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Transmission line ice disaster early warning method based on ice thickness prediction using GM(1, 6) model

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ABSTRACT The operation of the electricity system faces the difficulty of minimizing ice damage to transmission lines. Due to the uncertainty of transmission line icing thickness, accurate prediction of icing thickness is very important to guide transmission line planning and power grid anti-icing design effectively. Scientific and reasonable early warning assessment of conductor icing is also helpful to make timely and accurate response measures to the possible freezing disaster risk, so as to effectively ensure the safe and stable operation of power grid and reduce the occurrence of the freezing disaster. Based on this, this paper proposes a multi-factor prediction model based on GM (1, 6) grey theory, which considers the transmission line conductor icing model under the influence of multiple meteorological factors. Based on the conductor icing model, the conductor icing degree can be predicted in real time according to meteorological parameters, so as to realize the purpose of transmission line conductor icing disaster risk early warning. It is worth noting that the paper improves the traditional grey model by adding random data functions, which makes the model solve the problem of inaccurate prediction of small samples. Finally, a case study is carried out, and the icing disaster risk is divided into five levels. It is found that the maximal prediction error of icing thickness based on GM (1, 6) grey theory multi-factor prediction model is 10.06%(The average value is only 4.22%), and the accuracy of transmission line conductor icing disaster risk early warning is 88.9%. In addition, a certain safety margin value is added to the predicted value near the critical value of icing thickness, reducing the probability of judging the high-risk level as low-risk. Applying risk early warning method in ice areas can guide the anti-ice work of transmission line.

INDEX TERMS Icing disaster; icing prediction; fault early warning; GM (1, 6) model

I. INTRODUCTION

Since the beginning of this century, there has been a discernible increase in the frequency of severe weather events[1-3], resulting in significant damage inflicted upon the national economy. Icing disaster[4, 5] on power transmission line poses a severe threat to the safe and reliable operation of power grid (Power system icing disaster are shown in Figure 1), which must be attached a great deal of importance to[6-8]. Icing disaster on power transmission line ranks as one of the most severe meteorological disasters for electric power system. It is essential to develop a reliable forecasting model to warn about the ice thickness in advance and give people enough time to prepare for potential accidents[9, 10].

There is a variety of other approaches, but they can be categorized into these three categories. Physical, statistical, and intelligent forecasting methods are the three approaches that can be utilized today to research transmission line icing predictions. Icicles affect the formation of ice loads, and the only way this effect can be effectively accounted for is through numerical modeling that considers all of the important physical processes and how they interact with one another.

(a)

(b)

FIGURE 1. Power system icing disaster: (a) Collapse of towers caused by icing; (b) Iced transmission line.

The early research on transmission line icing is based on the physical model. The most fundamental presumptions, the most fundamental ideas of logic, the validity of mathematical formulas, and the comprehensiveness of physics are all taken into consideration. After that, an updated and thorough physical model was presented in the paper[11], which was then tested using a restricted data set from a wind tunnel. In addition, load cell evaluations of actual icing loads on an existing 315-kV line are correlated to hourly measurements of ambient temperature, wind speed, precipitation rate, and the number of Ice Rate Meter (IRM) signals. This is done in order to establish a numerical model for precipitation icing accretion on overhead line conductors[12]. It is difficult to accurately predict the desirable icing thickness using these physical models because of the challenges associated with measuring certain parameters, such as the radius of liquid water and the adhesion coefficient in the icing process.

Statistical models, such as the multiple linear regression icing models [13], the extreme value model [14], and others, adopt mathematical-statistical methods to forecast icing thickness, in contrast to what the physical model considers. This model has a certain effect on the prediction of icing thickness. For example, the findings of the analysis[14] show that GPD is more appropriate than P-III and GEV for the icing data acquired from Lvcongpo Mountain. This is beneficial because it helps to fairly determine the design ice thickness of conductors for transmission lines. The statistical model performs poorly in generalization ability and has poor icing forecasting accuracy due to the involvement of numerous hypotheses and icing-affecting factors.

With the development of computer technology, artificial intelligence prediction algorithm has been widely used in recent years[15-18]. Reference [19] proposed a short-term prediction model of transmission line icing thickness based on a grey support vector machine and analyzed the methods of eliminating bad data and data preprocessing. The accuracy and applicability of the model prediction are verified by comparing the model prediction results with the measured data of the maximum ice thickness. Literature [20]collected the monitoring data of China Southern Power Grid's online monitoring system from 2011 to 2016. The paper first used the time series analysis method to process the icing data and proposed an integrated empirical mode decomposition (EEMD) method to decompose the meteorological data adaptively. The influence of noise and outliers in high-dimensional data is reduced, and the inherent law of time frequency is used to analyze ice data effectively. The experimental results show that the prediction model based on EEMD time frequency is more accurate than the prediction model based on original data. Compared with the five prediction models of random forest, support vector machine, BP neural network, Elman neural network, and Bayesian network, the prediction accuracy is improved by 0.47%, 2.93%, 1.85%, 0.92%, and 1.86%, respectively. The intelligent forecasting methods model also has some shortcomings. They require a high amount of data, but obtaining transmission line icing, and meteorological data is relatively tricky, so the ice thickness prediction method of small sample data is essential.

In recent years, the grey theory has been utilized in various sectors[21-24], especially in the prediction model, and its accuracy in predicting outcomes in certain domains is comparable to or even exceeds that of the neural network technique[25-27]. GM (1, N), for instance, was proven to be applicable to forecast the pollution on insulators in circumstances of insufficient information with less data for the building model, according to the research that was published in the literature[23]. In addition, taking into account a more significant number of environmental elements is beneficial to increasing the accuracy of the predictions made by the GM (1, N) model.

Therefore, this paper proposes a multi-factor prediction model based on the grey theory (GM (1, N)). Based on the GM (1, N) model of conductor icing, the degree of conductor icing can be predicted in real-time according to meteorological parameters to achieve the purpose of risk early warning of transmission line icing disaster. In ice areas, the risk warning method can guide the anti-ice work of transmission lines.

II. APPLICATION OF GM (1, N) IN THE PREDITION OF CONDUCTOR ICING

The study of information (partially clear and partially ambiguous) in relation to the phenomenon of uncertainty is the focus of grey theory, which is a subfield of applied mathematics [28-30]. The notation GM (1, N) denotes the first-order grey model. It possesses n variables, one of which is a dependent variable, while the remaining variables are independent. Some prediction methods that are based on big data become infeasible when only a small amount of information is available; consequently, grey models can be created based on grey theory to calculate a small number of outputs with fewer (usually at least 4) information data when only a small amount of information is available. Because disordered data and unsystematic data could be exponential by the accumulated generating operation (AGO), the first order differential equation is a useful tool for describing how a system behaves. Through the process of solving the differential equation, the time response solution will be achieved. By using the inverse cumulative generation operation, the predicted value can be reverted to the sequence it was based on (IAGO).

To be more specific, in the case when there are n variables, such as $x_1, x_2, \ldots x_n$, and each variable has m associated data, then it is possible to build n time series $x_i^{(0)}(k)$, as shown in equation (1):

$$x_i^{(0)}(k)=\{x_i^{(0)}(1),\ x_i^{(0)}(2),\cdots,\ x_i^{(0)}(m)\}$$
$$i=1,2,\ldots,n;\ \ k=1,2,\ldots,m. \tag{1}$$

GM (1, N) model can be developed in four steps after the first series have already been determined. These steps include accumulating generating operation, determining the driving parameters, determining the approximate response of the GM (1, N) model, and forecasting using the inverse accumulated generating operation. The following are the steps that were taken:

(1) Accumulated generating operation.

First, N series $x_i^{(0)}(k)$ may be processed by using Accumulated Generating Operation, Next, $x_i^{(1)}(k)$ as the 1st-order AGO series of $x_i^{(0)}(k)$ can be calculated according to equation (2) and (3).

$$x_i^{(1)}(k)=\{x_i^{(1)}(1),\ x_i^{(1)}(2),\cdots,\ x_i^{(1)}(m)\} \tag{2}$$

$$x_i^{(1)}(k)=\sum_{j=1}^{k}x_i^{(0)}(j)$$
$$k=1,2,\ldots,m \tag{3}$$

(2) Determining the driving parameters.

It is possible to generate the nearest neighbor mean sequence $z_1^{(1)}(k)$ of $x_1^{(1)}(k)$, which can be computed using equation (4) and (5).

$$z_1^{(1)}(k)=\left\{z_1^{(1)}(2),\ \ z_1^{(1)}(3),\cdots,\ \ z_1^{(1)}(k)\right\}$$
$$k=2,3,\cdots,m \tag{4}$$

$$z_1^{(1)}(k)=\frac{\left[x_1^{(1)}(k)+x_1^{(1)}(k\text{-}1)\right]}{2}$$
$$k=2,3,\cdots,m \tag{5}$$

The equation that can be used to define the whitening differential equation for the GM (1, N) model is (6).

$$\frac{dx_1^{(1)}}{dt}+ax_1^{(1)}(k)=\sum_{i=2}^{n}b_i x_i(k) \tag{6}$$

The driving parameters are denoted by "b_i", while the development parameter is denoted by "a". The driving factors are represented by the letter "b_i", which stands for the levels of influence that the *i-th* variable has on the dependent variable. In addition, if the value of "b_i" is greater than zero, the *i-th* variable positively influences the dependent variable. On the other hand, if "b_i" is less than zero, it has a detrimental effect on the variable that is being relied upon.

Then the GM (1, N) model is as follows：

$$x_1^{(0)}(k)+az_1^{(1)}(k)=\sum_{i=2}^{n}b_i x_i(k) \tag{7}$$

Parameter column A=[a, b_1, b_2,…,b_{n-1}]^T. According to the least squares method, the estimation $\hat{A}$ of parameter A can be derived using equation (8).

$$\hat{A}=(B^T B)^{-1}B^T Y \tag{8}$$

Where the matrix B can be determined by equation (9), Y is shown in equation (10).

$$B=\begin{bmatrix} -z_1^{(1)}(2) & -x_2^{(1)}(2) & \cdots & -x_n^{(1)}(2) \\ -z_1^{(1)}(3) & -x_2^{(1)}(3) & \cdots & -x_n^{(1)}(3) \\ \vdots & \vdots & \cdots & \vdots \\ -z_1^{(1)}(m) & -x_2^{(1)}(m) & \cdots & -x_n^{(1)}(m) \end{bmatrix} \tag{9}$$

$$Y=\begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{bmatrix} \tag{10}$$

(3) Calculating approximate response of GM (1, N) model.

The solution of the equation can be obtained by substituting the grey parameter into equation (6), as presented in equation (11).

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$$\hat{x}_1^{(1)}(k+1) = x_1^{(0)}(1) - \frac{1}{a}\left[\sum_{i=2}^{n} b_i x_i^{(1)}(k+1)\right]e^{-ak} + \frac{1}{a}\sum_{i=2}^{n} b_i x_i^{(1)}(k+1) \tag{11}$$

(4) Prediction by using the inverse accumulated generating operation.

Finally, $\hat{x}_1^{(0)}(k+1)$ is the k+1 phase predicted value of time series $\hat{x}_1^{(0)}(k)$, which can be obtained through the inverse accumulated generating operation as is shown in equation (12).

$$\hat{x}_1^{(0)}(k+1) = \hat{x}_1^{(1)}(k+1) - \hat{x}_1^{(1)}(k) \tag{12}$$

To utilize GM (1, n) model to forecast the quantity of conductor icing, we must first collect data on all affecting parameters and icing thickness. Then, the initial sequence $x_1^{(0)}(k)$ and N-1 influence factor sequence $x_i^{(0)}(k)$ of conductor icing can be determined.

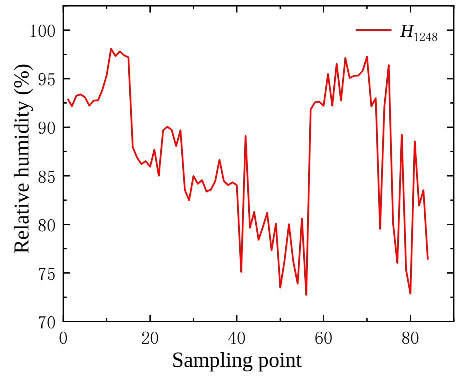
By solving the grey equation shown in formula (7), the grey parameter $\hat{A}$ can be determined, including the system development parameter a and the driving parameter b_i. The influence degree of each influencing factor on the conductor icing amount are determined according to the value of b_i. In addition, when b_i is negative, it indicates that the corresponding factors have a positive impact on icing. The greater the absolute value of b_i, the greater the impact on the icing thickness. Finally, according to the model, the icing thickness under various influencing factors can be estimated. Through the real-time prediction of the icing thickness, the early warning of conductor icing disaster can be realized.

III. TRANSMISSION LINE ICE DISASTER EARLY WARNING MODEL BASED ON GM (1, 6)

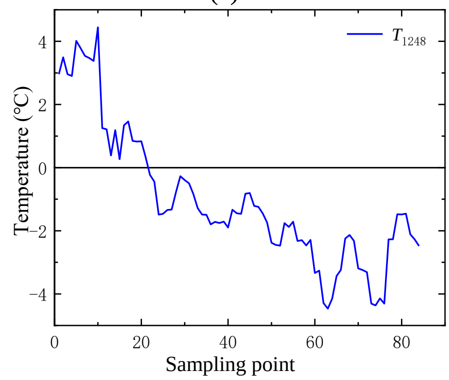
A. Data samples

The main causes of icing are freezing rain and supercooled liquid water droplets in the air. However, there is almost no freezing rain on the transmission lines in the studied area. The main reason for icing is the supercooled water droplets in the crosswind. A small amount of freezing rain can also be attributed to the influence of liquid water droplets. Generally, the meteorological department will not directly provide the supercooled liquid water content data, but it is closely related to relative humidity, wind speed and meteorological temperature. Thus, it is also considered the other two main factors that affect the icing of conductors: wind direction and altitude.

Therefore, five influencing factors of icing are considered: temperature, wind speed, relative humidity, wind direction and altitude. The icing prediction model in this paper belongs to a six-factor (5 independent variables, 1 dependent variable) grey model.



(a)



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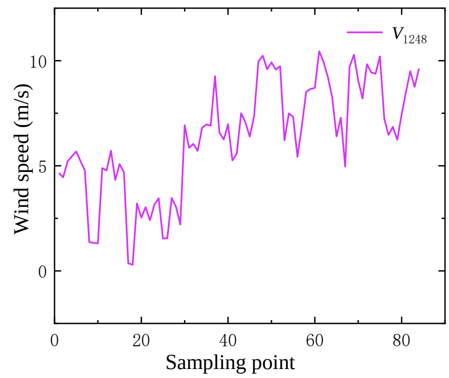
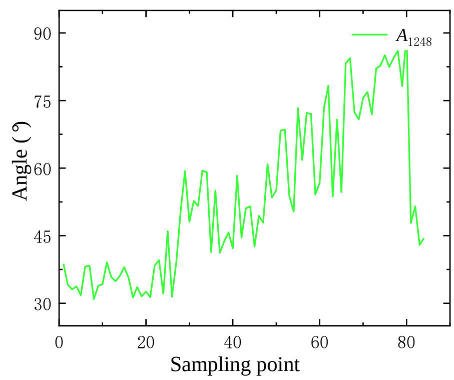


(c)



(d)

FIGURE 2. Meteorological data of 1248m altitude. (a) Relative humidity; (b) Meteorological temperature; (c) Wind speed; (d) Included angle between wind direction and conductor.

This paper collects meteorological data and icing thickness data of an icing cycle. The collection period is 7 days, accumulating 4 sampling points, corresponding to 4 altitudes. Taking the altitude of 1248m as an example, the collected meteorological data and icing thickness are shown in Figure 2-3.

It can be seen from the figure that the ice thickness increases with the decrease of temperature and the increase of ambient wind speed. However, the relative humidity fluctuates greatly, and there is no obvious trend on the whole.

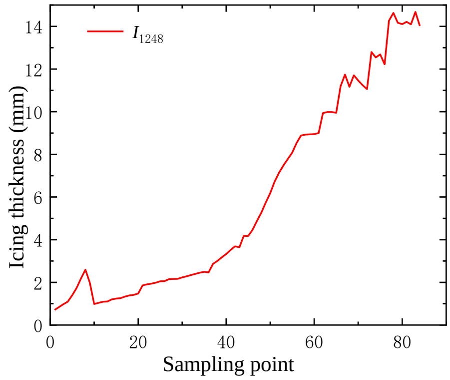


FIGURE 3. Icing data at 1248m altitude

In addition, comparing the icing data at different altitudes, it is found that in the same place, when the altitude rises, the icing thickness also increases correspondingly.

B. Early warning process of conductor icing disaster

Generally, according to the impact degree and scope of transmission line icing events, the risk level of transmission line icing status is divided into five levels according to the range of icing thickness: Level 1, level 2, level 3, level 4 and level 5, which are mild, general, moderate, serious and unusually serious, and are represented by $L1$, $L2$, $L3$, $L4$ and $L5$, as shown in Table 1.

TABLE I
FIVE LEVELS OF ICING RISK

Icing thickness	Level	Possible disaster impact degree	Representation symbol
0~5	1	mild	$L1$
5~10	2	general	$L2$
10~20	3	moderate	$L3$
20~30	4	serious	$L4$
30~	5	unusually serious	$L5$

As shown in Figure 4, combined with the multi-factor prediction model mentioned above and the method of wire icing risk classification, the transmission line icing thickness and the corresponding early warning level can be directly obtained according to the environmental parameters through the process shown in Figure 4.

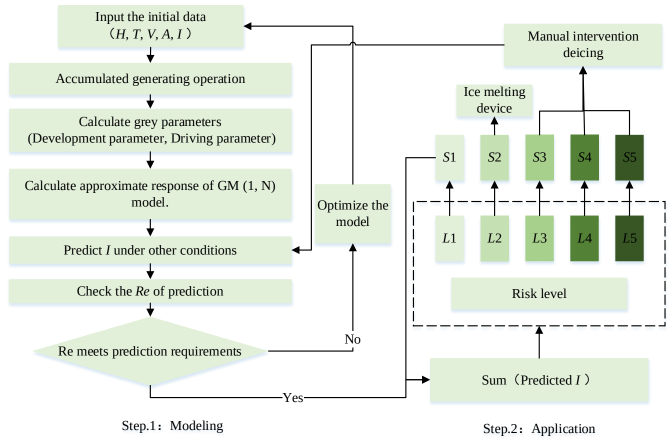


FIGURE 4. Flow chart of model calculation and icing risk early warning.

Different transmission line icing risk levels correspond to different solutions.

S1: for example, the level 1 icing hazard is low, and the transmission line icing can usually fall off freely without special treatment.

S2: Grade 2 icing easily falls off when using the ice melting device; no special treatment is required.

S3: however, the level 3 icing hazard is relatively large, and the general ice-melting device is weak, requiring manual deicing.

S4: Level 4 icing will cause more severe losses, so it is necessary to arrange manpower and ice-melting devices in advance to minimize the losses caused by ice disasters.

S5: for level 5 icing, it is necessary to start the corresponding plan to ensure that the ice melting device can be arranged at the first time. It is essential to accurately predict and evaluate the disaster level, and arrange more manpower to ensure safety.

C. Case analysis

In this paper, the calculation method of the model is specially treated during the case analysis. Because the grey model is suitable for small sample input, this paper uses random function to extract 5-10 sample points each time for circular modeling. The number of cycles is 20, and the model parameters with the lowest prediction error are applied to the case analysis. The paper selects 18 groups of unexpected modeling data as validation data. The prediction results of the validation data and the corresponding risk levels are shown in Table 2. Mv is measured value, Cv is calculated value, D is deviation, Prl is predicted risk level, Pr is prediction results.

It is found that the maximal prediction error of icing thickness based on GM (1, 6) grey theory multi-factor prediction model is 10.06%(The average value is only 4.22%), and the accuracy of transmission line conductor icing disaster risk early warning is 88.9%. It can be found that the accuracy of ice thickness prediction is high, but there will be errors in the early warning process the high-risk level is mistaken for the low-risk level. In the discussion section, we will propose improvement measures.

TABLE II
EARLY WARNING RESULTS OF ICING RISK.

No.	Mv (mm)	Cv (mm)	D (mm)	Re	Prl	Pr
1	4.29	4.57	0.28	6.58%	*L1*	√
2	3.57	3.83	0.27	7.46%	*L1*	√
3	12.79	12.75	-0.04	-0.30%	*L3*	√
4	7.42	7.80	0.38	5.08%	*L2*	√
5	7.14	7.17	0.03	0.36%	*L2*	√
6	6.24	6.64	0.40	6.35%	*L2*	√
7	9.45	10.06	0.61	6.40%	*L3*	×
8	4.12	4.00	-0.12	-2.99%	*L1*	√
9	3.76	4.14	0.38	10.06%	*L1*	√
10	5.71	5.71	0.01	0.12%	*L2*	√
11	4.36	4.63	0.27	6.13%	*L1*	√
12	5.86	6.17	0.31	5.25%	*L2*	√
13	5.25	5.30	0.06	1.05%	*L2*	√
14	10.01	9.27	-0.74	-7.39%	*L2*	×
15	5.83	5.64	-0.19	-3.17%	*L2*	√
16	3.35	3.50	0.15	4.54%	*L1*	√
17	4.38	4.44	0.06	1.46%	*L1*	√
18	4.27	4.32	0.05	1.24%	*L1*	√

IV. DISCUSSION

In this section, we first compare the prediction accuracy of the improved GM(1,N) model with that of the traditional BP neural network model. Then, for the error of risk level prediction, this paper proposes a solution (A certain safety margin value).

Firstly, we used the traditional BP neural network model to build the training model based on the data in this paper. It is worth noting that the training data is consistent with the cycle modeling data of GM (1, N) model. Based on this, the prediction error bands of the two models can be obtained. As shown in Figure 5 (a) and (b), it is obvious from the figure that although their overall prediction results are consistent with the test data, the GM (1, N) model has a narrower error band. The specific errors of the two models are further calculated, as shown in Figure 5 (c). The maximum prediction error of BP neural network model is - 26.86%. It is 2.7 times of the maximum error of GM (1, N) model proposed in this paper. This shows that the GM (1, N) model proposed in this paper is superior to the traditional BP neural network model in applying multi-factor conductor icing prediction.

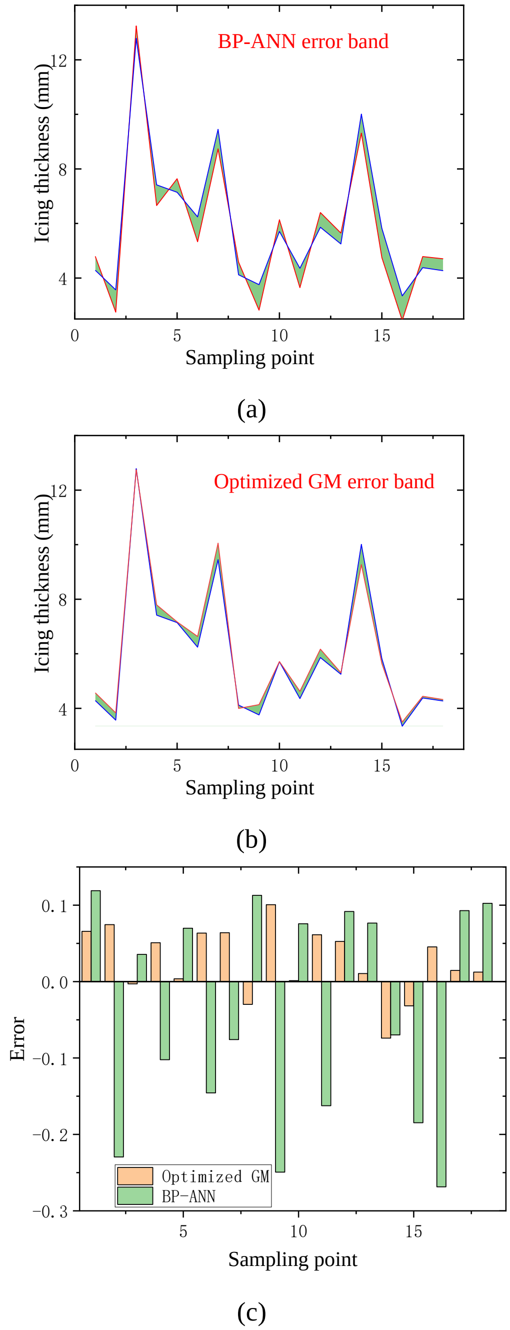


FIGURE 5. Error comparison of two prediction models (the improved GM(1,N) model in this paper and the traditional BP neural network model). (a) BP-ANN model error band; (b) improved GM(1,N) model error band; (c) Error of the two prediction models.

Secondly, it can be seen from the case analysis results that there are errors in the classification of risk levels in groups 7 and 14. However, from the calculation results, it can be seen that the prediction error of icing thickness of group 7 and group 14 is only 6.40% and -7.39%. Therefore, it can be found that under the premise of a small prediction error of icing thickness, the error of risk classification is easy to occur at the critical points of different levels. A certain safety margin value is added to the predicted value near the critical value of icing thickness, which can reduce the probability of judging the high-risk level as the low-risk level.

V. CONCLUSION

In ice area, applying risk early warning method can guide the anti-ice work of transmission line. Therefore, this paper studies the transmission line ice disaster early warning method based on ice thickness prediction using the GM(1, 6) model. The work and conclusions of this paper are as follows.

(1)This paper proposes a multi-factor prediction model based on GM (1, 6) grey theory, which considers the transmission line conductor icing model under the influence of multiple meteorological factors.

(2)The grey model is suitable for small sample input, so the calculation method of the model is specially treated during the case analysis.The traditional grey model was improved by adding random data functions.. This improved method makes the model applicable to the prediction of icing data.

(3)A case study is carried out, and the icing disaster risk is divided into five levels. It is found that the maximal prediction error of icing thickness based on GM (1, 6) grey theory multi factor prediction model is 10.06%(The average value is only 4.22%), and the accuracy of transmission line conductor icing disaster risk early warning is 88.9%.

(4) This paper proposes a solution for the error of risk level prediction (A certain safety margin value). A certain safety margin value is added to the predicted value near the critical value of icing thickness, which can reduce the probability of judging the high-risk level as the low-risk level.

(5) The GM (1, N) model proposed in this paper is superior to the traditional BP neural network model in applying multi-factor conductor icing prediction.

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