Technical Research of Crane Reliability Control Based on Neural Network

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***Abstract*—This paper study control problems of tower crane operational reliablity. Observational variables of crane running status are employed as input vectors, status codes of reliablity are employed as output vectors, on-line neural network model is set to monitor tower reliablity of crane running status. Cross validation methods is utilized to train neural network, therefore, defect of lacking traning samples are overcome, generalization ability of neural network is assured. Monitor experiments show that status type can be judged by neural network for crane running status validation samples and those samples with noise. A kind of valid and steady control technique is provided for reliablity of crane status.**

Keywords-neural network; crane; reliability; model.

I. INTRODUCTION

Crane served as large-scale mechanical equipment of industrial manufacture, its working range of stand-alone, lifting ability and monitor level unceasingly developed to large scale and automation. Due to crane structure and working characteristics, it is a big hidden risk factor for construction machinery. To guarantee normal work of hoisting equipment, monitoring crane running status[1-3] and crane fault diagnosis[4] become research focus in crane safety design. Artificial neural network has good ability of nonlinear mapping, autonomic learning and generalization, can be employed to build model for problem of complex system, especially nonlinear system. Yuegang Luo etc. employed neural network to diagnose damage of crane tubular prop[5], Jun Han employed neural network to diagnose crane bearing breakdown[6], Jingqiang Shang etc. employed neural network to diagnose tower crane fault[7], and achieved good results.

This paper employ neural network to build tower crane on-line monitoring model of running status reliability, cross validation methods is utilized to train neural network, and model robustness is studied by experiment. Results show that running status of tower crane can be judged accurately by BP neural network, valid forecast can be given for faults, A kind of valid and steady control technique is provided for reliablity of crane status.

II. PRINCIPLES OF BP(BACK PROPAGATION)NEURAL NETWORK

BP neural network is a multilayer feed forward neural networks trained by error back propagation algorithm. BP neural network can learn and store large amounts of input - output mode mappings, however, mathematical equation of this mapping is not needed.

Learning method of BP neural network is the steepest descent method, which adjust weights and threshold values of neural network by back propagation, to minimize error sum squares of the BP neural network. Topology structure of BP neural network model consists of input layer, hidden layers and output layer[7].

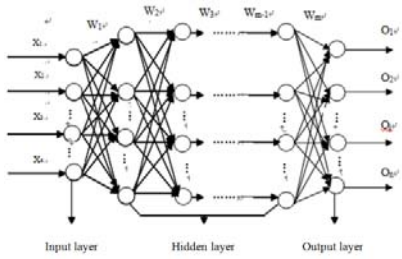

Figure 1. Structure chart of BP neural network

Forward-propagating and back propagation of BP neural network constitute its learning process. Forward-propagating means network computing, determine its output for given input; Back propagation is used for error propagation layer by layer, modify connection weight and threshold value. Algorithm step as below:

(1) Set variables and parameters of trainning network:

$X_k = [x_{k1}, x_{k2}, \ldots, x_{kP}], (k = 1, 2, \cdots, N)$ as input vector, i.e. trainning samples, total number of samples is N; $W_{PI}(n) = \left(w_{ij}\right)_{M \times I}$ as the nth iterative weights vector between the hidden layer and input layer I; $W_{PI}(n) = \left(w_{ij}\right)_{M \times I}$ as the nth iterative weights vector between the hidden layer J and the hidden layer I; $W_{PI}(n) = \left(w_{ij}\right)_{M \times I}$ as the nth iterative weights vector between the hidden layer J and output; $O_k(n) = [O_{k1}(n), O_{k2}(n), \cdots, O_{kN3}(n)]$ as actual output of the nth iterative network; $d_k = [d_{k1,} d_{k2}, \cdots, d_{kN3}], (k = 1, 2, \cdots, N)$ as expected output of trained network.

(2) Initialize the settings. Assigned to small random nonzero values for $W_{MI}(0), W_{IJ}(0), W_{JN3}(0)$.

(3) Afterwards, input samples X_k, $n = 0$.

(4) About input samples X_k, compute BP neural network input signal u and output signal v of every layer neuron in forward direction.

(5) Compute error e according to actual output $O_k(n)$ and actual expected output d_k by last step, judge whether meet the requirements, if meet the requirements, go to (8); If you don't meet ,go to (6).

(6) Judge if $n+1$ greater than the maximum iterative number. If greater than turn to(8), otherwise, compute local gradient δ of every layer for input sample X_k.

$$\delta_p^{N3} = O_p(n)(1 - O_p(n))(d_p(n) - O_p(n)), \quad (p = 1, 2, \cdots, N3) \tag{1}$$

$$\delta_j^J = f'(u_j^J(n)) \sum_{p=1}^{N3} \delta_p^{N3} w_{jp}(n), \quad (j = 1, 2, \cdots, J) \tag{2}$$

$$\delta_i^I = f'(u_i^I(n)) \sum_{j=1}^{J} \delta_j^J w_{ij}(n), (i = 1, 2, \cdots, I) \tag{3}$$

(7) Compute weight amendment Δw according to formula below, and amend weight, η is learning rate.

$$\begin{aligned} &\Delta w_{jp}(n) = \eta \delta_p^{N3}(n) v_j^J(n), \\ &w_{jp}(n+1) = w_{jp}(n) + \Delta w_{jp}(n), \\ &(j = 1, 2, \cdots, J; p = 1, 2, \cdots, P); \end{aligned} \tag{4}$$

$$\begin{aligned} &\Delta w_{ij}(n) = \eta \delta_j^J(n) v_i^I(n), \\ &w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n), \\ &(i = 1, 2, \cdots, I; j = 1, 2, \cdots, J); \end{aligned} \tag{5}$$

$$\begin{aligned} &\Delta w_{mi}(n) = \eta \delta_i^I(n) x_{km}(n) \\ &w_{mi}(n+1) = w_{mi}(n) + \Delta w_{mi}(n) \\ &(m = 1, 2, \cdots, P; i = 1, 2, \cdots, I) \end{aligned} \tag{6}$$

(8) Judge if whole samples be learned, if it is, turn to end, otherwise, go back(3).

III. BUILDING NEURAL NETWORK MODEL

6 variables of tower crane running status was selected as observed variables: lifting weight, load moment, lifting altitude, lifting amplitude, wind velocity and electromotor winding temperature, respectively. This 6 variables can be collected by sensors in tower crane service; Crane running status type can be devided into 5 categories: safe state, quasi-safe state, trasition state from safe to danger, quasi-danger state and danger state. The code for 5 state are: 10000, 01000, 00100, 00010, 00001, respectively; 25 groups of actual historical data of tower crane running status are showed [8] in Table 1.

IV. TRANING NEURAL NETWORK BY CROSS VALIDATION

To improve generalization ability and robustness, cross validation is utilized to train neural network and avoid lacking actual samples. The 25 random group of samples are divided into 5 parts according to sample serial number, each part has

TABLE I. TRAINNING SAMPLES

Sample number	state observation variables						State type encoding
	ifting weight	Load moment	Lifting altitude	lifting amplitude	electromotor wind velocity	encoding winding temperature	
1	6375	686	38.6	10.8	10.9	109	00100
2	6565	666	39	10.1	15	88	00100
3	6214	650	38.2	10.5	14.3	102	00100
... ...	... ...	... ...	... ...	... ...	... ...	... ...	... ...
24	6400	640	15	10	14	100	01000
25	1500	300	38.2	20	14	80	10000

The same length. Then, choose 4 parts of them to be training samples, and the rest part is choosed to be validation data. There are totall 5 selection methods. For every turn, BP algorithm is utilized to train neural network using training samples selected by 5 methods, respectively, and verified by its own validation samples.

The number of hidden layer neuron is set to be 20, Matlab software is utilized to train neural network. With each set of training samples, according to the BP neural network learning algorithm, through the adjustment of the error back propagation network weights and threshold, the BP neural network output and the actual value error sum of squares is gradually reduce to the set value. (As shown in Fig. 2) Afterwards, the corresponding validation samples are utilized to do monitoring experiment of running status reliability.

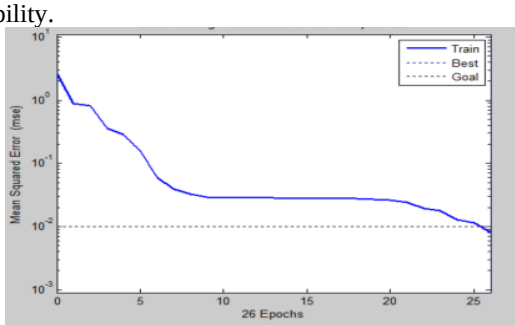

Figure 2.Tendency chart of network training error

The condition monitoring of 5 groups validation samples(each group has 5 validation samples) in the first round is:

c1 =(1,1,1,1,0),c2 =(1,0,1,1,1),c3 ＝ (0,0,0,0,0),c4 =(0,0,1,0,0),c5 =(0,1,1,1,1), monitoring results is recorded by 1 , when result is correct, otherwise is recorded by 0.

The condition monitoring of 5 groups validation samples in the second round is:

c1=(0,1,0,1,0),c2=(0,0,0,0,0),c3＝(0,0,0,1,0),
c4 =(0,0,0,0,0), c5 =(0,0,0,0,0)；

The condition monitoring of 5 groups validation samples in the third round is:

c1=(0,0,0,0,0),c2=(0,0,0,0,0),c3＝(0,0,0,0,0),
c4 =(0,0,0,1,0), c5 =(0,0,0,0,0)；

The condition monitoring of 5 groups validation samples in the fourth round is:

c1=(0,0,0,0,0),c2=(0,0,0,0,0),c3＝(0,0,0,0,0),
c4 =(0,0,0,0,0), c5 =(0,0,0,0,0).

After four rounds traning, The monitoring results accuracy of BP neural network has reached 100%. The weights and threshold values are :

IW = 0.0017 -0.0376 -0.0927 0.1587 0.1244 -0.2881
-0.0023 0.0214 0.1034 -0.0872 0.0770 0.0126
-0.0236 0.2915 0.0598 0.0199 -0.0823 -0.4855
-0.0104 0.1630 -0.2182 0.0359 0.1476 -0.1710
... ...

0.0039 -0.0012 -0.0663 0.0395 -0.2136 -0.0041
0.0133 -0.0996 -0.0500 -0.0066 -0.2880 -0.2697

LW = -0.3867 0.7533 -0.2243 0.2084 0.7851
0.6689 -0.6404 0.0775 -0.7554 0.4610
0.0500 0.2806 -0.4417 0.0804 -0.0232
-0.3520 0.3248 0.1856 -0.0816 -0.1776
... ...

-0.2060 -0.5835 -0.2858 0.0384 0.4822
-0.0997 -0.7738 -0.4427 -0.2132 -0.2239

b1 = -0.0874 -3.8007 1.5915 -12.1407 -1.3998 -3.6176 3.2714 -2.2147 -5.1854 -3.9477 1.6361 9.2134 0.5836 -0.8049 4.2353 -4.3173 -4.9536 -3.4632 4.4853 7.7144

b2 =-0.3298 0.6000 -0.2078 -0.2972 0.5198

Among them, IW is weight between input and hidden layers. LW is the weight between hidden layer and output layers. B1 is the threshold value of neurons in hidden layer, b2 is the threshold value of neurons in the output layer.

V. ROBUSTNESS EXPERIMENT OF BP NEURAL NETWORK

In order to illustrate the effectiveness and robustness of the trained BP neural network, the original 25 groups samples are added noise. 1 observation variable from 6 in each group is randomly choosed to be added proper noise, disturbance of experiment samples are obtained, shown in Table II:

TABLE II. DISTURBANCE OF SAMPLES

6379	686	38.6	10.8	10.9	109
6565	668	39	10.1	15	88
6214	650	38.4	10.5	14.3	102
... ...	... ...	... ...	... ...	... ...	... ...
6396	640	15	10	14	100
1505	300	38.2	20	4	80

Using the trained BP neural network model to monitor running status, output result shows that:

c=(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0).

The accuracy is 100%.

VI. CONCLUSIONS

We employ neural network to establish reliability monitoring BP neural network model of crane running status. 6 variables of tower crane running status are selected as observed variables: lifting weight, load moment, lifting altitude, lifting amplitude, wind velocity and electromotor winding temperature, respectively. Crane running status types are devided into 5 categories: safe state, quasi-safe state, trasition state from safe to danger, quasi-danger state and danger state, The 5 categories are encoded, respectively. Categories codes are utilized to be neural network output variables. We employ cross validation methods to trained network by actual sample data, better generalization ablility and robustness are achieved. Disturbance of experiment samples is added noise to do confirmatory experiment of running status monitoring. Results show that neural network has reached accuracy of 100%. The conclution is drawed that: BP neural network can monitor reliability of crane running status effectively, predict fault in time, have better robustness, therefore, can guarantee safety and reliability of crane running effectively.

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