

Multivariate Ice-Covering Prediction on Transmission Lines Using CEEMDAN-SC-LSTM and CNN-GRU-Attention Models

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In the power system, ice-covering on transmission lines in high-altitude areas can easily cause serious problems like increased line weight and wire breakage. To accurately predict the ice-covering and issue timely warnings to ensure the reliable operation, a method for predicting ice-covering in high-altitude areas based on Long Short-Term Memory (LSTM) and deep learning methods is proposed. In the feature extraction stage, a model for ice-covering feature extraction of transmission lines in cold regions based on CEEMDAN-SC-LSTM is proposed, combining spectral clustering, fully adaptive noise set empirical mode decomposition algorithm, and LSTM. This model can utilize the advantages of each algorithm to effectively decompose and cluster ice-covering data, extracting more representative features. A Multivariate Deep Regression (MDR) is built by integrating convolutional neural networks, gated recurrent units, and attention mechanisms, using the extracted features related to ice thickness changes as input. The experiment is based on a dataset collected from a specific main transmission line in a high-altitude mountainous area in western China from October 2024 to March 2025. The results showed that the prediction model had a coefficient of determination of 0.9887, an average absolute error of 0.0130, a root mean square error of 0.0142, and an average absolute percentage error of 1.2558%. Compared with baseline models such as support vector regression and random forest regression; the model can predict ice thickness more accurately. The early warning platform based on this method can effectively deliver ice-covering early warning, providing decision-making basis for power grid operation and maintenance. The warning platform based on this method can effectively deliver ice-covering warnings, providing decision-making basis for power grid operation and maintenance.

Povzetek: Študija predstavlja metodo globokega učenja za natančno napovedovanje in zgodnje opozarjanje na poledenitev visokonapetostnih daljnovodov, s čimer se izboljša zanesljivost obratovanja in vzdrževanja elektroenergetskega sistema.

1 Introduction

Ensuring the safe and stable operation of transmission lines in high-altitude regions is crucial for regional economic development and normal social functioning. However, the unique climate conditions in high-altitude regions make ice-covering on transmission lines a major threat to the operation [1]. The ice-covering phenomenon not only increases the weight of transmission lines, causing towers to deform or even collapse under excessive pressure, but also changes the electrical characteristics of the lines, leading to electrical faults such as flashover and short circuits. In severe cases, it can cause large-scale power outages and bring huge economic losses to society [2-3]. Driven by deep learning technology, it has shown great potential in time series prediction and feature extraction [4]. However, the time series data of ice-covering in high-altitude regions have characteristics such as nonlinearity, sudden changes, and uncertainty, as well as seasonal patterns, which make it difficult for traditional prediction methods to

accurately capture complex patterns in the data. There are many factors that affect the ice-covering, such as climate, terrain, and line characteristics, which are intertwined and further increase the prediction difficulty [5-6].

To monitor images of overhead power lines covered in ice, Hao et al. recognized insulator and ice type images of overhead power lines based on deep weakly supervised learning and transfer learning, which reduced the interference of external factors. The precision, recall, and average accuracy reached 86.6%, 91.3%, and 90.1%, and the recognition speed reached 8ms/image [7]. The ice layer poses a threat to power systems, and the generated heat can prevent the growth of the ice layer. Therefore, Huang proposed a preventive scheduling model to alleviate frost and ice-covering phenomena by optimizing the power loss distribution on ice-covering transmission lines. The preventive scheduling model could avoid ice-covering during mild ice disasters, and effectively suppress the growth of ice-covering during

severe storms when complete deicing was not possible [8]. To deliver early warning of ice-covering and ensure safe operation, Zhang et al. introduced a mesoscale digital intelligent weather forecasting technology that considered the micro terrain to monitor and warn ice-covering on provincial power grid transmission lines. This method achieved significant results in achieving precise line inspection, enhancing the anti-ice-covering and disaster reduction capabilities [9]. To optimize the reliability of power supply in the distribution network, Yan et al. analyzed the current status of direct current deicing technology. A deicing system consisting of two

sets of voltage source direct current deicing devices was proposed. The system had good effects on deicing and reactive power compensation, which could improve the power supply reliability [10]. Ice can reduce the electrical performance of insulators. To evaluate the ice-covering risk on insulators, Liang et al. built a method to automatically calculate the ice-covering parameters. The method could quantify the morphology and distribution of ice in the image, with a minimum processing time of 4.4s [11]. The summary of work is shown in Table 1.

Table 1: Summary of related work

Method	Dataset Type and Scale	Evaluation Metrics	Limitations	Reference
Deep Weakly Supervised Learning	Image data (quantity not specified)	Accuracy 86.6%, Recall 91.3%	Time-series characteristics not considered	Hao et al. [7]
Preventive Dispatch Model	Simulation data (scale not specified)	Inhibition effect on ice growth	Relies on power loss optimization	Huang [8]
Mesoscale Weather Forecast Technology	Provincial power grid monitoring data	Improved inspection accuracy and de-icing decision-making	Limited micro-terrain adaptability	Zhang et al. [9]
DC De-icing System	Experimental data	Improved power supply reliability	Ice prediction accuracy not quantified	Yan et al. [10]
Equal-Height Ridge Valley Analysis	Insulator image data	Single image processing time 4.4 seconds	Limited to morphological analysis, no prediction function	Liang et al. [11]
CEEMDAN-SC-LSTM+MDR	4320 time-series data points	R^2 , MAE	High model complexity	Research Method

In summary, existing research in the field of predicting and monitoring ice-covering on transmission lines has achieved results, but there are still certain shortcomings. Firstly, insufficient consideration is given to the complex characteristics of ice-covering data, and the time series data is nonlinear, abrupt, and seasonal, making it difficult for traditional methods to accurately capture patterns. In addition, the consideration of influencing factors is not comprehensive, and multiple factors such as climate, terrain, and power line characteristics are intertwined. Existing research has not been fully integrated. In addition, feature extraction methods are not efficient and accurate enough to extract key features from multivariate data, and prediction models have limitations in handling long-term dependencies and automatically focusing on important features, resulting in poor prediction accuracy. To address these challenges, an innovative method for predicting ice-covering in high-altitude regions based on Long Short-Term Memory (LSTM) and deep learning techniques is proposed. In the feature extraction stage, considering the complexity and diversity of ice-covering data, a Complete Ensemble Empirical Mode Decomposition with Adaptive Noise - Spectral clustering - LSTM (CEEMDAN-SC-LSTM) ice-covering feature extraction model is built by combining SC, CEEMDAN algorithms, and LSTM. The model fully leverages the strengths of various algorithms. It effectively

decomposes and clusters ice-covering data, thereby extracting more representative features. In terms of predictive model construction, combining CNN, GRU, and attention mechanism models, the extracted features related to changes in ice-covering thickness are used as inputs to construct a Multivariate Deep Regression (MDR) for predicting ice-covering based on deep learning and multivariate regression. Finally, based on this prediction method, a power grid line ice-covering warning platform suitable for high-altitude regions is designed based on data and models. The research aims to use this method to comprehensively and real-time monitor the ice-covering on transmission lines, and issue timely warnings when the risk of ice-covering first appears, thereby providing accurate and timely decision support for power grid operation and maintenance personnel. This study proposes the following core hypotheses: H1: The CEEMDAN algorithm outperforms standard EMD in decomposing multi-scale features of ice-covered data from high-altitude regions; H2: The MDR model integrating CNN-GRU-attention mechanism demonstrates significantly higher prediction accuracy than traditional models such as SVR and ANN.

2 Methods and materials

2.1 Construction of ice-covering feature extraction model integrating multiple algorithms

The traditional methods for predicting ice-covering on power grid lines are mainly based on meteorological parameters and simple physical models, which are difficult to accurately capture the dynamic process and inherent laws of ice-covering formation. The prediction accuracy and reliability are limited, and cannot satisfy the high requirements for safe and stable operation [12-14]. This study proposes a method for predicting ice-covering in high-altitude regions based on LSTM and deep learning techniques. However, the time series data of transmission line ice-covering presents nonlinearity, sudden changes, and uncertainty, and there are seasonal patterns, which increases the difficulty of analysis. In addition, there are many factors that affect ice-covering, including climate, terrain, and electrical characteristics. These factors are intertwined and jointly determine the severity and frequency of ice-covering. In addition, different types of ice-covering have different characteristics, such as rime, rime, etc. Accurately extracting their features requires comprehensively considering multiple factors, which further increases the complexity and challenge of feature extraction. To optimize the accuracy and efficiency, an ice-covering feature extraction model integrating multiple algorithms is developed by combining the SC algorithm, CEEMDAN algorithm, and LSTM network.

The research first collects various signals transmitted by transmission line sensors, and conducts detailed preprocessing to ensure data quality. Based on diverse real-time data resources in high-altitude regions, fixed data samples are carefully selected, and ice-covering feature extraction and accurate classification work are carried out. The collected transmission line data in high-altitude regions is normalized. The normalization is displayed in equation (1).

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

In equation (1), x represents the data sample. Next, the CEEMDAN decomposes the preprocessed transmission line data signals in high-altitude regions into some Intrinsic Mode Functions (IMFs). Compared with Variational Mode Decomposition (VMD) and Empirical Wavelet Transform (EWT), CEEMDAN demonstrates unique advantages in processing nonlinear and non-stationary ice-covering time series data. By adaptively adding noise and performing multiple decompositions, CEEMDAN effectively resolves the mode mixing issue inherent in traditional Empirical Mode Decomposition (EMD), more accurately extracting multi-scale features from ice-covering data. In contrast, VMD and EWT exhibit greater parameter sensitivity when decomposing complex signals, and their performance becomes less stable and accurate when handling ice-covering data with abrupt transition characteristics. After analyzing the frequency, energy,

and other characteristic parameters of these IMFs, the components most closely related to ice-covering characteristics are selected to achieve ice-covering recognition. When operating this algorithm, Gaussian white noise $n^i(t)$ is first added to signal $e(t)$ to generate experimental signal $e^i(t)$, as presented in equation (2).

$$e^i(t) = e(t) + n^i(t) \quad (2)$$

In the signal processing process, the EMD polarity decomposition method is uniformly applied to all obtained experimental signals. Based on this operation, the first-order mode decomposition signal I_1^i corresponding to each experimental signal can be obtained. Subsequently, the mean of these first-order mode decomposition signals is taken as the first-order mode component I_1 of the entire sequence, as shown in equation (3).

$$I_1 = \sum_{i=1}^I I_1^i \quad (3)$$

Finally, the predetermined steps are repeated to accurately calculate the modal components of each order until they cannot be further decomposed. The output results are input into the spectral clustering algorithm. This algorithm is used to construct a similarity matrix, and used as a basis to segment the data, thereby dividing different ice-covering state groups. When the spectral clustering algorithm starts running, it will deeply analyze the data and carefully construct a similarity matrix $\mathbf{W}_{ij}$ based on the similarity between each data point, as shown in equation (4).

$$\mathbf{W}_{ij} = \exp\left(-\frac{d^2(v_i, v_j)}{2\sigma^2}\right) \quad (4)$$

In equation (4), d signifies the distance between two sample points. v represents the data sample point. σ represents the scale parameter. $\mathbf{W}_{ij}$ is normalized to a Laplacian matrix, as shown in equation (5).

$$\begin{cases} L_{nor} = D^{-\frac{1}{2}} L D^{-\frac{1}{2}} = I - D^{-\frac{1}{2}} W D^{-\frac{1}{2}} \\ L_{nor} = D^{-1} L = I - D^{-1} W \end{cases} \quad (5)$$

In equation (5), I represents the identity matrix. D represents a diagonal matrix. Next, the feature decomposition of the Laplacian matrix is performed to calculate the eigenvalues and eigenvectors, and the eigenvectors related to the minimum non-zero eigenvalue are selected to form a new matrix. Finally, each row of the new matrix is taken as a point in a high-dimensional space. After clustering these points, the data is classified based on spectral properties.

Finally, the study takes the feature results extracted by the CEEMDAN algorithm as input for LSTM, and uses LSTM to classify the ice-covering features of transmission lines, accurately discriminating their ice-covering conditions. LSTM combines the memory storage function of traditional models with new LSTM functions [15-16]. The LSTM model optimizes the

long-term dependency phenomenon of the RNN model through input gates, forget gates, etc. The "gate" is designed to control the memory state, storage time, and distance data, as presented in Figure 1.

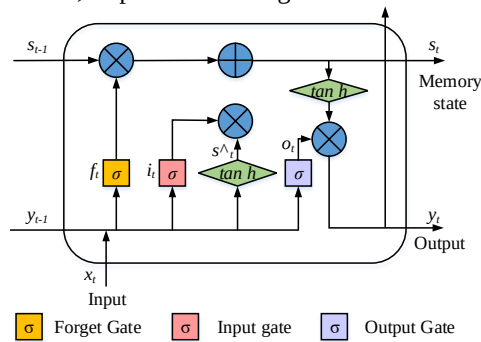


Figure 1: The LSTM structure

In Figure 1, the input gate i_t , output gate o_t , and forget gate f_t are presented in equation (6).

$$\begin{cases} i_t = \sigma(W_i[y_{t-1}, x_t] + b_i) \\ o_t = s(W_o[y_{t-1}, x_t] + b_o) \\ f_t = \sigma(W_f[y_{t-1}, x_t] + b_f) \end{cases} \quad (6)$$

In equation (6), W_i , W_o , and W_f signify the weight matrix of the corresponding "gate" at time t . b_i , b_o , and b_f signify the offset of the corresponding "gate" at t . x_t , y_t , and s_t respectively represent the input and output values at time t , as well as the memory state of the neuron. By training the LSTM network, the time series problem of ice-covering data in high-altitude regions can be effectively solved, accurately classifying ice-covering characteristics. Thus, the steps of the ice-covering feature extraction based on CEEMDAN-SC-LSTM are shown in Figure 2.

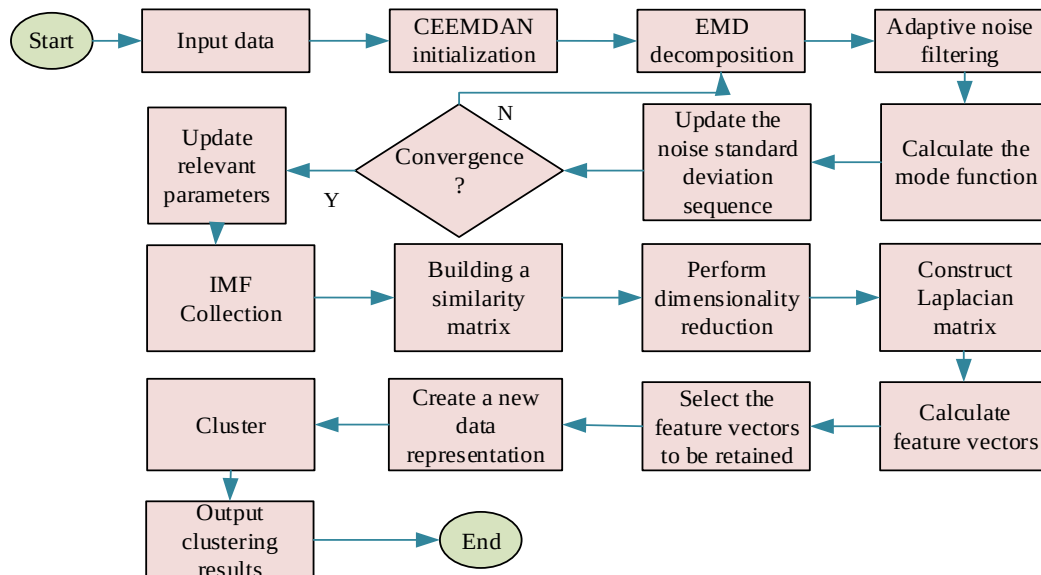


Figure 2: Flow chart of ice-covering feature extraction method for transmission lines based on CEEMDAN-SC-LSTM

In Figure 2, after inputting relevant data, the system first performs CEEMDAN initialization operation, followed by EMD decomposition. Subsequently, adaptive noise filtering is applied to the decomposed data to update the noise standard deviation sequence, and the steps of calculating the modulus function and constructing the Laplacian matrix are sequentially

completed. If convergence is not achieved, the parameters are updated, IMF is collected, and a similarity matrix is constructed. If convergence occurs, a new data representation is created and clustered, and the results are output. The complete architecture specification of the CEEMDAN-SC-LSTM model is shown in Table 2.

Table 2: CEEMDAN-SC-LSTM model architecture specifications

Model Components	Specific parameters	Activation function
CEEMDAN	Number of trials: 50, noise width: 0.2	No (signal decomposition algorithm, no activation function concept)
sc	Similarity matrix calculation method: Gaussian kernel function, scale parameter: adaptive adjustment according to data	No (cluster algorithm, no activation function concept)

LSTM	Number of layers: 2, hidden layer sizes: 20,10, dropout rate: 0.2	Forgetting gate, input gate, and output gate: Sigmoid function; generating new candidate memory vectors and final output working memory: Tanh function
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This study demonstrates multiple advantages of introducing the SC algorithm after applying the CEEMDAN algorithm to decompose transmission line data signals in high-altitude regions and obtain a series of IMFs. Firstly, while the decomposed IMFs from CEEMDAN contain abundant information, their varying correlation with ice coverage characteristics and inherent noise interference require specialized processing. The SC algorithm constructs a similarity matrix based on data point similarity, and then analyzes the frequency and energy characteristics of IMF to accurately distinguish ice related components and noise, forming different ice-covering state groups. Secondly, when applying LSTM for classification, the spectral clustering process enhances data clarity by creating well-defined cluster boundaries. This provides LSTM with more discriminative input features that can accurately learn different ice cover patterns, ultimately improving classification accuracy and efficiency.

2.2 Construction of ice-covering prediction model for transmission lines based on deep learning

After completing the feature extraction and classification, to accurately predict the ice-covering thickness, CNN, GRU, and attention mechanism models are combined. The extracted features related to changes in ice-covering thickness are used as inputs to the model, and an MDR model is constructed for predicting ice-covering. The CNN structure and GRU unit structure are shown in Figure 3.

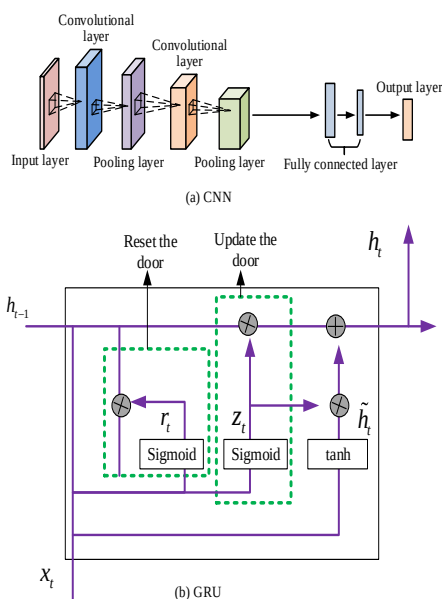


Figure 3: Schematic diagram of CNN and GRU

In Figure 3, the MDR first introduces the CNN to extract local spatial features from the input features. In the complex ice thickness prediction on transmission lines, traditional methods have certain limitations. CNN can effectively solve this challenge by converting meteorological data into image format, fully leveraging its own advantages, deeply extracting weather features, and significantly improving prediction accuracy [17-18]. Next, the GRU model is introduced to accurately input rich features extracted by CNN. With the unique mechanism of GRU, long-term dependencies hidden in time series data are deeply captured [19-20]. The description for GRU is presented in equation (7).

$$\begin{cases} z_t = \sigma(\mathbf{W}_z \cdot [\mathbf{h}_{t-1}, x_t]) \\ r_t = \sigma(\mathbf{W}_r \cdot [\mathbf{h}_{t-1}, x_t]) \\ \tilde{\mathbf{h}}_t = \tanh(\mathbf{W} \cdot [r_t \square \mathbf{h}_{t-1}, x_t]) \\ \mathbf{h}_t = (1 - z_t) \square \eta_{t-1} + z_t \square \tilde{\mathbf{h}}_t \end{cases} \quad (7)$$

In equation (7), z_t signifies the update gate. $\mathbf{h}_t$ signifies the new unit vector. r_t denotes the reset gate. $\mathbf{h}_t$ signifies the hidden state vector. Each $\mathbf{W}$ represents its corresponding weight matrix. Finally, to enable the MDR to automatically emphasis the most important features for predicting ice-covering thickness and further improve model performance, attention mechanisms are specifically introduced and attention layers are carefully designed. This layer takes the output processed by GRU as input, calculates attention weights accurately through a specific algorithm, and then performs weighted average processing on the output of GRU based on these weights. Based on the above steps, Figure 4 presents the implementation process of the MDR.

In Figure 4, during the implementation of the MDR, the network structure is first established, and the network loss function and evaluation function lay the foundation for model training. Next, the ice-covering dataset of transmission lines is collected and decomposed using the CEEMDAN method to extract more detailed features. Subsequently, a transmission line feature dataset is constructed and spectral clustering is performed to form training and testing sets. The later trains the network. After continuously adjusting the network parameters, the MDR can better learn the patterns in the data. After training, the performance is assessed using a test set to prove its predictive accuracy. The entire process, from data preprocessing to model training and evaluation, has formed a complete implementation plan for the ice-covering prediction model.

Finally, based on the real-time monitoring data collected by the mature power grid ice-covering sensor network, the study realizes centralized management, real-time data

monitoring, and remote transmission through the Internet of Things cloud platform, ensuring the integrity and timeliness of the original data. In the data processing stage, the CEEMDAN-SC-LSTM is used to complete key feature extraction. During the model construction process, multiple factors like environmental temperature,

humidity, and wind speed are comprehensively considered for dynamic correction, and the MDR predicts the ice-covering thickness. Finally, an intelligent early warning platform for power grid ice-covering suitable for high-altitude regions is designed. Figure 5 presents the overall architecture of the platform.

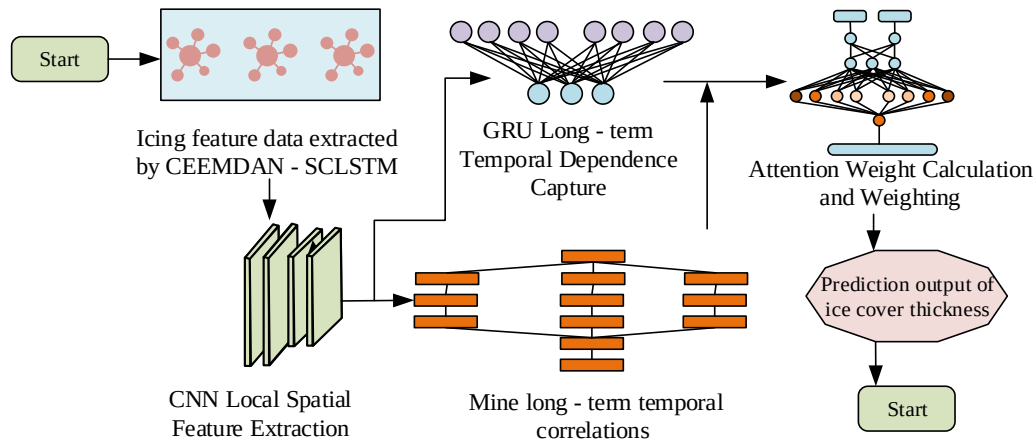


Figure 4: Implementation flowchart of MDR

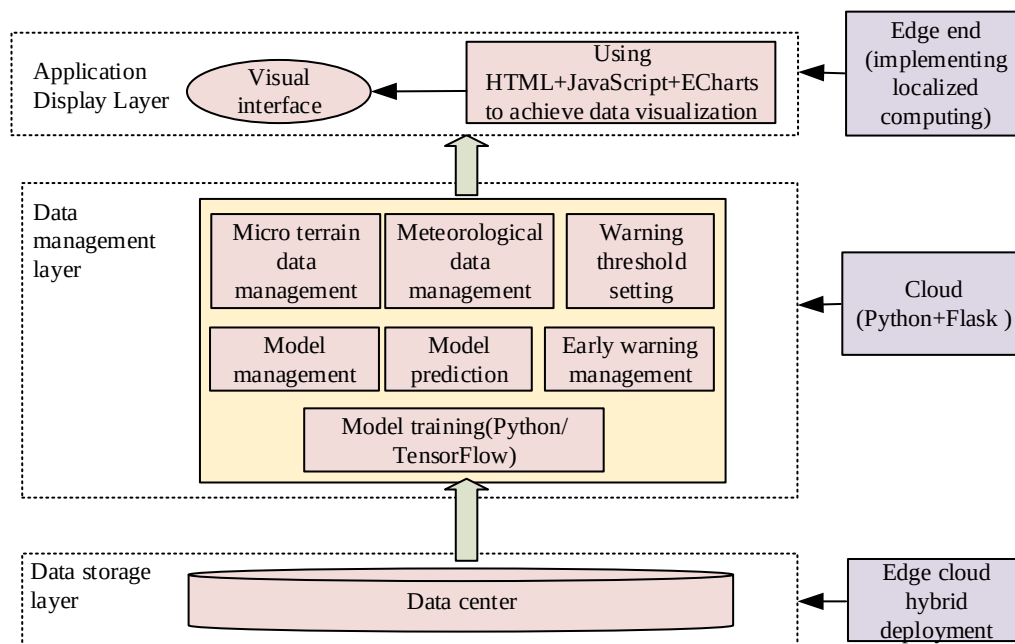


Figure 5: Schematic diagram of the ice-covering warning platform for power grid lines in high-altitude regions

In Figure 5, the platform is divided into four levels. The bottom layer is the data storage layer, composed of data centers, responsible for storing various types of data. Above it is the data management layer, which includes multiple modules such as micro terrain data management, meteorological data management, model management, model prediction, warning threshold setting, and early warning management. It also includes model training functions, which process and manage data. The upper layer is the application display layer, which visually

displays the processed information to users through a visual interface. The collaborative work between various layers, from data storage to management and processing, and finally visualization presentation, jointly realizes the early warning function of power grid line ice-covering in high-altitude areas. The hybrid method for ice-covering prediction on transmission lines in high-altitude regions, integrating CEEMDAN-SC-LSTM and MDR models, is presented in pseudocode in Table 3.

Table 3: Pseudocode of ice coverage prediction method for transmission lines in high-altitude regions

Pseudo code for predicting icing on transmission lines in high-altitude regions by integrating CEEMDAN-SC-LSTM and MDR models # CEEMDAN - SC - LSTM Feature Extraction Pseudocode def CEEMDAN_SC_LSTM_feature_extraction(data): # Data preprocessing normalized_data = normalize(data) # CEEMDAN decomposition imfs = CEEMDAN(normalized_data) # Select IMFs related to icing characteristics selected_imfs = select_imfs(imfs) # Spectral clustering similarity_matrix = build_similarity_matrix(selected_imfs) laplacian_matrix = build_laplacian_matrix(similarity_matrix) eigenvalues, eigenvectors = eigen_decomposition(laplacian_matrix) selected_eigenvectors = select_eigenvectors(eigenvalues, eigenvectors) clusters = spectral_clustering(selected_eigenvectors) # LSTM classification lstm_model = build_lstm_model() lstm_model.train(selected_imfs, clusters) features = lstm_model.extract_features(selected_imfs) return features # MDR Prediction Model Pseudocode def MDR_prediction_model(features): # CNN feature extraction cnn_output = cnn_feature_extraction(features) # GRU capturing long-term dependencies gru_output = gru_long_term_dependency(cnn_output) # Attention mechanism attention_weights = calculate_attention_weights(gru_output) weighted_gru_output = apply_attention(gru_output, attention_weights) # Predict ice thickness predicted_thickness = predict_ice_thickness(weighted_gru_output) return predicted_thickness
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3 Results

3.1 Model performance testing

To verify the proposed ice-covering prediction method based on LSTM and deep learning methods, the study first needs to test the CEEMDAN-SC-LSTM and MDR. To optimize the accuracy and efficiency of ice-covering feature extraction for transmission lines, targeted testing is conducted on typical datasets. The dataset originates from a specific main transmission line in a high-altitude mountainous area in western China. The region has an average elevation of over 2,000m, with terrain dominated by mountains and plateaus, featuring significant elevation changes, crisscrossing mountain ranges, and deep valleys. The complex topography leads to significant local variations in meteorological conditions, creating diverse microclimate environments. In terms of meteorological conditions, the region experiences consistently low temperatures throughout the year, with

particularly severe winters. The annual average temperature is between -5°C and 5°C, and the lowest temperature in winter can drop below -30°C. The humidity fluctuates greatly, ranging from 40% to 90%. Wind speeds also show distinct seasonal and regional variations, averaging 3-8 m/s annually, with speeds exceeding 15 m/s in special terrain areas like mountain passes and canyons. Precipitation is mainly concentrated in summer, although there is also significant snowfall in winter, with annual precipitation ranging from 400 to 800mm. These combined meteorological conditions result in frequent ice-covering on transmission lines in the region, providing rich data samples for research. The data collection spanned from October 2024 to March 2025, with hourly sampling frequency, yielding a total of 4,320 data points. The dataset is divided in an 8:1:1 ratio, with 3,456 training samples, 432 validation samples, and 432 test samples. This partition ensures sufficient training data for model learning while providing ample

validation and test samples to evaluate the model's generalization ability and predictive performance. The validation set is used to fine-tune hyperparameters and prevent overfitting, while the test set serves as the final evaluation benchmark for the model's performance on unseen data, ensuring its accuracy and reliability. The operating environment and parameter settings for this experiment are presented in Table 4.

Table 4: Experimental operating environment

Experimental environment		Setting
JRE	CUDA edition	11.4.0
	CPU	NVIDIA RTX4090Ti
	Internal memory	16.00GB
	Batch size	8
	Learning rate initial value	1e-5
	optimizer	Adam
	Software environment	MatlabR2018a
	Weight decay	1e-4
	Iterations	3,000
Hyperparameter	CNN layers	2

	Number of CNN convolution kernels	32 and 64
	Number of GRU layers	2
	Number of GRU units	20 and 10
	Attention unit quantity	50
	LSTM	Number of layers: 2, hidden layer sizes: 20,10, dropout rate: 0.2

In this study, a grid search method was employed to determine hyperparameters for CNN, GRU, and attention mechanism models. The process involved three steps: Firstly, defining the hyperparameter search range; Secondly, constructing a parameter grid; Finally, selecting the hyperparameter configuration with the lowest loss and highest accuracy based on validation set evaluation results. The hyperparameter tuning results are presented in Table 5.

Table 5: Hyperparameter tuning experiment results

Hyperparameter	CNN layers	CNN convolution kernels	GRU layers	GRU units	Attention unit quantity	Learning rate	Batch size	Accuracy	Loss value
Combination 1	1	1,632	1	105	30	1e-5	4	0.856	0.213
Combination 2	1	1,632	1	105	30	1e-5	8	0.872	0.198
Combination 3	1	1,632	1	105	30	1e-5	16	0.865	0.205
Combination 4	1	1,632	1	2,010	40	1e-4	4	0.881	0.189
Combination 5	1	1,632	1	2,010	40	1e-4	8	0.895	0.176
Combination 6	1	1,632	1	2,010	40	1e-4	16	0.889	0.182
Combination 7	2	3,264	2	105	50	1e-5	4	0.902	0.168
Combination 8	2	3,264	2	105	50	1e-5	8	0.925	0.145
Combination 9	2	3,264	2	105	50	1e-5	16	0.918	0.152
Combination 10	2	3,264	2	2,010	50	1e-4	4	0.936	0.138
Combination 11	2	3,264	2	2,010	50	1e-4	8	0.952	0.121
Combination 12	2	3,264	2	2,010	50	1e-4	16	0.947	0.128

As shown in Table 5, after comprehensively evaluating the model performance across different hyperparameter configurations, the final configuration (2-layer CNN with 32 and 64 convolution kernels; 2-layer GRU with 20 and 10 units; 50 attention units; learning rate of 1e-4; batch

size of 8) achieved the lowest loss and highest accuracy. This configuration delivered optimal performance on the validation set, providing more accurate predictions for ice-covering on transmission lines in high-cold regions.

After preprocessing the collected data, the MDR is trained on the self-built dataset, as presented in Figure 6. In Figure 6 (a), the loss of the MDR decreased with the iteration, from 0.1800 to 0.1084 in the training set and from 0.1362 to 0.0915 in the validation set, improving generalization ability. From Figure 6 (b), the MDR model had an accuracy of over 90% on both sets. The final accuracy was 96.93% and 98.21%. The MDR performs well in training and can be used for predicting ice-covering. To address the overfitting risks in the MDR model, the study implemented multiple mitigation strategies. Firstly, data normalization was applied during preprocessing to reduce fluctuations and improve convergence, effectively preventing overfitting on specific features. Secondly, regularization techniques were employed during training to constrain parameter

magnitudes and avoid excessive weight growth. Hyperparameter tuning, including learning rate adjustments and batch size optimization, was conducted to ensure stable training processes, while cross-validation was utilized to evaluate model generalization capabilities. By partitioning datasets into training and validation sets, the study comprehensively assessed model performance across different datasets, promptly identifying overfitting risks. Additionally, an early termination mechanism was implemented: When the validation loss stabilizes after a specified number of iterations, the training stops, effectively preventing overfitting. The SC is chosen as the comparative method in the experiment. Modal decomposition and feature extraction are performed on the same data, as displayed in Figure 7.

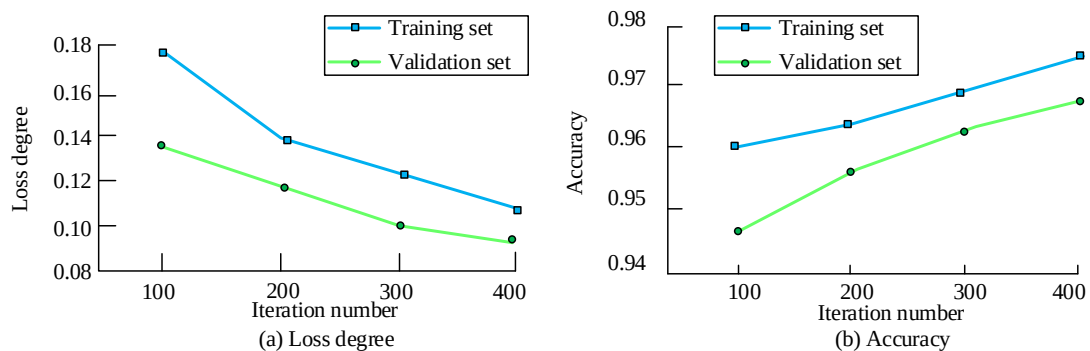


Figure 6: Training results of MDR model

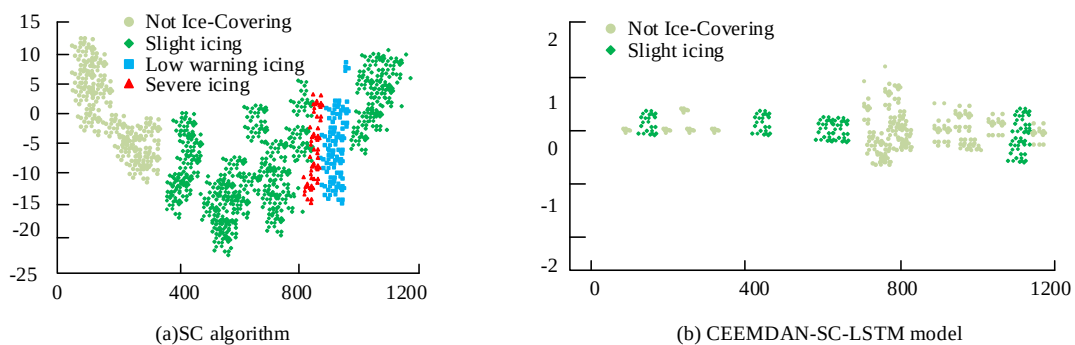


Figure 7: Comparison of feature extraction results of CEEMDAN-SC-LSTM model

Figure 7 (a) shows the raw data classification using the SC algorithm, and Figure 7 (b) displays the classification results of the CEEMDAN-SC-LSTM. From Figure 7 (a), when relying solely on spectral clustering for the extraction and classification of ice-covering features, the distribution of data points was relatively mixed. The data points of non-ice-covering, slight ice-covering, and low warning ice-covering states were intertwined, making it difficult to form clear and distinguishable clustering boundaries, resulting in difficulty in accurately identifying these degrees of ice-covering. However, for severe ice-covering, spectral clustering lacks effective mining of multi-scale features when processing complex time-series ice-covering data, resulting in large and inaccurate warning time judgments and inability to

timely and accurately identify severe ice-covering risks. From Figure 7 (b), the CEEMDAN algorithm first performs adaptive decomposition on the ice-covering data, mines multi-scale features, and combines the clustering advantages of SC with the learning ability of LSTM for time-series data. The clustering of data points in different ice-covering states is clear, the recognition accuracy is significantly improved, and the extracted features are richer and more comprehensive, accurately extracting and classify ice-covering features. This demonstrates the superiority of the model in ice-covering feature processing. The test results of DBSCAN, hierarchical clustering, SC algorithm, and the CEEMDAN-SC-LSTM model for the silhouette

coefficient, Davies-Boulding index, Calinski-Harabasz index, and Xie-Beni index are shown in Table 6.

Table 6: Quantitative performance evaluation results of the CEEMDAN-SC-LSTM model

Model	SC	CEEMDAN-SC-LSTM	DBSCAN	Hierarchical clustering
Silhouette coefficient	0.32	0.72	0.45	0.52
Davies-Bouldin Index	2.31	0.87	1.89	1.67
Calinski-Harabasz	45.78	120.65	78.32	92.15
Xie-Beni	0.48	0.21	0.35	0.3

As shown in Table 6, the CEEMDAN-SC-LSTM model outperformed all comparison algorithms across all metrics. Specifically, compared with the SC algorithm, the silhouette coefficient increased from 0.32 to 0.72, indicating significantly improved cohesion and separation in clustering results. The Davies-Boulding index decreased from 2.31 to 0.87, demonstrating more compact and well-separated clusters. The

Calinski-Harabasz index rose from 45.78 to 120.65, further validating the enhanced clustering quality. These quantitative metrics demonstrate that the SC algorithm achieves remarkable clustering improvements when combined with CEEMDAN and LSTM. The ablation results of the CEEMDAN-SC-LSTM model are presented in Table 7.

Table 7: Ablation results of the CEEMDAN-SC-LSTM model

Model	Coefficient of determination (R^2)	MAE	RMSE	MAPE	Classification accuracy
CEEMDAN-SC-LSTM	0.9887	0.0130	0.0142	1.2558%	97.1%
SC-LSTM	0.9423	0.0321	0.0356	3.1245%	92.5%
CEEMDAN-LSTM	0.9567	0.0289	0.0312	2.8765%	93.8%

As shown in Table 7, the CEEMDAN-SC-LSTM model outperformed all other models across all metrics. When CEEMDAN and LSTM components were removed, the classification accuracy dropped from 97.1% to 92.5% and 93.8%, respectively. The results demonstrate that the optimal data separability is achieved through their synergistic interaction.

Then, the CEEMDAN-SC-BP, CEEMDAN-SCNN, CEEMDAN-SCSVM, and CEEMDAN-SC-LSTM are used to classify the raw data (divided into no ice-covering, slight ice-covering, and low warning ice-covering areas), as shown in Figure 8.

Figure 8 displayed the ice-covering classification results of the CEEMDAN-SC-BP, CEEMDAN-SCNN, CEEMDAN-SC-SVM, and CEEMDAN-SC-LSTM. On the self-built dataset, the CEEMDAN-SC-BP model had the worst classification performance. Compared with the basic CEEMDAN-SC-SVM model, the CEEMDAN-SCNN and CEEMDAN-SC-SVM models partially improved their classification performance, with 11 misclassifications. The CEEMDAN-SC-LSTM had the best classification performance, with only 6 misclassifications and a classification accuracy of around

97.1%. Under the same experimental conditions, the MDR monitors the ice-covering situation from January to March 2025, as displayed in Table 8.

From Table 8, the MDR prediction model had good predictive performance. The accuracy was all above 96.5%, with the highest reaching 98.1%, demonstrating a high consistency between the predicted results and the actual situation. The R^2 was all close to 0.99, indicating that the model had strong explanatory power for ice-covering thickness. The maximum Mean Absolute Error (MAE) was 0.7mm and the minimum was only 0.2mm, demonstrating that the average error was small. The maximum MAPE was 4.00% and the minimum was 1.82%, reflecting a relatively small prediction error and high prediction accuracy. This further validates the effectiveness and reliability for predicting ice-covering. Finally, on the test set of the self-built dataset, the MDR is compared with the comparison models Support Vector Regression (SVR), Random Forest Regression (RFR), Gradient Boosting Regression Tree (GBRT), and Artificial Neural Network (ANN), as presented in Figure 9.

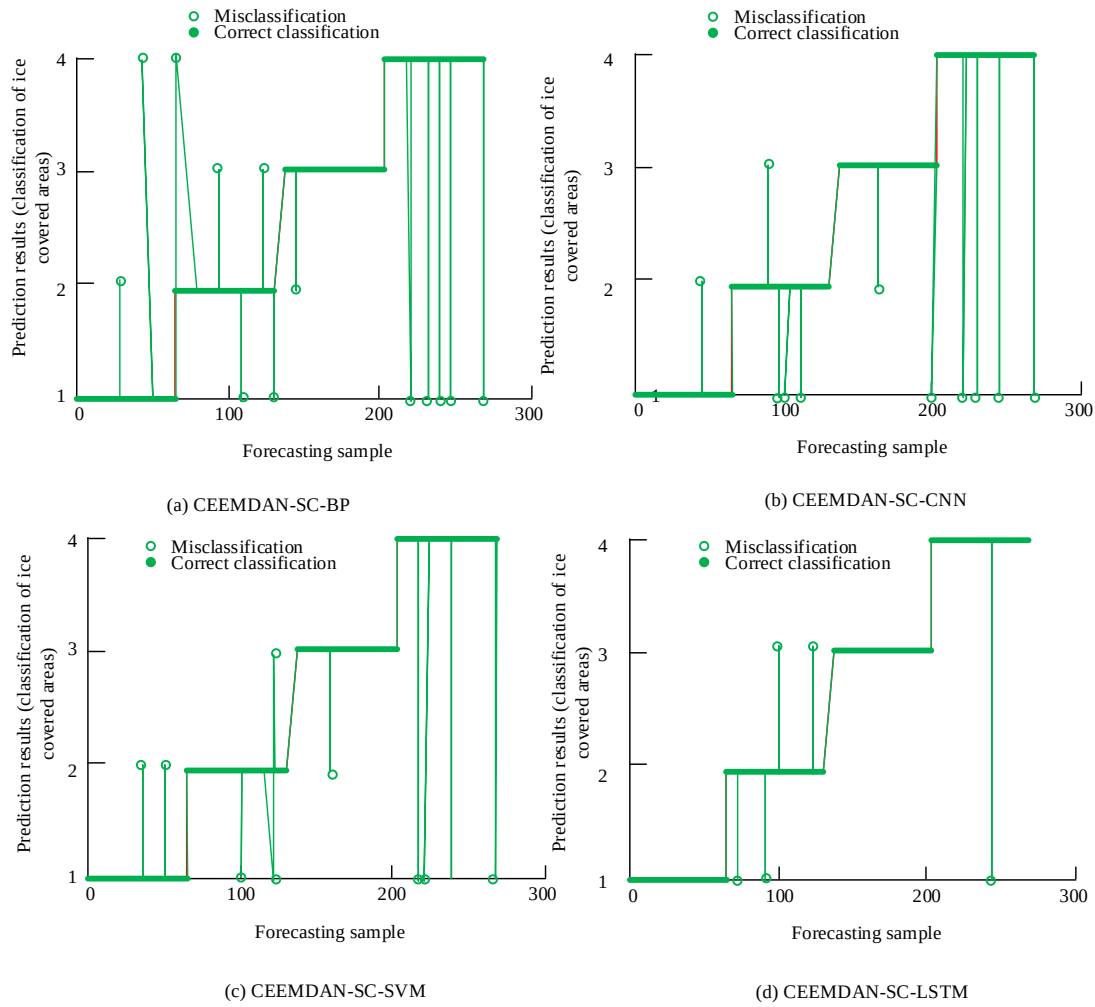


Figure 8: Comparison of classification results of ice-covering areas using different classification models

Table 8: Monitoring results of ice-covering from January to March 2025

Monitoring time	Actual ice thickness (mm)	Predicted ice thickness (mm)	MAE (mm)	MAPE (%)	Accuracy rate (%)	R^2	Variance	95% confidence interval
2025-01-10	10	9.6	0.4	4.00	96.5	0.9852	0.002	[9.55,9.65]
2025-01-20	15	14.5	0.5	3.33	97.2	0.9878	0.003	[14.45,14.55]
2025-02-05	20	19.3	0.7	3.50	97.8	0.9891	0.004	[19.25,19.35]
2025-02-15	22	21.6	0.4	1.82	98.1	0.9903	0.002	[21.55,21.65]
2025-03-05	8	7.8	0.2	2.50	96.9	0.9865	0.001	[7.75,7.85]

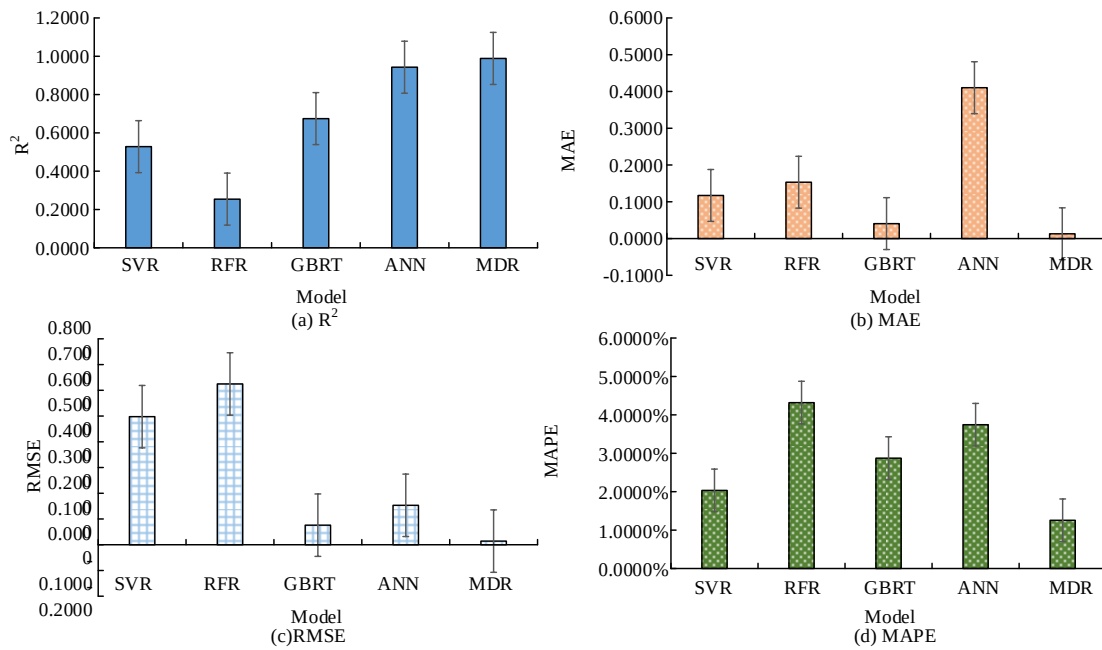


Figure 9: Comparison of MDR prediction models

Figure 9 shows the performance of MDR, SVR, RFR, GBRT, and ANN models in ice-covering prediction. From Figure 9 (a), the R^2 of the MDR model reached 0.9887, close to 1, indicating its strong explanatory power for ice-covering thickness, far higher than that of SVR (0.5281), RFR (0.2541), GBRT (0.6744), and ANN (0.9429). From Figure 9 (b), the MAE of the MDR model was 0.0130, which was the smallest among all models, indicating that the average error was the smallest. From Figure 9 (c), the MDR model was 0.0142, which also performed the best, reflecting its high prediction

accuracy. From Figure 9 (d), in the MAPE index, the MDR model was 1.2558%, outperforming other comparison models. Overall, the MDR model performs well in all indicators and can more accurately and stably predict the ice-covering thickness of transmission lines in high-altitude regions compared to other models. The test results of the MDR classification warning model and deep baseline models (LSTM-only, GRU-only, CNN-LSTM, and Transformer) in terms of accuracy, recall, F1 score, and overall accuracy derived from the confusion matrix are shown in Table 9.

Table 9: Performance comparison between MDR model and deep baseline model

Model	Precision (%)	Recall (%)	F1 (%)	Overall accuracy (%)
MDR	97.8	97.2	97.5	97.3
LSTM	91.5	90.8	91.1	90.9
GRU	92.3	91.6	91.9	91.7
CNN-LSTM	95.6	95.1	95.3	95.2
Transformer	96.4	95.9	96.1	96.0

As shown in Table 9, the MDR model demonstrated superior performance in ice-covering classification tasks, achieving 97.8% accuracy, 97.2% recall, 97.5% F1 score, and 97.3% overall accuracy, significantly outperforming all deep learning baselines. The LSTM-only and GRU-only models performed the worst due to their lack of spatial feature extraction capabilities and key feature focusing mechanisms, with overall accuracy below 92%, particularly showing higher errors in borderline classifications such as "slight icing" versus "low warning icing." Although the CNN-LSTM model incorporates spatial features through CNN, its classification metrics

remain over 2% lower than MDR, indicating that the attention mechanism prevents precise focus on critical icing features. While the Transformer model captures long-term temporal correlations, it underperforms in identifying local features of icing data (such as abrupt icing level transitions caused by micro-meteorological changes), resulting in 1.4% lower than that of MDR. This validates the architecture rationality of the MDR model, and its high performance ensures the accuracy of ice warning.

The generalization ability test results of the MDR model in specific regions are shown in Table 10.

Table 10: The generalization ability test results of MDR model in specific regions

Area	Season	R ²	MAE	MAPE
Eastern Plains	Winter	0.9234	0.0321	2.8765%
Southern hilly area	Winter	0.9012	0.0356	3.1245%
Northern mountainous area (non-original study area)	Winter	0.8876	0.0389	3.4567%

As shown in Table 10, the proposed model demonstrated adaptability across different regions and seasons, although its performance showed some decline. In the eastern plains and southern hilly areas, the model maintained an R² value above 0.9 with relatively low MAE and MAPE, indicating good predictive performance in these regions. However, in the northern mountainous area (non-original study region), the R² value dropped to 0.8876 while MAE and MAPE increased. This may be attributed to significant differences in terrain and climate conditions between the northern mountainous area and the original study region, which affect the model's prediction accuracy. Future work may involve collecting more regional and seasonal data to optimize and improve the model, thereby enhancing its generalization ability. The results of the MDR model ablation experiment are shown in Table 11.

Table 11: Results of MDR model ablation experiments

Model	R ²	MAE	RMSE	MAPE
MDR	0.9887	0.0130	0.0142	1.2558%
Remove CNN	0.9654	0.0215	0.0236	2.1548%
Remove GRU	0.9589	0.0248	0.0272	2.4876%
Remove attention mechanism	0.9732	0.0187	0.0203	1.8765%

As shown in Table 11, CNN, GRU, and the attention mechanism all play crucial roles in the MDR model. After removing the CNN, the R² was reduced to 0.9654

while increasing MAE, RMSE, and MAPE, demonstrating that the local spatial features extracted by CNN significantly contribute to ice thickness prediction. Eliminating the GRU further degraded performance, with R² dropping to 0.9589, indicating that the GRU's ability to capture long-term temporal dependencies substantially impacts prediction accuracy. Removing the attention mechanism can also lead to performance degradation, indicating that this component enables the model to automatically focus on key features, thereby improving prediction accuracy.

The ice-covering prediction model developed in this study, which integrates LSTM and deep learning techniques, demonstrates high accuracy through three key factors. Firstly, the dataset originates from transmission line corridors in a high-altitude mountainous region, where complex terrain and diverse meteorological conditions ensure rich diversity and representativeness, comprehensively capturing various ice-covering scenarios. Secondly, the CEEMDAN-SC-LSTM model effectively leverages the strengths of each component: CEEMDAN algorithm decomposes multi-scale features in ice data, SC algorithm performs precise clustering, while LSTM network processes temporal patterns to identify time-varying characteristics. Thirdly, the MDR prediction model combines CNN, GRU, and attention mechanism to optimize critical information utilization, significantly enhancing predictive performance.

3.2 Analysis of ice-covering warning for power grid lines in high-altitude regions

After verifying the effectiveness of the proposed CEEMDAN-SC-LSTM ice-covering feature extraction method and MDR prediction model, the study applies the proposed high-altitude area power grid ice-covering warning platform to a certain high-altitude mountainous area power grid line. The power grid lines in this high-altitude mountainous area often face serious ice-covering problems in winter, which poses a great threat to the power grid. The terrain in this area is complex, the climate is variable, the micro meteorological characteristics are obvious, the transmission lines are widely distributed, and some areas have inconvenient transportation, making manual inspection difficult. To timely and accurately grasp the ice-covering and deliver early warnings, this platform is used to monitor and predict line ice-covering, as displayed in Table 12.

Table 12: Monitoring results of ice-covering on power grid lines

Monitoring time	Actual ice thickness (mm)	Predicted ice thickness (mm)	Absolute error (mm)	Relative error (%)	Level of warning
2025-01-05 10:00	8	7.5	0.5	6.25	Light ice-covering
2025-01-10 14:00	12	11.2	0.8	6.67	Low warning ice-covering
2025-01-15 09:00	18	17.3	0.7	3.89	Low warning ice-covering

2025-01-20 11:00	25	24.1	0.9	3.6	Severe ice-covering
2025-01-25 13:00	5	5.3	0.3	6.0	Uncovered ice (close to threshold)

From Table 12, the predicted ice thickness by this method was close to the actual ice thickness, with a maximum absolute error of 0.9mm and a maximum relative error of 6.67%, indicating a relatively small overall error. The judged warning level was also consistent with the actual situation, and the warning accuracy was high. This indicates that the ice-covering prediction method based on LSTM and deep learning methods can effectively predict and deliver the ice-covering situation of transmission lines in high-altitude areas, providing timely decision-making basis, and helping to take measures to ensure the safe and stable operation.

4 Discussion

The CEEMDAN-SC-LSTM feature extraction model and MDR prediction model developed in this study demonstrated exceptional performance ($R^2=0.9887$) on the high-altitude mountainous dataset (October 2024-March 2025), significantly outperforming baseline models such as SVR ($R^2=0.5281$) and ANN ($R^2=0.9429$). This superiority stems from three key advantages: 1) multi-scale feature decomposition: The CEEMDAN algorithm adaptively extracts multi-modal features from ice-covered data, resolving the modal aliasing issue of traditional EMD (e.g., Reference [9] using only meteorological data), while SC clustering enhances feature separability. 2) Temporal modeling capability: The GRU-attention mechanism synergistically captures long-term meteorological patterns (e.g., Sudden temperature drop leads to ice formation), surpassing static image analysis methods in References [7] and [11]. 3) Regional adaptability: The model maintains high precision in complex micro-terrain areas (average altitude>2,000m), although its generalization in homogeneous climate zones (e.g., plains) requires further validation. Notably, the extremely low MAE (0.0130mm) may be limited by the seasonal bias of the dataset (dominated by winter data). Therefore, it is necessary to integrate annual data to evaluate the robustness of the model during the spring thawing period.

5 Conclusion

Ice-covering on transmission lines in high-altitude regions poses a serious threat to power grid. This study aims to accurately predict ice-covering conditions. Therefore, a prediction method for ice-covering was proposed based on LSTM and deep learning methods. In the feature extraction stage, a CEEMDAN-SC-LSTM-based ice-covering feature extraction model was proposed by combining SC, CEEMDAN, and LSTM. A MDR prediction model was constructed by combining CNN, GRU, and attention mechanism models, taking the extracted features related

to changes in ice-covering thickness as inputs. Finally, a power grid line ice-covering warning platform suitable for high-altitude regions was designed based on data and models to deliver real-time monitoring and warning. The classification accuracy was about 97.1%, the R^2 of the MDR model was 0.9887, and the MAE was 0.0130, demonstrating excellent performance in various performance indicators. The warning platform was applied to power grid lines in high-altitude mountainous areas, with a maximum absolute error of 0.9mm and a maximum relative error of 6.67% between predicted and actual ice-covering thickness, which could effectively provide warnings. However, there are issues with limited data samples and high model complexity in this study. Future research can collect more data, improve the model structure, make better predictions, and provide better support for the safe and stable running.

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