A mini-review on trading mechanisms of emerging joint energy markets with high shares of renewables

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The intermittence and unpredictability of large-scale renewable integration poses significant challenges to the operation of the electricity market. New paradigms of the joint electricity spot market (EM) and ancillary service market (ASM) incorporating frequency regulation (FR) and flexible ramping product (FRP) are considered as potential solutions, addressing the challenge of limited compatibility in the electricity market with the widespread integration of renewable sources. This work focuses on three critical technical obstacles: optimizing the joint market mechanisms, constructing bidding models, and exploring algorithmic solutions. This paper presents a brief review of recent research on bidding mechanisms, models, and strategies for the electricity joint market with high-penetration renewable integration. Furthermore, challenges and future research prospects of these issues are also discussed.

KEYWORDS

renewable sources, spot market, ancillary service market, market mechanisms, bidding model

1 Introduction

Global climate change problem has become increasingly serious in recent years, and reducing greenhouse gas emissions is one of the main challenges facing the industry. Burning fossil fuels at thermal power plants play a significant role in greenhouse emissions, accounting for over 60% of the European Union's total emissions (Andersson and Börjesson, 2021). Therefore, decarbonizing power sector, i.e., promoting wide-scale penetration of renewable generation to replace thermal generators, has drawn considerable attention from academia and industry (Bistline and Blanford, 2021). Nevertheless, the uncertainty and intermittence of renewable generations also threaten the security of power grid operation.

Facing these new challenges, the electricity market is considered the macro-level approach to achieving power system operation security, economic efficiency, and environmental friendliness. In order to accommodate the vast amount of renewable generation resources, the emerging features of the worldwide electricity market can be summarized as follows: (1) High penetration distributed resources such as photovoltaics and wind power are more inclined to generate and participate in the electricity market as stakeholders. (2) The demand for balancing products in the ancillary service market (ASM) has increased due to the necessity of hedging uncertainties caused by high penetrations of

renewable generations (Nelson and Johnson, 2020; Wang and Hobbs, 2015). For instance, the flexible ramping product (FRP) proposed by California ISO (CAISO) facilitates real-time (RT) balancing in a time slot of 5–15 min (Wang et al., 2020). Therefore, the joint energy spot market (EM) and ASM will become a dominant force in the global power industry, making it necessary to extensively study the joint market mechanism. This paper reviews the market mechanism optimization, the construction of the bidding models, and the algorithmic solutions.

2 Literature review

2.1 Current research on market mechanism optimization theory for large-scale penetration of renewable energy

Optimizing market mechanisms, typically grounded in microeconomic theory, involves the proposal of bidding or pricing mechanisms, which are then validated through equilibrium analysis. This process often models the market as an Equilibrium Problem with Equilibrium Constraints (EPEC). Worldwide research has explored the strategic bidding behaviors of large-scale renewable energy suppliers in electricity markets, such as wind farms, electric vehicle integrators, and energy storage facilities (Morales et al., 2010; Pousinho et al., 2013; Zugno et al., 2013; Alabdulwahab et al., 2016; Zou et al., 2016; Xiao et al., 2023). Some research has considered the collaborative operational bidding strategies of various renewable energy sources (Mohammadi et al., 2011; Vagropoulos et al., 2013; Agustin et al., 2016; Cao et al., 2024), while others have proposed short-term bidding strategies for virtual power plants that incorporate various flexibility resources (Rahimiyan and Baringo, 2016). Countries like Denmarkanticipate a complete transition to renewable energy for power supply by 2050, particularly in Northern Europe. However, China faces the challenge of being unable to replace fully traditional power plants with renewable energy sources in the short term (Jacobson et al., 2017). Consequently, when investigating the strategic bidding of large-scale renewable energy suppliers in the market, the presence of traditional power plants should not be overlooked alongside flexible resources like wind, solar, and energy storage. Furthermore, integrating carbon markets into the power market has prompted studies on the effects of European Union carbon emission trading rights and carbon emission costs on power market dynamics and generator bidding strategies (Weigt et al., 2013; Anke et al., 2020). With the spot market overlooking the carbon market's impact on power market transactions, electricity-carbon market mechanisms operate relatively independently in regions such as Guangdong Province.

Research on market mechanisms varies depending on the type of market. Some focus on the bidding and settlement mechanisms of the energy quantity market from the generation side (Ela et al., 2016; Mozdawar et al., 2022; Silva-Rodriguez et al., 2022), while others concentrate on the pricing and deployment strategies of ancillary services, primarily frequency regulation (Arteaga and Zareipour, 2019; Maria Luisa et al., 2019; Godoy et al., 2020; Stavros et al., 2020; Luis et al., 2022). These studies explore various market clearing methods (deterministic or stochastic) and compensation

mechanisms (pay-as-bid or opportunity cost payment). In the United States, markets such as CAISO and MISO independently trade, optimize, and price ramp capabilities, introducing a new ancillary service product, FRP (Casio, 2015; Navid and Rosenwald, 2024). This addition mitigates the uncertainty of system load and renewable energy variations, ensuring sufficient ramping capability to match net load changes and maintain system real-time balance. Although the introduction of FRP for joint market clearing can enhance the regulatory capacity of the system, research in this area is still in its nascent stages. Various studies have examined the market mechanisms of Energy Markets (EM) and Ancillary Service Markets (ASM) from different perspectives, including market time frames, equilibrium models based on non-strategic bidding (actual cost functions), incentive-compatible clearing mechanisms, and the formulation of Locational Marginal Pricing (LMP) (Sorourifar et al., 2018; Zhou et al., 2018; Wu et al., 2020; Zhang et al., 2020; Hu et al., 2021). In the joint optimization of the Energy Market (EM) and Ancillary Services Market (ASM), FPR does not possess the autonomy to bid independently.

The ultimate objective of optimizing market mechanisms is to maximize the overall social welfare of the integrated market. The mechanisms across different markets must be harmonized to gradually steer the bidding strategies of market participants towards Pareto optimality while preventing cross-market collusion arbitrage and market power abuse. For example, the compensation that market participants receive is tied to the difference between Day Ahead (DA) and real-time EM prices. If there are flaws in the market mechanisms, speculators can manipulate DA and real-time prices to reap substantial profits. However, the current evaluation of market mechanisms lacks quantitative indicators, making it challenging to verify their effectiveness. Indeed, existing market mechanisms, primarily established based on domestic and international experience and theoretical knowledge, are constrained by computational limitations. The efficiency and security of the market largely hinge on the bidding strategies of participants, but assessing the impact of market mechanisms on participants' bidding strategy preferences remains a formidable challenge. Thus, optimizing market efficiency and stability through empirical market mechanisms is not feasible.

2.2 Current research on the multi-agent bidding model of the electricity market

In the Multi-agent bidding model, human candidates with varying degrees of expertise in electricity markets will participate in the trading with a virtual market environment, representing different generation companies to submit their bids to maximize potential profits. After repeated bids submission, the game may gradually converge to the equilibrium, allowing for the detection of potential abuses of market power through the convergence procedure. The aforementioned process can be simulated as a two-layer bidding game model of GENCOs, and the solutions for this model are typically obtained through mathematical methods based on equilibrium models (Dou et al., 2016) and Agent-based Models (ABM) (Guevara C et al., 2012). A significant number of research on equilibrium models using mathematical programming

focused on optimizing bidding strategies, including chance-constrained stochastic optimization (Zhao et al., 2018; Hosseini et al., 2020), robust optimization (Pousinho et al., 2015; Baringo and Sánchez Amaro, 2017), and distributional robust optimization (Han and Hug, 2020; Hajebrahimi et al., 2020). However, the diverse operational characteristics (such as on-and-off or up-and-down constraints for switches and generators) and the immense scale of expanded power networks render these problems highly dimensional, non-convex, and subject to non-observable uncertainty. Consequently, using traditional optimization tools in these contexts becomes exceedingly complex and imposes a substantial computational load. The existing research regarding scale and market rules is overly simplified compared to real-world electricity markets. ABM is typically more flexible, as it allows us to model all market participants individually and treat them as distinct agents. Each agent continuously updates its data through repeated interactions with the simulated market environment. After repeated bidding, the game may gradually converge to an equilibrium state. It should be noted that potential market power abuse phenomena can be discovered through the convergence process, resembling a real electricity market (Azadeh et al., 2012). In the ABM model, heuristic algorithm models are commonly used (Boonchuay and Ongsakul, 2011a; Elsakaan et al., 2018; Kong et al., 2019a; Hematabadi and Foroud, 2019; Du et al., 2021; Qiu et al., 2023), including genetic algorithms (GA) (Boonchuay and Ongsakul, 2011a), particle swarm optimization (PSO) (Kong et al., 2019a), artificial immune system algorithms (AIS) (Qiu et al., 2023), bacterial foraging optimization (BFO) (Elsakaan et al., 2018), krill herd algorithms (KHA) (Hematabadi and Foroud, 2019), and water wave optimization (WWO) (Du et al., 2021). These algorithms are inspired by the cooperative behaviors of gregarious animals, evolution, and heredity and have exhibited superior computational performance compared to conventional mathematical programming techniques. Model-based intuitive learning and applying genetic algorithms are utilized separately to determine the optimal bidding curves, as demonstrated in (Zhang et al., 2014; Weidlich and Veit, 2008). However, these algorithms are designed to formulate the bidding strategy of individual agents, where each agent makes decisions independently without considering the actions of the competitors. Although numerous studies (Boonchuay and Ongsakul, 2011b; Javaid et al., 2017; Kong et al., 2019b) have utilized group optimization algorithms to model the dynamic bidding process, these methods yield the optimal Pareto frontier in a cooperative setting, where agents can freely exchange search strategies. Nevertheless, this study aims to find the Nash Equilibrium within a competitive bidding environment. This necessitates fully distributed training that precludes any communication among the participating GENCOs. This strategy ensures privacy and mitigates the risk of collusion, thereby preserving the competitive integrity of the bidding process. Consequently, these methods prove unsuitable for a competitive market where each agent seeks to achieve its objectives by adjusting its behavior in response to other agents. As the model-free characteristic of reinforcement learning techniques, they eliminate the need for intricate mathematical modeling, empowering the agent to pursue the optimal decision more conveniently through direct interaction with the environment. The comparison of various electricity market bidding models is presented in Table 1.

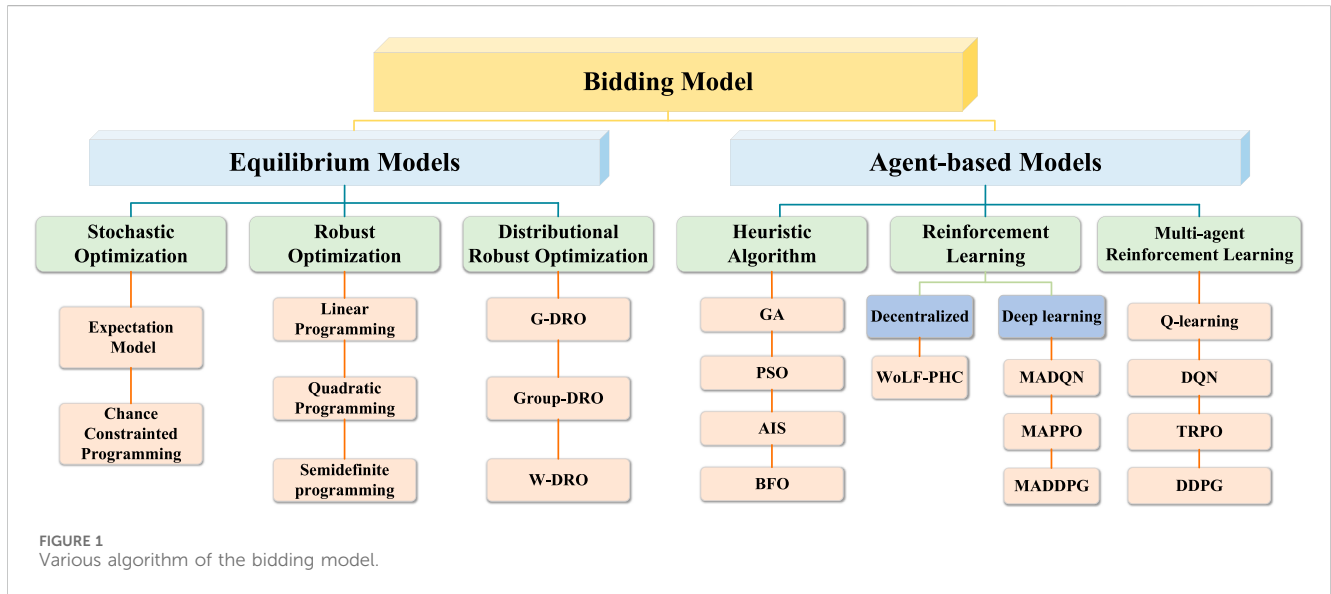## 2.3 Current research on bidding strategy algorithms of multi-agent market participant

This section comprehensively reviews the Reinforcement Learning (RL) fundamentals, encompassing all necessary concepts and algorithms that will be further utilized in elaborating the RL applications on marketized power systems presented in the subsequent sections. An RL algorithm comprises a model-based RL such as dynamic programming and model-free RL, further extending to value-based RL (including Q-learning, DQN and WoLF-PHC) and policy-search-based RL (including stochastic and deterministic policy gradient, Actor-critic (AC), Trust Region/Proximal Policy Optimization (TRPO/PPO), Deep Deterministic Policy Gradient (DDPG) methods). As a set of RL algorithms, numerous Q-learning algorithms have found broad application in the multi-agent electricity market for exploring bidding strategies. Najafi et al. (2019) present the development of a decentralized multi-agent model for bidding by Electric Vehicle (EV) owners, which is based on a Q-learning algorithm and crafted without the necessity for environmental modeling. For instance, Liu et al. (2021) introduced a quarter-hourly dynamic pricing strategy, leveraging the DDPG algorithm, to address the discretization issue encountered in traditional time-division pricing models. Lee et al. (2021) present an innovative energy trading system among Microgrids (MGs), incorporating a DDQN algorithm and a double Kelly strategy. Although these techniques have explored the dynamic interaction of numerous agents, the optimality search process relies on cooperation and communication among individual agents, which is inconsistent with competitive market bidding in the absence of knowledge about other rivals.

Qiu et al. (2023) and Elsakaan et al. (2018) employ the Multi-Agent-Based Models (MABM) for simulating market participant bidding models and consider the game issues of updating the multi-agent bidding strategies of energy suppliers in large power systems and regional integrated energy systems, respectively. However, in the process of making bidding decisions, multi-agents require historical bidding information of competitors. Although this model offers certain advantages compared to models with fully disclosed information, the real market is an incomplete information market. Indeed, in a real market, each participant only knows their own cost function and bidding strategy, lacking any information about other competitors (Hematabadi and Foroud, 2019). Moreover, market participants are unwilling to share their historical bidding information with competitors, rendering this algorithm still impractical for real-world market scenarios.

Zhao et al. (2022) list several Multi-agent Reinforcement Learning (MARL) methods and developed a time-varying model with an updating strategy to simulate bidding games with incomplete information. Gao et al. (2021) employ the WoLF-PHC method to ascertain the Nash Equilibrium (NE) in a pool-based energy market comprised of large-scaled wind turbines and EV aggregators. However, the computational performance is unstable with the increase of variables. Fang et al. (2021) introduce a market mechanism for double auctions in regional microgrids (MGs), utilizing a Multi-Agent Deep Q-Network (MADQN) algorithm to identify the optimal bidding strategy for these MGs. Furthermore, an Optimal Equilibrium Selection (OES) is

TABLE 1 Comparison of different bidding model of the electricity market.

Model	Algorithm		Multi-agent environment	Competitive environment	Speedy computation	Tractable in continuous space	Privacy protection	Sensitivity to hyper-parameters
Equilibrium models	Stochastic optimization		×	×	×	×	×	✓
	Robust optimization		×	×	×	×	×	✓
	Distributed robust optimization		×	×	×	×	✓	✓
Agent-based models	Heuristic algorithm		✓	✓	✓	✓	✓	✓
	Multi-agent Reinforcement Learning	Q-learning	×	×	✓	×	×	✓
		DDPG	×	×	✓	✓	×	✓
		DQN	×	×	✓	✓	×	✓
		WoLF-PHC	✓	✓	✓	×	✓	✓
		MAQ	✓	×	✓	×	×	✓
		MADQN	✓	✓	✓	✓	×	✓
		MAAC	✓	✓	✓	✓	×	✓
		MAPPO	✓	✓	✓	✓	✓	×
		MADDPG	✓	✓	✓	✓	✓	✓

FIGURE 1
Various algorithm of the bidding model.

proposed to guarantee benefit fairness, execution efficiency, and privacy protection during the interactive learning process of MADQN. Ye et al. (2023) introduced a generalized strategic bidding model for energy producers and solved it using the Deep Deterministic Policy Gradient (DDPG) method, which uses a neural network to estimate the optimal Q function. However, this algorithm based on policy gradient descent is constrained by the instability of the learning environment and the interaction of multiple agents, rendering it unsuitable for multi-agent environments. In Xu et al. (2018), Qiu et al. (2021), Li et al.

(2022), and Mehdipourpicha et al. (2023), the Multi-agent Deep Deterministic Policy Gradient (MADDPG) algorithm and its modified versions were used to simulate the bidding game in competitive electricity markets taking into account privacy protection. Overall, the computational performance of existing RL algorithms is highly sensitive to hyperparameters. Therefore, for the bidding simulation of large-scale electricity markets, adjusting hyperparameters significantly impacts them and affects simulation convergence's stability. Moreover, pressure on storage space can also make equilibrium point calculations time-consuming

and challenging. The applicability of these MARL algorithms in bidding strategy is compared as shown in Table 1. The bidding model with corresponding algorithms is summarized as Figure 1.

3 Challenges and future trends

Although the research mentioned above has played a significant role in integrating renewable energy into the optimal mechanism of the emerging joint energy and ancillary service market, this paper proposes three major technical challenges and future trends:

(1) Integrating large-scale renewable energy entities into the combined electricity spot and ancillary services markets has rendered the research into power market mechanisms increasingly complex. The inherent intermittency of renewable energy sources poses substantial threats to the reliability and safety of the power system, consequently impacting the dispatching, investment, and operation of the electricity market. Inadequate market mechanisms may lead to some renewable energy participants engaging in detrimental price competition or exploiting market power to establish monopolies, thereby affecting overall societal welfare and market efficiency. Furthermore, there has been little research on how to optimize the market mechanisms and improve market operational efficiency. With the penetration of large-scale renewable energy, future research could focus on investigating integrated electricity market mechanisms to address the aforementioned challenges. Integrated market encompasses the Energy Market (EM) and the Ancillary Services Market (ASM), which includes components such as Frequency Regulation (FR) and Flexible Ramping Product (FRP). It would be beneficial to develop pertinent evaluation metrics to optimize these market mechanisms effectively.

(2) The bidding model utilized in the current electricity market trading mechanisms is overly simplified, particularly in the market scale, the simulation of participant bidding strategies, and market rules. Compared to the real electricity market, this excessive simplification leads to a lack of reliability and credibility in the simulated results of the model. In response to the issues outlined above, future research should focus on MABM to simulate the bidding behavior of market participants in a competitive market environment. The model will explore the relationship among factors such as bidding, profitability, and market settlement conditions to validate and iteratively optimize the market mechanisms.

(3) Existing methodologies employed to solve bidding models of multi-agent market participants encounter limitations in computational performance. This is particularly evident in the bidding simulations of large-scale electricity markets, where adjusting hyperparameters in reinforcement learning methods can significantly impact the algorithm's convergence performance. Further research should explore a multi-agent deep reinforcement learning algorithm for the bidding model of market participants. The method safeguards agents' privacy, allowing them to fully exert their autonomy in bidding without any information exchange among them. Moreover, this approach successfully mitigates the influence of hyperparameters and exhibits excellent convergence properties.

4 Conclusion

In a carbon-constrained environment, the fundamental purpose of market mechanisms, with the electricity market as the primary tool, is to promote the development of the electricity industry towards cleaner, more efficient, and lower-carbon directions. It also aims to facilitate the large-scale penetration of renewable energy generation replacing fossil-fuel-based power generation. The intermittent and uncertain nature of large-scale renewable energy grid-integrated generation poses significant challenges to the operation of electricity markets. To address the issue of suboptimal compatibility in electricity markets, this paper reviews three aspects: the optimization of mechanisms in the integrated market of electricity spot and ancillary services, the construction of bidding models, and the resolution of associated algorithms. In addition, the challenges and potential future developments in the field are also discussed.

Author contributions

XG: Conceptualization, Writing–original draft, Writing–review and editing. CY: Data curation, Formal Analysis, Writing–review and editing. ZZ: Visualization, Writing–original draft. YW: Visualization, Writing–review and editing. YC: Visualization, Writing–original draft. ZM: Visualization, Writing–original draft.

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Conflict of interest

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