

Construction of a New Energy Settlement Index System and Market Operation Status Evaluation Model Based on Graphormer

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ABSTRACT With the gradual introduction of renewable energy into industrial energy systems, assessing the market operation of new energy settlement mechanisms in industrial parks has become a research task of practical significance. To address the complexity and uncertainty in this process, this paper proposes an innovative Graphormer–Temporal Convolutional Network (Graphormer-TCN) fusion model, aiming to construct a robust, end-to-end tool for assessing the market operation of new energy settlement mechanisms in industrial energy systems. The study establishes a unified input format using an indicator system covering actual generation, forecast deviation, curtailment, settlement, ancillary revenue, economic benefits, capacity factor, and equipment health. The Graphormer spatial layer models the transmission topology as a weighted graph, explicitly encoding connectivity and conduction strength via self-attention biases (edge weight position encoding and node centrality) to capture non-local network effects. The TCN time series layer then utilizes optimized causal convolutions to perform multi-scale analysis on the spatial encodings, characterizing short-term mutations and daily patterns to score market operation status. The model demonstrates stable, high accuracy with low average mean absolute errors (MAE) across wind, photovoltaic (PV), and storage (e.g., 0.017, 0.014, 0.015 over 24 hours). Crucially, this enhanced model reduces the average market transaction response time to approximately 120.5 milliseconds, significantly improving the operational efficiency of clustered industrial loads in high-frequency energy management, enabling rapid response to changes in production load, and driving a 9.6% increase in market operating revenue. This effectively promotes the efficient participation of industrial energy users in renewable energy assets and low-carbon transformation. Since the model directly uses power-network topology and conduction relationships, the work has a natural connection with electromagnetic energy-network operation in industrial parks.

INDEX TERMS new energy settlement mechanism, graphormer-tcn model, market operation assessment, power-network topology, electromagnetic energy systems

I. INTRODUCTION

WITH the rapid increase in the proportion of renewable energy, such as wind and photovoltaic power—a trend mirrored by the industry’s push for decarbonization and sustainable supply chains—the in-herent intermittency and volatility of these sources have brought unprecedented challenges. This volatility is particularly acute for energy-intensive and often clustered manufacturing facilities, complicating the accurate assessment of operational status and settlement mechanisms within the electricity market they participate in [1,2]. Therefore, building an efficient and accurate new energy market operation status assessment model, combined with a sound settlement indicator system design, has become key to achieving efficient new energy consumption and fair market transactions.

This paper aims to develop a high-precision market operational status assessment model for renewable energy settlement mechanisms, addressing the difficulty traditional methods have in capturing the spatiotemporal non-local dependencies and strong time variability of renewable energy output. We employ a joint modeling approach based on the Graphormer-TCN model, where the Graphormer captures the spatial relationships between renewable energy units, and the Temporal Convolutional Network (TCN) extracts multi-scale temporal dynamic features. Operational status scores are then generated through serial fusion and regression output layers. In its implementation, a new energy settlement indicator system covering wind farms, photovoltaic power plants, and energy storage units is first constructed. The indicator data is mapped to a graph structure and fed

into the Graphormer. Temporal dependencies are then captured using the TCN, ultimately outputting an operational status score. Experimental results show that the Graphormer-TCN model achieves Mean Absolute Error (MAE) values of 0.017, 0.014, and 0.015 for wind farms, photovoltaic power stations, and energy storage units, respectively, and Root Mean Square Error (RMSE) values of 0.019, 0.017, and 0.018, respectively. Compared with Graphormer, the Mean Absolute Percentage Error (MAPE) improves by 1.378%, 1.325%, and 1.734%, respectively. The market operating income increases by 9.6%, significantly improving the accuracy and reliability of market operating status assessments and providing a quantitative basis for the optimization of the settlement technical support system.

II. RELATED WORK

In evaluating the operating status of the new energy market, scholars have proposed various graph neural networks and improved methods. Zhu P *et al.* combined graph convolutional networks with semantic embedding to construct a powerful knowledge graph and integrated text semantics to achieve efficient secondary operation risk assessment. However, due to the limitations of the graph convolution receptive field, it is difficult to handle non-local dependencies [3]. Yang Y *et al.* used spectral graph convolution combined with an attention mechanism to predict short-term electricity prices. Although it can extract spatiotemporal features and node importance, it still tends to be a local aggregation [4]. Existing research shows that traditional graph neural networks struggle to handle non-local dependencies in evaluating the new energy market operating status. Although some models that apply the Transformer have improved the ability to model global dependencies, they lack deep integration with graph structures and effective characterization of dynamic time series features.

In recent years, time series modeling has been widely used to evaluate the operational status of new energy markets to capture the temporal variations of load, electricity prices, and market parameters. Jain R *et al.* proposed a Wavelet Transform–Auto Regression Integrated Moving Average (WT-ARIMA) hybrid model to predict day-ahead load and quantify the impact of uncertainty through value at risk and conditional value at risk. The model has better fitting accuracy than traditional ARIMA but is insufficient in capturing multi-scale nonlinear dynamics [5]. While these studies provide valuable insights into new energy market operations in terms of new energy settlement mechanisms, indicator system design, and optimization of settlement technical support systems, they still struggle to simultaneously account for non-local temporal and spatial dependencies and multi-scale dynamics, as well as inadequate real-time performance. Furthermore, most of these studies are based on new energy loads and electricity prices, leaving significant gaps in assessing market operational status.

Existing research mostly focuses on optimizing prediction accuracy but rarely fully considers the real-time constraints

and business characteristics of the new energy market, such as short settlement cycles, high-frequency fluctuations in prices and trading volumes, and the timeliness requirements of cross-regional scheduling. There are still deficiencies in multi-source heterogeneous data synchronization, cross-node information transmission delays, and rapid decision support. As a result, some methods perform well in experimental environments but are difficult to meet the dual needs of rapid response and stable output in real market operations.

III. CONSTRUCTION OF NEW ENERGY SETTLEMENT INDICATOR SYSTEM AND MARKET OPERATION STATUS EVALUATION MODEL

A. CONSTRUCTION OF NEW ENERGY SETTLEMENT INDICATOR SYSTEM

This paper focuses on the actual needs of the new energy settlement mechanism and constructs an indicator system covering power generation, forecast deviation, economic benefits, and operation quality based on multi-source data fusion and statistical analysis methods [6-8].

The actual power generation indicator of the new energy unit is defined. Let the set of new energy units be N . The formula for the actual power generation of the new energy unit in the unit period t is shown in (1).

$$P_i(t) = \int_{t-\Delta t}^t p_i(\tau) d\tau \quad (1)$$

In formula (1), $p_i(\tau)$ represents instantaneous power output, Δt represents the time interval length (value is 1 minute), and $P_i(t)$ represents actual power generation.

To measure the output forecast deviation, a forecast deviation index is constructed. To eliminate unit and scale differences, a normalized relative deviation index is used, as shown in formula (2).

$$\begin{cases} D_i(t) = P_i(t) - \hat{P}_i(t), \\ \tilde{D}_i(t) = \frac{D_i(t)}{P_i^{\max}} \end{cases} \quad (2)$$

In formula (2), $\hat{P}_i(t)$ represents the predicted power generation, $D_i(t)$ represents the predicted deviation, $P_i^{\max}$ represents the unit's historical maximum power generation, and $\tilde{D}_i(t)$ represents the normalized relative deviation.

For wind and solar power curtailment losses, a wind and solar power curtailment rate indicator is constructed, as shown in formula (3).

$$R_i^{\text{curt}}(t) = \frac{WT_i(t) + ST_i(t)}{P_i(t) + \epsilon} \quad (3)$$

In formula (3), ϵ represents a very small positive number to avoid division by zero. $WT_i(t)$ represents the amount of wind power curtailed, and $ST_i(t)$ represents the amount of solar power curtailed.

The economic benefit indicator is based on the settlement amount and ancillary service revenue. The unit time economic benefit indicator $E_i(t)$ is shown in formula (4).

$$E_i(t) = M_i(t) + A_i(t) \quad (4)$$

In formula (4), $M_i(t)$ represents the settlement amount, and $A_i(t)$ represents the ancillary service revenue.

To measure the stability of economic benefits, a time window is introduced, and the mean and variance of economic benefits within the window are defined, as shown in formula (5).

$$\begin{aligned} \bar{E}_i(t) &= \frac{1}{|W_I|} \sum_{\tau \in W_I} E_i(\tau), \\ \sigma_{E_i}^2(t) &= \frac{1}{|W_I|} \sum_{\tau \in W_I} (E_i(\tau) - \bar{E}_i(t))^2 \end{aligned} \quad (5)$$

In formula (5), W_I represents the time window. $\bar{E}_i(t)$ and $\sigma_{E_i}^2(t)$ represent the mean and variance of economic benefits within the window, respectively.

Operational quality indicators cover capacity factor and equipment health status. The capacity factor is defined as shown in formula (6).

$$C_i(t) = \frac{P_i(t)}{P_i^{\text{rated}}} \quad (6)$$

In formula (6), $C_i(t)$ represents the capacity factor, and P_i^{rated} represents the rated power of the new energy unit.

The equipment health status is represented by monitoring data $Hea_i(t) \in [0, 1]$, where 1 indicates good condition and 0 indicates a fault condition. This is calculated based on sensor data and anomaly detection mechanisms.

The overall formula for the new energy settlement indicator sequence is shown in (7).

$$x_i(t) = [P_i(t), \tilde{D}_i(t), R_i^{\text{curt}}(t), E_i(t), C_i(t), Hea_i(t), \dots] \quad (7)$$

In formula (7), $x_i(t)$ represents the sequence of new energy settlement indicators for the i -th unit. The sequence for all units is defined as X .

To address the problem of inconsistent data scale and dimension, standardization is used to ensure balanced numerical input of indicators. Considering the presence of missing values and outliers in new energy settlement data, a matrix recovery method based on low-rank matrix completion is used to preprocess the indicator matrix X to address the problem of missing observations. Formula (8) is shown [9,10]. To ensure the timeliness and responsiveness of the indicators, a sliding window statistical method is applied to smooth some economic benefit indicators.

$$\hat{X} = \min_{ZB} \|ZB\|_* + \frac{\beta}{2} \|\gamma_{\Omega}(ZB - X)\|_F^2 \quad (8)$$

In formula (8), ZB represents the completion matrix, β represents the regularization coefficient in preprocessing, and γ_{Ω} represents the observation mask operator.

To ensure that the eight dimensions of indicators (such as power generation, prediction deviation rate, curtailment rate, settlement amount, ancillary service revenue, economic benefit variance, capacity coefficient, and equipment health status) can effectively represent the operating status of new energy units in the same feature space, this paper performs unified normalization and weighting on each indicator during the data preprocessing stage. Z-score standardization is used to unify the scale of continuous indicators, making their mean 0 and variance 1; discrete or Boolean indicators (such as equipment health status) are embedded into the same feature dimension after one-hot encoding. Based on the importance and stability of the indicators in the operation of the new energy market, the entropy weight method is used to calculate objective weights to reduce the interference of subjective factors. Finally, a unified input vector for nodes is formed through weighted fusion, which serves as the input to the node feature matrix of Graphormer, ensuring the comparability and information balance of indicators of different dimensions in the spatial modeling stage. The architecture framework of the new energy settlement indicator system is shown in Figure 1.

In Figure 1, the framework is divided into three levels from top to bottom: the target layer, the criterion layer, and the indicator layer. The target layer clearly takes ensuring the stability and efficient operation of the new energy market as its core orientation; the criterion layer covers three key aspects: output and deviation, economic benefits, and operation quality; the indicator layer is further refined into specific quantitative indicators such as actual power generation, forecast deviation rate, wind and solar power curtailment rate, settlement amount, ancillary service income, economic benefit mean and variance, capacity factor, and equipment health status, which comprehensively reflect the operating status and market performance of new energy units and provide a scientific basis for subsequent market operation status evaluation and settlement technical support system optimization.

B. GRAPHORMER-TCN NEW ENERGY MARKET OPERATIONAL STATUS EVALUATION MODEL

Traditional temporal neural networks (TNNs) focus only on time-series dependencies, making it difficult to characterize the complex spatial relationships between new energy settlement units. While standard graph neural networks (GNNs) can capture spatial structural features, their ability to model temporal dynamics is insufficient, especially when dealing with non-stationary, multi-scale market state data, where they are prone to information lag and local overfitting. In contrast, the Graphormer-TCN model proposed in this paper achieves hierarchical decoupling and deep fusion of space and time in its structure: Graphormer explicitly models non-local spatial dependencies through centrality and edge

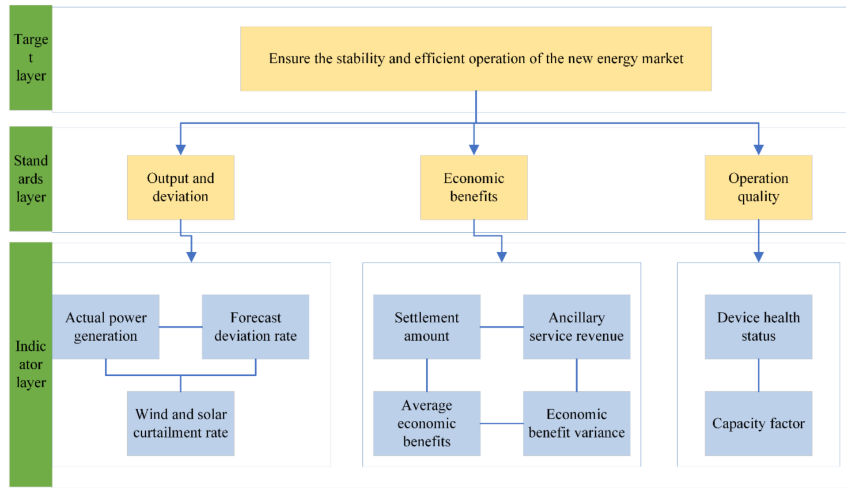


FIGURE 1. New energy settlement indicator system architecture framework

weight encoding, while TCN uses dilated convolutions and residual connections to capture long-range temporal dynamics. The sequential fusion of the two not only effectively compensates for the structural blind spots of a single model but also achieves a synergistic expression of spatial topology and temporal evolution features in the comprehensive evaluation of the new energy market's operating status, improving the model's stability and prediction accuracy.

1) Graphormer Model

This paper addresses the complexity of spatial dependencies in evaluating the operational status of new energy markets by constructing a Graphormer-based spatial modeling module. This module incorporates graph structure information and edge weight encoding, extending the Transformer self-attention mechanism to capture non-local, multi-hop dependencies.

The new energy market graph structure is defined as an undirected graph $G = (\hat{V}, \hat{E})$, where nodes $\hat{V}$ represent new energy settlement units or stations, and edges $\hat{E}$ represent physical connections or market transaction relationships between settlement units. The node feature matrix is derived from the new energy settlement indicators after normalization and other processing, and is now defined as $\hat{X}$. The core of Graphormer is to enhance the graph structure of the traditional Transformer's self-attention mechanism [11,12]. The self-attention calculation is shown in Equation (9).

$$Q = XW^Q, \quad K = XW^K, \quad V = XW^V \quad (9)$$

In formula (9), W^Q , W^K , and W^V represent the linear mapping matrices of query, key, and value, respectively.

Graphormer introduces the edge weight position encoding matrix O , and the element definition o_{ij} is shown in formula (10).

$$o_{ij} = PE(w_{ij}) \quad (10)$$

In formula (10), PE represents the learnable position encoding function of edge weights. The self-attention weight matrix is calculated as shown in formula (11).

$$a_{ij} = \frac{\exp\left(q_i^T k_j / \sqrt{d} + o_{ij}\right)}{\sum_{k=1}^N \exp\left(q_i^T k_k / \sqrt{d} + o_{ik}\right)} \quad (11)$$

In formula (11), q_i^T and k_j represent the query vector and key vector of the node, respectively, and $\sqrt{d}$ represents the scaling factor.

The multi-head attention mechanism further enhances the expressiveness of the model, as shown in formula (12).

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_\delta)W^O, \\ \text{head}_m = \text{Attention}(Q_m, K_m, V_m) = A_m V_m \quad (12)$$

In formula (12), W^O represents the output linear mapping matrix, and δ represents the number of heads. To capture the structural information of nodes, a node centrality encoding vector [13,14] is introduced, where each element represents the degree centrality of a node. By embedding it into the node features, the explicit fusion of structural information is achieved, as shown in formula (13).

$$\dot{X}' = \dot{X} + \hat{C}, \quad \hat{C} = [\hat{c}_1 w_{\hat{c}}, \hat{c}_2 w_{\hat{c}}, \dots, \hat{c}_N w_{\hat{c}}]^T \quad (13)$$

In formula (13), $w_{\hat{c}}$ represents the trainable centrality weight vector, and $\hat{C}$ represents the centrality encoding vector.

In this study, degree centrality is used as the primary metric to reflect the connectivity and transaction importance of renewable energy settlement units within the electricity market topology. Nodes with high degree centrality typically represent key hubs with settlement or energy interaction relationships with multiple generating units or market participants, making them more sensitive to market fluctuations. Considering the dynamic nature of the renewable energy

market, this paper updates the adjacency matrix and edge weights in real time within the data sampling window to reflect the time-varying characteristics of transaction relationships and physical connections, thus achieving dynamic adjustment of centrality encoding. This design ensures that the Graphormer spatial layer can balance real-time performance and structural stability when capturing structural changes in the renewable energy market, effectively improving the model's adaptability to dynamic market topologies. The Transformer encoding layer includes a multi-head self-attention sublayer and a feed-forward network (FFN) sublayer. Each layer uses residual connections and layer normalization, as shown in formula (14).

$$\begin{aligned} Z^{(l)} &= \text{LayerNorm}\left(\dot{X}^{(l-1)} \right. \\ &\quad \left. + \text{MultiHead}\left(\dot{X}^{(l-1)}, \dot{X}^{(l-1)}, \dot{X}^{(l-1)}\right)\right), \quad (14) \\ \dot{X}^{(l)} &= \text{LayerNorm}\left(Z^{(l)} + \text{FFN}\left(Z^{(l)}\right)\right) \end{aligned}$$

In formula (14), l is the encoding layer index, and FFN is the two-layer fully connected network. The formula of FFN is shown in (15).

$$\text{FFN}(z) = \text{ReLU}(zW_1 + b_1)W_2 + b_2 \quad (15)$$

In formula (15), W_1 and W_2 represent the weight matrices in the FFN, and b_1 and b_2 both represent biases.

Finally, by stacking multiple encoding layers, the model gradually aggregates global graph structure and feature information, outputting the final spatial encoding representation $H = \dot{X}^{(L)}$.

In the topology update mechanism of spatial modeling, the transmission topology of the renewable energy market remains generally stable, but its edge weights (transmission strength) are dynamically updated over time to reflect changes in actual operating conditions. Specifically, within each time sampling window (15 minutes), the system recalculates edge weights based on real-time data such as unit output, energy exchange volume, and settlement interaction frequency, characterizing the dynamic evolution of market trading relationships and power flow. This design enables Graphormer to capture the rapidly changing coupling strength and regional dependence characteristics in the operation of the renewable energy market while maintaining global topology consistency, thus improving the time-varying sensitivity and prediction accuracy of spatial modeling.

2) TCN Model

TCN adopts a one-dimensional causal convolution structure to ensure that time series prediction depends only on current and past data [15,16]. To expand the receptive field, a dilation coefficient is applied to implement dilated convolution. The formula for the convolution layer is shown in (16).

$$y^{(l)}(t) = \sum_{\hat{k}=0}^{\hat{K}-1} W^{(l)}(\hat{k}) \cdot h^{(l)}(t - d_l \cdot \hat{k}) + b^{(l)} \quad (16)$$

In formula (16), $h^{(l)}$ represents the input feature vector of the l -th layer, $W^{(l)}(\hat{k})$ represents the weight matrix of the $\hat{k}$ -th convolution kernel of the l -th layer, $b^{(l)}$ represents the bias vector, and $y^{(l)}$ represents the convolution output of the l -th layer.

The dilation coefficient increases with the number of layers and is set to $d_l = 2^l$, ensuring that the receptive field expands exponentially and can capture long-range temporal dependencies.

To alleviate the vanishing gradient problem in deep network training, a residual connection mechanism is adopted, and the output of the l -th layer is defined as shown in formula (17).

$$h^{(l+1)}(t) = \text{ReLU}\left(y^{(l)}(t) + h^{(l)}(t)\right) \quad (17)$$

In formula (17), $h^{(l+1)}(t)$ represents the output of the l -th layer after residual processing.

After each convolutional layer output, a layer normalization operation is applied to normalize the activations in the channel dimension, as defined in formula (18).

$$\hat{h}^{(l+1)}(t) = \frac{h^{(l+1)}(t) - \mu^{(l+1)}}{\sigma^{(l+1)}} \odot \iota^{(l+1)} + \varrho^{(l+1)} \quad (18)$$

In formula (18), $\iota^{(l+1)}$ represents the trainable scaling parameter; $\varrho^{(l+1)}$ represents the translation parameter; and $\odot$ represents element-wise multiplication.

The study constructs a TCN stack consisting of L layers of dilated convolutional residual blocks. The receptive field is expressed as (19) [17,18]. By selecting appropriate L and K , the receptive field is guaranteed to cover the entire historical sequence, achieving multi-scale temporal dynamic capture.

$$R = 1 + (\hat{K} - 1) \sum_{l=0}^{L-1} d_l = 1 + (\hat{K} - 1)(2^L - 1) \quad (19)$$

In formula (19), R represents the receptive field. The output sequence is shown in formula (20).

$$Z_i = \left[\hat{h}^{(L)}(1), \hat{h}^{(L)}(2), \dots, \hat{h}^{(L)}(T) \right] \quad (20)$$

In formula (20), Z_i represents the output sequence.

To further enhance the model's adaptability to periodicity and non-stationarity, a gating mechanism (Gated Activation Unit, GAU) is applied in combination with residual connections, as shown in formula (21).

$$z^{(l)}(t) = \tanh\left(W_f^{(l)} * h^{(l)}(t)\right) \odot \sigma\left(W_g^{(l)} * h^{(l)}(t)\right) \quad (21)$$

In formula (21), $*$ represents the dilated convolution operation, and $W_f^{(l)}$ and $W_g^{(l)}$ represent the filtering and gated convolution kernels, respectively.

Finally, this paper applies global average pooling to the TCN output to match the subsequent model fusion structure, as shown in formula (22).

$$z_i = \frac{1}{T} \sum_{t=1}^T Z_i(t) \quad (22)$$

In formula (22), z_i represents a fixed-dimensional feature vector.

The “optimized causal convolution” in this paper is primarily reflected in the adaptive design of the dilation rate and kernel structure, rather than the introduction of additional attention mechanisms. In the TCN layer, this paper employs an exponentially increasing dilation coefficient $d=\{1,2,4,8\}$ and dynamically adjusts the kernel size and number of channels to adapt to market fluctuations at different time scales. This design allows the model to cover a wider temporal receptive field while maintaining computational efficiency, effectively capturing everything from short-term market price disturbances to daily load fluctuations. Gated activation units (GAUs) and layer normalization are integrated into the convolutional block to stabilize gradient propagation and improve robustness to non-stationary time series, achieving overall optimization of temporal modeling performance.

3) Model Fusion and Output Layer Design

To fully leverage Graphormer’s spatial modeling capabilities and TCN’s temporal dynamics, this paper adopts a serial fusion architecture, using the spatial features output by Graphormer as input to the TCN module. Graphormer first processes the spatial data of new energy settlement indicators, generating a node-level spatial encoding representation. This spatial encoding sequence is then input into the TCN temporal module, which utilizes dilated causal convolution to capture multi-scale dynamic dependencies in the temporal dimension, achieving deep fusion and joint modeling of spatiotemporal information. The structure of the Graphormer-TCN new energy market operational status assessment model is shown in Figure 2.

In Figure 2, the input multidimensional spatiotemporal data of new energy settlement indicators is cleaned and normalized in the data preprocessing module before being input into the Graphormer module. Graphormer accurately captures the non-local spatial relationships between new energy units through centrality coding, spatial coding, and edge coding. The spatial feature sequence output by Graphormer is then input into the TCN module, which uses dilated causal convolution, residual connections, and gated activation units to deeply explore the multi-scale dependencies of temporal dynamics. Finally, the fused feature vector is fed into the regression layer to complete the prediction of market operation status scores. In the output layer design, for each

new energy unit, this paper applies a linear regression layer to predict the operation status score, as shown in formula (23).

$$\hat{y}_i = w_{\text{out}}^\top z_i + b_{\text{out}} \quad (23)$$

In formula (23), $\hat{y}_i$ represents the operating status score of the new energy unit, $w_{\text{out}}^\top$ and b_{out} represent the regression weight vector and bias term, respectively.

To avoid overfitting and enhance the generalization ability of the model, L2 regularization is introduced in the output layer, and the regularization loss is defined as shown in formula (24).

$$\text{Loss}_{\text{reg}} = \lambda_1 \|w_{\text{out}}\|^2 \quad (24)$$

In formula (24), λ_1 represents the regularization coefficient in the output layer.

C. MODEL TRAINING AND OPTIMIZATION

This section outlines the training procedures and optimization strategies employed for the proposed Graphormer-TCN model. The focus is on the design of the loss function, model optimization techniques, and the experimental setup for evaluating model performance.

1) Loss Function Design

To quantify prediction errors, the Mean Squared Error (MSE) is adopted as the primary loss function, as defined in Equation (25):

$$\text{Loss}_{\text{MSE}} = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N \left(y_i^{(j)} - \hat{y}_i^{(j)} \right)^2 \quad (25)$$

In Equation (25), $y_i^{(j)}$ denotes the actual operating status score vector of the new energy unit, while $\hat{y}$ represents the predicted score vector. To mitigate overfitting and enhance generalization, an L2 regularization term is incorporated into the objective function. The comprehensive loss function is given by Equation (26):

$$\text{Loss}(\Theta) = \text{Loss}_{\text{MSE}} + \lambda_2 \|\Theta\|^2 \quad (26)$$

In Equation (26), Θ represents the parameter set, λ_2 is the regularization coefficient, $\text{Loss}(\Theta)$ denotes the total loss function, and Loss_{MSE} represents the prediction loss. The addition of L2 regularization penalizes large parameter values, thereby improving the robustness and generalization capability of the model.

2) Model Optimization

The Adam optimizer is utilized for parameter updates, with its iterative update rule presented in Equation (27) [19-21]:

$$\Theta_t = \Theta_{t-1} - \eta \frac{\hat{w}_t}{\sqrt{\hat{\rho}_t + \hat{\epsilon}}} \quad (27)$$

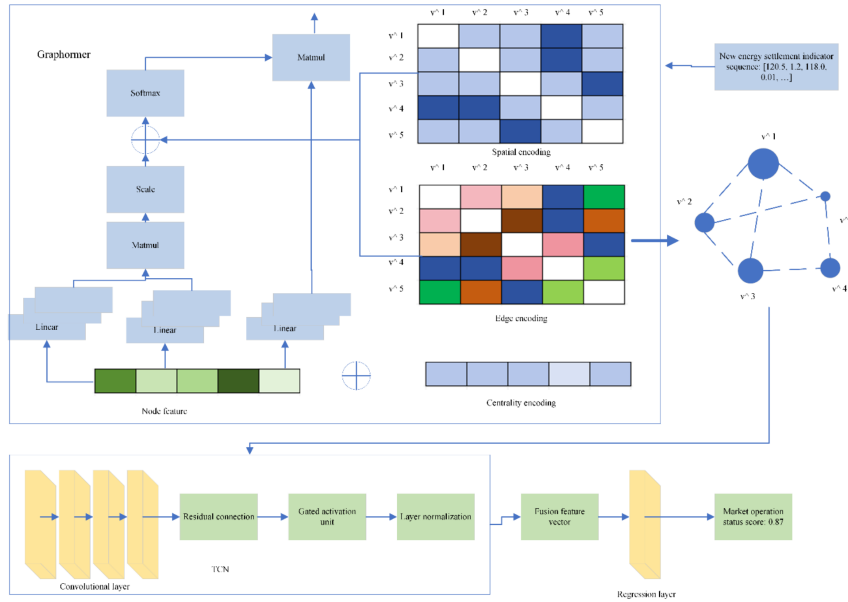


FIGURE 2. Graphormer-TCN new energy market operation status evaluation model structure

In Equation (27), η is the learning rate, and $\hat{\epsilon}$ is a small constant to prevent division by zero. To further enhance training stability and convergence, a learning rate warm-up and decay strategy is implemented. The initial learning rate is linearly increased from a small value to a predefined peak value, stabilizing the early training phase. Subsequently, the learning rate is adjusted according to the cosine annealing decay strategy, as described in Equation (28) [22]:

$$\eta_t = \eta_{\min} + \frac{1}{2} (\eta_{\max} - \eta_{\min}) \left(1 + \cos \frac{t\pi}{T_{\max}} \right) \quad (28)$$

In Equation (28), $\eta_{\max}$ denotes the peak learning rate, $\eta_{\min}$ is the minimum learning rate, and $T_{\max}$ represents the maximum number of iterations. This dynamic adjustment of the learning rate facilitates effective exploration and exploitation during optimization, reducing the likelihood of premature convergence or stagnation in local minima.

IV. NEW ENERGY MARKET OPERATION STATUS EVALUATION EXPERIMENT

This section describes the experimental design for assessing the performance of the proposed model in the context of new energy market operation status evaluation.

A. EXPERIMENTAL DATA

The experimental evaluation is conducted using real-world operational data from the Nanjing regional renewable energy power market. The dataset comprises three categories of renewable energy units: wind farms, photovoltaic (PV) power plants, and energy storage units, collectively capturing the operational characteristics of a diversified energy portfolio under the renewable energy settlement mechanism. Specifically, the dataset includes 25 wind farms, 30 PV power plants, and 15 energy storage units, totaling 70 units. The

data spans the entire calendar year of 2023, with a sampling frequency of 15 minutes. It encompasses real-time output data, settlement transaction records, and key performance indicators such as equipment health status for each unit. All data undergo rigorous quality inspection and preprocessing, including cleaning and normalization, to ensure reliability and consistency for subsequent analysis.

B. EVALUATION METRICS

Model performance is quantitatively assessed using three standard evaluation metrics: MAE, RMSE, and MAPE. The formulas for these metrics are as follows:

MAE is defined in Equation (29):

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (29)$$

In Equation (29), y_i is the true value, and $\hat{y}_i$ is the predicted value for instance i .

RMSE is given in Equation (30):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (30)$$

MAPE is formulated in Equation (31):

$$\text{MAPE} = \frac{100\%}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (31)$$

These metrics comprehensively evaluate both the magnitude and relative accuracy of the predictions, facilitating robust model comparison.

C. EXPERIMENTAL PLAN

The experimental design adheres to the principles of reproducibility, comparability, and application-specific relevance. A unified metric system and standardized preprocessing pipeline—including time alignment, interpolation, normalization, and graph construction—are applied across all experiments. The dataset is chronologically partitioned into training, validation, and test sets in a 70%/15%/15% ratio. All models employ identical sliding window lengths and batch training procedures to ensure fair comparison. Training is conducted with early stopping, scheduled learning rate adjustment, and L2 regularization. Hyperparameters are optimized using Bayesian search on the validation set. Evaluation encompasses both predictive accuracy (MAE, RMSE, MAPE) and operational performance metrics (inference time, throughput). Means and confidence intervals are reported for the test set to establish statistical significance and validate the practical utility of the proposed method in market operation status assessment and settlement mechanisms. Comparative experiments involve the main Graphormer-TCN model and multiple baseline models, including Graphormer, GCN-LSTM, GCN-TCN, ST-GAT (Spatio-Temporal Graph Attention Network), GAT-TCN, Transformer, and LSTM-GRU (Long Short-Term Memory-Gated Recurrent Unit). The analysis covers generalization capability, spatiotemporal dependency modeling, and the contribution of individual indicators in the settlement index system. Model outputs are integrated into a simulated settlement technical support system for further evaluation of settlement error rate, dispute reduction ratio, and other operational metrics. Quantitative results demonstrate the advantages of the Graphormer-TCN model in capturing spatiotemporal dependencies and supporting settlement scenarios.

The key experimental hyperparameters are summarized in Table 1.

TABLE 1. Experimental Hyperparameters

Parameter Name	Value/Range
Number of graph nodes	58
Hidden dimensions	128
Number of layers	4
Number of attention heads	8
Dropout ratio	0.1
Number of training rounds	300
Convolution kernel size	3
Number of channels	[64, 128, 128, 256]
Dilation factor	[1, 2, 4, 8]
Batch size	64
Learning rate	1×10^{-4}
Weight decay	1×10^{-5}
Early stopping patience	20

V. MARKET OPERATION STATUS ASSESSMENT RESULTS

A. COMPARISON OF FORECASTED AND ACTUAL MARKET OPERATION STATUS CURVES

The comparison between the market operation status forecast and the actual curve is illustrated in Figure 3.

As shown in Figure 3, among the three types of renewable energy units, the predicted curve for photovoltaic power plants exhibits the best overall fit with the actual curve. The fluctuation trends of all models in the photovoltaic scenario are largely consistent with the actual operating conditions, especially during peak and valley periods.

B. MARKET OPERATION STATUS ASSESSMENT ACCURACY

To evaluate the market operation status assessment capabilities of the constructed new energy settlement mechanism, this paper compares the accuracy of different models on three types of new energy units: wind farms, photovoltaic power stations, and energy storage units. The results are presented in Figure 4. To enable a unified comparison of the operating status of different types of new energy units, this paper normalizes the market operation status index, limiting its value range to the interval [0, 1]. Here, 0 represents the lowest operating efficiency or the weakest market performance, while 1 denotes optimal operation or the most stable market state. The normalized index not only eliminates dimensional differences but also ensures the comparability and stability of the model when evaluating different energy types.

In Figure 4(a), the Graphormer-TCN model achieves a MAE of 0.017, a RMSE of 0.019, and a MAPE of 2.134% for wind farms, significantly outperforming the Graphormer (MAE: 0.024, RMSE: 0.031, MAPE: 3.512%). The GCN-LSTM model achieves an MAE of 0.034, an RMSE of 0.043, and a MAPE of 6.874%. The Transformer performs the worst, with an MAE of 0.044, an RMSE of 0.055, and a MAPE of 9.305%. Compared with the Graphormer, the Graphormer-TCN model reduces the MAE, RMSE, and MAPE by approximately 0.007, 0.012, and 1.378%, respectively.

In Figure 4(b), for the PV sample, the Graphormer-TCN model achieves an MAE of 0.014, an RMSE of 0.017, and a MAPE of 1.02%, representing reductions of approximately 0.006, 0.008, and 1.325%, respectively, compared to the Graphormer (MAE: 0.020, RMSE: 0.025, MAPE: 2.345%). The absolute errors of all models for PV are generally lower than those for wind power, with the Graphormer-TCN model achieving the most significant improvement in MAPE. For the energy storage unit in Figure 4(c), the Graphormer-TCN model achieves MAE, RMSE, and MAPE values of 0.015, 0.018, and 1.678%, respectively, which are approximately 0.009, 0.012, and 1.734% lower than those of the Graphormer (MAE: 0.024, RMSE: 0.030, MAPE: 3.412%). Compared with other spatiotemporal models, such as GCN-TCN and GAT-TCN, the Graphormer-TCN model also exhibits less sensitivity to fluctuations and more stable multi-step prediction capabilities in energy storage scenar-

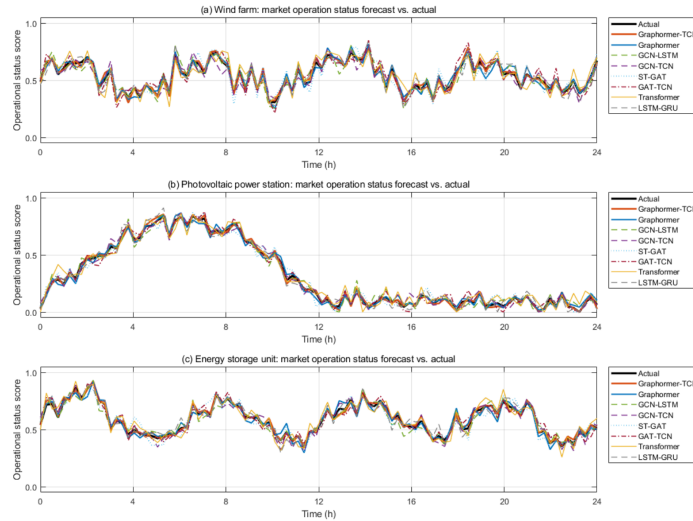


FIGURE 3. Comparison of market operation status predictions and actual curves. Figure 3(a): Wind farm; Figure 3(b): PV power station; Figure 3(c): Energy storage unit

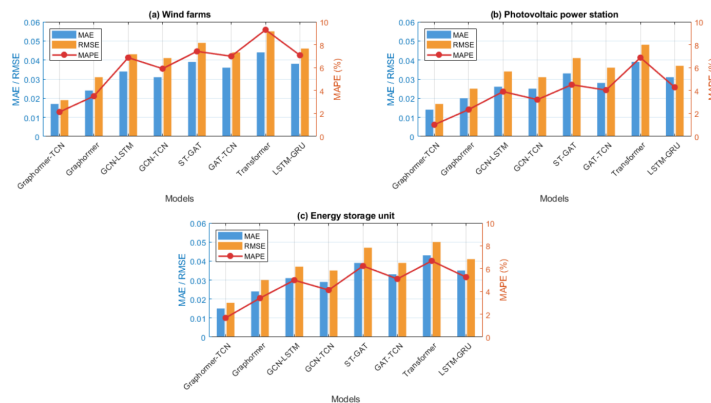


FIGURE 4. Market operation status assessment accuracy. Figure 4(a): Wind farm; Figure 4(b): Photovoltaic power station; Figure 4(c): Energy storage unit

ios. The experiment uses the Graphormer-TCN model as a benchmark to conduct a paired t-test on other models. The experimental steps are as follows:

(1) For each type of new energy unit (wind farm, photovoltaic power station, energy storage unit), 30 paired observations are obtained by dividing the test set by time.

(2) For each comparison model, the paired difference sequence is calculated.

(3) Null hypothesis (H_0): There is no significant difference in the average MAE between the benchmark and the comparison model; alternative hypothesis (H_1): There is a significant difference in the average MAE between the benchmark and the comparison model.

(4) Calculate the sample mean, sample standard deviation, and t statistic.

(5) Use a two-tailed test; significance level and marking rules:

The t-test results are shown in Table 2.

The paired t-test results in Table 2 show that the

Graphormer-TCN model significantly outperforms the other comparison models in terms of MAE accuracy for all three types of new energy units: wind farms, photovoltaic power plants, and energy storage units, with the differences being highly significant ($p < 0.01$). In the wind farm evaluation, the Graphormer-TCN model achieves a t-value of -6.124 ($p = 3.39E-06$) compared to the Graphormer model and a t-value of -16.842 ($p = 4.10E-19$) compared to the worst-performing Transformer model. In the photovoltaic power plant evaluation, the lowest significant difference also occurs in the Graphormer comparison ($t = -4.215$, $p = 1.20E-04$), while the Transformer model shows the greatest difference ($t = -12.106$, $p = 1.90E-12$). In the energy storage unit evaluation, the Graphormer-TCN model achieves a t-value of -5.013 ($p = 1.10E-05$) compared to the Graphormer model and -11.354 ($p = 3.20E-13$) compared to the Transformer model. All other models also show significant differences across the three new energy units.

TABLE 2. T-test results

Comparison model	Wind farms			Photovoltaic power plants			Energy storage units		
	t	P	Significance	t	P	Significance	t	P	Significance
Graphormer	-6.124	3.39E-06	**	-4.215	1.20E-04	**	-5.013	1.10E-05	**
GCN-LSTM	-11.023	9.80E-13	**	-6.742	2.10E-07	**	-6.598	3.50E-07	**
GCN-TCN	-9.821	1.20E-10	**	-6.432	5.80E-07	**	-6.301	9.90E-07	**
ST-GAT	-14.512	5.60E-16	**	-9.904	4.90E-11	**	-9.013	7.90E-11	**
GAT-TCN	-12.301	2.10E-13	**	-7.825	7.10E-09	**	-7.201	6.50E-08	**
Transformer	-16.842	4.10E-19	**	-12.106	1.90E-12	**	-11.354	3.20E-13	**
LSTM-GRU	-13.215	3.20E-14	**	-8.491	2.30E-09	**	-8.942	1.20E-10	**

Note: ** indicates the result is still significant after correction, with a significance level of $p < 0.01$.

C. GRAPHORMER SPATIAL ATTENTION HEATMAP VISUALIZATION

The visualization of the Graphormer's spatial attention heatmap is shown in Figure 5.

As illustrated in Figure 5, the wind farm heatmap displays significant local dependence, with high attention weights between neighboring nodes, demonstrating the model's strong ability to capture the local clustering effects of wind farm output. The PV power plant heatmap exhibits moderate correlation and a somewhat random distribution, reflecting the uneven impact of lighting conditions and geographic distribution on output. The energy storage unit heatmap highlights the influence of core nodes, with certain units assigned high attention weights, demonstrating the model's ability to identify the dominant role of key regulatory nodes in overall market operations.

D. VERIFICATION OF SPATIOTEMPORAL DEPENDENCY MODELING

To explore the effect of spatiotemporal dependency modeling, the experiment analyzes the trends of MAE and RMSE as the time window length changes for wind farms, photovoltaic power stations, and energy storage units at time window lengths of 6, 12, 24, 48, and 72, respectively. The results are shown in Figure 6.

In Figure 6, as the time window increases from 6 to 12 to 24 to 48 to 72, the MAE and RMSE of all three types of renewable energy units reach their minimum values when the window is 24. The MAE for wind farms decreases from 0.025 at a window of 6 to 0.017 at a window of 24, and the corresponding RMSE decreases from 0.028 to 0.019. When the window continues to increase to 48 and 72, the MAE rises to 0.018 and 0.019, respectively, and the RMSE increases to 0.020 and 0.021. The MAE for photovoltaic power plants decreases from 0.018 at window 6 to 0.014 at window 24, and the RMSE decreases from 0.022 to 0.017. These values rise slightly to 0.015 MAE and 0.018 RMSE in windows 48 and 72. Energy storage units perform similarly to photovoltaic units, with MAE decreasing from 0.020 (window 6) to 0.015 (window 24) and RMSE from 0.023 to 0.018. However, these values recover to 0.016 MAE and 0.017 RMSE in windows 48 and 72, respectively.

E. CONTRIBUTION OF EACH INDICATOR OF THE NEW ENERGY SETTLEMENT INDICATOR SYSTEM TO THE MODEL OUTPUT RESULTS

To further analyze the role of various indicators in the new energy settlement mechanism within the market operation status assessment model, this paper quantitatively evaluates the contribution of key indicators in the indicator system design to the model's output, providing a reference for optimizing the settlement technical support system. The contribution of each indicator in the new energy settlement indicator system to the model output is shown in Figure 7.

Figure 7 reveals significant differences in the contributions of various indicators to the output of the market operation status assessment model. Actual power generation contributes the most, accounting for 18.7%, followed by settlement amount (16.5%) and forecast deviation rate (14.3%), which together constitute the main influencing factors, totaling 49.5%. Indicators with moderate contributions include mean economic benefit (12.1%), wind and solar curtailment rate (10.2%), and ancillary service revenue (9.8%), totaling 32.1%. These primarily reflect differences in renewable energy operating efficiency and market participation depth. Indicators with low contributions include economic benefit variance (7.6%), capacity factor (6.9%), and equipment health (3.9%), together accounting for only 18.4%, indicating that their marginal impact on the overall model forecast is relatively limited.

F. REAL-TIME ANALYSIS

To evaluate the model's usability and deployment cost in actual scenarios of new energy settlement mechanisms and settlement technology support system optimization, this paper conducts comparative tests on the response time, inference time, throughput, resource utilization, and update frequency of each model. The results are presented in Table 3.

TABLE 3. Real-time analysis results

Model	Response time (ms)	Inference time (ms)	Throughput (nodes/s)	Resource utilization (%)	Update frequency (min)
Graphormer-TCN	120.5	85.3	320.5	73.2	5
Graphormer	210.7	150.4	180.2	81.6	10
GCN-LSTM	260.9	195.7	140.4	77.5	15
GCN-TCN	145.8	98.6	290.1	69.4	6
ST-GAT	300.2	220.5	120.3	84.7	20
GAT-TCN	165.4	110.2	260.7	71.8	7
Transformer	240	160	200	79.9	12
LSTM-GRU	280.6	210.8	130.5	75	10

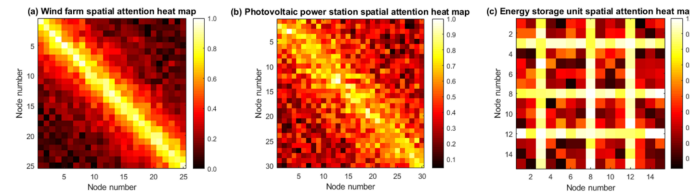


FIGURE 5. Graphormer spatial attention heatmap visualization. Figure 5(a): Spatial attention heatmap for a wind farm; Figure 5(b): Spatial attention heatmap for a photovoltaic power station; Figure 5(c): Spatial attention heatmap for an energy storage unit

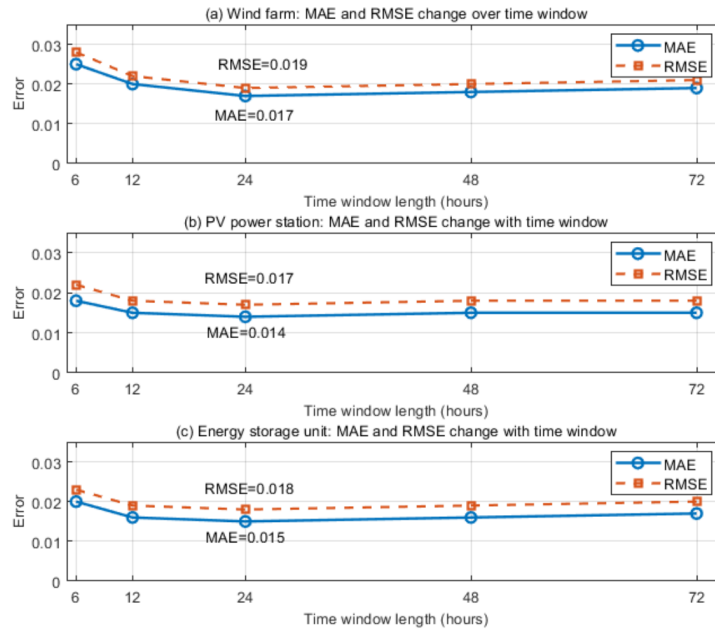


FIGURE 6. Verification of spatiotemporal dependency modeling. Figure 6(a): MAE and RMSE trends with time window length for wind farms; Figure 6(b): MAE and RMSE trends with time window length for photovoltaic power plants; Figure 6(c): MAE and RMSE trends with time window length for energy storage units

Table 3 shows the average response time and inference time of the Graphormer-TCN model, which are 120.5 ms for response and 85.3 ms for inference. These are approximately 90.2 ms and 65.1 ms shorter than those of the Graphormer model (210.7 ms and 150.4 ms, respectively). Compared to ST-GAT (300.2 ms for response and 220.5 ms for inference), these reductions are approximately 179.7 ms and 135.2 ms, respectively. In terms of throughput and resource utilization, the Graphormer-TCN model has the highest processing capability per unit time, with a throughput of 320.5 nodes/s, while Graphormer achieves only 180.2 nodes/s and ST-GAT 120.3 nodes/s. The resource utilization rate of the Graphormer-TCN model is 73.2%, lower than Graphormer's 81.6%, indicating that it maintains high throughput without significantly increasing computing resource utilization. In terms of update frequency, the Graphormer-TCN model supports an update cycle of every 5 minutes, significantly outperforming most baselines (Transformer: 12 minutes; ST-GAT: 20 minutes).

G. GENERALIZATION EVALUATION

To verify the predictive capabilities of the constructed market operation status assessment model under the new energy settlement mechanism for untrained time periods and unseen new energy units, this paper quantitatively analyzes the MAE and RMSE of the model across different years and for various types of new energy units to assess the model's generalization and robustness. The results are shown in Figure 8. Figure 8 displays test data for PV power plants in different time periods.

Figure 8(a) illustrates the forecast performance of PV power plants in different years. Supported by the new energy settlement mechanism, the model demonstrates robust cross-time generalization, with error indicators decreasing slightly year by year. In 2020, the MAE and RMSE were 0.016 and 0.019, respectively, decreasing to 0.013 and 0.016 in 2024, demonstrating that the model maintains stable and gradually improving forecast accuracy even during untrained periods. This trend is primarily due to the robust capture of high-contribution indicators such as actual power gen-

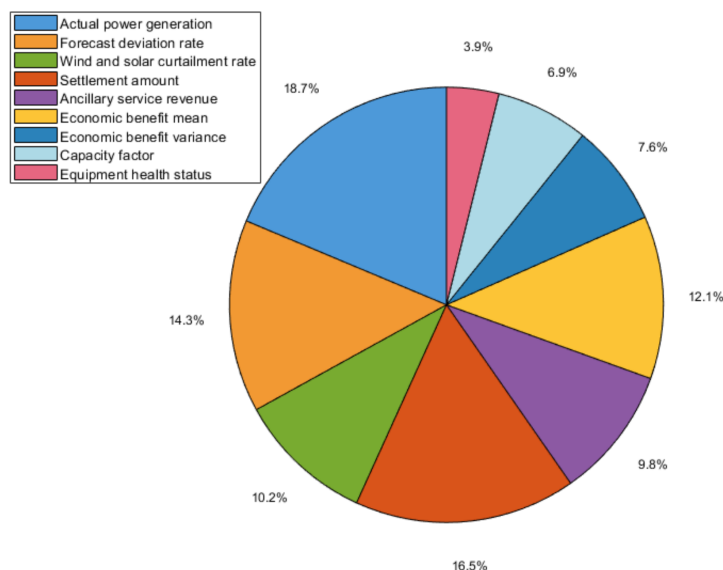


FIGURE 7. Contribution of each indicator of the new energy settlement indicator system to the model output results.

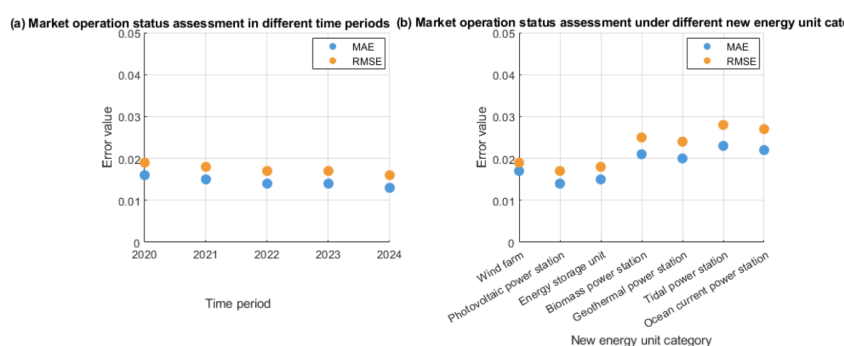


FIGURE 8. Market operation status evaluation across different time periods and new energy unit categories. Figure 8(a): Market operation status evaluation across different time periods; Figure 8(b): Market operation status evaluation for different new energy unit categories

eration and forecast deviation rate in the indicator system design and the enhanced representativeness of historical data during the training process. This ensures the model's robustness across diverse climates, load fluctuations, and market operating conditions. In the generalization test for renewable energy unit categories not shown in Figure 8(b), errors are significant for biomass power plants, geothermal power plants, tidal power plants, and ocean current power plants. The RMSE for tidal power plants reaches as high as 0.028, and for ocean current power plants, 0.027. However, compared to photovoltaic power plants, wind farms, and energy storage units, there are no significant differences, indicating relatively stable performance. Tides and ocean currents are significantly affected by geography and tidal cycles, and the sampled data is sparse, making model generalization more difficult for these categories. Targeted training samples and feature characterization for these units are needed in the optimization of the settlement technical support system.

H. OPTIMIZATION EFFECT OF THE SETTLEMENT TECHNICAL SUPPORT SYSTEM

To verify the actual effect of the constructed new energy settlement mechanism in optimizing the settlement technical support system, this paper conducts a comparative analysis of different models in terms of indicators such as average settlement time, settlement error rate, reduction ratio of settlement dispute rate, and improvement rate of market operation income. The results are shown in Figure 9.

In Figures 9(a) and 9(b), the Graphormer-TCN model performs best under the new energy settlement mechanism in terms of average settlement time and settlement error rate, with an average settlement time of only 12.3 seconds, significantly faster than the Graphormer (16.2 seconds) and GCN-TCN (14.9 seconds), and 13.5 seconds shorter than the traditional Transformer (25.8 seconds). Regarding the settlement error rate, the Graphormer-TCN model achieves only 0.8%, compared to 1.5% for GCN-LSTM and 2.0% for ST-GAT. In Figures 9(c) and 9(d), the Graphormer-

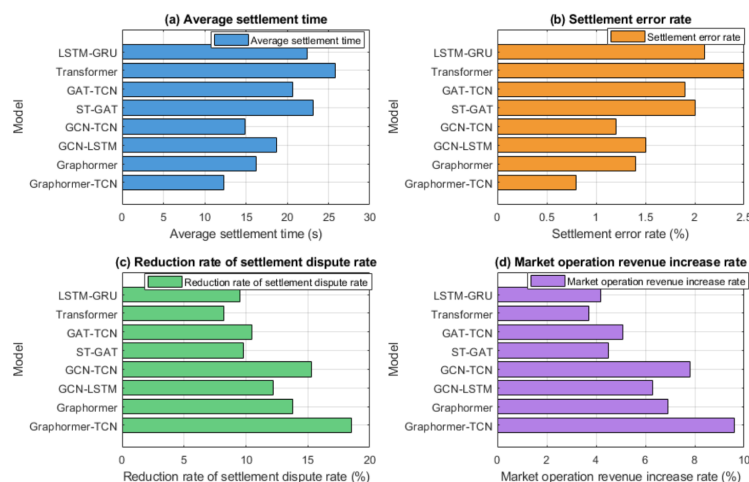


FIGURE 9. Optimization results of the settlement technical support system. Figure 9(a): Average settlement time; Figure 9(b): Settlement error rate; Figure 9(c): Reduction in settlement dispute rate; Figure 9(d): Increase in market operating revenue.

TCN model also demonstrates significant advantages, reducing the dispute rate by 18.5%, exceeding both GCN-TCN (15.3%) and Graphormer (13.8%), and increasing the rate by 8.7% compared to ST-GAT (9.8%). In terms of revenue improvement, the Graphormer-TCN model achieves a 9.6% improvement, surpassing both Graphormer (6.9%) and GCN-TCN (7.8%), while the Transformer model achieves only 3.7%.

Although the renewable energy settlement indicator system constructed in this paper is based on the regulatory logic and data structure of the Nanjing electricity market, its design concept has strong universality and can serve as a reference for other regional markets. The indicator system follows the internationally accepted three-tiered logic of energy balance, economic settlement, and operational quality in its dimensional division and statistical framework, thus possessing portability in electricity markets such as those in the United States and the European Union. However, it should be noted that the calculation methods and data availability of some indicators (such as settlement amount and ancillary service revenue) differ under various regulatory mechanisms. If applied in heterogeneous market environments, the weights and data interfaces of economic indicators need to be appropriately adjusted according to local market rules to ensure the comparability and applicability of the index system.

VI. CONCLUSION

To address the aforementioned spatiotemporal complexities impacting the industry's energy integration, this paper introduces a novel approach: the construction of a new energy settlement indicator system and a market operation status assessment model based on the powerful Graphormer-TCN architecture. This method achieves true end-to-end joint modeling, seamlessly integrating indicator system design, intricate spatial dependency modeling of clustered energy users, and robust multi-scale time series analysis of their

renewable power supply. First, an indicator system covering actual power generation, forecast deviation rate, wind and solar curtailment rate, settlement amount, ancillary service revenue, economic benefit mean and variance, capacity factor, and equipment health status is constructed and mapped to a graph structure for input into Graphormer. Subsequently, node-level multi-scale time series features are captured using TCN. Combined with serial fusion and regression output layers, operational status scores for wind farms, photovoltaic power plants, and energy storage units are produced. Experimental results show that within a 24-hour window, the MAE for wind power, photovoltaic power plants, and energy storage are 0.017, 0.014, and 0.015, respectively. This MAPE improves by 1.325% to 1.734% compared to Graphormer alone, resulting in a 9.6% increase in market operating returns and effectively supporting the optimization of the settlement technical support system. The shortcoming of this paper is that the model's generalization ability for extremely rare new energy units, such as tidal and ocean current energy, is still limited. Building upon the successful foundational model, future work will focus on further enhancing the robustness and broad applicability of this assessment tool by introducing more diverse operational data—such as specific machine load profiles and detailed supply chain logistics—and integrating enhanced graph time series modeling strategies to better adapt the market assessment model to the evolving, dynamic energy demands of global production networks.

AUTHOR CONTRIBUTIONS

Conceptualization – Xiaolu Wang; methodology – Xiaolu Wang, Xiaoqiang Xue, Yulong Lin and Shihua Lu; investigation – Xiaolu Wang and Yulong Lin; writing-original draft preparation – Xiaolu Wang, Xiaoqiang Xue, Yulong Lin and Shihua Lu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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