THE REGRESSION MODEL OF TRANSMISSION LINE ICING BASED ON NEURAL NETWORKS

Sun Muxia, Dai Dong*, Hao Yanpeng, Huang Xiaoting
School of Electric Power, South China University of Technology, Guangzhou, China
*Email:ddai@scut.edu.cn

Abstract: This paper addresses the regression model of the transmission line icing based on BP Neural networks. The Model is built for estimating the ice height on power line. The field data used for the regression model comes from the Early Warning System for Disasters (Icing) of China Southern Power Grid, which includes the ambient temperature, relatively humidity, mean wind speed, wind direction, atmospheric pressure and the equal ice height. The results from the application of the BP model are in well agreement with the field data, indicating that the model can be very useful both for estimating the icing loads on transmission lines, and alarm the coming icing events when a further short-term forecasting system for the field climate data is available.bstract of the submitted paper. The abstract should be according to the text and alignment formatting.

1. INTRODUCTION

The icing on transmission line was and is still a problem for power networks. After the icing disaster in 2008, an important task for the South China Power Grid is to perfect the icing alarm system of over head transmission lines. Our work is in purpose to give regression models to estimate the equal height of power line icing, using the micro-climate data of each tower monitored by the Early Warning System for Disasters (Icing) of China Southern Power Grid, which includes the ambient temperature, relatively humidity, mean wind speed, wind direction, atmospheric pressure and equal ice height. The models are expected to be used in short-term alarm system of the ice events in the future. We use BP neural networks as the learning machine to find the best regression functions. Experiments show that the BP models estimate the icing events in the test sets very well.

Specifically, we built a BP neural network for each separated monitored tower. In this paper, the statistical learning theory is introduced in this paper to give a theoretical direction for building the BP networks. Then the data preprocessing techniques was carefully used. In the end of the paper, we give the experiments and results of our models, and make a short conclusion.

2. RESULTS AND DISCUSSION

The results show that the BP neural networks estimate the power line icing well, although the accuracy of the regression models change from tower to tower.

3. CONCLUSION

Experiments and results show that the BP neural network estimates the icing events well. However, more data and experiments are required, as the icing events we have collected is still rare, and for most towers, the maximum ice height we have observed is very low, e.g., less than 1cm. Thus, more tests for the effectiveness of the regression model build by BP neural networks, especially in the cold regions, are still needed.

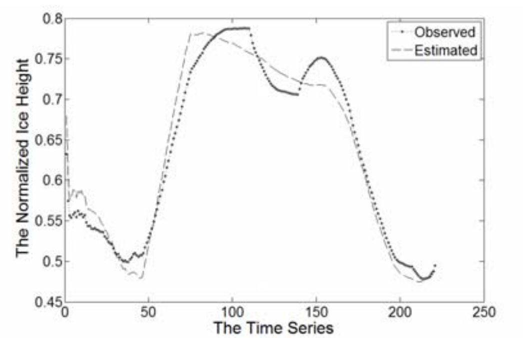

Figure 1: An icing event at a monitored transmission line in Guangxi Province in 2009.

Table 1: Estimating the Icing Events.

The Tower Number	The number of the icing data	The best neuron number in the hidden layer	The mean square error
1	1296	9	0.00097
2	1000	9	0.00142
3	326	10	0.00113
4	315	9	0.02031

4. REFERENCES

[1] Savadjiev K, Farzaneh M. “Modeling of Icing and Ice Shedding on Overhead Power Lines Based on Statistical Analysis of Meteorological Data”, IEEE Trans Power Delivery, 2004, vol. 19(2), pp.715-721.

[2] Farzaneh M, Savadjiev K. “Statistical analysis of field data for precipitation icing accretion on overhead power lines”, IEEE Trans Power Delivery, 2005, vol. 20(2), pp.1080-1086.

[3] Larouche E , Rouat J , Bouchard G, et al. “Exploration of Static and Time Dependent Neural Network Technique for the Prediction of Ice Accretion on Overhead Line Conductors,” 9th International Workshop on Atmospheric Icing of Structures. Chester, United Kingdom, Session 2, 2000.

[4] Makkonen L. “Modeling Power Line Icing in Freezing Precipitation. Atmospheric Research”, 1998, vol. 46, pp. 131–142.

[5] Shao J, Laux S J, Trainor B J, Pettifer R E W. “Nowcasts of temperature and ice on overhead railway transmission wires. Meteorology Appicationl”, 2003, vol. 10,pp. 123–133.

[6] Maralbashi-Zamini S. “Developing Neural Network Models to Predict Ice Accretion Type and Rate on Overhead Transmission Lines.” http://theses.uqac.ca/these_pdf.php?idnotice=030012635&type_pdf=TI&temp=0

[7] Farzaneh, Masoud (Ed.), Atmospheric Icing of Power Networks, CA: Springer, 2008.

[8] Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Introduction to Data Ming. CA: Pearson Addison-Wesley, 2006.

[9] Jiawei Han, Micheline Kamber, Data Mining, Second Edition : Concepts and Techniques. CA: Morgan Kaufmann, 2006.

The Regression Model of Transmission Line Icing Based on Neural Networks

Sun Muxia, Dai Dong *, Hao Yanpeng, Huang Xiaoting
School of Electric Power
South China University of Technology
Guangzhou, China
**Email:ddai@scut.edu.cn*

***Abstract*—This paper addresses the regression model of the transmission line icing based on BP Neural networks. The Model is built for estimating the ice height on power line. The field data used for the regression model comes from the Early Warning System for Disasters (Icing) of China Southern Power Grid, which includes the ambient temperature, relatively humidity, mean wind speed, wind direction, atmospheric pressure and the equal ice height. The results from the application of the BP model are in well agreement with the field data, indicating that the model can be very useful both for estimating the icing loads on transmission lines, and alarm the coming icing events when a further short-term forecasting system for the field climate data is available.**

Keywords-Transmission line icing; regression model; BP neural network; field data

I. Introduction

The icing on transmission line was and is still a problem for power networks. After the icing disaster in 2008, an important task for the South China Power Grid is to perfect the icing alarm system of over head transmission lines. Thus, the Early Warning System for Disasters (Icing) of China Southern Power Grid, i.e., EWSD of CSG, a system monitors the climate and other parameters of the power lines in south china has been built in five provinces of south China. This system gives the micro climate data of each monitored tower, including the ambient temperature, relatively humidity, mean wind speed, wind direction, atmospheric pressure and equal ice height. Our work is in purpose to give empirical icing models to estimate the equal height of power line icing, so that a short term icing alarm system might be established with the help of a numerical micro climate forecast system in the future. Considering the success of the additive model based on the data from the Mont Belar test site, we use regression models and the climate data provided by the monitoring system to estimate the power line icing. We use BP neural network as the learning machine to find the best regression function. Experiments show that the BP models estimate the icing events very well, which were independent from the training data sets. As the BP networks can update themselves online by training themselves automatically, they have a significant potential to be applied in the practical power line icing estimating.

Specifically, we built a BP neural network for each separated tower, for the monitored towers are distributed in such different geographic and atmospheric environment, and the correlation between ice height and the input climate variables seems dependent from the location of the monitored tower, as the important climate parameters, such as the icing rate and the precipitation rate are absent here. As the icing events for each tower is quite limited, the problem is to build the regression functions by BP network at the lowest risk with limited data samples. Thus, the statistical learning theory is introduced, which gives a theoretical direction for building the BP network, and several data preprocessing techniques was used. In this paper, we will first discuss the data and its preprocessing, then introduce our regression model based on BP neural networks, and in the end, give the experiments and results of our models, and make a short conclusion.

II. The Regression Model based on BP Neural Networks

A. *The basic regression model for transmission line icing*

According to the statistical learning theory, the basic regression estimation problem for a learning machine k is to minimize the risk functional

$$R(\alpha)=\int (f(\vec{x},\alpha)-y)^2 dF(\vec{x},y) \tag{1}$$

where $\vec{x}$ is the vector of the independent variables, y is the dependent variable, $F(\vec{x},y)$ is the united probability distribution of $\vec{x}$, y ,and α is the parameter. The conditional expectation function of $F(\vec{x},y)$

$$f(\vec{x},\alpha_0)=\int y dF(y\,|\,\vec{x}) \tag{2}$$

minimizes the risk functional $R(\alpha)$, so that the key for the learning machine k to minimize $R(\alpha)$ is to estimate $f(\vec{x},\alpha_0)$ in the set $\{f(\vec{x},\alpha)\,|\,\alpha\in\Lambda_k\}$, where Λ_k is a set of parameter α given by k .

The learning machines use empirical data to minimize $R(\alpha)$. As the risk functional of the set of the empirical data $M=\{(\vec{x}_i,y_i)\,|\,i=1,2...l\}$ (l is the number of the data samples, and $(\vec{x}_i,y_i)$ is usually assumed as independent and identically observations of $F(\vec{x},y)$), or the Empirical Risk Functional

$$R_{\mathrm{emp}}(\alpha)=\frac{1}{l}\sum_{i=1}^{l}[f(\vec{x}_i,\alpha)-y_i]^2 \quad (3)$$

is usually inconsistent with $R(\alpha)$, we have the SRM principle for learning machines such as BP neural network, which points out we should take a indirect way by minimize $R_s(l,k)$, the bounds of the generalization ability of the learning machines, as

$$R_s(l,k)=R_{\mathrm{emp}}(\alpha_{\mathrm{emp},k})+\Phi(l/h_k) \quad (4)$$

$$R_s(l,k)\ge R(\alpha_{\mathrm{emp},k}) \quad (5)$$

Where $\alpha_{\mathrm{emp},k}$ minimizes $R_{\mathrm{emp}}(\alpha)$ in the function set A_k, and the symbol $\Phi(l/h_k)$ is the confidence interval, which decided by l, and the VC dimension of learning machine k.

B. The BP neural network

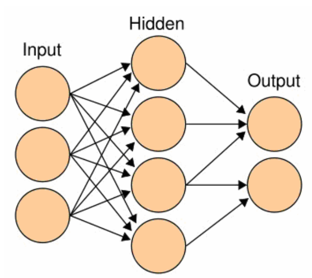

Figure 1. a BP neural network with one hidden layer.

The Hecht-Nielsen Theorem shows that a BP neural network with at least one hidden layer could approximate any continuous function. The fitting function of BP neural network with one hidden layer is

$$f(\vec{x},\alpha)=\sum_{i=1}^{n}N_i(\vec{x})=\sum_{i=1}^{n}w_{2_i}S(u_i) \quad (6)$$

where $u_i=\lambda_i(\vec{w}_{1_i}^T\vec{x}-b_i)$, $\vec{x}$ is the input vector, y is the output variable, and n is the number of the hidden layer neurons. For the hidden neuron i, $N_i(\vec{x})$ is the output of the neuron, with the sigmoid function $S(u_i)$, and the neuron parameters λ_i, $\vec{w}_{1,i}$, $w_{2,i}$, b_i. In this paper, we use BP network with one hidden layer to fit the regression functions. The steps to minimize $R_s(l,n)$ (The hidden layer neurons number n fixes the structure of the BP network with one hidden layer) for the BP networks is：

Step1. Choose a small n, so that the confidence interval $\Phi(l/h_n)$ is fixed.

Step2. For each possible n, minimize $R_{\mathrm{emp}}(\alpha)$, and get the fitting function $f(\vec{x},\alpha_{\mathrm{emp},n})$。

Step3. For each n, calculate the empirical risk function $R_{\mathrm{test}}(\alpha)$ for the test data set which is independent of the training data set. Assume that $R_{\mathrm{test}}(\alpha)\approx R_s(l,n)$, the number of the hidden neurons n_0 which minimize $R_s(l,n)$ is got. Here, $f(\vec{x},\alpha_{\mathrm{emp},n_0})$ is the best estimation given by the BP network with one hidden layer of $f(\vec{x},\alpha_0)$.

III. PREPARE YOUR PAPER BEFORE STYLING

A. The input data

The monitoring system of the EWSD of CSG provides various data. For neural networks, the input data, including the independent variables and the dependent variable, should be carefully chosen. Because of the absent of the icing rate and the precipitation rate, we chose the equal ice height H rather than the ice accumulating rate as the dependent variable. For the icing alarm system in future, the independent variables should be easy to forecast in short term. Thus, we chose the available climate variables as the independent variables, including the ambient temperature T, relatively humidity W, mean wind speed V, wind direction A, and the atmospheric pressure P.

The monitoring system takes sample of the climate variables every 10 or 15 minute. The database is consisted of all the data monitored from the year 2008 to 2010. The continuous icing events in the database constitute the training set and test set for the BP neural networks.

B. The deviation detection in databases

While the database contains different kinds of error, the deviation detection techniques are required. The error data we have commonly observed in the database included the isolate points and the continuous breakdown caused by hardware failure. To find the two kinds of error in the data flow, we designed a deviation detection algorithm in time series, which is based on the statistical analysis of the climate variables. The algorithm uses a series of confidence intervals to check whether the value or the increasing rate of a data is out of them. Then, the criterions which classify the two kinds of error are used to classify the error data.

We also use the k-nearest neighborhood algorithm to detect the outliers left in the database after using the deviation detection algorithm. As the icing data is very rare, the two algorithms are used in the whole database rather than in each training and test set. The results of these two algorithms are showed in fig 1. and fig 2.

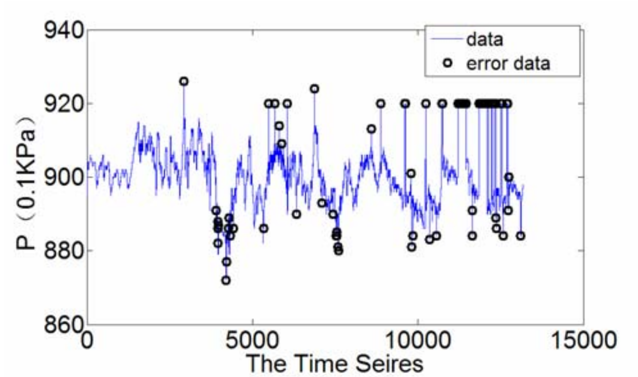

Figure 2. the Deviation Detection in Time Series.

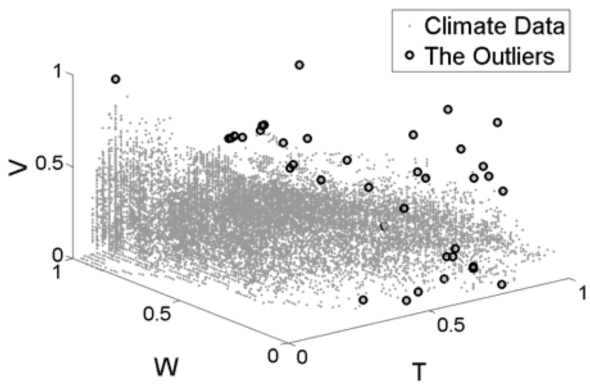

Figure 3. the Outlier Detection based on k-Nearest Neighborhood Algorithm.

C. The repair and smooth of data

The data lost or distinguished by the deviation detection techniques needs to be repaired. We use the training d has to be normalized to repair the data. As the repaired data is still with some random measure error, we use the moving average method to smooth the data flow.

D. The normalization of data

The training data for BP network usually has to be normalized. Here, we use the linear normalized method, where the normalized data

$$u_G = (u - u_{\min}) / (u_{\max} - u_{\min}) \qquad (14)$$

Here, u is the original data value, $u_{\min}$ is the minimum value of u, $u_{\max}$ is the maximum value of u.

IV. The Experiments and Results

In this paper, we use the BP neural network to estimate the icing events in the test set for the 4 classical monitored transmission line at different place of south china. The results are showed in Fig. 3, Fig. 4 and Tab. 1.

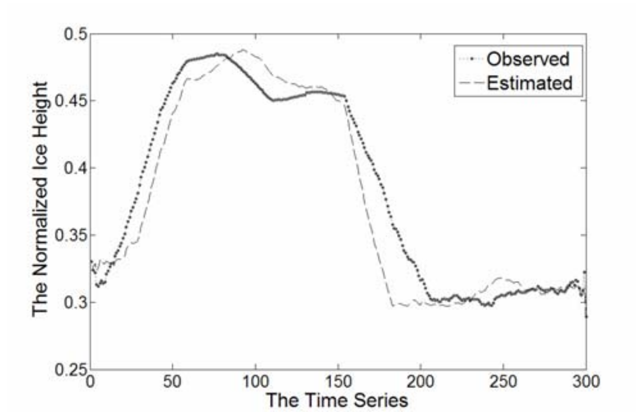

Figure 4. An icing event at a monitored transmission line Guizhou Province in 2009.

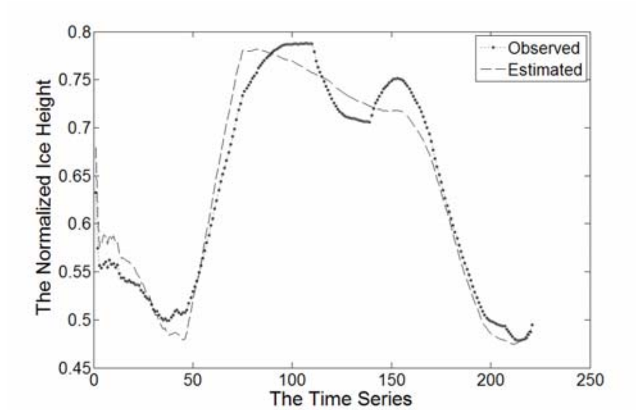

Figure 5. An icing event at a monitored transmission line in Guangxi Province in 2009.

TABLE I. ESTIMATING THE ICING EVENTS.

The Tower Number	The number of the icing data	The best neuron number in the hidden layer	The mean square error
1	1296	9	0.00097
2	1000	9	0.00142
3	326	10	0.00113
4	315	9	0.02031

The results show that the BP neural networks estimate the power line icing well, although the accuracy of the regression models change from tower to tower, and occasionally they does not work such well, e.g., at the line No.4. One reason explains this phenomenon is that the icing data, especially the data of the classical icing events is still very rare, so that the performance of BP neural network would not always be steady. Another reason is that the important characters of the transmission line icing events, e.g., the icing rate, is absent here. We could expect a regression model without the input I would have a higher risk, though quite enough for a short-term icing alarm system.

V. Discussion

This paper deals with regression model based on BP neural network for estimate the power line icing. The input of the neural network includes the ambient temperature, relatively humidity, mean wind speed, wind direction, atmospheric pressure and equal ice height. The data we use was carefully preprocessed. Experiments and results show that the BP neural network estimates the icing events well. However, more data and experiments are required, as the icing events we have collected is still rare, and for most towers, the maximum ice height we have observed is very low, e.g., less than 1cm. Thus, more tests for the effectiveness of the regression model build by BP neural networks, especially in the cold regions, are still needed.

Acknowledgment

This work was supported by the National Key Supporting Program for Sci & Tech Research during the 11st Five-Year Plan Period of China (2009BAA23B01-8) and the Natural Science Foundation of Guangdong Province, China (10151064101000008).

References

[10] Savadjiev K, Farzaneh M. “Modeling of Icing and Ice Shedding on Overhead Power Lines Based on Statistical Analysis of Meteorological Data”, IEEE Trans Power Delivery, 2004, vol. 19(2), pp.715-721.

[11] Farzaneh M, Savadjiev K. “Statistical analysis of field data for precipitation icing accretion on overhead power lines”, IEEE Trans Power Delivery, 2005, vol. 20(2), pp.1080-1086.

[12] Larouche E , Rouat J , Bouchard G, et al. “Exploration of Static and Time Dependent Neural Network Technique for the Prediction of Ice Accretion on Overhead Line Conductors,” 9th International Workshop on Atmospheric Icing of Structures. Chester, United Kingdom, Session 2, 2000.

[13] Makkonen L. “Modeling Power Line Icing in Freezing Precipitation. Atmospheric Research”, 1998, vol. 46, pp. 131–142.

[14] Shao J, Laux S J, Trainor B J, Pettifer R E W. “Nowcasts of temperature and ice on overhead railway transmission wires. Meteorology Appicationl”, 2003, vol. 10,pp. 123–133.

[15] Maralbashi-Zamini S. “Developing Neural Network Models to Predict Ice Accretion Type and Rate on Overhead Transmission Lines.” http://theses.uqac.ca/these_pdf.php?idnotice=030012635&type_pdf=TI&temp=0

[16] Farzaneh, Masoud (Ed.), Atmospheric Icing of Power Networks, CA: Springer, 2008.

[17] Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Introduction to Data Ming. CA: Pearson Addison-Wesley, 2006.

[18] Jiawei Han, Micheline Kamber, Data Mining, Second Edition : Concepts and Techniques. CA: Morgan Kaufmann, 2006.