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Green Electricity Premium Forecasting and Cost Burden Warning for Chinese Industrial Users Based on a Spatio-Temporal Graph Attention Network

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Abstract: Under the background of carbon peaking and carbon neutrality, the increasing consumption of renewable electricity by industrial users has made green electricity premium an important factor affecting enterprise operating costs and low-carbon transition decisions. However, existing studies mainly focus on historical measurement and policy discussion, while insufficient attention has been paid to the dynamic forecasting of green electricity premium and the early warning of cost burden risks. To address this issue, this paper constructs a province–industry–month spatio-temporal dataset by integrating green electricity trading data, coal-fired benchmark electricity price data, industrial cost data, energy structure data, electricity transmission data, and green certificate market data. Based on this dataset, a Spatio-Temporal Graph Attention Network for Cost Risk Warning, namely ST-GAT-CRW, is proposed. The model constructs a multi-relation graph by combining geographical adjacency, electricity transmission, and price correlation relationships, uses a Graph Attention Network to capture spatial linkages among province–industry nodes, and adopts a Transformer Encoder to model temporal dependencies of green electricity premium. Meanwhile, a multi-task learning framework is designed to simultaneously conduct green electricity premium forecasting and cost burden risk classification. Comparative experiments with Autoregressive Integrated Moving Average, Vector Autoregression, Extreme Gradient Boosting, Long Short-Term Memory, Transformer, Graph Convolutional Network-Long Short-Term Memory, and Graph Attention Network-Long Short-Term Memory show that the proposed model achieves better forecasting accuracy and stronger high-risk identification capability. The results provide a quantitative decision-support method for green electricity procurement, differentiated subsidy design, and cost-sharing mechanism optimization.

1. Introduction

Against the backdrop of the ongoing pursuit of "carbon peaking and carbon neutrality" and the accelerated transformation of the energy structure [1-2], the industrial sector, as a major contributor to my country's energy consumption and carbon emissions, directly impacts the low-carbon transformation of the manufacturing industry through its green energy consumption levels. Promoting renewable energy consumption by industrial users is a crucial path to reducing carbon emissions from industrial production and enhancing the green competitiveness of enterprises. However, given the current immaturity of green electricity trading mechanisms, inter-regional transmission systems, and the green electricity certificate market, a price difference—the green electricity premium—remains between green electricity and conventional thermal power. For energy-intensive industries, SMEs, and enterprises in eastern load centers, this green electricity premium can directly increase their production and operating costs, compress profit margins, and further weaken market competitiveness. Existing research defines the green premium as the additional cost paid by industrial users for consuming renewable energy compared to conventional thermal power, and further proposes a cost burden rate indicator to measure the actual cost pressure on different industrial users. Therefore, accurately predicting the trend of green electricity premium changes and identifying the cost burden risks for industrial users in advance has become a critical issue that urgently needs to be addressed in the process of industrial green transformation.

The green electricity premium is not a static, isolated indicator, but is influenced by multiple factors [3-4], including regional resource endowment, green electricity supply and demand, inter-provincial transmission capacity, industry electricity intensity, green electricity certificate market prices, and macroeconomic energy price fluctuations. Spatially, there is a significant misalignment between my country's renewable energy resources and industrial load centers. Resource-rich areas such as the Northwest and Southwest have relatively abundant green electricity supply, while the eastern coastal areas have concentrated industrial loads and higher green electricity demand, easily leading to higher green electricity premiums. From an industry perspective, different industries exhibit significant differences in electricity intensity, profit levels, and cost transmission capabilities. Even with the same green electricity price, high-energy-consuming and low-profit industries face significantly higher cost pressures. Temporally, with the expansion of green electricity trading, the development of the green electricity certificate market, and adjustments in policy mechanisms, the green electricity premium exhibits dynamic fluctuations. Therefore, relying solely on traditional statistical methods such as autoregressive integral moving average models and vector autoregressive models, or on historical measurements and static regression analysis, is insufficient to fully characterize the spatiotemporal linkages of the green electricity premium, and also fails to meet the needs of future cost risk warnings and policy decision support.

To address the aforementioned issues, this paper focuses on the prediction of green electricity premiums and early warning of cost burdens for industrial users in China. It constructs a multi-source spatiotemporal dataset at the province-industry level and proposes a spatio-temporal graph attention network model for cost risk warning, namely, Spatio-Temporal Graph Attention Network for Cost Risk Warning (ST-GAT-CRW). First, based on green electricity trading prices, thermal power benchmark prices, industrial electricity consumption, industry cost structures, regional energy structures, and green electricity certificate market data, this paper constructs an indicator system for green electricity premiums and cost burden rates. Then, using "province-industry" as graph nodes, it integrates geographical adjacency relationships, power transmission relationships, and price correlation relationships to construct a multi-relationship spatiotemporal graph structure. On this basis, it utilizes a Graph Attention Network (GAT) to extract spatial correlation features between different regions and industries, and combines this with a time-series attention mechanism to characterize the dynamic changes in green electricity premiums, ultimately achieving future prediction of green electricity premiums and identification of cost burden risk levels. By further transforming the prediction results into low-risk, medium-risk, and high-risk levels, this paper provides a quantitative basis for green electricity procurement management by industrial users, differentiated government subsidy policies, and market regulation of green electricity certificates.

The main innovations of this paper are reflected in three aspects. First, this paper expands the research on green electricity premiums from traditional historical measurement and static assessment to a future-oriented intelligent prediction and risk early warning problem, constructing a prediction framework suitable for the cost management of green electricity consumption by industrial users. Second, this paper proposes a province-industry multi-relationship graph modeling method, incorporating geographical adjacency, power transmission, and price correlations into the graph structure, which can more fully characterize the spatial linkage characteristics of green electricity premiums between regions and industries. Third, this paper designs a model for cost burden early warning, simultaneously completing green electricity premium regression prediction and cost burden risk classification early warning within the same framework, and comparing and validating it with other methods, thereby improving the model's prediction accuracy, risk identification capability, and practical application value.

2. Indicator Definition and Problem Modeling

2.1. Definition of Green Electricity Premium

Green electricity premium is the core object of the forecasting task in this study. In this paper, green electricity premium is defined as the additional unit electricity cost paid by industrial users when consuming renewable electricity compared with conventional coal-fired electricity. Specifically, the green electricity trading price reflects the actual price paid by industrial users when purchasing renewable electricity through the green electricity trading market, while the coal-fired benchmark electricity price reflects the benchmark cost of conventional coal-fired power generation in a given region. The difference between the two is defined as the green electricity premium.

The green electricity premium is calculated as follows:

$$GEP_{i,j,t} = P_{i,j,t}^{green} - P_{i,t}^{coal} \tag{1}$$

where $GEP_{i,j,t}$ denotes the green electricity premium of the j-th industry in the i-th province during period t; $P_{i,j,t}^{green}$ denotes the green electricity trading price of the corresponding province and industry during period t; and $P_{i,t}^{coal}$ denotes the coal-fired benchmark electricity price of the i-th province during period t. Since the coal-fired benchmark electricity price usually has strong regional characteristics, it is set as a province-level benchmark variable in this study. In contrast, the green electricity trading price is influenced by regional supply and demand, industrial electricity consumption structure, and green electricity trading demand.

2.2. Definition of Cost Burden Rate

Measuring the green electricity premium alone cannot fully reflect the actual cost pressure of industrial users. Industrial users in different regions, of different scales, and in different industries vary significantly in electricity consumption, profitability, cost structure, and cost pass-through capability. The same green electricity premium may only represent a minor fluctuation in operating costs for large and high-profit enterprises, but may create substantial operating pressure for small and medium-sized enterprises, energy-intensive industries, or low-profit industries. Therefore, this study further introduces the cost burden rate to measure the relative impact of the additional green electricity cost on the total cost of industrial users.

The cost burden rate is calculated as follows:

$$CR_{i,j,t} = \frac{Q_{i,j,t}^{green} \times GEP_{i,j,t}}{C_{i,j,t}} \times 100\% \tag{2}$$

where $CR_{i,j,t}$ denotes the cost burden rate of the j-th industry in the i-th province during period t; $Q_{i,j,t}^{green}$ denotes the green electricity consumption of the corresponding province and industry during period t; $GEP_{i,j,t}$ denotes the green electricity premium; and $C_{i,j,t}$ denotes the total cost of the corresponding industrial users in the province–industry unit.

2.3. Construction of Risk Warning Labels

After calculating the green electricity premium and cost burden rate, this study further converts the cost burden rate into cost burden risk levels, thereby constructing label variables for the classification warning task. The purpose of this treatment is to enable the model not only to predict the specific value of future green electricity premium, but also to determine whether industrial users are likely to enter a state of high cost pressure. For government departments, risk levels can serve as an important reference for differentiated subsidies, green credit support, and green certificate market regulation. For industrial users, risk levels can help them adjust green electricity procurement strategies and production energy-use arrangements in advance [5-6].

In this study, cost burden risk is divided into three categories: low risk, medium risk, and high risk. The classification criteria are shown below in Table1.

Table 1: Cost burden risk.

Cost burden rate (CR)	Risk level	Label
(CR<0.5%)	Low risk	0
(0.5%< CR<1%)	Medium risk	1
(CR>1%)	High risk	2

Among them, low risk indicates that the green electricity premium has a relatively small impact on the total cost of industrial users, and enterprises can usually absorb this part of the cost through internal cost management or normal business operations. Medium risk indicates that the green electricity premium has already exerted certain pressure on enterprise costs, and its subsequent trend should be monitored. High risk indicates that the green electricity premium has a significant impact on the operating costs of industrial users, and relevant users may require government subsidies, green financial support, or market-based cost-sharing mechanisms.

Through the above label construction method, the cost burden warning problem is transformed into a multi-class classification problem. In other words, the model not only outputs the predicted value of future green electricity premium, but also further outputs the cost burden risk level of each province–industry node. This design enables the proposed model to serve both numerical forecasting and risk identification, thereby improving the practical application value of the study.

2.4. Formalization of the Research Problem

After defining the indicators and constructing the risk labels, this study further formulates the research problem as a province–industry-level spatio-temporal graph forecasting problem. In this paper, "province–industry" is used as the basic research node, and each node represents the green electricity consumption and cost burden status of a specific industrial sector in a specific province. For example, "Guangdong–non-ferrous metal smelting," "Jiangsu–chemical raw material manufacturing," and "Xinjiang–ferrous metal smelting" can all be regarded as different research nodes. This treatment can capture both regional differences in resource endowment and industrial differences in electricity intensity and cost structure [7-8].

Let the set of all province–industry nodes be defined as:

$$V = \{v_1, v_2, \cdots, v_N\} \tag{3}$$

where N denotes the total number of nodes. Each node contains a set of feature variables in different periods, including green electricity trading price, coal-fired benchmark electricity price, green electricity consumption, total industrial cost, industry profit rate, renewable energy installed capacity ratio, green certificate price, and inter-provincial electricity trading relationship. Accordingly, the input feature matrix can be constructed as:

$$X_t \in R^{N \times F} \tag{4}$$

where X_t denotes the feature matrix of all nodes during period t, N denotes the number of nodes, and F denotes the number of features contained in each node [9]. When T consecutive historical periods are considered, the model input can be expressed as:

$$X = \{X_{t-T+1}, X_{t-T+2}, \cdots, X_t\} \tag{5}$$

In terms of graph structure, this study constructs a multi-relation adjacency matrix to describe the spatial correlations among different province–industry nodes. The associations among nodes mainly come from three aspects. The first is geographical adjacency, which means that neighboring provinces may have similar energy supply and demand environments. The second is electricity transmission, which means that inter-provincial green electricity trading and electricity transmission relationships may affect green electricity price linkages among different regions. The third is price correlation, which means that nodes with similar historical green electricity premium trends may have potential linkage characteristics. Therefore, the comprehensive adjacency matrix is defined as:

$$A = \alpha A_{geo} + \beta A_{power} + \gamma A_{corr} \tag{6}$$

where A_{geo} denotes the geographical adjacency matrix, A_{power} denotes the electricity transmission relation matrix, A_{corr} denotes the price correlation relation matrix, and α, β, and γ denote the weight coefficients of the three types of relations, respectively. Through this multi-relation graph structure, the model can simultaneously capture the influence of regional proximity, electricity mobility, and price linkage on the changes in green electricity premium.

Based on the above definitions, the research tasks of this paper can be divided into two parts. The first part is the green electricity premium forecasting task, which predicts the green electricity premium of each province–industry node in the next h periods based on the multi-source features and graph structure relationships over the past T periods:

$$GEP_{t+1:t+h} = f(X_{t-T+1:t}, A) \tag{7}$$

The second part is the cost burden risk warning task. Based on the predicted green electricity premium, the future cost burden rate is calculated by combining green electricity consumption and the total cost of industrial users, and the corresponding risk level is then identified:

$$CR_{t+1:t+h} = \frac{Q_{t+1:t+h}^{green} \times GEP_{t+1:t+h}}{C_{t+1:t+h}} \times 100\% \tag{8}$$

$$\hat{Y}_{t+1:t+h} = g(CR_{t+1:t+h}) \tag{9}$$

where $\widehat{GEP}_{t+1:t+h}$ denotes the predicted green electricity premium in the next h periods, $\widehat{CR}_{t+1:t+h}$ denotes the predicted future cost burden rate, $\hat{Y}_{t+1:t+h}$ denotes the predicted cost burden risk level, $f(\cdot)$denotes the green electricity premium forecasting function, and $g(\cdot)$denotes the risk level mapping function.

3. Data Construction and Methodology Design

3.1. Data Sources

This study focuses on green electricity consumption by Chinese industrial users. The research unit is defined as “province–industry–month.” In this setting, “province” is used to capture regional differences in resource endowment, electricity supply and demand, and green electricity trading conditions; “industry” is used to capture differences in electricity intensity, cost structure, and cost affordability across industrial sectors; and “month” is used to capture the dynamic changes in green electricity premium over time. For example, “Guangdong–non-ferrous metal smelting–January 2023,” “Jiangsu–chemical raw material manufacturing–January 2023,” and “Xinjiang–non-ferrous metal smelting–January 2023” can each be regarded as a specific observation sample. Through this setting, the regional heterogeneity, industrial heterogeneity, and temporal fluctuation of green electricity premium can be jointly described.

The data used in this study mainly include six categories: green electricity trading data, coal-fired benchmark electricity price data, industrial sector data, energy structure data, electricity flow data, and green electricity certificate market data. The main variables and functions of each type of data are shown in the following Table 2.

Table 2: Cost burden risk.

Data type	Main variables	Function
Green electricity trading data	Green electricity transaction price, transaction volume, trading region	Calculate green electricity premium and reflect green electricity market trading levels
Coal-fired benchmark electricity price data	Provincial benchmark price of coal-fired power generation	Serve as the benchmark price for calculating green electricity premium
Industrial sector data	Total industrial cost, operating revenue, profit rate, industrial electricity consumption	Calculate cost burden rate and describe sectoral cost affordability
Energy structure data	Wind power installed capacity, photovoltaic installed capacity, share of renewable energy capacity	Describe regional green electricity supply capacity
Electricity flow data	Inter-provincial transaction volume, transmission direction, sending and receiving provinces	Construct the electricity transmission graph
Green electricity certificate market data	Green electricity certificate price, certificate trading volume	Reflect market coordination mechanisms and changes in environmental value

3.2. Data Preprocessing

Due to the diverse data sources used in this paper, the statistical definitions, time frequencies, and variable units vary. Therefore, unified data preprocessing is necessary before model training.

First, time frequency standardization is performed on data from different sources. Since green electricity trading data, electricity price data, and industrial sector data may have different statistical frequencies (annual, quarterly, or monthly), this paper uniformly sets the research frequency to monthly. For data with an original annual or quarterly frequency, methods such as linear interpolation, year-on-year decomposition, or industry seasonal weighting are used to convert it to monthly data. For data already having a monthly frequency, alignment is performed according to the month.

Second, missing values are handled. For a small number of randomly missing continuous variables, linear interpolation or the mean of the same industry within the same province is used for imputation. For price variables, interpolation using prices from adjacent months is prioritized. For variables with relatively stable changes, such as industry costs and electricity consumption, imputation is performed based on past and future trends. If a province-industry node is continuously missing for a long period, the data at that node is considered incomplete and is removed from the sample set.

Third, outlier reduction is performed. Variables such as green electricity transaction prices, transaction volumes, industry costs, and electricity consumption may exhibit outliers due to extreme transactions, statistical errors, or short-term policy shocks. To reduce the interference of extreme values on model training, this paper performs 1% quantile reduction on continuous variables, replacing observations below the 1% quantile with the 1% quantile and observations above the 99th quantile with the 99th quantile.

Price data is flattened. Since price data from different periods can be affected by inflation and changes in macroeconomic price levels, this paper uses the base year's price level as a reference to flatten green electricity transaction prices, thermal power benchmark prices, and green electricity certificate prices, ensuring comparability across different periods. The flattened price variables more accurately reflect price changes in the green electricity market itself, rather than the impact of general price level changes.

Finally, the model input features are standardized. Continuous features are standardized using Z-scores, resulting in a mean of 0 and a standard deviation of 1. The standardization formula is as follows:

$$x' = \frac{x-\mu}{\sigma} \tag{10}$$

where x denotes the original variable, μ denotes the mean of the variable in the training set, σ denotes the standard deviation of the variable in the training set, and x' denotes the standardized variable.

3.3. Province–Industry Graph Structure Construction

Green electricity premium is affected not only by factors within a single province or a single industry, but also by regional electricity flows, green electricity supply-demand patterns, and price linkage relationships. Therefore, this study defines each "province–industry" unit as a graph node and constructs a multi-relation graph structure to describe the spatial correlations among nodes. Unlike traditional time-series models that only focus on the historical changes of individual samples, the graph structure can explicitly describe the associations among different regions and industries, providing a foundation for subsequent graph neural network modeling.

Each province–industry combination is defined as a node. The set of all nodes is expressed as follows:

$$V = \{v_1, v_2, \cdots, v_N\} \tag{11}$$

where V denotes the node set, v_N denotes the N-th province–industry node, and N denotes the total number of nodes. Node features include green electricity trading price, coal-fired benchmark electricity price, green electricity transaction volume, industrial electricity consumption, total industrial cost, industry profit rate, renewable energy installed capacity ratio, and green electricity certificate price. Edges between nodes are used to describe the association strength among different province–industry nodes.

This study constructs three types of relation matrices: the geographical adjacency matrix, the electricity transmission matrix, and the price correlation matrix.

The first type is the geographical adjacency matrix A_{geo}. If two provinces are geographically adjacent, they may share similar energy consumption environments, industrial structures, and electricity market conditions. Therefore, connections are established between the corresponding nodes. For different industry nodes within the same province, internal industry association edges can also be established to capture the linkage characteristics of different industries facing the same regional electricity market environment.

The second type is the electricity transmission matrix A_{power}. Due to the spatial mismatch between renewable energy resources and industrial load centers in China, resource-rich regions in the northwest and southwest usually serve as green electricity sending regions, while eastern coastal load centers mainly serve as green electricity receiving regions. Therefore, if there are inter-provincial green electricity transactions, cross-regional electricity transmission, or clear sending-receiving relationships between two provinces, electricity transmission edges are established between the corresponding nodes. This matrix reflects the influence of green electricity flows from resource-rich regions to load centers on prices and premiums.

The third type is the price correlation matrix A_{corr}. Even if two nodes have no direct geographical adjacency or explicit electricity transmission relationship, a high similarity in their historical green electricity premium trends indicates that they may be affected by similar market or policy factors. This study measures the price linkage between nodes using the correlation coefficient between historical green electricity premium series. When the correlation coefficient between two nodes exceeds a given threshold, a price correlation edge is established between them.

By integrating the above three types of relationships, the final multi-relation adjacency matrix is constructed as follows:

$$A = \alpha A_{geo} + \beta A_{power} + \gamma A_{corr} \tag{12}$$

where A denotes the comprehensive adjacency matrix, A_{geo} denotes the geographical adjacency matrix, A_{power} denotes the electricity transmission matrix, A_{corr} denotes the price correlation matrix, and α, β, and γ denote the weight coefficients of the three types of relationships, respectively.

3.4. ST-GAT-CRW Model Structure

After constructing the province–industry spatio-temporal graph, this study designs a Spatio-Temporal Graph Attention Network for Cost Risk Warning, abbreviated as ST-GAT-CRW. The core objective of this model is to complete two tasks under a unified framework: forecasting future green electricity premium and identifying cost burden risk levels based on the forecasting results. The model consists of four modules: a multi-source feature embedding module, a spatial graph attention module, a temporal sequence modeling module, and a multi-task output module.

First, the multi-source feature embedding module maps different types of input variables into a unified feature space. Let the input feature matrix of all nodes at period t be denoted as:

$$X_t \in R^{N \times F} \tag{13}$$

where N denotes the number of nodes and F denotes the input feature dimension of each node. Since different variables have different dimensions and semantic meanings, a linear mapping is used to transform the original features into low-dimensional hidden representations:

$$H_t^0 = X_t W_e + b_e \tag{14}$$

where H_t^0 denotes the embedded node features, and W_e and b_e denote the learnable weight matrix and bias term, respectively. This module maps energy market variables, industrial economic variables, and regional structure variables into unified vector representations that can be learned by the model.

Second, the spatial graph attention module extracts spatial association features among different province–industry nodes. This study adopts the GAT, to perform weighted aggregation of neighboring nodes [10-11]. For node i and its neighboring node j, the attention coefficient between them is defined as follows:

$$e_{ij} = LeakyReLU\left(a^T[Wh_i \,||\, Wh_j]\right) \tag{15}$$

where h_i and h_j denote the feature representations of node i and node j, respectively; W denotes the linear transformation matrix; a denotes the attention weight vector; and $[\ ||\ ]$ denotes the vector concatenation operation. Then, the Softmax function is used to normalize the attention coefficients:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})} \tag{16}$$

where α_{ij} denotes the influence weight of node j on node i, and N_i denotes the set of neighboring nodes of node i. Finally, the spatial representation of node i can be expressed as:

$$h_{i'} = \sigma\left(\sum_{j \in N_i} \alpha_{ij} W h_j\right) \tag{17}$$

where $\sigma(\cdot)$ denotes a nonlinear activation function. Through this module, the model can automatically identify which province–industry nodes have stronger influence on the green electricity premium changes of the target node, thereby improving spatial relationship modeling capability.

Third, the temporal sequence modeling module captures the dynamic evolution of green electricity premium over time. Considering that green electricity premium is affected by long-term factors such as policy adjustment, market supply and demand, green certificate prices, and energy structure changes, this study adopts Transformer Encoder to model historical temporal features. After the spatial graph attention module, the model obtains the node spatial feature sequence over T consecutive periods:

$$H = \{H_{t-T+1}, H_{t-T+2}, \cdots, H_t\} \tag{18}$$

Transformer Encoder learns the dependencies among different historical periods through the multi-head self-attention mechanism [11-12]. The attention calculation process is expressed as:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{19}$$

where Q, K, and V denote the query matrix, key matrix, and value matrix, respectively, and d_k denotes the dimension of the key vector. Finally, the multi-task output module generates both green electricity premium forecasting results and cost burden risk levels [13-14]. For the green electricity premium forecasting task, the model outputs the predicted values for the next h periods through a regression layer:

$$GEP_{t+1:t+h} = Linear(H_t^{final}) \tag{20}$$

For the cost burden risk warning task, the model calculates the cost burden rate based on the predicted green electricity premium and outputs the probability distribution of risk levels through a classification layer:

$$\hat{Y} = softmax(W_c H_t^{final} + b_c) \tag{21}$$

where $\hat{Y}$ denotes the predicted risk level, and W_c and b_c denote the weight matrix and bias term of the classification layer, respectively [15].

3.5. Loss Function Design

Since the proposed model includes both green electricity premium forecasting and cost burden risk warning tasks, a multi-task joint loss function is adopted for training. Green electricity premium forecasting is a regression task, while cost burden risk warning is a classification task. Joint training enables the model to learn the variation pattern of green electricity premium while also considering the influence of prediction results on risk level classification, thereby improving the practical application value of the model.

For the green electricity premium forecasting task, this study adopts mean squared error as the regression loss function:

$$L_{reg} = \frac{1}{N}\sum_{i=1}^{N}(GEP_i - GEP_i)^2 \tag{22}$$

where GEP_i denotes the true green electricity premium, $\widehat{GEP}_i$ denotes the predicted green electricity premium, and N denotes the number of samples. Mean squared error gives a higher penalty to larger prediction deviations, which helps improve forecasting accuracy.

For the cost burden risk warning task, this study adopts the cross-entropy loss function:

$$L_{cls} = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \tag{23}$$

where C denotes the number of risk categories. In this study, $C = 3$, corresponding to low risk, medium risk, and high risk. $y_{i,c}$ denotes the true label of sample i in category c, and $\hat{y}_{i,c}$ denotes the predicted probability that sample i belongs to category c.

The total loss function of this study is defined as follows:

$$L = L_{reg} + \lambda L_{cls} \tag{24}$$

where L denotes the total loss function, L_{reg} denotes the green electricity premium forecasting loss, L_{cls} denotes the cost burden risk classification loss, and λ denotes the loss weight of the classification task. By adjusting λ, the model can balance its learning focus between numerical forecasting and risk identification.

4. Experimental Design

4.1. Experimental Environment

The model in this paper is implemented using the Python language and the PyTorch deep learning framework. The graph neural network part is completed using the PyTorch Geometric or DGL framework.

4.2. Comparison Models

To comprehensively validate the predictive performance of the ST-GAT-CRW model, this paper selects traditional time series models, machine learning models, deep learning models, and spatiotemporal graph neural network models as comparison methods. Specifically, these include autoregressive integral moving average models, vector autoregressive models, extreme gradient boosting models, long short-term memory neural networks, Transformer models, combined graph convolutional networks and long short-term memory neural networks, combined graph attention networks and long short-term memory neural networks, and the proposed ST-GAT-CRW model.

This experiment comprises two tasks: green electricity premium prediction and cost burden risk early warning. For the green electricity premium prediction task, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) are used as evaluation indicators.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{25}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{26}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{27}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{28}$$

For the cost burden risk warning task, accuracy, precision, recall, F1-score, and AUC are used as evaluation metrics.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{29}$$

$$Precision = \frac{TP}{TP + FP} \tag{30}$$

$$Recall = \frac{TP}{TP + FN} \tag{31}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{32}$$

$$AUC = \int_0^1 TPR(FPR)dFPR \tag{33}$$

5. Results Analysis and Discussion

5.1. Spatial Distribution Analysis of Green Electricity Premium

Province-level sample analysis reveals significant regional differences in green electricity premiums. Eastern coastal areas and some load centers in central China generally exhibit higher premium levels because of stronger industrial electricity demand, relatively limited local renewable electricity supply, and additional costs associated with inter-regional electricity transmission and green electricity consumption. In contrast, renewable-energy-rich regions in Northwest and Southwest China generally show lower premium levels owing to stronger wind and solar power supply capacity and comparatively favorable green electricity trading conditions.

These findings indicate that green electricity premiums are closely related to regional resource endowment, electricity supply–demand structure, and inter-provincial transmission relationships. The observed regional heterogeneity also demonstrates that an independent time-series model may be insufficient to fully characterize the dynamic variation of green electricity premiums, thereby supporting the introduction of spatial relation modeling in the proposed framework.

5.2. Analysis of Cost Burden Differences across Industries

While green electricity trading prices have a certain degree of universality within the same region, different industries exhibit significant differences in cost burden rates due to variations in electricity intensity, cost structure, profit margins, and price transmission capabilities. Industry comparisons show that high-energy-consuming industries such as non-ferrous metal smelting, ferrous metal smelting, chemical raw material manufacturing, and non-metallic mineral products generally have higher cost burden rates, while relatively low-energy-consuming industries such as computer electronics, instrumentation, and general equipment manufacturing have lower cost burden rates.

The main reason for this difference is that high-energy-consuming industries have higher electricity consumption per unit of output, and the green electricity premium is further amplified by their larger electricity consumption scale. Simultaneously, some high-energy-consuming industries have lower profit margins and limited product price transmission capabilities, making it difficult to fully pass on the additional costs of green electricity to downstream markets, thus increasing the risk of a high cost burden. As shown in Figure 1, the design of green electricity support policies should not only focus on the green electricity premium itself but also differentiate based on industry electricity intensity and cost affordability.

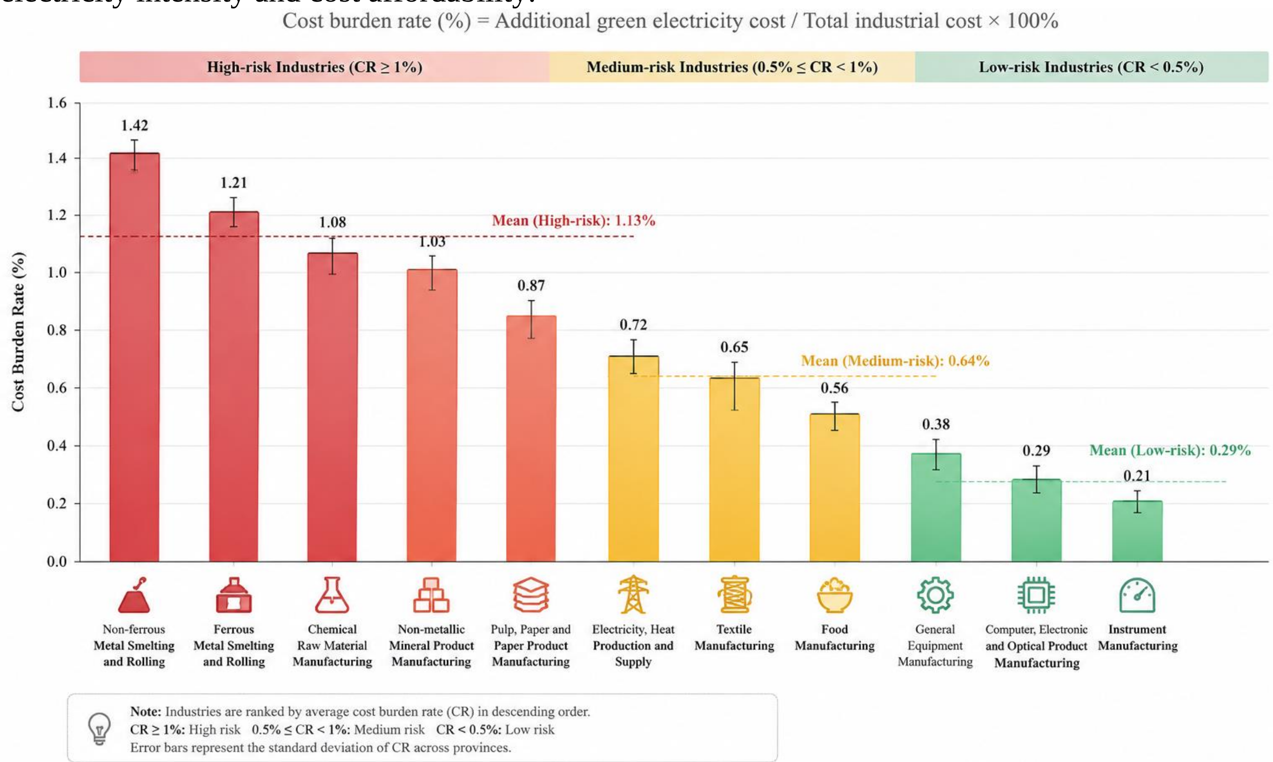

Figure 1: Comparison of cost burden ratios across different industries.

5.3. Analysis of Green Electricity Premium Forecast Results

To verify the predictive performance of the proposed ST-GAT-CRW model, this paper compares it with several previously mentioned models, as shown in Figures 2 and 3.

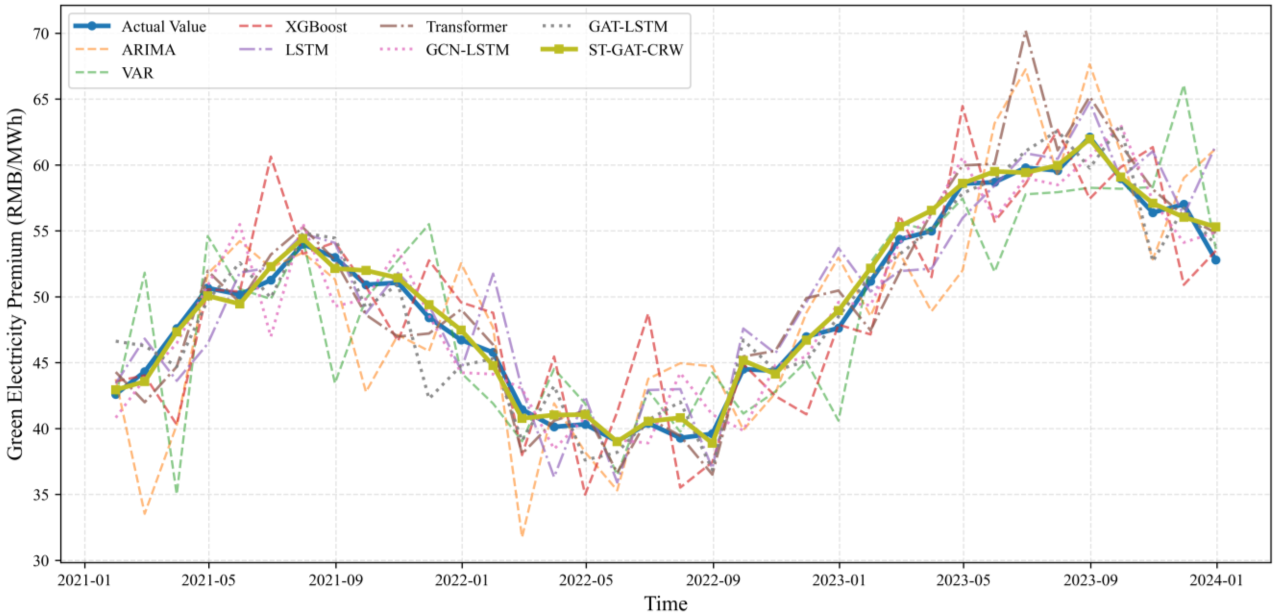

Figure 2: Comparison chart of actual and predicted values of green electricity premium.

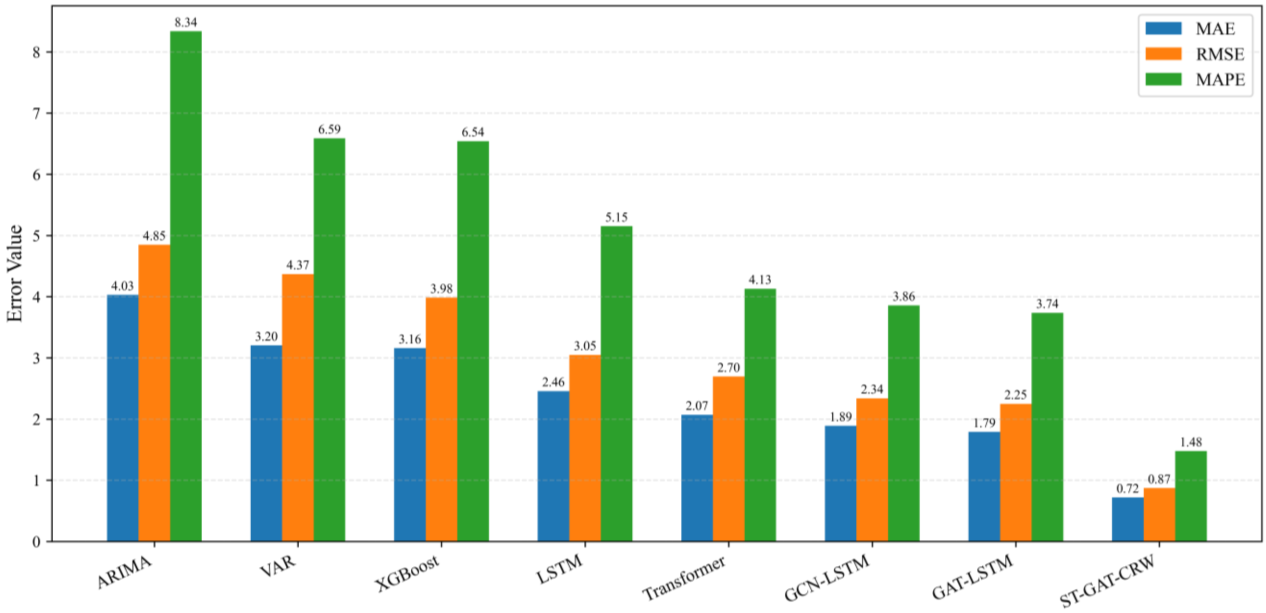

Figure 3: Comparison of prediction errors of different models.

The comparison between the actual and predicted values of the green electricity premium reveals that ARIMA and VAR can characterize some linear trends in the green electricity premium, but their ability to capture short-term fluctuations, nonlinear changes, and cross-regional linkages is weak. XGBoost has some learning ability for nonlinear features, but its stability in continuous-time prediction tasks remains limited due to the lack of an explicit time-dependent modeling mechanism. LSTM and Transformer perform better in time series modeling, effectively tracking the dynamic trends of the green electricity premium. Transformer, relying on its attention mechanism, can capture dependencies over a longer time span, resulting in better overall prediction performance than traditional recurrent neural network models.

5.4. Analysis of Cost Burden Risk Early Warning Results

After forecasting the green electricity premium, this paper further calculates the future cost burden rate by combining the green electricity consumption and total industrial costs of each province and industry node, and classifies them into low-risk, medium-risk, and high-risk levels based on the cost burden rate threshold.

As shown in Figure 4, the heat map of cost burden risk levels reveals that high-risk nodes are mainly concentrated in eastern load centers and high-energy-consuming industry combinations. For example, industries such as non-ferrous metal smelting, ferrous metal smelting, chemical raw material manufacturing, and non-metallic mineral products generally have high cost burden rates because their green electricity premium is more easily amplified by their large electricity consumption scale due to their high electricity intensity per unit output. Meanwhile, major industrial provinces in the east, such as Guangdong, Jiangsu, Zhejiang, and Shandong, are more likely to have medium- to high-risk nodes due to strong demand for green electricity, relatively insufficient local renewable energy supply, and the potential to bear certain costs of inter-regional power transmission and green electricity consumption. In contrast, resource-rich regions such as the Northwest and Southwest have relatively lower overall risk levels due to their stronger green electricity supply capacity.

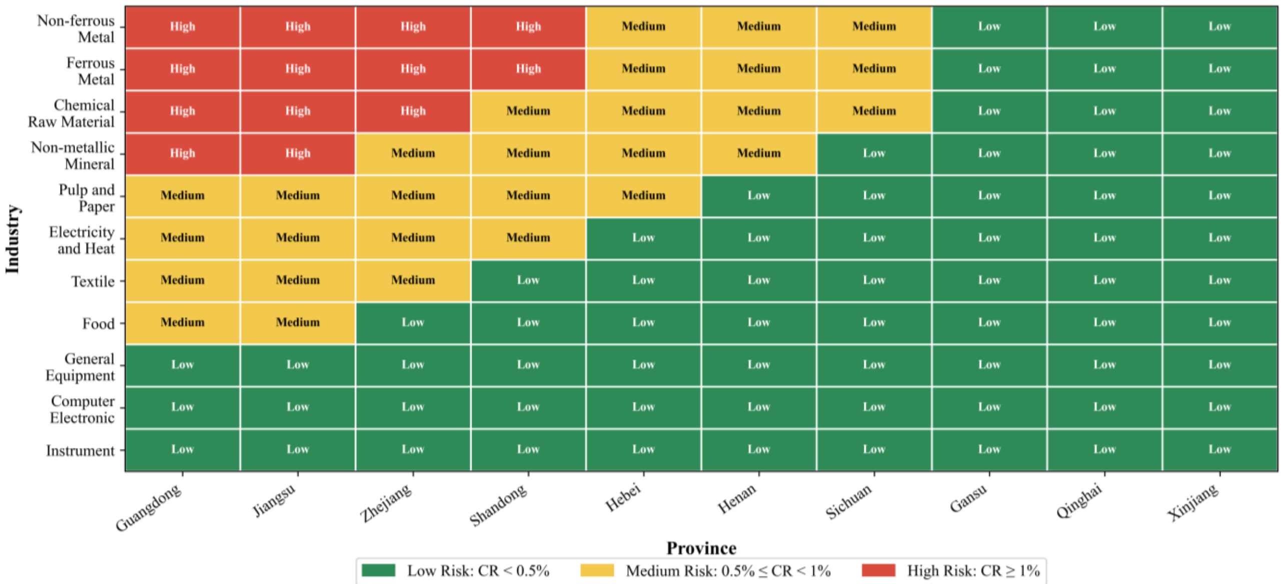

Figure 4: Cost burden risk level heat map.

Table 3 shows the risk warning results of different models. Traditional time series models ARIMA and VAR perform relatively poorly in risk classification tasks, mainly because they struggle to fully characterize nonlinear features and spatial relationships. XGBoost improves the learning ability of nonlinear features, but its ability to express temporal dependencies and graph structure relationships is insufficient. LSTM and Transformer perform better in time series modeling, thus improving overall classification performance. Furthermore, the introduction of graph structures into GCN-LSTM and GAT-LSTM further enhances risk identification capabilities, indicating that spatial relationships between province-industry nodes play a crucial role in cost burden risk warning.

Table 3: Comparison of Cost Burden Risk Warning Results of Different Models.

Model	Accuracy	Precision	Recall	F1-score	AUC
ARIMA	0.742	0.701	0.646	0.672	0.781
VAR	0.758	0.718	0.668	0.692	0.796
XGBoost	0.814	0.791	0.748	0.769	0.861
LSTM	0.836	0.815	0.776	0.795	0.884
Transformer	0.854	0.837	0.803	0.820	0.902
GCN-LSTM	0.876	0.862	0.834	0.848	0.925
GAT-LSTM	0.891	0.879	0.856	0.867	0.941
ST-GAT-CRW	**0.923**	**0.914**	**0.902**	**0.908**	**0.967**

Compared to the models mentioned above, the proposed ST-GAT-CRW achieves the best results in Accuracy, Precision, Recall, F1-score, and AUC, with a particularly significant advantage in Recall for high-risk categories. This demonstrates that the proposed model can not only accurately predict green electricity premiums but also more effectively identify industrial users who may face high cost pressures in the future. For policy early warning scenarios, the recall rate of high-risk categories is particularly important, as missing high-burden users could lead to delays in subsidy support, green credit, and risk intervention. Therefore, the advantages of ST-GAT-CRW in high-risk identification can further enhance the model's practical application value.

5.5. Interpretability Analysis of Attention Weights

To further explain the prediction mechanism of the ST-GAT-CRW model, this paper visualizes and analyzes the node weights learned by the graph attention layer. Graph attention weights reflect the degree of attention the model pays to other relevant nodes when predicting the green electricity premium for a specific province/industry node. Higher weights indicate a greater influence of the neighboring node on the prediction result of the target node. Therefore, by analyzing attention weights, we can further determine whether changes in the green electricity premium are jointly influenced by regional adjacency, power transmission, and price linkages.

Figure 5: Visualization of attention weights.

As shown in Figure 5, the visualization results of the graph attention weights reveal a strong correlation between some renewable energy-rich provinces and eastern load centers. For example, the attention weights between green electricity sending regions such as the Northwest and Southwest and load centers such as Guangdong, Jiangsu, and Zhejiang are relatively high, indicating that inter-provincial green electricity transmission relationships affect changes in the green electricity premium in load center regions. When the green electricity supply capacity, inter-regional transmission scale, or transaction price in resource-rich areas changes, the green electricity procurement cost in eastern load centers may also fluctuate.

Meanwhile, high-energy-consuming industries within the same region also exhibit significant correlation characteristics. For example, industries such as non-ferrous metal smelting, ferrous metal smelting, chemical raw material manufacturing, and non-metallic mineral products typically exhibit strong connections in attention maps. This indicates that, within the same regional electricity market environment, although different industries have different cost structures and profit margins, their green electricity trading prices and cost burdens still show a certain degree of correlation.

5.6. Analysis of Cost-Sharing Mechanism Application

After identifying high-cost-burden risk nodes, this paper further conducts scenario simulations using a cost-sharing mechanism involving enterprises, government, and the market to analyze the mitigation effect of different cost-sharing methods on the cost burden rate of industrial users. This paper sets up five typical scenarios: no cost-sharing, sole enterprise burden, joint enterprise-government burden, joint enterprise-market burden, and joint enterprise-government-market burden, and compares the changes in cost burden rate at high-risk nodes under different scenarios.

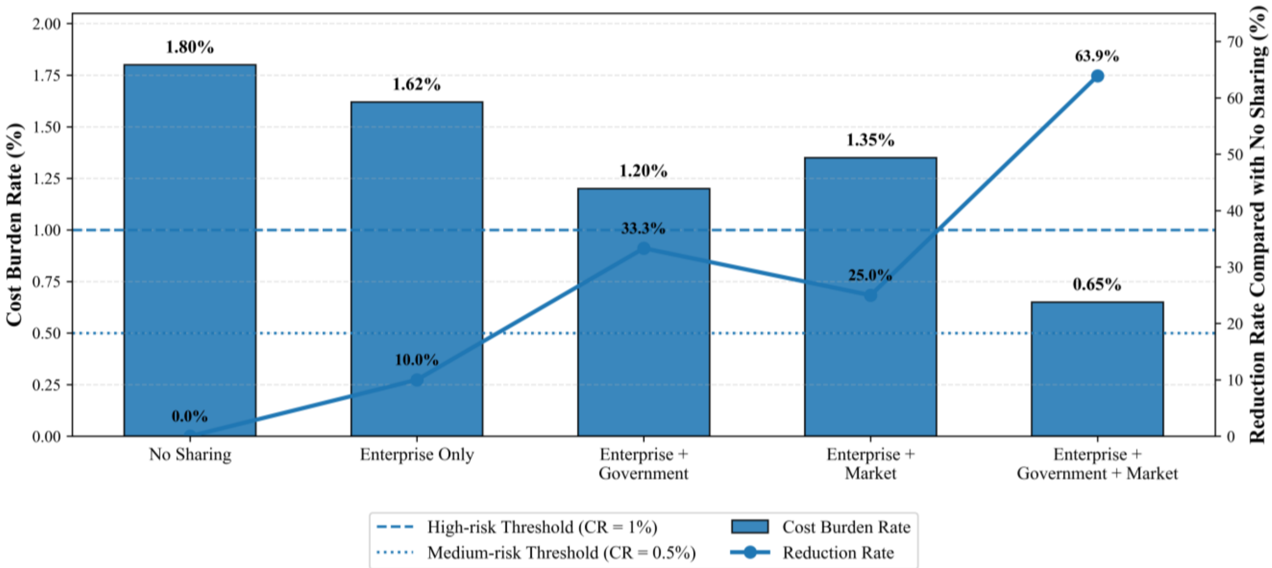

Figure 6: Comparison of cost burden reduction effects under different cost-sharing mechanisms.

As shown in Figure 6, in the no-cost-sharing scenario, the cost burden rate at high-risk nodes is significantly higher than the 1% risk threshold, indicating that the green electricity premium will place significant operational pressure on some energy-intensive industries and enterprises in eastern load centers. If only enterprises bear the burden, although they can reduce some pressure through energy-saving renovations, optimized electricity consumption curves, and internal cost management, the overall burden reduction is limited, and the high-risk state is not fundamentally alleviated. After introducing government subsidies, the actual cost burden rate of enterprises decreases significantly, indicating that policy subsidies can directly support high-burden users. The introduction of a market-based cost-sharing mechanism, along with the return of revenue from green electricity certificates, green credit, and market-based trading adjustments, can reduce enterprise costs to some extent.

6. Conclusion

This paper addresses the challenges of predicting green electricity premiums and providing early warning of cost burden risks faced by Chinese industrial users in their green electricity consumption. It constructs a multi-source spatiotemporal dataset at the province-industry-month level and proposes the ST-GAT-CRW spatiotemporal graph attention network model for cost burden early warning. The study first defines two core indicators: green electricity premium and cost burden rate, further transforming the additional cost of green electricity compared to conventional thermal power into a quantitative expression of the operating cost pressure on industrial users. Then, it integrates three types of relationships—geographical adjacency, power transmission, and price correlation—to construct a province-industry multi-relationship graph structure. The graph attention mechanism and Transformer temporal modeling module are used to simultaneously characterize the spatial linkage characteristics and temporal variation patterns of the green electricity premium. Experimental results show that there are significant spatial differences in green electricity premiums across different regions. Eastern load centers have relatively higher overall premium levels due to high demand for green electricity, insufficient local renewable energy supply, and higher inter-regional transmission costs. Resource-rich regions such as the Northwest and Southwest have relatively lower premium levels due to abundant wind and solar resources and strong green electricity supply capacity. Meanwhile, significant differences exist in cost burden rates across different industries, with energy-intensive industries such as non-ferrous metal smelting, ferrous metal smelting, chemical raw material manufacturing, and non-metallic mineral products being more prone to higher cost burden risks. Compared to other models, the ST-GAT-CRW proposed in this paper outperforms both green electricity premium prediction and cost burden risk early warning tasks.

This study indicates that the green electricity premium is not simply a price difference issue, but a complex spatiotemporal problem simultaneously influenced by regional energy endowment, electricity supply and demand structure, inter-provincial transmission relationships, industry electricity intensity, and cost affordability. Therefore, in the process of industrial green transformation, it is necessary to dynamically predict the green electricity premium and further identify the cost burden risks at different provincial-industry nodes. Simulations of the cost-sharing mechanism based on model prediction results show that if only enterprises bear the green electricity premium, energy-intensive industries and small and medium-sized industrial users may remain in a high-risk state for a long time; while a joint enterprise-government-market cost-sharing mechanism can effectively reduce the cost burden rate at high-risk nodes through internal absorption by enterprises, government subsidies, green certificate revenue feedback, and green financial support. Therefore, the ST-GAT-CRW model proposed in this paper not only provides a technical method for predicting green electricity premiums, but also offers quantitative references for governments to formulate differentiated subsidy policies, improve the market regulation mechanism for green electricity certificates, optimize inter-provincial green electricity trading arrangements, and for industrial users to adjust their green electricity procurement strategies. Future research could further incorporate more granular enterprise-level data, real-time green certificate trading data, carbon market price data, and green electricity trading data over longer time spans to improve the model's predictive accuracy and policy applicability.

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