Fault diagnosis of Wind Turbine Pitch Systems based on Kohonen network

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Keywords: Kohonen neural network, Similarity function, Fault diagnosis, Pitch system **Abstract.** The wind turbines has a lot of operational failure parameters and some isolated sample; what's more, so direct use of neural networks for fault diagnosis easily lead to performance decreased. For this situation, we propose use of similarity function combined with Kohonen neural network for fault diagnosis: first use similarity function method to eliminated the redundant information for samples optimized; then due to the vagueness and uncertainty that exists between fault symptoms and causes of failure, it needs fuzzy clustering based on Kohonen neural network to solve, so the optimized samples input Kohonen network to obtain various type of standard fault model, then put the test samples in the model, its results were compared with the standard fault sample can get the type of fault. Simulation results show that: in the wind turbine pitch system use the fault diagnostic method, establish the relationship model accuracy is relatively high, able to make quick and accurate diagnosis of the turbine pitch systems operational status and fault type.

Introduction

Due to the more and more complexity of wind turbine equipment and increasingly high degree of automation, once the equipment or system failure would cause huge economic losses, it is necessary to make a fault diagnosis system to find the cause of the fault in time,in order to improve the safety and reliability of equipment operation .With the development of smart technology, the artificial neural network has been widely studied and applied in fault diagnosis^[1]. The most common method is to fault diagnosis based on BP neural network,but the BP neural network in practical application exist the following disadvantages ^[2]: Firstly, the existence of local minimization problem, the second is to select the network hidden layer nodes without theoretical basis, mostly using empirical test, increasing the complexity of the algorithm, the third is redundant sample affect the accuracy results of diagnostic .Because the wind turbine has many fault parameters and exist fuzziness, randomness and uncertainty between faults and fault symptoms, so the essence of fault diagnosis is classification decision problem based on the multi-source fault features, that mean the fault diagnosis systems need fuzzy clustering method to completed. Considering the above problem, fault diagnosis of wind turbines based on Kohonen neural network of clustering idea can be used.

Kohonen neural network is a kind of self-organizing competitive neural network, it use an unsupervised learning algorithm and forward adjustment neural network model, it able to identify the sample characteristics and complete automatic clustering [3]. The purpose of this paper is to use a

similarity function to eliminates data redundancy, get the optimized sample data, and then input the Kohonen neural network, get fault diagnosis model. For wind turbine pitch fault system, the use of the fault diagnosis method obtain an accurate fault type.

Similarity function

During the wind turbine on operation, it save a lot of historical and real-time data, when use the large sample of data created artificial neural network modeling, it existence the problem of large amount of computation, low computational accuracy and poor real-time, so it is necessary to take effective measures to eliminate redundant data optimized the samples. The idea of use similarity function to eliminate redundant information is [4]: a large number of operational data generated in the process of wind turbine operation, calculating the similarity between any two sets of data samples, if the sample data similarity values exceeds the threshold value, the data samples can be removed in order to optimization modeling sample data, this the similarity function paper,

is:
$$S_{ij} = \exp\left(-\frac{1}{\delta} \|x_i - x_j\|^2\right)$$
, δ is the normalization function, it defined as:

$$\delta = \sum_{i=1}^{m} (\max R_i - \min R_i), R_i \text{ is the i-th index data set , m is the number of elements contained in each}$$

group of samples. If the similarity value calculated through the similarity function closer to 1, then the two sets of data containing the more same data information.

Kohonen neural network

Kohonen network topology: consists of an input layer, and a output layer(competition layer) distribution in the two-dimensional plane. Kohonen neural network belong to unsupervised learning, thorough self-organizing map adjusting the network weights, make the one neuron of neural network output layer only matching for a particular input pattern^[5].

Kohonen neural network algorithm core ideas is^[6]: When the fault sample input to the neural network, the output layer neurons will calculated the distance between the input samples and neuron output layer weights ,which get the minimum distance will as the winning neuron. Adjusting the distance between the winning neuron and its surrounding neurons weights ,so winning neuron and the surrounding weights will continue to close the fault samples. After repeated training,the connection weights of each neuron has a certain distribution,this distribution make the similarity of sample cluster to neurons representative of all types, make the similar neurons with similar weight coefficient ,the different types of neurons has obvious difference coefficient.

Kohonen network training step [3,7]:

- 1) initialize the network weights: w = rand(n, K) the number of fault samples is n, competitive layer dimension is K
- 2) winning point calculation: calculation the euclidean distance d_i between the fault

samples
$$X = (x_1, x_2...x_n)$$
 and the output layer neurons $j : d_j = \left| \sum_{i=1}^m (x_i - w_{ij})^2 \right|$, make the minimum

distance competition layer neurons as the winning node output neurons.

3) adjustment weight : use $Nc(t) = (t|find(norm(pos_t, pos_r) < r))$ and

 $\omega_{ij} = \omega_{ij} + \eta (X_k - \omega_{ij})$ adjustments the node weights of winning node and its neighborhood radius r,

where pos_c, pos_t respective the location of neurons c and t, norm function calculates the distance

between two neurons. Networks can complete the clustering capabilities because the neighborhood radius r and the learning rate with the evolution of the number will linearly decline, so that the input data will gradually enter the winning node cluster center.

4) determine whether or not the end of the diagnostic algorithm, if conditions did not reach the end, return to step (2).

Fault diagnosis process shown in Fig 1:

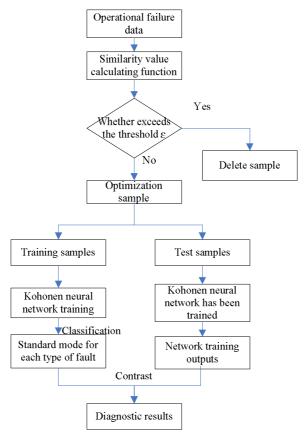


Fig 1 Fault diagnosis process

Fault diagnosis based on Kohonen network of wind pitch system

The basic process of fault diagnosis based on Kohonen network is ^[3]: according to the actual failure, determine the number of input layer and competitive layer, thereby establishing Kohonen neural network topology,input the fault sample which through similarity function optimized for Kohonen neural network training,the similar fault category samples will be gathered together in a network of neurons in the competitive layer; Then the test samples input to the already trained neural network model, one output layer neural element will have a maxinum value at its output terminal by weight adjustment,the network based on the location of neurons matched with fault standard sample mode, then can obtain the fault type of input test samples.

Wind pitch system fault sample pretreatment

Select three common faults from pitch system as follows: fault 1: pitch motor high temperature ,which trigger condition is the pitch motor temperature higher than 150 degrees continuous 3s; fault 2: pitch encoder fault , which trigger condition is the wind detected pitch rotary encoder output values overflow signal; fault 3: pitch capacitor voltage imbalance fault, its trigger condition is a low voltage capacitor pitch, duration 3s larger than the capacitance of the high pitch plus half the voltage 4V, fans reported this fault; According to the fault trigger conditions selected fault characteristic parameters: wind speed, wind turbine power, generator speed, generator speed, pitch angle, pitch rate, pitch cabinet capacitor high voltage, pitch motor temperature. When use a similarity function to optimizing the sample, the fault diagnosis timeliness and accuracy depend on the threshold selection, from literature [4] we known when threshold $\varepsilon = 0.98$ the similarity function has best effect of removing redundant information. Collection 60 groups of fault data, use similarity function filter 25 sets of sample data, with 20 sets of data as Kohonen neural network training samples , and the remaining five sets of data as the test data. First of all to normalization the date :input=mapminmax(x);

Build fault diagnosis model

(1)set network parameters

Samples from three different fault types of pitch system, selected 15 fault characteristic: Wind speed, generator speed, power, # 1pitch angle, # 2 pitch angle, # 3pitch angle, # 1 pitch rate change # 2 paddle rate, # 3pitch rate, # 1 pitch cabinet capacitor high voltage, 2 # pitch cabinet capacitor high voltage, 3 # pitch cabinet capacitor high voltage, 1 # pitch motor temperature, 2 #motor temperature

pitch,3 # pitch motor temperature; this 15 characteristic parameters indicated by $x_1 \sim x_{15}$. Therefore,

the neural network input layer nodes n = 15; two-dimensional distribution of the competition layer is 6 rows 6, so K = 36. Initialize the network weights w:

w = rand (In, K);

(2) building and training model: the optimized fault samples will be input to Kohonen neural network build model: net = newsom (minmax (input), [6 6]);

bet different training times:

net.trainparam.epochs = (10,50,100,200,500);

training model: net = train (net, input);

predicted output: y = sim (net, input);

vec2ind function can converted the output results to one-dimensional of node position: yc = vec2ind(y);

different training times has difference training results are shown in Table 1, pitch motor temperature fault use u1 represents; pitch encoder failure use u2 representation; pitch capacitor voltage unbalance fault use u3 representation.

Table 1 training results

		Tuoto Tuamming Toballo				
Sample	fault	output node locations				
number	type	training 10times	training 50times	training 100times	training 200times	training 500times
1	u1	1	30	18	31	30
2	u1	1	30	18	26	30
3	u1	1	36	12	25	36
4	u1	1	34	5	19	35

_	5	u1	1	36	6	25	36
	6	u2	4	8	26	30	19
	7	u2	4	8	26	30	19
	8	u2	4	3	31	35	31
	9	u2	4	2	31	35	31
	10	u2	4	1	33	28	33
	11	u3	4	1	33	1	22
	12	u3	4	12	36	1	18
	13	u3	1	12	36	1	18
	14	u3	1	12	36	1	18
	15	u3	1	6	35	7	6
	16	u3	1	6	35	7	6
	17	u3	35	16	19	9	4
	18	u3	36	19	8	5	8
	19	u3	36	31	1	12	1
	20	u3	36	31	1	12	1
	training	g time/s	0.521	1.103	3.361	8.210	17.005

analysis:

table 1 shown that :when the training times is 10 ,it indistinguishable faults 1 and fault 3, when the training times is 50 and 100,it indistinguishable fault 2 and fault 3; when the training times for 200, it can clearly distinguis the three faul type.

Unoptimized 50 sets of samples input Kohonen neural network training results shown in table 2:

Table 2 unoptimized sample training results

		1 1				
failure	Sample	output n	output node locations			
type	number	training 200times	training 500times			
u1	1-20	31,27,28,12,36	16,11,21,23,18			
u2	21-40	12,17,1,7,21	27,28,31,35,36			
u3	41-60	21,16,22,13,17	2,4,9,18,12			
training times/s		19.003	28.996			

analysis:

from the table 2 results we can see that: the input samples has a lot of redundant information, so the network output node location can not classify the actual three types of faults, and the computing time is relatively long.

(3) The test sample input the Kohonen neural network, the training times were set to 200 and 500 ,use Kohonen network treat test samples for testing, the results shown in table 3:

Table 3 test results

Sample	Sample Actual Diagnostic output n			ode locations	
number	failure	results	training 200times	training 500times	
21	u1	u1	25	36	
22	u1	g1	25	36	
23	u2	u2	30	19	
24	u2	u2	35	31	
25	u2	u2	29	33	
	training times/s	3	7.023	18.798	

analysis:

from table 3 we can see, when the training steps is 500:the test sample has correctly gathered to the table 2 node position. training steps for 200 network make the 21-24 test sample correct gathered to table 2 node position, but the 25th sample is not completely coincide with the nodes in table 2.

Deal with methods: After 200 times of training, the Kohonen neural network corresponding position of competitive layer excitatory neurons shown in figure 3, where u1, u2, u3 is training results, s1, s2 is a test results. Kohonen network output exist the quantitative evaluation of diagnosis results, evaluation indicators are: geometric distance $d_i = \sqrt{[(r-r^*)^2 + (s-s^*)^2]}$ between test diagnostic sample output position with known failure modes, where r^* , s^* is the test sample in the Kohonen network output flat location, r, s is the standard failure mode position on the output plane; evaluation principle:pitch system diagnosis predict failure type the more similar of standard fault model , the geometry more closer of competitive layer neuron [8].

Fig2 location node						
u3				u3		
u3		u3			u3	
u1						
u1	u1		u2	s2	u2	
s1					u2 u2	
u1				u2 s2	u2	
				s2		

analysis:

from yhe fig.2 diagnosis results can be seen: s1 and u1 completely overlap, that is means the test sample is a pitch motor high temperature failure; 25 samples for diagnosis s2, after computational geometry distance ,its minimum geometric distance is u2, so the test fault type is pitch encoder failure, also get the correct diagnosis.

Summary

By the above experimental results can be seen, when the unoptimized samples input Kohonen network it unimplemented the fault classification, but the improved algorithm first use of a similarity function eliminate redundant information to optimize the sample, and then using the optimized samples for Kohonen neural network training, can achieve accurate classification of pitch system three fault types, forming a standard sample failure mode; the optimized test samples input the Kohonen neural network fault diagnosed model, the result can accurately classify the samples to the standard fault model, this model achieve an accurate fault identification. Fault Diagnosis method based on similarity function and Kohonen neural network has a speed and accuracy characteristics, providing an effective solution to the complex problem of fault diagnosis. The diagnosis method has a good reference value for wind turbine operational failure of farm.

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