A Critical and Comprehensive Handbook for Game Theory Applications on New Power Systems: Structure, Methodology, and Challenges

Bo Yang, Yimin Zhou, Yunfeng Yan, Shi Su, Jiale Li, Wei Yao, Hongbiao Li, Dengke Gao, and Jingbo Wang

***Abstract*—To effectively promote renewable energy development and reduce carbon dioxide emissions, the new power system integrating renewable energy sources (RES), energy storage (ES) technology, and electric vehicles (EVs) is proposed. However, the generation variability and uncertainty of RES, the unpredictable charging schedule of EVs, and access to energy storage systems (ESS) pose significant challenges to the planning, operation, and scheduling of new power systems. Game theory, as a valuable tool for addressing complex subject and multi-objective problems, has been widely applied to tackle these challenges. This work undertakes a comprehensive review of the application of game theory in the planning, operation, and scheduling of new power systems. Through an analysis of 143 research works, the applications of game theory are categorized into three key areas: RES, ESS, and EV charging infrastructure. Moreover, the game theory approaches, payoff/objective functions, players, and strategies used in each study are thoroughly summarized. In addition, the potential for game theory based on artificial intelligence is explored. Lastly, this review discusses existing challenges and offers valuable insights and suggestions for the future research directions.**

***Index Terms*—Game theory, new power system, operation and scheduling, planning, SimuNPS.**

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I. INTRODUCTION

With the depletion of fossil energy and the deterioration of the environment [1]–[3], achieving a clean and sustainable energy supply is becoming the focus of discussions [4]–[7]. As a key area in the energy transition and carbon emission reduction, the new power system effectively promotes energy transformation and supports sustainable development [8]. However, the stochastic nature and uncertainties of renewable energy sources (RES) generation [9]–[11], coupled with the rise of distributed energy storage systems (ESSs) [12]–[14] and electric vehicles (EVs) [15], [16], pose significant challenges for decision-makers in the planning and operation of power systems [17]–[20].

Specifically, on the electric transaction side, the generation market transitions from a monopolistic structure to a competitive one, driven by power decentralization [21]–[23], leading to a greater diversity of decision-making entities involved in power market. On the demand side, the emergence of active electricity loads such as EVs, characterized by high randomness and strict power quality requirements, further complicates the interaction between power generation and consumption [24]–[26]. These challenges above enhance the complexities of managing diverse decision-making entities and their objectives in the planning, operation, and scheduling of new power systems [27]–[29].

Game theory is a powerful tool for solving intricate subjects and multi-objective problems [30]–[32]. Initially, the applications of game theory in power systems can be traced back to the power market, which falls within the realm of economics. Over time, game theory has been applied in various areas of power systems, such as energy markets [33], [34], power system reliability [35]–[37], and demand side management [38], [39], which is the main pillar of the new power grid. With the development of power systems, the analysis methods based on game theory are also advancing. Consequently, there exists a notable difference between the game models based on the characteristics of the new power system and the traditional power system [40]. Furthermore, the specific comparison is presented in Table I.

TABLE I
COMPARISON OF GAME THEORY MODELS IN POWER SYSTEM

Comparison elements	Traditional power system	New power system
Decision agents	Dominated by large companies (e.g., centralized power producers, main power grid)	Distributed generation (DG), ESSs, EVs virtual power plant etc. emerged
Player characteristics	Fixed players, limited number, and dominated by large companies	Various types and numerous quantities of players, and multiple entities involved
Mathematical models	Dominated by non-cooperative games (e.g., Cournot, Bertrand)	Multiple types of game theory coexisted
Solution methods	Dominated by iterative/circular search algorithms and basic optimization algorithms	Dominated by parallel or distributed algorithms and learning theory-based solution methods

Some reviews highlight the wide range of game theory applications in power systems. For instance, game theory methods applied in areas like energy trading, energy balancing, grid planning, and system reliability are discussed in [41]. Meanwhile, reference [42] investigates the applications of game theory in power systems from the perspectives of cooperative games, static games, dynamic games, and evolution games. In addition, reference [43] examines cooperative game theory applications across multiple aspects of power systems, providing a comprehensive citation network analysis. Furthermore, the applications of evolutionary games in sustainable energy and the game processes between each subject in graphs are summarized in [44]. Additionally, reference [45] reviews coalitional game theory in power systems, demonstrating its applicability, challenges, and limitations via a case study. While these studies provide broad overviews of game-theoretic approaches, several limitations remain. Clear trends for future research and a comprehensive summary of game theory elements are not adequately addressed in [41]–[45]. To address the limitations, this paper undertakes a more in-depth and comprehensive review of the applications of game theory in new power systems, serving as a handbook for future research, whose main contributions are summarized as follows.

1) A review and categorization of 79 game-theoretic studies focused on RES, ESS, and EV charging infrastructure, classified into two main perspectives: planning, operation, and scheduling.

2) A comprehensive summary of basic game elements (players, strategies, payoff/objective functions), solution methods, and variable interpretations, providing easy access to essential information for readers.

3) Two valuable and quantified evaluation criteria (complexity and applicability) for each game theory model are proposed in Section II, with corresponding ratings presented in Tables A1−A7 which are presented in Appendix A.

4) The innovative methodologies for integrating artificial intelligence (AI) and game theory are analyzed, highlighting the potential and broad application prospects of combining AI with game theory.

The rest of this paper is organized as follows. Section II presents the evaluation criteria and review methodology. The basic model and structure of game theory are introduced in Section III. Furthermore, Section IV proposes the applications of game theory. Besides, the introduction of AI-based game theory is delivered in Section V. Section VI provides a comprehensive discussion. Finally, conclusions and perspectives are given in Section VII.

II. EVALUATION CRITERIA AND REVIEW METHODOLOGY

A. Evaluation Criteria

In this section, the studies summarized in Tables A1−A7 are evaluated in terms of complexity and applicability. Furthermore, the setting conditions of complexity and applicability are given as follows:

1) Complexity and applicability are rated with a maximum of five *;

2) * represents very low, ** represents low, *** represents medium, **** represents high, ***** represents very high;

3) The usage of each element, listed in Table II, contributes to an additional level, e.g., one additional *.

The comprehensive evaluation criteria of complexity and applicability are as follows. Complexity is mainly evaluated by the game model and objective function, which account for the same weight. Therefore, the complexity of a study will be equivalent to half the total number of elements it contains in the complexity column of Table II, measured in terms of asterisks *. Specifically, if a study comprises five elements of complexity, it will be assigned a complexity rating of two and a half *, which will be rounded up to three * for the purpose of representation.

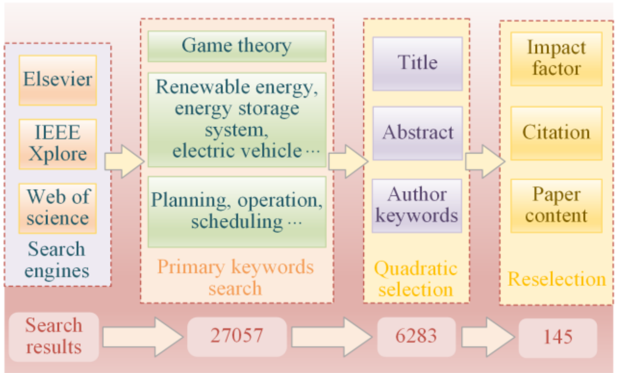
Applicability is mainly evaluated by the case study. Specifically, a study possesses an equal number of elements from the applicability column in Table II as it has *, indicating its level of applicability.

TABLE II
ELEMENTS OF EVALUATION CRITERIA

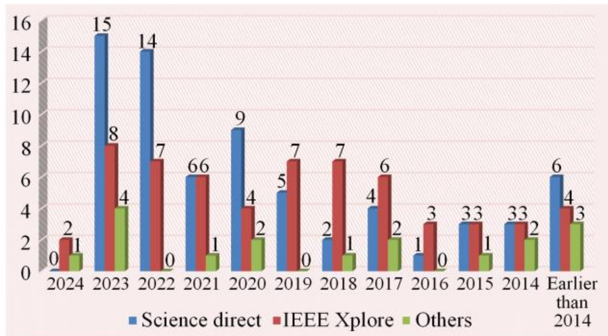
Serial number	Complexity		Applicability
	Objective function	Game model	
1	Multiple variables (five or more)	Dynamic game	Actual power grid
2	Multiple objective functions (two or more)	Multi-level structure	Real data
3	Nonconvexity	Evolution mechanism	Standard model of power grid
4	Using approximation or simplification	Incomplete formation	Real case studies
5	Complex mathematical expression	Multi-stage game	Reasonable game model for specific scenario

B. Review Methodology

Similar to [46], a review methodology is conducted in this paper, and the execution procedure for the review methodology is shown in Fig. 1(a). Firstly, three searching engines (Elsevier, IEEE Xplore and Web of Science) are utilized to obtain relevant references in the last decade, and 27057 results are obtained. Furthermore, the primary search key words are applied, including game, planning, scheduling, operation, renewable energy, integrated energy system, energy storage system, electric vehicle, electric vehicle charging station, new power system, and reinforcement learning. In addition, the synonyms of these primary search keywords, such as capacity allocation, sizing, location, dispatch, energy management, navigation, smart grid, and Markov games etc., are also used. Moreover, Booleans (and, or, not) are employed to link the search words for forming the final search formula. Secondly, a quadratic selection is carried out by screening title, abstract, author keywords, resulting in 6283 outcomes. Finally, a total of 145 papers are selected based on their citation, journal impact factor and paper content, with 79 of these being meticulously chosen for an in-depth discussion. Particularly, some published earlier than 2014, but more representative articles are traced. In Fig. 1(b), the 'Others' includes well-known databases such as Wiley Online Library, Springer link, MDPI and China National Knowledge Infrastructure.



(a)



(b)

Fig. 1. Review methodology of related references. (a) Execution procedure. (b) Research statistics.

III. FUNDAMENTALS OF GAME THEORY

This section introduces the game theory fundamentals encompassing the basic models and comprehensive classifications. The part A covers three fundamental components of the game model and presents a simplified mathematical representation. The part B offers a comprehensive classification from multiple perspectives.

A. Basic Model and Structure of Game Theory

Game theory is a mathematical theory that refers to the process in which multiple decision-makers, depending on their respective information, simultaneously or successively, once or repeatedly, select strategies from their feasible strategy sets under certain static or dynamic conditions, and implement them to ultimately obtain the best profits [47]. In short, forming a game should include at least three elements: player, strategy and payoff.

Player refers to the decision-making agent, exhibiting attributes of independent decision-making, autonomous action, whether they are individuals or organizations. A game with n players is usually called an n-player game, and $i\,(i \in \mathbb{N}, \mathbb{N} = 1,2,3,\cdots,n)$ can be used to represent any player in the game.

Strategy refers to the actions that each player can adopt in the game, and players have diverse strategies available to them. Let S_i represent the set of pure strategies for player i, and let $s_i(s_i \in S_i)$ denote the specific strategy chosen by player i. Each of the n players independently selects a strategy, contributing to the formation of a strategy set $s=(s_1,s_2,\cdots,s_n)$, which is called strategy composition. The set of all such strategy combinations, denoted as S, is formally defined as the product of each player's strategy set S_i, the expression of S is as follows:

$$S = S_1 \times \cdots \times S_n = \prod\nolimits_{i\in\mathbb{N}} S_i \tag{1}$$

The payoff, which is a function of the strategy composition $\boldsymbol{s}$, represents the goal that each player strives to achieve within the game:

$$u_i:\ S_i \rightarrow \mathbb{R} \tag{2}$$

where u_i denotes the payoff of player i.

After the three basic elements are determined, a normal-form game model can be established, as follows:

$$G = \{N;S;u\} \tag{3}$$

where G is the three tuples of a game model; $u=\{u_1,u_2,\ldots u_n\}$ denotes the set of payoffs.

B. Classification of Game Theory

As illustrated in Fig. 2, game theory can be categorized into completely rational game and evolutionary game based on the players' rationality degree. Furthermore, a completely rational game is further divided into cooperative game and non-cooperative game [42].

Non-cooperative game is characterized by the absence of binding agreements among players, which can be categorized into static game with complete information [48], static game with incomplete information [49], dynamic game with complete information [50], and dynamic game with incomplete information.

Different from non-cooperative game, cooperative game involves agreements between players. The essence of the cooperative game lies in forming coalitions and benefits allocations. The benefits allocation methods mainly include Shapley value [51], [52], nucleolus [53], and core [54], [55], which are based on the agreements and individual contributions.

Unlike completely rational game, evolutionary game theory reflects the irrational behaviors of players [44]. The strategies and behaviors of the evolutionary game players evolve through mechanisms including inheritance, variation, and selection. Therefore, players can adjust their strategies based on the past successes or failures for adapting to the changing environment and opponent actions.

According to other criteria, game theory can be further divided into various additional types. Based on the number of players, game theory is categorized into single-player, two-player, and multi-player games. Furthermore, game theory can be classified according to the strategy employed: pure versus mixed, continuous versus discrete, and finite versus infinite games. The progression of the games determines whether it falls under static, dynamic, or repeated game categories. Besides, the nature of payoff differentiates game into zero-sum, non-zero-sum, variable-sum and constant-sum games. Lastly, concerning the information structure, game theory is divided into complete and incomplete information games (pertaining to payoff information), perfect and imperfect information game (pertaining to the game's procedural information).

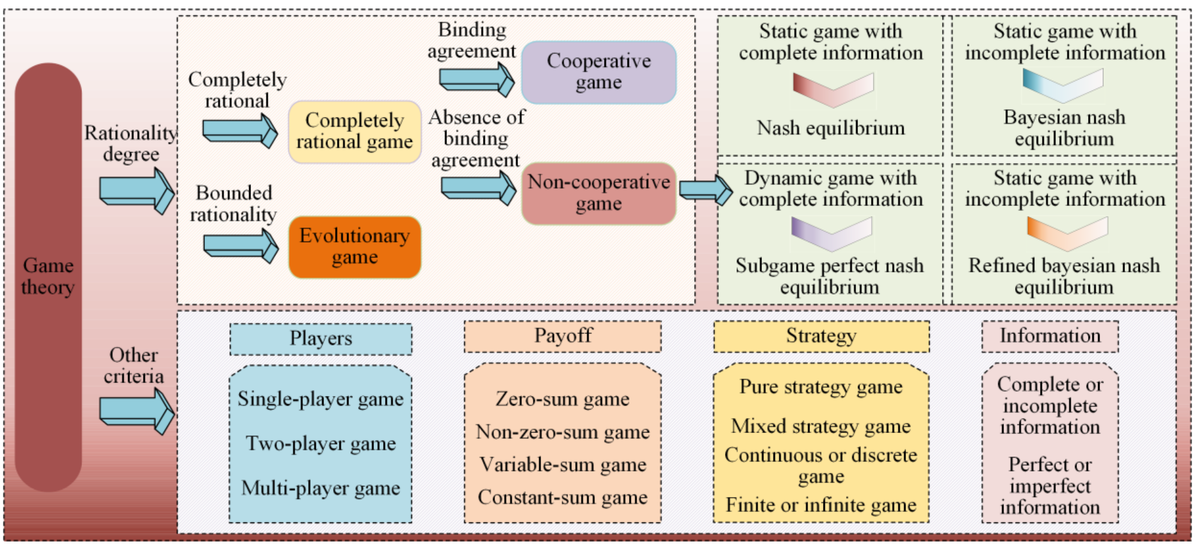


Fig. 2. Illustration of the game theory classifications.

IV. Applications of Game Theory in New Power System

This paper presents a comprehensive review of 71 game theoretic-based studies on RES, ESS, and EV charging infrastructure. The basic game elements and solution method are completely sorted out in this section. Finally, the complexity and applicability of each study are objectively scored according to the evaluation criteria in Section II.

A. Applications in Renewable Energy Sources

As illustrated in Fig. 3, the integrated energy system (IES) is capable of integrating different forms of energy resources to achieve optimal utilization and interactive supply of energy. However, the integration of RES makes the decision-making process between RES and power grid more complex, which leads to the uncertainty of operation conditions and the diversification of decision-making agents in IES. Game theory offers a novel mathematical instrumentality and a research framework for the analysis of multi-agent decision-making challenges that arises subsequent to the integration of RES into IES. Furthermore, Fig. 4 showcases a representative application scenario where game theory is utilized within this domain. Specifically, during the planning and investment phase of RES, non-cooperative game can aptly describe the investment competition among diverse DG operators (DGOs), and their competitive strategies are usually the planning scheme of DGs, which specifically includes the capacity and access location of DGs. Once RES are operational, a cooperative game is employed to delve into the co-operative optimal scheduling problem that arises among wind turbine (WT), photovoltaic (PV) and ESS. This approach enables the exploration of optimal strategies for coordinating the output of these diverse distributed resources, ultimately maximizing the absorption of RES. With the advent of IES, RES is integrated with other forms of energy units. Therefore, IES operator (IESO) is introduced to serve as a bridge between source and load. Based on the relationship between supply and demand, IESO sets the prices for energy sales and purchases, strategically acquiring energy from IES at a lower rate and subsequently selling it to loads at a higher price, thereby generating profits through the price differential. Generation units and users within IES actively adjust their production and energy consumption plans in response to the price signals released by IESO. In the context of multiple IESs, Nash bargaining game can emerge among them to achieve complementarity between IESs at a lower cost through negotiations over energy prices. In this paper, the applications of game theory in RES are divided into two areas: RES planning, RES operation and scheduling.

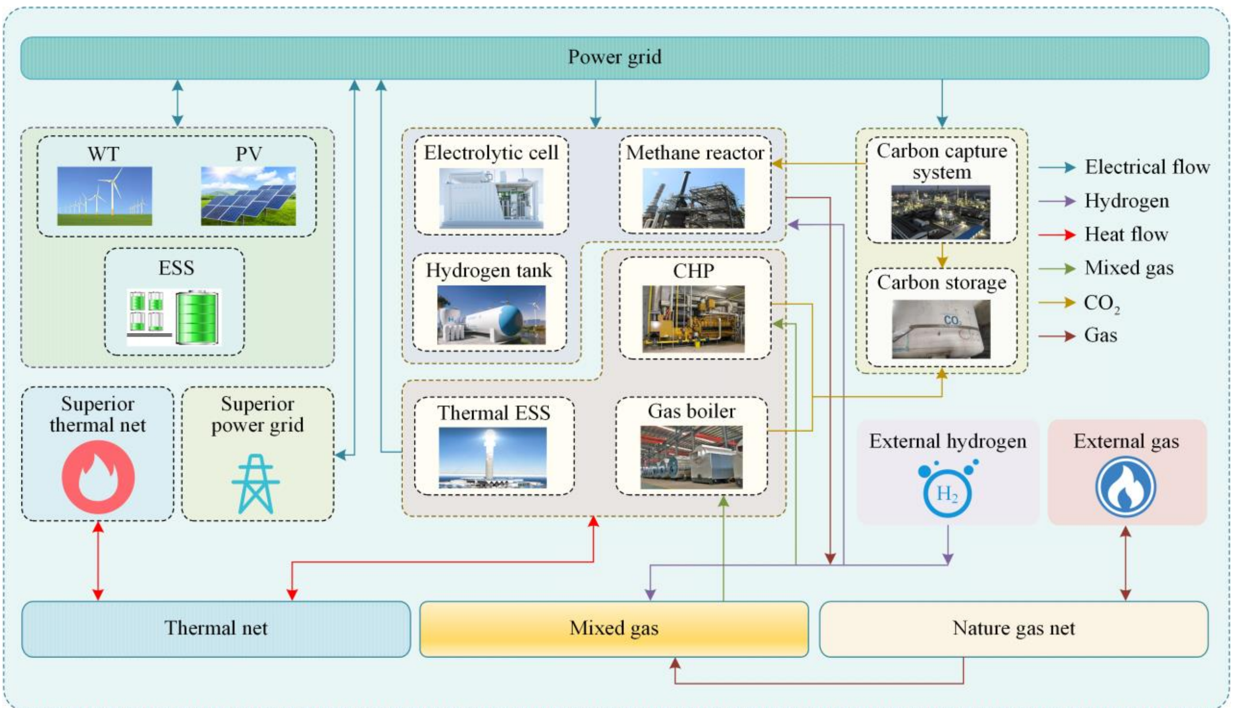


Fig. 3. Typic configuration of IES with RES.

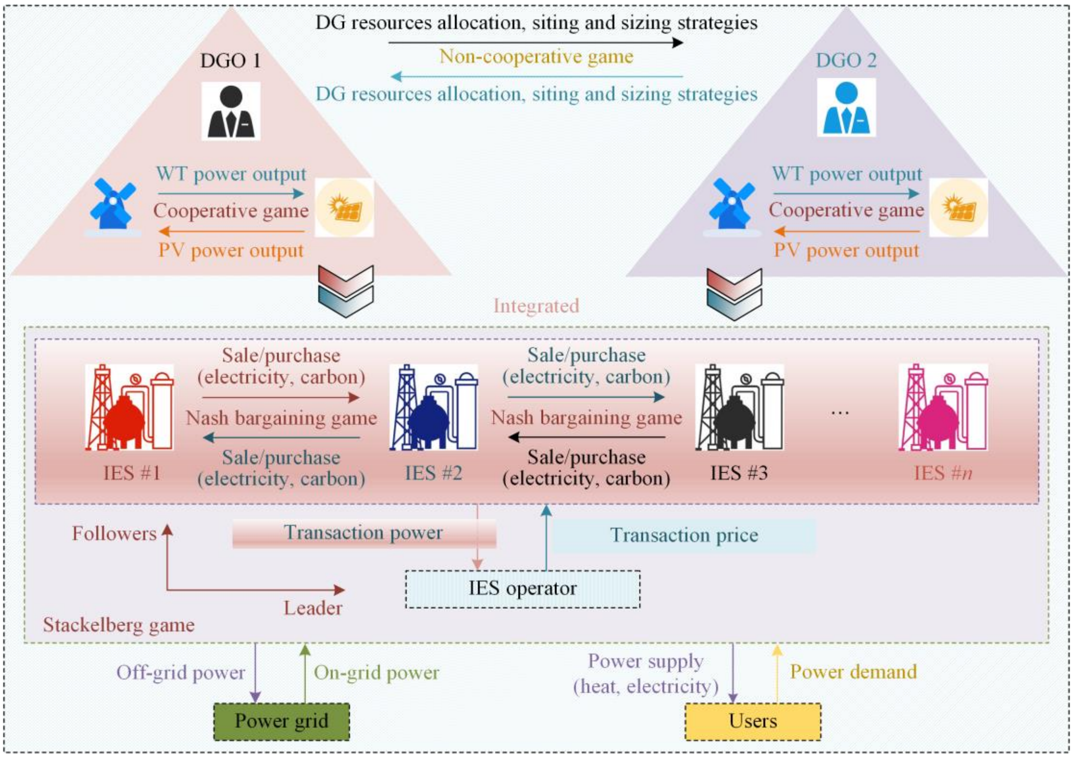


Fig. 4. Typical applications of game theory in RES.

1) Renewable Energy Sources Planning

Privatization of significant energy sectors, unbundling of vertically integrated energy companies, and the influx of numerous new DG technologies are causing planning to become increasingly regional and complex [56]. Several authors propose RES planning procedures that consider these changes. Naturally, game theoretic-based approaches play a significant role in RES planning, which is summarized in Table A1.

Distributed generation expansion planning (DGEP) has been a long-term planning problem for decades, posing challenges for both distribution generation companies (DGCs) and regulators. In earlier studies, DGEP problem was usually modeled as a game between multiple DGs or investment companies, where each DG or investment company maximized their profits to decide the expansion capacity [57]–[60]. Later, with the deregulation of power and multi-party participation of the upper sectors and distribution network (DN), generation expansion planning (GEP) market became more intricate [61]. For this reason, a multi-level Stackelberg game is introduced to model DGEP problem [62].

IES integrates multiple complementary energy sources [63], encompassing both RES generation system and ESS. Besides, the combined heat and power (CHP) system enhances the interactions among entities in IES. Therefore, cooperative game is often used to model interactions among entities in IES [64]–[68]. To maximize the profits of the coalition and realize the optimal profits allocation, the overall profits of IES are usually taken as the objective function within the cooperative model.

2) Operation and Scheduling of Renewable Energy Sources

The stochastic nature of WT and PV poses significant challenges to the operation and scheduling of the power system [69], [70]. To cope with these challenges, game theoretic-based approaches are employed.

Distributed energy resource (DER) scheduling primarily includes maintenance scheduling and output scheduling. Reference [71] presents a maintenance scheduling solution through a dynamic game. Besides, references [72]–[79] formulate the optimal distributed scheduling schemes for DG. Among them, references [74] and [79] consider the charging/discharging behaviors of EVs to make their distributed scheduling strategies closer to reality. In addition, references [80] and [81] use cooperative game to model the strategic behaviors of DERs, and a conclusion that an alliance can get more profits is delivered.

The optimal scheduling problems of IES are studied in [82]–[87]. Among them, references [82], [83], [85]–[87] model the strategic behaviors between operators and IES as a Stackelberg game, considering the master-slave relationship between upper operators and IES. Reference [84] studies the applications of shared ESS and proposes a day-ahead scheduling model based on a cooperative game. Moreover, references [88] and

[89] examine the optimal operation strategy of IES as well as emphasizing that the typical operation strategy of IES revolves around cooperation. This cooperative nature makes cooperative game a suitable approach for investigating the cooperative operation strategy. Above all, detailed game models of RES operation and scheduling are summarized in Table A2.

B. Applications in Energy Storage System

At present, some scholars adopt game-theoretic approaches to study the behaviors of ESS investors and operators participating in the investment market and electricity market. In this paper, the types of ESS depicted in Fig. 5 are divided into battery ESS, hydrogen ESS, and thermal ESS.

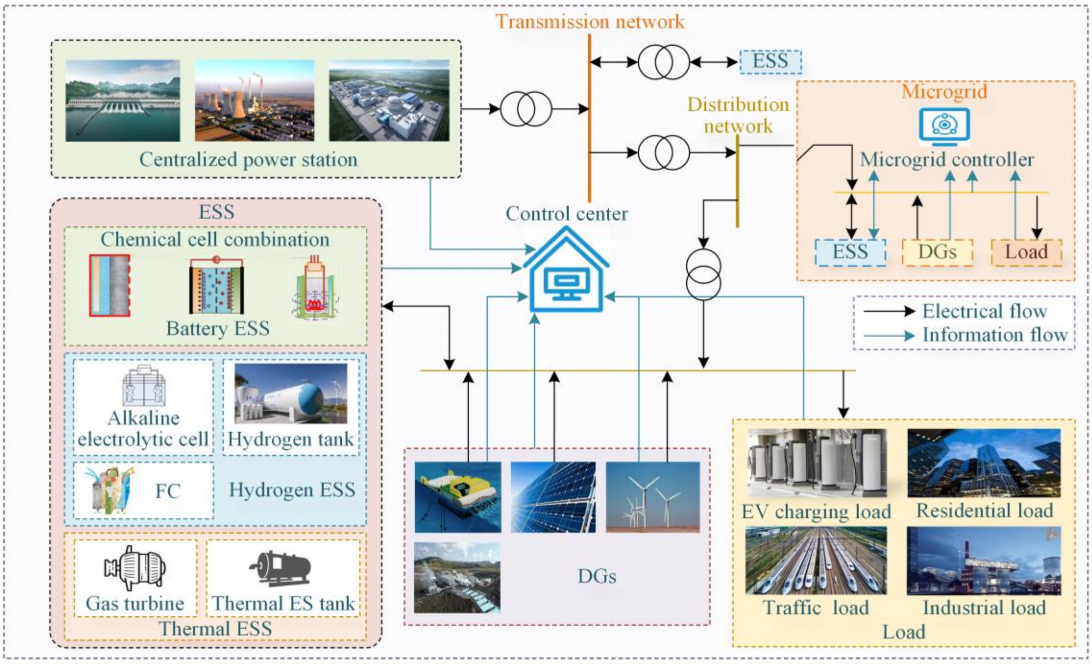


Fig. 5. Typical configuration of the power grid with ESS.

1) Energy Storage System Planning

Multi-agent game theory has emerged as a new research hotspot in ESS planning. ESS operated by different agents tends to adopt diverse game strategies across various application scenarios and under varying objectives. As depicted in Fig. 6, ESS and power generation units in RES clusters prefer a shared and cooperative game approach to achieve optimal allocation of ESS capacity. On the grid side, ESS operators, operating in a competitive electricity market, are more inclined towards non-cooperative games. By combining the level of market competition and their technological advantages, they determine their planning strategies through non-cooperative games with other ESS investors. On the user side, due to the varying scales of ESS, both cooperative and non-cooperative games may coexist. Users have abundant production and sales of diversified energy sources such as electricity, heat, and hydrogen, but most of their ESS capacities for these resources are relatively small. Consequently, ESS can either aggregate and participate in transactions cooperatively or engage in individual peer-to-peer (P2P) transactions. Based on these transaction mechanisms, a combination of cooperative and non-cooperative games is suitable for ESS planning.

In battery ESS planning, investors usually combine multiple battery energy storage (ES) devices to complement each other to meet the load demand considering the generation intermittent [90], [91]. In addition, the competitive behaviors among various battery ESS investors affect the investment returns. To maximize the profits of investors, some insightful suggestions are proposed in [92].

In hydrogen ESS planning, references [93] and [94] investigate the behaviors of investors in competitive markets. Notably, a comparative analysis demonstrate that limited rational players can gain more revenue [94]. Besides, reference [95] proposes an optimal capacity configuration method of hydrogen ESS for 5G base stations.

In thermal ESS planning, references [96] and [97] present the optimal capacity allocation schemes in the planning stage. Furthermore, reference [98] analyzes the impact of government policies on the promotion of thermal ES products, offering valuable insights for the thermal ESS planning. Above all, detailed game models of ESS planning are summarized in Table A3.

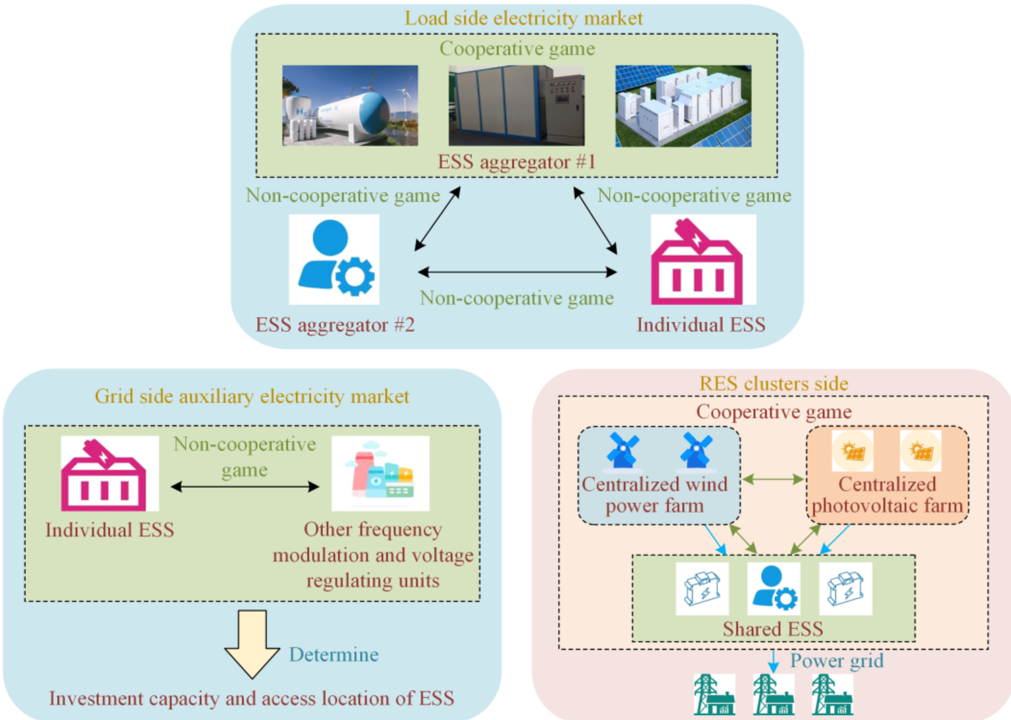


Fig. 6. Schematic of typical applications of game theory in ESS.

2) Operation and Scheduling of Energy Storage System

An operation cost analysis of ESS by Poonpum reveal that ES technology can be applied to the power grid on a large scale only when ESS costs are reduced significantly [99]. Hence, the economic operation and scheduling of ESS emerge as a prominent area of focus.

Energy arbitrage [100] is a common operation and scheduling model for ESS to participate in the electricity market. Specifically, as ESS administrators, microgrid operators coordinate the charging and discharging processes of ESS and set energy prices to minimize costs and maximize profits. To highlight the leadership role of microgrid operators in ESS, Stackelberg game is applied in [101]–[104]. Besides, microgrid operators are also responsible for consultation and cooperation with other microgrids [105] and IES [103], [106] to ensure the common benefits of microgrids. Furthermore, power output regulation for generation system [107] and demand response (DR) [108] are discussed as two typical applications of thermal ESS. Remarkably, reference [107] model the input and output ports of IES as energy hubs, effectively capturing the intricate interplay among diverse energy forms. Above all, detailed game models of ESS operation and scheduling are summarized in Table A4.

C. Applications of Electric Vehicle Charging Infrastructure

In recent years, the proliferation of EVs and charging infrastructures have brought great challenges to scheduling and planning. On one hand, the planning of EV charging infrastructure has to be coordinated with DN which is influenced by the preferences of EV owners and transportation networks. On the other hand, more flexible scheduling strategies are needed to cope with the charging/discharging behaviors of EVs.

Specifically, EVs are regarded as DER for long-term parked. Meanwhile, vehicle to grid (V2G) [109] technology can be applied to improve the stability of the grid and reduce the charging cost of the owners. Since multiple players with different objectives influence the optimal planning and scheduling strategies, game theoretic-based approach has been adopted to investigate this problem. In this paper, the applications of game theory in EV charging infrastructure are divided into two areas: EV and electric vehicle charge station (EVCS)

1) Electric Vehicle

The applications of game theory in EV scheduling are divided into EV charging navigation and EV charging energy management.

The EV charging navigation process is illustrated in Fig. 7, where various EVCSs compete to attract more EVs by strategically setting electricity prices to maximize their profits. Simultaneously, EVs determine their charging location and electricity demand based on real-time electricity prices, road conditions, and charging station availability. Accordingly, Stackelberg game effectively describes the leadership role of dynamic electricity prices on EVs in the aforementioned process

[110]–[112]. However, the above literature ignores the limited rational behaviors of EV users and the competition among various EVCSs. Hence, reference [113] proposes a two-layer model that take these factors into account. Moreover, the choices regarding the battery swapping stations are considered in [114].

Besides, EV aggregators play a crucial role in EV charging energy management, notably through V2G technology [115]–[117]. By leveraging EVs as DER, EV aggregators actively engage in services like energy trading, DR, and frequency regulation within the electricity market. Consequently, V2G represents a prevalent and lucrative avenue for EV aggregators to generate profits. Subsequently, the advent of vehicle-to-everything technology further broadens the profit avenues for EV aggregators [118]. Moreover, to prevent a simultaneous influx of numerous EVs into the network, EV aggregators dynamically modify the EV charging schedule [119] or engage in time-of-use demand-side response programs [120]. Furthermore, reference [121] presents a noteworthy solution to effectively address the challenge of significant fluctuations in charging power within intricate environments. Finally, detailed game models of EV scheduling are summarized in Table A5.

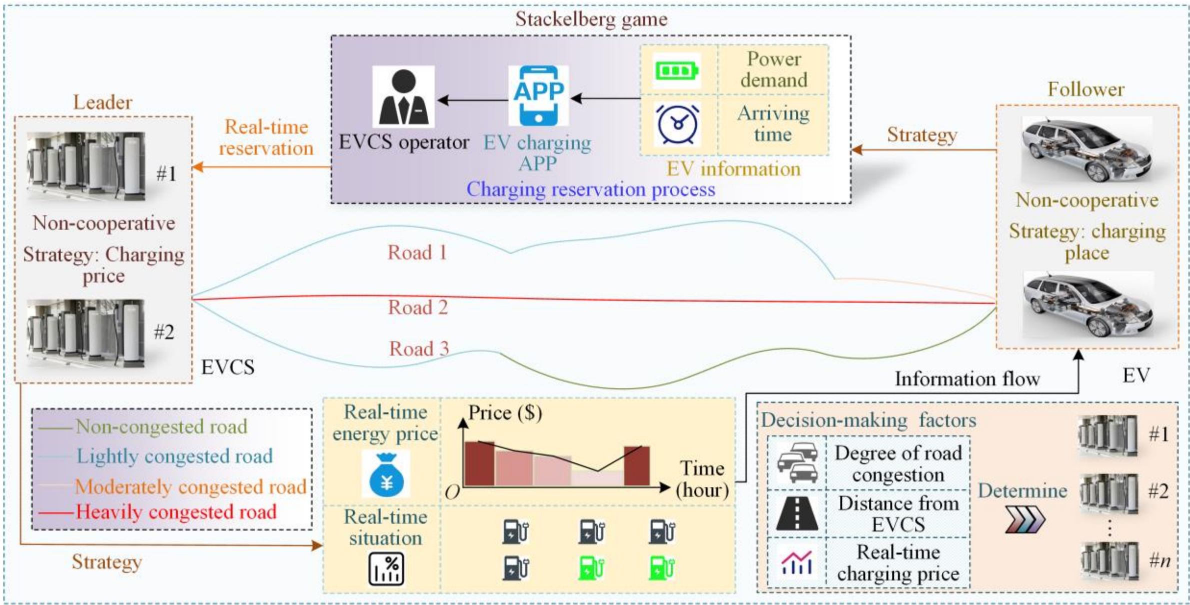


Fig. 7. Schematic diagram of the EVs scheduling.

2) Electric Vehicle Charge Station

The applications of game theory in EVCS are divided into operation of EVCS and EVCS planning. As an intermediary entity situated between the power generation sector and load, the optimal operation strategies of EVCSs need to consider the supply side and the load side. On the supply side, EVCSs possess the ability to establish energy trading agreements with IES [122] or dedicate energy supply units [121], enabling EVCSs to procure electricity at a lower cost. On the load side, EVCSs can dynamically determine real-time electricity prices based on grid load conditions, effectively reducing the charging costs for EV users and simultaneously enhancing electricity sales profitability [123]–[127].

Several factors influence EVCS planning, including user charging behaviors, traffic considerations, distribution company (DisCo) management plans, and policies. Specifically, EV users' preferences [128], [129] as well as their participation in DR programs [130] significantly impact the planning outcomes. Additionally, the potential impact on traffic once the charging station is built must be considered [131]. However, it is possible to conflict with DisCo's plans considering that EVCS operators belong to private sectors [132]. Hence, it is crucial to address potential conflicts and find suitable solutions for coordination. Moreover, the policies including promoting lower charging prices and higher EV adoption rates gradually become important drivers for EVCSs construction [133]. Above all, detailed game models of EVCS operation and planning are organized in Table A6.

V. GAME THEORY BASED ON ARTIFICIAL INTELLIGENCE

As AI technology advances, meta-heuristic algorithms (MHAs) and machine learning have emerged as significant contributors to game theory. In this section, game theory approaches based on MHAs and reinforcement learning are introduced, respectively.

A. Game Theory Based on Meta-heuristic Algorithms

MHAs are the combination of a random algorithm and a local search algorithm, which are primarily utilized for resolving intricate optimization challenges, searching and optimizing within the solution space to identify the optimal solution or an extremely close approximation solution.

1) Introduction of Game Theory Based on Meta-heuristic Algorithms

Nash equilibrium serves as a crucial concept within game theory, signifying a state where once every player has adopted their individually optimal strategy, no individual player can accrue further advantages by unilaterally deviating from their chosen strategy. In intricate game problems, particularly those involving multi-leader and multi-follower dynamics, the pursuit of Nash equilibrium poses significant challenges when relying solely on conventional mathematical methods, even when the existence of Nash equilibrium has been theoretically established [41]. However, MHAs excel in finding Nash equilibrium within intricate solution spaces, attributed to their superior search ability. Compared with traditional mathematical methodologies, MHAs boast the benefits of accelerated solution speeds and generalization capabilities. Notably, the majority of game problems inherently possess a multi-objective character, which aligns with the purpose of multi-objective MHAs. Consequently, MHAs exhibit a high degree of compatibility with game theory.

2) Applications of Game Theory Based on Meta-heuristic Algorithms

Currently, the applications of MHAs-based game theory primarily focus on strategy delivering and Nash equilibrium solving [134], which are summarized in Tables A1−A6 and marked with "(MHA)." Generally, the strategies of each player are developed randomly at first, and then the Nash equilibrium is solved iteratively by employing the search and convergence properties of MHAs. To deliver a clearer introduction, an optimal economic scheduling of IES through MHAs-based game theory is delivered [135]. As described in Section IV, driven by load demands and the objective of profits maximizing, IESO establishes the purchase and sale prices for electricity, heat, and gas energy, then procures energy from IES at a reduced cost and subsequently resells it to consumers at a premium price. IES actively responds to the price strategy delivered by IESO, and dynamically adjusts the output scheme to optimize the profits. Given these intricate game dynamics, a master-slave game framework based on genetic algorithm (GA) is well-suited to model the strategic interactions between the two entities, where IESO takes the role of the leader and IES serves as the follower. Firstly, IESO formulates an initial price strategy and subsequently delivers the price strategy to IES. Upon receiving this strategy, IES determines the optimal output scheme and sends it back to IESO. IESO then computes its revenue by evaluating this transmitted output scheme. Subsequently, the crossover and mutation mechanisms inherent in GA are employed to iteratively refine the price strategy of IESO iteratively. This process is repeated until GA converges to a Nash equilibrium point. Ultimately, GA yields both the optimal price strategy for IESO and the corresponding optimal scheduling plan for IES. Obviously, the choice of algorithm type and game framework can be tailored to diverse application contexts. For instance, in complex game environments, like multi-leader multi-follower games, improved MHAs can be selected to expedite the iterative solution process and enhance its precision. Nonetheless, the MHAs-based game approaches have limitations. The iterative solution can be time-consuming in scenarios where the game dynamics are exceedingly intricate, leading to high computational costs. Furthermore, inherent constraints in the algorithm may result in solutions that fall into the local optimum.

B. Game Theory Based on Multi-agent Reinforcement Learning

In the MHAs-based games, the players are still assumed to be fully rational. However, the advent of multi-agent games has softened these rationality requirements, rendering it more realistic to portray players with limited rationality. Currently, multi-agent games based on reinforcement learning are a focal point. Essentially, this approach enables the adaptive refinement of strategies, which not only improves the decision-making ability of individual agents but also enhances the algorithm's performance in the intricate interactions among agents, through the learning mechanism.

1) Markov Decision Process

Markov decision process (MDP) is the basic mathematical theory of reinforcement learning, which reflects the repeated interaction process between an agent and its environment. The specific process is as follows.

At time t, the state of environment is s_t, the agent receives the environment's reward r_t, and makes a decision based on the strategy function π, and then performs the action a_t. The environment, after being affected by the action a_t, updates its state s_t to s_{t+1}, and gives the agent a reward r_{t+1} in return. In an MDP, the objective of the agent is to maximize the expected reward, whose expectation function is expressed as follows:

$$E_{s_{t+1}\sim p(\cdot|s_t,a_t)}\left[\sum_{t\geq 0}\gamma^{i-t}r(s_t,a_t,s_{t+1})\middle|S_t=s,a_t\sim\pi(\cdot|s_t)\right] \quad (4)$$

where E is the expectation function; γ denotes the rate of discount; p is the state transition function; and S denotes the state space.

2) Multi-agent Reinforcement Learning Games

Multi-agent game, also known as Markov game (MG), can be represented by six tuples:

$$\left\{N, S, (A^i)_{i\in\mathbb{N}}, p, (r^i)_{i\in\mathbb{N}}, \gamma\right\} \tag{5}$$

where N is the finite set of agents; A^i represents the set of strategy of player i, also named action space, $a_t^i \in A^i$, $r^i : S\times\left(\prod_{i\in\mathbb{N}} A^i\right)\times S \to R^i \subset \mathbb{R}$ is the reward function.

Besides, the state value function $V_{\pi^i}^i(s)$ and action value function $Q_{\pi^i}^i(s,a^i)$ of player i in MG are as follows:

$$V_{\pi^i}^i(s) = E_{s_{t+1}\sim p(\cdot|s_t,a_t),a_t^i\sim\pi^i(s_t),a_t^{-i}\sim\pi^{-i}(s_t)}\left(\sum_{k=0}^{\infty}\gamma^{k-1}r\right) \tag{6}$$

$$Q_{\pi^i}^i(s,a^i) = E_{s_t\sim p(\cdot|s_t,a_t),a_t^i\sim\pi^i(s_t),a_t^{-i}\sim\pi^{-i}(s_t)}\left(\sum_{k=0}^{\infty}\gamma^{k-1}r\right) \tag{7}$$

Equations (6)–(7) show that for agent i, the value of a state s depends not only on its own strategy π^i, but also on the decisions π^{-i} made by all other agents.

3) Combination of Game Theory and Reinforcement Learning

The game theory methods based on reinforcement learning, are widely applied in various fields of power system, including optimal scheduling [136]–[141], power market [142], [139], and optimal planning [143]. When reinforcement learning is combined with specific game methods, it becomes adept at efficiently resolving specific challenges encountered within power systems. Furthermore, a detailed summary is organized in Table A7.

The leader-follower paradigm in Stackelberg games offers a distinct decision hierarchy and an interactive framework, which facilitates the combination of reinforcement learning and game theory. Specifically, the dynamic interactions in Stackelberg game are highly consistent with the iterative trial-and-error learning and strategy refinement process of reinforcement learning, fostering a mutually beneficial environment where players can collectively enhance each performance and optimize decision outcomes. Therefore, Stackelberg games based on reinforcement learning are often applied in the power market with a management nature [139], [143].

The integration of reinforcement learning and cooperative game is mainly reflected in the reward function [138]. A well-constructed reward function serves as a pivotal determinant of an agent's behavioral preference across varying states and propensity for inter-agent cooperation. Commonly, principles governing profit distribution in cooperative game theory, notably marginal contribution [144], are frequently employed as a framework for devising effective reward functions.

Non-cooperative games based on reinforcement learning primarily focus on the generation of adversarial strategies and the solution of Nash equilibrium in complex environments. In scenarios where a competitive dynamic exists among multiple agents, modeling these agents within a non-cooperative game framework becomes crucial to ensure that their strategies adopt an adversarial stance. The aforementioned methodology is typically employed to characterize the competitive behaviors exhibited by individual agents within scheduling markets, illustrative examples include the competitive interplay among multiple microgrids operating within such markets [139], [140].

VI. Discussions

By reviewing 79 relevant papers across five key elements-game theory approach, objective function, players, solution methods, and strategies-this paper provides an in-depth discussion on the applications of game theory in new power systems. The key insights are summarized as follows.

1) Different game theory models are suitable to address distinct challenges in new power systems. For example, dynamic games are frequently used to capture the strategic interactions between players in RES planning studies. Specifically, the Stackelberg games are more appropriate to represent the leadership role of management in the RES generation sector when the government or related management is involved. In addition, cooperative game can better characterize the complementary and mutually beneficial relationship between various energy sources within IES.

2) In RES operation and scheduling studies, a bi-level game framework, based on Stackelberg and cooperative game theory (as presented in [86]), effectively describes detailed and specific RES scheduling scenarios. However, the intricacy of such models often makes finding the Nash equilibrium difficult.

3) Non-cooperative game theory is commonly used for planning ESS capacities, focusing on maximizing the profits of various investors. In these cases, the non-cooperative games between lower-level players are typically constrained by upper-level players. As a result, a bi-level framework that incorporates both non-cooperative and Stackelberg games is highly suitable for modeling the interactions between management, investors, and multiple stakeholders.

4) For ESS operation and scheduling, Stackelberg and cooperative games are ideal for capturing the strategic behaviors between players. On one hand, the charging and discharging behaviors of ESS depend on the real-time load status of the grid. On the other hand,

ESS needs to coordinate and collaborate with the generation department to realize peak-cutting and valley-filling.

5) In EV infrastructure scheduling studies, appropriate power pricing policies can encourage residents to adjust their power consumption, thus maximizing the profits for both EVCS and users under a Stackelberg game. In addition, Nash bargaining or cooperative game is established between the supply and EVCS, allowing EVCS to purchase electricity at lower costs. Moreover, a non-cooperative game is used to describe the competitive bidding behaviors among EVCSs from different manufacturers.

6) The charging preference of EV users play a significant role in the planning of EVCSs, making it essential to model games from the user's perspective.

7) In real economic activities, players often exhibit bounded rationality. Hence, compared with classical game theory, evolutionary game can better reflect the dynamic evolution process of irrational decision-maker strategies.

8) The new power system, characterized by high penetration of RES and electronic devices, imposes stringent demands on modeling and simulation methods. SimuNPS, released by Shanghai KeLiang Information Technology Co., Ltd., emerges as a viable solution to the aforementioned challenges. With its flexibility, diverse array of power models, and a wealth of customizable functions, SimuNPS represents a comprehensive platform for meeting the evolving demands of the modern power system.

Although game theory has been widely used in new power systems, there are still some challenges that need to be discussed.

1) As the power system undergoes decentralization and vertical reforms, the number of agents continues to rise, fostering intricate patterns of competition and cooperation among them. Notably, ESS operators occupy diverse roles across the grid side, load side, and centralized RES generation farm. Consequently, developing a game model and framework that accurately captures the complexity of these interactions is a crucial topic for further exploration.

2) Any game problem in power system depends on a feasible Nash equilibrium solution method. However, the large number of decision-making agents, coupled with vast strategy spaces and diverse objective functions, leads to significant computational complexity. Even if a Nash equilibrium exists, the problem of multiple solutions adds another layer of difficulty. Therefore, the research and development of Nash equilibrium solving methods that strike a balance between applicability, efficiency, and completeness present a significant challenge.

3) The MHAs-based game methods exhibit resilience against environmental variations, enabling them to effectively tackle black box issues while ensuring the privacy of participants. Nevertheless, in complex game scenarios, MHAs often encounter long computation times and poor solution accuracy for Nash equilibria, making performance optimization an ongoing challenge.

4) The game methods based on multi-agent reinforcement learning represent a promising new direction. However, several unresolved scientific challenges remain, including the dimensional explosion of game strategy sets and the limited generalization capabilities when applied to power systems.

VII. Conclusion and Future Trend

This paper undertakes a critical survey on the applications of game theory in new power system. Firstly, two valuable and quantified evaluation criteria and the review methodology are proposed. Meanwhile, the foundational models and classification of game theory are introduced. Secondly, the reviewed articles, mentioned above, are discussed in categories, and the game elements and solution methods are summarized. Then, AI-based game methods are introduced and the feasible examples are given. Finally, a comprehensive discussion is organized. It is noteworthy that this paper comprehensively organizes the game elements and solution methods featured in the reviewed articles. Meanwhile, the AI-based game methods are systematically introduced. As investigated from all the research, the selection of game players, game frameworks, and solution algorithms are critical issues in analyzing the new power system from a game theory perspective. In addition, several main conclusions are summarized as follows.

1) The cooperative game primarily addresses the issue of profit distribution, while the Stackelberg game focuses on DR and the constraints imposed by the superior department. Besides, the evolutionary game captures long-term bidding behaviors exhibited by irrational agents participating in the scheduling market.

2) Selecting suitable game theory methodologies and objective functions chosen based on real-world scenarios is essential for improving the accuracy and applicability of game models.

3) Game theory emerges as a pivotal tool in addressing this multi-agent optimization challenge, offering a vital framework for solving the intricate issues of demand-side management.

4) AI-based game-theoretic approaches, especially the machine learning game-theoretic approaches, require substantial computation capabilities to demonstrate their performance.

However, some limitations remain in this paper, the survey of AI-based game methods is still insufficient and the scope of research survey is slightly broad. Therefore, in the future research, we will narrow the scope and focus on the integration of AI algorithms and game theory. Besides, this paper also provides a comprehensive overview of the promising future trends of game theory in new power systems, encompassing applications and solution methods, as follows:

1) The tripartite coordination decision, involving microgrids, DG and ESS, constitutes a classical game-theoretic problem in the future microgrids. Currently, the advancements in game theory within this domain primarily center around leveraging cooperative games to explore energy exchange mechanisms, pricing strategies, and optimal scheduling. Meanwhile, non-cooperative games are employed to address the microgrid load-balancing challenges posed by RES generation uncertainties, and multi-stage dynamic games are employed to handle transactions within microgrids.

2) Currently, P2P transaction model has emerged as a key mechanism in microgrid electricity markets, promoting distributed decision-making and collaborative autonomy. Transactions within P2P encompass not only traditional energy sources such as electricity, heat, and gas but also green certificates and carbon emission rights. Increasingly, game theory is used to investigate P2P trading strategies for these assets.

3) As EVs and mobile ESS become more prevalent, the significance of demand-side management has been emphasized. Presently, the majority of research employs Stackelberg game to model demand-side response mechanisms. In the future, the challenge of demand-side management can be effectively framed as a multi-stage dynamic master-slave game problem, offering a more comprehensive and dynamic approach to tackle this evolving issue.

4) The intelligent operation of IES based on game theory is a frontier research topic. Installing data acquisition systems to intelligently formulate operational strategies for each entity within the IES is a significant challenge.

5) As game environments grow more complex, AI-based game theory has been increasingly used in power systems. Firstly, MHAs are widely utilized in solving game problems because of their robust applicability. However, with the development of AI, multi-agent reinforcement learning with superior performance has received more attention. At present, most research believe that the game method based on reinforcement learning is a critical research direction for the future.

APPENDIX A

TABLE A1
CHRONOLOGICAL SUMMARY OF RESEARCHES ON RES PLANNING

Applications	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
DER	[57] 2010	Dynamic game	Maximizing payoffs of generation companies	Backward induction method	DGCs	DGCs: capacities of wind, CHP and micro-turbine (MT)	***	**
	[58] 2013	Non-cooperative game with Cournot model	Maximizing profits of investors	Dynamic programming algorithm	Investment firms	Investment firms: capacities of wind power stations and gas engine resources	***	***
	[59] 2013	Mixed game	Minimizing investment costs of DG; minimizing system power losses; maximizing improvement in the voltage profile	Fuzzy multi-weight decision-making method	Investment cost agent, loss agent and voltage profile agent	Investment cost agent: total costs; losses agent: total losses; voltage profile agent: voltage index	****	**
	[60] 2015	Dynamic game	Maximizing payoffs of DGCs	Backward induction method	DGCs	DGCs: capacities of wind power stations, CHP and MT/fuel cell (FC)	***	**
	[62] 2021	Upper level: Stackelberg game; lower level: non-cooperative	Maximizing profits of distribution network operator (DNO); maximizing profits of DGO; maximizing profits and minimizing costs of demand response operator (DRO)	Upper level: GA; lower level: particle swarm optimization (PSO). (MHA)	Upper level: leader: DNO; follower: DGO. Lower level: DNO and DRO	Upper level: DNO: line building and upgrading strategies of active DN; DGO: DG resources allocation, siting and sizing strategies. Lower level: DNO: electricity price; DRO: load adjustment strategies	*****	****

Continued

Applications	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
IES	[64] 2012	Cooperative game	Maximizing coalition value	PSO (MHA)	Wind power stations, PV power stations and storage batteries	Wind power stations, PV power stations and storage batteries: corresponding capacities of each player	**	***
	[65] 2021	Cooperative game	Maximizing profits of coalition value	PSO (MHA)	PV power station, wind power prosumers and shared ESS	PV power station, wind power prosumers and shared ESS: corresponding capacities of each player	**	***
	[66] 2021	Cooperative game	Maximizing profits of the coalition value	PSO (MHA)	Wind power stations, PV power stations and ES	Wind power stations, PV power stations and ES: corresponding capacities of each player	**	***
	[67] 2021	Coalitional game	Maximizing profits of the coalition value	PSO (MHA)	PV power stations, ESS and charging piles (CPs)	PV power stations and CPs: total capacities; ESS: capacities of batteries and bilateral converters	**	***
	[68] 2022	Cooperative game	Maximizing profits of the coalition value	Imperialist competitive algorithm	Wind power stations, PV power stations and battery ESS	Wind power stations, PV power stations and battery ESS: corresponding capacities of each player	**	***
	[145] 2022	Non-cooperative game theory	Maximizing total economic incomes of each player	PSO (MHA)	Wind power stations, PV power stations and EV aggregators	Wind power stations, PV power stations and EV aggregators: capacity allocation plan and income	***	**

TABLE A2
CHRONOLOGICAL SUMMARY OF RESEARCHES ON OPERATION AND SCHEDULING OF RES

Applications	Ref.	Game theory Approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
DER	[71] 2010	Dynamic game	Maximizing profits of DGCs	Not mentioned	DGCs	DGCs: maintenance plan	***	**
	[72] 2015	Cooperative game	Maximizing profits of each energy cell or a coalition	Relaxation algorithm and Nikaido-Isoda function	Utility cells and energy cells	Energy cells: total power output; utility cells: providing energy to sell or maintain the reliability of the system	**	***
	[73] 2015	Evolutionary game	Minimizing dispatching costs of each DG	Distributed algorithm	DG agents	DG agents: power output capacity	***	****

Continued

Ap-plica-tions	Ref.	Game theory Approach	Objective function	Solution method	Player	Strategy	Com-plexity	Ap-plica bility
DER	[80] 2015	Cooperative game	Maximizing profits of virtual power plant in the retail market and the reasonable profits allocation among DERs	Shapley and nucleolus	DERs	DERs: offering/selling or bidding/purchasing corresponding to the desired amount of power totally injected to the grid in a time period	***	****
	[74] 2016	Two-person zero sum game	Minimizing maxi-mum total operation cost caused by PV power	Two stages of relaxation algo-rithm	Grid dis-patchers and nature	Grid dispatchers: PV output, dispatching period, electricity price; nature: some variables under the control of nature, such as the actually available PV power	**	***
	[75] 2017	Population game	Minimizing costs of dispatching	Strategy revisions	DG agents	DG agents: various active power dispatch levels	***	****
	[76] 2017	Non-cooperative game	Minimizing costs of each microgrid	Phasor measure-ment unit enabled distributed algo-rithm	Different microgrids	Different microgrids: active power injection and voltage angle	***	**
	[81] 2017	Upper level: cooperative game; lower level: non-cooperative game	Lower level: maxim-izing profits of DER generators; upper level: achieving op-timal allocation of coalitions	Lower level: Nikaido-Isoda function and relaxation algo-rithm; upper level: Shapley, nucleo-lus and merge &Split	Lower level: DER gener-ators; upper level: energy dis-tricts (EDs)	DER generators: offer-ing price and energy quantity; EDs: coalition strategies (choosing to align with other EDs or not)	*****	****
	[77] 2017	Population game theory	Maximizing profits of all generators	Replicator dy-namics algorithm	Convention-al DG and renewable DER gener-ators	Conventional DG and renewable DER gener-ators: dispatched power capacities	***	****
	[78] 2018	Stackelberg game theory	Maximizing revenues of microgrids; max-imizing customers energy consumption while paying less	Self-defined iterative algorithm	Leaders: customers; followers: microgrids	Customers: amount of required energy to be taken in each time slot; microgrids: price per unit energy based on the total requested energy by the connected cus-tomers	****	**
	[79] 2022	Evolutionary game theory	Minimizing system operating cost and maintaining voltage stability	PSO (MHA)	PV-ESS agent, EV agent and load agent	PV-ESS agent: ESS charging/discharging schedule; EV agent: EV charging schedule; load agent: DR partici-pation schedule (incen-tive value)	***	****

Continued

Applications	Ref.	Game theory Approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
IES	[82] 2021	Upper level: Stackelberg game; lower level: cooperative game	Maximizing benefits of superior energy network; maximizing incomes of the internal system	PSO (MHA)	Upper level: leader: superior energy network; follower: park system. Lower level: park IES, gas supply system and park users	Superior energy network: real-time energy purchasing price; park system: energy purchasing plan; park IES: sold surplus electricity; park user: join in DR or not. Gas supply system: join in power-gas conversion or not	*****	****
	[83] 2022	Stackelberg game	Maximizing benefits of IES operator; minimizing operation and environmental costs	Double mutation differential evolution algorithm	Leader: IES operator; follower: IES	IES operator: power purchasing and selling price; IES: equipment operation output, purchasing or selling power	****	**
	[84] 2022	Cooperative game	Maximize profits of the cooperative alliance	Alternating direction method of multipliers with a warm start and dual update accelerated iteration strategies	R-LIES, S-LIES and power companies	R-LIES: rental and charging/discharging plan; S-LIES: shared power capacities; power companies: power transmission capacities	**	***
	[88] 2022	Cooperative game	Minimizing total operating costs of IES; minimizing CO_2 emission	Improved GA (MHA)	All energy supply equipment operators	All energy supply equipment operators: constraints of system operation	***	***
	[85] 2022	Stackelberg game	Maximizing profits of integrated energy operator (IESO); minimizing energy costs	Karush-Kuhn-Tucker (KKT) condition, YALMIP and Cplex	Leader: IESO; follower: user	IESO: energy price; user: energy consumption	****	***
	[89] 2023	Cooperative game	Maximizing benefits of cooperative alliance; power payments transaction	Alternating directional multiplier method	Building IES individuals	Building IES individuals: selling or purchasing electricity and carbon	***	***
	[86] 2023	Upper level: Stackelberg game; lower level: non-cooperative game	Maximizing revenues of energy retailer (ER); maximizing revenues of energy supplier; minimizing daily costs of user	GA nested quadratic programming (MHA)	Upper level: leader: ER; followers: users, energy suppliers. Lower level: energy suppliers	Stackelberg game: ER: energy selling price and energy procurement strategy; energy suppliers: power price; users: power demand. Non-cooperative: energy suppliers: power price	*****	***
	[87] 2023	Stackelberg game	Minimizing total cost; minimizing operation cost	PSO (MHA)	Leader: regional dispatching centre (RDC); follower: community integrated energy systems (CIESs)	RDC: energy purchase and carbon trading; CIESs: power output, operation scheme and integrated load DR volume	****	****

TABLE A3
CHRONOLOGICAL SUMMARY OF RESEARCHES ON ESS PLANNING

Applications	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applica bility
Battery ESS	[90] 2015	Cooperative game	Maximizing revenues of each battery	GA (MHA)	Lead-acid battery, lithium-ion battery and vanadium redox flow battery	Lead-acid battery, lithium-ion battery and vanadium redox flow battery: the capacities respectively used for load shifting	**	***
	[92] 2017	Stackelberg game	Minimizing total costs of follower agents	Multiply distributed optimization algorithm	Leader: DisCo; follower: wind farms, solar stations and demand	DisCo: battery ESS capacities allocation scheme; wind farms, solar stations and demand: true demand gap	***	****
	[91] 2019	Static cooperative game	Minimizing discarded PV power; maximizing net incomes of the PV-ES stations	Firefly algorithm (MHA)	Lithium iron phosphate battery, vanadium redox flow battery and valve regulated lead acid battery	Lithium iron phosphate battery, vanadium redox flow battery and valve: the capacities allocation of battery	***	**
Hydrogen ESS	[93] 2017	Cournot game	Maximizing net present value of investors	KKT optimality condition and PATH solver	Investment firms	Investment firms: dispatchable and storable capacities, dispatchable power output capacities, ESS input and output capacities	**	***
	[95] 2022	Non-cooperati ve game	Minimizing comprehensive costs of the system	Improved PSO (MHA)	Wind power stations, PV power stations and hydrogen ESS investors	Wind power stations, PV power stations and hydrogen ESS investors: investment in respective capacity	***	****
	[94] 2023	Evolutionary game	Minimizing costs of each investor	Differential evolution game algorithm (MHA)	Two microgrids in acquaintance society	Investment strategy: invest or not invest in another microgrid; capacity scale: capacity installation of Wind power stations, PV array, FC, electricity and hydrogen storage tank	***	**
Thermal ESS	[98] 2016	Evolutionary game	Maximizing profits of electric heat storage producers; using payoff matrix instead: maximizing benefits of customs	Repeated game with dynamic equation	Government and electric heat storage producers	Government: incentive policy on electric heat storage; producers: production plan of electric heat storage	***	**
	[96] 2017	Cooperative game	Maximizing alliance total profits	Upper level: using the result of the lower level; lower level: YALMIP toolbox	Thermal power plant and wind farm	Thermal power plant: cooperating/non-cooperating with wind farm; wind farm: cooperating/non-cooperating with thermal power plant	***	**
	[97] 2018	Non-cooperative game	Achieving optimal capacity allocation of thermal power plant heat storage and determining optimal peak electricity price of wind farm	Grid search method	Thermal power plant and wind farm	Thermal power plants: capacity of heat storage tank; wind farms: peaking electricity price	****	***

TABLE A4
CHRONOLOGICAL SUMMARY OF RESEARCHES ON OPERATION AND SCHEDULING OF ESS

Applications	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
Battery ESS	[101] 2017	Stackelberg game	Maximizing payoffs of aggregators	Calculating matrix of expected values of payoffs	Leader: independent system operator; follower: DR aggregators	Independent system operator: transaction price and transaction power; DR aggregators: biding decisions (bidding high, low or marginal cost)	***	****
	[105] 2022	Robust game	Minimizing costs of each microgrid	Column and constraint generation algorithm and distributed algorithm based on PSO (MHA)	Microgrids	Each microgrid: battery ESS capacity and energy consumption scheduling	***	***
	[102] 2023	Two stage and bi-level Stackelberg game	Leader, supplier-side system: maximizing supply profits; upper level: follower, user-side system: minimizing life cycle cost; lower level: minimizing operation cost	Solution for Stackelberg game: iterative-based distributed algorithm; solution for user-side model: KKT optimality condition	Leader: supplier-side system; follower: user-side system. Upper level: ESS installation agent; lower level: ESS dispatch agent	Supplier-side system: monthly basic price; user-side system: normal net load; ES installation agent: ESS installation capacity; ESS dispatch agent: state of charge/maximum load	*****	****
Hydrogen ESS	[103] 2020	Cooperative and Stackelberg game	Maximizing profits of microgrids operator; maximizing profits of energy consumers	Nikaido-Isoda function	Leader: microgrids operator; follower: energy consumers	Microgrids operator: energy price; energy consumers: energy demand	****	****
	[104] 2023	Stackelberg game	Maximizing total profits of microgrids alliance; minimizing total costs of users	Chaotic PSO (MHA)	Cooperative game: microgrids; stackelberg game: leader: multi-microgrid energy system (MMES); follower: users	Microgrids: whether to interact with other microgrids; MMES: power output, interactive power of equipment, amount of purchased power and energy price; users: load transfer, curtailment and thermal load usage	***	****
	[106] 2023	Cooperative game	Minimizing total operating costs; minimizing carbon emission	A hybrid PSO-simulated annealing optimization algorithm based on beetle antennae search	Renewable energy suppliers, power system and hydrogen ESS	Renewable energy suppliers: power generation scheduling; power system: power generation scheduling; hydrogen ESS: charge/discharge (hydrogen) scheduling	***	****
Thermal ESS	[107] 2021	Incomplete information game	Minimizing costs of each energy hub	Harsanyi transformation and Bayesian law	Energy hubs	Energy hubs: electricity input from grid and electricity trading volume per hour	****	***
	[108] 2022	Bargaining game	Maximizing consumer's welfare	Nash bargaining solution	Energy consumers	Energy consumers: day-ahead energy profile	**	***

TABLE A5
CHRONOLOGICAL SUMMARY OF RESEARCHES ON EV

Applications	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
Scheduling of EV	[113] 2015	Hierarchical game—upper level: non-cooperative game; lower level: evolutionary game	Maximizing revenues of EVCSs; maximizing profits of EVs	PSO (MHA)	Upper level: EVCSs; lower level: EVs	EVCSs: charging price; EVs: charging place and charging energy demand	****	****
	[110] 2018	Stackelberg game	Minimizing operation costs; maximizing payoffs of EVCSs; maximizing payoffs of EVs	Backward induction algorithm	Leader: system operator; follower: EVs and EVCSs	System operator: surcharge to EVCSs; EVCSs: electric price; EVs: charging place and charging energy demand	***	****
	[119] 2018	Non-cooperative game	Maximizing payoffs of the aggregators	Backward induction algorithm	Aggregators	Aggregators: charging time and energy demand	**	***
	[111] 2019	Stackelberg game	Maximizing profits of EVCSs; maximizing profits of plug-in hybrid EVs	Self-defined iterative algorithm	Leader: EVCSs; follower: plug-in hybrid EVs	EVCSs: charging price; plug-in hybrid EVs: charging place	***	****
	[115] 2020	Stackelberg and cooperative game	Maximizing profits of EVs and EV aggregator; maximizing social welfare	Self-defined iterative algorithm	Leader: EV aggregator; follower: EVs	EV aggregator: energy price; EVs: charge/discharge power	****	***
	[120] 2020	Dynamic game	Minimizing peak valley difference; minimizing charging costs	Solve differential equations	Power grid and EVs	Power grid: time-sharing electricity price; EVs: charging place and power demand	****	***
	[116] 2021	Non-cooperative game	Minimizing total energy costs of smart charge station (CS)	Newton fixed-point method	PEV	PEV: charging time and power demand	**	***
	[121] 2021	Two-stage non-cooperative game	First stage: maximizing profits of battery, PV power station and Grid; Second stage: maximizing profits of EVs	KKT condition and self-defined iterative algorithm	First stage: PV power station, battery and grid; Second stage: EVs	Battery: charge/discharge capacities; PV power station: power output capacities; Grid: power output capacities. EVs: charging demand	***	***
	[112] 2022	Stackelberg game	Maximizing revenues of EVCS; minimizing costs of EV customers	Multi-agent advantage actor-critic algorithm	EVs and EVCS agents	EVCS agents: electric price; EVs: charging time and location	****	****
	[117] 2022	Dynamic game	Minimizing costs of parking lot; Minimizing costs of EVs	Self-defined iterative algorithm	Parking plot and EVs	Parking plot: charging/discharge power; EVs: buying/selling power	****	****
	[118] 2023	Non-cooperative game	Minimizing costs of energy community	Accelerated distributed augmented Lagrange method	Charging EVs, trading EVs and prosumers	Charging EVs: charging capacity; trading EVs: free battery capacity; prosumers: amount of selling/purchasing energy	***	***
	[114] 2023	Non-cooperative game	Minimizing battery swapping costs of EVs	Self-defined iterative algorithm	EVs	EVs: available battery swapping station	***	**

TABLE A6
CHRONOLOGICAL SUMMARY OF RESEARCHES ON EVCS

Applications	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
Operation and scheduling of EVCS	[123] 2015	Non-cooperative game	Maximizing revenues of the EVCSs	Best response algorithm	EVCSs	EVCSs: electricity price	***	**
	[124] 2018	Stackelberg game	Maximizing revenues of EVs	Self-defined iterative algorithm	Leader: recently arrived plug-in EV; follower: previously arrived plug-in EVs	Plug-in EV: charging reservation (charging power demand and time)	***	****
	[125] 2018	Stackelberg game	Maximizing profits of EVs; maximizing benefits of fast CS	KKT conditions	Leader: fast CS; follower: EVs	Fast CS: energy reserve prices; EVs: charging and reserve plan	****	***
	[122] 2020	Nash bargaining game	Minimizing operation costs of IES; minimizing costs of EVCSs	Distributed algorithm based on modified benders decomposition	IES and EVCSs	IES: amount of selling/purchasing energy; EVCSs: amount of electricity purchased from IES or energy market	****	**
	[126] 2021	Stackelberg game	Maximizing benefits of PVCS; minimizing costs of EV users	Self-defined iterative algorithm	Leader: PVCS; follower: EV users	PVCS: electricity real-time price; EV users: charging power and time.	****	**
	[127] 2022	Stackelberg game	Minimizing costs of facility; Minimizing costs of EV users	Backward induction method	Leader: facility manager; Follower: EV users.	Facility manager: charging power; EV users: charging time and required energy quantity	****	***
EVCS planning	[128] 2015	Bayesian game	Maximizing profits of charging service providers	Self-defined iterative algorithm	Charging service providers	Charging service providers: EVCS placement policy	***	****
	[131] 2018	Mixed game	Minimizing cost of each EV	Self-defined heuristic algorithm (MHA)	EV users in different zone	EV users: charging area	*****	****
	[132] 2019	Nash bargaining game	Maximizing fast CS bargaining problem function	Lagrange multipliers technique	Fast CS operator and DisCo	Fast CS operator and DisCo: energy price, fast CS capacity and candidate location.	****	***
	[130] 2019	Stackelberg game	Maximizing total profits of CisCo; maximizing profits of customs	Self-defined distributed algorithm	Leader: DisCos; follower: EVCSs	DisCos: energy price; EVCSs: demand schedule	****	****
	[133] 2020	Evolutionary game	Maximizing profits of investors	Small world network	Candidate stations	Candidate stations: turn to electric CS or gas station after investment	***	****
	[129] 2022	Hedonic game	Maximizing sum of individual utilities of EV users	k-means clustering with group agent partitioning and placing event	EV users	EV users: EVCS that can be selected	***	**

TABLE A7
GAME THEORY BASED ON REINFORCEMENT LEARNING

Application	Ref.	Game theory approach	Objective function	Solution method	Player	Strategy	Complexity	Applicability
Optimal scheduling	[136] 2023	Stochastic game	Minimizing the operating cost of microgrids	Multi-agent soft actor-critic and multi-agent win or learn fast policy hill-climbing	Multiple microgrids	Energy management and biding strategy for multiple microgrids	***	***
Energy community designing	[143] 2022	Stackelberg game	Maximizing the profits of microgrids	Monte-Carlo tree search	Microgrid energy management systems	Microgrid management strategy	***	***
Optimal scheduling	[137] 2023	Multi-agent Nash game	Maximizing the profits of source side; minimizing the operation cost of grid side; minimizing the cost of load side	Nash-Q learning	Source side, grid side, and load side	Power consumption and output scheme	**	***
Optimal scheduling	[138] 2021	Two-layer cooperative game	Upper layer: maximizing the energy selling profits; lower layer: minimizing the cost of energy hubs	Multi-agent deep deterministic policy gradient	Upper layer: energy hubs; lower layer: units within energy hub	Upper layer: strategy of trading power; lower layer: units operation strategy	****	**
Microgrid market	[142] 2020	Markov game	Maximizing the benefits of total agents	Multi-agent reinforcement learning	RES, demand users, battery ESS	RES: power output of PV and WT; Demand users: power consumption plan; ESS: charge and discharge strategy	***	****
Microgrid market and optimal scheduling	[139] 2021	Upper layer: Stackelberg game; lower layer: non-cooperative game	Upper layer: maximizing the expected revenue; minimizing the total cost of DNO; lower layer: minimizing the total cost of generation	Win-or-learn-fast policy hill-climbing	Upper layer: leader: virtual microgrids; follower: active DN. Lower layer: virtual microgrids	Upper layer: leader: devoted capacity to energy and ancillary market; follower: energy and ancillary service procurement. Lower layer: energy dispatching strategy	*****	****
Optimal scheduling	[140] 2023	Non-cooperative game	Maximizing the individual and overall benefit of microgrids	Q-learning	Multiple microgrids	Output power of each microgrid	**	***
Optimal scheduling	[141] 2020	Deterministic game	Maximizing the operational profits of battery ESS	Q-learning	Multiple battery ESS agents	Charging/discharging strategy	**	***

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AUTHORS' CONTRIBUTIONS

Bo Yang: writing review and editing, writing original draft, and conceptualization. Yimin Zhou: writing original draft and data curation. Yunfeng Yan: writing review, editing, and supervision. Shi Su: funding acquisition and formal analysis. Jiale Li, Hongbiao Li, and Dengke Gao: visualization and data curation. Wei Yao and Jingbo Wang: supervision and resources. All authors read and approved the final manuscript.

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AVAILABILITY OF DATA AND MATERIALS

Please contact the corresponding author for data material request.

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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