Price-Simulation Oriented Forecasting of Individual Bidding Behaviors in Electricity Markets

Jinyu Liu, Feiran Yun, Zhen Xu, Jinhang Li, Chongqing Kang, Hongye Guo*
State Key Laboratory of Power System Operation and Control
Department of Electrical Engineering
Tsinghua University
Beijing, China
liu-jy23@mails.tsinghua.edu.cn, yfr22@mails.tsinghua.edu.cn, z-xu24@mails.tsinghua.edu.cn,
lijinhan24@mails.tsinghua.edu.cn, cqkang@tsinghua.edu.cn, hyguo@tsinghua.edu.cn

***Abstract*—Forecasting individual bidding behaviors in electricity markets is crucial for accurate price simulation and market analysis. However, existing approaches face two key challenges: effectively encoding high-dimensional, rule-constrained bidding curves and optimizing for price simulation accuracy rather than just bidding power accuracy. This paper proposes a novel Individual Behavior Forecasting (IBF) framework that addresses both challenges through two key innovations. First, we apply the Neural Network Supply Function (NNSF), which efficiently encodes market participant bidding behaviors using neural network input-output relationships, providing higher flexibility compared to traditional clustering and dimensionality reduction methods. Second, we propose a Price-Simulation Oriented Forecasting (PSOF) objective that directly optimizes price prediction accuracy during training, rather than focusing solely on bidding power accuracy. Our approach leverages the derivative of the NNSF to minimize price prediction errors, incorporating a stability correction term to ensure stable training. Experimental validation on ERCOT market data demonstrates significant improvements: the proposed method achieves 8.26% and 34.08% relative improvements in individual and system power forecasting accuracy, respectively, while reducing price prediction errors by 6.76% to 56.76% across different price intervals compared to previous approaches. These results demonstrate the effectiveness of price-simulation oriented forecasting for enhancing electricity market simulation accuracy and policy analysis.**

***Index Terms*—electricity market, bidding behavior, price forecasting, neural networks, market simulation**

I. Introduction

The bidding behavior of electricity market participants is a crucial factor influencing market prices, especially in extreme market events [1]. As the number of price-sensitive participants has increased in recent years, the impact of their bidding behavior on market prices has become more significant [2]. Therefore, forecasting the influence of market participants' bidding behavior on market prices has become more important [3].

To forecast the behavior of electricity market participants and their impact on electricity prices, it is essential to efficiently predict the actions of these participants through historical data. This research direction has experienced rapid development in recent years. Based on the prediction target, relevant methods can be divided into aggregate behavior forecasting (ABF) and individual behavior forecasting (IBF).

ABF focuses on forecasting market aggregate supply curves (ASC) to determine the overall market clearing price and quantity. Current research forecasts the ASC of spot electricity markets mainly through structural bid-stack models [4], hidden dimension forecasting neural networks [5], and monotonic generative models [6]. However, ASC only represents the aggregate behavior of the market and does not capture the individual behavior of the market participants.

IBF, which models the actions of each market participant, is a critical element for enhancing the accuracy of electricity market simulations and has garnered increasing attention. Existing research has improved prediction accuracy and interpretability by proposing various machine learning frameworks. For instance, [7] utilized clustering methods to classify different bidding patterns in spot markets, enabling classified prediction of individual unit bids and tracing the market conditions that drive bidding changes. [8] predicted market participant bidding behavior through ensemble learning models, achieving high-accuracy spot market behavior prediction in the Australian electricity market. Furthermore, [9] compared the performance of multiple machine learning models in predicting strategic behavior and analyzed the prediction effectiveness under different levels of information disclosure using permutation importance.

However, several challenges remain to be addressed in order to further improve market analysis using IBF:

First, the high-dimensional and rule-constrained electricity market bids need to be better encoded. In most electricity markets, individual bids consist of monotonic, increasing price-power pairs with 10+ dimensions for each time period. This bid format is characterized by high dimensionality and constraints (bidding pair values must be in monotonic order). These characteristics make encoding bidding behavior challenging. Previous studies have employed dimensionality reduction methods such as clustering [7] and principal component analysis [8], but the flexibility in representing bids remains

This work was supported by the Smart Grid-National Science and Technology Major Project under Grant 2025ZD0808000. (Corresponding author: Hongye Guo, E-mail: hyguo@tsinghua.edu.cn)

979-8-3315-8138-1

limited.

Second, the IBF needs to be further improved to enhance the accuracy of price simulation. Although price simulation is one of the most important applications of IBF [10], traditional IBF methods [7]–[9] often separate the minimization of behavioral prediction errors from the minimization of price simulation errors of forecasted individual bidding strategies. Considering even slight deviations in the predicted individual bidding strategies may result in substantial errors in the simulated market clearing prices, it is essential to more effectively integrate price simulation objectives into the IBF frameworks.

To address these two challenges, this paper proposes a novel IBF framework and a new price-simulation oriented forecasting (PSOF) objective, respectively, capable of achieving high-accuracy power and price forecasting. Specifically, the innovations of this paper are as follows:

- First, this paper proposes a novel IBF framework that efficiently encodes market participant bidding behaviors based on a framework called Neural Network Supply Function (NNSF) [11], thereby improving the flexibility of representing individual bids.
- Second, this paper introduces a PSOF-based IBF objective. This method innovatively incorporates price-simulation accuracy into the IBF, directly optimizing price prediction accuracy during the IBF training stage, which significantly improves the effectiveness of electricity price simulations.
- Finally, our research achieved high-accuracy IBF in testing on the ERCOT market in the United States, significantly improving the accuracy of simulated prices based on IBF, and enhancing market price forecasting accuracy by 6.76% to 56.76%.

The rest of this paper is organized as follows: In Section II, we formulate the problem of forecasting real-time market bidding behaviors after day-ahead market clearing. In Section III, we propose the NNSF IBF framework and the PSOF IBF objective. In Section IV, we evaluate the effectiveness of the proposed method on the ERCOT market in the US. In Section V, we conclude the paper.

II. Problem Formulation

The problem of forecasting real-time market bidding behaviors after day-ahead market clearing is studied in this paper. We study the problem from the system operator's perspective, which means day-ahead bidding data are available to the predictor. This problem is important for assessing the real-time market circumstances before the actual market clearing and helping the system operator make better decisions.

The input to the forecasting problem consists of all information available after day-ahead market clearing. Specifically, this includes: (1) historical system data over the past h days, including system day-ahead prices, day-ahead transaction volumes, real-time prices, and real-time generation; (2) system day-ahead prices and total transaction volume for the operating day; (3) historical actual generation of the forecasted individual unit over the past h days; (4) forecasts for demand and wind/solar output for the operating day. As this study does not focus on load forecasting, we assume that the predictor can access accurate real-time net load. This setting corresponds to the upper bound performance of price prediction.

The label of the forecast task is the predicted individual bidding curves for market participants, including both supply and demand bids for each interval within the operating day. In this study, we only consider fuel generator bidders for simplicity. The proposed method can also be applied to other generators

The main challenge of this problem lies in how to effectively extract the relationships between the market observations and the bidding behaviors of diverse individual participants.

III. Methodology

In this section, we propose the NNSF IBF framework and the PSOF IBF objective.

A. IBF Framework

The proposed forecasting framework is illustrated in Fig 1. This is the first approach that adopts the NNSF [11] for IBF.

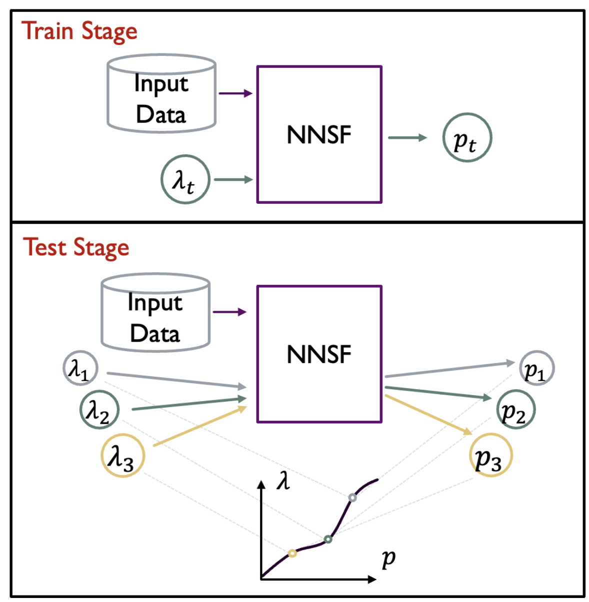

Fig. 1. Illustration of the NNSF IBF framework. The framework consists of a training stage and a testing stage. In the training stage, the Neural Network Supply Function (NNSF) is trained using historical data. In the testing stage, the generator's supply curve is obtained by sampling at different price points.

An NNSF is a neural network that has a price input and a power output. Because this neural network can be used to represent the *supply function* of an electricity market generator, it is called the NNSF. During the training stage, the NNSF can be trained by supervised learning. Its input consists of the market observations and the actual market clearing price. Its output label is the generator's generating power. Subsequently, during the testing stage, the generator bidding curves can be derived by sampling the input-output relationship of the NNSF.

979-8-3315-8138-1

This bidding encoding method has both high flexibility and efficiency. In terms of flexibility, in contrast to approaches that employ clustering [7] and dimensionality reduction [8] to encode generator supply curves, this paper utilizes the input-output relationship of neural networks to represent bidding behaviors. Owing to the strong representational capacity of neural networks, this approach is capable of modeling a wide variety of bidding behaviors. For efficiency, instead of treating each bidding curve as one large, high-dimensional input and output, we break it down into many pairs of price and power values. These pairs are fed into the neural network as separate inputs and outputs, which helps avoid problems from having too much information at once and also allows the network to be trained in parallel.

The input data is first processed by a bidirectional Long Short-Term Memory (LSTM) to extract temporal features. The market price information is then incorporated, and the combined features are passed through an Multi-Layer Perceptron (MLP) to produce the final prediction. The detailed network parameters are listed in Section IV.

B. Price-Simulation Oriented Forecasting Objective

Previous IBF in electricity markets aimed to minimize the prediction error of units' bidding curves, and the forecasting objective was to minimize the absolute error of the predicted bidding powers. However, this forecasting approach may lead to inaccurate electricity prices in market simulations because the accuracy of the bidding power is not sufficient to ensure the accuracy of the market clearing price. To address this challenge, this paper proposes a forecasting objective that directly optimizes the accuracy of electricity price prediction during the IBF training stage.

The proposed PSOF objective wants to minimize the price change required to make the NNSF's output equal to the actual market clearing power (p). For example, if the NNSF's original price prediction is $p_{\text{pred}} = \text{NNSF}(\lambda_t)$, the PSOF objective wants to minimize $|\Delta\lambda|$ such that $p = \text{NNSF}(\lambda_t + \Delta\lambda)$. This objective can also be understood as approximately minimizing the price deviation between the predicted market clearing price and the actual market clearing price. The objective function is as follows:

$$\text{Minimize: } \frac{|p - p_{\text{pred}}|}{\sigma(k \cdot \frac{\partial p_{\text{pred}}}{\partial \lambda} + b)} \tag{1}$$

where $p_{\text{pred}} = \text{NNSF}(\lambda_t)$ is the power prediction of the NNSF at the actual market price λ_t. $|p - p_{\text{pred}}|$ denotes the absolute deviation of the NNSF's power prediction, and $\frac{\partial p_{\text{pred}}}{\partial \lambda}$ represents the partial derivative of the NNSF's power output with respect to the price input at λ_t. The term $|p - p_{\text{pred}}| / \left(\frac{\partial p_{\text{pred}}}{\partial \lambda}\right)$ indicates the magnitude of adjustment required for the NNSF's input price, under a linear approximation around λ_t using $\frac{\partial p_{\text{pred}}}{\partial \lambda}$. The forecasting objective is to minimize this price adjustment magnitude to make the NNSF's power prediction match the actual market power.

In addition, $\sigma(k \cdot \frac{\partial p_{\text{pred}}}{\partial \lambda} + b)$ is a correction term introduced to enhance the stability of training. σ is the sigmoid function, k and b are the slope and intercept of the sigmoid function, respectively. Given NNSF's derivative $\frac{\partial p_{\text{pred}}}{\partial \lambda}$ is non-negative [11], the correction term scales the partial derivative of the NNSF's power output between $\sigma(b)$ and 1. By scaling the partial derivative to a controlled range, the PSOF objective can be more stable during training.

The new forecasting objective proposed in this paper differs from traditional approaches that minimize power error or behavioral error; instead, it directly optimizes the error in price prediction, thereby providing stronger support for price simulation based on behavioral forecasting.

IV. Experiments

In this section, we validate the effectiveness of the proposed method in forecasting generation unit outputs and market prices using real-world electricity market data. The study focuses on the ERCOT market in the United States, utilizing electricity price data from years 2021 and 2022 as the dataset. Among the data, the first 85% is allocated to the training set and the remaining 15% to the test set. The scope of forecasting includes all thermal power units in the market (gas, coal, and nuclear). The rest of the units are considered as negative load and are not price responsive.

To demonstrate the validity of the proposed innovations, we compare our method against existing approaches and their variants. All methods use essentially the same neural network architecture and input data, but differ in their bidding strategies and loss functions. The compared methods include: (1) NNSF-PSOF: the proposed method; (2) NNSF-PSOF (w/σ): a variant of the proposed method without the σ correction term. (3) NNSF-MAE: a variant of the proposed method that employs the traditional mean absolute error (MAE) bidding power forecast error as the loss function; and (4) Baseline: the IBF approach proposed in [9], which directly predicts individual bids and their corresponding power outputs; (5) Price Forecast (PF): The standard price forecasting paradigm, which utilizes the same advanced BiLSTM network and is based on the same information set as the NNSF, directly predicts the real-time price; (6) DayAhead Price (DA): Using the DayAhead market price as a predictor output, reflecting how well DA market price can predict the real-time price;

A simplified electricity market clearing model is adopted in this study. It is assumed that the market demand equals the sum of the actual power outputs of all units in operation. The target price is the ERCOT market clearing price (MCP) without scarcity pricing price adders. Additionally, it is assumed that all generation units and loads are located at the same node, so the system power balance equation is simplified to $\sum$ generation $= \sum$ demand. In such a scenario, if IBF has perfect price prediction ability, the price prediction error will be zero.

The proposed method is trained through supervised learning. The PyTorch training framework is used with the Adam optimizer and RTX5090 GPU (32GB memory). The parameters for the learning algorithm are shown in Table I.

TABLE I
HYPERPARAMETERS USED IN THE PROPOSED METHOD

Symbol	Description	Value
h	Days of historical information	4
k	Slope parameter	$\$600/p_{\max}^i$
b	Intercept parameter	-3
lr	Learning rate	0.001
$batch\_size$	Batch size	128
n_l	LSTM hidden dimension	256
n_m	MLP hidden dimension	256
n_λ	Market price encoding dimension	256

Next, we evaluate the effectiveness of the proposed method using two key metrics: power forecast error and price forecast error.

A. Power Forecast Error

Power forecast error is defined as the relative deviation between the predicted and actual unit power under the actual market clearing price, reflecting the accuracy of power forecasting in IBF. We consider two types of power forecast errors: individual unit power forecast error and system power forecast error.

The individual power forecast error is calculated as shown in Eq. (2). This metric represents the weighted average of the relative error in predicted unit outputs, with weights given by each unit's maximum power:

$$\text{Individual Power Error} = \frac{\sum_i |p^i - p_{\text{pred}}^i|}{\sum_i p_{\max}^i} \tag{2}$$

Here, p^i denotes the actual output of unit i under the actual market clearing price, p_{pred}^i denotes the predicted output of unit i at the actual market clearing price, and $p_{\max}^i$ is the maximum output of unit i.

The system power forecast error is computed as Eq. (3). This metric quantifies the relative error in predicting the total system output:

$$\text{System Power Error} = \frac{\left|\sum_i p^i - \sum_i p_{\text{pred}}^i\right|}{\sum_i p_{\max}^i} \tag{3}$$

These two metrics measure the prediction accuracy of the algorithm at both the individual unit and system levels. The forecasting errors of the compared methods for individual units and for the aggregated system are presented in Table II.

TABLE II
COMPARISON OF POWER FORECAST ERRORS FOR DIFFERENT METHODS

Bid	NNSF	Baseline	NNSF
Objective	**MAE**	**MAE**	**PSOF**
Individual Power MAE (%)	**4.00**	4.36	5.10
System Power MAE (%)	**1.18**	1.79	1.58

It can be observed that NNSF improves the accuracy of power forecasting. When using MAE as the prediction objective, NNSF achieves a 0.36% improvement in individual power forecasting accuracy over the Baseline (a relative improvement of 8.26%) and a 0.61% improvement in system power forecasting accuracy (a relative improvement of 34.08%). To understand this effect from the perspective of neural network architecture, a significant advantage of NNSF lies in its use of additional price inputs (refer to Fig 1), which may play a key role in performance enhancement.

At the same time, it is evident that the NNSF trained with PSOF exhibits weaker performance in power forecasting. This is mainly because PSOF training does not directly optimize the error in power prediction but rather aims to minimize the error in price after power outputs have been corrected to their true values.

B. Price Forecast Error

The price forecast error quantifies the accuracy of the predicted market clearing price relative to the actual observed price. Specifically, it is calculated as the absolute difference between the predicted price and the true market price, i.e., $|\lambda_{\text{pred}} - \lambda|$. This metric provides a straightforward measure of the effectiveness of the IBF approach in forecasting market prices based on unit bid predictions.

The mean absolute deviations and error distributions of the proposed algorithm in various price intervals are illustrated in Fig 2, with detailed data presented in Table III. In Fig 2, all methods' performance are compared to the DayAhead Price as 100% error reference.

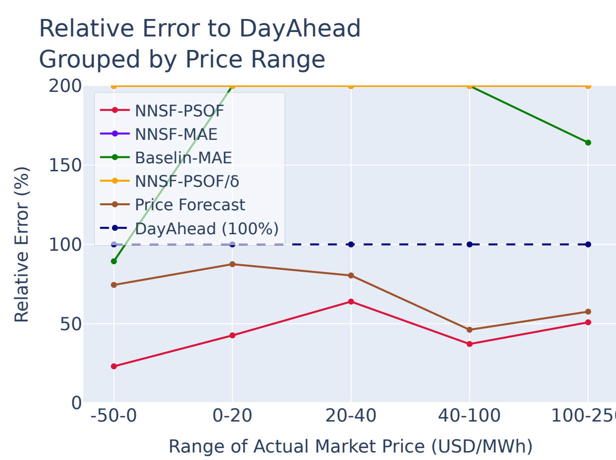

Fig. 2. Relative Performance Compared to DayAhead Price as Prediction Target by Price Range

It can be seen that the NNSF-PSOF method achieves high-precision price forecasting. According to the data in Table III, adopting the PSOF training objective significantly improves the price prediction accuracy of IBF. Compared with the traditional IBF method (Baseline-MAE), NNSF-PSOF achieves lower forecasting errors across all price intervals. Specifically,

979-8-3315-8138-1

TABLE III
MEAN ABSOLUTE PRICE ERROR BY PRICE RANGE AND METHOD (USD/MWH)

Bid Objective	NNSF PSOF	PF /	DA /	Baseline MAE	NNSF MAE	NNSF PSOF/σ
-50–0	**5.7**	18.5	24.8	22.2	104.3	99.2
0–20	**4.8**	9.9	11.3	36.76	156.76	109.2
20–40	**4.6**	5.8	7.2	28.7	224.1	143.7
40–100	**5.5**	6.8	14.8	76.76	377.5	303.5
100–250	**42.1**	47.7	82.8	135.9	562.6	633.1

the mean absolute error is reduced by 74.3%, 84.8%, 84.0%, 92.3%, and 69.0% in the -50–0, 0–20, 20–40, 40–100, and 100–250 USD/MWh intervals, respectively. This substantial reduction greatly enhances the usability of IBF for price simulation applications.

The NNSF-PSOF forecasting approach also outperforms the Price Forecast method across all price intervals. This result suggests that simulating market agent behavior—by leveraging more granular, individual-level information—can improve forecasting accuracy compared to directly predicting the market price. The advantage is more evident in the low-price intervals (-50–0) and (0–20) USD/MWh.

Comparing the performance of PSOF to PSOF/σ and NNSF-MAE, we can see that the PSOF objective and its σ correction term are both important for high-precision forecasting with NNSF. If we apply NNSF with MAE as the prediction objective, the performance is significantly worse than the baseline. Additionally, removing the σ term from PSOF causes large prediction errors due to unstable gradients when the denominator in Eq. (1) is near zero.

However, the performance of NNSF-PSOF in predicting short-term high price spikes is still limited. Fig 3 presents the predicted market supply curve and clearing price for a given scenario. It can be observed that, for short-term high price spikes in real-time markets, NNSF-PSOF is not able to accurately simulate these circumstances. Therefore, the prediction performance for such scenarios requires further improvement in future research.

V. CONCLUSION

This paper presents a novel framework for forecasting the behavior of individual participants in electricity markets. The framework introduces two key innovations: (1) a *Neural Network Supply Function* that efficiently encodes high-dimensional, rule-constrained bidding behaviors through neural network input-output relationships, and (2) a *Price-Simulation Oriented Forecasting* objective that directly optimizes price prediction accuracy during training rather than focusing solely on bidding curve accuracy. Empirical evaluation on ERCOT market data demonstrates that the proposed framework significantly outperforms previous individual behavior forecasting methods. These results illustrate the potential of individual behavior forecasting for accurate electricity market simulation and policy analysis.

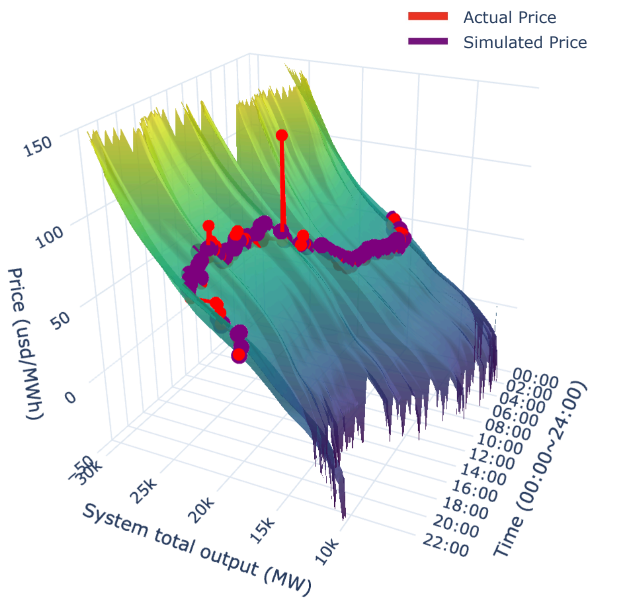

Fig. 3. System Supply Curve Visualization. This figure illustrates the aggregated supply curve constructed from individual unit bids, providing a comprehensive view of the market supply structure across price levels.

REFERENCES

[1] M. Ghamkhari, A. Sadeghi-Mobarakeh, and H. Mohsenian Rad, "Strategic bidding for producers in nodal electricity markets: A convex relaxation approach," *IEEE Transactions on Power Systems*, vol. 32, no. 3, pp. 2324–2336, Jun. 2016.

[2] J. Schölzel, M. Tings, S. Henn, R. Streblow, and D. Müller, "Comparative analysis of bidding strategies for auction-based local energy markets," *Energy*, 2024.

[3] Q. Tang, H. Guo, D. Kirschen, and C. Kang, "Understanding bidding strategies of intermittent renewables in negative price environments: A theoretical and empirical analysis," *Advances in Applied Energy*, 2025.

[4] R. Carmona and M. Coulon, "A survey of commodity markets and structural models for electricity prices," in *Quantitative Energy Finance: Modeling, Pricing, and Hedging in Energy and Commodity Markets*, F. E. Benth, V. A. Kholodnyi, and P. Laurence, Eds. New York, NY: Springer, 2014, pp. 41–83.

[5] H. Guo, Q. Chen, K. Zheng, Q. Xia, and C. Kang, "Forecast Aggregated Supply Curves in Power Markets Based On LSTM Model," *IEEE Transactions on Power Systems*, vol. 36, no. 6, pp. 5767–5779, Nov. 2021.

[6] D. Foronda-Pascual and A. M. Alonso, "Prediction of matching prices in electricity markets through curve representation," *Energies*, vol. 16, no. 23, p. 7812, Nov. 2023.

[7] A. Pasotti, "Prediction and interpretation of bids in the italian electricity market for ancillary services," 2020.

[8] Q. Tang, H. Guo, K. Zheng, and Q. Chen, "Forecasting individual bids in real electricity markets through machine learning framework," *Applied Energy*, vol. 363, p. 123053, Jun. 2024.

[9] D. P. Brown, D. O. Cajueiro, A. Eckert, and D. Silveira, "Evaluating the role of information disclosure on bidding behavior in wholesale electricity markets," *Energy Economics*, vol. 146, p. 108505, May 2025.

[10] J. R. Birge, A. Hortaçsu, and J. M. Pavlin, "Inverse optimization for the recovery of market structure from market outcomes: An application to the MISO electricity market," *Operations Research*, vol. 65, no. 4, pp. 837–855, Aug. 2017.

[11] J. Liu, H. Guo, Y. Li, Q. Tang, F. Huang, T. Chen, and H. Zhong, "Reinforcement learning based bidding method with high-dimensional bids in electricity markets," *Journal of Modern Power Systems and Clean Energy*, vol. 13, no. 4, pp. 1373–1382, Jul. 2025.