PREDICTION MODEL FOR POWER TRANSMISSION LINE ICING LOAD BASED ON DATA-DRIVEN

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Abstract: **How to monitor and predict icing load of power transmission lines are important problems for the reliability of power grid. A model based on data-driven is presented here to predict the icing load of transmission line, which is available to forecast the icing disaster of it. The fitfulness, which influencing the prediction results of icing load, is analyzed and discussed in this paper. According to the results of simulation, this model has a good accuracy of prediction if the training data and prediction data are in the same icing process. If the icing process is not same but contiguous, it also can predict the degree of icing load qualitatively.**

Keywords: prediction model; transmission line icing; data-driven; BP neural networks ;

I INTRODUCTION

Icing of electrical power transmission lines, exposed above ground level, is a very serious problem in many countries. Especially in the early of 2008, Central Southern of China, it caused the collapse of towers, flash over of insulators or gallop of conductors. These accidents induced significant financial losses to domestic and industrial electrical power users directly. Accordingly, design of monitoring system is extraordinary necessary for transmission line icing, and theories and instruments related to it were studied all over the world.

The normal models and methods for monitoring icing is various, such as mechanical model [1], experiment model based on micro-meteorology parameters [2], Makkonen model [3] and edge of image extraction model [4], which are avail in practice. But none of them are both correct and complete in predicting icing load. Mechanical model has advantages in estimation to the status of lines icing, which is timely and exact, but the instruments for sampling the data are expensively and it is unable to forecast the icing status. Experiment model could predict icing load by which only some micro-meteorology parameters, such as the environment temperature, the humidity, the wind velocity, the wind direction, the rainfall and the snowfall, but there are some given experiential parameters in this model. If the micro-meteorology forecast information has been known, the icing loads can be predicted by this model.

But experiment model based on micro-meteorology parameters is founded in special condition, and it is not enough robust if the environment changes [5][6][7]. On the other hand, the history meteorology data from icing monitoring system have been recorded continuously and these are important factors for lines icing. Consequently, it is significant to mine the helpful information from the history data by some intelligent algorithms.

A model based on data-driven is presented here to predict the load of power transmission line icing, which utilize some meteorology forecast information from weather station and the history meteorology data from icing monitoring system. According to the results of simulation, the icing load in Tao-Luo-Xiong Transmission Line is predicted and it is helpful for departments of power grid to take actions.

II PREDICTION MODEL BASED ON DATA-DRIVEN

In this paper, the means of multi-source information fusion and machine learning (neural networks) are avail to found the model for icing load prediction. It is shown as Fig.1:

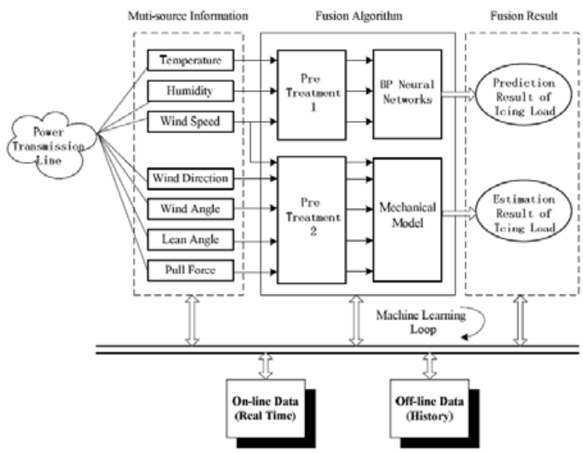

Fig.1 Prediction Model Based on Data-driven for Icing Load

In this model, the on-line data, such as wind speed, wind direction, wind angle, lean angle, pull force, are fusion to estimate the icing load timely and exactly, based on mechanical model. The result of estimation are shown in the surveillance center and recorded in the data-base for off-line data.

The off-line history data, such as temperature, humidity, wind speed and the estimation result of icing load in the same time, are used for training the BP neural networks and establish the prediction model. It is a process of machine learning loop, shown as Fig.2:

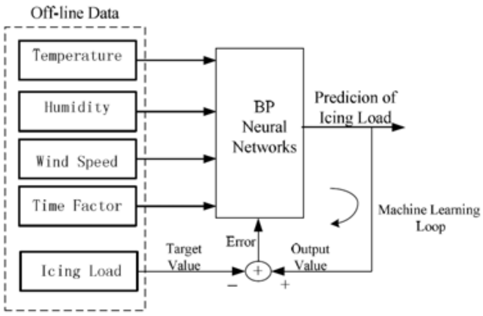

Fig.2 Machine Learning for BP Neural Networks

BP neural networks are learning with a teacher. The history icing load is the teacher to provide it with a desired response for training. The neural networks parameters are adjusted under the combined influence of the training vector and the error signal. The error signal is defined as the difference between the desired response (target value) and the actual response (output value) of the networks.

This adjustment is carried out iteratively in a step-by-step fashion with the aim of eventually making the total error obtain the minimum[11][12]. This method does not need to require any statistical information of monitoring data or the mathematic models, we use signals collected from multi-sensors as BP neural network input and to train BP neural network as above. Consequently, the prediction model for icing load is founded and if knowing the forecast meteorology information, we will prediction the icing load of power transmission lines and take the actions for disaster.

Coming back to Fig.1, it is obvious that, not only on-line data, but also off-line data are utilized sufficiently to prediction the icing load of power transmission lines. The model is based on data-driven, not mathematic formulas.

III Simulation and Analysis

As the model showing in figure.1, micro-meteorology data, such as the environment temperature, the humidity, the wind velocity, the wind direction and mechanics data of insulator in the same time, such as pull force, wind angle, lean angle, etc., are acquired from an on-line monitoring system of Tao-Luo-Xiong Transmission Line, in the Northwest of Yunnan Province, China.

The data are collected from all kinds of sensors and recorded every 20 minutes from November 14th to 24th, in 2009. Temperature curve, humidity curve, wind speed curve and icing load curve are shown as Fig.3. It is necessary to point that the icing load curve is achieved by the mechanical model as Fig.1.

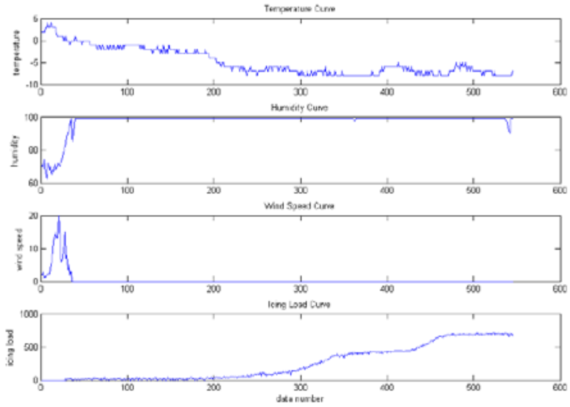

Fig.3 Meteorology Data (temperature, humidity, wind speed) and ice weight Curves

As Fig.3 showing, it is obviously that the icing load is increasing with the temperature decreasing, humidity around 99% and wind speed close to zero. These are the characters of ice rain and the meteorologists have point out that phenomena of transmission line icing often happens in the weather of ice rain. But it is difficult to prediction the increasing process of icing load by thermodynamic and hydromechanical models, such as Makkonen model [3].

In this paper, for the goal of predicting the increase process of icing load, we select the data from 1st to 450th , showing in Fig.3, to be used as the input data for BP neural network modeling, including the temperature, humidity, wind speed, icing load and time factor. we select the meteorology data from 500th to 510th , regarded as the forecast data from weather bureau, to be used as input data for BP neural network, which has been established. So we can achieve the prediction results as table.1 showing.

Table 1. The Predicion Results of Icing Load

Prediction Value (kg)	Actual Value (kg)	Error (kg)
685.2	673.1	12.09
685.4	650.8	34.59
685.6	662.4	23.19
685.8	652.4	33.45
686.1	664.4	21.7
686.3	653.4	32.94
684.1	630.7	53.41
685.3	651.7	33.58
684.3	649.5	34.79
683.8	627.8	56.02
686.1	656.4	29.66

In the eleven results of prediction, as showing in table.1, the average error is 33.2kg, the maximal error is 56.02kg, and the minimal error is 12.09kg.

However, if we predict the next icing process in the same transmission line, from January 3rd to 11th in 2010, the results are shown in Fig.4.

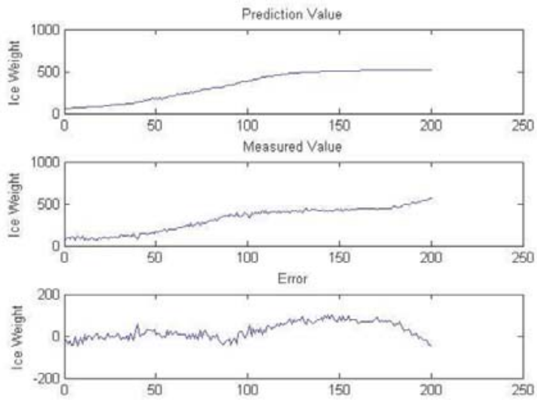

Fig.4 The Prediction Results of Icing Load (2010.1.3~2010.1.11)

It is evident that the errors in this case are bigger than those in table.1 and the maximal error close to 146kg, which is 25% of actual value. But the increasing trend of prediction is correct comparing the actual icing load (ice weight).

Machine learning is a good method for utilizing history data to found the prediction model if the training data and prediction data are in the same icing process. As showing in table.1, the average error is 33.2kg and the maximal error is 56.02kg, which is more less than 10% of the actual value.

However, the process of transmission line icing is fitful, icing or melting often happens alternately in a few months. Though the prediction model has been founded by using the history data in icing process k, but it is not well suitable for process k+1 or others. The results are obviously to confirm it in Fig.4. The causes would be as follows:

Cause 1: The methods of machine learning, such as neural networks, SVM, KDD, are typical black box models. The precision of model is decided by the data of training. If the data for founding the model are not enough to include all kinds of possible input and output, the model will not be suitable to describe the mapping relationship between them.

Cause 2: The transmission line icing is a complex process and it can be classified to four styles, which including rain icing, fog icing, wet snow and mix icing of rain and fog. The increasing process of icing is very different in the four styles. The load of icing increases more rapidly in rain icing and mix icing, but the temperature, humidity and wind speed, used to train the learning model, are not all the impact factors for them.

Cause 3: The shape and distributing along the transmission line are important factors for icing load. Icing process is often going with shelling and melting, which happen according to them. Wind direction, the time of sunlight, direction of sunlight and other meteorology factors influent the shape and distributing of line icing.

Consequently, the different process of icing has different impact factors and it is necessary to modify the model which founded by others. However, it does not mean that the model, established in process k, is useless for process k+1. Contiguous two icing processes have the most approximative meteorology characters, and the increasing trend of transmission line icing, in process k+1, can be perfectly predict by the model established in process k. As figure.6 showing, the trend of icing load changing is matching between actual (measured) value and prediction value, and the error is fluctuating around zero. It is convenient to predict the degree of icing load, such as slight, middle, serious and imperil, which are qualitative prediction results, but not quantitative. Those are available for power grid department to take timely actions and reduce the calamity losses.

IV CONCLUSIONS

The process of transmission line icing has complexity arising from heterogeneous information sources, multi-modal signals, high nonlinearities, strong interactions among variables or system states. The advantage of using automatic monitoring systems for power transmission line is that a large number of process data is available for the diagnosis of it. As complex line icing processes cannot be easily represented using accurate mathematical models, the method based on data-driven must be considered.

In this paper, a model based on data-driven is presented to predict the load of power transmission line icing, which utilize some meteorology forecast information from weather station and the history meteorology data from icing monitoring system. The fitfulness, which influencing the prediction results of icing load, is analyzed and discussed here.

According to the results of simulation, this model has a good accuracy of prediction if the training data and prediction data are in the same icing process. If the icing process is not same but contiguous, it also can conveniently predict the degree of icing load.

These conclusions avail to predict the icing disaster of Tao-Luo-Xiong Transmission Line.

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