A Study on Prediction of Transmission Line Icing Thickness Based on Ada-Boost and LS-WSVM

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Abstract **— The icing of transmission lines affects the security and reliability of power grid. The accurate prediction of icing thickness of transmission line is the effective premise and basis for preventing and avoiding the freezing disaster. Based on the high dimensional nonlinear feature of transmission line icing prediction, a transmission line icing thickness prediction method based on the combination of Ada-Boost and LS-WSVM model was put forward in this paper. The method firstly, applied the wavelet kernel function to the LSSVM model so as to get a LS-WSVM regression model with a stronger nonlinear fitting ability. Then a strong LS-WSVM regression was achieved by weighting the multiple weak LS-WSVM regression through the learning and training of the training samples applying the AdaBoost algorithm. Finally, the nonlinear relationship between the transmission line icing influence factors and ice thickness was established by well-trained LS-WSVM strong regression to make accurate prediction of ice thickness. The numerical example showed that the method had a strong accuracy in the icing thickness prediction, and could be an effective tool to predict the icing thickness of transmission lines.**

Keywords - AdaBoost algorithm; Wavelet kernel function; LS-WSVM model; Icing thickness prediction

I. INTRODUCTION

The transmission line icing is a great threat to the safety and reliability of the grid and the freezing disasters have become major issues of power systems in our country [1], which drastically affect the social production and people's life, causing enormous economic losses [2]. The prediction of icing thickness on transmission lines can be a prospective understanding of the possibility and risk of the freezing disaster. Therefore, icing prediction is the basic work in preventing and avoiding the freezing disasters and has important significance.

At present, the research of transmission line icing thickness prediction generally aims at mining and analysis icing factors to establish all kinds of icing prediction models based on the forming principle of icing and fluid movement rules. The models can be roughly divided into three kinds: mathematical-physical model, statistical model and the intelligent prediction model. The mathematical-physical models includes Imai model [3], Lenhard model [4], Goodwin model [5], Makkonen model [6], line icing numerical model [7]and improved icing thickness weighing method [8]proposed by Dejie Dong and others. These models mainly are built according to the growth mechanism and thermodynamic process of icing to do the prediction. So the results of these models are experiment results, which are different from the real icing situation, causing the prediction accuracy low. Statistical models such as icing growth rate-temperature model, icing growth rate-wind direction model and multiple linear regression model of icing [9], do not consider the process of ice accretion but deal with the historical data based on the statistical methods. These models have the advantages of simple calculation, but can’t fit the nonlinear characteristics of icing data well. The prediction will be seriously affected and the accuracy is low if the sample data is complex and diverse. Besides, the intelligent prediction models such as the fuzzy prediction model [10], back propagation neural network (BPNN) [11], support vector machine (SVM) [12], multi variable grey prediction model proposed by Hongwei Liu and others [13], adaptive network fuzzy inference forecasting model proposed by Yi Liu [14] and the combination forecasting model based on fuzzy logic and neural network proposed by Xiaoning Huang and others [15], are the combination of modern computer technology and mathematical science. These models have strong learning and processing capabilities and can be a good solution to high dimensional nonlinear problems with high prediction accuracy. But because of the defects of the intelligent prediction model in the icing forecast field at present, there are questions of excessively fits, slow convergence speed, trapping in local optimum and so on, which reduces the level of fitting the nonlinear characteristics of icing data and affects the icing prediction accuracy [16].

Aiming at these shortages of icing prediction models, a transmission icing thickness prediction model based on AdaBoost and LS-WSVM was put forward in this paper. The input variables were transformed into the high dimension space by using the wavelet kernel function in LS-WSVM model and the optimal hyper plane was obtained in the high dimension space, which improved the accuracy of the model. Multiple weak LS-WSVM regression machine were integrated to a strong LS-WSVM regression machine by adopting AdaBoost algorithm, indicating AdaBoost-LS-WSVM model had higher learning efficiency and better prediction accuracy. Finally, the example showed that the method proposed in the paper had not only higher prediction accuracy but also better predictive performance than other single algorithm, which provided a more reliable tool and method for transmission line icing prediction.

II. ADABOOST ALGORITHM AND LS-WSVM MODEL

A. Ada-Boost Algorithm

Ada-Boost is an iterative algorithm, which can be used to train different weak regressions on the same training set and integrate these regressions to a strong one through weighting these weak regressions. Firstly, every sample has the same weight. Then, the weights of sample are updated according to the regression accuracy in training. The lower the regression precision of the sample is, the greater the weight. And the new sample distribution is got. Next, according to the new weight of the sample, some samples are selected for the next iteration and weights are updated again. Finally, multiple weak regressions are obtained and then integrated to a strong regression according to the weights updated [17].

The specific implementation steps of AdaBoost algorithm are as follows [18].

Given the training sample set, $S\{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\}$, the maximum iterations T, the regression estimate relative error threshold ϕ.

(1) Initialize the weights of the samples. That is to say, the initial probability of each training sample is $D_1(i)$, $D_1(i)=1/n$. The error rate is ε_t, $\varepsilon_t=0$.

(2) When the number of iterations t is bigger than T, turn to (3). Otherwise, the steps are as shown below.

1) Regression with training samples which have weights, $f_t(x)\to y$.

2) Calculate the relative error of each training sample.

$$\mathrm{ARE}(i)=\left|\frac{f_t(x_i)-y_i}{y_t}\right| \qquad (1)$$

3) Calculate the error rate of the regression model, $\mathrm{f_t(x)}$.

$$\varepsilon_t=\sum_{i:\mathrm{ARE_t(i)}>\phi} D_t(i) \qquad (2)$$

4) Update the weights $\mathrm{D_t}$ of the samples.

$$D_{t+1}(i)=\frac{D_t(i)}{Z_t}\times\begin{cases}\beta_t & \text{if } \mathrm{ARE_t(i)}\le\phi\\ 1 & \text{otherwise}\end{cases} \qquad (3)$$

Where, $\mathrm{Z_t}$ is the constant for renormalizing the weights of the samples, and $\sum_{t=1}^{n} D_{t+1}(i)=1$.

5) Set $t=t+1$.

6) Turn to (2).

(3) The training is over and the strongest regression machine is obtained. For given testing samples, the testing result is as follow.

$$f_{\text{final}}(x)=\boldsymbol{F}(f_1(x),f_2(x),\ldots,f_{\mathrm{T}}(x)) \qquad (4)$$

B. LS-WSVM Model

LSSVM is an extension of SVM. The input vectors are nonlinearly cast to the high-dimensional space to construct the optimal decision surface. Then the inequalities of SVM model are transformed to the equations by applying risk minimization principle, which reduces the computational complexity and accelerates the speed of operation [19].

Suppose a given sample set, $\boldsymbol{T}=\{(x_i,y_i)\}_{i=1}^{N}$. The total number of samples is N. The regression model is shown as follow.

$$y(x)=\boldsymbol{w}^T\bullet\varphi(x)+b \qquad (5)$$

Where, $\varphi(*)$ is the high dimensional space which the training samples are projected onto. $\boldsymbol{w}$ is weight vector and b is bias.

For the LSSVM model, the optimization problem can be described as follow.

$$min\frac{1}{2}\boldsymbol{w}^T\boldsymbol{w}+\frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i^2 \qquad (6)$$

$$s\cdot t\quad y_i=\boldsymbol{w}^T\phi(x_i)+b+\xi_i, i=1,2,3,\cdots N \qquad (7)$$

To solve the problem above, the Lagrange function is built.

$$L(\boldsymbol{w},b,\xi_i,\alpha_i)=\frac{1}{2}\boldsymbol{w}^T\boldsymbol{w}+\frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i^2-\sum_{i=1}^{N}\alpha_i\left[\boldsymbol{w}^T\phi(\mathrm{x_i})+b+\xi_i-y_i\right] \qquad (8)$$

Where, α_i is Lagrange multiplier. Then take the derivative to each variable of function and let it be zero to obtain the following.

$$\begin{cases}\dfrac{\partial L}{\partial \boldsymbol{w}}=0\rightarrow \boldsymbol{w}=\sum_{i=1}^{N}\alpha_i\varphi(x_i)\\ \dfrac{\partial L}{\partial b}=0\rightarrow\sum_{i=1}^{N}\alpha_i=0\\ \dfrac{\partial L}{\partial \xi}=0\rightarrow\alpha_i=\gamma\xi_i\\ \dfrac{\partial L}{\partial \alpha}=0\rightarrow \boldsymbol{w}^T+b+\xi_i-y_i=0\end{cases} \qquad (9)$$

The problem can be transformed to the following after eliminating $\boldsymbol{w}$ and ξ_i.

$$\begin{bmatrix}0 & \boldsymbol{e}_n^T\\ \boldsymbol{e}_n & \boldsymbol{\Omega}+\gamma^{-1}\cdot I\end{bmatrix}\cdot\begin{bmatrix}b\\ a\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \qquad (10)$$

Where,

$$\boldsymbol{\Omega}=\varphi^T(x_i)\varphi(x_i) \qquad (11)$$

$$\boldsymbol{e}_n=[1,1,\ldots,1]^T \qquad (12)$$

$$\alpha=[\alpha_1,\alpha_2,\ldots,\alpha_n] \qquad (13)$$

$$y=[y_1,y_2,\ldots,y_n]^T \qquad (14)$$

Solve the linear equations above and the following can be got.

$$y(x)=\sum_{i=1}^{N}\alpha_i K(\boldsymbol{x}_i,\boldsymbol{x})+b \tag{15}$$

In this paper, the wavelet kernel function is selected [20-21].

$$K(\boldsymbol{x}_i,\boldsymbol{x})=\prod_{i=1}^{N}\psi(\frac{x_i-x_i'}{\sigma_i}) \tag{16}$$

The wavelet function is used as the kernel function of LSSVM model instead of the conventional radial basis kernel function to be put in the regression equation, $y(x)$.

$$y(x)=\sum_{i=1}^{N}\alpha_i\prod_{i=1}^{N}\psi(\frac{x_i-x_i'}{\sigma_i})+b \tag{17}$$

$$\psi(x)=\cos(1.75x)\cdot\exp(\frac{-x^2}{2}) \tag{18}$$

Then the LS-WSVM regression equation can be described as follow.

$$y(x)=\sum_{i=1}^{N}\alpha_i\prod_{i=1}^{N}\{\cos[\frac{1.75(x_i-x_i')}{\sigma_i}]\cdot\exp[\frac{-(x_i-x_i')^2}{2}]\}+b \tag{19}$$

III. LS-WSVM MODEL OPTIMIZED BY ADABOOST

The regression prediction of transmission line icing thickness using AdaBoost-LS-WSVM algorithm, should select key indicators of icing thickness firstly. According to the present analysis, the transmission line icing thickness is high correlated with temperature (x_1), humidity (x_2), wind speed (x_3) and atmospheric pressure (x_4).

The performance of a single LS-WSVM model is not high no matter how to turn the kernel function or the parameters of model when used for regression calculation of high dimensional data. So the single LS-WSVM model can be regarded as a weak regression machine. For any weak regression machine, AdaBoost algorithm can improve its precision. But the AdaBoost algorithm is not good at dealing with high dimensional data and LS-WSVM cleverly avoids this problem by kernel function. Therefore, the combination of them two can be a good solution to the problem of regression prediction with high dimensional data.

The specific steps of AdaBoost-LS-WSVM strong regression machine are as follows.

Step1 Select the training set, $(x_{i1},x_{i2},x_{i3},x_{i4},y_i)$, $i=1,2,\ldots,\mathrm{n}$, $x_{i1},x_{i2},x_{i3},x_{i4},y_i\in\mathrm{R}$. And the given maximum number of iterations is T. The given threshold for judging the predicted value right or wrong is $\varphi(0<\varphi<1)$. The weight distribution of the training data is $D_1(i)$, when the number of iterations t is 1. And the initial error is ε_t.

$$D_1(i)=1/n \tag{20}$$

Step2 Train the weak LS-WSVM regression machines according to the weight distribution and establish regression model, $f_t(x)\to y$. Then calculate the training set error.

$$ARE_t(i)=\left|\frac{f_t(x_i)-y_i}{y_i}\right| \tag{21}$$

Otherwise, the error rate of $f_t(x)$ is calculated by the following formula.

$$\varepsilon_t=\sum_{i:\left|\frac{f_t(x_i)-y_i}{y_i}\right|>\phi}D_t(i) \tag{22}$$

Then calculate $\beta_t=\varepsilon_t^n$, n=1,2,3. The weights, Dt, are updated using the following formula.

$$D_{t+1}(i)=\frac{D_t(i)}{Z_t}\times\begin{cases}\beta_t,\mathrm{ARE}_t(i)\le\phi\\1,\text{otherwise}\end{cases} \tag{23}$$

Where, Zt is normalization factor.

Step3 Let $t=t+1$, and return to step2 until the end of the iteration.

Step4 Give the output of the strong regression machine.

$$f_{fin}(x)=\frac{\sum_{i=1}^{t}\left[\lg\frac{1}{\beta}\right]f_t(x)}{\sum_{i=1}^{t}\left[\lg\frac{1}{\beta}\right]} \tag{24}$$

According to the steps above, the process of AdaBoost-LS-WSVM regression machine algorithm is shown in figure 1.

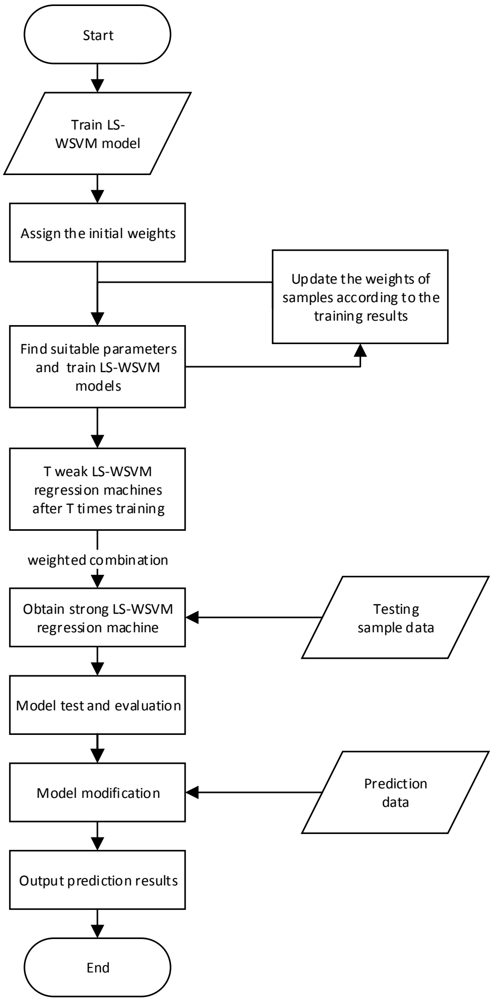

Fig.1 Flow Chart of AdaBoost-LS-WSVM Algorithm

IV. EMPIRICAL ANALYSIS

To verify the effectiveness and feasibility of the method proposed, the icing thickness data and meteorological data of Hunan 220kV Qian Ping line from T8:45 February 27 in 2007 to T10:30 March 1 in 2007 were selected as the sample data in the paper. There are 200 groups of data and part of them are shown in Table I below. The first 180 groups of data were used as the training data while the remaining 20 groups were as the testing data to verify the validity of the model.

In the paper, relative error(RE), mean absolute percentage error(MAPE) and mean square error(MSE) were choose as the evaluation indexes for the icing prediction models.

$$\mathrm{RE} = {|y_i - \hat{y}_i|}\Big/{y_i} \times 100\% \qquad (25)$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \qquad (26)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (27)$$

Temperature (x_{i1}), humidity (x_{i2}), wind speed (x_{i3}) and atmospheric pressure (x_{i4}) were as the model input variables while icing thickness as the model output variable. The strong LS-WSVM regression machine was obtained after training the AdaBoost-LS-WSVM regressions with training samples. Then the testing samples were put into the strong regression to test and verify the model. Some original data are shown in table I. Besides, the LS-SVM prediction model, support vector machine (SVM) prediction model and BP neural network prediction model were also adopted to calculate the icing thickness for the test samples in this paper for comparison. The prediction results of each model are shown in Figure 2 and the evaluation results of each model are shown in Table II while the relative errors are in Figure 3.

The parameters of each model were set as follows.

The LS-SVMLabv1_8 toolbox was used to bulid LS-SVM prediction model. Set type='unction estimation', kernel='RBF_kernel'. The regularization parameter was got by the cross validation and C was 20.4581. The nuclear parameter, σ was 2.6431.

The svmdark software was used for training SVM model after the format conversion of sample data. The parameters of SVM model, C was 33.617, epsilon was 0.7302, σ was 0.6892 by the cross validation.

The structure of three layer BP neural network was set as 4-10-1. And the transfer function in hidden layer was tansig while purelin in output layer. The learning function was learngdm and the learning rate was set to 0.005. The number of training times was set to 5000.

From table II, it can be known that the MaxRE and MinRE values of AdaBoost-LS-WSVM model are both less than the other three models, which shows that the prediction accuracy of LS-WSVM-AdaBoost model in the icing thickness is higher than that of LS-SVM model, SVM model and BP model. It is because that the weak LS-WSVM model is improved based AdaBoost algorithm and the strong one is got. From the MAPE results, it can also be seen that the MAPE value of AdaBoost-LS-WSVM model, 2.8% is less than that of the other three models, 4.36%, 5.16% and 7.58%, indicating AdaBoost-LS-WSVM model has the highest overall prediction accuracy and stronger nonlinear mapping abilities. So it is more suitable for the prediction of transmission line icing thickness. From the MSE values, it can be seen that the MSE value of AdaBoost-LS-WSVM model, 10.20% is also less than that of the other three models, 24.17%, 35.64% and 70.58%, indicating that the prediction results of AdaBoost-LS-WSVM model are the most close to the true values. In addition, AdaBoost-LS-WSVM model has most stable prediction results and strongest prediction accuracy.

TABLE I. SAMPLE DATA OF ICING THICKNESS

	Order	Temperature / □	Humidity / %	Wind speed/ m/s	Atmospheric pressure / Mpa	Icing thickness / mm
Training samples	1	-6	85	7.0	821.56	4.27
	2	-7	85	5.0	826.83	3.69
	□	□	□	□	□	□
	179	-7	85	2.4	826.14	10.2
	180	-7	84	3.0	823.17	7.7
Testing samples	181	-6	84	5	823.91	9.83
	182	-6	83	5	826.66	3.56
	□	□	□	□	□	□
	199	-8	80	4	827.57	10.21
	200	-8	80	7	825.23	10.93

TABLE II. EVALUATION INDEX VALUES OF EACH MODEL

Error /%	LS-WSVM-AdaBoost model	LS-SVM model	SVM model	BP model
MaxRE	7.52	10.33	11.18	22.06
MinRE	0.81	1.36	1.95	2.10
MAPE	2.80	4.36	5.16	7.58
MSE	10.20	24.17	35.64	70.58

Fig. 2 is the comparison between the real icing thickness values of testing samples and the predicted thickness values of each model. From the figure, it can be seen that the prediction value curve of AdaBoost-LS-WSVM model is more adjacent with the true value curve than the other models. Besides, the prediction curves of the other three models have great volatility and are not close to the real data curve. The icing thickness prediction further proves that AdaBoost-LS-WSVM algorithm proposed in this paper has better prediction performance.

Fig. 3 is the comparison between the relative errors for testing samples of the 4 models. The maximum absolute relative error values of AdaBoost-LS-WSVM, LS-SVM, SVM and BP prediction model are respectively 7.52%, 10.33%, 11.18% and 22.06%, indicating that AdaBoost-LS-WSVM model has the highest prediction accuracy and the strongest robustness. The figure also shows that AdaBoost-LS-WSVM model has the smallest overall relative error. And LS-SVM and SVM models come second while BP prediction model has the biggest relative error. It proves that AdaBoos-LS-WSVM model predicts most accurately and has best nonlinear mapping abilities, which is more suitable for the prediction of line icing thickness.

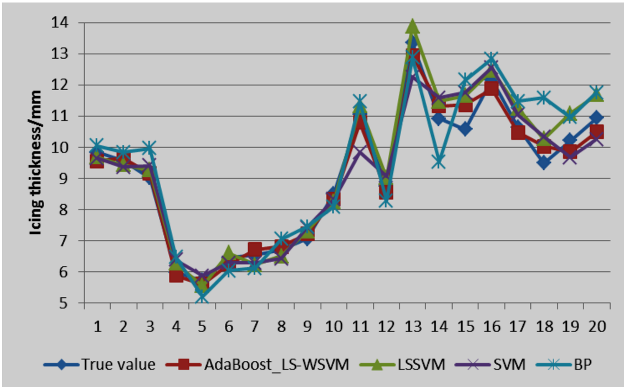

Fig.2 The Prediction Results Line Chart of Each Model

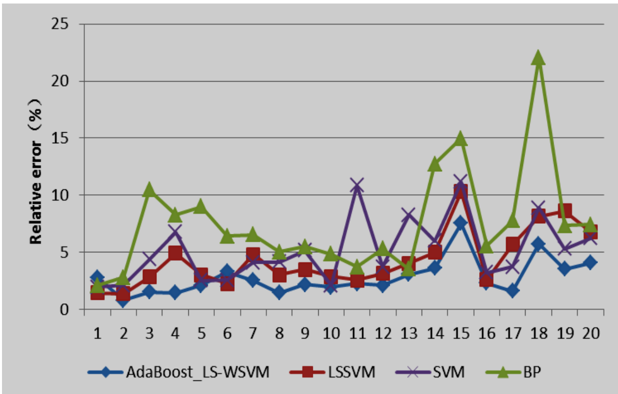

Fig.3 The Relative Error Line Chart of Each Model

V. CONCLUSION

Aiming at the high dimension and nonlinear characteristics of icing prediction of transmission line, a method based on the combination of AdaBoost model and LS-WSVM regression model was proposed in this paper to predict the transmission line icing thickness. Through the example, the following conclusions can be drawn.

(1) AdaBoost-LS-WSVM regression model in this paper

has strong prediction abilities and is suitable for the short-time prediction of transmission line icing thickness. So AdaBoost-LS-WSVM model can be an effective tool for short-term prediction of transmission line icing thickness.

(2) LSSVM algorithm can approach to any function with high accuracy by using the wavelet kernel function instead of the traditional Gaussian kernel function to eliminate redundancies of Gaussian function, which improves the nonlinear processing abilities and generalization abilities of LSSVM regression model.

(3) AdaBoost-LS-WSVM icing thickness prediction model has a higher precision than the traditional intelligent icing thickness prediction models such as LSSVM model, SVM model and BPNN model. This is because multiple weak LS-MSVM regression machines are integrated to a strong one by AdaBoost so as to improve the learning efficiency and prediction accuracy of the model.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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REFERENCES

[1] Farzaneh, Masoud, ed. "*Atmospheric icing of power networks*." *Springer Science & Business Media*, 2008.

[2] Li, Cheng-rong, et al. "*Research issues for safe operation of power grid in China under ice-snow disasters*." *Power System Technology* 32.4: 14-22,2008.

[3] Imai, I. "*Studies on ice accretion*." *Researches on Snow and Ice* 3.1: 35-44,1953.

[4] Lenhard, R. W. "*An indirect method for estimating the weight of glaze on wires*." *Bull. Amer. Meteor. Soc* 36.3: 1-5,1955.

[5] Goodwin III, Edwin J., et al. "*Predicting ice and snow loads for transmission line design*." *Predicting Ice & Snow Loads for Transmission Line Design*, 1983.

[6] Makkonen, Lasse. "*Modeling power line icing in freezing precipitation*." *Atmospheric Research* 46.1: 131-142,1998.

[7] LIU shengchun, SI Jiajun, GUO Hao, et al. "*Numerical and experimental study on accreted ice on conductor of transmission lines*." *Proceedings of the CSEE*,(S1): 246-255,2014.

[8] DONG Dejie. "*Measurements for improving weight on both sides of perch's ice thickness of the wire*." *Electrical Engineering*, 16(4): 52-55,2015.

[9] Yufang, Liao, and Duan Lijie. "*Study on estimation model of wire icing thickness in Hunan Province*." *Transactions of Atmospheric Sciences (in Chinese)* 33.4: 395-400,2010..

[10] LIU Jun, LI Anjun, ZHAO Liping. "*Ice thickness prediction model based on T-S fuzzy neural network*." *Hunan electric power*, 32:1-4,2012.

[11] Sheng, Chen, et al. "*Short-term Prediction for Transmission Lines Icing Based on BP Neural Network*." *Power and Energy Engineering Conference (APPEEC)*, 2012 Asia-Pacific. IEEE, 2012.

[12] DAI Dong, HUANG Xiaoting, DAI Zhou, et al. "*Transmission line icing regression model based on support vector machine*." *High Voltage Technology*, 2013, 39.

[13] LIU Hongwei, LU Jiazheng, LAI Xunyang, et al. "*Short-term multi-variable grey model in predicting icing thickness on transmission lines*." *High Voltage Engineering,* 41(10),2015..

[14] LIU Yi. "*Adaptive network fuzzy inference forecast model for icing of transmission lines*." *China New Technologies and Products*,(20): 2-3,2015.

[15] HUANG Xiaoning, XU Rui, XU Jiahao. "*Analysis of the characteristics for on-line monitoring data and research of the forecast model of the line icing in southern mountain area*." *Power System Protection and Control*, 23: 111-116,2015.

[16] PENG Chi, LUO Hong, HUANG Huan, et al. "*Classification and Distribution Characteristics of Ice Coating on Wires in Guizhou*." *Southern Power System Technology*,04: 84-89,2015.

[17] YU Shuang, DING Yuhan, LIU Guohai, et al. "*LSSVM-adaboost inversion soft sensing method for a biologic fermentation process*." *Computers and Applied Chemistry*, 2014(11).

[18] LI Yaqin, YANG Huizhong. "*The fuzzy support vector regression ensemble algorithm based on the improved Adaboost.RT*." *2009 China Intelligent Automation Conference (Second Edition)*, 2009.

[19] Guo, Cui Ling, Y. U. Li-Jian, and S. L. Zeng. "*Research on Urban Traffic Flow Prediction Based on LS-WSVM*." *Logistics Engineering & Management* 9: 038,2012.

[20] LI Kun, TAN Mengyu. "*Stock prediction based on Wavelet Support Vector Machine*." *Statistics and Decision*,(6): 32-36,2014.

[21] Li Xiao and Xu Jinjun. "*Landslide deformation prediction based on Wavelet Analysis and Least Square Support Vector Machine*." *Journal of Geodesy & Geodynamics* 29.4:127-130,2009.