

Fire Risk Assessment of Transmission Line Based on BP Neural Network

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Abstract

With global warming, the increasing forest fires have caused trips and outages frequently along transmission lines, which is a serious threat to the operation stability of power grids. Impact factors on transmission line fires are numerous and the current risk assessment methods could hardly handle the complex nonlinear relationship between risks and factors, therefore, a method based on BP neural network is presented to assess fire risk of transmission line in this paper. Firstly, risk assessment system would be established according to impact factors on transmission line fire. Then, based on neural network model, the complex nonlinear relationships between fire risk grade and evaluation factors could be built. Finally, combined with GIS technology, risk assessment on transmission line fire would be done. The applicability and accuracy of this method have been explored by a fire risk assessment of transmission line in Shanxi province. The result shows that the BP neural network based model has good recognition effect, credibility, and consistent with the survey result on transmission line fire risk in the region over the years.

Keywords: *transmission line; forest fire; risk assessment; BP neural network*

1. Introduction

With rapid development of electric power industry in China, more and more transmission lines have been built through forest. While, to develop hydroelectric resources in the southwest, this kind of situation is getting more prominent. With global warming and more frequent human activities in forests, the probability of forest fire along transmission lines has been increasing. Fires would not only burn forest, but also damage transmission lines to result trip or outage so that the operation stability of power grid is threatened, and people's life is consequently influenced. Therefore, risk assessment on transmission line forest fire is very significant and meaningful.

Many scholars have been researching on forest fire risk assessment. In literature [1], grey theory model and hierarchical analysis method are applied to analyze forest fire risk. In literatures [2] and [3], a GIS based method to assess fire and flood risk is proposed. In literature [4], a fire risk assessment index system is established on hierarchical analysis method. In literature [5], a neural network based fire risk assessment method is presented.

In this paper, an assessment index system is established based on geographical analysis, and a BP neural network method to assess forest fire risk is put forward based on historical

data of transmission line forest fire of recent years in Shanxi province, and an assessment has been done with this method. The result proves it valid and accurate under the condition of lack of data materials and experience.

2. Modeling and Analysis

2.1. Overview of the Studied Area

Shanxi Province is located on the east coast of Yellow River's middle reaches, and on the west loess plateau of North China Plain with the latitude of $34^{\circ} 34' \sim 40^{\circ} 44'$ and the longitude of $110^{\circ} 14' \sim 114^{\circ} 33'$. It is about 682 km long and 385 km wide. Its area is 150,600 square kilometers, accounting for 1.6% of the national territory area.

Landforms in this studied area are mainly mountain plateau and widely covered with loess. The terrain on this highland undulates and shows the northeast higher and the southwest lower. Its geomorphic type is complicated and divers including mountains, hills, terrace and plain and few waters. Due to mountains on its east, it is weakly influenced by the Marine climate but strongly by the temperate continental monsoon climate. What's more, the zonation of its latitude is obvious so that the hydrothermal condition varies widely. Therefore, from its southeast to northwest, a warm temperate climate zone and a temperate climate zone are respectively formed, and two vegetation belts of summer green broadleaved forest in warm temperate zone and grassland in temperate zone are consequently formed.

2.2. Assessment System on Fire Risk of Transmission Lines

Risk usually refers to the probability that a loss occurs in a specific circumstance on a particular time. Fire risk of transmission lines involves numerous factors such as disaster-inducing factors, disaster-formative environment factors, disaster-affected object factors and so on, therefore, a comprehensive assessment on forest fire risk would be done with considering dangerousness, vulnerability, and disaster prevention & mitigation capacity in this paper.

2.2.1. Principles to Choose Indexes: So-called index system is a systematic combination of various indexes which would reflect fire disasters of transmission lines and help to thoroughly analyze status quo and patterns on fire disaster in depth [6]. The below principles should be followed to construct fire risk evaluation index system [7, 8].

- **Scientific:** All selected indexes should be scientific to reflect the natural and social-economic attributes of forest fire disasters.
- **Representative:** All selected indexes should be well-representative with high impact so that the number of indexes is as least as possible to simplify index system.
- **Independent:** It is possible that information from each index may repeat. Therefore, all selected indexed should be independent from each other.
- **Feasible:** All selected indexes should be easy to access. They should be directly or indirectly valued and quantified so to build model and conduct assessment.

2.2.2. Forest Fire Risk Index System of Transmission Lines: According to above mentioned principles to choose indexes, in this paper, three first-grade indexes of transmission line fire risk are set as dangerousness index, vulnerability index, and disaster prevention & mitigation capacity index. What's more, numerous second-grade indexes are set as showed in Figure 1.

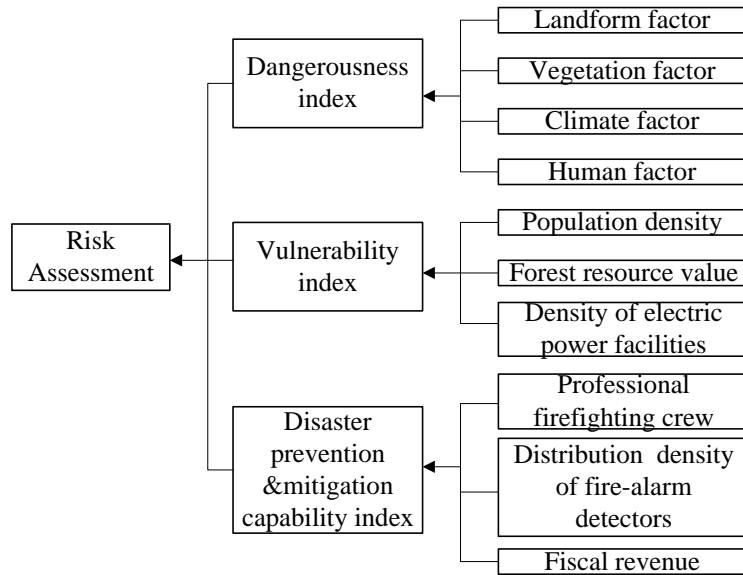


Figure 1. Risk Assessment Index System

- **Dangerousness index:** Dangerousness index refers to the possibility to occur disasters. The core lies on various disaster-triggering factors, among them, only those natural and human factors, which cause and significantly influence forest fire, could be picked out as dangerousness indexes. According to regional features in this studied area, related factors are classified into four types as landform factor, vegetation factor, climate factor and human factor as second-grade dangerousness index.
- **Vulnerability index:** Vulnerability index refers to the degree of vulnerability for each disaster-affected object in this study area, including vulnerabilities of life and of economy. Therefore, selected indexes should reflect the direct forest-fire-caused damage on people's life and properties around transmission lines. In this paper, three second-grade indexes are picked out as population density, forest resource value, and density of electric power facilities.
- **Disaster prevention & mitigation capacity index:** Disaster prevention & mitigation capacity index refers to capabilities to deal with a sudden forest fire and to diminish loss and damage to disaster-affected objects. Therefore, to describe disaster prevention abilities before a fire and emergency response abilities after a fire, three second-grade disaster prevention & mitigation capacity indexes are selected as professional firefighting crew, distribution density of fire-alarm detectors, and fiscal revenue.

2.3. Risk assessment Method on Forest Fire Disaster

Fire risk is a result of interaction among disaster-inducing factors, disaster-formative environment factors, and disaster-affected object factors around transmission lines. Their relationships are nonlinear, uncertain and random so that the effect degree of each factor on fire risk is hardly described in accuracy.

To solve the above problems, neural network model would be applied to assess fire risk of transmission lines in this paper. Artificial neural network is a complex network composed of a large number of neurons. It can imitate human brain's function to store and process information. It is a mathematical model to simulate human brain's thinking. It can figure out

the nonlinear mapping relationships between input and output variables when there are no exact relationships. Besides, it is self-adapting, self-organizing and self-learning.

2.3.1. BP Neural Network Model: At present, BP neural network is the most widely used and the most perfect artificial neural network model. It is composed of input layer, hidden layers and output layer. There is usually a single hidden layer in practice. The input layer will help to put the external information into the neural network. The output layer will help to make a corresponding decision based on entered information. The hidden layer will help to store parameters of neural network. The model structure is shown in Figure 2.

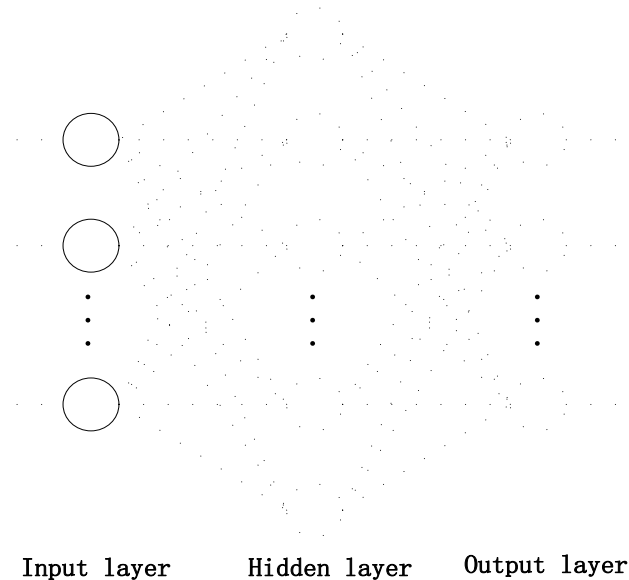


Figure 2. BP Neural Network Model

2.3.2. Procedures of BP Algorithm: The structure of BP network is determined by the number of network layers, the number of each layer's nodes, and the excitation function of nodes. Network learning is conducted in a teacher-companying mode, namely, network's parameters will be adjusted according to the training sample and the objective function. The steps of BP algorithm are shown below.

Step1. To initialize neural network

Input samples and output samples would be pretreated and normalized following the below formula.

$$x = \frac{x^* - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

Here x^* is the untreated sample's value, and x is the treated sample's value. x_{\max} and x_{\min} respectively stand for the maximum value and the minimum value in original samples.

Step 2.To establish training sets

After normalization, input vector could be worked out as below.

$$X = [x_1, x_2, \dots, x_M] \quad (2)$$

Expected output vector could be set as below.

$$D = [d_1, d_2, \dots, d_L] \quad (3)$$

Step3. Feed-forward calculation of BP neural network

● To calculate input & output values on hidden layer

The input value of node j on hidden layer is as below.

$$net_j = \sum_{i=1}^M w_{ij} x_i \quad (4)$$

The output value of node j on hidden layer is as below.

$$O_j = f(net_j) = \frac{1}{1 + e^{-(net_j - \theta_j)}} \quad (5)$$

In the formula, $f(\square)$ is excitation function which is S-type nonlinear here.

● To calculate input & output values on output layer

The total input value of node k on output layer would be calculated as below.

$$net_k = \sum_{j=1}^q w_{jk} O_j \quad (6)$$

The practical output value of node k on output layer would be calculated as below.

$$O_k = f(net_k) \quad (7)$$

Step4. To adjust the weights of BP network

The objective function is set as cost function of average error as below.

$$E = \frac{1}{2} \sum_{k=1}^L (d_k - O_k)^2 \quad (8)$$

By adjusting network's weights to minimize cost function E , the modifier formula of output layer weights is shown below.

$$w_{jk}(t+1) = w_{jk}(t) - \eta \frac{\partial E}{\partial w_{jk}} + \alpha [w_{jk}(t) - w_{jk}(t-1)] \quad (9)$$

The modifier formula of hidden layer is here below.

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E}{\partial w_{ij}} + \alpha [w_{ij}(t) - w_{ij}(t-1)] \quad (10)$$

Step5. To repeat or end the above process of learning

The judgment that if the value of E meets requirement, would be made. Namely, when the error has converged to the present value or frequency of learning is greater than the preset maximum, the learning process is end, or it will be redo from step2 by picking the next learning samples and its corresponding expected output value.

Step6. To test the well-trained network

Test samples would be put into the well-trained network, and then the test result would be analyzed.

In the above training process, step3 is a forward propagation and step4 is a backward propagation in the BP network, while step6 is the application of the well-trained network.

2.3.3. Establishment of forest fire risk assessment model: Based on above mentioned theory and algorithm on BP neural network, forest fire risk assessment model should be established in the following process. Firstly, a reasonable network structure should be built in terms of forest fire features. Secondly, according to assessment index system and grading of risk, training samples would be built and corresponding expected output value would be set. Then, the BP network could be trained until it converges to the preset value. Finally, the well-trained BP network would be tested. The detailed process is shown in Figure 3.

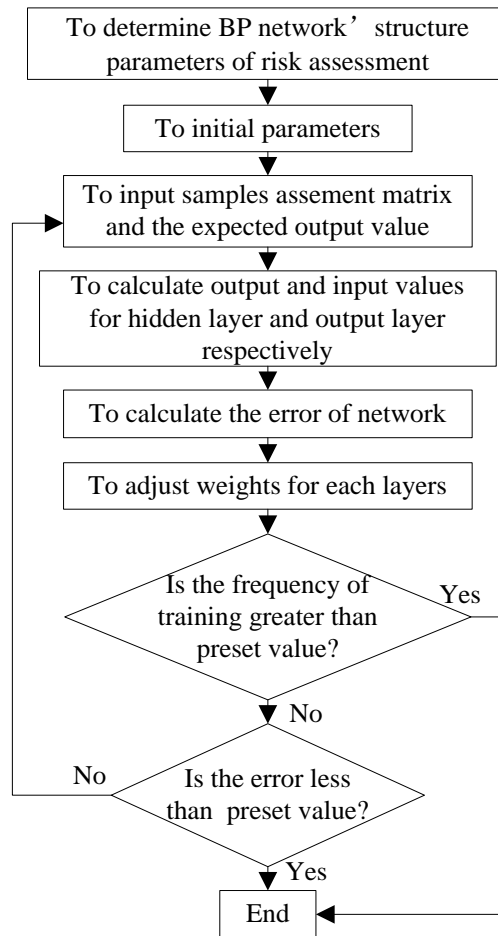


Figure 3. Flowchart for Risk Assessment Model based on BP Neural Network

2.4. Case Study

In this paper, forest fire disasters of transmission lines for recent years in Shanxi province have been studied by applying the risk assessment method discussed above. The validity of this method has been proved.

2.4.1. Input of Assessment Model: Forest fire risk assessment is composed of dangerousness assessment, vulnerability assessment, and disaster prevention & mitigation capacity assessment. According to the established forest fire risk assessment index system, second-grade indexes are taken as assessment factors, and then the number of neurons for input layer of assessment model equals to the number of those factors. The total number of neurons is 10 here.

Variable of each assessment factor is showed in Table 1. Since the dimension and the value range for each factor are great different, direct input of those 10 assessment factors would obviously slow down network's learning and reduce network's accuracy. Therefore, those factors should be normalized at first.

Table 1. Variables of Assessment Factors

Index	Factor	Variable
Dangerousness	Landform	X_1
	Vegetation	X_2
	Climate	X_3
	Human	X_4
Vulnerability	Population density	X_5
	Forest resource value	X_6
	Density of electric power facilities	X_7
Disaster prevention & mitigation capability	Professional firefighting crew	X_8
	Density of fire-alarm detectors	X_9
	Fiscal revenue	X_{10}

2.4.2. Assessment for Hidden Layer: In this paper, a three-layer BP neural network is used. There is one hidden layer. The number of neurons is no less than $2m/3$ (m is the number of neurons on input layer), consequently, the number of neurons on hidden layer should be no less than 7. For a good effect on convergence, the number of neurons on hidden layer is set as 8 after experiments.

2.4.3. Output of Assessment Model: Forest fire risks are classified into 3 grades of low risk, moderate risk, and high risk, which would be output from BP neural network using numeric of 1, 2, and 3 respectively. The number of neurons on output layer is 1. Therefore, the structure of BP neural network based transmission line forest fire risk assessment model is 10-8-1 in this case.

2.4.4. Learning Sample Set of Assessment Model: Selecting learning sample set is vital to model's establishment. According to the established transmission line forest fire risk

assessment index system, learning sample set is built where the number is no less than $2(m + 1)n$ (m is the number of neurons on input layer, and n is the number of neurons on output layer). In this case, 100 samples in the study area are selected, and the grade of risk is worked out using comprehensive assessment. 60 samples are randomly picked out as training samples and the left 40 samples is as test samples.

2.4.5. Training of Assessment Model: According to established model, simulation has implemented using a program written in Matlab. The training error is set as $1e-4$, and then the normalized training samples are put into BP neural network. The process of error's convergence is shown in Figure 4. After training for 4562 times, the error finally converged to the precision preset.

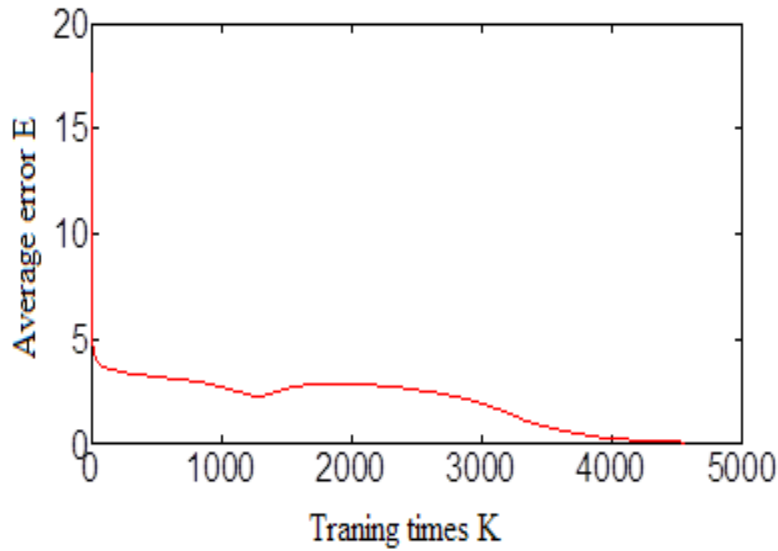


Figure 4. Convergence Process for Training Samples in BP Neural Network

After training, the weight vector of output layer is below.

$$w_2(8,1)^T = [10.7209, 5.2522, 8.1256, 12.0357, 5.6418, -5.8142, -5.8116, -2.3185]$$

And the weight vector of hidden layer is below.

$$w_1(10,8) = \begin{bmatrix} 1.4239, 6.2502, -1.6028, -0.2317, -3.2161, 4.1461, 4.5148, 3.2584 \\ 2.0317, 0.1772, -4.9022, 2.8448, -0.0355, -0.2529, -0.1879, 1.4275 \\ 6.1427, 3.8980, -6.1254, -5.2666, 5.9410, 4.6378, 4.4635, 3.9708 \\ 6.3213, 0.9410, -7.8639, 1.6815, -1.0390, 2.8751, 2.0627, 0.3061 \\ 0.7946, 2.1583, 7.9000, -1.5623, -0.2176, 2.0583, 1.9428, 1.6085 \\ -0.9916, 0.6971, -5.2181, 2.8166, -1.0650, 2.9533, 2.4922, 1.9798 \\ 3.3451, -0.2717, 1.0977, 12.9819, -1.8631, 0.4508, 0.0520, 0.7591 \\ -13.4822, 0.9412, 1.9684, 7.6450, 0.9953, 2.9147, 3.2534, 2.6227 \\ -0.51035, 0.8250, 12.1129, 2.1261, -0.6272, -1.4400, 1.3358, 1.2291 \\ -10.4822, 0.7212, 1.5434, 8.6250, 0.2933, 3.2167, 2.2384, 2.3253 \end{bmatrix}$$

2.4.6. Test of Assessment Model: The left 40 samples are used to test the well-trained BP neural network and verify the validity of this model. Samples are normalized and put into the network, the practical and expected output values of risk grade are compared in Table 2.

Table 2. Comparison on Risk Grade

Sample No.	Expected risk grade	Practical risk grade
1	1	1.0045
2	1	1.0009
3	1	0.9994
4	2	1.9991
5	2	2.0014
6	1	0.9947
7	1	0.9948
8	3	3.0001
9	1	0.9951
10	3	2.9996
11	3	2.9994
12	3	3.0027
13	3	3.0018
14	3	2.9999
15	1	0.9956
16	1	1.0056
17	1	1.0005
18	2	2.0007
19	2	2.0013
20	2	2.0007
21	1	1.0013
22	2	2.0004
23	2	1.9996
24	2	1.9963
25	2	1.9978
26	3	3.0010
27	3	3.0085
28	3	2.9991
29	3	3.0025
30	3	3.0012
31	3	2.9981
32	2	2.0012
33	2	2.0006
34	2	1.9999
35	1	1.0052
36	1	0.9989
37	1	0.9996
38	1	1.0019
39	2	1.9989
40	2	1.9993

2.5. Assessment Result and Analysis in the Study Area

According to the above method, transmission line forest fire risk assessment in a certain area of Shanxi province is implemented. The area is about 25,000 square kilometers, which is divided into 25,000 grids with a grid unit of $1km \times 1km$. In each grid, all assessment factors

are involved. The data of each grid is put into the well-trained network to compute the risk grade. Then the values of risk grade are plotted on the GIS map [9] of this area to show the distribution of forest fire risk as in Figure 5.

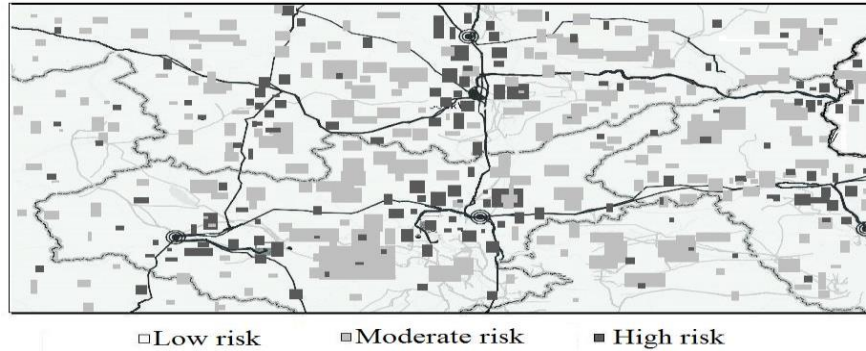


Figure 5. Distribution of Forest Fire Risk along Transmission Lines in Studied Area

In this area, low fire risk is account for 52.57% of the total area with 13143 grids, moderate fire risk is 34.86% with 8715 grids, and high fire risk is 12.57% with 3142 grids as shown in Figure 6.

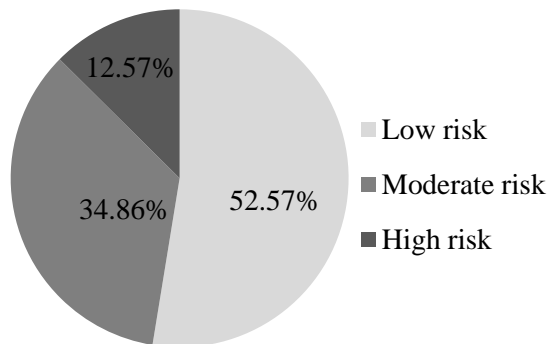


Figure 6. Area Percentage for each Risk Grade

In Figure 5, it can be seen that high fire risk mostly occurs in areas with a large population and dense transmission lines, and forest fire is caused by human factors there with a higher probability and a larger loss of life. Moderate fire risk often appears in counties with a small population or areas with a small scale of transmission lines, and forest fire usually brings less loss on electric power facilities. Low fire risk is always in areas with a sparse population and few transmission lines, the possibility to occur forest fire is small or sometimes forest fire occurs here with no any loss. The above result is identical to the practical surveyed situation for recent years which proves the validity of BP neural network-based fire risk assessment model.

3. Conclusion

A BP neural network-based risk assessment method for forest fire of transmission lines is suggested in this paper. This method is applied to build assessment index system, to establish nonlinear relationships between factors and risk grades based on BP network model, and

finally to assess forest fire risk in an area of Shanxi province. The result from model is highly consistent with the one from survey, which shows that this neural network assessment model is reliable and effective to recognize forest fire risks.

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