Neurocomputing 74 (2011) 2573–2581

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Predicting the probability of ice storm damages to electricity transmission facilities based on ELM and Copula function ☆

Hongming Yang [a], Wenjun Xu [a], Junhua Zhao [b,*], Dianhui Wang [c], Zhaoyang Dong [d]

[a] School of Electrical and Information Engineering, Changsha University of Science and Technology, Changsha, PR China
[b] School of Electrical Engineering, Zhejiang University, Hangzhou, Zhejiang, PR China
[c] Department of Computer Science and Computer Engineering, La Trobe University, Melbourne, Australia
[d] Centre for Intelligent Electricity Networks, The University of Newcastle, Newcastle, Australia

ARTICLE INFO

Available online 12 May 2011

Keywords:
Copula function
Extreme learning machine
Joint probability distribution
Electricity transmission lines and towers
Ice storms

ABSTRACT

In this paper, a novel method based on extreme learning machine (ELM) and Copula function is proposed to predict the damages to electricity transmission facilities during ice storms. The ELM is firstly trained based on the historical data of wind speed, freezing precipitation, temperature, as well as the distribution parameters of wind and ice loads. The ELM can then be employed to predict the distributions of the real-time wind and ice loads on electricity transmission facilities. Furthermore, the correlation between wind load and ice load is modeled with Copula functions. On the basis of ELM and Copula function, the joint probability distribution of wind and ice loads can be finally formulated and applied to predict the potential damages to electricity transmission facilities such as transmission lines and towers. The proposed method is tested with a real dataset to demonstrate its effectiveness.

1. Introduction

As severe natural disasters, ice storms pose serious threats to the security of the electricity transmission system. An ice storm will cause large-scale ice accretion on transmission lines and towers; the ice load on certain transmission lines can significantly exceed the limit it can afford. The ice accretion and strong wind also can together cause the collapses of transmission lines and towers. The ice storm that attacked northeastern United States and eastern Canada in January 1998 caused a severe blackout in which the electricity supply of about 1.5 million households was interrupted [1]. In January 2008, continuous ice storms struck most parts of China and caused serious power outages. During the ice storms, a total of 1196 km transmission lines were damaged and 4017 transmission towers collapsed. The transmission systems in some areas lost their functions completely. Above facts indicate that ice storms are serious threats to power system security; therefore it is essential to study the ability of transmission facilities to withstand their impacts.

Concerning the ice storm damages to transmission facilities, some studies have been conducted on meteorological analysis, ice thickness prediction, transmission line loading and transmission reliability assessment. In [2], the models of wind speed and freezing precipitation are established based on the meteorological analysis of ice storms. In [3], by analyzing historical ice thickness data, an ice thickness forecasting method considering temperature, wind speed and freezing precipitation is proposed. In [4], the Gumbel extreme value distributions of wind load and ice load on transmission lines are derived. In above studies, the real-time variations of meteorological factors are not taken into account, which influences the accuracy of these methods. In [5–10], novel universal approximation, incremental and online algorithms have been developed based on the modifications of extreme learning machine. In [11–13], ELM has been employed to solve real-world problems such as mental tasks classification, terrain reconstruction and cancer diagnosis. The fast training speed and superior performance of ELM have been demonstrated in these studies.

In [14], based on the wind speed, the wind load on the transmission tower with ice accretion, and correspondingly the reliability of the tower are calculated. In [15], a model is proposed to calculate the probability of transmission line damages caused by excessive wind and ice loads. Till now, no existing research has carefully studied the random and varying meteorological impacts of ice storms on both transmission lines and towers. In practice, the ice loads and wind loads on transmission facilities are not independent because they are

☆ This work was supported by the National Natural Science Foundation of China (71071025, 70601003), the Hunan Provincial Outstanding Youth Science Foundation of China (10JJ1010), the Program for New Century Excellent Talents in University of China (NCET-08-0676), the National Outstanding Youth Science Foundation of China (70925006) and the Key Scientific and Technological Project of Hunan Province (2008FJ1006).

* Corresponding author. Tel.: +61 432 018 731.
E-mail addresses: yhm5218@hotmail.com (H. Yang), fuxiharp@gmail.com (J. Zhao).

0925-2312/$ - see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.neucom.2010.12.039

both affected by similar meteorological factors. Therefore, the correlation between ice loads and wind loads should be appropriately modeled when we calculate the probabilities of ice storm damages. This issue however has not been properly addressed in existing researches.

In this paper, to overcome the two weaknesses of existing methods, an ELM based predictor is formulated to predict the probabilistic distributions of wind and ice loads. The ELM is trained based on wind speed, freezing precipitation, temperature, as well as the wind and ice load distribution parameters. Combined with the Copula function and the ELM based predictor, the joint probability distribution of wind and ice loads can be formulated to predict the probability of ice storm damages to transmission lines and towers. The proposed method can take into account both the real-time meteorological information, and the correlation between wind and ice loads. Comprehensive case studies based on a real dataset is conducted to verify the effectiveness of the proposed method.

2. ELM based transmission facility loading prediction

During the ice storm, the wind load and ice load on transmission lines and towers are closely related with the meteorological conditions. To accurately predict the wind and ice loads, it is important to appropriately model the impacts of wind speed, freezing precipitation and temperature. Because of its fast learning speed and good generalization ability, ELM is employed to model the nonlinear functional relationship between meteorological variables and the distributions of wind/ice loads.

Extreme learning machine [16–19] is a learning algorithm based on the single hidden layer feed forward neural network (SLFN). ELM not only has a much faster training speed than the back propagation (BP) algorithm and support vector machine (SVM), but also avoids many difficulties faced by the BP algorithm such as stopping criteria, learning epochs, local minima and the over-tuned problems. Also, ELM shows similar generalization performance to SVM in many classification problems [20–23]. The topological structure of an ELM network is shown in Fig. 1.

The proposed ELM network consists of three input nodes, which, respectively, represent average wind speed v, lowest temperature T and freezing precipitation p. The number of hidden layer nodes is H, which can be determined based on the training data. The output layer includes two nodes, which, respectively, represent the mean μ and standard deviation σ of the wind/ice loads distributions. The size of the training data is W.

The means and standard deviations of wind and ice loads distributions can be calculated as follows:

(1) Based on the historical data of wind speed and freezing precipitation, the ice loads on transmission lines and towers can be calculated as [24]

$$\begin{cases} M_{Li}^t = \rho_i \pi[(D+2R^t)^2 - D^2]L/576 \\ M_{Zi}^t = \pi R^t \alpha_h \alpha_d (d + R^t \alpha_h \alpha_d)\gamma l_T \times 10^{-3} \end{cases} \tag{1}$$

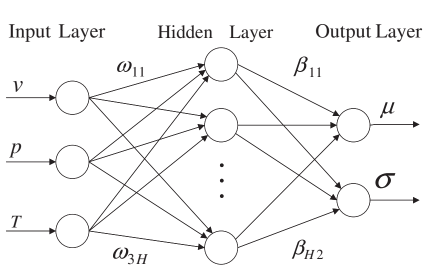

Fig. 1. The topological structure of an ELM network.

where M_{Li}^t and M_{Zi}^t, respectively, represent the ice loads on the transmission line and tower at time t, ρ_i is the ice density, D and L represent the diameter and length of the transmission line respectively, α_h is the altitude incremental factor, α_d is the ice thickness adjustment factor, γ is the ice weight per unit volume, l_T is the sum of the lengths of all components and R^t represents the ice thickness of both transmission lines and towers at time t. Similarly, the wind loads can be calculated as

$$\begin{cases} M_{Lv}^t = \vartheta S(v^t)^2(D+2R^t)L/12 \\ M_{Zv}^t = (v^t)^2 \rho C_d(\alpha) A_f/2 \end{cases} \tag{2}$$

where M_{Lv}^t and M_{Zv}^t represent the wind loads on transmission line and tower at time t, v^t represents the wind speed at time t, ϑ is the coefficient of wind load, S is the shape factor of the transmission line, ρ represents the air density, $C_d(\alpha)$ represents the drag coefficient corresponding to angle α of wind attack and A_f is the effective area of the structure.

(2) Based on the ice load data $M_{Li}^{t-W_1},\ldots,M_{Li}^{t-1},M_{Li}^t$ calculated with (1), we can estimate the normal distribution of ice load on the transmission line at time t as $F(M_{Li}^t) \sim N(\mu_{Li}^t,(\sigma_{Li}^t)^2)$. W_1 is the sample size for ice load density estimation, and satisfies $W_1 < W$. μ_{Li}^t and σ_{Li}^t, respectively, represent the mean and standard deviation of the ice load on the transmission line. The empirical histogram and the theoretical probability density curve of the ice load are given in Fig. 2. As seen in Fig. 2, the distribution of ice load is approximately normally distributed.

Similarly, the distributions of ice load on the transmission tower, as well as the wind loads on transmission lines and towers can also be estimated as $F(M_{Lv}^t) \sim N(\mu_{Lv}^t,(\sigma_{Lv}^t)^2)$, $F(M_{Zi}^t) \sim N(\mu_{Zi}^t,(\sigma_{Zi}^t)^2)$ and $F(M_{Zv}^t) \sim N(\mu_{Zv}^t,(\sigma_{Zv}^t)^2)$.

The output of the ELM network can be illustrated as

$$O_j = \sum_{i=1}^{H} \beta_i g(\omega_i X_j + b_i), \quad j = 1,2,\ldots,W \tag{3}$$

where $O_j = [\mu_j, \sigma_j^2]^T$ is the network output (dependent variables) of jth training sample; $X_j = [v_j,p_j,T_j]^T$ is the input (independent variables) of the jth training sample; $\omega_i = [\omega_{i1},\omega_{i2},\omega_{i3}]$ represents the weights of the connections between input nodes and the ith hidden node; b_i is the threshold of the ith hidden node; $\beta_i = [\beta_{i1},\beta_{i2}]^T$ is the weights of connections between the ith hidden node and the output nodes; $g(\cdot)$ represents the activation function in the hidden layer. The training of the ELM network is an

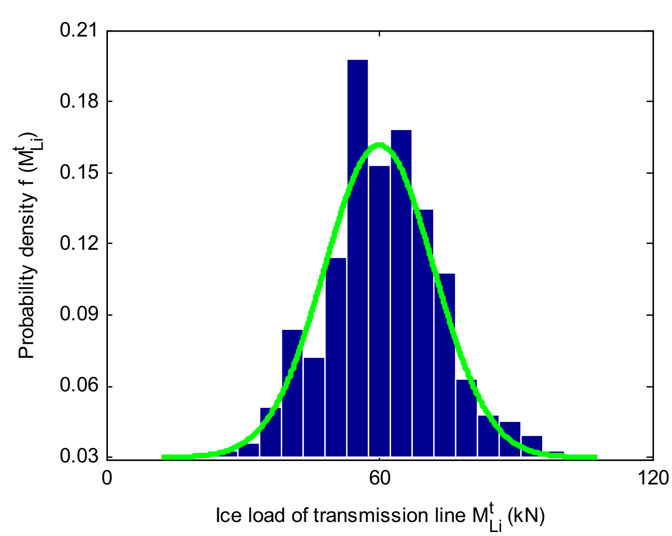

Fig. 2. Empirical histogram and theoretical probability density of ice load.