IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 8, 2019, accepted March 4, 2019, date of publication March 26, 2019, date of current version April 9, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2907635

Transmission Line Ice Coating Prediction Model Based on EEMD Feature Extraction

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This work was supported in part by the Natural Science Fund of Hubei Province under Grant 2017CFB598, Grant 2017CFB677, and Grant 2017CFB773, in part by the Natural Science Foundation of China (NSFC) under Grant 61572012, and in part by the Science and Technology Research Project of the Education Department of Hubei Province under Grant D20172203.

ABSTRACT Transmission line icing is a common natural phenomenon, but it is the most dangerous factor that severely threatens the safety and stability of the power grid operation. Transmission line icing involves many factors, including temperature, humidity, wind speed, light intensity, wire tension, pressure, and wind deflection angle. Because of the high dimensionality, nonlinearity, multi-modality, and heterogeneity of the data generated by these factors, it is difficult to establish an accurate prediction model based on these data adopting traditional data mining methods. How to establish an accurate and effective new model of transmission line icing prediction has become a key problem to be addressed urgently. To address these problems, the paper collects the data monitored by the China Southern Power Grid Online Monitoring System from 2011 to 2016 to study the prediction model of the icing level of the transmission lines. Since the values affecting the icing level are dynamically changing with time, this paper first uses the time series analysis method to process the icing data and proposes an ensemble empirical mode decomposition (EEMD) method to adaptively decompose the meteorological and mechanical data, which reduces the impact of noise and outliers in high-dimensional data, and maximizes the use of the inherent law of time-frequency to effectively analyze icing data. The feasibility of this method is verified with real data. The experimental results show that the prediction model based on EEMD time-frequency is more accurate than the prediction model based on the original data. Compared with the five prediction models as random forest, support vector machine, BP neural network, Elman neural network, and Bayesian network, the accuracy has increased by 0.47%, 2.93%, 1.85%, 0.92%, and 1.86%, respectively. In addition, this new method is more sensitive to the serious situation of icing on the transmission lines. Compared with the prediction model based on the original data, this method improves the accuracy of prediction for icing level 4 and 5 by 17.5%, 16.67%, 50%, 3.13%, and 10.26%, respectively.

INDEX TERMS Transmission line, EEMD, prediction model, ice coating.

I. INTRODUCTION

With the great development of human society, construction of smart cities has become an irreversible historical trend of the sustainable development of today's world and an effective way to solve numerous urban problems. The smart grid is the ''major artery'' of the future smart cities and is the key driving force for the development of smart cities. Large-scale transmission lines constitute an important part of the transmission of electric energy in smart grid. Therefore, improving the reliability and safety of transmission lines is an important factor in ensuring the safe and stable operation of the national power system. Transmission line icing is a common natural phenomenon, but it is the most dangerous

The associate editor coordinating the review of this manuscript and approving it for publication was Tie Qiu.

factor that severely threatens the safety and stability of the power grid operation. Therefore, there is an urgent need to conduct real-time multi-dimensional monitoring on the icing conditions of transmission lines, and to predict icing more accurately in order to ensure the security of transmission lines and the robustness of the transmission network.

Smart cities involve many fields as smart buildings, smart grids, transportation and medical services, urban public services, and urban ecological environments. Smart grid has become the most critical factor for the healthy development of smart cities. Smart grids will be combined with modern technologies such as artificial intelligence and Internet of Things to provide smarter and more convenient services for smart cities, to enhance relevant technology development and innovation, and to facilitate to achieve green living in cities. With the rapid development of China's economy and science technology, the demand for electricity has been increasing gradually, the power grid construction has been accelerated, and the transmission lines of various voltage levels have increased annually. The power grid systems have turned to be more large-scaled and intelligent, as shown in Fig. 1.

FIGURE 1. Transmission line [1,2].

Due to the uneven distribution of cities in China, the demand for electricity is different, resulting in the larger dispersion and wider coverage of transmission lines. In order to reduce the loss of electric energy during transmission, it is usually transmitted through EHV transmission lines. However, power stations are generally located in remote areas, resulting in long transmission distance, and along the way are usually areas with harsh geographical environment and complicated micro-meteorological conditions. In recent years, due to the global destruction of the ecosystem, climate change is abnormal, and extreme weather occurs more frequently. In particular, most of the transmission lines in the southern part of China often suffer severe freezing disasters, resulting in various icing accidents including broken or tripped transmission line, the collapse of transmission tower, and the insulator flash, as shown in Fig. 2. Icing lines cause huge economic losses to enterprises and brings security risks to the country and the people [3], [4]. The increasing urban population and the complexity of urban management have driven

FIGURE 2. Transmission line ice accidents [6,7].

local governments to use modern information technology to improve urban life and provide better public services [5]. In order to protect the lives and property of people and build a stable and friendly society, it is a key issue to be solved urgently to accurately predict the thickness of the ice on the transmission line and realize the safe and reliable operation of the power grid.

Transmission line icing is a common natural disaster, but has threatened the safe and stable operation of the power grid. Compared with other natural disasters, transmission line icing is particularly serious for grid security [8], [9]. Therefore, it is urgent to carry out real-time and multi-dimensional monitoring of the ice thickness of the transmission line and give accurate and effective prediction of the ice coating that may occur later soon so as to ensure the robustness of the entire power system and guarantee the safe and stable operation of the transmission line. With the accurate prediction of the ice thickness of the transmission line, the dynamic development trend of the ice thickness can be real-time detected, and reliable guidance can be provided for the relevant measures such as anti-icing and deicing of the transmission line. So that relevant officers and workers can make more correct decisions, prevent the occurrence of ice disasters more effectively, and improve the stability of the power system.

In recent years, people have been more concerned about ice coating of transmission lines, and gradually established a real-time online monitoring system, which has been developed rapidly and applied more widely. Since 2008, China Southern Power Grid has established an online monitoring system to ensure its safe and stable operation. The system collects large amount of unstructured data and structured data. Unstructured data contains image data. The structured data contains meteorological data and mechanical data such as temperature, humidity, wind speed, wind direction, rainfall, light intensity, and maximum-Minimum pulling force, wind angle under maximum-minimum pulling force, etc. Because the data are characterized as high dimensionality, non-linearity, multi-modality, heterogeneity, etc., it is difficult to establish an accurate prediction model based on these data with traditional data mining methods. At present, dealing with complex, multimodal ice coating data faces the following challenges:

1) According to the development trend, the data related to the thickness of ice coating shows geometric growth and the data dimension is getting higher and higher [10], [11]. However, only a small part of the high-dimensional features can reflect the true characteristics of the data. The "noise" in the data will obscure the real information [12] and affect the accuracy of the prediction model.
2) The nonlinearity, multimodality and heterogeneity of the data lead to the failure of traditional prediction models to meet the requirements of sequence mining. The data density is low, and there may be a high correlation between the various dimensions [13], which leads to the traditional prediction model not working well and the prediction accuracy is low.
3) Data contains unstructured data (picture data) and structured data (meteorological data and mechanical data). Traditional feature extraction methods cannot effectively process multimodal data. The diversity and complexity of the data lead to a large computational cost of the prediction model, and the prediction model is less robust.

To address these problems, this paper focuses on the prediction model of ice thickness of transmission lines. The time series analysis method is used to process the prediction model of the ice-covered data of the transmission line, and the ice-covered data is processed by time series to analyze the data features [14]. The paper adopts the Ensemble Empirical Mode Decomposition (EEMD) method, adapted from the time-frequency domain analysis method, to decompose adaptively the nonlinear and multi-modal ice-covered sequences, and explore its implicit modes to improve the anti-noise ability. we maximize the use of the inherent regular patterns, presented by these time-frequency characteristics, to analyze data effectively, and provide a basis for the establishment of subsequent models and improve the prediction accuracy of subsequent models.

II. RELATED RESEARCH

A. ICE COATING PREDICTION

Since the 1950s, China has begun to record detailed accidents related to ice-covered transmission lines, and has started related research work. Based on numerous research on ice coating phenomenon, ice coating mechanism, ice coating environment factors, ice formation conditions, various laws of icing conditions of electric circuits are summarized, and various models are proposed. Sun Caixin et al. proposed the heat balance equation of wire icing by analyzing the influence of various meteorological data on the thickness of ice on the transmission line under the critical condition of the wire [15]. Qing-Feng *et al.* studied the relationship between ice coating on transmission lines and local meteorological factors, and obtained a prediction model of transmission line ice coating [16]. Xingliang and Qiang studied the ice-covered experiments of different diameter conductors under various environmental parameters, and obtained a simulation model of ice coating on transmission lines [17]. Guiming established a mechanical model of the thickness of the ice on the transmission line and derived the formula for calculating the thickness of the ice on the transmission line [18]. Foreign researchers are also concerned about the ice coating of transmission lines and has made great achievements. The first seminar on ice coating for transmission lines was held in the United States, with the aim of allowing experts and scholars from various countries to exchange experiences on ice-covered research on transmission lines [19], [20]. The power departments of the United States, France, the United Kingdom and other countries have established observatories to monitor the icing of transmission lines. Japanese research institutes have conducted research on wires in wind tunnels, and analyzed the factors affecting the effects of ice coating on transmission lines. Canada conducted research based on data from natural ice observation stations and test sites to establish a regression model between each micro-meteorological parameter and the rate of ice coating. Y Ogawa et al. developed a quasi-distributed online monitoring system based on weighing method using fiber Bragg grating [21]. J Hosek et al. studied the impact of meteorological data on the dynamic capacity calculation of transmission lines [22]. Wang *et al.* studied the approximate analytical solution of a finite span and finite torsional stiffness [23]. Savadjiev and Farzaneh established a regression model between ice growth rates and various meteorological parameters [24].

Many countries have invested heavily in the research of ice coating on transmission lines, and conducted large-scale and in-depth research to explore the law of ice coating on transmission lines to reduce the impact of ice-covered disasters on transmission lines. According to the principle of ice formation on the transmission line and the law of fluid motion in the actual environment, the various ice-coating prediction models for transmission lines that the researchers have established are broadly divided into three categories:1) mathematical physics model; 2) statistical model; 3) intelligent prediction model. Mathematical physics model includes mathematical equations for icicle growth simulation and icing formation, such as the Goodwin model [25], the Makkonen model [26], and the Imai model [27]. The statistical model establishes the mapping relationship between the ice thickness of the transmission line and the environmental factor, regardless of the physical process of icing, such as the multiple linear regression model [28]. Mathematical physics models and statistical models are not suitable for solving nonlinear, complex, high-dimensional, multi-modal ice prediction problems. The intelligent computing model based on modern machine learning technology [29]–[31] has been widely used in transmission line ice prediction, and has achieved some results. The problem studied in the paper is the intelligent prediction model based on machine learning.

B. TIME SERIES

In recent years, as data storage and processor capabilities have increased, data has been stored in time-series manner in many applications [32]. For example, biomedical data (blood pressure, electrocardiogram), meteorological data, trajectory data, stock trading data, and etc. The rapid growth of time series data provides researchers with an opportunity to mine and analyze time series. The mining of time series has attracted a lot of interest from researchers and has been proven to provide effective information in all areas. In different fields there are many different goals, as sub-sequence matching, anomaly detection, pattern recognition, indexing, clustering, classification, visualization, prediction, and so on.

The time series is a dynamic ordered sequence that changes with time. At the time point

$T = \{t_1 t_2, \ldots, t_n\}$, the data point of length n is a collection of $X = \{x_1 x_2, \ldots, x_n\}$. Usually the definition of time series X is as follows:

$$X = \{(x_1, t_1), (x_2, t_2), \ldots (x_n, t_n)\} \; (t_1 < t_2 < \ldots < t_n) \quad (1)$$

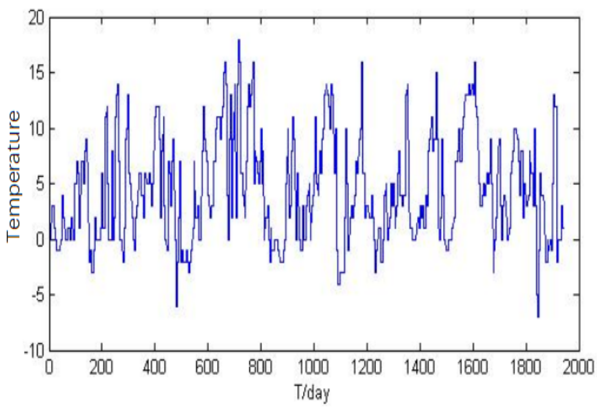


FIGURE 3. Time Series Example.

where $x_i = (x_{i1} x_{i2}, \ldots x_{ik})$ refers to a data point in a k-dimensional space, t_i refers to the time stamp of the corresponding x_i, Fig. 3 is the time series of monitored temperatures at Terminal CC2089 from 2011-2016 by China Southern Online Monitoring System. For the convenience of calculation, the time series is generally defined as follows:

$$X = \{(x_1), (x_2), \ldots (x_n)\} \quad (2)$$

Time series mining can detect valuable information and meaningful hidden distribution patterns. Time series is defined from three perspectives: 1) The statistic perspective: the dynamic ordered sequence of corresponding indicators over time is often affected by various accidental factors at a certain moment; 2) The mathematical perspective: the sequence $X = \{(x_1), (x_2), \ldots (x_n)\}$ formed by the effective observation value $x_i = (x_{i1} x_{i2}, \ldots x_{ik})$ at time t_i reflects the observed value of the recorded process; 3) The system perspective: the observed value x_i of a certain time t_i represents the state value of the system. The time series is different from ordinary static data, which evolves with time, reflects the whole dynamic characteristics and regularity of things, and the values of the sequences are not related to each other and are a pure random sequence. Time series are nonlinear and susceptible to various accidental factors, with mutations and uncertainties, but there are certain statistical laws on the time series as a whole, such as seasonality and periodicity. Most of the time series in nature and engineering are high-dimensional, nonlinear, complex data types, and neither is cyclical and stationary, and the frequency changes with time.

In the time series data mining, it is necessary to analyze the characteristics of the time series effectively, and adopt appropriate methods to deal with different types of time series and to mine more valuable information. For example, when faced with high-dimensional feature time series, the appropriate feature representation method, the dimensionality reduction method, and time series adaptive decomposition method can be used.

C. TIME DOMAIN FEATURE EXTRACTION

The time series is superficially disorganized, but the underlying laws can be found by analyzing some basic statistical features. The simplest time domain feature extraction involves many statistic tools, such as mean, variance, and other high-order statistics that have been used for time series clustering [33]. Of course, there are other more complex time domain features, such as the Lyapunov exponent [34], which has been used in machine learning. Shapelets are also widely used in classification [35] and unsupervised learning [36]. In addition, there are a series of general features in time series [37]. These features can effectively reflect the time-domain characteristics of time series to some extent and discover the laws of their implication.

1) SEASONAL

Time series are data collected on a regular basis and are seasonal in many time series data. This is a common feature of time series and is very important for the prediction of sequences. Given the original time series X, we define X∗ by Box-Cox [38] conversion:

$$X^* = \begin{cases} \frac{X^{\lambda}-1}{\lambda} & \lambda \neq 0 \\ \ln X & \lambda = 0 \end{cases} \quad (3)$$

where λ is a conversion parameter. The conversion parameter is to reduce the correlation between the observation error and the predictor, and the seasonality can be calculated by the following formula:

$$Seasonality\,(X) = 1 - \frac{Var\,(X^* - S - T)}{Var\,(X^* - T)} \quad (4)$$

where S and T represent seasonality and trends, respectively.

2) TREND

A time series trend is described as long-term behavior, excluding seasonal or random effects, which can be calculated by the following formula:

$$Trend\ (X) = 1 - \frac{Var\ (X^* - S - T)}{Var\ (X^* - S)} \tag{5}$$

3) NOISE

Time series have only a very small part of the higher dimensional features that can reflect the changing feature of the object, while other unrelated dimensions not only give less valuable information, but also can bring huge noise, which will cover up the real information and affect the accuracy of the model. A moving average filter can be used to quantify the noise.

4) OUTLIERS

In statistics, outliers are data points that represent significant deviations from other data in the sample. Often, outliers in a single data can alert statisticians to experiment anomalies or errors that may not be easily detected, and which greatly affect the accuracy of the model. Because of this, it is important to calculate and evaluate outliers to ensure proper analysis of the data.

5) SKEWNESS

Skewness is used to describe the degree of distribution of asymmetric statistical data. The magnitude of the absolute value of skewness reflects the degree of deviation of the entire time series. For a time-series X, it is calculated as follows:

$$Skewness\ (X) = \frac{\sum_{i=1}^{n} (X_i - \mu)^3}{n\sigma^3} \tag{6}$$

where μ represents the average value, σ represents the standard deviation, and n represents the time series length.

6) KURTOSIS

The kurtosis represents the steepness of the entire time series. For a time-series X, it is calculated as follows:

$$Kurtosis\ (X) = \frac{\sum_{i=1}^{n} (X_i - \mu)^4}{n\sigma^4} - 3 \tag{7}$$

where μ represents the average value, σ represents the standard deviation, and n represents the time series length.

7) AUTOCORRELATION

Autocorrelation, also known as sequence correlation or cross-correlation, is a mathematical representation of the similarity degree of a given time series itself between successive time intervals. Given a time series X, we can calculate the autocorrelation level by Box-Pierce [33] statistics.

$$Autocorrelation\ (X) = \frac{1}{h} \sum_{i=1}^{h} r_i(X)^2 \tag{8}$$

where h is the maximum interval (usually h is 15% of the length of the time series). The calculation of r_i (X) is as follows:

$$r_i\ (X) = corr_i\ (X_t, X_{t+i}) = \frac{\sum_{t=1}^{n-i} \left(X_t - \bar{X_t}\right)\left(X_{t+i} - \overline{X_{t+i}}\right)}{\sqrt{\sum_{t=1}^{n-i} (X_t - \overline{X_t})^2}\sqrt{\sum_{t=1}^{n-i} (X_{t+i} - \overline{X_{t+i}})^2}} \tag{9}$$

where n represents the length of the time series, and the stronger the time series randomness, the lower the result of the Box-pierce statistical value.

D. FREQUENCY DOMAIN FEATURE EXTRACTION

The most commonly used feature extraction methods based on frequency domain are Fourier transform and wavelet transform. For example, M Vlachos et al. use periodic features to cluster MSN query logs and ECG time series data by Fourier transform [39], [43]. Deng Kaixu et al. used wavelet transform to predict the trend of financial transaction data [40], [44].

1) FOURIER TRANSFORM

The Fourier transform is decomposing according to the frequency of the time series (or signal), to some extent similar to the notes that the music chord can be represented as amplitude (or loudness), as shown in Fig. 4. The Fourier transform of the time series itself is a complex-valued frequency function whose absolute value represents the component of the frequency in the original function, the complex portion of which represents the relative offset of the frequency based on the sine wave. The Fourier transform obtains the frequency domain characteristics of the time series by mathematical operations associated with time-frequency. The Fourier transform is not limited to the time function. For uniform

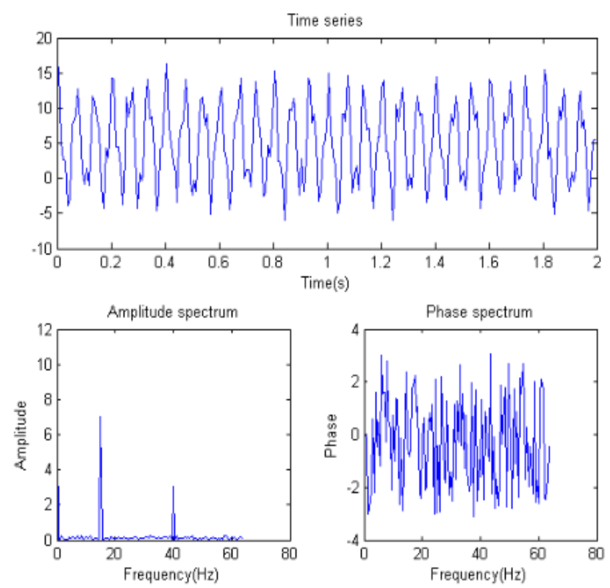


FIGURE 4. Fourier transform.

expression, the domain of the original function is usually called the time domain. Furthermore, the frequency domain can also be converted to the time domain, called the inverse Fourier transform. However, the Fourier transform does not explain the meaning of the instantaneous frequency, and the effect achieved when dealing with non-stationary time series is not ideal.

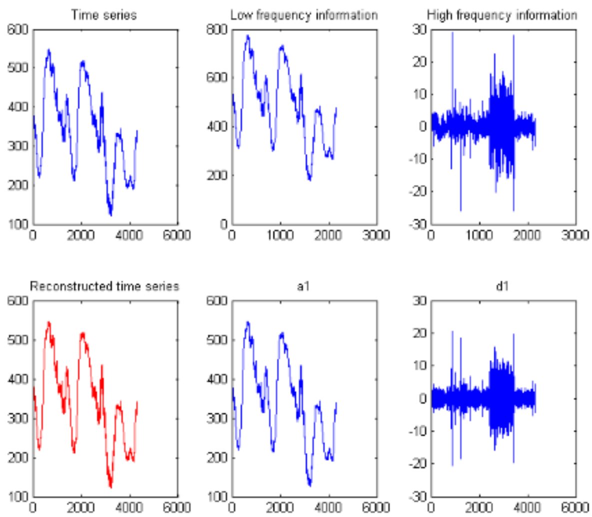


FIGURE 5. **Wavelet Transform.**

2) WAVELET TRANSFORMS

The wavelet transform can give the frequency of a signal in a specific time to achieve multi-scale decomposition of the signal, as shown in Fig. 5. There are many types of wavelets, which can be divided into stationary wavelets, tightly supported wavelets, simple mathematical expression wavelets, simple filter wavelets, etc. The simplest is Haar wavelet. Like a basis function in the Fourier transform, the wavelet function acts as wavelet transform's basis function. Once the wavelet basis ψ(x) is fixed, the wavelet basis {ψ((x-b)/a), (a, b) ∈R^+×R} can be transformed and expanded. It is convenient to take a special value to define the wavelet basis, a=2^(-j) and b=k•2^(-j) where k and j are integers. This choice of a and b is called key sampling and gives a sparse basis. Wavelet transform has greatly improved the processing of non-stationary time series, but it still can't decompose the signal adaptively, and the selection of wavelet base is difficult.

3) EEMD TIME-FREQUENCY FEATURE EXTRACTION METHOD

In the analysis and processing of nonlinear non-stationary signals, NE Huang et al. proposed a new time-frequency feature extraction method called Empirical Mode Decomposition (EMD) [41], [45].The Fourier transform requires time series to have stationary and linearity. As an alternative, wavelet is a multi-scale transform that can be used to analyze non-stationary signals, but still assumes linear conditions. To deal with these problems, EMD decomposes the signal into a set of better-performing Eigen mode functions [42] [(imf)]_j=([(imf)]_j1,[(imf)]_j2,…[(imf)]_jn), to obtain a relatively stable instantaneous frequency, as shown in Fig. 6.

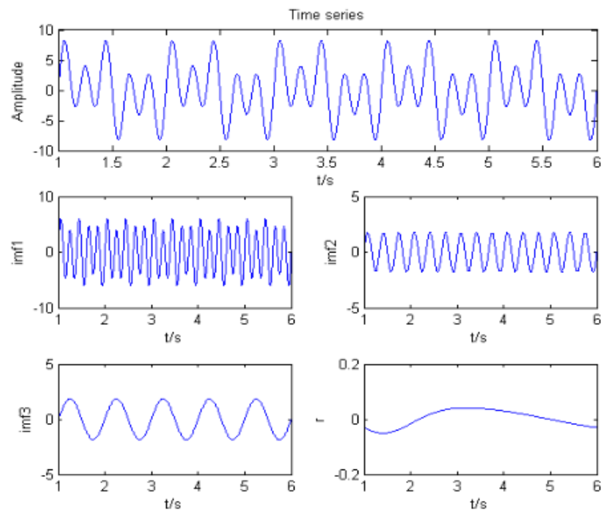


FIGURE 6. **Empirical Mode Decomposition EMD.**

Empirical mode decomposition is an adaptive tool for analyzing nonlinear and non-stationary signals. No preprocessing is required because it is a signal capable of analyzing non-zero mean values and is suitable for analyzing ride waves with no zero value between two consecutive extreme values. Unlike the Fourier transform and the wavelet transform, EDM has no fixed basis function, which is similar to PCA and ICA. The basis of decomposition depends on the signal.

Although EMD excellently solves the problem of non-stationary and nonlinear information feature extraction, it still has some problems as modal aliasing and spurious components. In order to overcome the shortcomings of EMD, Wu and Huang proposed a method of collective empirical mode decomposition (EEMD) [46] to improve EMD, and proposed a white noise-assisted analysis method, as shown in Fig. 7. The method superimposes white noise on the observed signal to equalize the distribution of the extreme points of the signal, without any prior knowledge the various scales of the signal can be clearly separated, and the adaptive decomposition can be achieved. The EEMD can decompose the modal components in the original sequence to obtain an intrinsic mode function (IMF) with the same characteristics. Because EMD uses the cubic spline interpolation algorithm multiple times in the fitting of the envelope, the envelope is overshoot or undershoot, and there is modal confusion (multiple scale features in the same IMF, or scale characteristics vary greatly) and endpoint effects (because there is no guarantee that the endpoint of the signal must be an extreme point, the envelope is not guaranteed to be accurate, and the error will extend inside the signal as the iteration proceeds). EEMD utilizes the EMD's scale separation ability and statistical features to segment the signal by uniformly adding white noise throughout the time-frequency space to

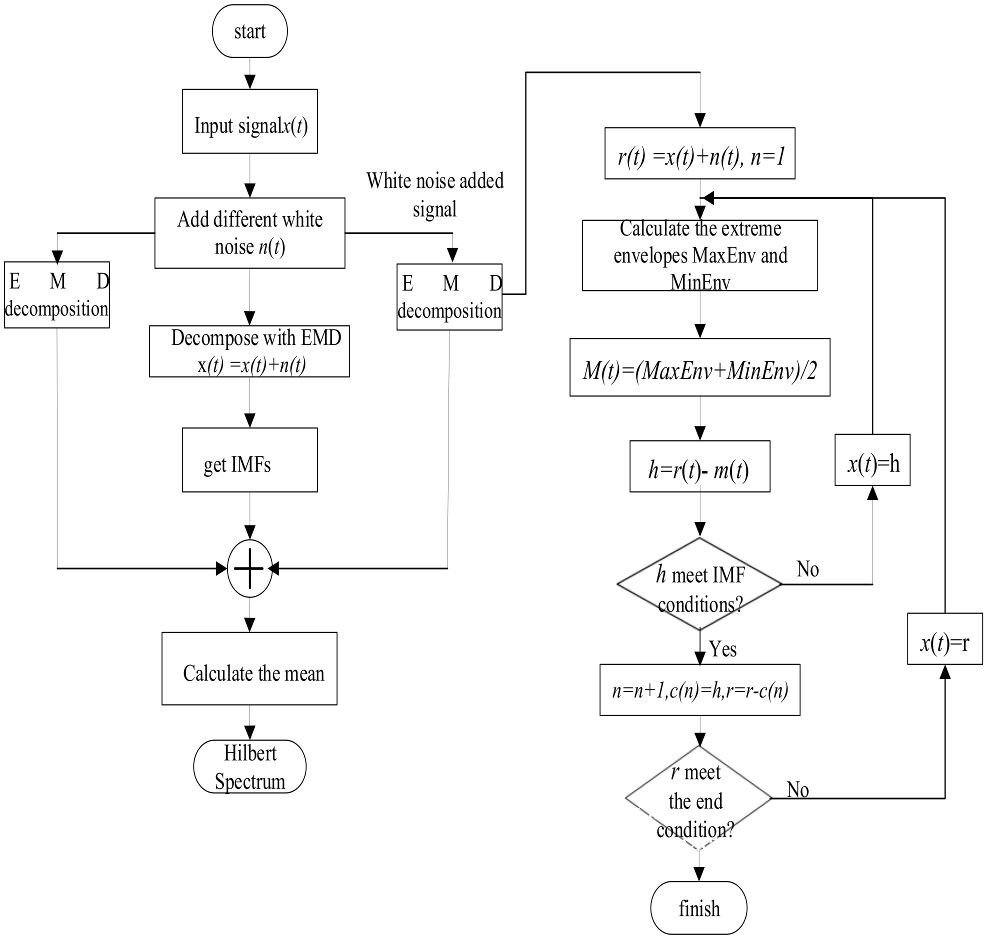


FIGURE 7. EEMD program flow chart.

solve the problem of modal aliasing and false components in EMD.

The EEMD splits the signal throughout the time-frequency space by the white noise. Any independent test has a high probability of producing an unrecognizable result. The reason is that the test is a mixed signal with added white noise. Of course, the amount of white noise that needs to be added is a value that needs to be artificially determined. White noise of different amplitudes has a significant effect on the problem of modal confusion. Different noise is added to each test signal, the average of all test results is used, and the test data set is large enough to minimize the effects of noise. In this case, we can treat the average after multiple decompositions as the final result, which is the signal itself that remains basically unchanged in many tests. At the same time, repeated and multiple addition tests are used to avoid the effects of noise. The EEMD algorithm steps are as follows:

1) Add normally distributed Gaussian white noise to the original signal x(t);
2) Decompose the mixed signal of the normally distributed Gaussian white noise into several Eigen mode components IMF and margin Rn by EMD;
3) Continuously add new white noise signal during the repetition of steps (1) and (2), repeat N times, and continuously add the resulting IMF;
4) Calculate the average of the IMF set as the final result. Different white noise additions will cause different decomposition results. Under normal circumstances, if the added white noise amplitude is too low, the problem of modal confusion cannot be suppressed. If the addition amplitude is too high, it will greatly increase the times of the average is solved. And the high-frequency components in the signal are not easily decomposed, and the amplitude should obey the Gaussian distribution.

III. ICE COATING MODEL BASED ON EEMD DECOMPOSITION

Time series analysis has been widely used in processing dynamic data and has made great achievements. Time-series analysis method for ice coating data can effectively reduce the influence of noise and outliers. It can also maximize the use of the inherent law presented by time-frequency features and effective analyze data so as to provide a basis for the establishment of subsequent prediction models. Time series analysis can ignore the effects of noise and outliers to obtain stable performance. Fig. 8 shows the time-frequency features of the temperature time series decomposed by EEMD in the ice coating data. All the IMF components after extraction are from high to low. The order is arranged to display. Usually the higher the frequency is, the higher the energy level is. The residual signal can be discarded because the energy is too low.

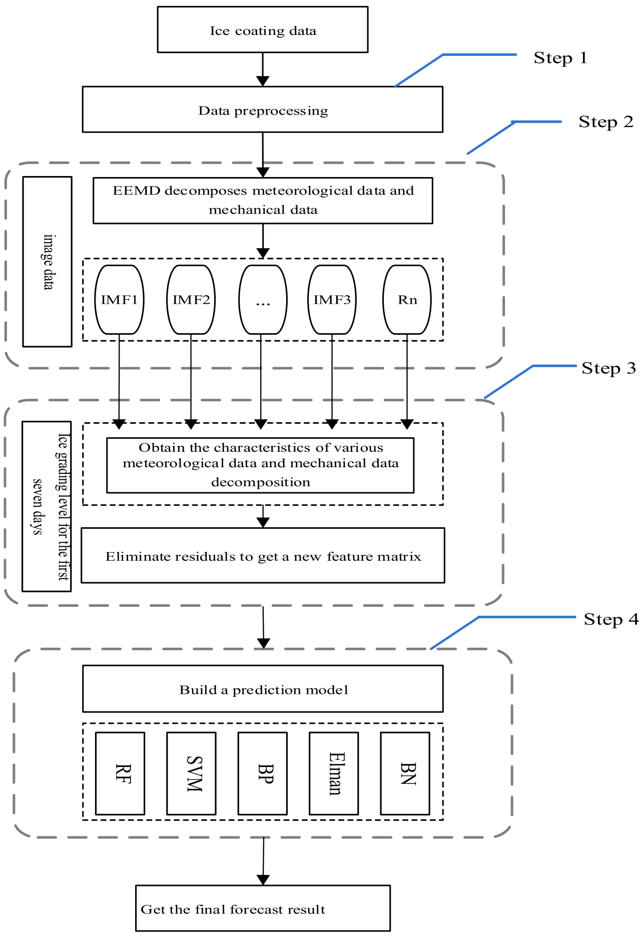


FIGURE 8. Time-frequency features of time series.

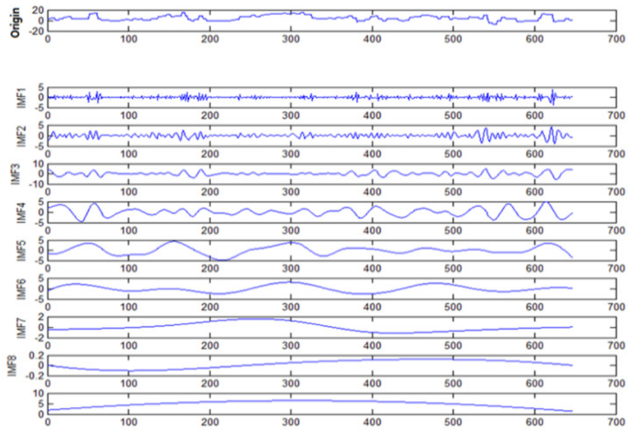


FIGURE 9. Adaptive Feature Extraction Algorithm Flow.

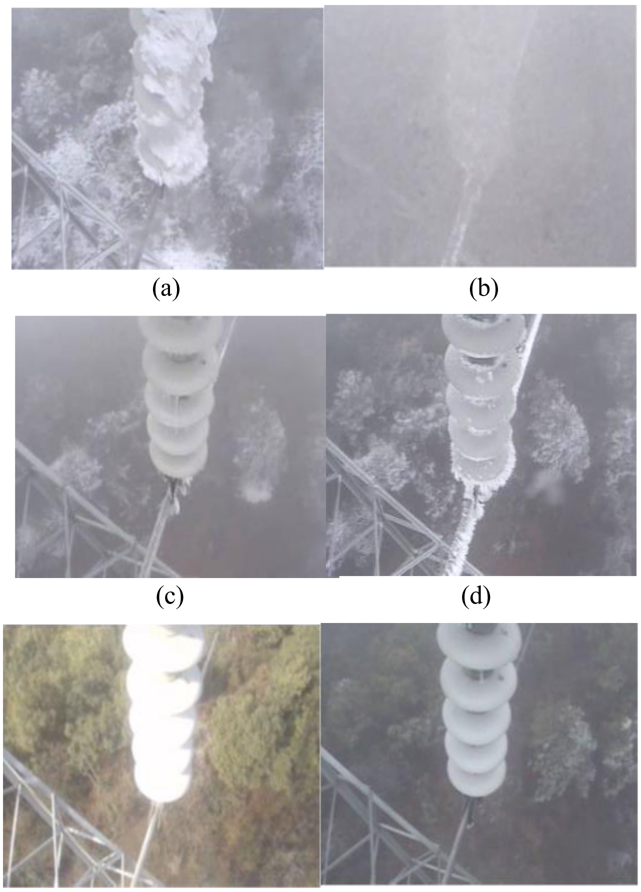
Since the relevant factors affecting the ice thickness of the transmission line are dynamically changing with time, this model uses EEMD to adaptively decompose the meteorological data and mechanical data in the ice coating data, and to decompose the original data into relatively single frequency and stable components so as to reduce the impact of various factors on the prediction of icing prediction. Then the image data and historical ice-level data are involved to establish a prediction model, which effectively improves the efficiency and accuracy of the prediction model. The flowchart is shown in Fig. 9. The specific implementation steps are as follows:

1) Pre-process all ice-coating data to eliminate noise and incomplete data;
2) Apply EEMD to decomposing meteorological and mechanical time series in ice coating data into a series of high-to-low frequency components IMFs (IMF1, IMF2,..., IMFn) and Rn, where Rn is the corresponding decomposition margin. The component is used to capture the instantaneous frequency and time domain mapping of the time-varying signal. These IMFs components are relatively more stable than the original time series, and there is no sudden sharp change in the time domain;
3) Exclude all meteorological data and mechanical data from the residuals after EEMD decomposition, and take image data and historical ice-level as the input of the prediction model;
4) The result of step (3) is used as the input of the prediction model to establish a prediction model of the transmission line, and the final prediction result can be obtained. The method considers five prediction models, namely RF, SVM, BP, Elman and BN.

IV. EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

This section details the specific design of the transmission line ice prediction model based on EEMD feature extraction and compares the results of the final prediction. Firstly, the specific design and implementation process of the method are introduced. Then the time series of EEMD decomposition is analyzed. The time series after decomposition is used to establish the prediction model and the results are discussed and analyzed. Finally, the decomposition results and other prediction results are obtained. A comparative evaluation was carried out to verify the feasibility of the method. The environment configuration of the experiment is as follows: operating system (Windows 7, 64-bit), CPU (Inter(R) Core (TM) i7-4770 3.40GHz), installed memory (32GB), programming software is MATLAB R2014a and Weka 3.8.

The data used in the paper is from the data monitored by China Southern Online Monitoring System Terminal CC2089 from 2011 to 2016. The data set can be divided into four parts, namely basic information data, picture data, meteorological data and mechanical data. The basic information data includes the terminal name and the recording date and time. These basic information data will not be used when the model is built. The meteorological data includes temperature, humidity, rainfall, light intensity, etc. Mechanical data includes maximum and minimum tension, tensile force, wind yaw angle, and etc. In addition, each data sample has a corresponding level of ice coating. The level is divided into 6 grades from 0 to 5, where 0 indicates that the transmission line is not covered with ice, and 1-5 means that the icing grade of the transmission line is getting worse and worse, as shown in Fig. 10. The icing grade is defined by the calculation model of the Electric Power Academy. The following pictures are provided by the relevant research team of Bruce Ling's Lab from Stanford University.



(a) (b) (c) (d) (e) (f)

FIGURE 10. Transmission line ice coating grade. (a) Grade 0. (b) Grade1. (c) Grade2. (d) Grade 3. (e) Grade 4. (f) Grade 5.

There are 1942 samples in this experiment, of which 2/3 (1295) were selected as training data, and 1/3 (647) were selected as test data. The number of each icing grade to be tested is shown in Table 1. Among them, the proportion of icing grade 0 is very large, and the data of other icing grades is less. But the higher the icing grade is, the more destructive the damage is to the grid. This is particularly true when it comes to grade 4 and grade 5, which have a great damage on the power system and should draw more attention from workers.

TABLE 1. Number of Each Ice-Covered Grade of Test Data.

Test Data	The number of each ice-covered grades
Level 0	539
Level 1	13
Level 2	1
Level 3	33
Level 4	17
Level 5	44

In this section, the ice-coating data based on EEMD feature extraction is modeled and compared with the model established by the original ice-coating data to verify the effectiveness and feasibility of the method. Among them, five kinds of common prediction models, random forest, support vector machine, BP neural network, Elman neural network and Bayesian network, are selected. The prediction accuracy of various different prediction models is shown in Table 2.

TABLE 2. Comparison of Different Prediction Models Based on Ice Coating Data.

prediction model	Raw Data	EEMD
RF	91.65%	92.12%
SVM	80.22%	83.15%
BP	83%	84.85%
Elman	85.94%	86.86%
BN	90.57%	92.43%

From the table, we can see that the prediction accuracy rates of the five prediction models based on the original data are: 91.65%, 80.22%, 83%, 85.94% and 90.57% respectively. The accuracy of the ice-covered prediction model based on EEMD feature extraction has been improved by 0.47%, 2.93%, 1.85%, 0.92% and 1.86% respectively, as shown in Fig. 11.

The number of correct predictions for each icing grade of different prediction models is shown in Table 3. The table shows the specific correct number of predictions for each icing level based on the raw data and the EEMD-based data prediction model. On the whole, the icing prediction model

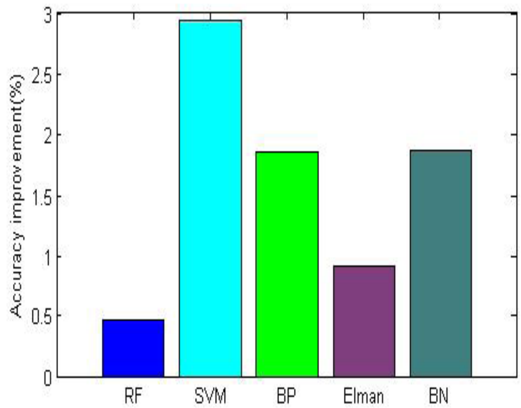


FIGURE 11. Accuracy improvement of each prediction model based on EEMD feature extraction.

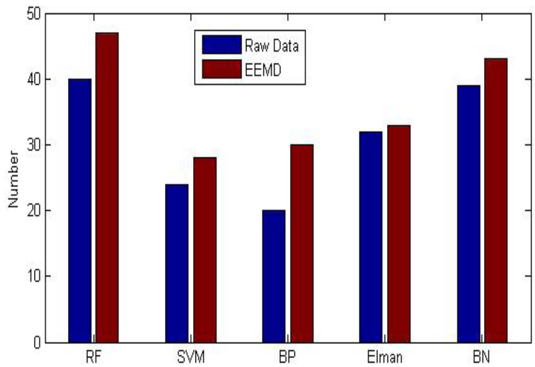


FIGURE 12. Correct prediction numbers of different predictive models.

of EEMD feature extraction performs better with higher accuracy.

In order to further assess the performance of the prediction model based on EEMD feature extraction, the paper evaluates RF, SVM, BP, Elman, BN prediction models by five performance indicators, RMSE, MAE, MAPE, R and NSEC, as shown in Table 4–5.

The table shows that the MAE values of each model based on the EEMD feature extraction are reduced, and the performance indicators are improved by more than 30%. The RMSE values of RF, SVM, Elman and BN are 0.8870, 0.6508, 0.7511 and 0.7542 respectively. Compared with the prediction model based on the original data, most models have relatively low MAPE and the performance have increased by more than 20%. In terms of R and NSEC, while different prediction models based on raw data and EEMD-based feature extraction have their own advantages, the prediction model based on EEMD feature extraction is better with lower error rates.

The transmission line icing grades 4 and 5 indicate that ice is extremely severe and the damage to the entire power system is more serious. This experiment counts the number of correct predictions for icing grades 4 and 5 based on raw data and EEMD-based feature extraction, as shown in Fig. 12.

TABLE 3. Number of Correct Predictions of Different Ice Level.

Predictive model	Ice coating grade	Raw Data	EEMD
RF	Level 0	536	537
	Level 1	0	0
	Level 2	0	0
	Level 3	17	12
	Level 4	16	16
	Level 5	24	31
SVM	Level 0	476	493
	Level 1	6	4
	Level 2	0	0
	Level 3	13	13
	Level 4	14	16
	Level 5	10	12
BP	Level 0	501	504
	Level 1	6	6
	Level 2	0	0
	Level 3	10	9
	Level 4	7	9
	Level 5	13	21
Elman	Level 0	517	520
	Level 1	4	2
	Level 2	0	0
	Level 3	3	7
	Level 4	9	8
	Level 5	23	25
BN	Level 0	531	532
	Level 1	3	2
	Level 2	0	0
	Level 3	13	21
	Level 4	16	15
	Level 5	23	28

As can be seen from the Fig.12, the data of correct predicting based on raw number for icing grades 4 and 5 of the

TABLE 4. Evaluation Values of Each Model Based on Raw Data.

Evaluation index	Raw Data				
	RF	SVM	BP	Elman	BN
RMSE	0.9765	0.7163	0.6752	0.7843	0.8459
MAE	0.2427	0.2844	0.2519	0.2566	0.2148
MAPE	0.0684	0.1613	0.1190	0.1188	0.0655
R	0.8163	0.8779	0.8924	0.8567	0.8297
NSEC	0.8735	0.9175	0.9267	0.9011	0.777

TABLE 5. Evaluation Values of Each Model Based on EEMD Feature Extraction.

Evaluation index	EEMD				
	RF	SVM	BP	Elman	BN
RMSE	0.8870	0.6508	0.7131	0.7511	0.7542
MAE	0.2117	0.2349	0.2365	0.2303	0.1793
MAPE	0.0629	0.1321	0.1087	0.1046	0.0770
R	0.7719	0.8997	0.8786	0.8708	0.8673
NSEC	0.8467	0.9319	0.9182	0.9093	0.8234

RF, SVM, BP, Elman and BN models are 40, 24, 20, 32 and 39 respectively. The correct number of predictions based on EEMD feature extraction, for icing grades 4 and 5 are: 47, 28, 30, 33 and 43. Compared with the prediction model based on original data, the method improved the prediction accuracy of icing grades 4 and 5 by 17.5%, 16.67%, 50%, 3.13% and 10.26% respectively. Therefore, each prediction model based on EEMD feature extraction is more sensitive to the serious situation of ice coating on transmission line. Prediction accuracy is higher when the ice coating level is higher, which has a better guiding role in preventing severe ice disaster.

V. CONCLUSION AND FUTURE WORK

The paper analyzes the ice coating factors affecting transmission lines as a time series, and proposes a prediction model based on time series analysis of transmission line ice coating to reduce the influence of noise and outliers in high-dimensional data. The method can adaptively decompose the meteorological data and mechanical data in the ice coating data, and maximizes the internal law of the time-frequency features to effectively analyze the icing data, which provides a basis for the establishment of the prediction model. Finally, the model is compared with the model based on original ice-coating data. The experimental results show that the proposed method has higher prediction accuracy and is suitable for various prediction models. In addition, the sums of correct predictions for icing grades 4 and 5 of based on original ice-coating data model and the EEMD-based feature extraction model are also calculated. The statistical results show that the method is more sensitive to the serious problem of ice coating on the transmission line, and the prediction accuracy is higher.

In terms of future work, it would be valuable and meaningful to continue this study. We can continue to explore some grid data processing methods. We can predict the icing level of transform lines by two stages: 1) structured and unstructured data feature extraction by local binary patterns; 2) radial basis function (RBF) Kernel based predicting for the processed data. Another obvious future research direction is to extract new feature from the unstructured and structured data and establish new prediction methods based on this work.

VI. ACKNOWLEDGMENTS

The authors should also thank the team of Xuefeng Ling from Stanford University which support us the data sources and valuable advises.

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