

Transmission line icing prediction based on DWT feature extraction

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Abstract. Transmission line icing prediction is the premise of ensuring the safe operation of the network as well as the very important basis for the prevention of freezing disasters. In order to improve the prediction accuracy of icing, a transmission line icing prediction model based on discrete wavelet transform (DWT) feature extraction was built. In this method, a group of high and low frequency signals were obtained by DWT decomposition, and were fitted and predicted by using partial least squares regression model (PLS) and wavelet least square support vector model (w-LSSVM). Finally, the final result of the icing prediction was obtained by adding the predicted values of the high and low frequency signals. The results showed that the method is effective and feasible in the prediction of transmission line icing.

1. Introduction

In recent years, frequent occurrences of all kinds of extreme weather caused by global climate abnormal variation have resulted in many transmission line icing disasters, which have caused power outages, leading to the destruction of a large number of fixed assets and huge economic losses [1-4]. Especially the freezing disaster happened in 2008 in southern China, caused great damage to the power system. It led directly to the collapse of 8709 base of 110 kV and above lines, the break of more than 2.07 million lines, the outage of 1497 substations, resulting in direct property loss of the State Grid Corporation of 10.45 billion and reconstruction funds of 390 million [5]. Through the lessons learned from the previous power grid icing disasters and the current grid development situation and global climate changes, the power grid in the future will still withstand the tests of freezing disaster. So we must discover the disaster in advance and prevent it as soon as possible. Therefore, the research on transmission line icing prediction has important practical application value.

At present, the research on transmission line icing prediction mainly according to the movement laws of fluids and heat transfer mechanism of transmission icing, focuses on establishing all kinds of icing prediction models combined with meteorological factors, environmental factors and line parameters. In general, the models can be divided into three categories: mathematical-physical models, statistical models and intelligent prediction models. Mathematical-physical models are built on the icing growth process by observing the physical process of ice formation to make prediction, including the Goodwin model [6] and the Makkonen model [7]. These models are put forward on the basis of experiments. However, their prediction accuracy is not ideal. Statistical models are based on the

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statistical theory and traditional statistical methods to process the historical data, not considering the physical process of the icing formation, such as the icing growth rate - temperature model, the icing growth rate - wind speed model, the icing growth rate - wind direction model, the extreme value model and the multiple linear regression model [8]. Statistical models have simple calculation and easy realization, but can't fit well on the nonlinear characteristics of icing. When the samples are complex, the prediction precision of statistical models will be seriously affected. Intelligent prediction models are established combined with modern computer technology and Mathematical Sciences. This kind of models can deal with high-dimensional nonlinear problems well and have high accuracy of prediction due to their powerful studying and generalizing ability. In the research of icing prediction, the most common intelligent models include support vector machine (SVM) model [9], BP neural network (BPNN) model [10], fuzzy theoretical model [11] and so on. The intelligent prediction models have achieved good effect in icing forecasting, but always have the phenomenon of over-fitting, slow convergence speed and the local optimum because of the defects of the model itself. Besides, they can't explain the nonlinear features of icing effectively, thus their prediction accuracy is affected.

For the sake of those problems, a method for icing prediction based on the discrete wavelet transform (DWT) feature extraction was proposed in this paper. DWT model can make infinite decomposition of the input signal to get smooth low-frequency signals and large wave of high frequency signals respectively. According to different frequency signals, the partial least squares regression model (PLS) and wavelet least squares support vector machine (w-LSSVM) were adopted to learn and fit them, so as to make accurate prediction. The method has the advantages of both the PLS model and the w-LSSVM model, which improves the accuracy of icing prediction. The simulation results show that the method proposed in this paper not only has higher prediction accuracy, but also has better prediction performance than other single algorithms and is more suitable for icing prediction in transmission line.

2. Feature extraction and prediction method

2.1. Feature extraction based on DWT

Discrete wavelet transform (DWT) is always used in computer image processing because it can decompose the image signals in different scale according to the different goals. The wavelet function usually can be expressed as follow [12].

$$\Psi_{a,\tau}(t) = a^{-\frac{1}{2}} \psi\left(\frac{t-\tau}{a}\right) \quad a > 0, \tau \in R \quad (1)$$

Where a is the wavelet scale stretch factor, τ is the wavelet shift factor. Generally, wavelet discretization aims at the parameters a, τ . Let $a = 2^j$, $\tau = 2^j \cdot T_s \cdot n$, the wavelet base function is here.

$$\Psi_{j,n}(t) = 2^{-\frac{j}{2}} \psi\left(\frac{t}{2^j} - n \cdot T_s\right) \quad j, n \in N \quad (2)$$

For any function $f(t)$, the discrete wavelet coefficient is as follow.

$$WT_f(j, n) = \int_R f(t) \overline{\Psi_{j,n}(t)} dt \quad (3)$$

Where, $\overline{\Psi_{j,n}(t)}$ is the dual function of $\Psi_{j,n}(t)$. The discrete wavelet coefficient WT_f can be used to build the function $f(t)$.

$$f(t) = \frac{1}{A} \sum WT_f(j, n) \cdot \psi_{j,n}(t) \quad (4)$$

Where, A is constant. The discrete wavelet transformation is shown in figure 1.

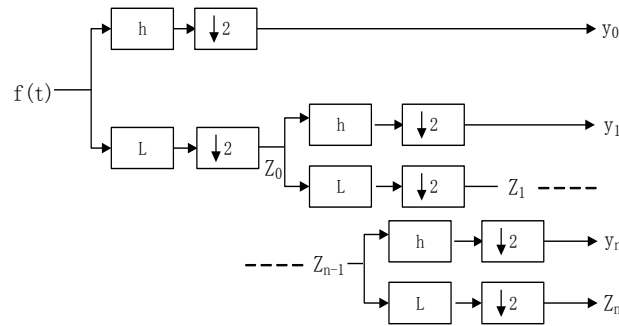


Figure 1. Discrete wavelet transformation.

The process of discrete wavelet transform can be represented as a decomposition tree composed of low frequency signals and high frequency signals. And the process of signal decomposition is iteration process. The signals will be decomposed into multi-level wavelet to obtain the lower frequency signals and higher frequency signals. In the practical application, the decomposition frequency is determined by the coefficient WT_f .

In icing forecasting, a group of high frequency signals ($y_0 \rightarrow y_n$) and a group of low frequency signals (Z_n) will be obtained during the discrete wavelet transform on the icing historical data. The low frequency signals are steady and smooth relatively, which are good for making linear regression according to the regression model. On the contrary, the high frequency signals generally show high nonlinear characteristics, which can be for learning and fitting according to the intelligent prediction model.

2.2. Icing prediction based on PLS

The low frequency signal curve obtained by DWT is relatively smooth and stable, so can be fitted by adopting the partial least squares linear regression model (PLS) [14] to make accurate prediction.

Assuming the meteorological factors, $x_j, j=1,2,\dots,m$, are independent variables and the icing thickness, y , is the dependent variable. And suppose that there are n samples.

The first step is to standardize the independent variables by using the following formulas:

$$\begin{cases} \mathbf{Y} = (\mathbf{Y}_0)_n \\ \mathbf{Y}_0 = [\mathbf{y} - E(\mathbf{y})]/S_y \end{cases} \quad (5)$$

$$\begin{cases} \mathbf{X} = (\mathbf{X}_0)_{n \times m} \\ (\mathbf{X}_0)_j = [\mathbf{x}_j - E(\mathbf{x}_j)]/S_{x_j} \end{cases} \quad (6)$$

Where, $\mathbf{X}$ is the standard matrix of the meteorological factors while $\mathbf{Y}$ is the standard matrix of the icing thickness. $E(y)$ is the mean value of y while $E(x_j)$ is the mean value of x_j . S_y and S_x are both mean square errors.

The second step is to extract the first principal component t_1 from the matrix $\mathbf{X} : t_1 = \mathbf{X}\mathbf{W}_1$, $\|\mathbf{W}_1\|=1$. And extract the first principal component u_1 from the matrix $\mathbf{Y} : u_1 = \mathbf{Y}\mathbf{C}_1$, $\|\mathbf{C}_1\|=1$.

The regression equations are showed as follow.

$$\mathbf{X} = t_1 \mathbf{P}_1^T + \mathbf{X}_1 \quad (7)$$

$$\mathbf{Y} = t_1 \mathbf{r}_1 + \mathbf{Y}_1 \quad (8)$$

Where, $r(x_i, y)$ is the correlation coefficient of x_i and y . $\mathbf{P}_1 = \mathbf{X}^T t_1 / \|t_1\|^2$, $\mathbf{r}_1 = \mathbf{Y}^T t_1 / \|t_1\|^2$. $\mathbf{X}_1$ and $\mathbf{Y}_1$ are residual matrixes of the regression equation.

The third step is to get the second principal component variable t_2 using the same method as above and replacing $\mathbf{X}$ and $\mathbf{Y}$ with $\mathbf{X}_1$ and $\mathbf{Y}_1$. Then the following equations are got.

$$X_1 = t_2 P_2^T + X_2 \quad (9)$$

$$Y_1 = t_2 r_2 + Y_2 \quad (10)$$

Cycle the process above until A principal components, $t_1, t_2, \dots, t_A$, are extracted. Then the order is determined by the cross validation test.

$$Q_A^2 = 1 - \frac{PRESS_A}{SS_{A-1}} \quad (11)$$

$$PRESS_A = \sum_{i=1}^n (y_i - \hat{y}_{A(-i)})^2 \quad (12)$$

$$SS_A = \sum_{i=1}^n (y_i - \hat{y}_{Ai})^2 \quad (13)$$

Generally, when $Q_A^2 < 0.0975$, the prediction ability of the model has no obvious improvement, so the algorithm stops and the order of the composite variables is A .

The fourth step is the multiple linear regression for Y to $(t_1, t_2, \dots, t_A)$ and the following formula is got.

$$\hat{Y} = r_1 t_1 + r_2 t_2 + \dots + r_A t_A \quad (14)$$

Because $t_1, t_2, \dots, t_A$ are the linear combinations of X , the following formulas are obtained.

$$t_i = X W_i^* \quad (15)$$

$$W_i^* = \prod_{k=1}^{i-1} (I - W_k P_k^T) W_i \quad (16)$$

Then from the formula above, the formula got is here.

$$\hat{Y} = r_1 X W_1^* + r_2 X W_2^* + \dots + r_A X W_A^* \quad (17)$$

Suppose that,

$$y^* = Y \quad (18)$$

$$x_i^* = X_i \quad (19)$$

$$\alpha_i = \sum_{k=1}^A r_k W_{ki}^* (i=1, 2, \dots, m) \quad (20)$$

The formula above is changed.

$$\hat{y}^* = \alpha_1 x_1^* + \alpha_2 x_2^* + \dots + \alpha_m x_m^* \quad (21)$$

The formula also can be written as follow further.

$$\hat{y} = \left[E(y) - \sum_{i=1}^m \alpha_i \frac{S_y}{S_{x_i}} E(x_i) \right] + \alpha_1 \frac{S_y}{S_{x_1}} x_1 + \dots + \alpha_m \frac{S_y}{S_{x_m}} x_m \quad (22)$$

In summary, the prediction results $\hat{y}$ can be calculated by the least square regression equation according to the meteorological data and the raw icing thickness data.

2.3. Icing prediction based on w-LSSVM

The high frequency signals got by DWT have strong nonlinear characteristics, which makes it hard to fit the data accurately using the common regression methods. Therefore, the least squares wavelet support vector machine (w-LSSVM) regression model was used to train and learn to make an accurate prediction for the icing thickness on the basis of establishing the relationship between meteorological factors and icing thickness in this paper.

LSSVM is a extension of SVM [13]. It cast the input vectors into the high dimension space by nonlinear mapping and constructed the optimal decision surface. Then the inequality operation of SVM was transformed to the operation of solving equations by applying the risk minimization principle, which reduced the computational complexity and accelerated the operation speed.

Set a given sample set $T = \{(x_i, y_i)\}_{i=1}^N$, the number of samples N . The regression model of the sample is here.

$$y(x) = \mathbf{w}^T \bullet \phi(x) + b \quad (23)$$

Where, $\phi(*)$ is a high dimensional space that the training samples are projected onto. $\mathbf{w}$ is the weight vector, b is the biased.

For LSSVM, the optimization problem was showed as follow.

$$\min \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \gamma \sum_{i=1}^N \xi_i^2 \quad (24)$$

$$s.t. \quad y_i = \mathbf{w}^T \phi(x_i) + b + \xi_i, i = 1, 2, 3, \dots, N; \quad (25)$$

To solve the problem above, the Lagrangian function was built.

$$L(\mathbf{w}, b, \xi_i, \alpha_i) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} \gamma \sum_{i=1}^N \xi_i^2 - \sum_{i=1}^N \alpha_i [\mathbf{w}^T \phi(x_i) + b + \xi_i - y_i] \quad (26)$$

Where, α_i is the Lagrange multiplier. The following can be got by performing derivatives on each variable.

$$\begin{cases} \frac{\partial L}{\partial \mathbf{w}} = 0 \rightarrow \mathbf{w} = \sum_{i=1}^N \alpha_i \phi(x_i) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^N \alpha_i = 0 \\ \frac{\partial L}{\partial \xi_i} = 0 \rightarrow \alpha_i = \gamma \xi_i \\ \frac{\partial L}{\partial \alpha_i} = 0 \rightarrow \mathbf{w}^T + b + \xi_i - y_i = 0 \end{cases} \quad (27)$$

The following problem can be got after eliminating $\mathbf{w}$ and ξ_i .

$$\begin{bmatrix} 0 & \mathbf{e}_n^T \\ \mathbf{e}_n & \boldsymbol{\Omega} + \gamma^{-1} \cdot I \end{bmatrix} \cdot \begin{bmatrix} b \\ \mathbf{a} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \quad (28)$$

Where, $\boldsymbol{\Omega} = \phi^T(x_i) \phi(x_i)$, $\mathbf{e}_n = [1, 1, \dots, 1]^T$, $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_n]$, $\mathbf{y} = [y_1, y_2, \dots, y_n]^T$.

The following could be obtained when the linear equations above were solved.

$$y(x) = \sum_{i=1}^N \alpha_i K(x_i, x) + b \quad (29)$$

Where, $K(x_i, x)$ is the kernel function.

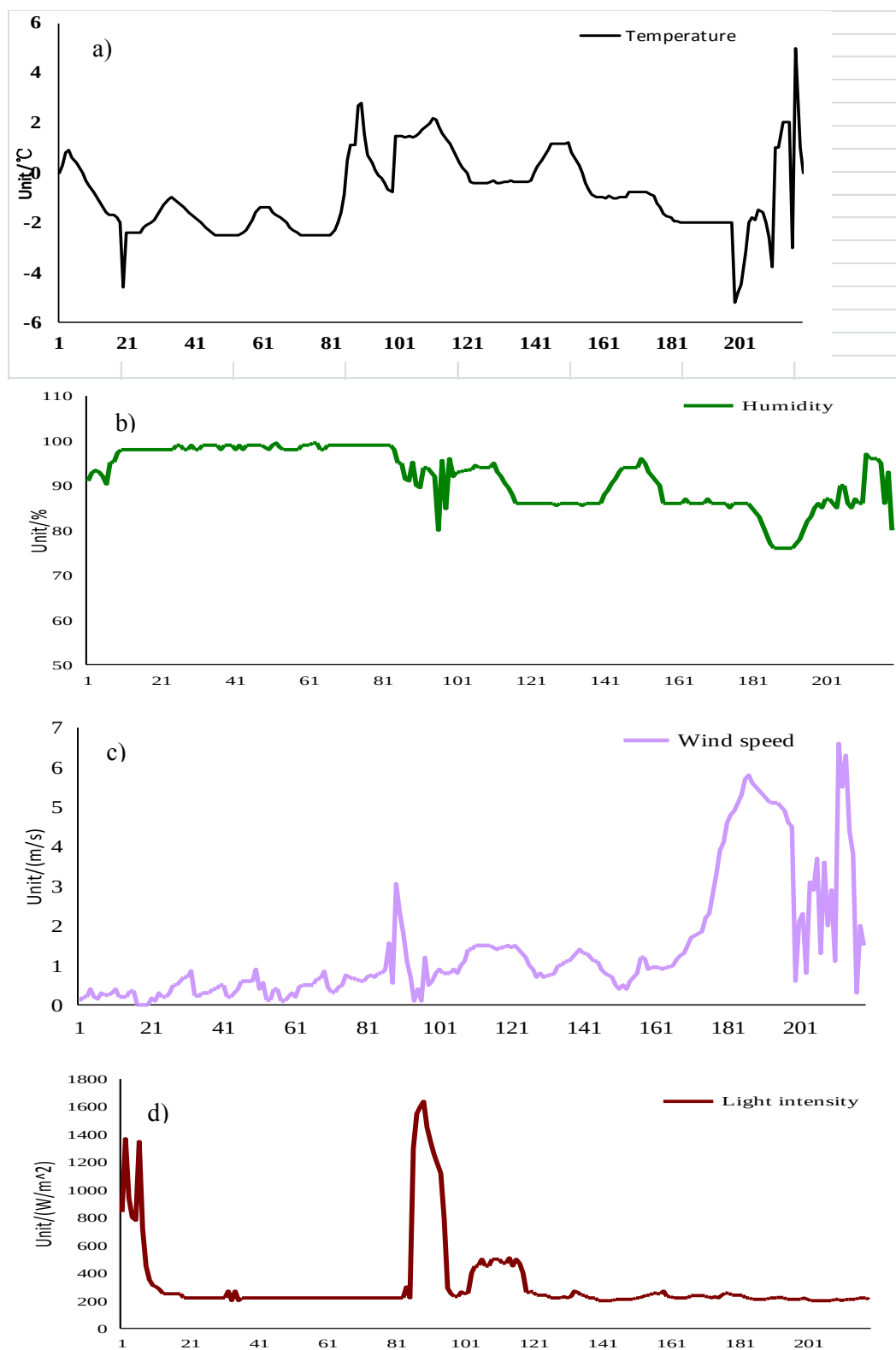
$$K(x_i, x) = \prod_{i=1}^N \psi\left(\frac{x_i - x'_i}{\sigma_i}\right) \quad (30)$$

Where, $\psi(x) = \cos(1.75x) \cdot \exp\left(\frac{-x^2}{2}\right)$. And the wavelet least squares support vector machine regression prediction model is followed [15].

$$y(x) = \sum_{i=1}^N a_i \prod_{i=1}^N \left\{ \cos\left[\frac{1.75(x_i - x'_i)}{\sigma_i}\right] \cdot \exp\left[\frac{-(x_i - x'_i)^2}{2}\right] \right\} + b \quad (31)$$

3. Experimental setup and analysis

The icing thickness data and micro meteorological data of one southern route of January 10, 2008 to March 10, 2008 were selected to carry on the simulation computation in the paper. The meteorological factors mainly include temperature, humidity, wind speed, light intensity and wind direction, as shown in figure 2.



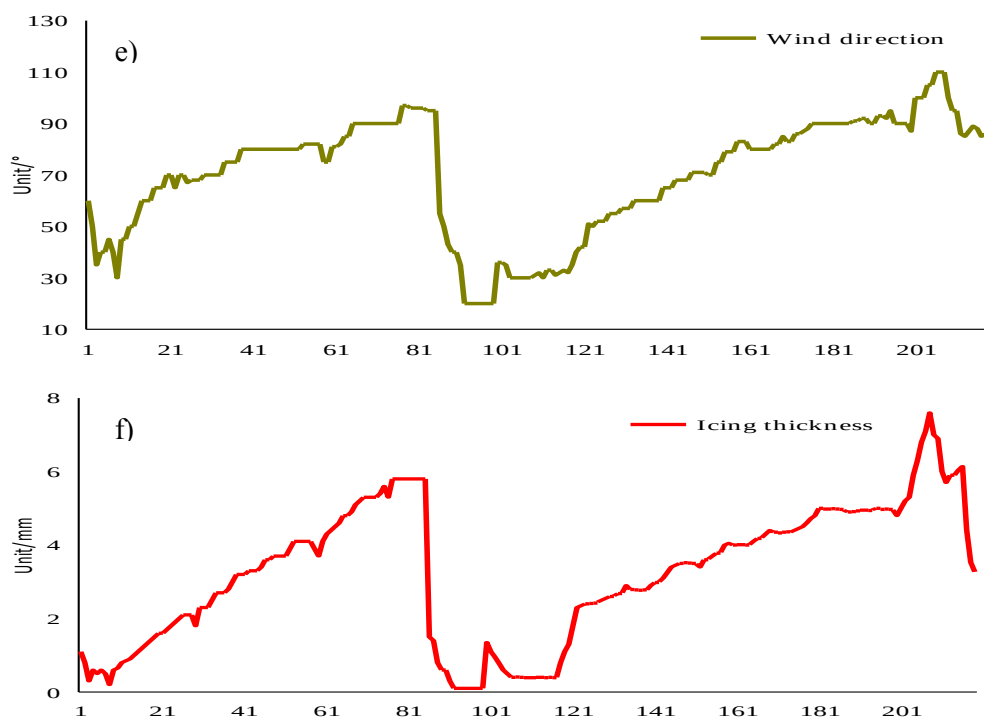


Figure 2. Meteorological data and ice thickness data graph.

The results were shown in figure 3 by using DWT decomposition and reconstruction on the icing thickness data above. The low frequency results reconstructed shown as curve D1 were smooth, the tendency of which could roughly reflect the original icing thickness data. For the high-frequency D1-D3 curves, they obviously showed stronger volatility. And the volatility gradually decreased from D1 to D3. Besides, the volatilities of the high frequency curves, D4 and D5, were not particularly different compared with other phases, indicating that five layers decomposition tree structure could meet the need of icing prediction well. Figure 4 included the original signal, reconstructed signal and the error signal between the two. Figure 4 showed that the error between the reconstructed signal and the original signal was very small after DWT processing, which fully met the expected accuracy.

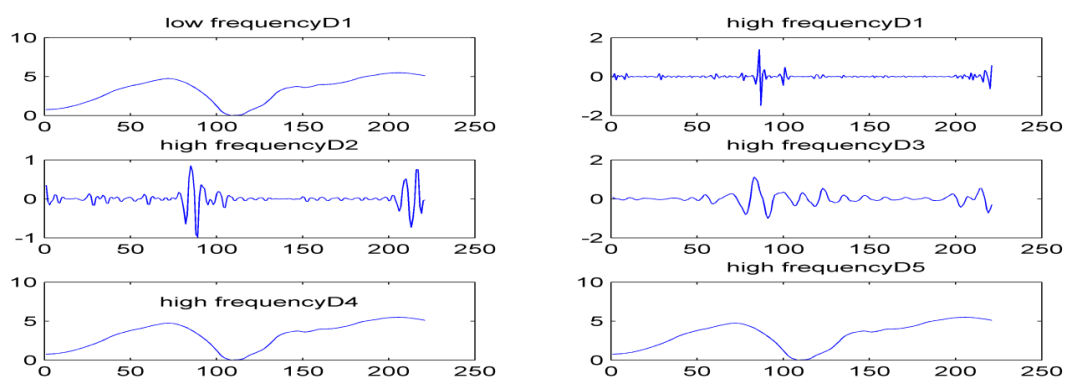


Figure 3. Decomposed frequency signal figures.

Furthermore, the first 200 sets of data were selected as the training sample data and the remaining 21 sets of data were as testing sample data. The meteorological factors were taken as the input while the ice thickness data as output. 21 groups of icing thickness prediction value $Z_0(i)$ were obtained by adopting PLS model to fit the low-frequency curve D1. And 21 groups of icing thickness prediction

value $Y_j(i)$ were obtained by adopting w-LSSVM model to fit the high-frequency curves D1-D5. Then the final icing prediction result was got by adding all prediction results.

$$f(i) = \sum_{i=1}^{21} \sum_{j=1}^5 (Z_0(i) + Y_j(i)) \quad (32)$$

In addition, in order to compare with other models, the PLS model, SVM model and BP neural network model were also used to predict the icing thickness of the 21 sets of data and the results were shown in table 1 and figure 5.

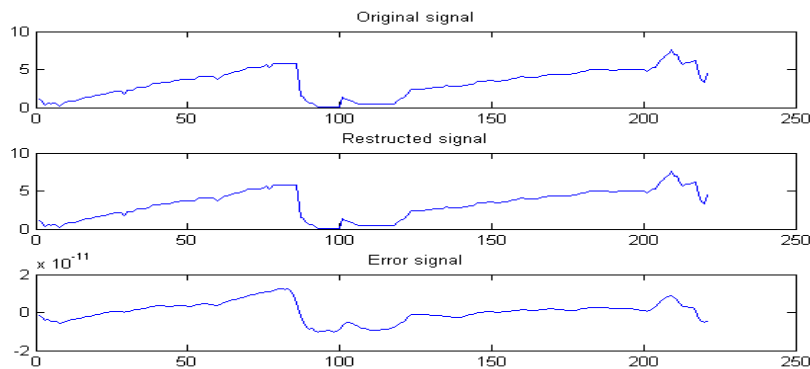


Figure 4. The original signal、reconstructed signal and error figures.

Table 1. Forecast results and error values of each model.

	Actual Value(cm)	The proposed method	Error (%)	PLS	Error (%)	SVM	Error (%)	BP	Error (%)
1	4.8	4.71	-1.88	4.57	-4.79	4.7	-2.08	4.65	-3.12
2	5	5.1	2.00	4.67	-6.60	4.82	-3.60	4.77	-4.60
3	5.2	5.32	2.31	4.93	-5.19	4.95	-4.81	5.01	-3.65
4	5.3	5.21	-1.70	5.14	-3.02	5.19	-2.08	5.42	2.26
5	5.9	5.8	-1.69	5.76	-2.37	5.77	-2.20	5.69	-3.56
6	6.3	6.17	-2.06	6.03	-4.29	6.12	-2.86	6.09	-3.33
7	6.8	6.7	-1.47	6.62	-2.65	6.67	-1.91	6.92	1.76
8	7.1	7.25	2.11	6.88	-3.10	6.92	-2.54	7.26	2.25
9	7.6	7.48	-1.58	7.26	-4.47	7.4	-2.63	7.37	-3.03
10	7	7.13	1.86	6.76	-3.43	7.29	4.14	6.82	-2.57
11	6.9	6.85	-0.72	7.21	4.49	6.78	-1.74	6.68	-3.19
12	6	6.14	2.33	6.34	5.67	5.92	-1.33	6.25	4.17
13	5.7	5.76	1.05	5.61	-1.58	5.81	1.93	5.69	-0.18
14	5.9	5.82	-1.36	5.68	-3.73	5.8	-1.69	5.75	-2.54
15	5.9	5.75	-2.54	5.56	-5.76	5.73	-2.88	5.66	-4.07
16	6.04	6.17	2.15	5.83	-3.48	5.91	-2.15	5.9	-2.32
17	6.14	6.04	-1.63	5.88	-4.23	5.94	-3.26	5.85	-4.72
18	4.42	4.33	-2.04	4.57	3.39	4.31	-2.49	4.25	-3.85
19	3.53	3.41	-3.40	3.29	-6.80	3.42	-3.12	3.65	3.40
20	3.27	3.36	2.75	3.1	-5.20	3.37	3.06	3.43	4.89
21	4.48	4.52	0.89	4.66	4.02	4.57	2.01	4.25	-5.13

In order to evaluate the predictions of the models above accurately, the maximum absolute percentage error (MaxAPE), the mean absolute percentage error (MAPE), the median absolute percentage error (MdAPE) and relative error (RE) were adopted in the paper [11].

$$MaxAPE = \max \left(\left| \frac{f(i) - \hat{f}(i)}{f(i)} \right| \right) \times 100\% \quad (33)$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{f(i) - \hat{f}(i)}{f(i)} \right| \times 100\% \quad (34)$$

$$MdAPE = Med_i \left(\left| \frac{f(i) - \hat{f}(i)}{f(i)} \right| \right) \times 100\% \quad (35)$$

$$RE = \frac{f(i) - \hat{f}(i)}{f(i)} \times 100\% \quad (36)$$

Where, $f(i)$ is the original value, $\hat{f}(i)$ is the predicted value, $i = 1, 2, \dots, N$.

The calculation results of relative error (RE) were shown in table 1 and figure 6. And the calculation results of other indicators were shown in table 2.

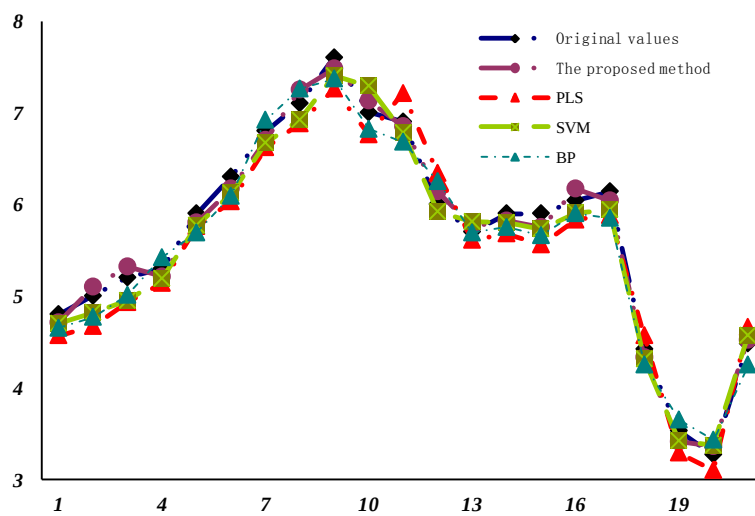


Figure 5. The prediction results line chart of each model.

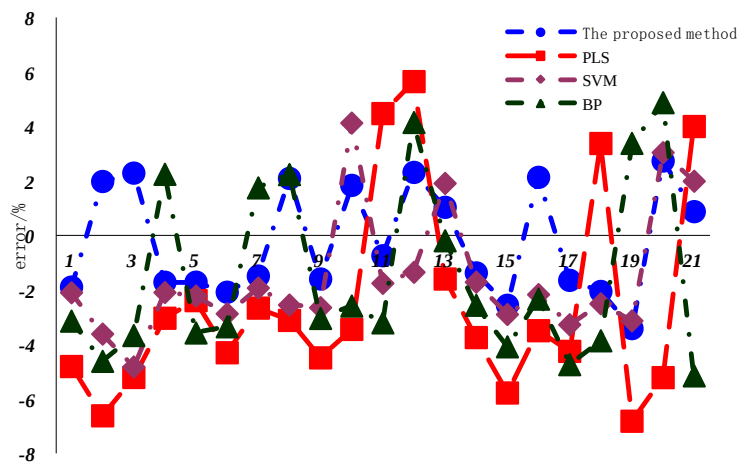


Figure 6. The relative error line chart of each model.

From table 1 and figure 6, the relative error line of the method put forward in the paper is much closer to the X axis than that of the other three methods, indicating that it is better to fit the icing nonlinear characteristics after DWT decomposition and improve the accuracy of the prediction of icing thickness. In addition, the relative error line of SVM is closer to the X axis than that of BP and PLS, meaning that the overall error of SVM is less than that of BP and PLS, so the nonlinear fitting

ability of SVM is stronger than that of BP and PLS. However, the relative error line of PLS has the biggest volatility and is the farthest away from the X axis, indicating that it is not suitable to learn and fit the high-dimensional, nonlinear characteristics of icing data using PLS model only, which is more suitable for the application of icing prediction for low-frequency signal after DWT decomposition.

As shown in table 2, the MaxAPE value of the method in the paper was 3.4%, the MAPE value was 1.88% and the MdAPE value was 1.875%. They were obviously smaller than the evaluation index values of other methods in the table. It showed that it can significantly improve the prediction accuracy by using different methods to predict the icing thickness for different frequencies signals and add the predicted results after DWT decomposition. The prediction of high frequency signal could reflect the robustness and learning performance of w-LSSVM model while the prediction of low frequency signal could avoid the problems occurred when using PLS model only and fit the trend of curve better.

Table 2. Evaluation index values of each model.

	The proposed method	PLS	SVM	BP
MaxAPE/%	3.40	6.8	4.81	5.13
MAPE/%	1.88	4.2	2.6	3.27
MdAPE/%	1.875	4.235	2.489	3.333

4. Conclusion

In this paper, the icing prediction model based on DWT feature extraction was proposed aiming at the nonlinear characteristics of icing thickness of transmission lines. First of all, the historical icing data was decomposed by using DWT and a set of high frequency signals ($y_0 \rightarrow y_n$) and a set of low frequency signals (Z_n) were obtained. Secondly, PLS model and w-LSSVM model proposed in the paper were used to fit and forecast for the low frequency signal that was smooth and the high frequency signal that has strong volatility respectively. Then the final predicted result of icing thickness was got by adding the predicted value of PLS and the predicted value of w-LSSVM. Finally, the algorithm was verified by the example of one south line and the results showed that the icing prediction accuracy of the method proposed in this paper was much higher than that of PLS, SVM and BP. It indicated that it could make full use of PLS model and w-LSSVM model respectively after DWT decomposition, which could improve the robustness of the algorithm so as to improve the accuracy of the icing prediction.

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