] Y. Tang, J. Ling, C. Wu, N. Chen, X. F. Liu, and B. T. Gao, "Gametheoretic optimization of bilateral contract transaction for generation companies and large consumers with incomplete information," *Entropy*, vol. 19, no. 62, p. 272, Jun. 2017. doi: 10.3390/e19060272.
- [147] S. Maharjan, Q. Y. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "From demand response in smart grid toward integrated demand response in smart energy hub," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 189–199, Jan. 2016. doi: 10.1109/TSG.2015.2431324.
- [148] X. S. Zhang, T. Bao, T. Yu, B. Yang, and C. J. Han, "Deep transfer Q-learning with virtual leader-follower for supply-demand Stackelberg game of smart grid," *Energy*, vol. 133, pp. 348–365, Aug. 2017. doi: 10.1016/j.energy.2017.05.114.
- [149] F. Wei, Z. X. Jing, P. Z. Wu, and Q. H. Wu, "A Stackelberg game approach for multiple energies trading in integrated energy systems," *Appl. Energy*, vol. 200, pp. 315–329, Aug. 2017. doi: 10.1016/j.apenergy.2017.05.001.
- [150] S. Y. Gong, "Bi-level economic dispatch model for large electricity retailer," Ph.D. dissertation, School Electr. Inf. Eng., Tianjin Univ., Tianjin, China, Nov. 2016, pp. 19–30.
- [151] H. P. Fan and M. Yu, "A new two-stage game framework for power demand/response management in smart grids," in *Proc. IEEE 14th Int. Conf. Netw. Sens. Control*, Calabria, Italy, Aug. 2017, pp. 1–6. doi: 10.1109/ICNSC.2017.8000133.
- [152] G. E. Asimakopoulou, A. L. Dimeas, and N. D. Hatziargyriou, "Leaderfollower strategies for energy management of multi-microgrids," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 1909–1916, Dec. 2013.
- [153] Z. Liu, X. L. Zhang, and J. Lieu, "Design of the incentive mechanism in electricity auction market based on the signaling game theory," *Energy*, vol. 35, no. 4, pp. 1813–1819, Apr. 2010. doi: 10.1016/ j.energy.2009.12.036.

- [154] S. Misra, S. Bera, T. Ojha, and L. Zhou, "ENTICE: Agent-based energy trading with incomplete information in the smart grid," *J. Netw. Comput. Appl.*, vol. 55, pp. 202–212, Sep. 2015. doi: 10.1016/j.jnca.2015.05.008.
- [155] M. Sola and G. M. Vitetta, "Demand-side management in a smart microgrid: A distributed approach based on Bayesian game theory," in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Venice, Italy, Jan. 2015, pp. 656–661. doi: 10.1109/SmartGridComm.2014.7007722.
- [156] M. Sola and G. M. Vitetta, "A Bayesian demand-side management strategy for smart micro-grid," *Technol. Econ. Smart Grids Sustain. Energy*, vol. 1, no. 1, p. 8, 2016. doi: 10.1007/s40866-016-0008-z.
- [157] X. F. Liu, B. T. Gao, C. Wu, and Y. Tang, "Bayesian game-theoretic energy management for residential users in smart grid," in *Proc. IEEE Int. Conf. Cyber Technol. Autom. Control Intell. Syst.*, Chengdu, China, Sep. 2016, pp. 67–71. doi: 10.1109/CYBER.2016.7574797.
- [158] D. B. Fang and X. J. Wang, "A double auction model for transaction between generation company and large customer in electricity market," *Power Syst. Technol.*, vol. 29, no. 6, pp. 32–36, Mar. 2005.
- [159] G. Chen, C. Wang, S. Xie, B. Zhou, and M. L. Tang, "Study on bargaining of large power consumer's direct buying based on game theory," *Power Syst. Technol.*, vol. 28, no. 13, pp. 75–79, Jul. 2004.
- [160] Z. F. Tan, H. Bai, L. Li, and F. Yan, "Bayesian learning model based dynamic game for pricing between power consumers and generators," *East China Electr. Power*, vol. 37, no. 3, pp. 384–388, Mar. 2009.
- [161] D. B. Fang, X. J. Wang, F. R. Ouyang, and C. Ye, "Bayesian Nash equilibrium bidding strategies for generation companies," in *Proc. IEEE Int. Conf. Electr. Utility Deregulation, Restruct. Power Technol.*, Hong Kong, Oct. 2004, pp. 692–697. doi: 10.1109/DRPT.2004.1338072.
- [162] B.-G. Kwon, S.-C. Lee, D.-S. Choi, and J.-H. Kim, "Application of Bayesian-Cournot Nash game model in establishing bidding strategy with incomplete information among non-cooperative generation companies," *IFAC Proc. Volumes*, vol. 36, no. 20, pp. 927–931, Sep. 2003. doi: 10.1016/S1474-6670(17)34592-5.
- [163] D.-B. Fang, X.-J. Wang, Y.-X. Zhang, K. Liu, P. Wang, and Z.-Y. Zhu, "A double auction Bayesian model with supplier and demander in open bilateral electricity market," *Power Syst. Technol.*, vol. 27, no. 12, pp. 1–5, Dec. 2003.
- [164] J. Richter and J. Viehmann, "The value of information in explicit crossborder capacity auction regimes in electricity markets," *Energy Policy*, vol. 70, pp. 74–84, Jul. 2014. doi: 10.1016/j.enpol.2014.03.023.
- [165] S. Yue, Y. Yu, W. Chen, S. Wang, and X. Bu, "Application of Bayes auction pricing method in electricity distribution market," *Autom. Electr. Power Syst.*, vol. 28, no. 1, pp. 16–19, Jan. 2004.
- [166] Q. Zhang, J. J. Cai, C. Y. Li, H. Z. Liu, and D. Li, "The negotiation strategy of discharging price of electric vehicle based on fuzzy Bayesian learning," *Proc. Chin. Soc. Electr. Eng.*, vol. 38, no. 1, pp. 61–71, Jan. 2018. doi: 10.13334/j.0258-8013.pcsee.162593.
- [167] P. Wang, H. C. Yang, Y. H. Wu, and R. M. He, "Bayesian equilibrium of long-term contract negotiation means in electricity market," *Autom. Electr. Power Syst.*, vol. 27, no. 16, pp. 30–34, Aug. 2003.
- [168] X. H. Zhang and Z. Ye, "Bayesian game model on electric power bidding under uncertain demand," J. Syst. Eng., vol. 22, no. 2, pp. 215–219, Apr. 2006.
- [169] R. Selten, "Reexamination of the perfectness concept for equilibrium points in extensive games," *Int. J. Game Theory*, vol. 4, no. 1, pp. 25–55, Mar. 1975. doi: 10.1007/978-94-015-7774-8_1.
- [170] R. B. Myerson, "Refinements of the Nash equilibrium concept," Int. J. Game Theory, vol. 7, no. 2, pp. 73–80, 1978.
- [171] Y. H. Lang, Game Theory and Its Application, Shanghai, China: Shanghai Univ. Finance & Economics Press, 2015.
- [172] F. Q. Zhu, *Game Theory*, Beijing, China: Economy & Management Publishing House, 2013.
- [173] Y. F. Luo, A Course in Game Theory. Beijing, China: Tsinghua Univ. Press, 2007.
- [174] S. Y. Xie, Economic Applications of Game Theory. Shanghai, China: Fudan Univ. Press, 2002.
- [175] G. Persiano, Algorithmic Game Theory. Berlin, Germany: Springer, 2009.
- [176] A. Badri and M. Rashidinejad, "Security constrained optimal bidding strategy of GenCos in day ahead oligopolistic power markets: A Cournot-based model," *Elect. Eng.*, vol. 95, no. 2, pp. 63–72, Jun. 2013. doi: 10.1007/s00202-012-0240-z.
- [177] L. F. Cheng, T. Yu, X. S. Zhang, and L. F. Yin, "Machine learning for energy and electric power systems: State of the art and prospects," *Autom. Electr. Power Syst.*, vol. 43, no. 1, pp. 15–31, Jan. 2019. doi: 10.7500/ AEPS20180814007.

- [178] L. F. Cheng, T. Yu, X. S. Zhang, L. F. Yin, and K. Q. Qu, "Cyber-physicalsocial systems based smart energy robotic dispatcher and its knowledge automation: Framework, techniques and challenges," *Proc. Chin. Soc. Electr. Eng.*, vol. 38, no. 1, pp. 25–40, Jan. 2018. doi: 10.13334/j.0258-8013.pcsee.171856.
- [179] L. F. Cheng and T. Yu, "Dissolved gas analysis principle-based intelligent approaches to fault diagnosis and decision making for large oil-immersed power transformers: A survey," *Energies*, vol. 11, no. 3, p. 913, Apr. 2018. doi: 10.3390/en11040913.
- [180] L. F. Cheng and T. Yu, "Smart dispatching for energy Internet with complex cyber-physical-social systems: A parallel dispatch perspective," *Int. J. Energy Res.*, to be published. doi: 10.1002/er.4384.
- [181] G. Scutari, D. P. Palomar, F. Facchinei, and J. S. Pang, "Convex optimization, game theory, and variational inequality theory," *IEEE Signal Process. Mag.*, vol. 27, no. 3, pp. 35–49, May 2010.
- [182] Q. Lu, S. W. Mei, and Y. Z. Sun, Nonlinear Control of Power System. Beijing, China: Tsinghua Univ. Press, 2008.



TAO YU (M'11) received the B.Eng. degree in electrical power system from Zhejiang University, Hangzhou, China, in 1996, the M.Eng. degree in hydroelectric engineering from Yunnan Polytechnic University, Kunming, China, in 1999, and the Ph.D. degree in electrical engineering from Tsinghua University, Beijing, China, in 2003. He is currently a Professor with the School of Electric Power, South China University of Technology, Guangzhou, China. His special fields of interest

include nonlinear and coordinated control theory, artificial intelligence techniques in planning, and operation of power systems.

...



LEFENG CHENG (S'18) received the B.Eng. degree from the College of Information Science and Engineering, Huaqiao University, Quanzhou, China, in 2012, and the master's degree from the School of Electric Power, South China University of Technology, Guangzhou, China, in 2015, where he is currently pursuing the Ph.D. degree. His major research interests include power system reliability analysis, game-theoretic methods and its application in electricity market, and machine

learning algorithms in the operation, optimization, and control of newgeneration energy and electric power systems.