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Application of Improved Wavelet Neural Network in Fault Diagnosis

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Abstract: This article has presented an improved wavelet neural network modal. It is a network that can increase inputting dimensions dynamically and divide the feature into two sections. When the network detects the equipment, the first section is selected as input and creates a simple network. If the output shows no detection, one dimension will be added. But the input is directly driven to output the result and doesn't change the original network structure. In the article turbine generators are detected by the improved wavelet neural network. The results show that the network can provide correct judgment quickly and effectively and the diagnosis is reliable.

Keywords: Wavelet neural network; the network structure; turbo generator, fault diagnosis;

INTRODUCTION

There are strong couping between equipment of the large complex machine. Therefore most trouble are not single failure but multiple failure situations[1-2]. At present, in the fault diagnosis of turbine generators the application of neural networks are mostly concentrated on the recognition of a single fault. For example, the literature[3] establishes a neural network based on BP algorithm for turbine generators and takes the field diagnostic test with good results. However, it is limited in the single fault diagnosis. For the characteristics of multiple faults of turbine generators, this article improves the wavelet neural network: the input dimensions of the network are added dynamically. No mater for single fault or multiple faults, the improved wavelet network can give the correct diagnosis and the result is reliable..

IMPROVED STRUCTURE OF THE WAVELET NEURAL NETWORK

Materials

Usually the input and output nodes of wavelet neural network is certain[4-5]. However, the input and output determines the selection of hidden nodes. If the input is excessive, the network will be very huge and impact online real training and practical application effectiveness.If too little, the test may be a failure. Fault itself may have a lot of features, but a good network model should try to compress the number of input and output nodes and reduce the input dimension possibly. Therefore, this article presents a network that can add input dimension dynamically. The network divides the feature into two sections. When it detects the equipment, the first section is selected as input and creates a simple network. If the output shows no detection, one dimension will be added. But the input is directly driven to output the result and doesn't change the original network structure. It is shown as figure 1.

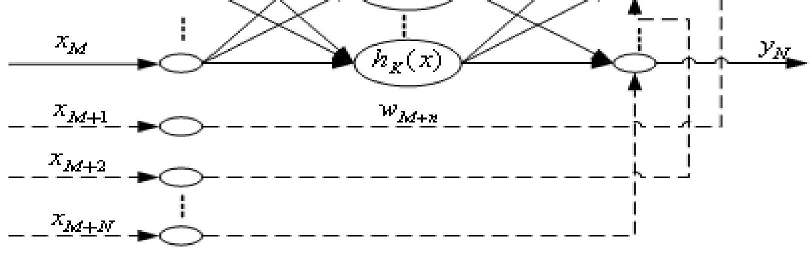

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Fig.1 Improved structure of the wavelet neural network

Mexicanhat wavelet is selected to apply in hidden layer and its expression is $h(t)=(1-t^2)e^{-\frac{1}{2}t^2}$. The output of the network is not a simple weighted sum but the first weighted sum of the network hidden layer wavelet nodes are transformed by the Sigmoid function to the final network output.

IMPROVED TRAINING ALGORITHM OF THE WAVELET NEURAL NETWORK

Take the optimization objective function as a cost function,

$$E=\sum_{p=1}^{p}E_n^p=\frac{1}{2P}\sum_{p=1}^{p}\sum_{n=1}^{N}(Y_n^p-y_n^p) \quad (1)$$

In formula: Y_n^p is the desired output of n st node p st training of output layer.

y_n^p is the actual output of n st node p st training of output layer

Output of hidden layer:

$$O_k^p=h(\frac{net_k^p-b_k}{a_k}) \quad , \quad net_k^p=\sum_{m=1}^{M}w_{km}x_m^p \quad (2)$$

Output of output layer:

$$y_n^p=f(net_n^p) \quad , \quad net_m^p=\sum_{n=1}^{N}w_{nk}O_k^p \quad (3)$$

Wavelet neural network training algorithm progressively update the connection weights between neurons and stretch factor, translation factor of wavelet

$$w_{nk}(t+1)=w_{nk}(t)-\eta\sum_{p=1}^{P}\delta_{nk}+\lambda\Delta w_{nk}(t) \quad ,$$

$$w_{km}(t+1)=w_{km}(t)-\eta\sum_{p=1}^{P}\delta_{km}+\lambda\Delta w_{km}(t) \quad (4)$$

$$a_k(t+1)=a_k(t)-\eta\sum_{p=1}^{P}\delta_{ak}+\lambda\Delta a_k(t) \quad ,$$

$$b_k(t+1)=b_k(t)-\eta\sum_{p=1}^{P}\delta_{bk}+\lambda\Delta b_k(t) \quad (5)$$

$$\delta_{nk}=\frac{\partial E_n^p}{\partial w_{nk}}=(Y_n^p-y_n^p)y_n^p(1-y_n^p \quad ,$$

$$\delta_{km}=\frac{\partial E_n^p}{\partial w_{km}}=\sum_{n=1}^{N}(\delta_{nk}w_{nk})\frac{\partial O_k^p}{\partial net_k^p}x_m^p \quad (6)$$

$$\delta_{a_k}=\frac{\partial E_n^p}{\partial a_k}=\sum_{n=1}^{N}(\delta_{nk}w_{nk})\frac{\partial O_k^p}{\partial a_k} \quad ,$$

$$\delta_{b_k}=\frac{\partial E_n^p}{\partial b_k}=\sum_{n=1}^{N}(\delta_{nk}w_{nk})\frac{\partial O_k^p}{\partial b_k} \quad (7)$$

Assume that $t^{'}=\dfrac{net_k^p-b_k}{a_k}$

$$\frac{\partial O_k^p}{\partial net_k^p}=-3\frac{\mathrm{t}^{'}}{\mathrm{a_k}}\cdot e^{(-t^{'2}/2)}+\frac{\mathrm{t}^{'3}}{\mathrm{a_k}}\mathrm{e}^{\left(-t^{'2}/2\right)} \quad (8)$$

$$\frac{\partial O_k^p}{\partial a_k}=3\frac{\mathrm{t}^{'2}}{\mathrm{a_k}}\cdot e^{\left(-t^{'2}/2\right)}-\frac{\mathrm{t}^{'4}}{\mathrm{a_k}}.e^{\left(-t^{'2}/2\right)} \quad (9)$$

In formula: η is the rate of learning, λ is factor of momentum

a_k, b_k is successively stretch factor, translation factor of wavelet

Detailed algorithm :

Step 1:initialization of grid parameter:set initial value to a_k , b_k , w_{km}, η, λ ,and the input sample counter m=1;

Step 2:import the learning sample and relevant desired output Y_n^p ;

Step 3:calculate the output value of hidden and output layer through formula 2 and 3;

Step 4:calculate the error E_n^p through formula 1 and gradient vector through formula 6 to 10;

Step 5: $m=m+1$,if $m<P$,go to step 4;otherwise,calculate the cost function E ,

modify the grid parameter through formula 4 and 5 and calculate DE ,if $DE<0$,set $\eta=\eta+a\eta$, $a\in(0,1)$,otherwise set , $a\in(0,1)$;

Step 6:judge whether $E(t)\le\varepsilon$, $\varepsilon>0$ or not.If it is yes,stop network studying and go to step 7,

If it is not,set m=1,and go to step 2,learn again;

Step 7:judge whether distinguishment is finished or not,if it is yes,stop the algorithm;

Step8: add to one-dimension sample $i=i+1$, calculate output directly, set initial weights value w_{M+i} and calculate output value $O_l^p=f(\sum_{n=1}^{N}\mathrm{w_{nk}}O_k^p+\sum_{i=1}^{L}w_{M+i}x_{M+i}^p$ again;

Step 9:judge whether $E(t)\le\varepsilon^{'}$, $\varepsilon^{'}>0$ or not,if it is yes, go to step 7, if it is not,adjust the value w_{M+i} and learn again.

DIAGNOSIS EXAMPLE OF THE IMPROVED WAVELET NETWORK

Merits of Agent-oriented modeling

Three common faults of turbine generator group:unbalance F_1 ,asymmetry F_2 ,film oscillation F_3 .For every typical fault,this paper selects three groups spectrum value to make up relevant 9 groups learning samples,as illustrated in table 1.This paper uses f to represent the rotational frequency of turbine generator group,and select the relevant vibration amplitude of characteristic frequency 0.01～0.39f，0.40～0.49f，0.50f，0.51～0.99f，1.0f，2.0f，3.0～5.0f，>5.0f as the input of neural network,then fuzzily processes input value and represents them with $X_1 \sim X_8$.Table 2 shows the recognition results of BP network to single fault and multiple faults .Table 3 shows the recognition results of improved wavelet network to single fault sample and multiple faults sample.

Seen from Table 2, BP neural network has good ability to identify a single fault sample , but for the case of multiple faults, there are two sets of samples appearing the case missed. With the increasing number of faults, the case-missed situation will be more serious ,and sometimes even appears diagnosis-wrong situation (recognise a fault that there does not exist as represented). Clearly, a single fault trained BP network has low recognition rate to multiple faults. Table 3 shows that improved wavelet network model for the turbine generator group fault diagnosis are able to make accurate and reliable judgments to both single or double fault conditions .

Table 1, network learning sample

bulleted	Sample input								Fault sample output		
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	F_1	F_2	F_3
1	0.01	0.11	0.12	0.17	0.97	0.35	0.11	0.05	0.9	0.1	0.1
2	0.02	0.02	0.06	0.18	0.91	0.25	0.09	0.05	0.9	0.1	0.1
3	0.01	0.01	0.07	0.14	0.94	0.23	0.00	0.10	0.9	0.1	0.1
4	0.02	0.02	0.01	0.02	0.47	0.61	0.38	0.20	0.1	0.9	0.1
5	0.01	0.01	0.01	0.02	0.38	0.68	0.10	0.08	0.1	0.9	0.1
6	0.03	0.00	0.02	0.01	0.45	0.42	0.18	0.19	0.1	0.9	0.1
7	0.04	0.84	0.16	0.14	0.26	0.05	0.03	0.00	0.1	0.1	0.9
8	0.01	0.96	0.18	0.12	0.28	0.01	0.02	0.01	0.1	0.1	0.9
9	0.05	0.91	0.13	0.21	0.22	0.05	0.03	0.00	0.1	0.1	0.9

Table 2,recognition results of BP network to faults

bulleted	The actual fault	Sample input								Diagnostic output		
		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	F_1	F_2	F_3
1	F_1	0.03	0.01	0.02	0.02	0.97	0.10	0.02	0.04	0.73	0.13	0.17
2	F_2	0.02	0.03	0.01	0.02	0.36	0.48	0.40	0.20	0.07	0.86	0.15
3	F_3	0.04	0.89	0.01	0.01	0.20	0.04	0.03	0.01	0.19	0.09	0.88
4	F_1+F_2	0.01	0.03	0.01	0.02	0.87	0.45	0.33	0.20	0.33	0.64	0.08
5	F_1+F_3	0.04	0.91	0.02	0.01	0.92	0.02	0.04	0.02	0.55	0.06	0.59
6	F_2+F_3	0.03	0.95	0.03	0.01	0.32	0.45	0.26	0.25	0.06	0.44	0.68

Table 3,diagnostic results of improved wavelet network

bulleted	known fault	input sample								The output of the improved wavelet neural network model		
		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	F_1	F_2	F_3
1	F_1	0.02	0.01	0.02	0.02	0.97	0.10	0.02	0.04	0.90	0.14	0.12
2	F_2	0.02	0.03	0.01	0.02	0.35	0.47	0.40	0.20	0.07	0.92	0.07
3	F_3	0.04	0.09	0.01	0.01	0.20	0.04	0.03	0.01	0.10	0.09	0.90
4	F_1+F_2	0.01	0.03	0.01	0.02	0.96	0.46	0.32	0.20	0.82	0.75	0.09
5	F_1+F_3	0.04	0.92	0.02	0.01	0.92	0.02	0.04	0.02	0.82	0.07	0.89
6	F_2+F_3	0.03	0.94	0.03	0.01	0.32	0.45	0.26	0.25	0.09	0.80	0.90

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