Electricity Spot Market Risk Identification and Multi-Dimensional Early Warning Based on Improved Transformer

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ABSTRACT Reliable risk identification and early warning in electricity spot markets are increasingly important for intelligent power communication infrastructures and electromagnetic information systems that support real-time monitoring and dispatching. To address the challenges posed by high-frequency, heterogeneous, and strongly coupled market data, this study proposes an improved Transformer-based framework for electricity spot market risk identification and multidimensional early warning. The proposed method integrates multi-source operational data through temporal embedding and multi-channel feature encoding, enabling effective representation of electricity price fluctuations, dispatch instructions, transaction behaviors, and load responses. An enhanced self-attention mechanism is employed to capture long-range temporal dependencies and dynamic interactions, while a lightweight classifier performs hierarchical risk categorization. Furthermore, a multi-dimensional warning mechanism incorporating spatial location, subsystem characteristics, and temporal risk evolution is established to support adaptive operational decision-making. Experimental results demonstrate an overall risk identification accuracy of 93.2%, an average F1-score of 0.88, a dispatch subsystem localization accuracy of 97.3%, and a trend identification accuracy of 94.2% with only 3.1 minutes of response delay during risk escalation. The proposed framework provides an effective solution for intelligent risk perception and dynamic monitoring in complex electricity markets and offers methodological insights for communication-enabled energy systems and electromagnetic sensing environments requiring reliable real-time information processing.

INDEX TERMS electricity spot market, transformer, multi-source data fusion, risk identification, electromagnetic sensing

I. INTRODUCTION

With the continuous deepening of the reform of the electricity market, the electricity spot market has gradually become an important part of the power system operation; simultaneously, the industry is undergoing a similar evolution toward highly responsive, market-driven production models that necessitate integrating real-time data on consumer preference and raw material trading to maintain competitive agility. The operation of the electricity spot market relies on a large amount of complex, multi-source heterogeneous real-time data, including electricity price fluctuations, dispatching behavior, transaction matching, and user load response [1,2]. These data show a high degree of coupling and complexity in time and space. As a key platform supporting market transactions and dispatching management, the electricity spot software system bears the important responsibility of risk identification and early warning, and the power grid operation environment is becoming increasingly complex [3,4]. The multi-dimensionality and dynamic changes of electricity market data characteristics have greatly increased the difficulty of risk identification.

In recent years, scholars have conducted extensive research on the identification and early warning of power system risks. Related research focuses on the design of system risk detection and early warning mechanisms using data-driven and machine learning methods [5,6]. Some studies use traditional machine learning methods such as support vector machines, decision trees, and neural networks to analyze power system risks, and combine data fusion and other technologies to build identification models for specific risk types or data sources [7-9]. These deficiencies limit the intelligence and real-time level of risk warning mechanisms, making it difficult for existing research results to meet the needs of electricity spot market software systems for efficient risk management, and difficult to support the dual challenges of electricity market mechanism complexity and real-time performance. In addition, existing research has not fully explored the impact of different market mechanisms (such as bidding mechanisms, pricing rules) and changes in new energy penetration on the distribution of risk types, and most methods are difficult to effectively model the complex interactive relationships between multi-source heterogeneous data under the traditional machine learning framework. In response to the above challenges—which are broadly applicable to complex, highly coupled industrial systems, including the volatile forecasting environment — this paper proposes a study on the operation risk identification and multi-dimensional early warning mechanism of the electricity spot software system based on the improved Transformer structure. Based on the fusion of multi-source heterogeneous data, the study designs a time embedding coding module to enhance the model's processing ability for multi-dimensional inputs, uses a self-attention mechanism with position encoding to enhance the ability to capture long-term dependencies and dynamic changes, and combines a lightweight classifier to achieve dynamic classification of risk levels. Finally, a multi-dimensional early warning mechanism is constructed to achieve hierarchical response and dispatch intervention. In the design of the method, this paper fully considers the complexity of the actual electricity spot market, applies a feature encoding strategy that coexists with time sensitivity and spatial heterogeneity, and optimizes the identification stability in high-frequency fluctuation scenarios through the Transformer structure. The research process covers multi-source data modeling, multi-dimensional embedding structure design, attention mechanism extraction, risk label classification, and hierarchical warning mechanism output. Through system design and experimental verification, this paper aims to improve the accuracy of risk identification and real-time warning capabilities of the electricity spot market software system, enhance the system's adaptability to complex operating environments, and provide technical support for the safe and stable operation of the electricity market. The overall framework constructed is not only scalable, but can also be applied to other high-risk business scenarios in the power system, and has strong practical promotion value and industry adaptation potential.

II. DESIGN OF RISK IDENTIFICATION MECHANISM UNDER MULTI-SOURCE FUSION

A. MULTI-SOURCE DATA MODELING OF ELECTRICITY SPOT SYSTEM

1) Collection and Preprocessing of Multi-Source Data

To ensure that the high-frequency dynamics and strong coupling characteristics are not weakened during the feature adaptation stage, this paper adopts a strategy of preserving the original temporal resolution in the embedding encoding design. Although all multi-source data are uniformly resampled to a 1-minute granularity during the preprocessing stage, no dimensionality reduction or smoothing aggregation is performed. Discrete-time encoding uses a sine-cosine function to uniquely map each time step, completely preserving the precise temporal location of events. The multi-channel CNN uses small convolutional kernels (3/5/7) in parallel to extract local high-frequency patterns, rather than global averaging or pooling operations, thereby effectively capturing the instantaneous mutation features in signals such as trading volume and scheduling instructions. More importantly, the output of this encoding is directly used as the input of the Transformer, and its original time step size (60 steps) is completely preserved in the self-attention layer, allowing the model to model the coupling relationship between long-term dependencies and short-term fluctuations without losing temporal resolution.

The data used in this study covers the main dimensions of the electricity spot market, including electricity price fluctuation series, dispatch behavior logs, transaction matching records, and user-side load response data [10,11]. The electricity price data is collected at minute intervals, covering the past three years of trading periods, to ensure the integrity of high-frequency fluctuation characteristics. The dispatch behavior data comes from the dispatch center log, which includes dispatch instructions, equipment status changes, and dispatch response timing, with a recording interval ranging from 10 seconds to 1 minute. The transaction matching records are refined to the second level, reflecting the matching event time and transaction volume in detail. The user load response data is based on smart meter sampling, with a sampling frequency of 5 minutes.

To ensure the consistency and synchronization of data time series, the data of different time granularities is first resampled. All data are resampled to a unified time step of 1 minute, and linear interpolation is used to fill missing values. For the discrete signal of the equipment status in the dispatch log, the state encoding method is used to convert it into a numerical sequence. The numerical attributes such as transaction volume and price in the transaction matching data are smoothed by statistical windows to reduce the impact of instantaneous abnormal fluctuations on the model. The load response data is processed by a sliding window denoising filter to eliminate sampling noise.

Figure 1 shows the simulation results of multi-source data for electricity market modeling. The horizontal axis is the time (hour) within a day, and the vertical axis represents the electricity price (¥/MWh), load (MW), transaction volume (MWh), and user response rate (%). Figure 1(a) shows the intraday changes in electricity prices, showing obvious peak and valley characteristics, and around the 5th and 18th hours, it shows the periodic fluctuations of electricity prices throughout the day and two obvious price peaks. Figure 1(b) is the power load data, which reflects the superposition effect of industrial load and residential load. The load shows obvious intraday periodic fluctuations over time, with obvious peaks from 6:00 to 17:00, higher than other time periods. At the same time, affected by industrial

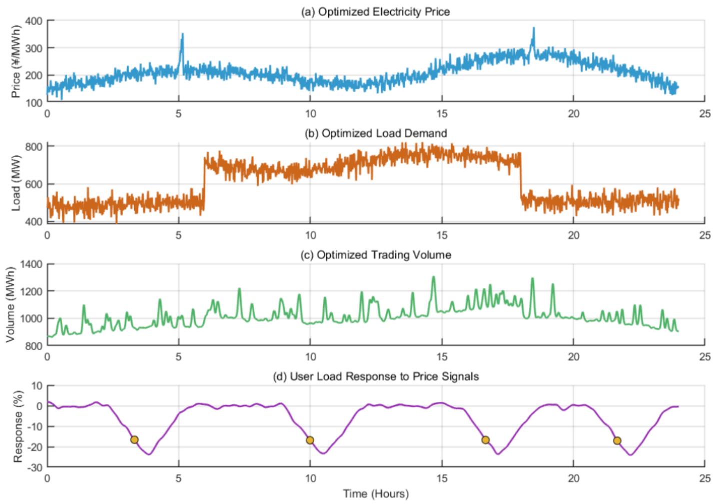

FIGURE 1. Four dimensions of data in the electricity spot market. (a) Electricity price time series fluctuation curve; (b) User load demand curve; (c) Market transaction matching electricity quantity time series diagram; (d) User response behavior to electricity price signal

electricity consumption, the load increases during the noon period. Figure 1(c) shows the electricity trading volume. The trading volume is driven by both electricity price and load in the intraday fluctuation, and there are multiple pulse peaks, reflecting the market trading activity. Figure 1(d) shows the load response of users to price signals. Four response events occur within 24 hours. The user load drops significantly in a short time and then gradually recovers, simulating the feedback behavior of elastic load to the price mechanism. The data of four dimensions reflects the operating characteristics of the electricity spot market and provides a multi-dimensional dynamic input basis for the subsequent Transformer-based risk identification model. The multi-source data integrated in this study includes four core streams: (1) Continuous numerical data: electricity price (¥/MWh), load (MW), and transaction volume (MWh), with a sampling frequency of 1 minute;

(2) Discrete event data: dispatch instructions (including device ID, action type, and execution status), with a sampling interval of 10 seconds to 1 minute; (3) User response behavior: load change rate (%) based on smart meters, sampled every 5 minutes and aligned after sliding filtering; (4) System status labels: manually labeled risk levels. A multi-channel CNN is dedicated to processing transaction behavior data (including transaction volume, frequency, and price change rate). Three sets of convolutional kernels (3/5/7) capture local patterns within 3-minute, 5-minute, and 7-minute windows, respectively. The outputs are concatenated and mapped to a 128-dimensional space, avoiding uniform convolution operations on heterogeneous features, thereby preserving the structural characteristics of each data stream.

2) Feature Alignment and Fusion

The first step in multi-source data fusion is the time series alignment of features. By unifying the timestamp index of all pre-processed data, a synchronized multi-dimensional time series matrix is constructed. The feature dimensions cover key indicators such as electricity price fluctuation, dispatch instruction encoding, matching transaction volume, and load change rate. To eliminate the problem of dimensional difference and inconsistent numerical scale, all features are standardized by Z-score, and the calculation method is Formula 1:

$$\tilde{x}_i = \frac{x_i - \mu_i}{\sigma_i} \tag{1}$$

x_i represents the original value of the i-th feature, and μ_i and σ_i are the mean and standard deviation of the feature, respectively.

After normalization, the sliding time window method is used to slice the data sequence. The window length is set to 60 minutes (that is, 60 time steps), and the step length is 5 minutes to ensure that the model input contains sufficient historical information and dynamic change characteristics. The multi-source features in each time window are integrated into a tensor form with a shape of (T,F). Among them, T=60 is the number of time steps, and F is the total dimension of the feature, covering all fused data.

B. DESIGN OF MULTI-DIMENSIONAL INPUT EMBEDDING CODING STRUCTURE

1) Dispatch Feature and Electricity Price Trend Coding

This section designs an improved time embedding module for the time series feature data after multi-source fusion of the electricity spot system, which is used to encode the dispatch feature, electricity price trend, and transaction behavior features, respectively [12,13], and enhance the Transformer's ability to distinguish and express inputs of different dimensions. This design effectively solves the problem that the traditional Transformer model has in-sufficient semantic understanding of different data types when processing diversified input features, and improves the accuracy of feature fusion and the ability to capture time series dependencies.

First, for the time series data of dispatch features, an embedding layer based on discrete time coding is constructed. The dispatch features include dispatch instruction encoding, equipment state changes, and execution delays, all of which are expressed in the form of discrete events. By periodic sine and cosine encoding of timestamps, the formulas are defined as Formula 2 and Formula 3:

$$PE(pos, 2i) = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{2}$$

$$PE(pos, 2i+1) = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right) \tag{3}$$

pos is the time position; i is the dimension index; dmodel is the embedding dimension, which is set to 64. This coding captures the time interval and periodicity characteristics of dispatch events, and improves the model's sensitivity to dispatch time dynamics. The discrete dispatch state is further converted into a vector through one-hot encoding, and combined with the time encoding to form a complete dispatch input embedding.

Secondly, for the trend characteristics of electricity prices, a continuous numerical embedding based on sliding window statistics is designed. Taking a 1-hour window as a unit, the four statistics of the mean, variance, maximum, and minimum of the electricity price are calculated to form a four-dimensional feature vector. Subsequently, a two-layer fully connected neural network is used to perform nonlinear mapping on the vector and output a 64-dimensional continuous feature embedding. This method not only retains the fluctuation details of electricity prices, but also captures complex nonlinear relationships through neural networks, thereby enhancing the expression ability of electricity price trends.

2) Trading Behavior Encoding and Multi-Source Embedding Fusion

Again, for trading behavior features, including indicators such as matching transaction volume, transaction price, and transaction frequency, a multi-channel convolutional neural network (CNN) is used for encoding. By designing three different convolution kernel sizes (3, 5, and 7) to capture multi-scale local features, the convolution layer output is uniformly mapped to a 128-dimensional feature space. This encoding fully explores the potential local patterns and high-frequency fluctuations in trading data, and enhances the model's ability to identify market trading dynamics.

During the model training process, batch normalization and dropout (ratio 0.2) are used to regularize the encoding output to avoid overfitting. The parameters of the embedding layer are automatically adjusted through back propagation, and end-to-end optimization is achieved by combining the overall risk identification task. This embedding coding design lays a solid foundation for the subsequent feature extraction based on the attention mechanism, ensuring the accuracy and stability of the expression of multi-source complex inputs in the deep model.

Figure 2 shows the multi-dimensional embedding coding architecture design for risk identification in the electricity spot market. Three-way parallel processing is used for heterogeneous input features: the dispatch feature is generated by discrete time encoding (sine and cosine position encoding) combined with state unique hot encoding to generate a 64-dimensional embedding; the electricity price trend is processed by sliding window statistics (mean, variance, maximum, minimum) and a two-layer fully connected network to form a 64-dimensional embedding; the transaction behavior feature is extracted by a multi-scale CNN (convolution kernel size 3/5/7) 128-dimensional embedding. After the three-way features are concatenated into a 256-dimensional unified vector, they are processed by batch normalization and Dropout (0.2) regularization, and the final output integrated embedding vector is used as the Transformer encoder input.

C. TEMPORAL FEATURE EXTRACTION MODULE BASED ON ATTENTION MECHANISM

1) Structural Design of Self-Attention Mechanism

The proposed "improved Transformer structure" is mainly reflected in three aspects: First, it introduces absolute position encoding aligned with the embedding dimension (dimension 256), rather than relying solely on content embedding, strengthening the model's perception of temporal absolute position; second, it adopts an 8-head multi-scale self-attention mechanism, focusing on short, medium, and long time spans respectively through different attention heads (as shown in Figure 3), to achieve joint modeling of sudden disturbances and periodic fluctuations in the electricity market; third, it expands the hidden layer dimension of the standard Transformer's feedforward network (FFN) from the default 2048 to 512 to adapt to the input with compressed feature dimensions in this task, improving the efficiency of nonlinear expression. This structure does not involve architectural reconstruction of the Transformer backbone, but rather targeted optimizations at the input embedding, attention granularity, and network capacity levels, enabling the model to remain lightweight while better suited to the high-frequency, heterogeneous, and strongly coupled data characteristics of the electricity spot market. The multi-head attention mechanism maps the input to three matrices: query (Q), key (K), and value (V). The calculation formula is shown in Equation 4:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

d_k is the dimension of the key vector, which is set to 64. This mechanism avoids the problem of numerical

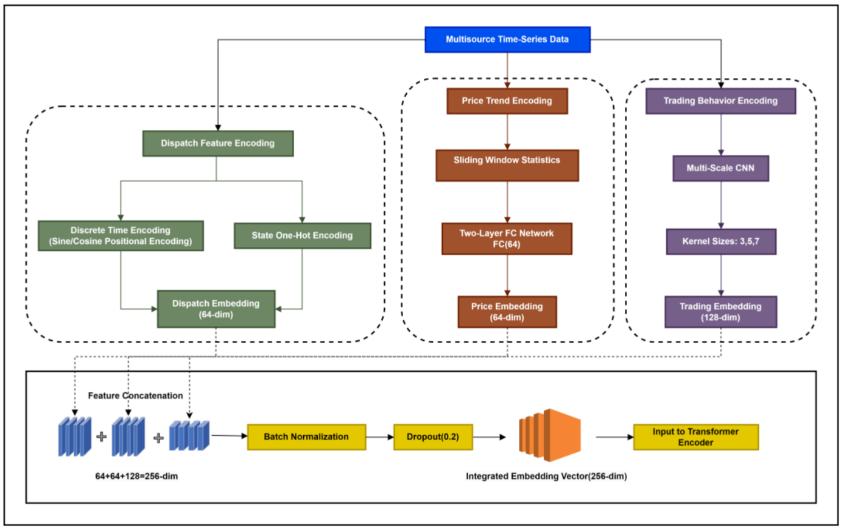

FIGURE 2. Multi-dimensional embedding coding architecture design for risk identification in the electricity spot market

instability in high-dimensional vector calculations by scaling the dot product calculation. The multi-head design performs 8 independent attention calculations in parallel, and the final results are spliced and output through linear mapping. This structure ensures that the model can pay attention to information on different time scales at the same time, and improves the ability to capture mutation points, lag effects, and periodic patterns.

Figure 3 shows the three sets of attention weight matrices of the improved Transformer in the electricity spot market risk identification model. The horizontal axis represents the target time step; the vertical axis represents the source time step; the color depth reflects the model's attention intensity at different time points. Matrix 1 presents a narrow range focus mode, with weights concentrated near the main diagonal, reflecting a strong dependence on recent time steps, and is suitable for capturing short-term risks such as load mutations. Matrix 2 shows a medium range of attention, with a more dispersed weight distribution, reflecting the ability to model medium-term time series associations such as dispatch instruction transmission. Matrix 3 shows a wide range of attention, which can focus on the current state and capture periodic fluctuations at the same time, including the intraday rules of electricity prices, simulating the coupling relationship between short-term anomalies and long-term periodic characteristics in the electricity market. The three matrices together constitute a multi-scale feature extraction mechanism, which significantly improves the ability to express complex risk patterns.

2) Feature Extraction and Dynamic Capture Process

The input of the self-attention module is the multi-dimensional time series embedding fused in the previous stage. After passing through the multi-head attention layer, it is then nonlinearly mapped through a fully connected feed-forward network (FFN). FFN contains two linear layers with a ReLU activation function in the middle. The hidden layer dimension is set to 512, which significantly improves the complexity of feature expression. Layer normalization and residual connection mechanisms are embedded in the model structure to alleviate the problems of gradient disappearance and training instability and ensure the effective training of deep models.

D. CONSTRUCTION OF DYNAMIC CLASSIFIER FOR OPERATION RISK

1) Lightweight Multilayer Perceptron Structure Design

After completing the temporal feature extraction based on the Transformer encoder, this paper constructs a set of lightweight multilayer perceptron (MLP) classifiers as the core module for risk level determination [14- 15]. The classifier consists of three fully connected layers, and the number of nodes in the input layer is consistent with the output dimension of the Transformer, both of which are 256. The first hidden layer is set with 128 neurons; the second hidden layer is set with 64 neurons; the output layer is set to 3 nodes according to the number of risk categories, corresponding to high risk, medium risk, and low risk categories, respectively. ReLU activation function is used between layers to apply nonlinear transformation and improve the model expression ability.

2) Risk Level Classification Process

The classification process first takes the 256-dimensional feature vector output by the Transformer code as input, and then passes through two layers of nonlinear mapping and output layer linear transformation in sequence. The specific expression is shown in Formula 5:

$$\begin{cases} z_1 = \mathrm{ReLU}(W_1 h + b_1) \\ z_2 = \mathrm{ReLU}(W_2 z_1 + b_2) \\ y = \mathrm{softmax}(W_3 z_2 + b_3) \end{cases} \tag{5}$$

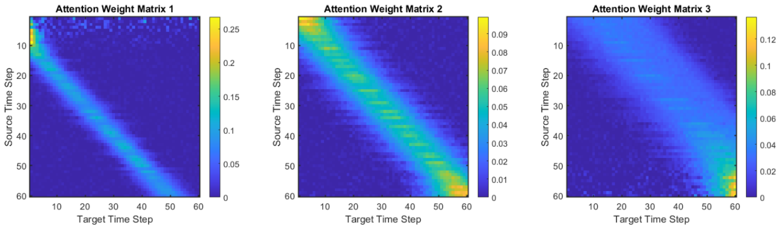

FIGURE 3. Three sets of attention weight matrices

$h \in R^{256}$ is the output of the Transformer code; Wi and bi represent the weight matrix and bias vector of the layer, respectively; $y \in R^8$ is the risk level probability distribution. The softmax function ensures that the output conforms to the probability distribution characteristics, so that the final judgment is based on the maximum probability category. The cross entropy loss function is used for optimization during the model training process to improve the classification accuracy by minimizing the error between the predicted distribution and the true label. The risk level classification refines the system operation safety situation, supports the dispatcher to respond quickly to abnormal conditions, and enhances the real-time and accuracy of risk identification. The lightweight design enables the classifier to have low computational overhead and latency, adapt to the dynamic characteristics of high-frequency electricity spot market data, and realize system online risk update and timely feedback.

Figure 4 shows the training performance and classification effect of the operation risk dynamic classifier. The horizontal axis is the training round (Epoch), and the vertical axis corresponds to the loss value (left Y axis) and the accuracy (right Y axis). It shows that in the process of 300 iterations, the training loss gradually decreases to about 0.01, and the validation loss also stabilizes to a lower level. At the same time, the training and validation accuracy rates are both stable at around 0.90, and the model converges well. The right figure is the standardized confusion matrix. The horizontal axis is the risk level predicted by the model (low, medium, and high), and the vertical axis is the actual risk level. It can be seen from the matrix that the prediction accuracy of the model in the three categories is high. The accuracy of the medium and high risk categories reaches 90%, and the low risk also reaches 85%. The overall classification performance is reliable and effectively supports the refined discrimination of dynamic operation risks.

E. MODEL INTEGRATION AND OPTIMIZATION

To further improve the risk identification performance, the classifier applies an early stopping mechanism to monitor the validation set loss and prevent overfitting during training. The optimizer uses Adam; the initial learning rate is set to 0.001; the weight decay parameter is 0.0001 to ensure the stability and generalization ability of parameter updates. In addition, the model uses batch input (batch size=64) during training to promote smooth gradient estimation and training convergence speed.

F. DESIGN OF MULTI-DIMENSIONAL WARNING MECHANISM OUTPUT

1) Construction of Warning Signal Hierarchical Output System

It should be clearly pointed out that the risk level output by the model is not a single global label, but a spatiotemporal risk tensor at the node level. Specifically, the Transformer classifier outputs the risk level of each power grid node independently, thus naturally carrying a "location" dimension. Through a predefined node-subsystem mapping table (e.g., node IDs 1–50 belong to the scheduling subsystem, and 51–100 belong to the power generation subsystem), node-level predictions can be aggregated to the "subsystem" level. The "risk trend" is calculated by applying a sliding window difference to the risk level sequence of each node over the past 24 hours. Therefore, multidimensional early warning is not a post-processing decomposition of a single output, but rather a parallel prediction by the model at fine-grained spatial units, naturally deriving the three dimensions through structured metadata and time series analysis.

Based on the identification results of the above-mentioned operation risk dynamic classifier, this paper designs and constructs a multi-dimensional warning mechanism covering node location, power subsystem, and risk trend changes to achieve hierarchical output of warning signals. First, the nodes in the electricity spot software system are numbered and classified according to their geographical location and grid topology to form a node location index system. The risk level of each node is dynamically output by the classifier, and data is collected and grouped in combination with its power subsystem affiliation (such as power generation, transmission, distribution, etc.). The node risk level is updated with the time series, and a risk time curve is constructed to characterize the change of risk trend. Through the statistical sliding window technology, the window length is set to 24 hours to achieve dynamic monitoring and trend analysis of risk fluctuations in the short term. The trend change is calculated by difference to obtain Formula 6:

$$\Delta R_t = R_t - R_{t-\tau} \tag{6}$$

R_t is the risk level value at time t, and τ is the time difference interval, which is usually set to 1 hour to capture the trend of risk increase or decrease.

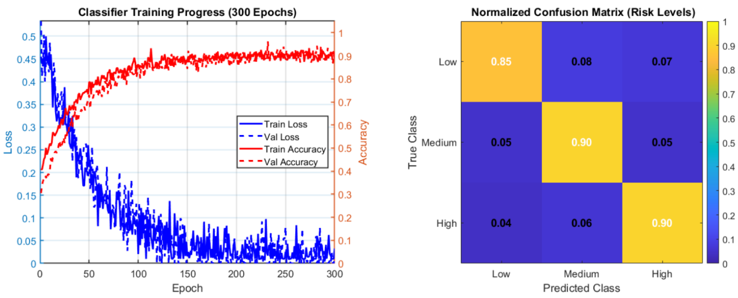

FIGURE 4. Training performance and classification effect of the operation risk dynamic classifier

2) Dispatch Intervention Suggestion Generation Mechanism

Based on the multi-dimensional warning signal, the system integrates the dispatch intervention suggestion module. This module generates targeted intervention strategies based on the warning level and risk trend, combined with the characteristics of the power subsystem and the functional attributes of the node. The intervention suggestions cover aspects such as adjusting the electricity price mechanism, optimizing the dispatch of generator sets, load-side demand response, and fault prevention measures. The automatic matching of strategies depends on the rule base and the dynamic decision engine. In addition, to ensure the scalability and flexibility of the early warning system, the early warning output and dispatch recommendations are designed with modular interfaces to support data interaction and functional integration with the existing power management system. The system transmits risk information and intervention instructions through standardized data protocols (such as IEC 61850) to ensure accurate and timely information transmission.

Figure 5 shows two key perspectives in the multidimensional early warning mechanism. The left figure depicts the risk distribution of each node in different power subsystems, with the horizontal axis being the node ID and the vertical axis being the risk trend change (Risk Trend, ΔR). The color represents the subsystem to which the node belongs (generation, transmission, distribution, and energy storage), and the symbol shape represents the current risk level (low, medium, and high). High-risk power generation nodes show a significant negative trend, while nodes 45 to 50 and 20 to 25 are mostly in a high-risk state. The right figure shows the inhibitory effect of dispatch intervention measures on the risk index in a specific time period (8.3 to 10 hours), with the horizontal axis being time (hours) and the vertical axis being the composite risk index. The original curve shows that the risk rises rapidly during this time period, while the risk drops significantly after the intervention, achieving about 34.7% risk mitigation, verifying the synergistic effectiveness of the multidimensional monitoring mechanism and the response dispatch strategy in dynamic operation.

III. RISK IDENTIFICATION CAPABILITY VERIFICATION SYSTEM

The experimental dataset used in this study is derived from the real operation data of a provincial electricity spot trading platform, covering the full-cycle market transaction records and system operation status information for the past 30 days. The dataset contains electricity price fluctuation sequences, dispatch instruction logs, user load response data, transaction matching details, and system operation condition annotations, all of which are collected at the minute-level time granularity, with high frequency, multi-dimensional, and strong time series characteristics.

A. PREDICTION ACCURACY EVALUATION

Accuracy is one of the basic performance indicators of the risk identification system, which measures the proportion of correctly identified in the classification results. During the evaluation process, the risk level output by the model is compared with the real labels annotated manually one by one, and the proportion of all correctly identified labels in the prediction results to the total prediction samples is calculated. The accuracy evaluation is statistically analyzed separately in different risk level categories (high, medium, and low) to reflect the model's overall prediction ability. The evaluation data is collected from an actual electricity spot trading platform, covering the full amount of time series data within a 7-day operation cycle, ensuring that the verification process covers a variety of operation scenarios. The test set samples do not participate in the model training, and independent division is used to ensure the objectivity and credibility of the evaluation results. The evaluated models include: Proposed, SVM (Support Vector Machine), RF (Random Forest), CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory), Transformer, and LightGBM (Light Gradient Boosting Machine).

Figure 6 shows the performance comparison of the proposed model and multiple mainstream methods in the task of power equipment fault prediction. In the left figure, the horizontal axis is the name of different models, and the vertical axis represents the overall prediction accuracy (%). It can be seen that the accuracy of the proposed method is as high as 93.2%, which is significantly better than traditional models such as SVM (82.1%) and CNN (85.2%), indicating its advantage in overall identification ability. The right figure

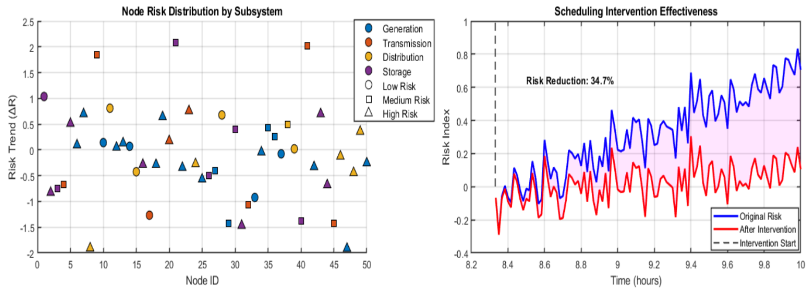

FIGURE 5. Analysis of node risk distribution and dispatch intervention effect

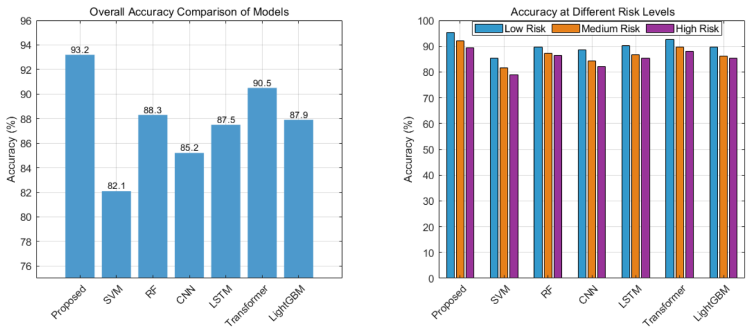

FIGURE 6. Performance comparison of the proposed model and multiple mainstream methods in the task of power equipment fault prediction

shows the accuracy performance of each model at different risk levels (low, medium, and high). The horizontal axis is still the model, and the vertical axis is the accuracy of each level. The three colors represent three types of risks. It can be observed that the proposed method still maintains an accuracy of 89.5% in high-risk scenarios, which is significantly higher than SVM's 78.9% and CNN's 82.1%, indicating that it is more stable in high-risk state identification and is suitable for high-demand scenarios such as early warning and precise diagnosis of power systems, further highlighting the comprehensive advantages of the model in practicality and robustness.

B. EVALUATION OF PRECISION, RECALL, AND F1 VALUE

To comprehensively measure the stability and reliability of the model in different risk identification, precision, recall, and F1 value are used as complementary indicators. Precision reflects the proportion of samples identified as low, medium, and high risks that are actually risks, while recall indicates the proportion of real risk samples successfully identified by the model. F1 value, as the harmonic mean of the two, effectively reflects the performance of the model when the sample distribution is uneven. During the evaluation process, the above indicators are calculated with three risk levels as the target categories, and key data is extracted through confusion matrix for statistical analysis to further judge the identification ability and generalization performance of the model under abnormal conditions. Random forest (RF) is used as the baseline model for comparison with the model in this paper.

TABLE 1. Classification performance of the proposed model and the baseline model under three types of power risk levels

Model	Risk Level	Precision	Recall	F1-Score
Proposed	High Risk	0.91	0.88	0.89
Proposed	Medium Risk	0.85	0.83	0.84
Proposed	Low Risk	0.89	0.93	0.91
Proposed	Average	0.88	0.88	0.88
Baseline (RF)	High Risk	0.83	0.76	0.79
Baseline (RF)	Medium Risk	0.78	0.72	0.75
Baseline (RF)	Low Risk	0.82	0.85	0.83
Baseline (RF)	Average	0.81	0.78	0.79

Table 1 shows the classification performance of the proposed model and the baseline model (RF) under three types of power risk levels, including three core indicators: precision, recall, and F1 value, which comprehensively evaluates its performance in risk identification tasks of different degrees. Combined with the data, it can be seen that the proposed model performs particularly well in the high-risk category, with a precision of 0.91, a recall of 0.88, and an F1 value of 0.89, which is significantly better than the corresponding values of the baseline model (0.83, 0.76, and 0.79), indicating that it can more accurately identify and capture key risk signals. In the low-risk category, the F1 value of this model is 0.91, which is also higher than the 0.83 of the RF model, indicating that it has good overall identification stability. The average F1 value of the three risk levels is 0.88, which is nearly 11.4% higher than the baseline model's 0.79. This fully demonstrates the comprehensive advantages of this method in power equipment fault diagnosis and multi-level risk classification tasks.Especially in dealing with uneven sample distribution or abnormal disturbances, it shows stronger robustness and generalization ability.

Given that power system risk identification is a typical imbalanced classification problem, this paper not only reports the overall accuracy but also provides a fine-grained evaluation of each risk level using precision, recall, and F1 score. The model achieves an F1 score of 0.89 on the high-risk category, significantly outperforming the random forest baseline (0.79). Furthermore, the model's AUC-ROC value on the test set is 0.94, further validating its stability in identifying high-risk events under different thresholds. The overall accuracy is only used as a comprehensive performance reference; the core judgment criteria are the high-risk F1 score and early warning capability.

C. EVALUATION OF RISK PREDICTION LEAD TIME

The actual value of risk prediction lies not only in accurate identification, but also in the effective prediction of future operating status. To measure the model's ability to identify potential risk events in advance, the prediction lead time is applied as a key evaluation indicator. In the specific evaluation, the timestamp when the system first issues an early warning for a high-risk state is recorded and compared with the start time of the actual risk event to calculate the average advance prediction time. Multiple risk scenarios with mutation characteristics are set in the dataset, such as sudden increase in load, jump in electricity price, frequency disturbance, etc., and the average lead time and standard deviation of the model in each scenario are counted. This indicator can reflect the model's sensitivity and foresight ability to sudden or trend risks in dynamic scenarios, and verify its practicality in scheduling auxiliary decision-making.

Figure 7 shows the lead time performance and prediction effect comparison of the risk prediction model proposed in this paper in different risk scenarios. The horizontal axis of the left figure is 10 typical power system risk scenarios, and the vertical axis represents the prediction lead time (minutes). The error bar shows the fluctuation range of the prediction mean and ± 1 standard deviation of the model in different scenarios. It can be seen that in 10 scenarios such as frequency disturbance and voltage overlimit, the prediction lead time of the model in this study is significantly better than the benchmark model. In the frequency disturbance scenario, the average lead time of this model is 32.1 minutes, while the benchmark model is only 25.7 minutes. The right figure takes the jump in electricity price as an example, with the horizontal axis being time (hours) and the vertical axis being risk probability, showing the comparison of the actual risk curve with the prediction results of 15 minutes in advance and 6 minutes in advance. This model can accurately capture the risk trend before the risk rises, indicating that it has obvious advantages in time series prediction accuracy and response speed. Especially in actual operation, it can reserve more sufficient reaction time for system dispatch.

D. MULTI-DIMENSIONAL WARNING POSITIONING ACCURACY EVALUATION

The warning mechanism proposed in this study needs to precisely output warning information at the node, subsystem, and overall system levels, so it is necessary to verify the system's risk positioning ability in the spatial dimension. The warning positioning accuracy evaluation takes the location of known risk events as a reference, locates the risk labels generated by the system on the topological network diagram, matches them with the actual risk locations, and counts the number of positioning error nodes and coverage ratios. By verifying several typical risk events in different power subsystems, the perception granularity and resolution capabilities of the model in terms of geographic location and functional modules are evaluated. This evaluation helps to determine whether the model has the ability to precisely deploy warning strategies after multidimensional feature fusion.

Figure 8 shows the evaluation results of the positioning accuracy of the multi-dimensional warning system in the power system. The left figure is a node-level positioning error distribution diagram, with the horizontal axis representing the positioning error (in terms of the number of nodes) and the vertical axis representing the frequency of occurrence. The results show that most of the errors are concentrated within 1.5 nodes, indicating that the model has high accuracy in fine-grained positioning. The right figure shows the fault location accuracy of each subsystem. The horizontal axis is different power subsystems, including power generation, transmission, distribution, energy storage, etc., and the vertical axis is the positioning accuracy (%). Among them, the dispatching subsystem ranks first with an accuracy of 97.3%, which is significantly higher than the system average (93.6%), highlighting the high sensitivity of the model to abnormal dispatch instructions; the positioning accuracy of key infrastructure such as power generation (96.7%) and substations (95.1%) is also outstanding, verifying the model's monitoring ability for the core links of the power grid. It is worth noting that the accuracy of the trading subsystem (89.7%) and renewable energy (90.2%) is relatively low, which is closely related to the high volatility of market trading data and the uncertainty of new energy output, but it is still above the threshold, indicating that the system still maintains reliable performance in complex scenarios. The stable performance of intermediate links such as transmission (94.2%), distribution (92.8%), and communication (94.6%) confirms the balanced detection ability of the early warning mechanism in the entire power chain, and provides technical support for multi-dimensional risk collaborative management and control.

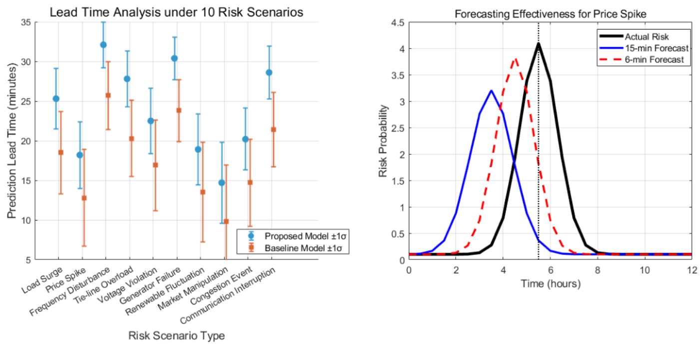

FIGURE 7. Comparison of the lead time performance and prediction effect of the model in different risk scenarios

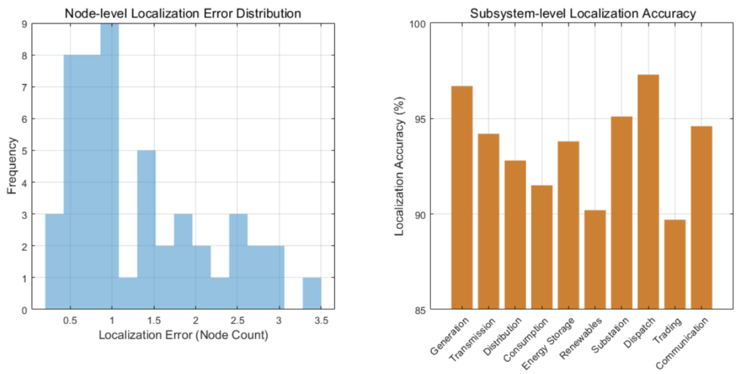

FIGURE 8. Evaluation results of the positioning accuracy of the multi-dimensional warning system in the power system

E. RISK TREND IDENTIFICATION STABILITY ASSESSMENT

During the operation of electricity spot, some risks have the characteristics of periodic fluctuations and periodic increases. Accurately identifying trend changes is the key to ensuring the stable operation of the system. This assessment uses a sliding window mechanism to perform trend analysis on the risk level sequence output by the model and compares it with the actual risk evolution process. The focus is on the stable response ability of the model in the stages of risk increase, mitigation, and repeated fluctuations. By setting the trend identification sensitivity threshold, the trend classification accuracy of the model in scenarios with different magnitudes of risk changes is observed to verify its ability to characterize the evolution of medium- and longterm risks in a dynamic environment and its stability.

TABLE 2. Trend identification accuracy and average response delay of the model at different risk change stages

Trend stage	Identification accuracy (%)	Average response delay (minutes)
Risk Increase	94.2	3.1
Risk Mitigation	91.8	2.8
Risk Fluctuation	89.6	4.5
Risk Stability	93.0	2.5
Sudden Risk	90.5	3.8
Risk Declining	92.1	3.0
Average Level	91.9	3.3

Table 2 shows the trend identification accuracy and average response delay of the model at different risk change stages, reflecting the model's ability to capture the dynamic evolution of risks and its response speed. In the risk increase stage, the trend identification accuracy reaches 94.2% at the highest, and the average response delay is 3.1 minutes, indicating that the model can capture the rapid increase of risks early and accurately, which helps to take preventive measures in time. In the risk mitigation stage, the identification accuracy is 91.8%, and the delay time is short, 2.8 minutes, indicating that the model still maintains high sensitivity and response speed when the risk decreases. The identification accuracy in the risk fluctuation stage drops slightly to 89.6%, and the response delay increases to 4.5 minutes, reflecting that the model's identification difficulty increases when facing complex fluctuations, but the overall performance remains stable. In addition, the accuracy in the risk stability stage is 93.0%, with a delay of 2.5 minutes, indicating that the model can effectively identify the stable state of risks and avoid false alarms.

F. DISCUSSION OF MODEL LIMITATIONS AND ROBUSTNESS

While the proposed model demonstrates excellent performance in typical operating scenarios, its generalization ability under structural abrupt changes or extreme events remains limited. For example, when encountering unprecedented regulatory policy shifts (such as emergency adjustments to electricity price caps), large-scale grid disconnection of renewable energy sources, or collective strategy changes by market participants, the model may experience recognition delays or misjudgments due to training data distribution shifts. The current version is primarily trained on historical stable operating data and does not explicitly introduce adversarial examples or stress testing scenarios. Future work will integrate causal inference with online learning mechanisms, improving the model's robustness to unknown perturbations through incremental fine-tuning and uncertainty quantification. Although this study does not cover such extreme cases, it validates its short-term generalization ability on 30 days of experimental data including typical abnormal events such as load spikes and electricity price jumps, providing a preliminary feasible solution for high-risk business scenarios.

IV. CONCLUSION

This paper focuses on the operational risk identification and early warning problems faced by the electricity spot software system in a multi-source heterogeneous high-frequency data environment, and constructs a high-dimensional feature fusion and dynamic risk identification mechanism based on the Transformer model. By uniformly modeling multi-source data such as electricity price, dispatch, transaction, and load, designing a multi-dimensional embedding structure, and improving the attention mechanism, the model's ability to capture time series correlation and mutation risks is effectively improved. On this basis, a lightweight classifier is integrated to realize risk level discrimination, and a hierarchical multi-dimensional early warning mechanism is constructed to support power dispatch intervention decisions. The experimental results show that the excellent performance of the model in the risk identification of the elec-tricity spot market fully verifies its effectiveness: with the support of multi-source information fusion and dynamic early warning mechanism, the overall prediction accuracy reaches 93.2%; the trend identification accuracy in the risk rising stage is 94.2%, and the response delay is only 3.1 minutes; the average F1 value of various risks reaches 0.88, which is significantly better than the 0.79 of the random forest (RF) model; the positioning accuracy of the dispatch subsystem is also as high as 97.3%. The research provides a practical and deployable intelligent auxiliary means for the safe operation of software systems in complex electricity market environments, which has practical value in improving the resilience of power grid operation and market stability.

AUTHOR CONTRIBUTIONS

Conceptualization – Yin Ma, Xiaodong Pang, Hao Li, Yanqiu Ji, Zhen Niu and Wentao Feng; methodology – Yin Ma, Xiaodong Pang, Hao Li, Yanqiu Ji, Zhen Niu and Wentao Feng; investigation – Yin Ma, Xiaodong Pang, Hao Li, Zhen Niu and Wentao Feng; writing-original draft preparation – Yin Ma, Xiaodong Pang, Hao Li, Yanqiu Ji, Zhen Niu and Wentao Feng.

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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