A Novel Application of BP Neural Networks to Evaluate the Safety of Power Grid in Wildfire Disasters

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***Abstract* — Increasing national demands for electric energy have meant the continuous operation of transmission power lines at high capacity and across-regions. Numerous risk factors impact transmission lines resulting in increasing frequency of fire in hot weather and threatening the security and stability of the grid. This paper picks 10 indices from three aspects of meteorological factors, environmental factors and line factors to build a comprehensive evaluation model of grid wildfire disaster using the BP neural network. By training and testing with Matlab, it shows that both training error and testing error are small. The model is vital in studies to assess the risks in the continuous use of high capacity power lines.**

Keywords - bias tunnel; neural network, grid wildfire disaster, safety comprehensive evaluation.

I. INTRODUCTION

Power system is an energy supply system which modern society relies on [1]. With the improving of electrification of social production and living standards, power grid construction continues to expand and the transmission line with large capacity and cross-regional was put into application continuously. However, when accidents occur, it will trigger a chain reaction [2-3]. The security and stability of system will be affected. What's more, it will affect the economy and people life.

Recently, the blackout caused by wildfire disasters occurred frequently. On one hand, it is due to the transmission lines are in unattended forest zone; on the other hand, with the increasing frequency of high fire danger weather, fire disaster threatens the security and stability of grid. Fire disaster has become a major threat factor to the security and stability of grid [4-6].

Grid enterprises are difficult to avoid disasters such as fire accident completely because of the instantaneousness and complexity of the electricity production. Therefore, Grid enterprises should attach great importance to the assessment and response of wildfire disaster [7]. Particularity of grid operation should be recognized clearly and right decisions should be taken when wildfire disaster happened. So that the probability of accidents could be reduced and the system operation could keep stable and safe [8].

II. ESTABLISHMENT OF EVALUATION INDEX SYSTEM

This paper analyzed quantity of example of wildfire disaster. There are three aspects of impact factors of wildfire which are meteorological factors, environmental factors and line factors. Then an evaluation index system of grid wildfire disaster is established from these aspects. The index system is showed as table 1.

TABLE 1 EVALUATION INDEX SYSTEM OF GRID WILDFIRE DISASTER

	First Stage	Second Stage	
Evaluation Index System Of Grid Wildfire Disaster	Meteorological Factors	Average Precipitation	C_{12}
		Relative Air Humidity	C_{13}
		Average Wind Speed	C_{14}
		Drought Duration	C_{15}
	Environmental Factors	Vegetation Density	C_{21}
		Vegetation Type	C_{22}
		Burning Times	C_{23}
	Line Factors	Line Density	C_{31}
		Rate Of Equipment Failure	C_{32}
		Line-To-Ground Distance	C_{34}

A. *Meteorological factors.*

① Average precipitation. Precipitation is a data to measure the rain in an area. The unit of average precipitation is mm. the few the average precipitation, the easier happened of wildfire disaster.

②Relative air humidity. At a certain temperature and certain volume of air, the less water vapor contains, the more easily fuel burn.

③Average wind speed. Velocity is the rate of movement of air relative to the Earth at a fixed location. A common unit of wind speed is m/s. Not only can wind accelerate the evaporation of water, but also can make to promote the spread of fire. It makes difficult to firefighting.

④Drought duration. Prolonged drought render makes fuel on the ground hard to absorb moisture which makes fuel burned easily.

B. Environmental factors.

①Vegetation density. As the fire combustible material, the more vegetation, the more twigs and leaves for burning. It can lead to wildfire easily.

②Vegetation type. Vegetation is related to wildfire, too. Normally, the vegetation with small leaves, conifer and loose structure is more easily to burning.

③ Burning times. Besides spontaneous combustion caused by the climatic and geographical factors, the ignition sources of wildfire contain man-behavior of burning off a field.

C. Line factors.

①Line density. The more network equipment in unit area, the greater the likelihood of catastrophic wildfires caused by power grid.

② Rate of equipment failure. The rate of network equipment failure reflects the network resilience in the same fire conditions. China's power grid system uses a grid construction standard provision of national unity for construction. Duration of use and later maintenance of power equipment are difference among different area. Rate of equipment failure can reflect the health of network equipment.

③ Line-to-ground distance. The smaller the distance between line and ground, the more vulnerable the line is by wildfires.

III. SAFETY COMPREHENSIVE EVALUATION MODEL OF GRID WILDFIRE DISASTER

A. Establishment of neural network model.

In the learning algorithm of neural networks, BP neural network algorithm is most widely used. Based on BP neural network, this paper proposed a new safety evaluation of grid wildfire disaster which can avoid the subjectivity bringing by artificial determining and improve the accuracy of evaluation results.

BP neural network, also known as back propagation network, is a typical feedforward network. It has three or more layers which mainly composed of the input layer, hidden layer and output layer. Each layer can full connect with other layers.

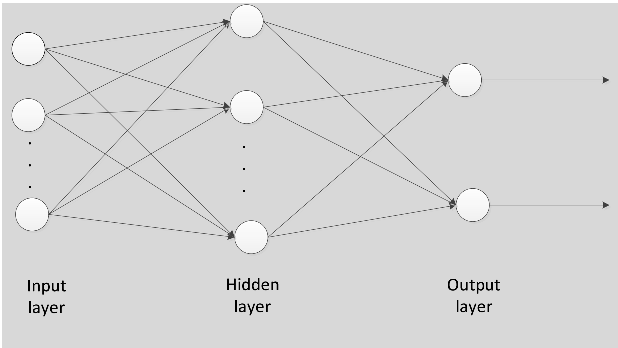

Fig.1 Structure of BP neural network.

Learning process of BP network is composed of the information forward propagation and error back propagation. The status value in each layer will affect the state of next layer. If it cannot get the desired output in the output layer, it transferred back propagation. In this time, error signal is transmitted from the output layer to the input layer and adjust the connection weights between the layers and each neuron offset value. In this way the error signal is decreasing. When the error is less than the allowable value, network training is ended.

The BP neural network learning algorithm steps are shown in Figure 2:

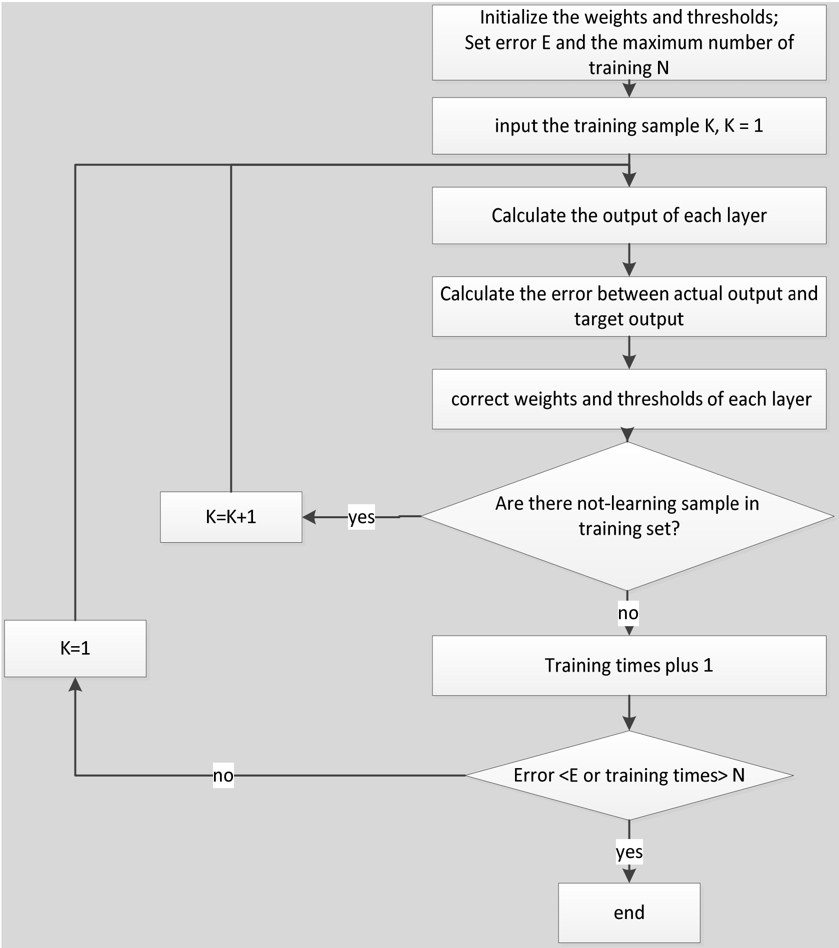

Fig.2 BP neural network learning algorithm steps.

There is a BP neural network which has n neurons in input layer, p neurons in hidden layer and q neurons in output layer. The paper defined variables as follows: Input vector is ; output vector is ; the desired output vector is ; the number of sample data is ; the error function is:

$$e = \frac{1}{2}\sum_{o=1}^{q}(d_{o_m}(k) - y_{o_m}(k))^2 \qquad (1)$$

Step 1: Network initialization. Each connection weights were assigned a random number within (-1, 1). Set error functions e, calculating the exact value ε and the maximum number of study M.

Step 2: Randomly select k-th input sample and the corresponding desired output .

Step 3: Calculate the input and output value of each neuron in hidden layer.

Step 4: calculate the error function with the network desired output and actual output and fix the layers weights and thresholds.

Step 5: calculate the global error and then see whether it meets the requirements. When the error reaches a preset accuracy or the learning times > maximum number, the training is ended. Otherwise, select the desired output corresponding next learning samples and return to the step 3.

B. Training and testing of comprehensive evaluation of grid wildfire disaster safety model.

In the BP neural network topology, the number of hidden layers of the network is the key to determining the number of neural network. It impacts the performance directly. Studies have shown that when each node has different boundaries, it can use a network with one hidden layer to approach for a continuous function over a closed interval. Therefore, this paper set three layers for comprehensive evaluation of grid wildfire disaster safety model which are input layer, hidden layer and output layer.

To ensure nonlinear of BP neural network model, the function from input layer to hidden layer takes logsig function which is nonlinear S-type logarithmic transfer function. While the function from hidden layer to output layer uses purlin function which is linear function. And the training function is trainlm.

The number of input layer nodes is determined by the practical problems. In this research, there are 10 indexes. So the input layer nodes of this model are 10. Under the same consideration, because the output of BP neural network model is the score of safety comprehensive evaluation of grid wildfire disaster, the output layer nodes is 1.

In the BP neural network, the number of hidden layer nodes has a greater impact on prediction accuracy of model. If the nodes is too fewer, network cannot learn well and the accuracy is also affected. If there are too many nodes, the training time will increase and the network will be over-fitting. So the Best hidden layer nodes Reference formula is:

$$L < \sqrt{(m+n)} + a \tag{2}$$

L is the node number of hidden layer. m is the node number of input layer while n is the node number of output layer. a is a constant between 1~10. Firstly, it determines the approximate range of the node number based on the formula. And then final result is confirmed by network training.

IV. SIMULATION ANALYSIS

Based on information of wildfire disaster prone areas in Hunan province, this paper select Select meteorological data vegetation and line data as sample data and carry out simulation study. Each index is determined by expert scoring method. There are five levels of 1.0, 0.7, 0.5, 0.3, and 0.1. The higher the score, the higher fire risk level. And the comprehensive scores are calculated based on the index score. 20 fire-prone point safety evaluations are in the table 2 and table 3.

TABLE 2 SAFETY EVALUATION DATA OF GRID WILDFIRE DISASTER

Number	Average Precipitation	Relative Air Humidity	Average Wind Speed	Drought Duration	Vegetation Density
1	0.3	0.3	0.7	0.5	1
2	0.7	1	0.3	0.3	0.7
3	0.3	0.5	0.7	0.7	0.5
4	0.3	0.3	1	0.5	0.3
5	0.5	0.7	0.5	0.1	0.5
6	0.3	0.3	0.7	0.5	1
7	0.7	0.3	0.3	0.7	0.7
8	1	0.7	1	0.1	1
9	0.5	0.3	0.7	0.3	0.3
10	0.7	1	0.5	0.3	0.7
11	0.3	0.5	1	0.1	1
12	0.5	0.7	0.1	0.7	0.5
13	1	0.7	0.7	0.1	1
14	0.5	0.5	1	0.5	0.1
15	0.7	0.7	0.5	0.3	0.7
16	0.1	0.5	0.7	0.7	0.3
17	0.3	0.5	0.3	0.1	1
18	0.3	0.3	0.7	0.1	0.1
19	0.1	0.1	1	0.5	0.1
20	0.3	0.1	0.1	0.1	1

TABLE 3 SAFETY EVALUATION DATA OF GRID WILDFIRE DISASTER

Number	Vegetation Type	Burning Times	Line Density	Rate Of Equipment Failure	Line-To-Ground Distance	Comprehensive Scores
1	1	0.3	0.5	0.5	0.7	0.65
2	0.5	0.5	0.1	0.5	1	0.64
3	0.3	0.7	1	0.7	0.7	0.49
4	0.7	0.1	0.5	0.5	1	0.44
5	0.5	1	0.5	0.5	0.5	0.52
6	1	0.5	0.3	0.3	0.7	0.63
7	0.5	0.7	0.5	1	0.5	0.63
8	0.5	0.5	0.7	0.3	1	0.82
9	0.7	0.7	0.1	0.5	0.5	0.46
10	0.7	0.3	0.5	0.5	0.7	0.66
11	1	0.1	0.3	0.5	1	0.68
12	0.5	0.5	0.5	0.7	0.5	0.51
13	1	0.5	0.5	0.1	0.5	0.80
14	0.5	0.3	0.3	0.5	1	0.43
15	0.7	0.5	0.7	0.3	0.5	0.62
16	0.5	0.1	0.1	0.1	0.3	0.30
17	1	0.5	0.3	0.7	0.7	0.64
18	0.5	0.1	0.5	0.5	0.3	0.30
19	0.7	0.5	0.3	0.7	1	0.35
20	0.7	0.3	0.1	0.5	0.3	0.52

It takes three layers in the BP neural network structure of this model. The 10 neurons of input layer correspond to the 10 index value. There is only one output layer neuron that grid wildfire disaster evaluation results. The number of hidden layer is 21. The function from input layer to hidden layer takes logsig function and the training function is trainlm. The setting learning rate is 0.01. The maximum number of training is 1000 and error accuracy is 0.001.

The paper select 15 typical set of data as a training set to train the neural network. The rest five groups as a test set to be evaluated. Network training results are shown in Table 4. Simulator evaluation results of five tests are shown in Table 5.

TABLE 4 BP NEURAL NETWORK TRAINING RESULTS

Number	Expert Evaluation	Training Results	Training Error [%]
1	0.65	0.645	-0.1
2	0.64	0.639	0.1
3	0.49	0.491	0.2
4	0.44	0.441	0.2
5	0.52	0.524	-0.1
6	0.63	0.633	0.1
7	0.63	0.635	0.1
8	0.82	0.818	0.3
9	0.46	0.461	0.2
10	0.66	0.660	-0.2
11	0.68	0.676	0.1
12	0.51	0.509	0.2
13	0.80	0.804	-0.1
14	0.43	0.433	0.2
15	0.62	0.624	0.1

TABLE 5 BP NEURAL NETWORK TESTING RESULTS

Number	Expert Evaluation	Testing Results	Training Error [%]
16	0.30	0.299	0.1
17	0.64	0.644	0.2
18	0.30	0.303	-0.2
19	0.35	0.348	0.1
20	0.52	0.523	0.3

As can be seen from the training and test results, not only are the all training sample very close to actual operation, but also the result of testing sample is very close.

V. CONCLUSIONS

Recently, the transmission line with large capacity and cross-regional was put into application continuously. Most of these lines are in the unattended forest zone. There are a lot of risk factors which impact the transmission line. With the increasing frequency of high fire danger weather, fire disaster threatens the security and stability of grid.

This paper picked 10 indexes from three aspects of meteorological factors, environmental factors and line factors and built a comprehensive evaluation model of grid wildfire disaster based on the BP neural network. By training and testing with Matlab, it shows that both training error and testing error are small. The model has a good effect. With this model, it can get the score quickly to evaluate the safety of grid wildfire disaster. It shows that the safety comprehensive evaluation model of grid wildfire disaster operate with high precision and speed. The model is objective and universal.

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