Game-theoretic Applications for Decision-making Behavior on the Energy Demand Side: a Systematic Review

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***Abstract*—As an essential characteristic of the smart grid, energy demand users are being transformed from passive roles to active decision-makers. To analyze their decision-making behaviors, game theory has been widely applied on the demand side. This paper focuses on the classification and in-depth analysis of recent studies that propose game-theoretic approaches for decision optimization of multiple demand users. This analysis classifies scenarios into various game participant categories, including distributed energy prosumers, small- and middle-sized users, and large energy consumers. The in-depth analysis of each scenario, covering non-cooperative game, cooperative game, Stackelberg game, Bayesian game, and evolutionary game, is conducted by analyzing market operation mechanisms, model assumptions/formulations, and solution methods. Based on a comprehensive review of such studies, it is concluded that game-theoretic applications on the demand side can benefit both the grid and the users, e.g., reductions in the peak-to-average ratios and energy costs of the users. The prospects for the applications of game theory on the demand side are discussed, including application scenarios and methodologies. The overview presented in this paper is expected to support researchers in comprehending typical game-theoretic concepts, keeping with the latest research developments, and identifying new and innovative applications for the energy demand side.**

***Index Terms*—Energy demand side, game theory, Game-theoretic application, demand response, decision-making behavior.**

I. INTRODUCTION

The second industrial revolution brought us into the electrical age. Ever since, the development of society has been inseparable from the widespread use of electricity [1]. Primary energy in the power industry has gradually developed from fossil energy sources to diversified energy sources, such as, wind/solar energy, hydroelectricity, and nuclear energy [2], [3]. However, with the growing demand for electricity in social development, coupled with environmental concerns like carbon emissions [4], [5], the issue of power energy has attracted widespread attention. There is an increasing need to explore solutions that can address the challenge of balancing the supply and demand of energy while ensuring environmental sustainability. In recent years, distributed energy technologies, such as photovoltaic (PV) and wind power generation, have had an influence in relieving supply-demand conflict from the energy source side [6], [7]. In addition to increasing the installed capacity of distributed generation on the source side, addressing the issue from the demand side is also a viable and effective solution [8], [9].

Generally, demand users can be divided into residential, commercial, and industrial users according to their energy consumption characteristics [10]. Residential and commercial users, who belong to small- and middle-sized users, can realize the flexibility of load and relieve the pressure of energy supply via a demand response (DR) program [11]. Industrial users, who belong to large energy users, can interact with the source side through the retail market to improve the reliability of energy supply [12]. Because of the massive numbers of demand users, and especially the emergence and popularization of distributed generation, determining the optimal strategy for demand users has become extremely challenging. Moreover, as power market reform progresses, the composition of energy sellers has evolved beyond traditional generation companies on the supply side to also include prosumers on the demand side [13]. Therefore, traditional optimal approaches for the single-subject decision-making can no longer satisfy the need of multi-subject decision-making. Accordingly, game theory is a perfect tool in solving these decision problems on the demand side [14], [15].

Game theory has been shown to be useful in studying how multiple decision-making stakeholders can maximize their interests by optimizing their decisions. The

Received: April 22, 2023
Accepted: December 4, 2023
Published: March 1, 2024
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DOI: 10.23919/PCMP.2023.000219

major difference between game theory and other optimization theories is that decision makers' interests in the game will be affected by each other when any subject changes its strategy. Game theory was first applied in the economic field, and then in politics, military, biological evolution, etc. In the field of electrical engineering, game theory was first applied in the power market, especially for the optimization problem of generation companies on the energy source side [16]. With the increasingly prominent position of the demand side, introducing an excellent decision-making method will contribute to efficient operation of the power grid [17]. Consequently, in the past decade, game theory has been extensively applied on the energy demand side. In this paper, a systematic review is conducted on these approaches from three aspects: distributed energy prosumers, small- and middle-sized users, and large energy consumers. In summary, the main contributions are:

1) A comprehensive framework is proposed to investigate game-theoretic approaches in decision-making problems, which involves identifying and analyzing game behavior, modeling theory, and application scenarios on the energy demand side.

2) A comprehensive review of the state-of-the-art researches are studied, where the components of these applications are elaborated from participants, modeling assumptions, objective, and operational mechanism. Typical applications covering the three types of users are examined.

3) Based on the identified shortcomings of existing research, future application scenarios and methodologies are proposed. These are expected to contribute to the development of demand-side game theory.

The remainder of this paper is organized as follows. In Section II, game theory on the energy demand side is introduced. The applications are reviewed in Section III. Section IV provides insight into the potential of future applications. Section V concludes the paper.

II. Game Theory and Behavior on Energy Demand Side

A. Game Theory

Game problems can be traced back to the oligarchic competition model in the early 19th century. After the Nash equilibrium (NE) problem of NG is solved [18], [19], game theory has been applied in different fields. Generally, a complete game contains at least three basic elements [20]: player, strategy, and payoff. In addition to those three essential elements, some other elements need to be covered for some special games. For example, types of players and the brief have to be introduced in describing an incomplete information game. Game theory can be divided into classical game and evolutionary game (EG) based on player's rationality. Players in the classical game have perfect rationality, while players in EG only require limited rationality [21]. Moreover, the classical game can be classified into non-cooperative game (NG) and cooperative game (CG) based on whether players cooperate or not, and static or dynamic game based on whether players make decisions orderly. The games can be classified to classical game and evolutionary game based on whether players have perfect rationality. The classical game forms are presented in Table I.

TABLE I
ILLUSTRATION OF CLASSICAL GAME

Category	Game form	Classification rule
Classical game	Non-cooperative game	Whether players cooperate or not
	Cooperative game	
	Static game	Whether players make decisions orderly
	Dynamic game	
	Complete information game	Whether game information is public or private
	Bayesian game	

B. Game Behavior Classification on the Energy Demand Side

In the traditional power market, there is fierce competition between the energy generation side and seller side, which can be described as various games. Demand users are limited to passively accepting energy prices set by the seller side, without any direct competitive relationship with either the seller or generation side. However, as the power market evolves and distributed energy sources such as distributed generation, energy storage, and electric vehicles (EVs) emerge, demand users have the opportunity to actively engage in energy trading. Figure 1 shows that demand users can be divided into three categories, including distributed energy prosumers, small- and middle-sized users, and large energy consumers [22], [23].

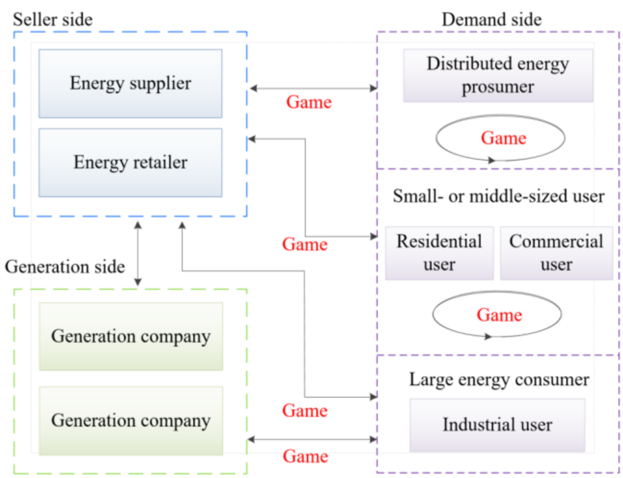

Fig. 1. Game behavior on the energy demand side.

Distributed energy prosumers can make bilateral transactions with the seller side. Small- and middle-sized users can purchase energy from different energy retailers. Large consumers can also purchase energy from the generation side via direct power-purchase trading [24], [25]. That is, in an open market environment, demand users will be free to choose energy sellers and sell energy to the seller side or other users with distributed energy. Consequently, there must exist complex and fierce game behaviors on all of the demand, seller and generation sides. According to the energy trading mode between different subjects on the demand side, game behavior can be divided into the following three categories.

1) Game for Distributed Energy Prosumers (Game 1)

Demand users with distributed energy belong to energy prosumers, who can trade as energy sellers in the market. To obtain better profits, prosumers will formulate games with other prosumers, suppliers, and retailers.

2) Game for Small- and Middle-Sized Users (Game 2)

Small- and middle-sized users, including residential users and commercial users, occupy an important position on the demand side. These users can change their energy consumption mode to reduce energy cost under the incentive of the energy price mechanism. Therefore, small- and middle-sized users will formulate games with other users, suppliers, and retailers.

3) Game for Large Energy Consumers (Game 3)

Large energy consumers, such as industrial users, have a high energy demand level. To reduce their energy cost, large energy users can choose to trade directly with generation companies. In such direct power-purchase trading, both sides want to maximize their self-interests, and thus, there must exist game behavior between large users and generators. It needs to be noted that, when large consumers purchase energy from the seller side, the trading is similar to (2), which can be analyzed under Game 2.

C. Game-Theoretic Approach on the Energy Demand Side

The main existing game-theoretic approaches on the energy demand side are summarized in Table II. Note that, Stackelberg game (SG) belongs to dynamic NG and Bayesian game (BG) belongs to NG with incomplete information. To specify their applications on the demand side, they are distinguished from NG.

TABLE II
GAME-THEORETIC APPROACHES ON THE ENERGY DEMAND SIDE

Game form	Main application scenarios	Main concerns
Non-cooperative game	Game 1 and 2	Design payoff function to guarantee the existence of NE
Cooperative game	Game 1, 2, and 3	Design payoff allocation mechanism to guarantee the stability of coalition
Stackelberg game	Game 1, 2, and 3	Solve NE problem of SG
Bayesian game	Game 1, 2, and 3	Establish type space and joint probability distribution
Evolutionary game	Game 2	Design replication dynamic equation and analyze evolutionary equilibrium

1) Non-Cooperative Game

NG is widely employed on the demand side since the game individuals generally have profit-seeking behavior. For the formulated NG on the demand side, more attention is focused on the design of the profit function to guarantee the existence of NE. Because of the diversity and complexity of practical problems, especially when many participants are involved in the game, searching NE of the game is a vital task. Generally, NG can be formulated as follows [26]:

1) Player: Demand users, who can be energy users, energy prosumers, or a microgrid.

2) Strategy: Each player selects its decision strategy to maximize its payoff and such strategy set can be an energy consumption scheduling vector or energy selling vector.

3) Payoff: The payoff of a player mainly consists of energy cost or utility, which can be described as:

$$P_n(x_n, \boldsymbol{x}_{-n}) = f_n(x_n, \boldsymbol{x}_{-n}) \tag{1}$$

where x_n represents the strategy of player n and $\boldsymbol{x}_{-n} = [x_1, \cdots, x_{n-1}, x_{n+1}, \cdots, x_N]$ denotes the strategy vector for all players other than player n.

To guarantee the existence and uniqueness of NE, $f_n(x_n, \boldsymbol{x}_{-n})$ needs to be continuous and concave in x_n for each fixed value $\boldsymbol{x}_{-n}$. Meanwhile, strategy x_n for any player should be in a convex, closed, and bounded space [27]. The strategy space is generally constructed according to the constraint conditions of decision-making behavior. Under NE, no rational player would benefit by deviating from the optimal strategy x_n^*, which is expressed as:

$$P_n(x_n^*, \boldsymbol{x}_{-n}^*) \geqslant P_n(x_n, \boldsymbol{x}_{-n}^*) \tag{2}$$

where $\left(x_n^*, \boldsymbol{x}_{-n}^*\right)$ is NE of the game. The solution of NE is a complex but critical problem. Hence, the research on NG concentrates on the proof of the existence and the solution of NE [27].

2) Cooperative Game

Overall payoff of a coalition in CG is generally higher than the sum of an individual's payoff in NG. Such difference in the payoff is called cooperative surplus [28]. However, considering the selfishness of participating individuals, if the allocation of coalition profit is unfair, it is highly likely that the coalition would be disintegrated rapidly. Therefore, for the CG on the demand side, more attention is given to the design of the payoff allocation mechanism [29]. Typically, the payoff allocation mechanism is designed according to the marginal contribution of each participant. In a CG $(\mathcal{N}, v(\mathcal{N}))$, in which $\mathcal{N}$ represents the coalition consisting of $|\mathcal{N}|$ players and $v(\mathcal{N})$ is the payoff, the marginal contribution of player n can be defined as:

$$\Delta v_{\mathcal{S}}^{n} = v(\mathcal{S} \cup \{n\}) - v(\mathcal{S}) \quad \forall n \notin \mathcal{S} \tag{3}$$

where $\mathcal{S} \subseteq \mathcal{N} \setminus \{n\}$ is any sub-coalition other than player n and $v(\mathcal{S} \cup \{n\})$ represents the payoff of new coalition containing $\mathcal{S}$ and n.

Based on the marginal contribution, the payoff of player n in the coalition can be expressed as:

$$v_{\mathcal{N}}^{n} = \sum_{\mathcal{S} \subseteq \mathcal{N} \setminus \{n\}} \alpha_{\mathcal{S}}^{n} \Delta v_{\mathcal{S}}^{n} \tag{4}$$

where $\alpha_{\mathcal{S}}^{n}$ is the allocation principle of the coalition's payoff. The most common allocation principle is the Shapley value [30], given as:

$$\alpha_{\mathcal{S}}^{n} = \frac{|\mathcal{S}|!(|\mathcal{N}| - |\mathcal{S}| - 1)!}{|\mathcal{N}|!} \tag{5}$$

Then, the solution set of the formulated CG can be expressed as $\mathcal{V}_{\mathcal{N}} = \{v_{\mathcal{N}}^{1}, v_{\mathcal{N}}^{2}, \cdots, v_{\mathcal{N}}^{N}\}$. Additionally, before the allocation of coalition profit, the optimization of overall payoff belongs to the single-agent optimization, whose optimal solution can be obtained by a general optimization algorithm [31].

3) Stackelberg Game

SG is a dynamic game behavior, in which both sides in the game make decisions successively because of the asymmetry of their market positions. Both sides constitute a leader-follower relationship. Therefore, such game behavior is often applied in scenarios where one side is an energy seller and the other is a large energy consumer. However, because of the need to consider the follower's strategy as the leader formulates their own strategy, the process of searching for an equilibrium solution in the SG can often be complex and arduous. For an SG, the optimization problem can be expressed as:

$$\begin{array}{cc} \text{Leader problem} & \text{Follower problem} \\ \begin{cases} \min\limits_{x_n, y_m} f_n(x_n, y_m) \\ \text{s.t. } g_n(x_n, y_m) \geqslant 0 \\ \quad\ h_n(x_n, y_m) = 0 \end{cases} & \begin{cases} \min\limits_{y_m} f_m(x_n, y_m) \\ \text{s.t. } g_m(x_n, y_m) \geqslant 0 \\ \quad\ h_m(x_n, y_m) = 0 \end{cases} \end{array} \tag{6}$$

where player n is the leader and player m is the follower; $f_n(x_n, y_m)$ and $f_m(x_n, y_m)$ are payoffs of player n and m, respectively; while x_n and y_m are their strategies; g_n, h_n, g_m, h_m, are the constraints.

To obtain the equilibrium of SG, the Karush-Kuhn-Tucker (KKT) condition is often used [32]. By introducing the KKT condition, the follower problem can be embedded into the leader problem. Consequently, SG is degenerated into single-level optimization problem. To better understand how KKT works, a real example can be found in [32].

4) Bayesian Game

In real-world game-theoretic problems, there is often incomplete information. Game participants cannot fully obtain the decision-making process, payoff or other information on opponents. To solve such a problem, a Bayesian rule is introduced into the game to describe the probability characteristic of the incomplete information [33]. BG has another two factors as well as three basic elements [34]: the type of player and the probability distribution of the types. These are briefly described below:

1) Type of player: Types are usually used to define the incomplete information of participants. Assuming that player n has $\boldsymbol{T}_n$ types, its type space can be expressed as $\boldsymbol{T}_n$ and the type space combination for all participants can be described as $\boldsymbol{T} = \boldsymbol{T}_1 \times \boldsymbol{T}_2 \times \cdots \times \boldsymbol{T}_N$.

2) Belief: Belief is a probabilistic inference of the actual type of other participants according to the available information, and can be calculated as:

$$PR(\boldsymbol{t}_{-n} \mid \boldsymbol{t}_n) = \frac{PR(\boldsymbol{t}_{-n}, \boldsymbol{t}_n)}{PR(\boldsymbol{t}_n)} = \frac{PR(\boldsymbol{t}_{-n}, \boldsymbol{t}_n)}{\sum\limits_{\boldsymbol{t}_{-n} \in \boldsymbol{T}_{-n}} PR(\boldsymbol{t}_{-n}, \boldsymbol{t}_n)} \tag{7}$$

where $\boldsymbol{t}_n$ is the type of player n; and $PR(\boldsymbol{t}_{-n}, \boldsymbol{t}_n) = PR(\boldsymbol{t}_n)$ represents the joint probability distribution when the type combination of all participants is $\boldsymbol{t} \in \boldsymbol{T}$.

From the belief (7), the incomplete game can be expressed in the following form [35]:

$$EP_n(\boldsymbol{t}_n) = \sum_{\boldsymbol{t}_{-n} \in \boldsymbol{T}_{-n}} P_n(\boldsymbol{t}_n, \boldsymbol{x}_n(\boldsymbol{t}_n), \boldsymbol{x}_{-n}(\boldsymbol{t}_{-n})) PR(\boldsymbol{t}_{-n} \mid \boldsymbol{t}_n) \tag{8}$$

where payoff $EP_n(t_n)$ is the payoff of player n with type $\boldsymbol{t}_n \in \boldsymbol{T}_n$. This demonstrates that the key technology for solving the information game mainly depends on establishing the Bayesian probability model. Therefore, for BG on the demand side, the description of the incomplete information probability distribution is one of the main concerns.

5) Evolutionary Game

The above game theory belongs to the classical game theory, in which game players have absolute rationality. However, in real systems, it is unrealistic to assume that participants are completely rational. Accordingly, the EG is proposed based on the fact that participants have bounded rationality, i.e., the participants in EG can only make a rational strategy through some learning mechanisms (e.g., imitation or random selection) [36]. Therefore, an EG mainly focuses on the replication dynamic equation and evolutionary equilibrium. The replication dynamic equation depicts dynamic characteristics of population and evolutionary equilibrium shows the final evolution state of the game. By designing an appropriate replication dynamic equation, the population can gradually achieve its evolutionary equilibrium. Generally, the replication dynamic equation is designed in the following form [37]:

$$\dot{\gamma} = \left[f(x, \gamma) - \bar{f}(x, \gamma) \right] \gamma \tag{9}$$

where γ is the proportion of players choosing strategy x; $\dot{\gamma}$ is the dynamic adjustment of proportion; $f(x, \gamma)$ is the fitness function under strategy x and proportion γ; and $\bar{f}(x,\gamma)$ is the expected fitness value. On the demand side, profit or utility functions are often taken as the fitness function.

III. Game-Theoretic Applications on the Energy Demand Side

A. Game for Distributed Energy Prosumers

Distributed energy prosumers on the demand side can make a two-way energy trading with a power grid company or other prosumers via energy storages, distributed power generations, and EVs. A typical scenario for distributed energy prosumers is shown in Fig. 2, while Fig. 3 shows a typical energy system of a residential prosumer. To reduce energy cost or increase economic profit, the prosumer has to consider multiple factors in the dispatching process of energy output, such as energy market price and load matching degree. Given that such factors are tightly correlated with market participants, the application of game theory can provide an effective way for prosumers to make decisions. At present, the game-based approach for distributed energy prosumers mainly contains NG, CG, SG, and BG.

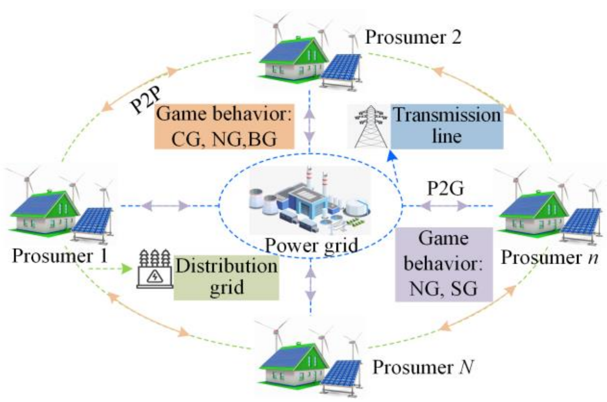

Fig. 2. Typical scenarios for distributed energy prosumers.

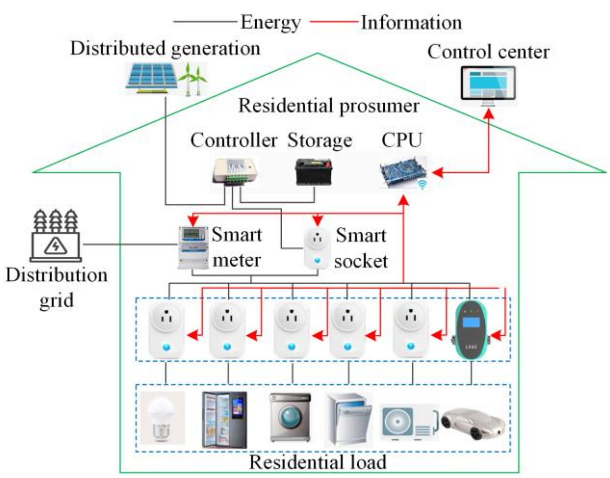

Fig. 3. Energy system of a residential prosumer.

1) Non-cooperative Game

Under an NG pattern, the proposed scenarios in existing researches can be divided into two categories, i.e., one is to describe the game behavior in the trading among prosumers and the power grid company, and the other is to describe the game behavior in the trading among prosumers. In the former, prosumers can only make a two-way energy trading with a power grid company. This is defined as peer-to-grid (P2G) energy trading. In the latter, the energy trading is permitted among prosumers, and is defined as peer-to-peer (P2P) energy sharing/trading.

In P2G scenarios, the game approach is generally formulated via constructing an energy cost/profit function as game payoffs and energy consumption/output scheduling as game strategies [38], [39]. Then, by solving the NE problem, the optimization of energy cost/profit can be achieved by the prosumers in the game. It is good to hypothesize that the DR capability of residential users influences the distributed PV penetration with NG theory [40]. In this case, the cost of user's energy consumption for a year is modeled as the game payoff function, and the load commitment and battery operation pattern are taken as the decision-making strategy. After formulating the game model, the corresponding NE is generally obtained with an iterative algorithm [41]. In [42], NE is achieved by solving the optimization problem with the Nikaido-Isoda/Relaxation algorithm. Except for energy economy, P2G scenarios with NG can also take operational systems into consideration, such as bus voltage, overall system loss, and system reliability [43]. It is workable to focus on analyzing DR's impact on operation parameters through the NG approach, including peak-to-average ratio, bus voltage, and total system loss [44].

P2P scenarios are based on energy sharing among prosumers. Because of flexible energy dispatching, P2P energy trading is an effective way to manage prosumers-based energy [45]. However, since prosumers typically belong to different owners, there must exist inherent competition in the energy sharing process considering the profit-hunting nature of individuals. In such situations, energy balance over the P2P system has to be considered. Consequently, non-cooperative behavior in P2P scenarios is actually a generalized Nash game problem with global constraints [46]. Reference [47] constructs a generalized Nash game model among prosumers in P2P sharing, where the interactions among prosumers in the game process are dynamically reflected via decision-making state transition probability. Additionally, some researchers take P2G and P2P patterns into one scenario. For example, the proposed scenario in [48] assumes that all prosumers can perform both P2G and P2P according to load requirements. Simulation results show that, compared with P2G trading, the outcome of the multi-objective function has a better performance in the P2P energy trading pattern. The summary of the NG for distributed energy prosumers is presented in Table III.

TABLE III
THE SUMMARY OF NG FOR DISTRIBUTED ENERGY PROSUMERS

Reference	Game player	Game strategy	Game objective	Solution method
[38]	DR users	Energy trading amounts with community storage	Minimize cost during time periods	Iterative algorithm
[39]	Virtual power plants	Price bidding strategy	Minimize operation cost	Genetic algorithm
[40]	Smart home consumers	Energy sold to/bought from grid	Minimize energy expenditure in a whole year	Newton-based algorithm
[41]	Smart Buildings	Energy consumption	Minimize overall cost	Iterative algorithm
[42]	Prosumers and consumers	Price bidding strategy	Maximize the expected profit	Nikaido–Isoda/relaxation algorithm
[45]	Retailers and prosumers	Exchanging power	Realize the contradictory objectives of the various players	Nikaido–Isoda/relaxation algorithm
[46]	Prosumers	Generation power and power interaction	Minimize energy cost	Nesterov's method
[47]	Prosumers	Load distribution	Maximize the subjective utility	Dynamic interval adjustment method
[48]	Prosumers	Capacity of distributed generation	Annual profit and the loss of power supply probability	Particle swarm optimization algorithm

2) Cooperative Game

In the CG-theoretical scenarios containing distributed energy prosumers, all game prosumers operate as a coalition, one where members are willing to share energy/profit with other prosumers. Prosumers can borrow/lend renewable energy from/to their neighboring prosumers. this is similar to the P2P energy trading mode [49]. Therefore, to guarantee the stability of partnership, the research concentrates on designing fair allocation mechanisms of coalitional payoff [50]. Currently, the most common allocation mechanisms are analyzed via the Shapley value [51] and the Nash bargaining solution [52].

For the Shapley value-based method, reference [53] proposes two coalitional game-theoretic methods for minimizing the energy cost of residential prosumers. One is based on the scenarios in which prosumers share their renewable energy and storage spaces, while the other assumes that prosumers can sell energy to energy consuming users. After formulating the coalitional cost optimization models, the cost savings are distributed to each prosumer according to the Shapley value. Similarly, in [54], although the coalitional payoff is not distributed with the Shapley value, the proposed Myerson value rule is still based on the marginal contribution of each prosumer, which has the same allocation mode as (4). However, not all coalitional payoffs based on Shapley value can ensure the allocation fairness to maintain coalition's stability, especially when the founded model is not convex [55]. Therefore, from the prospect of the integrality of the theoretical system, it is generally indispensable to prove the allocation fairness and stability for the formulated CG approach.

For the Nash bargaining solution-based method, the participants in the coalition care more about individual interests than they do with the Shapley value-based method. Hence, after obtaining the coalitional profit, participants rush to strive for the best interest via negotiation [56]. For example, in the proposed scenario [57], prosumers and community energy storage develop their strength in the cooperation, e.g., prosumers provide superfluous energy while community energy storage is responsible for storing the energy. The coalition will collapse if anyone quits from the cooperation. Therefore, it is difficult to allocate the coalitional profit according to the marginal contribution of the individual since the contribution of each participant is essential to the coalition. Cheating behavior is also discussed in the case where prosumers try to obtain more profit by providing false information. The summary of CG for distributed energy prosumers is presented in Table IV.

TABLE IV
THE SUMMARY OF CG FOR DISTRIBUTED ENERGY PROSUMERS

Reference	Coalition	Coalitional strategy	Coalitional objective	Allocation mechanism
[50]	Households	Energy sold to/bought from grid	Maximize the expected profit	Nucleolus-based solution
[51]	Prosumers	Generation amount	Maximize the profit	Shapley value
[52]	Passive/Active users	Energy consumption scheduling	Maximize individual cost	Nash bargaining solution
[53]	Households	Energy sharing strategy	Minimize the cost of electricity	Shapley value
[54]	Prosumers	Trading quantity and price	Minimize the cost of electricity	Myerson value
[55]	Communities	Power generation and consumption	Maximize the profit	The worst-case excess minimization
[56]	Residential users	Energy consumption	Minimize individual bill and system peak demand	Nash bargaining solution
[57]	PV prosumers and community storage	Energy sharing profile	Minimize social energy cost	Nash bargaining solution

3) Stackelberg Game

In the traditional energy trading mode without the penetration of distributed energy prosumers, the SG generally consists of retailers and energy consumers, where retailers are considered to be the leader with a leadership advantage, while energy consumers are the follower and follow the leader's decisions. However, with the appearance of distributed energy prosumers, the master-slave relation among game players becomes diversified in the SG. At present, according to the master-slave relation, SG generally contains two categories: one is similar to the traditional energy trading mode [58], and the other is that some prosumers are considered as the leader and other prosumers or power grid company are the followers [59].

For the first category of SG, retailers act as the leader who usually determines energy price for prosumers to maximize the self-profit or social welfare, while prosumers act as the followers who generally determine energy consumption and generation to minimize their costs [60]. For example, reference [61] proposes an SG-based mechanism considering storage, PV generation, and all class of household appliances. In the formulated game model, the master-level model is built based on the retailer's profit to optimize the energy real-time price, while the slave-level model is designed based on the energy cost and satisfaction constraints to obtain the optimal energy demand. Similarly, an SG approach is put forward in [62] for trading between the microgrid operator and prosumers. The microgrid operator, taken as the leader, has a responsibility to coordinate the energy sharing among prosumers to maximize profit, while the prosumers, taken as the followers, operate as a coalition to maximize their utilities and these will be regulated by each prosumer's contribution to the actual profit of the operator.

For the second category of the SG, the scenarios generally assume that prosumers who have superfluous produced energy will take part in the trading as the leader, while other prosumers or consumers who have a deficit in energy demand will purchase energy from the superfluous prosumers as followers [63]. In fact, such scenarios belong to typical P2P scenarios. Different from the non-cooperative or CG behaviors in the P2P scenarios, the application of the SG in P2P has considered the dominant position of energy surplus prosumers who retain more decision-making power in the trading. In [64], a robust SG approach is formulated for aggregate prosumers to manage day-ahead energy where it is constructed with the consideration of the uncertainty of distributed energy and market price. In the formulated scenarios, prosumers are divided into one superior and multiple inferior prosumers. The superior prosumer acts as the leader and is responsible for formulating the internal price mechanism and energy consumption scheduling strategy of the aggregate prosumers, while inferior prosumers act as followers who respond to the price signal issued by the superior prosumer. A double auction-based SG-theoretical approach is designed in [65], where each prosumer can choose its role (i.e., a buyer or a seller) according to its energy consumption and generation at each time slot. That is, the master-slave relation is not fixed in the energy trading.

4) Bayesian Game

Compared with NG for distributed energy prosumers, BG-based scenarios take the incomplete information into consideration, such as energy price or player privacy. In [66], [67], incomplete information is described with probability distribution characteristics, Markov state transition probabilities, etc. Then, based on the description of the incomplete information, the expected payoff function can then be formulated with a Bayesian formula, which is the payoff of the BG. Finally, the solving algorithm is designed for Bayesian NE, which is similar to NG.

The scenario in [68] assumes that the residential community provides a charging and discharging service for EVs but the service fee standard is unknown to other communities. Thus, communities are classified as different types based on the probability characteristic of the fee standard. Then, the incomplete information scenario is described as a BG. As for the proof of the existence of Bayesian NE and the distributed algorithm, the basic principle and the iterative process are similar to the applications in NG. Similarly, an energy trading BG model is built aiming at the optimal dispatching of EVs, where the incomplete information is caused by the stochastic characteristics of EVs [69]. To describe such incomplete information, the expected payoff is constructed by Bayesian probability over the estimation of other players' types, and then a best response is made to the decision behaviors of others. To increase the penetration of distributed generations, reference [70] build a BG model for the scenario where only partial game information is shared among consumers. A game-based DR algorithm is designed with stepwise price to obtain different equilibrium states according to information sharing degree among categorized consumers. Simulation results show that consumers who are willing to share maximal information will increase payoffs. It also demonstrates that the BG will reduce the payoffs of players because of the loss of partial game information.

B. Game for Small- and Middle-sized Users

Despite the modest energy requirements of small- and medium-sized users, their substantial numbers endow them with considerable potential in DR initiatives. The electricity market mainly attracts small- and middle-sized users to actively participate in DR by adjusting the market price mechanism. A typical scenario for small- and middle-sized users is shown in Fig. 4. At present, under various market price mechanisms, the application of game theory for small- and middle-sized users mainly contains NG, CG, SG, BG, and EG.

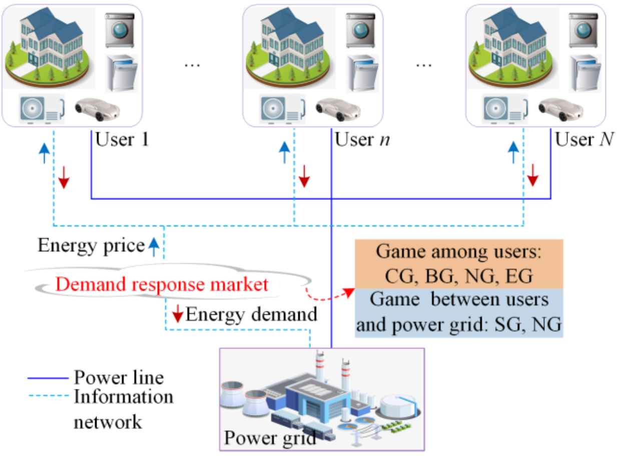

Fig. 4. Typical scenarios for small- and middle-sized users.

1) Non-cooperative Game

Among game-theoretic approaches for small- and middle-sized users, the NG has the most extensive applications since it can precisely describe the profit-seeking behaviors of residential/commercial users [71]. The existing researches are mainly being carried out from the following two aspects: one is to describe the game behavior in the scenarios containing one energy seller and multiple users; and the other is for scenarios containing multiple energy sellers and users. In the former, the main focus is on the design of a market mechanism (e.g., market price mechanism) in order to guarantee the existence and uniqueness of NE for NG among residential/commercial users, who have the same decision-making positions in the DR process [72]. In the latter, it mainly concentrates on the strategical interaction between energy sellers and users, and the non-cooperative competition behavior among interior sellers/users [73].

For the scenarios containing one energy seller and multiple users, the energy cost function or the billing mechanism for an energy seller (or a utility company, an energy provider) is designed first. The NG is then formulated to minimize energy cost or peak-to-average ratio [74]. Finally, the existence of NE and the distributed algorithm are presented according to the formulated game approach. This can be shown in a typical model, where an energy price model is expressed as [75]:

$$p_h(L_h) = a_h(L_h)^{b_h} + c_h \tag{10}$$

where $a_h > 0, b_h \geqslant 1, c_h \geqslant 0$ are price parameters and L_h is energy demand during time slot h.

As the price model will degenerate into the energy pricing form in [76] when the value of b_h is set as 1, NG is formulated to minimize the user's total cost and the corresponding NE is unique when parameter b_h satisfies $b_h < 3 + 4/(N-1)$, where N is the number of game players. As shown in the simulation using the designed energy price model, users are encouraged to participate in DR to shift peak-time energy consumption. Some common functions are summarized in Table V. Additionally, in recent years, considering the limitation of single small- and middle-sized users on DR performance, a form called the 'aggregator' is introduced into the DR market with game-theoretic application [77], [78]. The related research has a similar research process to [74]–[76], but the energy consumption scheduling is executed at cluster-level. For instance, reference [79] proposes a NG-based strategy for cluster-level buildings to schedule energy consumption. In this study, the building clusters are regarded as game players, who take part in the competition with other clusters for the purpose of minimizing the daily energy bill of the buildings.

TABLE V
THE SUMMARY OF ENERGY COST/PRICE AND UTILITY/SATISFACTION FUNCTION

Energy cost/price function	Energy utility/satisfaction function	Reference
$p_h(L_h) = a_h L_h \log(L_h + 1)$	$U_h(L_h) = 1 - \mathrm{e}^{-a_h L_h}$	[72]
$p_h(L_h) = a_h(L_h)^{b_h} + c_h$		[75]
$C_h(L_h) = a_h L_h^2 + b_h L_h + c_h$		[74], [76]–[79]
$C_h(L_h) = -a_h \log\left(1 - \frac{L_h}{b_h}\right)$		[82]
$C_h(L_h) = a_h L_h^2 + b_h L_h + c_h$	$U_h(L_h) = \begin{cases} a_h L_h - \frac{b_h}{2}(L_h)^2 & 0 \leqslant L_h \leqslant \frac{a_h}{b_h} \\ b_h(L_h)^2 & L_h > \frac{a_h}{b_h} \end{cases}$	[83]

For the scenarios containing multiple energy sellers and users, NGs will be formulated for the seller and demand sides, respectively. The interaction between seller and demand sides is completed via energy price and demand. This is similar to the interaction in the SG. For example, in [80], two NGs are built: seller and demand side games. In the first game, the profit maximization problem for energy sellers is formulated with the bidding mechanism, while in the second game, users aim to maximize the daily payoff. Based on the two games, the existence and uniqueness of the corresponding NE are analyzed. Simulations performed for 3 energy sellers and 1000 users show that the superior performance of the proposed mechanism in flattening load level and increasing seller side profit and demand side payoff. Similarly, reference [81] propose a double-sided NG based on the supply function equilibrium and the energy consumption scheduling models. To search the two NEs of the double-sided game, the gradient ascent and Rosen's gradient projection methods are applied. The summary of energy cost/price and the utility/satisfaction function is presented in Table V, where the meaning of p_h, a_h, b_h, c_h, L_h is consistent with (10), i.e., $C_h(L_h)$ and $U_h(L_h)$ represent the energy cost and energy utility/satisfaction for consuming energy L_h.

2) Cooperative Game

Compared with the application of CG for distributed energy prosumers, small- and middle-sized users cannot realize the cooperative interaction via energy exchange. However, they can negotiate their energy consumption and obtain the Pareto optimal strategy to reduce energy cost or increase energy utility for the formulated coalition [84]. Alternatively, from the cluster-level, load aggregators participating in the DR market can reach agreements on DR bidding price or energy trading amount via CG theory. Considering that users may quit from the cooperation to increase self-profit, the punishment mechanism for betrayal is often discussed in a CG [85].

In [86], a cooperative DR strategy is proposed to reduce user energy costs where the non-cooperative behavior in the cooperation was accounted for. Here, a cooperative DR model is formulated by minimizing coalition's total cost, including discomfort cost and energy cost. To force all members to be in the coalition, a special energy price model is designed to detect user's non-cooperative behavior with a Cartel mechanism, and selfish users will be punished by a punishment rule. For a CG among load aggregators, reference [87] puts forward a bargaining-based cooperative model. In the game mechanism, seller and demand sides collaboratively decide the energy trading amount and the associated payments. To allocate the increased benefit from cooperation among these participants, Nash bargaining theory is employed, which can guarantee the fairness of the allocation. As the Nash bargaining theory is developed from the initial disagreement point which is the equilibrium solution of the SG among distribution company and aggregators, it indicates that game participants will gradually tend to cooperation for a higher profit when they cannot achieve more from NG. Different from [87], a Shapley value-based CG is proposed to determine the incentive scheme of load aggregators in [88]. In the proposed framework, a fairness allocation strategy with Shapley value is designed to enhance the willingness of users in the DR. A case study with IEEE benchmark distribution networks shows that the proposed framework can achieve fairness rebate allocation among aggregators.

3) Stackelberg Game

In the SG approach for small- and middle-sized users, the master-slave relation among game players is largely clear. That is, energy supply side (i.e., energy retailer [89], utility company [90], and power grid [91]) or energy management side (i.e., energy management center [92] and load aggregator [93]) participates in the game as leader, while the energy demand side (i.e., household appliances and EVs) is in the follower position. For the follower, the optimization problem generally aims to minimize/maximize energy cost/utility, whereas for the leader, the optimization goals have diversified forms, which can be divided into profit-oriented and social welfare-oriented forms. For the profit-oriented leader, the maximization of the trading profit is the sole aim [90], [94], while for the social welfare-oriented leader, other optimization goals are also considered, such as user satisfaction cost and demand fluctuation cost [95].

In the researches on the SG-theoretical approach with the profit-oriented leader, there are basic modeling process. That is, the energy supply side mainly focuses on the optimization of offering energy price to increase income or profit, whereas the energy demand side will schedule energy consumption behavior to decrease energy cost or increase energy utility. The differences in the existing research approaches depends on whether consideration is from the trading scenarios or the optimal model design. It can be seen that an SG is first designed between a single utility company and users [96]. However, studies have found that such a trading mode will lead to monopoly and discourage other users from participating in the DR. Then, an SG among multiple utility companies and users is proposed. This can promote competition in the electricity market. Different from the framework in [96], the researchers in [97] focus on the design of the utility function that can better shape the objective function. Some studies take the system operation constraints into consideration in designing a DR framework with an SG [98], whereas reference [99] introduces voltage and current shadow costs in describing the competition among a load aggregator and flexible users, where a network-constrained SG framework is formulated.

In the researches on SG-theoretical approach with a social welfare-oriented leader, the leader has various optimization targets, such as increasing the DR satisfaction, reducing the fluctuation of energy demand [100], or minimizing the mismatch between supply and demand sides [101]. To obtain feasible results, the optimization targets are usually converted into economic objective functions that can be combined and optimized with the leader's trading income. For instance, reference [100] develops a non-cooperative Stackelberg model considering the influence of load fluctuation and users' dissatisfaction. To achieve the goal of minimizing the load fluctuation, the fluctuation cost is designed as a quadratic form about the difference between the energy demand in a certain period and the average demand in a whole day. At the same time, some studies are not just at the economic level. In [102], an objective function is formulated for utility company (leader) to determine the optimal generation strategy while meeting the energy demand of users. Generally, such a modeling method will perform better on the pursued target than the economic-based way since the pursued target may be weakened in the economic-based way. The summary of SG for small- and middle-sized users are presented in Table VI.

TABLE VI
THE SUMMARY OF SG FOR SMALL-AND MIDDLE-SIZED USERS

Reference	Leader/follower	Solution method	Main contribution
[89]	Retailers/customers	Interior point method	Consider the constraint of EV charging requirements
[91]	Power grids/buildings	Backward induction	Develop the basic and enhanced interaction strategies based on identified Nash equilibria
[93]	Aggregators/EVs	Gradient descent method	Consider the uncertainty in the energy demands
[94]	Retailers/devices	Interior point method	Propose a light-weight DR scheme based on the Stackelberg model without iterations
[95]	Retailers/consumers	Genetic algorithm	Study how electric storage space heating loads can be optimally controlled using price signals
[96]	Utility companies/customers and EVs	Particle swarm optimization	Prove that EVs will discourage other customers to participate in DR programs
[97]	Retailers/consumers	Adaptive diffusion algorithm	Propose a framework that can optimize aggregate cost, utility, and retailer's profit simultaneously
[100]	Power dispatching center/users	NSGA-II algorithm	Consider the influence of load fluctuation and users' dissatisfaction
[102]	Utility companies/users	Iterative algorithm	Adopt a pricing function to encourage users to join the proposed game

4) Bayesian Game

The BG-theoretical approach has not been extensively applied to the small- and middle-sized users. Different from the application of the BG for distributed energy prosumers, in which the incomplete information can come from distributed generation, market price, or participants privacy, existing researches for small- and middle-sized users mainly concentrates on the description of incomplete information from the behavior characteristics of game players, such as energy consumption level (i.e., high, moderate, or low) [103], and bidding habit (i.e. bid high, bid low, etc.) [104].

More specifically, a model is built to analyze the energy trading problem between the grid and the users as a BG, in which the real-time energy demand and energy price belong to incomplete information [103]. To describe the incompleteness of information, the probability-based strategy for user's demand and grid's price are formulated respectively by dividing the energy demand level and the energy price into different types (i.e., high, moderate, or low). Accordingly, the payoff function of the BG is founded and its Bayesian NE is proved to be unique. Simulation result shows that the utility of the grid in the proposed scheme can increase by approximately 40% over that in the scenario where energy demand with packet loss is not estimated and received directly. Aiming at the BG among load aggregators, studies have been carried out in [104], [105], where the BG is employed to describe the competition among load aggregators, in which each aggregator has imperfect information on other opponents' costs. Thus, each load aggregator will evaluate the strategic biddings of other aggregators using different scenarios that contain various bidding strategies (i.e., bid high, bid low, etc.). Under the assumption, game participants are divided into different types that can be described with probability distribution. After this, the expected profit of the aggregator is formulated by building the conditional probability about the types of game participants and the profit function of the participants with the corresponding types.

5) Evolutionary Game

In the EG, game participants are assumed to have bounded rationality and make decisions based on imitation or random selection. Therefore, the EG-theoretical approach for small- and middle-sized users mainly focuses on the decision-making behavior from the layer of the user population. It should be noted that the primary purpose is to analyze the selection dynamics of the population with the designed replicator dynamics. The application scenarios with EG mainly fall into two categories.

One scenario is to analyze the dynamic process of the user population on energy consumption behavior, e.g., users decide whether to be in the DR or other kind of energy consumption mode [106]. In [107], the decision-making issues in DR are investigated from the perspective of multi-population EG. In the formulated scenario, each user has two incompatible strategies during each period of DR, i.e. in DR or not in DR. User's expected profit consisting of DR incentive profit and comfortable utility will be different for different choices. To analyze the dynamic trend of the population of users choosing to be in DR, the replication dynamic equation is designed according to the form in (9). Simulation results show that the DR incentive mechanism plays an important role in promoting the user population to participate in DR. This can provide a decision basis for the DR project. In [108], users can make a choice from feed-in tariff or real-time tariff and microgrids can decide whether the operation is on isolated or grid-connected state. Accordingly, the equilibrium strategy of microgrid is deduced for both stable and flexible users.

The other scenario is for the energy trading market with multiple energy sellers, e.g., users select which one to purchase energy [109], [110]. In such scenario, the energy trading mode is similar to the mode in the application scenarios of the NG or SG containing multiple energy sellers and multiple users. The difference is that the dynamic process of the user population choosing which one to purchase energy is the emphasis in the scenario with the EG. For instance, a two-level game is modeled in [111] to solve the energy trading problem between utility companies and residential users, in which residential user behavior is described as an EG. According to the EG theory, the selection dynamics of the population are designed by comparing individual utility and average utility. A case study illustrates that users will choose one utility company with a certain probability and the population choosing any company will tend to in a stable state. The semi-tensor product theory is often applied in the formulation of an EG. For example, in [112], a scenario is proposed where individual communities can switch between grid power and local power to purchase energy based on the strategies of their neighbors. Then, the semi-tensor product is introduced into the model to solve the formulated EG systematically.

C. Game for Large Energy Consumers

Figure 5 shows the typical scenarios for large energy consumers. With the increase of power market reform, energy trading for large energy consumers has multiple forms, in which the two main trading forms are the most popular at present [113]. One form is similar to the trading for small- and middle-sized users, where the energy seller side is usually the power grid company, retailer, or utility company [114], where the other form is that large energy consumers can purchase energy directly from an energy generation company because of the high energy demand level. Since both sides want to improve their interest in the trading of direct power purchase, game theory can be applied to provide the decision-making basis for the purchasing and selling strategy. At present, the game-based approach for large energy consumers has covered CG, SG, BG, and EG.

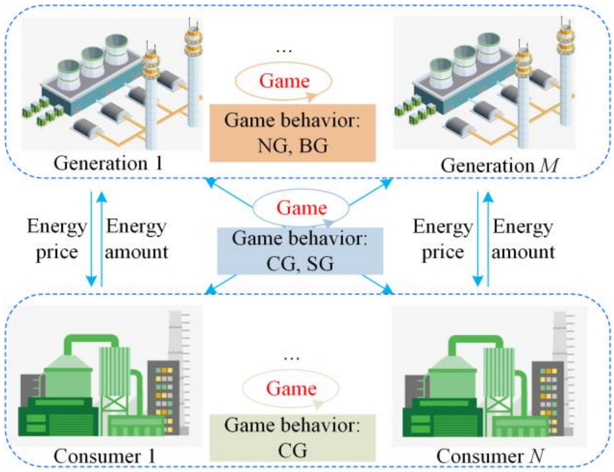

Fig. 5. Typical scenarios for large energy consumers.

1) Cooperative Game

In the application of the CG for large energy consumers, the direct power purchase transaction is usually completed via negotiation between energy generators and large consumers. Since there is no middleperson who will earn profit in the trading, the direct power purchase transaction can make higher profit margins. To allocate such profit reasonably, energy generations and large consumers can make bilateral contract with Nash bargaining process to guarantee the interest of both sides [115].

In [116], a negotiation process is proposed to sign a financial bilateral contract between the generation company and load-serving entity considering a locational marginal pricing mechanism. Since the bilateral contract is an essential risk-hedging instrument in the trading, both sides can negotiate to achieve a favorable balance between expected profits and financial risk exposure. Simulation results show that different degrees of risk aversion and deviation in locational marginal pricing estimation will have a systematic impact on the negotiation agreement. In [117], a bilateral pricing game-theoretic approach is formulated to balance and maximize bilateral profits for wind-thermal combined generation, in which the profit distribution is realized by the Nash negotiation process. By analyzing specific examples, it demonstrates that the proposed direct power purchase trading mechanism can achieve a win-win situation between generations and large consumers.

2) Stackelberg Game

The SG has the most extensive application for large consumers since it can precisely describe the master-slave position between generation companies and large consumers in the trading. Existing researches show that the related work is conducted basically from the two main trading forms mentioned above [118].

In the trading form that is similar to the trading for small- and middle-sized users, researches focus not only on the strategy optimization for large consumer, but also discuss the application from the overall load level, including residential, commercial, and industrial loads. Such researches are similar to the game-theoretic application for small- and middle-sized users from energy trading mechanism or method architecture. For example, reference [119] proposes a one-leader and N-follower SG to describe the decision-making behaviors of network operator and customers. In the proposed game model, except for the model of residential users, industrial consumers, acting as a part of followers, are also modeled to maximize their profit. Similarly, to formulate an SG-based framework involving massive DR resources, reference [120] establishes a comprehensive resource management mechanism for large industrial consumers and small- and middle-sized customers.

In the research on the direct power purchase trading form, related work is presented mainly for bilateral contracts and incentive-based DR. A good example can be found in [121], where an SG is constructed to sign energy bilateral contracts, in which large consumers and generation companies act as the leaders and the followers, respectively. After a generation company and a large consumer finalize energy prices and quantity, they are allowed to sign a bilateral contract if their agreed energy quantity satisfies all network constraints. Compared with the research that only considers the bilateral contract, incentive-based DR scenarios generally assume that large consumers can reduce their energy consumption in the trading, and that, the trading will contain more participants, including the generation, grid, and demand sides. For instance, reference [122] studies the impacts of incentive-based DR on power grid, generation companies, and industrial users in the direct power-purchase trading. Research results show that the power grid companies should implement DR since all the participants will obtain the benefits.

3) Bayesian Game

Although the electricity market is gradually opening, lots of information is still private. Therefore, it is inevitable that incomplete information game theory will be employed to describe the decision-making behavior in market competition. At present, in applications of the BG for large energy consumers, incomplete information is generally considered from the generation side, such as the bidding price and generation cost.

In [123], a scenario is proposed where large consumers can trade with generation companies directly. To describe the incomplete information about the bidding price parameter of each generation company, a BG model is formulated among multiple generation companies. In the game, each company can evaluate the private information of other companies according to type space combination and probability distribution. Simulation results demonstrate that information incompleteness has a negative influence on game player's payoff. A similar study can be found in [124], where the researchers analyze the direct bilateral bidding transactions between generation and large energy consumers based on the BG. In this paper, the cost of generation is unknown to other generators and is subjected to a uniform distribution. Basically, Bayesian NE can be obtained by solving the maximization problem of the generation's and consumer's utility.

IV. Prospects for Applications of Game Theory on the Energy Demand Side

A. Prospects from Perspective of Application Scenarios

1) Energy Scheduling Strategy for Prosumers

Ongoing reform in the electricity market has led to the integration of prosumers equipped with distributed energy as an essential component of energy sellers. Nevertheless, energy scheduling for prosumers will face many challenges, especially as their numbers continue to rise. Therefore, game-theoretic approaches are worth further research in the related application scenarios.

For the power grid, the massive access of distributed energy will certainly affect its security and stability. Therefore, it is meaningful to study how to coordinate the trading period and power among distributed energy clusters to maintain power system's safety and steady operation, whereas CG theory is suitable for analyzing such a problem. By introducing relevant indicators to measure the interactive power fluctuation between prosumers and energy suppliers, the coalition can use the collaborative optimization function to reduce the impact. Additionally, distributed generation, energy storage, and EVs can be used as auxiliary equipment for regulating the grid's frequency. It is worthwhile to conduct intensive studies with a CG to formulate optimal strategies for achieving better performance. The allocation of income obtained by the coalition in providing frequency service is also a feasible direction in this field.

For prosumers, in the past, the power and capacity of distributed power generation, and energy storage were mainly optimized to satisfy self-demand. Nevertheless, when users are permitted to sell energy to energy suppliers or other users, the configuration of distributed energy needs to consider not only their own demand, but also the trading income and the impact of other prosumers on the trading market. In this case, the optimal configuration of distributed energy for prosumers is expected to be solved with an NG. For instance, the investment, operational and maintenance costs, and the trading income can be comprehensively considered. Then the NG model can be built among prosumers to search NE as the optimal configuration.

2) Energy Purchasing Strategy for Large Consumers

With the improvement and development of trading mechanisms in direct energy-purchase, large consumers who are sensitive to energy price can purchase energy from different markets, including forward contracts, options, and spot markets. Energy price and its fluctuation are different in different markets. Therefore, for large consumers, how to reasonably distribute the purchased energy in each market to reduce energy cost is a critical problem. For a generation company, how to make price quotation strategy in each market to attract more consumers is also an inevitable problem. Such problems can be solved with an SG. The basic process is to build energy purchasing strategy models for large consumers and price quotation strategy models for generation companies, respectively. Then, a distributed algorithm is designed to solve the equilibrium problem. Here, the efficiency of the algorithm is also an important research direction.

In addition, the information about large consumers and generation companies may be concerned with a privacy issue, i.e., points unknown to other competitors. Most existing researches assume that the cost function or quotation of generation company is unknown information. However, in the real market, the unknown information is much more than that, such as, the maximum capacity of the generation company, load demand of large consumers, and energy price in the spot market. Consequently, when there are many kinds of unknown information in the trading, the problem can be solved with a BG. The critical problem is how to divide type space and calculate the joint probability distribution based on the probability characteristics of unknown information.

3) Demand Response for Small- and Middle-sized Users

There are significant differences in energy consumption behaviors, load types and consumption views among small- and middle-sized users. Most existing DR programs with game-based approaches have not fully considered the differences of users, resulting in inaccurate scheduling results compared with the real-world system. Therefore, the following research directions need to be further studied.

For residential users, in most existing researches, there is a hidden assumption that all residential users are willing to participate in DR. Then, users will be involved in game competitions to maximize self-profit. However, in real life, it is impossible to attract all users to be in DR, and therefore, to attract more users, the DR mechanism should take behavioral characteristics of users into consideration. For example, an economic compensation mechanism in the residential DR is an important factor, while consumer psychology theory has to be considered in the construction of the DR game-based model. Since a DR project may take a long time to implement, some users may participate while others may exit during the period. Therefore, considering the dynamic participation of users, it is necessary to employ repeated game theory to analyze the competition over long time scales.

For commercial users, the air conditioners are the main flexible DR resource, which can be aggregated to participate in DR by load aggregator. On the premise of guaranteeing user comfort, the load aggregator controls the operation of air conditioners to reduce energy demand and then obtain profit from the energy suppliers. In such scenarios, the problem of how to balance DR effect and cost can be solved through Nash negotiation theory. That is, DR effect and cost can be regarded as two negotiating individuals and each part takes its own optimal goal as the basis for decision-making. After multiple rounds of games, both sides reach a compromise, so as to obtain the equilibrium between DR effect and cost. The conflict of interest between the energy supply company and the aggregator can be effectively analyzed by zero-sum game theory. For market share competition of load aggregators, this problem can be solved with an NG or BG.

B. Prospects from Perspective of Application Methodologies

1) Applications of Potential Game Theory

By reviewing the existing research on game-theoretic approaches, it is found that proving the existence of an equilibrium solution is indispensable. The complex proof limits further applications of game theory. To solve this problem, the potential game provides a novel solution [125]. NE in the potential game can be guaranteed with finite improvement properties, thus avoiding the tedious proof. Reference [126] proposes a potential game approach to solve the economic dispatch problem. Also, the optimization process in the potential game is open and dynamic, whose convergence can be achieved with no limits to type or number of players. However, at present, researches on the application of the potential game have not been concerned extensively on the demand side. Therefore, it has a great potential for applying such game theory to describe game behavior for users, especially for heterogeneous and numerous residential users.

Additionally, to guarantee that the optimal solution of each game player satisfies constraint conditions from the overall level (e.g., the energy balance constraint), the game model has to satisfy the coupled constraints among all players. To handle the complicated coupled constraints effectively, reference [127] extends the potential game to a state-based potential game by introducing auxiliary state variables to handle the constraints. Therefore, the state-based potential game also deserves to be studied for demand side users, especially for game behavior with complicated coupled constraints.

2) Applications of Complex Network Game Theory

Demand users generally have the problem of low rationality and their decisions may influence each other.

Especially for residential users, herd behavior will have a non-ignorable impact on decision-making process. For example, whether some residential users participate in DR may depend on the participation of their neighbors or friends. Therefore, their decision behavior may heavily depend on their rationality and social network. Considering the complex relationships of social networks, complex network game theory can contribute to research on decision strategy.

From Fig. 6, game behavior on the social network can be translated into complex network game behavior. To quantitatively analyze the influence among user nodes in the decision-making process, graph theory can be introduced to characterize the association relationship among users. As seen in Fig. 6, a node $V(D)$ represents a demand user, the edge $E(D)$ represents whether the two nodes have association relationship, and $\Psi(D)$ is a correlation function to measure the degree of influence. Based on such a complex network game structure, individual/coalitional interaction behavior can be analyzed for DR population evolution or coalition cooperation considering the complexity of social networks.

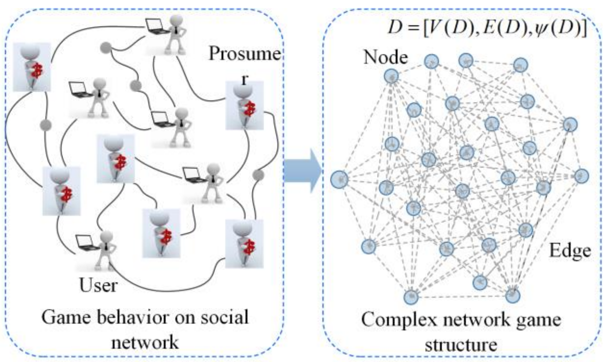

Fig. 6. Game behavior in a complex network.

3) Distributed Algorithm for Nash Equilibrium

For the applications of game theory on energy demand side or in power systems, it is necessary to search for the equilibrium of the formulated game-theoretic model. In existing research, the widest solution algorithm is designed based on the following game process:

1) Each game player selects its strategy randomly.

2) One player updates the strategy for maximal payoff by solving optimal problem.

3) The new strategy is broadcasted to other players, and, other players update the strategies for maximal self-payoff in turn.

4) Repeat the steps of (2) and (3) until no player updates the strategy. Such equilibrium state is NE.

Figure 7 shows the strategic interaction in the game process for N game players. In such a distributed algorithm, complex game information interaction is inevitable among game players. It demonstrates that each player has to broadcast strategy to other players via a communication network in step (3). From the computational perspective, it is hard to handle the problem for the scenarios with a large number of users, because computational complexity grows rapidly with the increase in players. It can be seen that the running time of the algorithm reaches 231.65 s with only 15 players [68]. Therefore, the game theory in power systems is mainly applied in optimizing the planning decision, such as, day-ahead energy consumption scheduling. For the scenarios considering the trading decision in real-time, it is difficult for the existing algorithm to search the equilibrium solution on a real-time scale. Moreover, from the perspective of communication, frequent information interaction can cause communication jam. Therefore, to improve the feasibility and further development of the game approach in power systems, it is significant to design the distributed algorithm that can reduce the communications among players and improve solution efficiency.

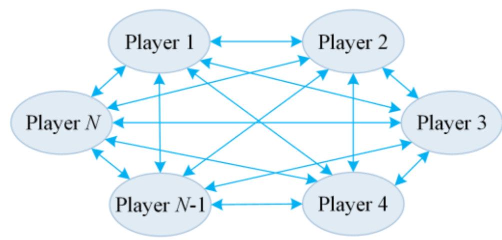

Fig. 7. Strategy interaction in the game process.

V. Conclusion

The open market environment and multi-agent decision-making characteristics on the energy demand side provide a promising opportunity for the application of game theory. This paper aims to review the state-of-the-art research and development in game theoretical approaches pertaining to the demand side, with specific focus on three key aspects: classification, methodology, and application scenarios. The literatures reviewed in the work reveals that NG, CG, SG, BG, and EG are the main applications used to describe the decision-making behavior of demand users, and the application scenarios mainly contain P2G/P2P trading, DR scheduling, and energy direct trading for distributed energy prosumers, small- and middle-sized users, and large energy consumers. The results derived from these studies demonstrate that the integration of the energy demand side with game-theoretic applications contributes to more efficient and economic power systems.

Based on the existing researches, we suggest prospects for promising applications of game theory on the demand side. For application scenarios, more game-based scenarios can be introduced catering to the needs of demand side users. Similarly, more game-based modeling theories should be introduced to describe the competitive behaviors, such as potential game theory and complex network game theory.

In recent years, energy consumption has become the main source of carbon emissions [128]–[130], e.g., carbon emissions in the power industry account for about 40% of the whole emissions in China. Therefore, solving the problem of carbon emissions in the power industry will be the key to achieve the goal of carbon neutrality. Under such a global national macro policy, game theory will have more extensive applications on the energy demand side. With the applications of game theory in multiple decision-making, a large number of demand users can be absorbed into an energy consumption scheduling scheme, to improve terminal energy efficiencies and reduce carbon emissions. In this paper, game theory researches are reviewed and prospects are discussed in detail. Related work is expected to provide some worthwhile thoughts for the application of game theory on the demand side.

ACKNOWLEDGMENT

Not applicable.

AUTHOR'S CONTRIBUTIONS

Zhenya Ji: collect all the materials, write the manuscript. Xiaofeng Liu: write, review, edit, and revise the paper. Difei Tang: revise the grammar of the paper. All authors read and approved the final manuscript.

FUNDING

This work is financially supported by the National Natural Science Foundation of China (No. 52107100) and the Basic Science (Natural Science) Research Project of Jiangsu Higher Education Institutions (No. 23KJB470020).

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

DECLARATIONS

Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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