A multi-agent simulation model considering the bounded rationality of market participants: an example of GENCOs participation in the electricity spot market

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Abstract. The concept of bounded rationality has garnered substantial attention and interest from scholars since its inception. It is widely recognized that in complex systems, decision-making by its members is bounded by cognitive limitations. In this context, multi-agent simulation has emerged as a popular tool to model complex systems. One important question is how to incorporate the bounded rationality of market participants in such simulations. This paper proposes a novel multi-agent simulation model that considers the bounded rationality of GENCOs(generation companies) in electricity markets. Unlike other models, our proposed model enhances the experience and decision-making ability of power GENCOs during the training phase and simulates their errors in predicting market information and making decisions during the simulation phase. This enables the model to evaluate the results of the market under the influence of bounded rationality and to compare them with the equilibrium results. To assess the extent to which different market mechanisms deviate from equilibrium results under the influence of bounded rationality, we propose evaluation metrics. The implications of our work are significant as it enables the exploration of incentive-compatible mechanism designs. Finally, we perform a numerical analysis of compensation fee mechanisms in several electricity markets using our proposed model.

Keywords: Bounded rationality · Multi-agent simulation · Power market simulation · Deep reinforcement learning.

1 Introduction

In research on the simulation of complex systems in human society such as economic markets, a majority of normative economic models assume perfect information and perfect rationality. Though such assumptions can simplify the solution and analysis of complex problems, they may lead to deviation between the simulation results and the real world, which cannot be explained[11]. As a large and complex economic system, the electricity spot market is subject to both physical constraints of the power system and policy constraints of electricity as a public service product, which has increased many uncertainties in the operation of the electricity spot market due to external factors. Moreover, power (electricity) market participants need to make complex decisions in extremely limited time periods based on limited market information (either partially or late disclosed) for each delivery period. Therefore, it is an appropriate scenario to study the bounded rationality[3] of participants by the simulation of electricity markets.

Simulation of electricity spot market[14] is often used to verify the effectiveness of power market mechanism design, and vice versa, the correct reflection of the market mechanism is also a proof of the effectiveness of the simulation. Participants (usually modeled as computer agents) carry out repeated static games in the power market, and the mechanism designers assess the effectiveness of market mechanisms by solving for market equilibrium. Since the results of the spot market are affected by the decisions of all participants, scholars have conducted extensive research on the bidding behavior of market participants, especially GENCOs[10], and analyzed it using game theory methods. In order to quickly solve specific problems, these studies have simplified the simulation process to varying degrees, modeling the decision-making behavior of generation companies based on bilevel optimization[12] or simulating the dynamic bidding process based on heuristic algorithms[9]. These studies consider the game of all members, but require each member to have complete information, ignoring the problem of incomplete information in the real electricity market, that is, generation companies cannot know the strategies of other generation companies or the parameter values of the ISO clearing model.

In order to solve the problems mentioned above, in the field of power market simulation, it is most common to use the model-free reinforcement learning (RL) algorithms to model each and every GENCO, and use multi-agent simulation to solve the equilibrium of the spot market [17]. It should be noted that most research on agent-based GENCO modeling is based on the assumption of complete rationality (that is, GENCOs are always able to and tend to maximize their own utility) [5]. However, in a real power market, this assumption is rarely met, and thus, the market results may seriously deviate from the expectations of market designers due to the irrational behavior of the GENCOs. Considering the bounded rationality of market participants, the actual bidding behavior of some participants may deviate from the theoretical optimal strategy obtained under the assumption of complete rationality [5]. This phenomenon is observed in the actual power markets. For example, in a data-driven analysis of the actual bidding data of GENCOs in the Australian power market [4], it is found that the bidding behaviors of some GENCOs deviate from the theoretical optimal strategy; and paper [7] points out the failure of many market mechanisms is due to the participants violating the assumption of perfect rationality.

The bounded rationality theory and its developed prospect theory (PT) by Nobel Prize winners Daniel Kahneman and Amos Tversky [8] provide tools for analyzing the irrational behavior of GENCOs, and in recent years, some studies on power market simulations have focused on this aspect. For example, paper [15] used prospect theory to model GENCOs and observe non-cooperative games in the day-ahead market. Paper [16] established a two GENCOs game model and analyzed the impact of information asymmetry on Nash equilibrium. Based on these theories, bounded rationality was considered in modeling GENCOs, but these studies only partially considered bounded rationality and simplified both the strategies of GENCOs and the power market environment, reducing the practical significance for power market mechanism design.

In summary, it is an effective technical route to use multi-agent simulation considering participants' bounded rationality for the simulation of complex socio-economic systems such as power market. However, the current research is less concerned with the bounded rationality of GENCOs, or only considers the irrationality in the decision-making process (for example, considering the risk aversion psychology [1]), while ignores the impact of the complexity of the power market mechanism itself on GENCOs (GENCOs make wrong predictions of the power market scenario because they cannot obtain information in time or have obtained wrong information). At present, there is still a lack of effective power market simulation tools that can consider the bounded rationality of GENCOs and conduct dynamic simulation to support the evaluation of power market mechanism design.

The contributions of this paper include:

1. A multi-agent simulation model considering GENCOs' bounded rationality is proposed. In this model, GENCOs' bounded rationality is reflected in the fact that they misjudge the power market information without knowing it and make decisions that deviate from the optimal decision. Distinguish from other bounded rationality models, the model establishes a GENCO's confidence in the training stage (different from the "non-confidence" model that modifies the income function with uncertainty), and in the verification stage, the model makes the GENCO make wrong predictions and bid in the spot market, so as to analyze the market state when it is impacted.
2. The deep reinforcement learning(DRL) algorithm is used to model the GENCOs, so that they can process the multi-dimensional continuous information, such as electricity price and cleared volume, and output the three-part quotation (a complex quotation structure) that can express the non-monotonic cost [13].
3. Based on the multi-agent simulation considering the bounded rationality of GENCOs, some counterintuitive phenomena in actual electricity market mechanisms have been reproduced. In order to increase revenue, GENCOs often have different bidding strategies in different environments in the market, such as different load curves. Therefore, their inaccurate predictions of the environment may result in irrational bidding. This article uses numerical simulations to verify to what extent defective or imperfect mechanism design, in situations where predictions are inaccurate, will expose GENCOs to external information interference and deviate them from actual cost bidding.

2 Model

2.1 Organization of the electricity market

This paper analyzes the common LMP(Locational Marginal Price)-based market mechanism, which is adopted by power markets such as PJM in the United States and Guangdong in China. Figure 1 demonstrates that the day-ahead (DA) market is structured for simulation. Every period, ① GENCO's decision model makes a decision based on the status information from the previous cycle. ② The GENCOs convert the model's output data into a three-part offer, comprising energy price, no-load price, and start-up price[13], and submits it to the ISO. ③ After collecting all offers, ④ the ISO performs market clearing , ⑤ and settlement to obtain the winning power and revenue of each GENCO, ⑥ sending the market results back to the corresponding GENCO. ⑦ After receiving the market result, GENCOs process the data and convert it into a reinforcement learning state as the RL algorithm's input for the next cycle.

In the actual electricity market, each GENCO cannot know the bidding strategy and corresponding market revenue of other GENCOs, nor do they know the ISO's latest market clearing parameters. Therefore, the data of one GENCO is "Invisible" to other GENCOs. This paper uses the same environment for power market simulation, employing a Partially Observable Markov Decision Process (POMDP). In a NE, GENCOs have no incentive to change their strategies since they have sufficient experience and consensus in imperfect information.

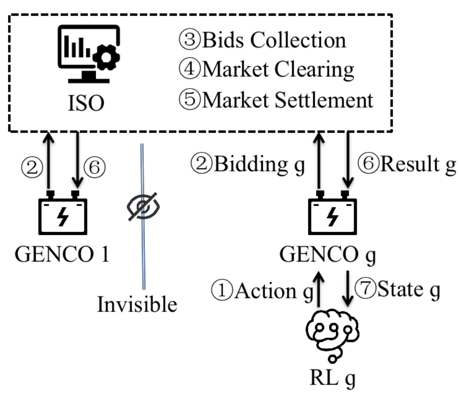


Fig. 1. Electricity spot market organization.

2.2 Simulation Model Considering the Bounded Rationality of GENCOs

Previous studies have adopted two approaches to modeling bounded rationality [5]: 1) process approximation bounded rationality models, which simulate finite rationality by introducing an approximation function in the decision making process, and, 2) strategy statistics bounded rationality models, which require analysis based on actual data and use statistical methods to approximate the decision distribution of the GENCO. The above models focus on the decision making process of the GENCO, making it consider more information in the decision making process (e.g. the conditional value-at-risk, CVaR[1]).

However, in actual market operations, bidding from GENCOs are limited by time constraints and information processing capabilities , and they tend to offer based on market information disclosure and experience. This decision process is confidential.

The model proposed in this paper considers this decision confidence, enabling GENCOs to thoroughly learn information in different electricity market scenarios during the training phase. To overcome the generalization capability of current DRL algorithms' limitations, each GENCO has multiple RL models and uses different models for different scenarios to make decisions. Most uncertainty in the electricity spot market is due to the market boundary information's uncertainty (e.g., load curve), making it common practice to generalize typical discrete scenarios and use different decision methods.

After training for each typical scenario, validation is performed using a 'confident' power generator agent trained in that scenario, in which GENCOs are exposed to events where their simulation predictions are incorrect and they must rely on a wrong RL model to make decisions.

At the end of the training phase, validation is performed using "confident" GENCO agents, passing incorrect market information to some or all of the GENCOs so that they invoke the wrong RL model and make the wrong decision. The ISO calculates the market outcome and evaluates the metrics. Based on the results, the researchers analyze potential problems with the market rules to assess their resilience to shocks. The market designers aim to guide the participants' behavior through the electricity spot market mechanism's design to improve the resilience of the market rules to shocks without altering the optimal market outcome and help manage unexpected situations.

The simulation model proposed in this paper is presented in Figure 2 and explained in detail as follows.

During the training phase (the upper part of Figure 2)

1. ISO presets N_s typical scenarios with different market boundary information, and the m^{th} scenario $S_m \in \{S1, S2 \ldots S_{Ns}\}$.
2. each scenario S_m is used for training purposes, where the parameters of S_m(market boundary conditions, such as load curves), are fixed, and the RL model Φ_g^m is trained for each GENCO g under S_m. All GENCOs play an infinitely repeated game and the ISO obtains the market equilibrium.
3. The decision model $\rho_g = \{\Phi_g^1, \Phi_g^2 \ldots \Phi_g^m\}$ for GENCO g is derived from this process.
4. The above steps are repeated for each market rule θ in the set of rules to be studied Θ, to obtain the decision model ρ_g^θ for GENCO g under different rules.

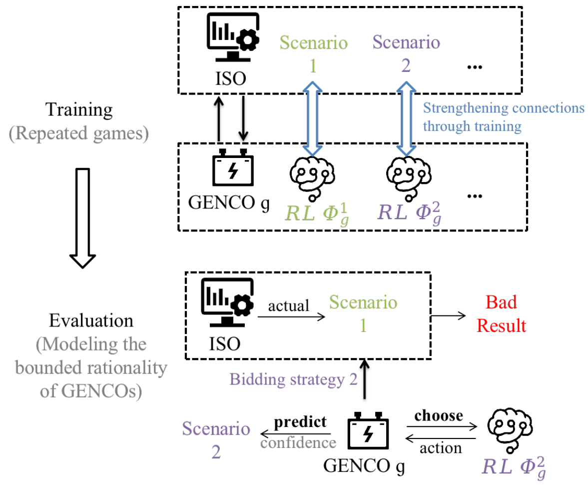


Fig. 2. Simulation model schematic.

During the evaluation phase (the lower part of Figure 2)

1. During the evaluation phase, it is assumed that each GENCO g can correctly predict the current scenario S_m and make a decision. The result R_m^{base} obtained by ISO, is used as the baseline to calculate market indicators I_m^{base}(such as generation cost, electricity cost, and average electricity price), which represent the equilibrium state of the electricity market under ideal conditions.
2. Different contingency events E^i are designed to simulate GENCOs misjudging current scenario S_m and making decisions(In the Figure 2, it is actually Scenario 1, but GENCO mistook it for Scenario 2). ISO then calculates the market outcome R_m^i, and the market indicator I_m^i. under the contingency. The deviation of the contingency from the base outcome can be used to evaluate the shock resistance of the market rule, which is denoted as A_m^i.

$$A_m^i = \frac{\left|I_m^i - I_m^{base}\right|}{I_m^{base}} \times 100\% \tag{1}$$

3. The maximum deviation is calculated for all contingencies and all scenarios for different market rules θ.
4. By assessing A_θ for different market rules, it is possible to determine the shock resistance of each rule, where the more shock-resistant the market rule, the smaller the A_θ.

3 Case Study

3.1 Set of Mechanisms to be Studied

In mechanism design, compensation can be added to market participants who fail to meet their participation constraints to encourage them to report their true costs, thereby promoting incentive compatibility. This is a well-established conclusion in economics. In actual market design, however, other considerations may lead to the adoption of non-compensatory or partially compensatory measures. This phenomenon is widespread in the current pilot areas of China's spot market. A quantitative analytical approach is needed to examine the impact of different compensation methods, including full, no, and partial compensation, on market efficiency.

This paper examines a set of market mechanism designs denoted as Θ, which includes the make-whole payment (MWP)[2] employed by PJM and the electricity market mechanisms adopted in several Chinese provinces. In the MWP mechanism, the ISO considers the offers submitted by GENCOs as their actual costs, also referred to as Offer Costs in this paper, which reflect their willingness to generate electricity. The ISO compensates GENCOs that have incurred losses, that is, those whose revenues are lower than their offer costs, by paying them the total amount of losses through a compensation fee. This fee is computed by determining the revenue earned by each GENCO for the entire day. The differences between other mechanisms and MWP are detailed in the Additional Notes in Table 1.

Table 1. Comparison of compensation fee mechanisms.

Symbols	Mechanism Name	Additional Notes
θ_1	Make-Whole Payment	Only the spot market is considered, consider full day losses, the loss is fully compensated.
θ_2	No compensation	No compensation payments to GENCOs
θ_3	Consider Long-term Contracts	ISO considers long-term contract revenue when approving GENCO's revenue.

3.2 Parameter Setting

For the simulation, we use the IEEE5 system data, which consists of five GENCOs with varying capacities and non-monotonic cost parameters. To represent each GENCO, we set up five Agent models, one for each GENCO. We employ the Soft Actor-Critic (SAC)[6] learning algorithm[24] for each RL model Φ_g^m. The Actor model of the SAC algorithm is a fully connected neural network with layers (5, 128, 5), while the Critic model's online and target networks are fully connected neural networks with (9, 128, 1). The activation function used in all the neural networks is the ReLU function.

To explore the performance of the proposed approach under various scenarios, we set up six typical scenarios, denoted as $S_m \in \{S_1, S_2 \ldots S_6\}$, where the load demand increases from low to high across different scenarios. For instance, the load in scenario S_1 is smaller than that in scenario S_2.

The input to the RL model Φ_g^m is a LMP vector, consisting of five elements. The output vector $\Pi = \{\pi_{energy}^1, \pi_{energy}^2 \ldots, \pi_{noload}, \pi_{startup}\}$ is processed into a three-part offer vector. For example, to calculate the no-load cost offer of a GENCO, we first obtain the GENCO's actual no-load cost, denoted as C_g^{noload}.

The GENCO's no-load offer, denoted as O_g^{noload}, is then computed as $(1 + 0.5 * \pi_{noload}) * C_g^{noload}$, where $\pi_{noload} \in (-1, 1)$ and $O_g^{noload} \in (0.5 * C_g^{noload}, 1.5 * C_g^{noload})$.

3.3 Baseline scenario simulation

Multi-agent simulations are performed for different mechanisms to calculate various market indicators in equilibrium, including the average electricity price $I_{m,price}^{base}$, total generation cost $I_{m,gc}^{base}$, and total purchased cost $I_{m,pc}^{base}$. Lower generation costs indicate a more efficient dispatch scheme, which can lead to reduced energy consumption for the same amount of electricity generated. Therefore, the mechanism designer's objective is to maximize social welfare, and lower purchase costs can help increase electricity consumption (taking into account load response), thus leading to higher social welfare.

Comparison of θ_1 and θ_2 Figure 3 presents a comparison of simulation results for mechanisms θ_1 and θ_2. The dynamic simulations demonstrate that when mechanism θ_1 pays uplifts to GENCOs, their willingness to deviate from the cost offer decreases, leading to lower market indicators such as $I_{m,price}^{base}$, $I_{m,gc}^{base}$, and $I_{m,pc}^{base}$. The simulation of this case reflects a counterintuitive phenomenon: on the surface, paying compensation to GENCOs would increase the financial burden and decrease social welfare. However, when considering the dynamic strategies of power generators, the opposite conclusion is reached - paying compensation fees would actually lower costs and increase social welfare. Traditional static simulations based on cost quotes cannot replicate this conclusion.

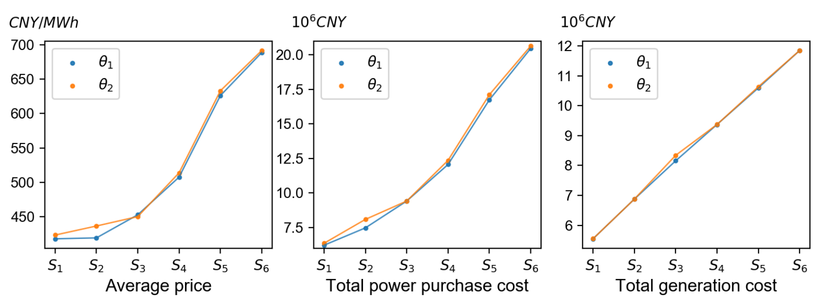


Fig. 3. Comparison of market indicators for θ_1 and θ_2.

Comparison of θ_1 and θ_3 When comparing θ_1 and θ_3, we consider the settlement of medium and long-term contracts, and set the volume of medium and long-term contracts as a prerequisite, allowing GENCOs to bid based on known contract volumes. The simulation results are shown in Figure 4. Mechanism θ_1 calculates the compensation fee by considering only the immediate revenue in the spot market, while mechanism θ_2 calculates the compensation fee by considering the difference in settlement of medium and long-term contracts, and uses the total revenue in both the contract and spot markets to calculate the compensation fee. Simulation results show that mechanism θ_3, designed to reduce the compensation fee through medium and long-term contracts, leads to a higher average electricity price and increased electricity purchase cost. The small difference in generation costs between the two mechanisms indicates that the distribution of winning bids by GENCOs is similar (as generation costs are only related to the distribution of winning bids by power GENCOs).

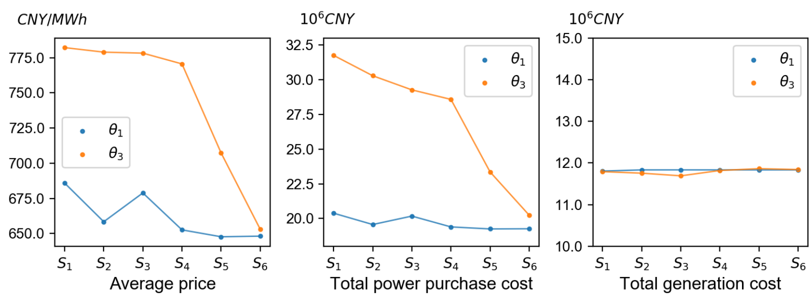


Fig. 4. Comparison of market indicators for θ_1 and θ_3.

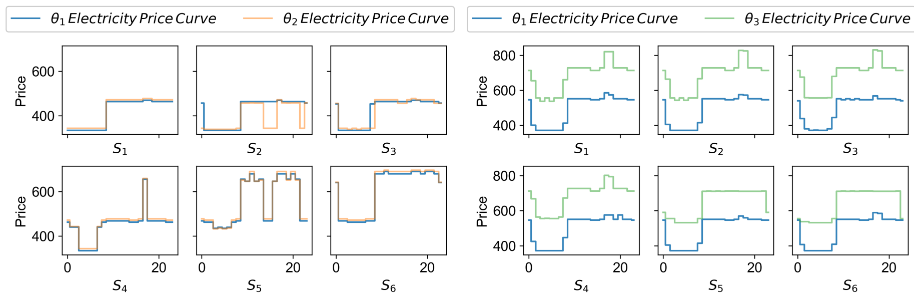
3.4 Simulation that Considering Bounded Rationality

Two event are considered in this section to compare the mechanisms θ_1, θ_2, and θ_3 in the context of bounded rationality of GENCOs.

In event E_1, some GENCOs are randomly selected to mispredict the current electricity market scenario. The contingency compares mechanisms θ_1 and θ_2, considering only the compensation fee of the spot market. For example, the selected GENCOs might think that the current scenario is S_1 while the actual scenarios are $S_1 - S_6$.

In event E_2, some GENCOs are randomly selected to mispredict the current electricity market scenario. The contingency compares mechanisms θ_1 and θ_3, considering the settlement of medium and long-term contracts. For instance, the selected GENCOs might think that the current scenario is S_6 while the actual scenarios are $S_1 - S_6$.

The price curve obtained from the simulation is depicted in Figure 5. The simulation results show that the price of mechanism θ_1 is more stable than the price of both mechanisms θ_2 and θ_3 when GENCOs have bounded rationality and mispredict the electricity market scenario. The simulation findings suggest that, under the realistic condition of bounded rationality of GENCOs, mechanism θ_1 is more effective in stabilizing the fluctuation of market prices, reducing the degree and probability of deviation of GENCOs from the actual cost quotation. A stable electricity price helps to avoid the distortion of market signals due to drastic fluctuations in electricity prices.



(a) Events E^1 (b) Events E^2

Fig. 5. Price curves when GENCOs forecast scenarios incorrectly.

3.5 Comparison of Market Indicators Considering Bounded Rationality

Table 2 displays the market deviations for event E^1 and E^2. The simulation results show that, in most cases, the A_m^i of θ_1 is smaller than that of the other mechanisms, indicating that θ_1 is more resilient to shocks. In contrast, θ_3 introduces more uncertainty into the settlement process and distorts the market information to a greater extent. As a result, GENCOs face more uncertainty in decision-making, and if their scenario forecasts are incorrect, it can cause more severe shocks to the market outcome.

Furthermore, it can be seen that wrong forecasts by GENCOs have a greater impact on the average electricity price $A_{m,price}^i$ and the cost of purchased electricity $A_{m,gc}^i$, and a smaller impact on the cost of generation $A_{m,gc}^i$. Since the calculation of generation costs is related to the distribution of the units' winning power output, and not the price, the errors in the GENCOs' cost offers have less impact on the ISO dispatch results. The cost of purchasing electricity receives the influence of the electricity price, so the missed offer, which distorts the price of electricity, increases the cost of purchasing electricity. In addition, high electricity prices decrease total electricity consumption due to load response, thus reducing social welfare, which contradicts the purpose of electricity markets.

Table 2. Comparison of the A_m^i under different mechanisms.

	E^1	S_1	S_2	S_3	S_4	S_5	S_6	E^2	S_1	S_2	S_3	S_4	S_5	S_6
$A_{m,price}^i$	θ_1	6.3	5.8	3.8	7.3	5.5	10.1	θ_1	1.2	1.2	1.0	1.2	1.2	1.2
	θ_2	12.3	1.4	4.1	5.9	4.6	9.0	θ_3	13.0	13.0	12.8	12.7	16.3	15.7
$A_{m,pc}^i$	θ_1	5.2	5.0	3.8	7.3	5.5	10.1	θ_1	1.2	1.2	1.0	1.1	1.2	1.2
	θ_2	12.3	1.4	4.1	5.9	4.6	9.0	θ_3	17.2	17.9	18.5	19.1	24.1	24.4
$A_{m,gc}^i$	θ_1	3.4	2.4	0.8	0.0	0.0	0.0	θ_1	0.2	0.2	0.1	0.1	0.2	0.2
	θ_2	3.5	0.0	0.0	0.0	0.0	0.0	θ_3	1.2	0.7	0.5	1.2	0.9	0.8

Based on the above results, the maximum market deviation A_θ is calculated, as shown in Table 3. The smaller the A_θ indicator is, the more shock-resistant the market mechanism is.

Table 3. Comparison of the A_θ under different mechanisms.

	$A_{\theta,price}$	$A_{\theta,pc}$	$A_{\theta,gc}$		$A_{\theta,price}$	$A_{\theta,pc}$	$A_{\theta,gc}$
θ_1	10.1	10.1	3.4	θ_1	1.2	1.2	0.2
θ_2	12.3	12.3	3.5	θ_3	16.3	24.4	1.2

4 Conclusion

This study proposes a multi-agent simulation model that considers the bounded rationality of GENCOs and presents indicators to evaluate the shock resistance of the electricity market. The simulation results demonstrate the effectiveness of the model and the evaluation mechanism while revealing counterintuitive issues in electricity market mechanism design.

When considering the bounded rationality of GENCOs in the face of market information misjudgments, dynamic simulations show that the MWP mechanism has better incentive compatibility, which can guide GENCOs to bid according to their true costs. MWP compensates for the losses of GENCOs and can even increase social welfare. The lack of a compensation mechanism will make GENCOs more willing to deviate from true cost bidding in order to avoid losses. Similar conclusions can be drawn when considering long-term contracts in settlement, which makes GENCOs' bids more vulnerable to external factors. Compared with other mechanisms, the MWP mechanism can reduce the impact of external information on GENCOs and thus mitigate the impact of misjudgments.

The multi-agent simulation model proposed in this paper can be extended to other economic systems. The model employs multiple RL algorithms to form a decision model for each market participant, which can adapt to different simulation scenarios and thereby reduces the generalization requirements of RL algorithms. During the multi-agent training phase, market participants acquire sufficient knowledge to simulate the diverse experiences of real-world individuals. In the validation phase, participants are provided with misleading guidance to prompt them to make erroneous decisions(For example, GENCOs misjudged the load curve due to incorrect weather forecasts), thereby simulating the imperfect information that occurs in real-world scenarios. The deviation between the market outcome and the equilibrium outcome, in the event of market members making wrong decisions, is compared and computed to analyze the degree of tolerance of the current economic system towards the bounded rationality of market participants.

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