

GridRiskNet: A Two-Stage Hybrid Model for Project Investment Risk Management of Power Grid Enterprises Using Big Data Mining

Hongzhi Gao*, Dekyi, Metok
State Grid Tibet Electric Power Co., Ltd., Lhasa 850000, China
E-mail: Djgy1108@163.com
*Corresponding author

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To enhance the power grid enterprise's ability to comprehensively perceive and dynamically assess investment risks in engineering projects, this study proposes a risk management model called GridRiskNet based on big data mining. This model integrates structured, unstructured, and spatiotemporal data and realizes intelligent identification of project risk probability distributions and potential impact ranges by constructing a two-stage hybrid modeling architecture. In the first stage, the model uses eXtreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) to extract static and dynamic features in parallel. In the second stage, it introduces Graph Attention Recurrent Neural Network (GA-RNN) to model risk propagation paths under the power grid topology. Meanwhile, this study combines Spatio-Temporal Graph Convolutional Network (ST-GCN) to improve the coupling expression of meteorological and text features. The experiment uses multi-source public data for verification, such as power infrastructure data from the U.S. Energy Information Administration, meteorological observation data from the National Oceanic and Atmospheric Administration, and power grid topology data from OpenStreetMap. The results show that GridRiskNet performs excellently in risk prediction stability and regional propagation modeling. Among them, the risk principal component analysis projection score in 2023 reached 7.779. This indicates that cost overruns, climate pressure, and equipment technology risks together form a high-risk cluster, with cost overruns increasing by 269% compared with 2018. In the State-of-the-Art comparison, GridRiskNet achieves an F1-score of 0.892, a Receiver Operating Characteristic - Area Under Curve of 0.962, a Risk Impact Radius error of approximately 4.8 km, and a Risk Entropy of 0.89; these are comprehensively better than existing methods. Moreover, the model has good cross-modal feature fusion and risk transmission mechanism identification capabilities, and can effectively characterize the spatiotemporal coupling risk features in complex power grid projects. Overall, this system can provide power grid enterprises with structured and interpretable risk index outputs and regional early warning support. Thus, it helps to improve the investment safety and operational and maintenance resilience of projects.

Povzetek: Predstavljen je GridRiskNet, dvofazni hibridni model za upravljanje investicijskih tveganj v elektroenergetskih projektih. S križnim združevanjem strukturiranih, besedilnih in prostorsko-časovnih podatkov ter uporabo XGBoost/LightGBM in GA-RNN izboljša napoved tveganj ($F1=0,892$, $AUC=0,962$) ter natančno modelira regionalno širjenje tveganj (napaka 4,8 km).

1 Introduction

With the accelerated promotion of energy transition and the construction of new power systems, the strategic position of power grid engineering projects in national energy security and clean energy consumption has become increasingly prominent [1]. However, power grid enterprises face problems such as the surge of multi-source heterogeneous data, highly uncertain engineering environments, and frequent external disturbances during project investment and construction. These problems make traditional risk management methods difficult to cover the dynamic risk chain throughout the whole

process from construction preparation, equipment deployment, to operation and maintenance support [2]. Especially against the backdrop of the rapid development of renewable energy, the risk types in project investment are constantly evolving. For example, the enhancement of climate extremeness, the swift change of equipment technology paths, and the increase in policy compliance costs all propose higher requirements for the intelligence and adaptability of risk early warning systems [3-5]. Therefore, constructing a big data mining-based intelligent risk assessment model has become a key path to improving the investment decisions' scientific nature and the power grid enterprises' resilience governance

capabilities [6, 7]. In the context of power market liberalization, the continuous increase in the proportion of renewable energy has made the risk management of geographical locations caused by network congestion increasingly important. Improving the ability to model location-related risks has become the core foundation for supporting project financing and investment feasibility assessment [8].

In recent years, artificial intelligence (AI) technologies have made remarkable progress in risk identification, modeling, and prediction. Model architectures represented by graph neural network (GNN), attention mechanisms, and deep semantic modeling have been gradually applied to financial risk control and energy dispatching [9, 10]. Some studies have attempted to introduce machine learning (ML) methods into the power engineering field. It includes using eXtreme Gradient Boosting (XGBoost) for classification and identification of construction anomalies, or employing a convolutional neural network (CNN) for trend prediction of construction period delays [11]. However, existing methods generally suffer from shortcomings such as a single model structure, weak data fusion capability, and difficulty in explaining cross-modal causal paths; these methods cannot effectively support power grid enterprises in achieving full-chain risk perception, dynamic quantification, and structural early warning in a multi-source data environment. Therefore, there is an urgent need to construct a multi-modal driven composite risk assessment system for power grid engineering scenarios.

To this end, this study proposes the GridRiskNet model based on big data mining, constructs a fusion mechanism for structured data, unstructured text, and spatiotemporal data. Thus, it realizes comprehensive modeling and dynamic evaluation of investment risks in power grid engineering projects. The study's main innovations encompass:

(1) Proposing a two-stage GridRiskNet model architecture: It integrates XGBoost and Light Gradient Boosting Machine (LightGBM) for risk capture, and models the propagation process of risks in the power grid topology through a Graph Attention Recurrent Neural Network (GA-RNN).

(2) Introducing Spatio-Temporal Graph Convolutional Network (ST-GCN) and cross-modal attention mechanisms: It enhances the model's expression capabilities for meteorological disturbances and regional structural information;

(3) Constructing a risk principal component projection index system based on Principal Component Analysis (PCA): It achieves structural clustering and projection analysis of high-dimensional risk samples, and supports the differentiated regional risk management needs of power grid enterprises.

Overall, the specific research question is whether multimodal data fusion and risk propagation modeling methods can enhance the comprehensive capabilities of risk classification, propagation path identification, and uncertainty quantification in complex power grid engineering projects. The target outcome is to achieve a

comprehensive portrayal of investment risks in power grid engineering projects by constructing a composite model that integrates structured, spatiotemporal, and text data. It also aims to verify the advantages of the proposed method in terms of risk identification accuracy, propagation path reducibility, and risk distribution stability. Thus, it supports power grid enterprises in risk early warning and decision optimization.

2 Related work

With the in-depth application of AI technologies and big data analysis methods in engineering management, investment project risk assessment has gradually shifted from traditional static analysis to intelligent prediction and dynamic modeling. Aiming at the insufficiency of risk assessment for manufacturing investments, Dong and Li proposed combining expert experience with big data mining to construct project risk indices and integrating CNN with Long Short-Term Memory (LSTM) for predictive modeling. In multiple sliding window tests, the model achieved a Receiver Operating Characteristic (ROC) value of 0.9366 and an average accuracy of 94.95%, demonstrating high prediction precision [12]. Loseva et al., facing the risk assessment task of regional franchising projects, constructed a big data-based credit rating model by combining the SPARK information system with ML methods. This verified the model's robustness in identifying abnormal risks through Spearman correlation and confusion matrix [13]. These studies have provided useful insights into introducing composite modeling methods and integrating expert judgment with data-driven mechanisms, gradually promoting the development of investment risk assessment towards intelligence and systematization.

Over the years, methods such as GNN, deep clustering, and multi-criteria decision-making have been widely introduced into investment evaluation and project classification, further enhancing the structural cognitive ability of risk assessment. Mostofi et al. constructed a construction project investment framework based on graph attention networks. This framework achieved a classification accuracy of over 98% in three sub-networks of region, country, and financing model, demonstrating the advantages of graph structure in modeling investment decision-making relationships [14]. Qi used regularized topic models and graph clustering methods to construct a financial investment "behavior circle". They mapped customer behaviors to the latent semantic space and realized risk classification of financial communities and investment plan recommendations through subgraph mining [15]. Moreover, Luo and Zhu proposed a deep neural network (DNN) model based on transfer learning for regional investment risk assessment. This model maintained high prediction accuracy (up to 92%) in the case of insufficient samples, demonstrating the potential of deep learning in solving unbalanced data problems [16]. These studies all reflect the integration trend of risk assessment models in recent years towards deep representation learning, multi-layer decision-making

structures, and complex graph relationship modeling.

Although existing studies have made positive progress in risk modeling methods, index system construction, and model accuracy improvement, there are still three main deficiencies. First, most current models focus on classification or regression prediction of risk probability, lacking the ability to model regional structural propagation characteristics. Second, the heterogeneity of multi-source data has not been fully utilized, and a unified representation for structured, spatiotemporal, textual, and other multimodal information has not been formed. Third, the interpretability and quantifiability of risk structure evolution must be enhanced, making it difficult to support dynamic scheduling and regional risk management of complex systems such as power grid projects [17]. In response to the above shortcomings, this study proposes a grid engineering project investment risk management system based on big data mining - the GridRiskNet model. This model reveals the changing trends of high-dimensional risk structures and supports grid enterprises in accurately perceiving and dynamically controlling investment risks at different regions and time scales.

3 GridRiskNet model based on big data mining

3.1 Realization process of GridRiskNet model

The proposed GridRiskNet model realizes intelligent assessment of investment risks in power grid engineering projects based on multi-source heterogeneous data fusion and a hybrid ML architecture. It first establishes a multimodal data preprocessing layer. For structured data (such as project budgets and equipment parameters), an adaptive normalization method is used to unify dimensions, ensuring the consistency of feature scales. For unstructured text data (including engineering logs and bidding documents), a fine-tuned Bidirectional Encoder Representations from Transformers (BERT) model is utilized to deeply extract semantic features, enhancing the risk perception ability of text information. For spatiotemporal data (such as construction trajectories and meteorological records), ST-GCN is introduced to jointly encode complex environmental features from two dimensions: spatial dependence and temporal dynamics [18, 19]. In the feature fusion stage, a cross-modal attention mechanism is designed, which can adaptively learn the weight relationships between different data modalities. Meanwhile, this mechanism can effectively integrate

multi-source features and generate unified and dense high-dimensional risk representation vectors, laying the foundation for multi-dimensional risk modeling [20].

At the core of modeling, GridRiskNet adopts a two-stage hybrid modeling framework. In the first stage, the improved XGBoost and LightGBM models run in parallel to jointly perform risk prediction on high-dimensional risk representation vectors. Specifically, XGBoost integrates a dynamic feature selection mechanism, which dynamically updates feature importance indices based on sliding window statistical features to enhance the response capability to dynamic risk factors. LightGBM incorporates a time-series-aware splitting criterion to strengthen the detection capability for time-series anomalies such as project schedule delays. The two models output the prediction probabilities of risk categories (i.e., risk probability vectors after Softmax) and sequences of feature importance scores [21].

In the second stage, GA-RNN is used as a meta-model, whose core innovation lies in fusing the dual output information from the first stage mentioned above. Specifically, GA-RNN takes the risk probability vectors of XGBoost and LightGBM as the main input; simultaneously, it introduces their feature importance score sequences as auxiliary features to form a comprehensively fused feature matrix. This matrix contains the risk prediction results from the previous stage; it also explicitly integrates the influence weights of features on the model output, thereby enhancing the ability to perceive risk propagation mechanisms [22]. Subsequently, based on this matrix, GA-RNN introduces a risk propagation graph structure and accurately models the transmission relationships between risk factors through an adjacency matrix. Moreover, it uses graph attention mechanisms and recurrent neural network (RNN) units to dynamically learn key nodes and main channels in risk propagation paths, extracting high-order interaction features.

The entire GridRiskNet model comprehensively optimizes classification cross-entropy loss, risk propagation graph reconstruction error, and feature stability regularization terms through an end-to-end joint training strategy. Finally, this model outputs a multi-dimensional risk assessment matrix covering risk probability distribution, potential impact range, and structural features. The entire system adopts an online incremental learning mechanism, which can continuously absorb real-time data flow to dynamically update model parameters; this achieves a high adaptability and continuous tracking of the risk environment of power grid engineering projects. The implementation process and pseudocode of GridRiskNet are illustrated in Figures 1 and 2.

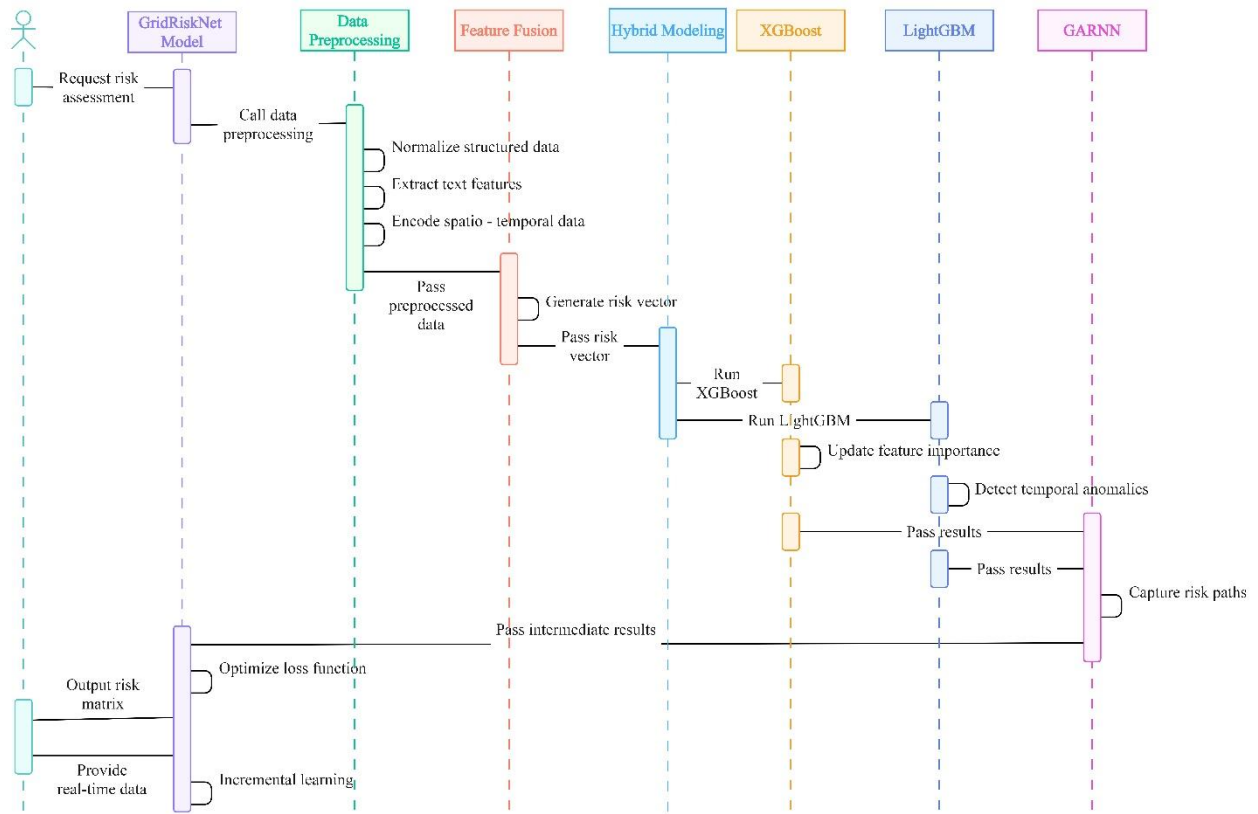


Figure 1: The implementation process of GridRiskNet

```

class GridRiskNet:
    def __init__(self, config):
        self.config = config
        self.preprocessor = MultiModalPreprocessor(config)
        self.feature_fusion = CrossModalAttention(config)
        self.first_stage = HybridEnsembleModels(config)
        self.risk_graph = RiskPropagationGraph(config)
        self.second_stage = GARNNMetaModel(config, self.risk_graph)

    def train(self, dataset):
        features = self.preprocessor.process(dataset)
        fused_features = self.feature_fusion(features)
        first_stage_preds = self.first_stage.train(fused_features, dataset.labels)
        self.second_stage.train(first_stage_preds, fused_features, dataset.labels)

        for epoch in range(self.config.epochs):
            preds = self.predict(dataset)
            loss = self._calculate_loss(preds, dataset.labels)
            self._update_models(loss)

    def predict(self, dataset):
        features = self.preprocessor.process(dataset)
        fused_features = self.feature_fusion(features)
        first_stage_preds = self.first_stage.predict(fused_features)
        return self.second_stage.predict(first_stage_preds, fused_features)

    def update_with_new_data(self, new_data):
        features = self.preprocessor.update_and_process(new_data)
        self.first_stage.update(features, new_data.labels)
        first_stage_preds = self.first_stage.predict(features)
        self.second_stage.update(first_stage_preds, features, new_data.labels)

class MultiModalPreprocessor:
    def process(self, dataset):
        return {
            'structured': self._process_structured(dataset.structured),
            'text': self._process_text(dataset.text),
            'spatiotemporal': self._process_spatiotemporal(dataset.spatiotemporal)
        }

    def _process_structured(self, data):
        return AdaptiveNormalization(data)

    def _process_text(self, data):
        return FineTuneBERT(self.bert_model, data)

    def _process_spatiotemporal(self, data):
        return STGCN(self.stgcn_params).forward(data)

class CrossModalAttention:
    def __call__(self, features):
        weights = self._compute_attention_weights(features)
        return weighted_sum(features, weights)

class HybridEnsembleModels:
    def __init__(self, config):
        self.xgboost = ImprovedXGBoost(config)
        self.lightgbm = ImprovedLightGBM(config)

    def train(self, features, labels):
        xgb_preds = self.xgboost.train(features, labels)
        lgbm_preds = self.lightgbm.train(features, labels)
        return combine_predictions(xgb_preds, lgbm_preds)

class RiskPropagationGraph:
    def __init__(self, config):
        self.adj_matrix = self._construct_adjacency_matrix(config.risk_factors)

    def _construct_adjacency_matrix(self, risk_factors):
        # Construct adjacency matrix based on domain knowledge or data learning
        pass

class GARNNMetaModel:
    def train(self, first_stage_preds, features, labels):
        # Train GA-RNN model
        pass

    def predict(self, first_stage_preds, features):
        # Predict risk assessment matrix
        pass

```

Figure 2: The pseudocode of GridRiskNet

3.2 Mathematical modeling principle of GridRiskNet model

Figure 1 shows the complete implementation process of the GridRiskNet model, covering the entire process from user-requested risk assessment to model output results and continuous updates. The model is built on multi-source heterogeneous data, fusing structured, unstructured, and spatiotemporal information, and achieves intelligent prediction of power grid project risks through multi-stage ML and graph modeling strategies. The key computational links in the model are described mathematically and logically as follows.

In the data preprocessing stage, the structured input data is first normalized. Let the original data matrix be:

$$\mathbf{X}_s \in \mathbb{R}^{n \times d_s} \quad (1)$$

$\mathbf{X}_s$ represents n records, and each record contains d_s structural features. Normalization calculation is as follows:

$$\tilde{\mathbf{X}}_s = \frac{\mathbf{X}_s - \mu_s}{\sigma_s + \epsilon} \quad (2)$$

μ_s denotes the column vector, indicating the average value of each column. σ_s represents the standard deviation (SD), and ϵ is a positive number to prevent the denominator from being zero. This processing ensures that the model has numerical consistency among different dimensional features.

For unstructured text data $\mathcal{T} = \{t_1, t_2, \dots, t_m\}$, semantic features are extracted by fine-tuning BERT model, and the output is:

$$\mathbf{H}_t = \text{BERT}(\mathcal{T}) = [\mathbf{h}_1; \mathbf{h}_2; \dots; \mathbf{h}_m], \mathbf{h}_i \in \mathbb{R}^{d_t} \quad (3)$$

$\mathbf{h}_i$ is the semantic vector of the i -th text, and the dimension is d_t . This step preserves the semantic relationship between text contexts and forms an important basis for the model to recognize risk semantics.

For spatiotemporal data including trajectory and meteorology, it is expressed as:

$$\mathbf{X}_{st} \in \mathbb{R}^{T \times N \times F} \quad (4)$$

T refers to the time step. N denotes the space node (such as the site number), and F represents the space-time characteristic dimension of each node. ST-GCN is used for modeling, and its core propagation equation is:

$$\mathbf{Z}^{(l+1)} = \sigma(\sum_{k=0}^K \mathbf{A}_k \mathbf{Z}^{(l)} \mathbf{W}_k) \quad (5)$$

$\mathbf{A}_k$ means the adjacency matrix of order k ; $\mathbf{Z}^{(l)}$ indicates the node representation of the l -th layer; $\mathbf{W}_k$ stands for the weight matrix; σ represents the activation function. This network structure can capture the linkage relationship between spatial topology and time evolution.

In the feature fusion stage, the model introduces cross-modal attention mechanism to automatically aggregate multi-source information. Let two modal features be $\mathbf{F}_i$ and $\mathbf{F}_j$ respectively, and their attention weights are calculated as:

$$\alpha_{i,j} = \frac{\exp(\mathbf{F}_i^T \mathbf{W}_a \mathbf{F}_j)}{\sum_k \exp(\mathbf{F}_i^T \mathbf{W}_a \mathbf{F}_k)} \quad (6)$$

After fusion, a unified risk representation vector is obtained:

$$\mathbf{F}_{fusion} = \sum_j \alpha_{i,j} \cdot \mathbf{F}_j \quad (7)$$

This mechanism enables the model to automatically

learn the most discriminating risk signal source when faced with heterogeneous features and semantic diversity.

The hybrid modeling framework is divided into two stages. In the first stage, the improved XGBoost and LightGBM models are run in parallel. The objective function of XGBoost reads:

$$\mathcal{L}_{xgb} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (8)$$

$\hat{y}_i = \sum_{k=1}^K f_k(\mathbf{x}_i)$, which represents the predicted value of sample i . $\Omega(f_k) = \gamma T_k + \frac{1}{2} \lambda \|\omega_k\|^2$ is the regular term of the k -th tree.

To adapt to the dynamic change of time, XGBoost integrates a sliding window statistical module to dynamically adjust the importance of features:

$$I_j^{(t)} = \sum_{s=t-w}^t \quad (9)$$

$\Delta G_j^{(s)}$ indicates the gain change of the j -th feature in the s -th time step. $I_j^{(t)}$ is a dynamic feature importance index within the XGBoost stage, used to reflect gain changes within the sliding window; it is also mainly applied to internal feature selection and dynamic weight adjustment of the first-stage model.

LightGBM introduces the split criterion of time series perception to enhance the ability of anomaly recognition. Let the time series samples be $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T\}$, and its splitting gain is defined as:

$$G_j = \sum_{t=1}^T w_t \cdot \left[\frac{(\sum_{i \in L_t} g_i)^2}{\sum_{i \in L_t} h_i + \lambda} + \frac{(\sum_{i \in R_t} g_i)^2}{\sum_{i \in R_t} h_i + \lambda} \right] \quad (10)$$

g_i and h_i are gradients and second derivatives. L_t and R_t represent the left and right sample sets of the current split, and $w_t = e^{-\beta(T-t)}$ is the time attenuation weight.

In the second stage, GA-RNN is used to capture the high-order risk path. Its node status is updated to:

$$\mathbf{h}_i^{(t)} = \text{GRU}(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} \mathbf{h}_j^{(t-1)}, \mathbf{h}_i^{(t-1)}) \quad (11)$$

$\mathcal{N}(i)$ indicates the neighbor set of node i . α_{ij} is the edge weight under the graph attention mechanism:

$$\alpha_{ij} = \frac{\exp(\text{LeakyReLU}(\mathbf{a}^T [\mathbf{W} \mathbf{h}_i \| \mathbf{W} \mathbf{h}_j]))}{\sum_{k \in \mathcal{N}(i)} \exp(\text{LeakyReLU}(\mathbf{a}^T [\mathbf{W} \mathbf{h}_i \| \mathbf{W} \mathbf{h}_k]))} \quad (12)$$

Finally, the system integrates three kinds of objectives: classification performance, graph structure reconstruction, and feature stability by jointly optimizing the overall loss function.

$\mathcal{L}_{ce}$ is the cross-entropy loss:

$$\mathcal{L}_{total} = \mathcal{L}_{ce} + \lambda_1 \cdot \mathcal{L}_{graph} + \lambda_2 \cdot \mathcal{L}_{reg} \quad (13)$$

The loss of graph structure consistency is:

$$\mathcal{L}_{graph} = \|\mathbf{A} - \hat{\mathbf{A}}\|_F^2 \quad (14)$$

The regular term of characteristic disturbance reads:

$$\mathcal{L}_{reg} = \sum_{j=1}^d \text{Var}(\nabla_{\mathbf{x}_j} \hat{y}) \quad (15)$$

On the system deployment level, GridRiskNet adopts online incremental learning mechanism. Let the current parameter be θ_t , and the model is updated after receiving new samples $(\mathbf{x}_t, y_t)$:

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla_{\theta} \mathcal{L}(\mathbf{x}_t, y_t; \theta_t) \quad (16)$$

η represents the learning rate. ∇_{θ} denotes the gradient operator. This mechanism ensures that the model has adaptive update abilities in a dynamic risk environment.

4 Experimental analysis of GridRiskNet model project investment risk management based on big data mining

4.1 Data used in the study

To verify the risk management capability of the GridRiskNet model for power grid enterprise engineering projects, the study uses three core public datasets for experimental validation and designs a fusion scheme for data heterogeneity. First, the structured data adopts the U.S. Energy Information Administration (EIA) power infrastructure dataset (<https://www.eia.gov/electricity/data.php>). Its API interface screens power grid engineering project data from 2018 to 2023, including budget, construction period, equipment models, and other fields. After extracting the original CSV-format data using Python's eia-python library, adaptive normalization is performed to eliminate dimension differences, which are associated with subsequent spatiotemporal data through project IDs and date fields. Second, the spatiotemporal data selects the National Oceanic and Atmospheric Administration (NOAA) Global Historical Climatology Network-Daily (GHCN-Daily) (<https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00861>). Daily values of temperature, precipitation, and wind speed are downloaded, and stations are matched to the project's geographic coordinates. The rnoaa toolkit converts them

into spatiotemporal tensors, from which meteorological risk features are extracted through ST-GCN encoding. The spatial topology data is obtained from the OpenStreetMap power network dataset (https://wiki.openstreetmap.org/wiki/Power_networks). The OSMnx library extracts GIS data of substations and transmission lines, constructing an adjacency matrix to model the physical connection of the power grid. For unstructured text data, engineering accident reports from 2018 to 2023 corresponding to EIA projects are manually screened from the Federal Energy Regulatory Commission (FERC) engineering accident report library (<https://elibrary.ferc.gov/eLibrary/search>). After parsing the text with Apache Tika, the fine-tuned BERT is input to generate semantic vectors.

The following fusion strategies are adopted to address the heterogeneity of multi-source data. 1) Temporal alignment: All data is uniformly converted to Universal Time Coordinated (UTC) timestamps and aggregated at a granularity of 1 day. 2) Spatial alignment: Meteorological stations, power grid nodes, and engineering sites are associated through GIS coordinate matching (error <1km). 3) Consistency of feature encoding: Structured data is normalized to [0,1], text vectors are unified into 768 dimensions via BERT, and spatiotemporal data is compressed into 256-dimensional features through ST-GCN. 4) Cross-modal attention mechanisms automatically learn the weights of each modality, assigning higher attention scores to extreme meteorological text descriptions (such as "hurricane damage"). The specific process of importing data into GridRiskNet is presented in Figure 3.

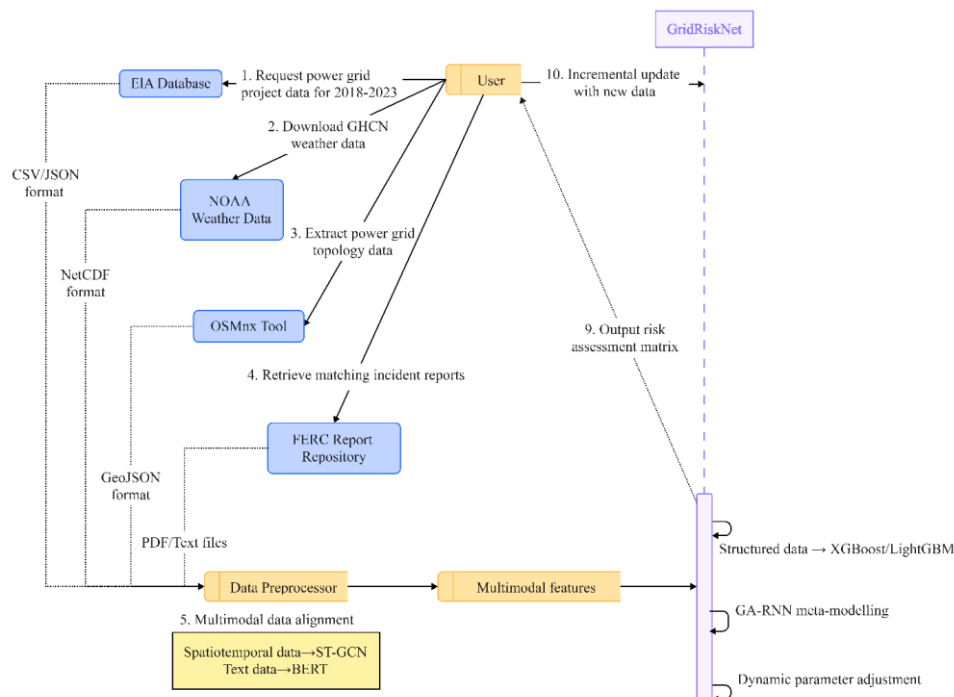


Figure 3: The specific process of importing data into GridRiskNet

4.2 GridRiskNet model's thinking on risk management ability analysis of power grid enterprises' engineering projects

The study is conducted from two aspects to effectively analyze the risk management capability of the GridRiskNet model for power grid enterprise engineering projects. First, at the level of risk probability distribution, the probability of risks such as budget overrun and construction period delay is evaluated based on structured data and spatiotemporal features [23]. Second, at the level

of potential impact scope, the propagation path of risks in the power grid topology is analyzed through GNN to identify high-risk nodes and their potentially affected surrounding areas. The model inputs the fused multi-dimensional features into a two-stage modeling framework and outputs a risk assessment matrix including the above two types of indices to support the refined and structured management and decision-making of power grid project risks [24, 25]. The entire analysis's key indices and evaluation criteria are exhibited in Tables 1 and 2.

Table 1: Explanation of key indices for analysis using the GridRiskNet model

Analytical dimension	Index	Data source/calculation method	Description
Risk probability distribution analysis	Risk PCA Projection Score	Principal component score of high-dimensional risk vector output by the GridRiskNet model after PCA dimensionality reduction	Reflecting the distribution position of samples in the risk principal component space, and is used to identify high-risk clustering or structural abnormal samples.
	Time-series Anomaly Frequency	The capture times of abnormal events in LightGBM	Monitoring the frequency of abnormal progress.
	Model Confidence Score	Softmax outputs the maximum probability value	Evaluating the credibility of the model output
	Risk Coefficient of Variation	The ratio of SD to the mean value of the risk probability distribution	Assessing the dispersion degree of risk probability distribution, the greater it is, the higher the risk instability is.
	Risk Importance Index	Comprehensive weighted scores of multiple dimensions	Representing the strength of risk influence
Analysis of the potential influence range	Risk Entropy	Information entropy calculation of risk probability distribution	The degree of uncertainty in evaluating risk results.
	Risk Propagation Path Length	Critical path length identified in GA-RNN	Length and complexity of the risk propagation path
	Node Vulnerability Score	The weighted average of the affected probability of each node in GNN	Reflect the vulnerability of nodes in the power grid
	Risk Impact Radius	Based on propagation path depth and the spatial adjacency matrix in the graph structure	Indicating the physical scope of risk propagation

Table 2: Criteria for determining key indices in the GridRiskNet model analysis

Index	Type	Criteria
Risk PCA Projection Score	Secondary calculation	- [0, 2) Low projection; [2, 5) Medium projection; ≥ 5 High projection, tending to abnormal samples or extreme types
Time-series Anomaly Frequency	Model output	- [0, 2) Normal; [2, 5) Early warning; ≥ 5 Abnormal
Model Confidence Score	Model output	- [0.9, 1] High credibility; [0.7, 0.9) Medium credibility; < 0.7 Low credibility
Risk Coefficient of Variation	Secondary calculation	- [0, 0.3) Stable; [0.3, 0.6) Fluctuating; ≥ 0.6 Highly unstable
Risk Importance Index	Secondary calculation	- [0, 40) Secondary; [40, 70) Important; [70, 100] Critical
Risk Entropy	Secondary calculation	- [0, 1) Low uncertainty; [1, 2) Medium; ≥ 2 High
Risk Propagation Path Length	Model output	- [1, 3) Local; [3, 6) Regional; ≥ 6 Global
Node Vulnerability Score	Model output	- [0, 0.4) Low; [0.4, 0.7) Medium; [0.7, 1] High
Risk Impact Radius	Secondary calculation	- [0, 5) Station level; [5, 20) Line level; ≥ 20 Regional level

In Table 2, the index equations involved in secondary calculation are as follows:

(1) Risk PCA Projection Score
Here, "Risk PCA Projection Score" measures the

position of a sample in the dominant risk structure within the risk feature space, revealing the main variation trends in complex multi-dimensional risk features. Specifically, this index is calculated based on the PCA method. First, it standardizes the annual high-dimensional risk features (such as cost overrun risk, environmental and climate pressure, etc.). Then, it extracts the first K principal component directions and measures the sample's projection value in the principal component space through eigenvalue weighting. This score reflects the degree of variance contribution of the sample along the principal component axis of risk, rather than a simple sum of the scores of each risk factor. Due to the different statistical distributions of risk features each year, this index changes with the year; it comprehensively reflects the overall trend of the risk structure of power grid projects in the current year and potential abnormal clustering characteristics. The calculation is expressed as:

$$s_i = \sum_{k=1}^K \lambda_k \cdot (\mathbf{u}_k^T (\mathbf{x}_i - \boldsymbol{\mu}))^2 \quad (17)$$

$\mathbf{x}_i$ represents the high-dimensional risk feature vector of the i -th sample. $\boldsymbol{\mu}$ indicates the sample mean vector. $\mathbf{u}_k$ denotes the feature vector in the direction of the k -th principal component. λ_k is the feature value of the k -th principal component, and K means the number of selected principal components.

(2) Risk Coefficient of Variation

This index is used to measure the relative dispersion of risk probability distribution, which is an important index reflecting risk instability. This index describes the fluctuation range of various risk probabilities in the whole by calculating the ratio of the SD of risk probability to the mean. A higher value indicates that the risk probability distribution is more dispersed and the overall instability is stronger. The expression is:

$$CV = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (p_i - \bar{p})^2}}{\bar{p} + \epsilon} \quad (18)$$

p_i denotes the prediction probability of Class i risk. $\bar{p}$ means the average value of various risk probabilities, and n represents the total number of risk categories.

(3) Risk Entropy

"Risk Entropy" measures the degree of uncertainty in the risk probability distribution, reflecting the discreteness and unpredictability of risk results. Based on information entropy theory, this index reveals the potential risk mixture in the system by calculating the entropy value of the probability of all risk categories. A higher risk entropy value indicates more uncertainties in

the system, which helps to identify complex and unpredictable risk scenarios, represented as:

$$H = - \sum_{i=1}^n p_i \cdot \log_2 (p_i + \epsilon) \quad (19)$$

H denotes the information entropy of risk distribution.

(4) Risk Importance Index

This index quantifies the comprehensive contribution of each risk feature to the overall risk assessment results. It reflects the importance level of each risk feature by weighted accumulation of the impact degree of each feature on the model loss and normalized averaging combined with model weights. Features with higher values play a greater role in the overall risk decision-making, expressed as:

$$RI_j = \frac{1}{T} \sum_{t=1}^T \left(\frac{w_j^{(t)} \cdot \Delta L_j^{(t)}}{\sum_{k=1}^d \Delta L_k^{(t)}} \right) \quad (20)$$

RI_j represents the risk importance index of the j -th feature, which is a risk importance index in the entire GridRiskNet framework. It is comprehensively calculated based on the feature weights and loss impact during the global model training process, belonging to a unified index at the global level. T means the number of model iterations or average times; $w_j^{(t)}$ refers to the model weight of the j -th feature in the t -th iteration; $\Delta L_j^{(t)}$ is the influence degree of the j -th feature on the loss function; d denotes the total number of features.

(5) Risk Impact Radius

It evaluates the spatial propagation range of risks in the power grid graph structure, serving as a key index for measuring the physical scope affected by risks. This index calculates the average impact radius of all risk source nodes in the network based on the power grid topology, geographical distance between nodes, and risk propagation probability. A larger value indicates a wider spatial propagation range of risk events, which is applied to regional risk impact analysis, as follows:

$$R = \frac{1}{N_s} \sum_{i=1}^{N_s} \sum_{j=1}^N t_{ij} \cdot d_{ij} \cdot p_{ij} \quad (21)$$

N_s represents the number of risk source nodes. N denotes the total number of nodes in the graph. t_{ij} is the adjacency relationship between nodes i and j (1 means connection). d_{ij} means the geographical distance between nodes. p_{ij} refers to the risk propagation probability from nodes i to j .

Figure 4 presents the pseudocode of the index implementation involving secondary calculation.


```

import math
import numpy as np

# 1. Risk PCA Projection Score
def compute_risk_pca_projection_scores(X, K):
    mu = np.mean(X, axis=0)
    X_centered = X - mu
    cov_matrix = np.cov(X_centered, rowvar=False)
    eigenvalues, eigenvectors = np.linalg.eigh(cov_matrix)
    sorted_idx = np.argsort(eigenvalues)[::-1]
    eigenvalues = eigenvalues[sorted_idx][:K]
    eigenvectors = eigenvectors[:, sorted_idx][:, :K]

# 2. Risk Coefficient of Variation
def compute_risk_cv(probabilities):
    mean_p = np.mean(probabilities)
    std_p = np.std(probabilities)
    epsilon = 1e-6
    return std_p / (mean_p + epsilon)

# 3. Risk Entropy
def compute_risk_entropy(probabilities):
    epsilon = 1e-6
    return -sum(p * math.log2(p + epsilon) for p in probabilities)

# 4. Risk Importance Index
def compute_risk_importance(weights, delta_losses):
    T = len(weights)
    D = len(weights[0])
    importance = [0.0] * D
    for j in range(D):
        for t in range(T):
            total_delta = sum(delta_losses[t][j])
            if total_delta == 0:
                continue
            importance[j] += weights[t][j] * delta_losses[t][j] / total_delta
        importance[j] /= T
    return importance

# 5. Risk Impact Radius
def compute_risk_impact_radius(adj_matrix, distance_matrix,
    propagation_probs, source_nodes):
    N = len(adj_matrix)
    total_radius = 0.0
    for i in source_nodes:
        for j in range(N):
            if adj_matrix[i][j] == 1:
                total_radius += distance_matrix[i][j] * propagation_probs[i][j]
    return total_radius / len(source_nodes)

```

Figure 4: Pseudocode of index implementation involving secondary calculation

The experimental environment and key parameters are detailed in Table 3.

Table 3: Experimental environment and key parameters arrangement of the study

Category	Configuration item	Parameter setting
Hardware environment	Computing platform	NVIDIA A100 (40GB memory) × 4
	CPU	AMD EPYC 7763 (64-core)
Software environment	Memory	512GB DDR4
	Deep learning framework	PyTorch 1.12 + CUDA 11.6
	GNN library	PyTorch Geometric 2.2.0
	Traditional ML library	XGBoost 1.6 + LightGBM 3.3.2
Model architecture	NLP toolkit	HuggingFace Transformers 4.25 (BERT-base)
	ST-GCN layer number	3 layers (hidden layer dimension =256)
	GA-RNN unit	Graph Attention Layer (number of heads =8) +GRU (hidden layer =512)
Training parameters	Transmodal attention mechanism	Multi-attention (number of heads =4, fusion dimension =1024)
	Batch size	256 (structured data)/32 (graph data)
	Initial learning rate	3e-4 (AdamW optimizer)
	regularization	L2 Weight Attenuation =1e-5+Dropout=0.3
	Early stop mechanism	The loss of verification set does not decrease for 10 consecutive rounds

The study designs ablation experiments before conducting formal experiments to verify the actual contribution of each core component of GridRiskNet. It seeks to quantitatively measure the impact of different modules on the model's overall performance from a systematic perspective. Specifically, four ablation versions are set by sequentially disabling the cross-modal attention mechanism, the risk propagation modeling module of GA-RNN, the dynamic feature selection module, and the risk propagation graph reconstruction term in the joint loss function. All experiments maintain

the same hyperparameter configuration on the complete dataset, focusing on evaluating three indices. These indices include risk classification performance (F1-score, Receiver Operating Characteristic - Area Under Curve (ROC-AUC)), risk propagation accuracy (Risk Impact Radius error), and uncertainty quantification ability (Risk Entropy). This experiment aims to clarify the mechanism of action of each module, especially their specific contributions to power grid risk transmission modeling, modal feature fusion, and risk stability control. The results of the ablation experiments are listed in Table 4.

Table 4: Ablation experimental results of the GridRiskNet model

Ablation version	F1-Score	ROC-AUC	Risk Impact Radius error (km)	Risk Entropy
Full GridRiskNet	0.892	0.962	4.8±0.9	0.89
No cross-modal attention	0.835	0.917	7.5±1.6	1.12
No GA-RNN	0.846	0.926	14.2±2.3	0.96
No dynamic feature selection	0.863	0.941	5.7±1.2	0.94
Risk-free propagation graph reconstruction	0.871	0.948	4.9±1.0	2.08

The results of the ablation experiments indicate that each module of GridRiskNet makes a significant contribution to the model performance. The cross-modal attention mechanism is particularly crucial in improving classification performance; after being disabled, the F1-score decreases by 6.4%, the ROC-AUC drops by 4.7%, and the Risk Entropy rises significantly. This shows that this module significantly impacts the collaborative perception of complex semantic and meteorological features. The risk propagation modeling module of GA-RNN notably improves the Risk Impact Radius error; after being disabled, the error increases sharply to 14.2 km, verifying its core role in power grid topology modeling. The dynamic feature selection module mainly enhances the temporal sensitivity of the model; its removal leads to a significant drop in F1-score, although it has a limited impact on propagation errors. The risk propagation graph reconstruction term has a significant effect on suppressing prediction fluctuations and

optimizing uncertainty quantification; its elimination causes a substantial rise in Risk Entropy. Overall, GridRiskNet achieves the unity of high performance and high robustness through the collaboration of various modules, with all components being indispensable.

4.3 Analysis Results of GridRiskNet model on risk management ability of power grid enterprises' engineering projects

4.3.1 Risk probability distribution analysis

GridRiskNet's annual Risk PCA Projection Score results for power grid enterprise engineering projects are summarized in Table 5.

Table 5: Annual Risk PCA Projection Score results

Year	Cost overrun risk C1	Ambient climate pressure C2	Equipment technical risk C3	Supply chain fluctuation C4	Policy compliance risk C5	Risk PCA Projection Score	Risk tendency
2018	1.235	0.873	-0.452	0.217	0.095	2.108	Middle projection (structural abnormality)
2019	0.892	0.654	-0.128	-0.304	0.062	1.546	Low projection
2020	2.874	1.982	1.235	-0.873	0.517	4.856	High projection (extreme type)
2021	1.023	1.457	0.782	0.396	-0.215	2.48	Middle projection
2022	3.125	2.769	2.014	1.358	-0.947	5.894	High Projection (abnormal clustering)
2023	4.562	3.217	3.058	2.146	1.372	7.779	High projection (extreme anomaly)

Table 5 shows that cost overrun risk (C1) and environmental climate pressure (C2) have always been the dominant risks, especially showing exponential growth after 2020. In 2023, C1 (4.562) increased by 269% compared with 2018 (1.235), which is highly consistent with the reality of global inflation and frequent extreme weather. The sudden turn positive (1.372) of policy compliance risk (C5) in 2023, to some extent, reveals the surge of compliance costs brought by the deepening of

the "double carbon" policy. The model reflects high-risk clustering scenarios such as C1-C3 in 2023 through the spatial distribution of principal components, reflecting the early warning of composite risks.

Based on the above analysis, the risk probability distribution analysis of grid enterprise engineering projects by GridRiskNet is organized, and the annual average results of other indices are shown in Figure 5.

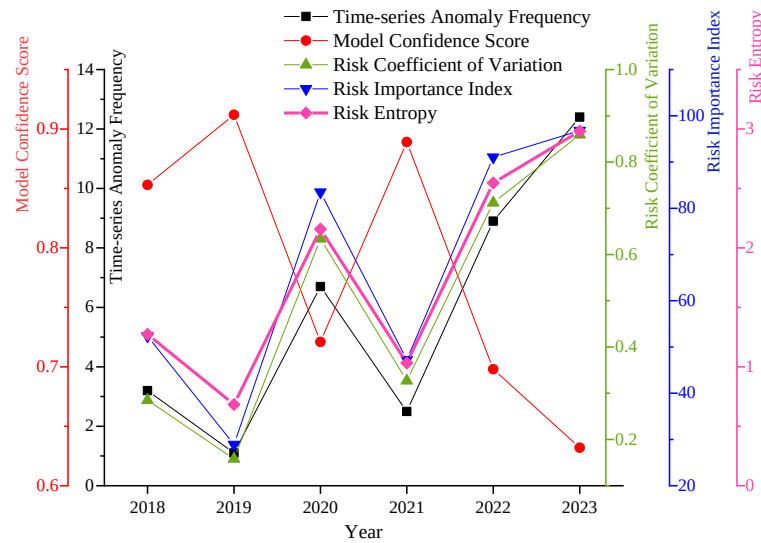


Figure 5: The annual average results of other indices in GridRiskNet risk probability distribution analysis

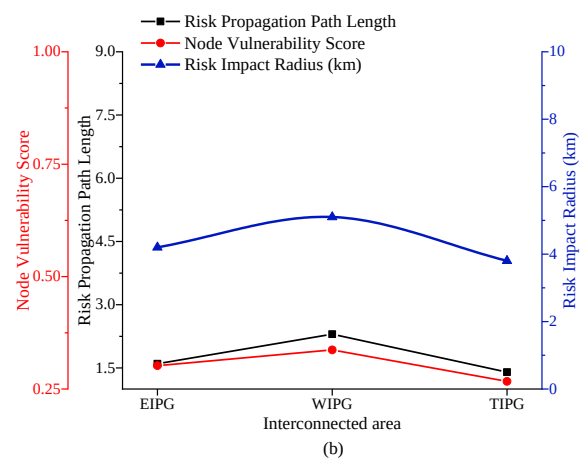
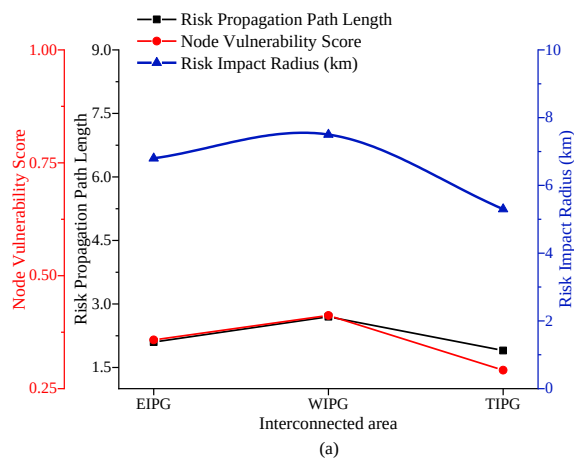
Note: The curves of each index correspond one-to-one with the corresponding color coordinate axes on the right

In Figure 5, regarding the frequency of time-series anomalies, the average annual growth rate of abnormal events during 2019–2023 reached 65.7%. The model objectively reflects the increasing complexity of risks through the continuous decline in confidence (from 0.912 to 0.632). The sudden increase in risk entropy (2.158) in 2020 preceded the peak of the importance index (83.47); this indicates that GridRiskNet can capture the implicit correlations of risk factors through information entropy. The synchronous increase in the coefficient of variation (from 0.712 to 0.859) and risk entropy (from 2.547 to 2.981) after 2022 reveals the transformation trend of risk distribution from centralized to discretized; this provides key evidence for power grid enterprises to optimize the allocation of risk reserve funds. The core advantage of the model lies in the quantitative modeling of the dynamic coupling relationship among the three dimensions of engineering anomalies, risk uncertainty, and impact degree. Meanwhile, it realizes the full-chain risk

assessment from "anomaly detection" to "impact prediction".

4.3.2 Analysis of potential influence range

The study divides the U.S. power grid into three major regions: The Eastern Interconnection Power Grid (EIPG), the Western Interconnection Power Grid (WIPG), and the Texas Interconnected Power Grid (TIPG). The EIPG covers the eastern, midwestern, and parts of southern U.S. states, extending northward to eastern Canada. The WIPG covers most western U.S. states, connecting with western Canada in the north and reaching parts of Mexico in the south. The TIPG includes most of Texas. These regional grids are interconnected at limited DC points but mostly operate independently. Based on this, GridRiskNet's analysis results on the potential impact scope of power grid enterprise engineering projects are displayed in Figure 6.



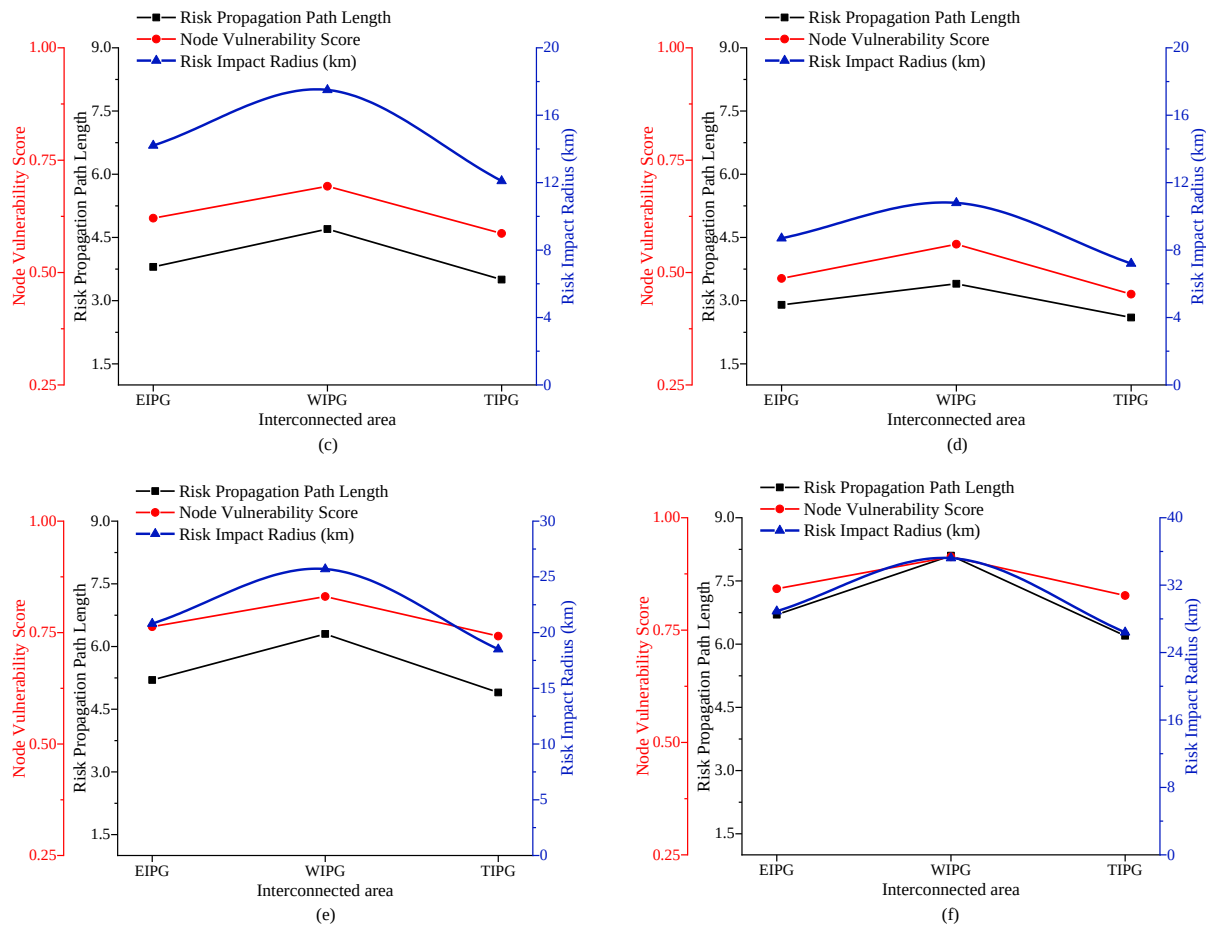


Figure 6: Analysis of GridRiskNet's potential impact on power grid enterprise engineering projects ((a) 2018; (b) 2019; (c) 2020; (d) 2021; (e) 2022; (f) 2023)

Note: The curves of each index correspond one-to-one with the corresponding color coordinate axes on the right

Based on index definitions and annual data, GridRiskNet demonstrates a scientific nature and structural insight in the analysis of potential impact ranges. First, for Risk Propagation Path Length, WIPG remains at a high level throughout the entire period, reaching 8.1 in 2023, significantly exceeding that of other regions. This gap is not accidental but a reflection of long-term structural characteristics, revealing the extensibility of transmission links in the western power grid due to complex terrain and diverse energy structures. Second, the changing trend of Node Vulnerability Score is more enlightening; the three major power grids' scores all rose sharply in 2020, with the average value doubling compared to the previous year. This synchronous surge highly aligns with the global external shock events in 2020, indicating that the model is highly sensitive to network vulnerability under systemic disturbances.

In addition, the Risk Impact Radius index essentially measures the physical diffusion capacity of risks from source nodes to the surrounding space; its calculation integrates network topology, geographical distance, and propagation probability. According to the data, WIPG's Risk Impact Radius rapidly increased from 10.8 km in 2021 to 25.7 km in 2022, and further to 35.2 km in 2023, with a cumulative increase of over 225% in two years. TIPG also showed a continuous expansion between 2022

and 2023, reaching 26.4 km in 2023, reflecting the significant cumulative effect of regional risk diffusion. This significant spatial diffusion trend is not caused by single-year fluctuations but by the accumulation of continuous transmission chains. Its essence is the scope expansion of power grid risks through multiple rounds of transmission and cross-node amplification, which is more obvious, especially in scenarios with multiple overlapping risks. The reason why GridRiskNet can effectively capture this phenomenon lies in the deep coupling of its GNN and propagation probability mechanism. It can dynamically track the evolution of risk paths and ranges in complex networks, thereby identifying the critical points and amplification effects of risk diffusion. Therefore, it possesses real value in regional risk monitoring and trend early warning. The capture of this cumulative diffusion trend reflects the model's structural sensitivity to "spatiotemporal overlapping risks", which far exceeds the single-description capability of traditional static indices.

4.3.3 Comparative Analysis of GridRiskNet and other models

To comprehensively evaluate the GridRiskNet model's effectiveness in investment risk management of

power grid engineering projects, this study designs two types of comparative experiments. The first type is a horizontal comparison with existing State-of-the-Art (SOTA) models. It selects representative models in risk assessment, regional propagation modeling, and uncertainty quantification in recent years, including methods such as CNN-LSTM, to ensure fair comparison under a unified dataset and the same task indices. The comparison covers risk classification performance (F1-Score, ROC-AUC), regional propagation accuracy (Risk Impact Radius error), and uncertainty quantification

ability (Risk Entropy) to reflect the model's comprehensive capabilities. The second type is a detailed comparison with classic baseline models, comparing individual methods such as XGBoost, LightGBM, ST-GCN, and BERT-BiLSTM. It focuses on examining the model's performance in robustness, spatial-temporal feature extraction, anomaly detection, etc. It highlights the advantages of GridRiskNet in multimodal data fusion, dynamic feature learning, and risk path modeling. The results of the two types of comparisons are exhibited in Tables 6 and 7.

Table 6: Comparison of the performance of GridRiskNet and SOTA models on the same dataset

Model	Researchers	F1-Score↑	ROC-AUC↑	Risk Impact Radius error $\pm\sigma$ (km) ↓	Risk Entropy↓
CNN-LSTM	Dong and Li (2025)	0.724	0.892	28.3 $\pm$ 4.1	1.87
The investment framework based on graph attention networks	Mostofi et al. (2025)	0.781	0.903	22.6 $\pm$ 3.8	1.52
Topic model clustering	Qi (2025)	0.698	0.841	-	2.03
DNN based on transfer learning	Luo and Zhu (2024)	0.763	0.885	-	1.68
GridRiskNet	The proposed model	0.892	0.962	4.8 $\pm$ 0.9	0.89

Table 7: Robustness comparison results of GridRiskNet and baseline models

Model	F1-Score	Risk Impact Radius error $\pm\sigma$ (km)	Recall for delay anomaly detection
XGBoost	0.712	32.5 $\pm$ 6.2	0.683
LightGBM	0.735	29.8 $\pm$ 5.4	0.721
ST-GCN	0.683	18.7 $\pm$ 3.5	0.592
BERT-BiLSTM	0.698	-	0.654
GridRiskNet	0.892	4.8 $\pm$ 0.9	0.937

The SOTA model's comparison experiment reveals that GridRiskNet achieves considerable leadership in risk classification, propagation modeling, and uncertainty quantification. Although the GAT investment framework performs well in traditional graph learning tasks, it cannot deeply integrate complex semantic features and meteorological data, leading to an underestimation of risks in some catastrophic events. In contrast, GridRiskNet fully captures the coupling relationship between accident texts and meteorological variables through cross-modal attention mechanisms and dynamic feature fusion, and is significantly superior to other models in F1-score and ROC-AUC. Meanwhile, its GARNN structure can accurately model risk transmission paths under power grid topology, greatly reducing Risk Impact Radius error. This verifies its high fitting ability to the physical characteristics of power grids. Regarding uncertainty control, GridRiskNet effectively suppresses

prediction fluctuations in high-risk scenarios through the risk propagation graph reconstruction mechanism in the joint loss function, minimizing Risk Entropy and showing stronger stability of risk distribution.

In the comparison with baseline models, GridRiskNet also demonstrates excellent robustness and overall advantages. Compared with XGBoost and LightGBM, GridRiskNet not only improves the F1-score but also is much higher than other models, showing strong adaptability in complex dynamic data environments. Concerning regional propagation accuracy, the Risk Impact Radius error of GridRiskNet fluctuates very little; it is far better than ST-GCN, which only considers spatiotemporal features, proving the effectiveness of its spatial topology and semantic information fusion strategy. Regarding time-series anomaly detection, GridRiskNet combines dynamic feature selection and time-series-aware splitting

strategies, notably improving the recall and detecting potential abnormal risks earlier. Overall, GridRiskNet outperforms existing mainstream methods in multi-dimensional tasks, having high accuracy and robustness; it also has a more suitable direction in key links of power grid engineering risk management, such as risk transmission, modal coupling, and dynamic prediction.

4.3.4 GridRiskNet training cost and efficiency analysis

Tests on computing cost and efficiency are conducted to evaluate the engineering practicality of

GridRiskNet. The training efficiency in a complete production environment is tested on an NVIDIA A100×4 cluster, with the following records. They encompass: (1) average convergence time in the training phase (in hours (h)); (2) maximum inference delay per sample in the inference phase (in milliseconds (ms)); (3) peak memory consumption (in gigabyte (GB)); (4) training time per 0.01 F1-Score (in h). Under the condition of meeting the needs of offline batch processing and periodic risk monitoring in power grids, the practical controllability of GridRiskNet is scientifically measured. The analysis results are suggested in Table 8.

Table 8: Analysis results of the training cost and efficiency of GridRiskNet and baseline models under the same dataset

Model	Convergence time (h)	Maximum inference delay per sample (ms)	Peak memory consumption (GB)	Training time per 0.01 F1-Score (h)
XGBoost	1.2	0.09	1.5	0.17
LightGBM	1.0	0.07	1.2	0.14
ST-GCN	8.5	0.36	5.1	1.25
BERT-BiLSTM	12.3	0.45	6.4	1.77
GridRiskNet	17.8	0.63	9.8	2.00

According to the results in Table 8, although GridRiskNet has a longer absolute training time (17.8 h) and higher single-sample inference delay (0.63 ms) than other models, its key index "training time per 0.01 F1-score" is 2 h, which is lower than that of BERT-BiLSTM (1.77 h), bringing greater benefits. This indicates that its high complexity effectively "exchanges for performance" with obvious non-linear returns. Moreover, the inference delay of 0.63 ms is still far lower than the acceptable threshold (usually at the second level) in offline power grid risk prediction, making it suitable for daily or even hourly scheduling scenarios. The memory consumption of GridRiskNet matches the typical Graphic Processing Unit configuration of power enterprises (<10 GB), making deployment feasible. Overall, although GridRiskNet has a higher training cost, it has the advantages of high performance returns, controllable inference, and resource affordability, thus making the feasibility for practical engineering applications.

4.4 Discussion

It should be explained that the experimental data of this study are based on U.S. sources (EIA, NOAA, OSM). However, the research on investment risk issues of power grid engineering projects has a high degree of commonality and structural consistency. The core lies in the complexity of the investment process, construction environment, and risk chain of power grid projects, not limited to specific countries. Cost overrun, climate pressure, equipment technical failure, supply chain fluctuation, and policy compliance risks (C1-C5) are five key risks commonly faced by global power grid projects. Among them, "policy compliance risk" is abstracted in the model as an index of institutional environment

uncertainty to describe the impact of policy changes on project risks. It essentially structurally summarizes policy volatility and does not depend on specific legal provisions. At the same time, GridRiskNet focuses on risk propagation mechanisms and multimodal feature fusion, and its methodology is a universal architecture for global engineering projects. Therefore, even with U.S. data, the revealed coupling relationships and propagation mechanisms of multi-source heterogeneous risks have high reference value for Chinese power grid enterprises.

Additionally, the advantages of GridRiskNet over existing SOTA models are reflected not only in the superiority of indices but also in innovative breakthroughs in methodological mechanisms. First, regarding risk classification, GridRiskNet introduces a cross-modal attention mechanism to deeply explore the coupling relationship between accident texts and meteorological features. It effectively makes up for the perception defects of traditional single-modal models in complex scenarios. This enables its F1-score and ROC-AUC to be significantly better than those of models such as GAT. Second, in regional propagation modeling, GridRiskNet is based on the GA-RNN structure and embeds a risk propagation graph reconstruction mechanism. It can dynamically identify key transmission paths in the power grid topology and accurately capture the risk diffusion process. Thus, it can minimize the Risk Impact Radius error and demonstrate high fitting ability to the physical structure of the power grid. Third, for uncertainty quantification, the joint loss function design of GridRiskNet integrates classification error, graph reconstruction error, and feature stability regularization terms. This helps to control prediction fluctuations in high-risk scenarios and reduces risk entropy to the lowest level. Compared with SOTA models that mainly rely on

traditional graph networks or single deep models, GridRiskNet realizes the collaborative optimization of structured, spatiotemporal, and semantic data. Its core innovation lies in the deep integration of the three mechanisms: "dynamic feature learning, propagation path modeling, and risk distribution stability". This not only improves model performance but also achieves a balance between the complexity of risk perception, path interpretability, and prediction stability, possessing high practical value and theoretical promotion potential.

5 Conclusion

This study constructs the GridRiskNet risk management system based on big data mining around the intelligent management needs of investment risks in power grid enterprise engineering projects. It also realizes the fusion modeling and dynamic evaluation of structured, unstructured, and spatiotemporal data. Through the two-stage modeling architecture, the model performs well in risk probability distribution identification and regional propagation path modeling. The experimental results show that GridRiskNet has strong risk structure identification and regional difference perception abilities under multiple indices. From 2020 to 2023, the Risk PCA Projection Score has significantly climbed, revealing the dominant position of cost overrun, climate pressure, and equipment risk in the evolution of engineering risks. At the same time, the model can effectively capture the changing trends of risk path length and impact radius in the analysis of the potential impact scope of each power grid region. Moreover, it can identify the propagation characteristics of structural vulnerability of the western power grid and the high-impact radius of the Texas power grid, providing quantitative support for regional risk management.

Although GridRiskNet shows strong comprehensive performance in the experiment, there is still room for further optimization. The current model still relies on a fixed attention mechanism in the fusion process between different data modalities, which struggles to fully characterize the dynamic coupling relationship between heterogeneous features due to time and place. In addition, the physical constraint mechanism is not introduced in the risk propagation modeling, and the mapping accuracy of the actual operation state of the power grid still has room for improvement. Follow-up research can further introduce reinforcement learning and physical graph embedding methods to improve the model's adaptability to dynamic environmental changes. Furthermore, expanding the model to broader scenarios such as new energy access and emergency dispatching supports the intelligent transformation of investment risk management of power grid enterprises in a pluralistic and complex environment.

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