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FAULT DIAGNOSIS OF INDUCTION MOTOR USING NEURAL NETWORKS

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Abstract:

The fault diagnosis theory and its methods for inductor motor are summarized. Based on the method of current spectrum, a neural network method to diagnose the broken bar number of inductor motor is presented. The training patterns and the diagnosis results for the neural network are given. The broken bar number of inductor motor is diagnosed directly according to the working status parameters. The method is high intelligent and very reliable.

Keywords:

Induction motor; Broken bar; Neural networks; Fault diagnosis

1. Introduction

The fault analysis and diagnosis of the electric motor are very important in equipment diagnosis technique. Because of the work principle and structure characteristics of electric motor, the diagnosis methods and techniques have many characteristics [1]. A fault of electric motor usually has many symptoms, for example, when a bar of squirrel cage induction motor is broken, many symptoms associated each other occur, such as vibration increment, starting time prolongation, stator current swing, slip enlargement, speed and torque undulation, temperature change, and so on. After one bar broken, if electric motor continues to run, the number of broken bar will easily increase, symptoms be more and more obvious, fault become more and more serious, and finally electric motor will be damaged.

On the other hand, many faults cause same symptoms. Many situation changes may cause electric motor fault, for example, load, condition and other operation etc, which all kinds of symptoms occur and the relation is very complicated. Therefore, it is very difficult to diagnose the faults of electric motor. For long time, many diagnosis techniques and methods have been obtained by a great deal of research work, such as current analysis, vibration diagnosis, temperature diagnosis, and so on. Some expert systems for fault diagnosis of electric motor have been developed [1-5].

Currently, research on fault analysis and diagnosis system is still a significant problem because (a) the relation between fault reason and symptom is very complex; (b) the capability of fault diagnosis system of motor is very limited; (c) for the artificial intelligence diagnosis system based on rule discursion, there are many problems such as knowledge obtaining and expression, rule match, and so on.

The principle and method of fault diagnosis of squirrel cage induction motor is discussed. On the basis of the analysis method of current spectrum, a diagnosis method based on neural network for the number of broken bar of induction motor is presented. From the condition parameters of motor, the method can directly identify the number of broken bar. This method is exact, reliable and intelligent in diagnosis.

2. Fault diagnosis theory of broken bar

The stator current frequency of the good induction motor is single, i.e. supply frequency. While rotor circuit has a fault, there are two side frequencies ($\pm 2sf$) in the stator current spectrum. The magnetomotive force of stator winding of induction motor is

$$m_1 = K_1 N_1 I_1 \sin[(\omega_0 - \omega_r)t - \phi] \quad (1)$$

where K_1 is a stator constant related to pole-pair number and winding coefficient; N_1 is the stator winding number per phase; I_1 is stator current, ω is the angular frequency of power, $\omega = 2\pi f$, f is current frequency, ϕ is the phase angle of rotor winding, $\phi = \theta - \omega_r t$, θ is the initial phase angle, ω_r is the rotating angular velocity of rotor.

When rotor circuit has a fault, the magnetomotive force of rotor winding is modulated by $\sin 2\phi$. So the magnetomotive force of rotor winding becomes

$$m_1 = \frac{K_2 N_2 I_2}{2}\{\cos[(3-2s)\omega t - 3\theta] - \cos[(1-2s)\omega t - \theta]\} \quad (2)$$

where s is slip, $s = (\omega - \omega_r)/\omega$, K_1 is a rotor constant related to pole-pair number and winding coefficient, N_1 is the rotor winding number per phase; I_1 is rotor current.

The first item in equation (2) has $3\omega t$ and 3θ, which will produce zero sequence magnetomotive force in three-phase stator winding and has no influence on the power supply current. The second item has a component $2s\omega$ less than supply frequency and makes stator winding produce three-phase current component $2s\omega$ less than supply frequency, which modulation makes stator current beat vary (beat wave) and rotor speed wave with two-time slip frequency. Speed wave reduces low-side frequency $\omega(1\text{-}2s)$ and current swing scope and produces up-side frequency $\omega(1+2s)$ and is increased by three-harmonic magnetic flux in modulation. Thus, the amplitude ratio of low-side frequency to supply frequency can directly reflect the damage degree of rotor.

Broken bar of squirrel cage motor brings unbalanced electromagnetic force that rotates around rotor and makes motor electromagnetic vibration. When the load increases, vibration also increases. The pulse wave with frequency $2sf$ occurs in stator current, which causes the side frequencies $\pm 2sf$ at supply frequency in current spectrum. Therefore, the amplitudes of side frequencies $\pm 2sf$ in current spectrum can be used to diagnose the number of broken bar. This is basic principle that the number of broken bar is diagnosed by the stator current spectrum of squirrel cage motor.

3. Fault diagnosis principle of current analysis

In normal running, the stator current of electrical motor has only supply frequency in theory. When there are faults in the rotor, additional side frequency $(1\text{-}2s)f$ occurs in stator current which amplitude is related mainly to rotor asymmetrical degree. It is possible to diagnose rotor faults by detecting amplitude of additional side frequency $(1\text{-}2s)f$ in stator current.

According to the principle of diagnosing broken bar by the stator current spectrum of induction motor, the fault strictness factor SF is defined as following:

$$SF = \frac{P(f-2sf)+P(f+2sf)}{P(f)} \tag{3}$$

where $P(f)$ is the spectrum amplitude at supply frequency; $P(f\pm 2sf)$ is the spectrum amplitude at side frequencies.

The SF is not same for different electrical motor and running condition. The relation of SF vs. rotor broken bar ratio and load is shown in Figure.1.

Figure 1 shows that the factor SF is not only related to number of rotor broken bar, but also to operating parameters such as load [1,3] etc. Thus, it is not available to determine motor condition only in accordance with the value of SF when diagnosing. Figure 2 shows the relation between the amplitude difference of current spectrum and load current when one broken bar occurs.

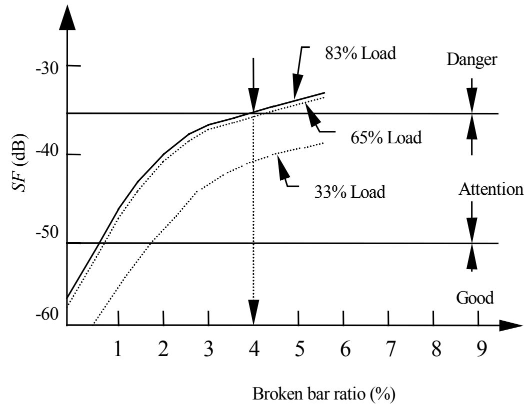

Figure 1. SF vs ratio of broken bar to load (0dB as the amplitude of base harmonic)

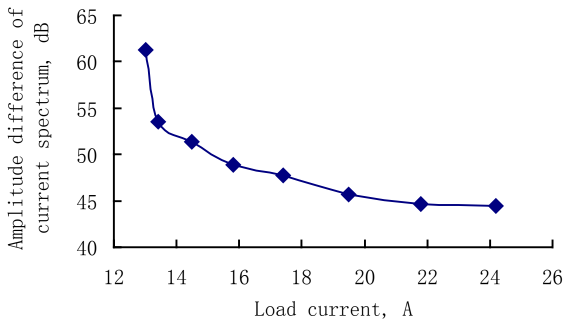

Figure 2. Amplitude difference of current spectrum vs load current when one broken bar

4. Diagnosing broken bar using neural networks

The fault of broken bar brings side frequency component $(1\text{-}2s)f$ in current of stator winding. The amplitude of side frequency is relative to many factors. Thus, it is very difficult to diagnose the number of broken bars only using amplitude of side frequency component, which is relative to broken bar number and other operating parameters. This complex nonlinear relation can be mapped by artificial neural networks.

4.1. BP networks

To diagnose the number of broken bars of motor rotor is an essentially classification problem in pattern space. The Back-Propagation (BP) networks are simple in structure and stable in operation. The BP networks have been successfully used for many applications, such as pattern recognition, nonlinear mapping, and so on. The BP networks including hide layers are capable of classification of arbitrary region of multidimensional space (i.e., for any mapping G from [0,1] to R in an arbitrary set L, there is a three-layer BP network that can approach to G in any way.) [20]. Thus, a three-layer BP networks are used to diagnose the number of broken bar.

For a three-layer BP networks shown as in Figure.3, given the input layer node number n, the output layer node number m, the hidden layer node number l, pattern number N, the input vector (x_1, x_2, …, x_n), the weight between input layer node and hidden layer node is w_{ji}, the input NET_j and output O_j of hidden layer node input are

$$NET_j = \sum_{i=1}^{n} (x_i * w_{ji}) \tag{4}$$

$$O_j = f(NET_j) \tag{5}$$

Generally, node activation function uses sigmoid function as

$$f(x) = \frac{1}{1+e^{-x}} \tag{6}$$

Suppose the connecting weight between output layer node k and hidden layer node j is w_{kj}, the node output of output layer k is

$$y_k = f(\sum_{j=1}^{l} (w_{kj} * O_j)) \tag{7}$$

The square error function is used. For all pattern, the total error is

$$E = \frac{1}{2} \sum_{p=1}^{N} \sum_{k=1}^{m} (y_{kp} - \hat{y}_{kp})^2 \tag{8}$$

where y_{kp} is the actual output of the nerve cell k at output layer for the pattern p; $\hat{y}_{kp}$ is the target output of the pattern p.

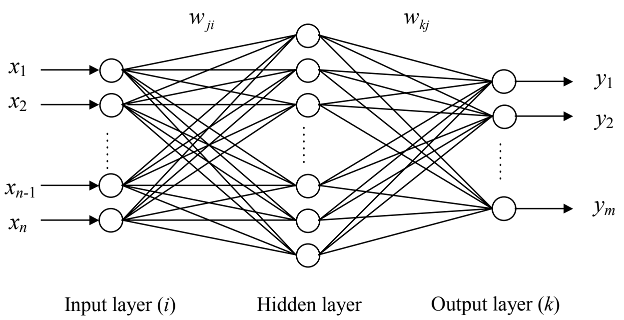

Figure 3. A three-layer BP networks

The BP algorithm is the grads descend method of nonlinear optimization algorithm. The learning algorithm of the BP networks is actually a batch learning method.

It is complicated to determine the node number of hidden layer of the BP networks. If the node number of hidden layer is too small, the network may not be trained or not strong, whereas, if the node number of hidden layer is too large, the training time may be too long and the error may not be the smallest. Therefore, there is a best node number of hidden layer. Generally, the node number of hidden layer n_1 can be given as following equation [6]

$$n_1 = \sqrt{n+m} + a \tag{9}$$

where n is the node number of input layer， m is the node number of output layer， a is a constant in the range 1-10.

4.2. BP networks for diagnosis of broken bar

Fault diagnosis is the pattern classification. The BP networks can sort input pattern space by nonlinear mapping and be applied extensively in pattern recognition and classification. It is a nonlinear function-mapping problem to diagnose the number of broken bar of motor rotor by amplitude of side frequency of current spectrum. Therefore, the BP networks can be used to diagnose the number of broken bar. A three-layer BP networks can approach the nonlinear function between the number of broken bar and the amplitude of current spectrum of motor as well as the other operation condition parameters.

4.2.1. Output layer

The output of BP networks must correspond to the number of broken bar. Generally, the number of rotor bar of large-scale and medium-scale squirrel cage motor is about 100. So assume the maximum number of broken bar N_m=100. The factor of broken bar number as output of BP networks is defined as

$$y=10(n+1)/N_m \tag{10}$$

where n is the number of broken bar.

If no broken bar, i.e. n=0, the BP network output y=0.1. If the number of broken bar is one, the BP network output y=0.2. So, the BP network output corresponds one-to-one to the number of broken bar.

According to the output of neural networks and equation (10), the broken bar number can be calculated as following

$$n_b=\mathrm{INT}(yN_m/10-0.5) \tag{11}$$

where n_b is the broken bar number; y is the output value of networks (broken bar factor)；INT is integer conversion.

4.2.2. Input layer

The normalized parameters of current spectrum components and working conditions are selected as the input nodes of neural network as following

$$x_1 = s \tag{12}$$

where s is the practice slip.

$$x_2 = s/s_r \tag{13}$$

where x_2 is the slip referred to the rated one; s_r is the rated slip.

$$x_3 = 20\lg(I_0/I^*)/100 \tag{14}$$

where x_3 is the amplitude level of current spectrum; I^* is the spectrum amplitude at the left side frequency; I_0 is the spectrum amplitude at the power frequency.

$$x_4 = N/N_m \tag{15}$$

where N is the total bar; N_m is the maximum bar, N_m=100.

$$x_5 = I/I_r \tag{16}$$

where x_5 is the current referred to I_r; I is the practice load current; I_r is the rated current.

$$x_6 = P_r/P_b \tag{17}$$

where x_6 is the rated power referred to P_b; P_r is the rated power; P_b is the maximum power, P_b=2000kW.

4.2.3. Hidden layer

According to equation (9), the node number of hidden layer should be in 3~13. In order to increase the generalized ability of BP networks, the node number of hidden layer n_1=15. Figure 4 is the BP networks for diagnosing broken bar number.

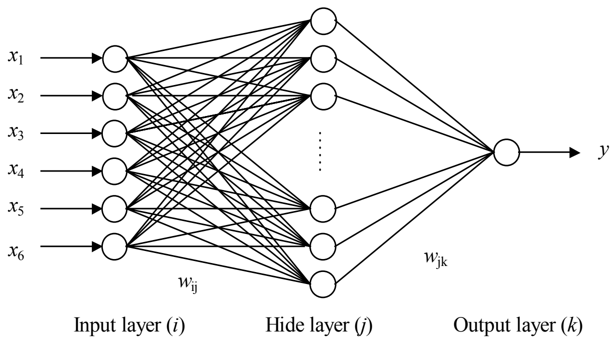

Figure 4. BP networks diagnosing broken bar number

4.3. Learning and test

According to the data shown in Table 1 from [1], the BP networks patterns shown in Table 2 are obtained. The first eight patterns are used to train the networks, and the last three patterns are used to test the networks. The training and test results are shown in Table 2 and Table 3. Error control value for training is given ε=0.00001. The training iteration is shown in Figure 5. From Table 2, the absolute errors between the network outputs and the object outputs for all training patterns are less than 0.015 after 18671 iterations. The diagnosis results of three test patterns in Table 3 are completely correct. It is shown that the BP networks have the very high diagnosis accuracy and good generalized ability.

5. Conclusions

The principle and methods of fault diagnosis for induction motor have been analyzed. Based on the current spectrum analysis, the neural networks method to diagnose the number of broken bar has been presented. The structure of neural networks, training patterns, and as well as the results of training and testing has been given. It is proved that this method can exactly diagnose the number of broken bar according to condition parameters.

Table 1. Broken bar number vs condition parameters

No	Broken bar number	Rated voltage (V)	Rated current (A)	Load current (A)	Speed (rpm)	Power frequency component(dB)	Side frequency (dB)	Spectrum difference (dB)
1	0	380	21.8	21.8	1430	115.6	51.6	64.0
2	1	380	21.8	21.8	1430	115.6	71.0	44.6
3	2	380	21.8	21.8	1430	115.6	78.4	37.2
4	3	380	15.1	15.1	1450	49.3	28.4	20.9
5	1	380	21.8	24.2	1420	116.4	72.0	44.4
6	1	380	21.8	19.5	1440	114.7	69.0	45.7
7	1	380	21.8	17.4	1450	113.7	66.0	47.7
8	1	380	21.8	15.8	1460	112.8	63.9	48.9
9	1	380	21.8	14.5	1470	111.9	60.5	51.4
10	1	380	21.8	13.4	1480	110.2	56.7	53.5
11	1	380	21.8	13.0	1490	110.9	49.6	61.3

Table 2. Learning patterns

No	Node Inputs						y	
	x_1	x_2	x_3	x_4	x_5	x_6	Desired	Output
1	0.047	1.000	0.640	0.51	1.000	0.012	0.1	0.101
2	0.047	1.000	0.446	0.51	1.000	0.012	0.2	0.215
3	0.047	1.000	0.372	0.51	1.000	0.012	0.3	0.303
4	0.033	1.000	0.209	0.26	1.000	0.009	0.4	0.412
5	0.053	1.143	0.444	0.51	1.110	0.012	0.2	0.211
6	0.040	0.857	0.457	0.51	0.895	0.012	0.2	0.213
7	0.027	0.571	0.489	0.51	0.725	0.012	0.2	0.209
8	0.013	0.258	0.535	0.51	0.615	0.012	0.2	0.208

Table 3. Test patterns

No	Node Inputs						Broken bar number	
	x_1	x_2	x_3	x_4	x_5	x_6	Actual	$n_b(y)$
1	0.033	0.714	0.477	0.51	0.798	0.012	1	1(0.195)
2	0.020	0.428	0.514	0.51	0.665	0.012	1	1(0.205)
3	0.013	0.286	0.613	0.51	0.596	0.012	1	1(0.181)

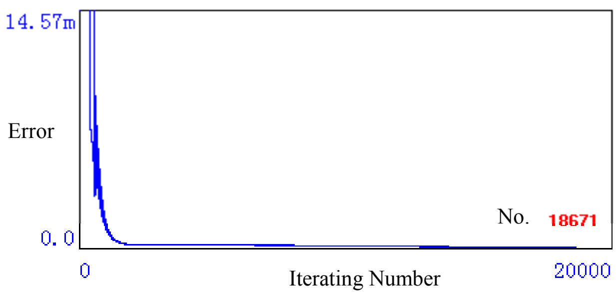

Figure 5. Training Iteration of BP networks

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