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Real-Time Electricity Price Forecasting with Dynamic Graph Convolution and Adaptive Temporal Fusion

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Abstract

INTRODUCTION: Real-time electricity price forecasting is critical for real-time dispatch, automatic generation control, spot trading and risk management in electricity markets.
OBJECTIVES: Since large-scale wind and photovoltaic renewable energy grid integration brings strong random fluctuation of renewable power output, real-time electricity prices exhibit stronger volatility, higher randomness and tighter time coupling than day-ahead prices; the randomness of renewable power is one core factor causing abrupt price jumps, leading conventional forecasting models struggle to capture dynamic spatial–temporal dependencies and sudden fluctuation patterns.
METHODS: To address these issues, this paper proposes a real-time electricity price forecasting model based on dynamic graph convolution (DGC), adaptive gated temporal fusion, and Transformer–BiGRU hybrid structure. The model uses a dynamic graph convolution module to model real-time changing topological correlations among power system features, introduces an adaptive gated fusion mechanism to enhance the weighting of real-time key features, and integrates Transformer and bidirectional GRU to capture both long-range global dependencies and high-frequency local fluctuations.
RESULTS: Experiments are conducted on real-time electricity price and real-time operation data from Shandong electricity market. Results show that the proposed model achieves average prediction accuracy of 88.2%, with MAE and MSE reduced to 0.071 and 0.009 respectively, which outperforms all baseline methods significantly.
CONCLUSION: The proposed method provides high-precision support for real-time market transactions, real-time scheduling and intelligent decision-making.

Keywords: Real-time electricity price forecasting; dynamic graph convolution; adaptive temporal fusion; Transformer-BiGRU; gated feature fusion

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1. Introduction

Driven by the continuous progress of the "dual carbon" goal and the accelerated construction of a new-type power system, renewable energy sources such as wind power and photovoltaic power have been integrated into the grid on a large scale and at a high proportion, making the interaction characteristics among generation, grid, load and storage of the power system increasingly complex. Meanwhile, the pilot scope of China's electricity spot market has been expanding, and the trading mechanism has been continuously improved, leading to a more market-oriented and refined electricity price formation mechanism [1-5]. As a result, the real-time electricity price signal has become increasingly central to power system operation and market transactions. Compared with day-ahead electricity prices, real-time electricity prices exhibit stronger randomness, higher volatility, and higher sensitivity to real-time operating conditions, with more pronounced short-term abrupt changes, which greatly increases the difficulty of accurate forecasting [6]. Real-time electricity price forecasting not only directly supports secure

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and stable operation services such as real-time grid dispatch, auxiliary service transactions, and peak shaving and frequency regulation [7], but also provides a critical basis for various market participants including power generation enterprises, electricity sales companies, and power users to make bidding decisions [8], manage risks [9], and optimize revenues [10]. Under the background of high proportion of new energy grid connected in the new power system, the power of wind power and photovoltaic power generation fluctuates violently within a day due to the random disturbance of weather, which directly disturbs the supply and demand balance of the system and induces the sharp rise and fall of real-time electricity price in a short time [11-13]. Therefore, the deep binding of high-precision real-time electricity price prediction and wind solar renewable energy output prediction is the key support for AI to enable the market-oriented consumption of new energy and improve the prediction of new energy generation income. It bears important theoretical value and engineering significance for improving the operational efficiency of the electricity market and ensuring the safe and economic operation of the power system [14].

Early studies on electricity price forecasting mostly relied on traditional statistical and machine learning methods. Auto regressive Integrated Moving Average (ARIMA) models and their improved variants have been widely used in stationary time series forecasting, but they struggle to effectively fit the nonlinear, non-stationary and multi-scale fluctuation characteristics of real-time electricity prices [15]. Linear models such as linear regression and ridge regression impose strict assumptions and fail to characterize the complex mapping relationship between electricity prices and multi-source influencing factors. Machine learning methods including Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting Decision Tree (GBDT) have improved forecasting performance through nonlinear mapping capabilities and perform stably in small-sample scenarios. However, they suffer from insufficient generalization ability and inadequate feature extraction when processing high-dimensional, strongly time-dependent and large-sample data, and cannot fully capture the deep-seated laws underlying real-time electricity prices [16].

The rapid development of deep learning has provided a new technical path for real-time electricity price forecasting. Recurrent Neural Networks such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) excel at mining time-dependent relationships and have been widely applied and achieved satisfactory performance in short-term electricity price forecasting. Benefiting from the multi-head self-attention mechanism, the Transformer model can efficiently capture long-range time dependencies, further enhancing time series forecasting capabilities. Nevertheless, most existing deep learning models focus solely on single time series feature modeling, ignoring the complex real-time spatial correlations among generation units, tie-lines, regional loads, renewable energy output, grid topology and other elements, leading to insufficient utilization of spatial information and low sensitivity of forecasting models to local disturbances. Furthermore, references [17-19] take historical average electricity price, historical load, historical energy price and other data as input sets, and construct real-time electricity price forecasting neural network models based on support vector machine, generative adversarial network and gated recurrent unit, respectively.

In recent years, Graph Neural Networks (GNNs) have offered an effective tool for spatial feature extraction in power systems. Some studies have combined Graph Convolutional Networks (GCN), Graph Attention Networks (GAT) with time series models to construct spatial-temporal joint forecasting models [20-24]. However, such models mostly adopt static graph structures with fixed nodes and edge weights, which cannot reflect the dynamic evolution of topological relationships caused by power flow transfer, topology adjustment [25], renewable energy fluctuations and load sudden changes in real-time scenarios, and are incompatible with the dynamic characteristics of real-time electricity prices [26]. In addition, real-time electricity prices are highly sensitive to real-time disturbances such as sudden load increase or decrease, drastic fluctuations of wind-solar power, rapid adjustment of tie-line power [27], and section congestion [28]. Existing models lack an adaptive enhancement mechanism for key features, tending to produce large errors during periods of sharp price fluctuations and resulting in insufficient forecasting stability [29].

To break through the above bottlenecks and fully exploit the spatial-temporal coupling characteristics and dynamic evolution laws of real-time electricity prices, this paper proposes a real-time electricity price forecasting model based on dynamic graph convolution and adaptive temporal fusion. The main contributions of this paper are as follows:

A Dynamic Graph Convolution (DGC) structure is constructed to dynamically update the graph topology driven by real-time operation data, accurately modeling the real-time changing spatial correlations and interaction characteristics among multiple nodes of the power system, and overcoming the adaptability limitations of static graphs.

An adaptive gated feature fusion mechanism is designed to realize dynamically weighted fusion of spatial and temporal features, automatically strengthening key features sensitive to electricity price mutations, and significantly improving the model's responsiveness and forecasting robustness in extreme fluctuation scenarios.

A Transformer–BiGRU hybrid forecasting module is proposed, which combines the Transformer's ability to capture long-range global dependencies with BiGRU's advantages in mining high-frequency local fluctuations and bidirectional temporal correlations, achieving joint modeling of global trends and local disturbances.

Extensive comparative experiments and ablation experiments based on real-time market data of Shandong power system verify the significant advantages of the proposed model in accuracy, stability and adaptability to extreme scenarios, which can provide high-precision decision support for real-time market transactions and real-time dispatch.

2. Real-Time Price Forecasting Model Construction

2.1. Real-Time Feature Selection and Dynamic Feature Update

As a direct reflection of the instantaneous supply–demand relationship in the electricity market, real-time electricity price exhibits typical characteristics including strong randomness, high volatility, and rapid time variability. Its formation and fluctuation mechanism are highly dependent on the real-time operating state of the power system. In practical electricity market operation scenarios, real-time electricity price is jointly driven by multi-dimensional real-time operational data, such as real-time load level, real-time wind and photovoltaic power output, tie-line transmission power, real-time positive/negative reserve capacity, real-time unit generation output, real-time grid topology and operating conditions. The instantaneous variation of each factor will trigger rapid response and nonlinear fluctuation of real-time electricity price, forming a high-dimensional, strongly coupled, and highly redundant original feature space.

To reduce feature redundancy, enhance the model's ability to capture key driving factors, and improve the interpretability and generalization performance of the forecasting process, this paper adopts the SHapley Additive exPlanations (SHAP) method to conduct systematic feature selection and importance quantification for multi-source attributes disclosed in real time in the electricity market. By calculating the marginal contribution of each real-time feature to the electricity price forecasting result, adaptive dimensionality reduction and key information retention of the high-dimensional feature set are realized. Finally, a core input feature set with strong real-time correlation, high driving contribution, and strong temporal correlation to real-time electricity price is selected, including real-time load, real-time wind power, real-time photovoltaic power, real-time tie-line power, real-time positive reserve, real-time negative reserve, real-time grid equivalent impedance, and real-time renewable energy curtailment rate. The above features can fully characterize the real-time state of both supply and demand sides, grid transmission capacity, reserve regulation margin, and renewable energy accommodation level of the power system, providing high-quality, low-redundancy, and strongly interpretable input support for the subsequent high-precision real-time electricity price forecasting model.

SHAP value is defined as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}\left[v(S \cup \{i\}) - v(S)\right] \quad (1)$$

where $v(\cdot)$ is the model output, S is a feature subset, and ϕ_i represents the marginal contribution of feature i. Features with large absolute SHAP values are selected as model inputs to ensure real-time responsiveness.

The SHAP plots of real-time electricity prices and real-time operational data are shown in Figure 1.

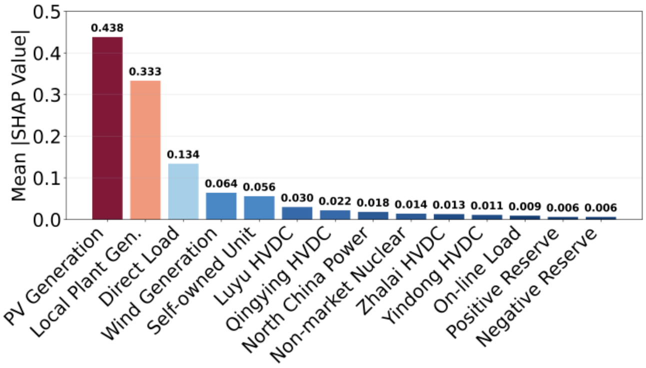

Figure 1. The SHAP plots of real-time electricity prices

2.2 Overall Model Framework

The proposed real-time electricity price forecasting model, as shown in Figure 2, is organically composed of four core functional modules. These modules work collaboratively to achieve the whole-process modeling from data preprocessing and spatiotemporal feature mining to time-series prediction. The specific structure and functions are described as follows:

Real-time Feature Preprocessing and Dynamic Feature Update Module

In response to the strong time-variability and high noise of real-time electricity prices, this module performs standardized preprocessing including outlier removal, missing value imputation, and normalization on multi-source real-time operation data such as raw real-time electricity prices, load, renewable energy output, and tie-line power, so as to eliminate dimensional differences and data noise interference. Meanwhile, based on the SHAP feature importance quantification method, it dynamically calculates the marginal contribution of each real-time attribute to electricity prices, adaptively screens core driving features highly correlated with real-time electricity prices, and removes redundant and weakly correlated variables. Finally, a model input feature set with high timeliness, low redundancy and strong correlation is constructed, laying a data foundation for subsequent high-precision forecasting.

Dynamic Graph Convolution (DGC) Spatial Feature Extraction Module

To accurately characterize the real-time changing spatial correlations among multiple variables in the power system, this module abstracts power system operation variables as nodes of a dynamic topological graph and adaptively updates the weight coefficients of edges between nodes according to the real-time operation state of the power grid, realizing the dynamic evolution of the graph structure. The dynamic graph convolutional network is used to aggregate neighborhood information and extract features, deeply mine the real-time interaction rules and spatial dependence characteristics among operation variables, and output high-dimensional feature vectors integrating spatiotemporal correlation information, effectively remedying the defect that traditional models ignore real-time spatial coupling.

Adaptive Gated Temporal Feature Fusion Module

To tackle the problem that real-time electricity prices are prone to sharp fluctuations caused by disturbances, this module introduces a learnable gated fusion mechanism to adaptively assign weights to spatial features output by dynamic graph convolution and temporal features. In extreme scenarios such as sudden price changes and price spikes, it automatically strengthens the weight proportion of sensitive key features and suppresses the interference of redundant information, realizing the deep coupling of spatial correlation and temporal regularity, and significantly improving the model's response speed and forecasting robustness in extreme fluctuation scenarios.

Transformer–BiGRU Hybrid Forecasting Module

As the core forecasting unit of the model, this module adopts a hybrid architecture of Transformer encoder and Bidirectional Gated Recurrent Unit (BiGRU). The Transformer is used to capture long-range and global temporal dependencies in electricity price series, while BiGRU is employed to mine high-frequency local fluctuations and bidirectional temporal correlation characteristics of the series. The two components complement each other, taking into account both global trend fitting and local disturbance capture. Finally, the predicted real-time electricity price at the next moment is output through mapping via a fully connected layer, realizing the joint and accurate modeling of the global trend and local disturbances of real-time electricity prices.

The framework realizes the closed loop of:
real-time feature input → dynamic spatial modeling → adaptive temporal fusion → real-time price prediction.

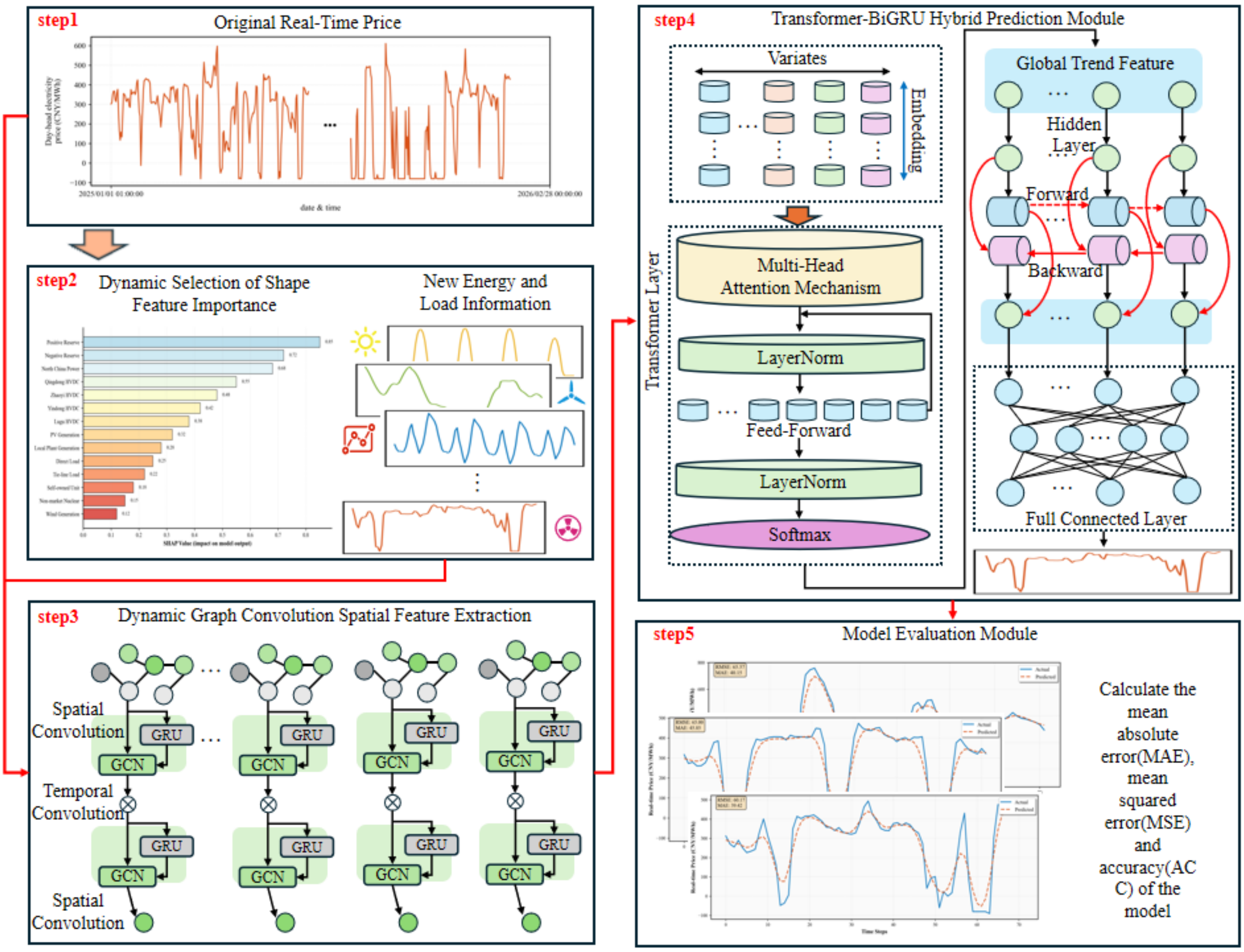

Figure 2. Real-time electricity price forecasting model

2.3 Dynamic Graph Convolution for Real-Time Spatial Feature Learning

Essentially different from the static graph network structures widely adopted in day-ahead electricity price forecasting, real-time electricity price has the inherent characteristics of instantaneity, strong volatility and high sensitivity. Its price formation mechanism is closely dependent on the real-time operating state of the power system, and the spatial correlations among key variables such as load, renewable energy output, tie-line power, reserve capacity and unit output in the system show rapid dynamic evolution.

In day-ahead electricity price forecasting scenarios, grid topology, unit commitment, regional power interaction and other factors remain relatively stable over a long-time scale, and static graphs with fixed structures can be used to model spatial dependencies. However, in real-time electricity price forecasting scenarios, the system operating state changes rapidly over time, and the coupling strength, influence direction and interaction mode among features are constantly changing. Static graphs cannot respond to sudden changes of the system state in a timely manner and are difficult to accurately characterize real-time spatial interaction rules, thus leading to insufficient capability of the model to capture extreme fluctuations such as price spikes and plunges. Therefore, real-time electricity price forecasting must rely on dynamic graph convolution technology that can adaptively update the topological structure to realize dynamic modeling of real-time spatial correlations in the power system.

The power system is constructed as a dynamic graph $g(t) = (v, \varepsilon(t))$, where nodes represent real-time operating variables, and edges represent real-time correlation intensity. Dynamic graph convolution update formula:

$$H^{(l+1)} = \sigma\left(\tilde{D}(t)^{-\frac{1}{2}} \tilde{A}(t) \tilde{D}(t)^{-\frac{1}{2}} H^{(l)} W\right) \qquad (2)$$

Where $\tilde{A}(t) = A(t) + I$ is the dynamic adjacency matrix with self-loop. $\tilde{D}(t)$ is the dynamic degree matrix. $H^{(l)}$ is the node feature. W is the trainable weight.

This module can capture real-time spatial interactions among features and improve sensitivity to sudden changes.

The dynamic graph convolution module constructed in this paper is designed to solve the above problems. Its core value lies in breaking through the fixed structure limitation of static graphs and realizing real-time dynamic update of graph topology and edge weights. This module abstracts multi-source operating characteristics of the power system as nodes in a dynamic topological graph and represents the real-time coupling relationship among characteristics as adaptively adjustable edges in the graph. By perceiving changes in the system operating state in real time, it dynamically reconstructs the connection relationship and weight distribution among nodes, so that the graph structure is always highly consistent with the actual state of the current power system. Under sudden working conditions such as sudden load increase, large fluctuations of wind and solar output, rapid adjustment of tie-line power and emergency response of reserve capacity, dynamic graph convolution can capture the reconstruction process of spatial interaction relationships among features in the first instance and reflect the instantaneous influence mechanism of various elements in the system in real time.

Through the aggregation and update mechanism of dynamic graph convolution, the model can deeply mine the nonlinear, time-varying and strongly coupled real-time spatial interaction relationships among various characteristics of the power system and transform the originally scattered and independent real-time operating variables into high-dimensional feature representations with spatiotemporal correlation information. This process significantly enhances the model's perception sensitivity to scenarios such as sudden system changes, rapid working condition switching and sharp electricity price fluctuations, and effectively remedies the hysteresis and static defects of traditional forecasting methods in characterizing spatial characteristics. It provides spatial feature support with high real-time performance, strong correlation and high distinguishability for subsequent temporal feature fusion and accurate real-time electricity price forecasting, making the overall model more suitable for the highly dynamic and fast-response forecasting requirements of real-time electricity prices.

2.4 Adaptive Gated Feature Fusion

Real-time electricity prices are prone to extreme fluctuations such as short-term surges, sharp spikes, and severe oscillations under scenarios including power supply–demand imbalance, large renewable energy output fluctuations, sudden tie-line power changes, and rapid reserve capacity regulation. Such abrupt signals are characterized by short duration, large amplitude, and concentrated driving factors, which impose extremely high requirements on the real-time capture capability and anti-disturbance robustness of forecasting models. To effectively enhance the model's ability to accurately capture abrupt changes and high-frequency fluctuations in real-time electricity prices, this paper proposes an Adaptive Gated Fusion Mechanism in the spatiotemporal feature interaction stage. Through a learnable gated structure, it realizes dynamic weighting of spatial and temporal features, enhancement of critical information, and suppression of redundant information, breaking through the limitations of traditional fixed-weight fusion methods at the feature fusion level.

The core design idea of the Adaptive Gated Fusion Mechanism is to equip the model with intelligent feature regulation capabilities of autonomous perception, autonomous allocation, and autonomous enhancement under different operating conditions. Taking the spatial correlation features output by the dynamic graph convolution module and the temporal dependency features extracted by the temporal encoding module as dual inputs, this mechanism generates adaptive gated coefficients via a nonlinear activation function. These coefficients are not fixed constants but dynamic variables updated online in real time according to electricity price fluctuation amplitude, system operating state, and feature importance. The magnitude of gated coefficients directly determines the proportion of spatial and temporal features in the final fused vector and can automatically adjust the contribution weights of different feature types according to the electricity price trend and system disturbance degree at the current moment, so as to achieve the adaptive regulation goal of "balanced fusion in stable periods and key enhancement in abrupt periods".

During periods of stable real-time electricity price fluctuations, the adaptive gate maintains an equal allocation state, allowing spatial correlation rules and temporal evolution trends to be equally represented. When the electricity price is detected to enter critical periods such as rapid rise, short-term surge, and spike formation, the Adaptive Gated Fusion Mechanism immediately triggers weight reconstruction, automatically identifying and strengthening the weights of key features most sensitive to electricity price abrupt changes. These include core features screened by SHAP, such as real-time load mutation component, tie-line power fluctuation component, reserve capacity shortage component, and renewable energy output plunge component. By instantaneously increasing the fusion proportion of key driving features, the model can quickly focus on the core incentives causing electricity price surges, significantly improving the tracking accuracy and response speed to extreme fluctuations such as spikes and jumps.

$$f_{\text{fusion}} = \sigma\left(W_f \cdot [h_{\text{graph}} \oplus h_{\text{time}}] + b_f\right) \tag{3}$$

$$h_{\text{adapt}} = f_{\text{fusion}} \cdot h_{\text{graph}} + (1 - f_{\text{fusion}}) \cdot h_{\text{time}} \tag{4}$$

Where h_{graph} is the dynamic graph feature, h_{time} is the temporal feature, and f_{fusion} is the adaptive gate.

Compared with traditional static methods such as weighted summation and concatenation fusion, the Adaptive Gated Fusion Mechanism has stronger condition adaptability, disturbance perception, and fluctuation capture accuracy. It can effectively improve the ability to characterize the non-stationary, nonlinear, and high-mutation characteristics of real-time electricity prices without increasing the overall model complexity. It provides purer, more focused, and more mutation-capable fused features for the subsequent Transformer–BiGRU hybrid forecasting module, and finally achieves high-performance prediction with accurate fitting in stable periods and sensitive capture in surge and plunge periods.

2.5 Transformer–BiGRU Hybrid Real-Time Forecasting Module

The fused features are fed into the hybrid forecasting module:

1.Transformer encoder captures long-range global dependency:

$$H_{\text{trans}} = \text{TransformerEncoder}(h_{\text{adapt}}) \tag{5}$$

The structure of the Transformer is shown in Figure 3.

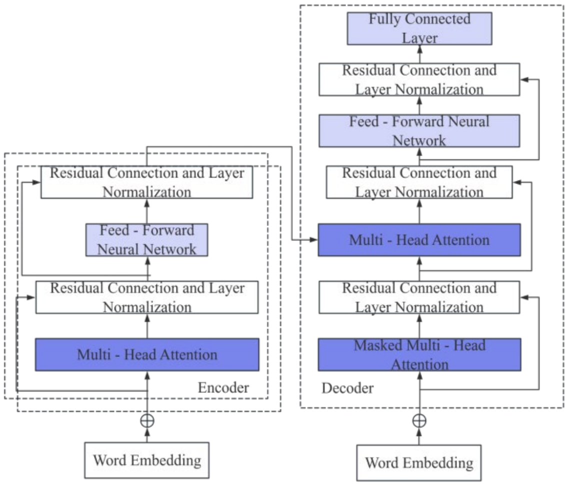

Figure 3. Structure of the Transformer

2.BiGRU captures high-frequency local fluctuation and bidirectional temporal correlation:

$$\begin{aligned} \vec{h}_t &= GRU(x_t, \vec{h}_{t-1}) \\ \overleftarrow{h}_t &= GRU(x_t, \overleftarrow{h}_{t-1}) \\ h_t &= \left[\vec{h}_t \oplus \overleftarrow{h}_t\right] \end{aligned} \tag{6}$$

3.Final prediction through fully connected layer:

$$\hat{y}_t = FC(h_t) \tag{7}$$

The model outputs the real-time electricity price at the next moment.

3. Experimental Validation

3.1 Dataset and Experimental Setup

The dataset employed in this study is obtained from the Shandong Electricity Trading Center, covering real-time electricity prices (hourly resolution and normalized to the 0–1 range) and comprehensive real-time power system operation data. The complete sampling period spans from January 1, 2025 to August 31, 2025, with data collected at hourly intervals to ensure real-time fidelity. The dataset is rationally split into a training set covering January to May for model learning and a test set covering June to August for unbiased performance evaluation. All experiments are implemented in Python 3.8 with the PyTorch deep learning framework, accelerated by an NVIDIA GeForce RTX 4060Ti 16GB GPU. The key hyperparameters are set as follows: batch size 64, initial learning rate 1×10^{-4}, input sequence length 120 using a real-time sliding window strategy, and single-step ahead prediction for real-time electricity prices.

3.2 Evaluation Metrics

To comprehensively, objectively and quantitatively evaluate the prediction accuracy, error level and generalization ability of the proposed real-time electricity price forecasting model, this paper selects three universal and practically applicable indicators as performance evaluation criteria: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Accuracy (ACC). Among them, MAE and MSE are used to measure the overall deviation between predicted and actual values, quantifying the model's error magnitude and sensitivity to fluctuations. The ACC index, from the perspective of practical electricity market applications, reflects the relative accuracy of predictions against real prices, which is more consistent with the actual needs of market transactions and dispatch decision-making. The three indicators complement each other and can fully characterize the comprehensive forecasting performance of the model in both stable and volatile periods. Their specific definitions and calculation formulas are given as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{8}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{9}$$

$$ACC = 1 - \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{y_i} \tag{10}$$

4. Results

4.1 Overall Performance Comparison

The real-time electricity price forecasting results are illustrated in Fig. 4. As can be seen from the figure, the prediction curve of the proposed model fits well with the actual electricity price curve. It can effectively capture the overall fluctuation trend and key peak-valley characteristics of real-time electricity prices, and accurately model the complex nonlinear mapping relationship between multi-source operation data of the power system and real-time market electricity prices. During stable periods, the model achieves extremely small prediction errors and excellent fitting precision. Even in sharp fluctuation intervals such as sudden surges, prominent spikes, and rapid drops of electricity prices, the model still responds quickly and tracks the variation trajectory of actual prices stably without obvious lag or deviation. This fully verifies the strong anti-interference ability, high robustness, and superior real-time electricity price forecasting performance of the proposed model under complex operating conditions.

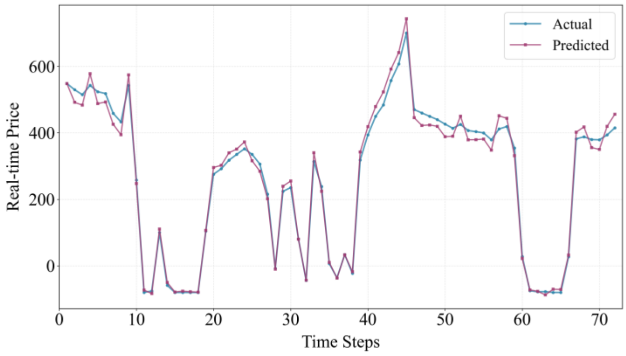

Figure 4. The real-time electricity price prediction results

Table 1 quantitatively compares the real-time electricity price forecasting performance of the proposed model with various mainstream benchmark models. As shown in the results, traditional temporal neural networks including Bidirectional Long Short-Term Memory (BiLSTM), Long Short-Term Memory (LSTM), and the single Transformer model achieve moderate forecasting performance, with prediction accuracy (ACC) of only 71%–75.3%. Their error indicators such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) are relatively high, making them difficult to fully meet the modeling requirements of real-time electricity prices with strong nonlinearity and high volatility caused by random wind-solar power output.

Table 1. Lists the performance comparison results of different prediction models

Model	MAE	MSE	ACC
BiLSTM	0.148	0.031	71.8%
LSTM	0.119	0.020	74.1%
Transformer	0.124	0.021	75.3%
GCN–LSTM	0.130	0.026	73.6%
GNN–Transformer	0.108	0.017	78.5%
TMIT	0.095	0.013	83.9%
GAT-Informer	0.086	0.011	85.8%
Proposed Model	0.071	0.009	88.2%

On this basis, conventional spatiotemporal hybrid models such as GCN–LSTM and GNN–Transformer lift prediction accuracy to a certain degree via spatial feature extraction, yet their ACC still stays below 79% due to fixed graph topology and rigid feature fusion, which cannot capture time-varying correlations triggered by fluctuating renewable generation. The recently proposed TMIT and GAT-Informer [30], as advanced deep learning approaches for new-energy-dominated electricity markets, further boost prediction accuracy to 83.9% and 85.8% respectively with optimized long-sequence modeling and graph attention strategies. Even so, these two cutting-edge methods lack dynamically adjustable topological construction and adaptive gated feature enhancement, leading to obvious prediction deviation during sharp price surges induced by wind and photovoltaic volatility. In contrast, the proposed model achieves significant optimization in all indicators, which fully validates the synergistic advantages of dynamic graph convolution, adaptive gated fusion, and the hybrid temporal architecture.

Compared with the optimal baseline GAT-Informer, the proposed model cuts MAE by 17.4% and increases prediction accuracy by 2.4%. Relative to the classic GNN–Transformer, the MAE is reduced by 34% and ACC is lifted by 9.7%. The proposed model can accurately track real-time price spikes and sudden drops, with more than 85% of the test points exceeding 80% accuracy. Under extreme fluctuation scenarios driven by volatile renewable power output, the model still maintains high stability.

Figure 5 provides a visual comparison of the prediction results obtained by each model.

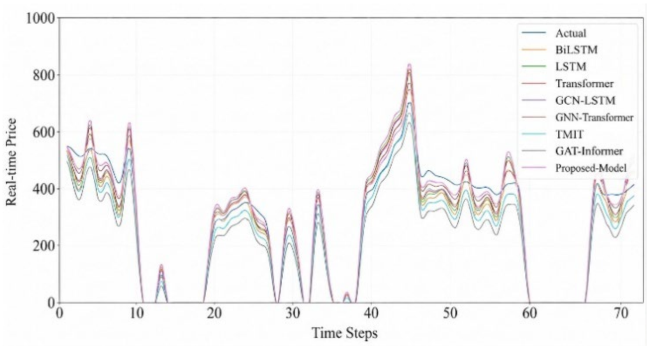

Figure 5. Prediction results of each model

4.2 Ablation Experiment Results

To systematically verify the effectiveness and contribution of each core functional module of the proposed model, this paper designs rigorous ablation experiments. By removing key modules one by one and comparing the forecasting performance, we quantitatively analyze the improvement of each component on the overall model accuracy. The experimental results are shown in Figure 6.

The ablation experiments are set as follows: taking the full model as the benchmark, we remove the Dynamic Graph Convolution (DGC) spatial feature extraction module, the adaptive gated temporal feature fusion module, and the BiGRU local temporal modeling module respectively, and conduct comparative tests under the same dataset and evaluation metrics. The results show that:

When the DGC module is removed, the model loses the ability to model the real-time spatial correlation among multi-variables in the power system. The prediction accuracy (ACC) drops sharply from 88.2% of the full model to 81.3%, a decrease of 6.9 percentage points. Meanwhile, error indicators such as MAE and MSE increase significantly, which fully validates the core role of dynamic graph convolution in capturing real-time spatial interactions and adapting to real-time electricity price scenarios.

When the adaptive gated fusion module is removed, the model adopts the traditional fixed-weight fusion method and cannot strengthen key features during price mutations. The prediction accuracy decreases to 82.6%, a drop of 5.6 percentage points, proving the key value of the adaptive gated mechanism in improving the model's fluctuation sensitivity and forecasting robustness.

When the BiGRU module is removed, the model only retains the Transformer encoder for global temporal modeling, and its ability to capture local high-frequency fluctuations declines. The prediction accuracy falls to 83.7%, a reduction of 4.5 percentage points, verifying the complementary advantage of the Transformer-BiGRU hybrid structure in collaborative modeling of global and local temporal features.

According to the comprehensive ablation results, the DGC module and adaptive gated fusion module contribute the most to improving real-time electricity price forecasting performance. The synergistic effect of the three core modules jointly guarantees the high-precision forecasting capability of the model in the whole period, especially in high-volatility scenarios, providing sufficient experimental support for the structural rationality and effectiveness of the proposed model.

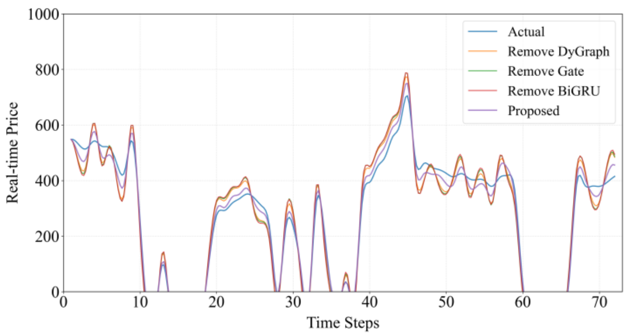

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Figure 6. Ablation Experiment Results

5. Discussion

Compared with existing day-ahead electricity price forecasting and traditional real-time price forecasting methods, the proposed model has three core technical advantages in real-time price scenarios. First, the dynamic graph convolution module breaks through the structural limitations of static graphs. It can track changes in power system operating states in real time, adaptively update graph topology and edge weights, and accurately model dynamically evolving spatial correlations among multi-source operating features. Compared with static graph methods with fixed topology, it is more suitable for the strong time-varying and fast-response forecasting requirements of real-time electricity prices, and effectively solves the hysteresis problem of traditional spatial modeling methods in real-time scenarios. Second, the adaptive gated fusion mechanism realizes dynamically weighted allocation of spatiotemporal features. It can automatically strengthen the weights of key driving features during sudden changes such as price surges and spikes, significantly improve the model's sensitivity to price fluctuations, effectively suppress redundant information interference, and enhance the forecasting stability and robustness of the model under extreme working conditions at the feature level. Third, the Transformer – BiGRU hybrid temporal forecasting architecture achieves collaborative modeling of global and local features. The Transformer encoder captures long-range global dependencies of price series, while the BiGRU network mines high-frequency local fluctuations and bidirectional temporal correlations. The two components complement each other and better fit the inherent characteristics of real-time electricity prices such as nonlinearity, non-stationarity, and multi-scale fluctuations.

Experimental results fully verify the superiority of the proposed model. It achieves high-precision forecasting on the full-time test set, and shows significant performance advantages over various benchmark models especially under extreme scenarios with high volatility and strong disturbances. It can provide accurate price support for businesses such as real-time transaction decision-making in electricity markets, real-time grid dispatch operation, and renewable energy accommodation optimization, with important theoretical research value and engineering application prospects.

6. Conclusions

Aiming at the forecasting difficulties of real-time electricity prices characterized by strong nonlinearity, high volatility, and fast time variation, this paper proposes a real-time electricity price forecasting model based on dynamic graph convolution and adaptive temporal fusion. The model works collaboratively through four core modules: real-time feature selection and preprocessing using the SHAP method, dynamic spatial correlation modeling of the power system based on dynamic graph convolution, adaptive weighted fusion of spatiotemporal features via an adaptive gated mechanism, and finally joint accurate forecasting of global trends and local fluctuations combined with the Transformer–BiGRU hybrid network.

Experimental results based on real-time operation data from actual electricity markets show that:The proposed model achieves excellent forecasting performance, with a prediction accuracy ACC of 88.2%, a mean absolute error MAE of 0.071, and a mean squared error MSE of 0.009;Compared with mainstream benchmark models such as BiLSTM, LSTM, Transformer, GCN-LSTM, and GNN-Transformer, the proposed model achieves significant improvements in all evaluation indicators, especially under extreme scenarios of sharp price fluctuations and sudden working condition changes;The model can provide reliable and high-precision real-time electricity price forecasts for all participants in the electricity market, and offer strong support for businesses such as real-time transaction bidding, risk management, and dispatch optimization.

Future work will be carried out in three aspects: first, carry out research on model lightweight deployment and acceleration optimization for edge computing scenarios; second, expand the model to multi-step real-time electricity price forecasting tasks to improve long-term sequence forecasting accuracy; third, build an integrated framework of "electricity price forecasting - transaction decision-making" to realize the deep coupling of forecasting results and market transactions, and further explore the engineering application value of the model.

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