Winding Fault Diagnosis of Induction Motor Using Neural Network

Myung-Hyun Song, Kyu-Nam Park, Hyeok-Jae Woo, Tae-Hun Lee and Min-Kwan Han *Member, KIMICS*

Abstract – This paper proposed a fault diagnosis technique of induction motors winding fault based on an artificial neural network (ANN). This method used Park's vector pattern as input data of ANN. The ANN are firstly learned using this pattern, and then classify between "healthy" and "winding fault" (with 2, 10, and 20 shorted turn) induction motor under 0, 50, and 100% load condition. Also the possibility of classification of untrained turn-fault and load condition are tested. The proposed method has been experimentally tested on a 3-phase, 1 HP squirrel-cage induction motor. The obtained results provided a high level of accuracy especially in small turn fault, and showed that it is a reliable method for industrial application

Index Terms – Induction motor, winding fault, Park's vector pattern, MCSA and Neural Network

I. INTRODUCTION

Induction motors play a very important role in the safe and efficient running of industrial plants and processes. But unexpected failures may cause large amount of loss, and fault diagnosis system is very important for safe operation and preventing rescue. The most common faults in squirrel-cage induction motors are bearing, stator, and rotor faults.

The stator winding of an induction machine is subject to stresses induced by a variety of factors, which include thermal overload, mechanical vibrations and voltage spikes caused by adjustable-frequency drives. Degradation and aging of winding insulation eventually leads to turn-to-turn faults in which a large circulating fault current of the order of twice the locked rotor current is induced in the fault loop. The heat generated in the winding, which is proportional to the square of the large fault current, cause the fault to rapidly progress to more severe faults such as phase-to-phase and turn-to-ground faults resulting in irreversible damage to the stator winding and core. Detection of a turn fault in its incipient stage prevents consequential damage to the motor and significantly reduces financial loss by minimizing the repair cost, additional manpower, and motor outage time.

The study of induction motor during fault conditions has been an area of ongoing interest for many years. Research has concentrated on using parameter estimation, spectrum analysis, artificial neural networks, and symmetrical component methods. T. Thomson etc. have presented the way of diagnosis for inter-turn stator fault using stator current spectrum analysis [1][2]. Zhang Peiming and Chen Li'an have simulated expected symptom to induction motor model with stator winding fault using Matlab Simulink [3]. G. B. Kliman and T. G. Habetler have used the negative sequence current and voltage, which happen from unbalanced machine operation and windings, and applied negative sequence impedance which is the ratio of negative sequence voltage to negative sequence current, as an indication of stator winding fault [4][5]. Filippetti and C. Franceschini etc has presented a diagnostic method based an artificial intelligence for stator winding faults [6]. D. S. B. Fonseca and A. J. M Cardoso etc have proposed Park's vector approach in order to diagnose a inter-turn fault [7][8]. And Benbouzid has investigated stator winding fault by using Park's vector pattern recognition, only stator open phase and stator voltage unbalance [9].

This paper presented the diagnosis method of the induction motor winding fault using neural network. Particularly, this experiment focused on the diagnosis of 2 shorted turns fault which is most difficult to find and the possibility of the diagnosis of untrained shorted turn fault and untrained load condition. The results of experiment showed that the neural net with Park's vector input is effective to classify the slight turn fault just like 2 turn and the untrained turn fault with untrained load condition.

II. PARK'S VECTOR APPROACH

Park's Vector components (i_D, i_Q) are defined as equations (1), (2) from 3-phase currents (i_A, i_B, i_C).

$$i_D = \left(\frac{\sqrt{2}}{\sqrt{3}}\right) i_A - \left(\frac{1}{\sqrt{6}}\right) i_B - \left(\frac{1}{\sqrt{6}}\right) i_C \quad (1)$$

Manuscript received November 26, 2004.

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$$i_Q = \left(\frac{1}{\sqrt{2}}\right) i_B - \left(\frac{1}{\sqrt{2}}\right) i_C \tag{2}$$

where i_Q is q axis current, i_D is d axis current.

Under ideal conditions, the Park's vector has the following components:

$$i_D = \left(\frac{\sqrt{6}}{2}\right) i_+ \sin(\omega t\ ) \tag{3}$$

$$i_Q = \left(\frac{\sqrt{6}}{2}\right) i_+ \sin(\omega t - \frac{\pi}{2}\ ) \tag{4}$$

where i_+ is maximum value of the current positive sequence (A), ω is angular supply frequency (rad/s), t is time variable(s)

The corresponding representation is a circular locus centered at the origin of the coordinates. In case healthy motor, it contains only positive-sequence, and makes the locus of Park's vector a perfect circular locus, which is shown in Fig.1 (a)

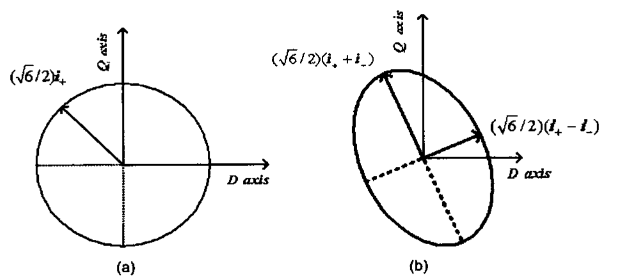

Fig. 1 Park's vector pattern (a) ideal case (b) fault case.

But stator winding with shorted turn contains asymmetrical factors in supply current. In this case, supply current is to the sum of positive and negative-sequence component (i_-). Relationship between the asymmetrical components and Park's vector is shown by Fig. 1 (b)

Park's vector patterns of healthy motor and winding fault motor are showed in Fig. 2. It shows that the more it has shorted turns, the more it is distorted. As we know, it is very difficult to detect the 2 turn short fault using Park's vector approach.

III. ARTIFICIAL NEURAL NETWORK

In recent year, artificial neural network (ANN) has generated considerable interest in the field of engineering as problem-solving tools. In this paper, the back-propagation algorithm is used for train the network. The fundamental element of ANN is a neuron which has

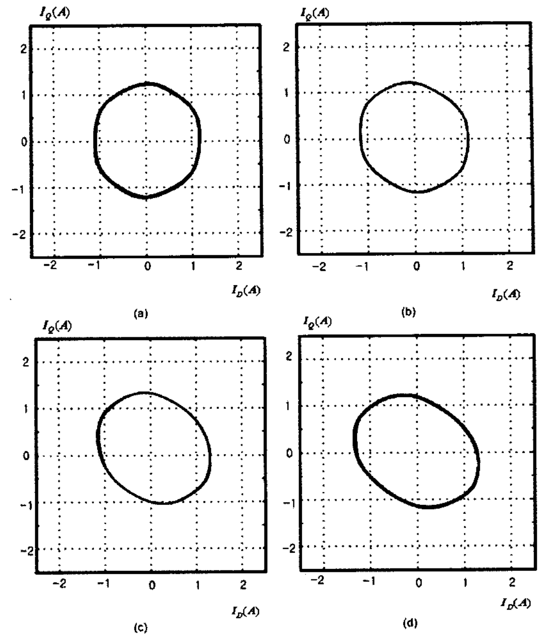

Fig. 2 Park's vector pattern (a) healthy motor (b) 2 shorted turns (c) 10 shorted turns (d) 20 shorted turns.

multiple inputs and a single output. Each input is multiplied by a weight and summed. And this input is passed to a transfer function which determines the response of neuron. The activity level of the j th neuron is obtained as

$$o_j = f_j(net_j) = f_j\left[\sum_i (w_{ji}x_i) + b_j\right] \tag{5}$$

where o_j is activity level of the j th neuron, net_j is input of the j th neuron, f_j is transfer function of the j th neuron, w_{ji} is connection weight form the i th to the j th neuron, x_i is activity level of the i th neuron in the prior layer, b_j is connection weight from the bias unit to the j th neuron.

The connection weight such as ω_{ji} are adjusted so that the average squared error between the network output and the target for a reference input is minimized. Training continues iteratively until the sum of the squared error is below a goal. The change of weight from the i th neuron to the j th is computed by

$$\Delta w_{ji}(t+1) = \eta \delta_j o_i + \alpha \Delta w_{ji}(t) \tag{6}$$

$$\delta_k = (t_k - o_k) f_k'(net_k) \tag{7}$$

$$\delta_m = f_m'(net_m)\left(\sum_k \delta_k w_{kj}\right) \tag{8}$$

where $\Delta w_{ji}(t)$ is the change in the weight w_{ij} at time t, t_k is desired output of the k th neuron in the output layer, η is learning rate, α is momentum

Equation (7) computes the k th neuron in the output layer, and (8) computes the m th neuron in the hidden layer. In (6), η and α are adjustable parameters.

In this paper, the training and testing of ANN used Park's vector patterns of each motor condition (healthy motor, 75 patterns, winding fault motor, 135 patterns). Input layer has a 56 neuron and output layer has one neuron. The training process used trial and error method to search the optimal NN configuration.

IV. EXPERIMENT SETUP

Experiment is conducted on a specially wound laboratory induction motor, rated at 380V, 60Hz, 1Hp, 1800 rpm. In order to allow tests to be performed at different load levels, a mechanical load was provided by a dc generator feeding a variable load. The schematic for the experimental setup is shown in Fig. 3 below.

The current data was firstly collected and then transformed 0-400Hz bandwidth. That Park's vector patterns are applied by the Neural Network and diagnosed the fault of motor.

The structure of stator winding using this test is shown in Fig. 4. One phase of the stator winding was installed the additional tap in 2, 4, 10, 20, 40 and 70th turn for stator winding fault condition.

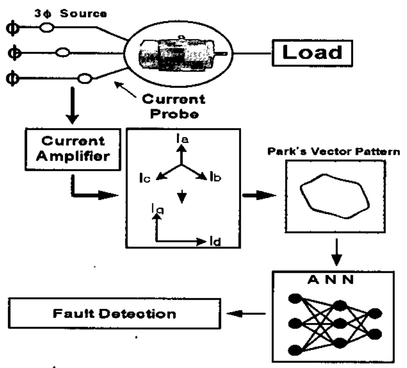

Fig. 3 The schematic for the experimental setup.

Fig. 4 The structure of stator winding fault.

V. EXPERIMENT RESULTS

A. Diagnosis of stator winding fault

In order to diagnose stator winding fault of induction motors, the data of a healthy motor with 0, 50, 100% load and winding fault motor with 2, 10, and 20 shorted turn of 0, 50, and 100% load were used for train and test of ANN. The output layer value '-1' corresponded to the 'healthy motor'. The output layer value '1' corresponded to the "stator winding motor". When the ANN has the configuration of 56, 70, 45, 30, 5 and 1 in the ANN training and testing, the ANN has the best results which have total error of 9.83e-06. Fig. 5 has shown the result of ANN testing has a high success rate.

Fig.6 has shown the result of ANN testing for untrained fault data on ANN train such as 2 shorted turn of 75% load and 6 shorted turn of 50% load. The output of this testing classified accurately healthy and winding fault motors. Also this described that this ANN can diagnose unused fault data as well as used fault data at ANN train, which can be adapted to any of the fault conditions

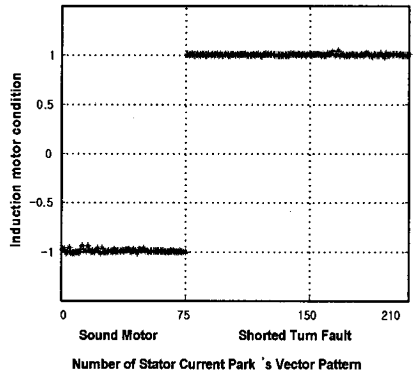

Fig. 5 The results of ANN testing for input data of healthy and winding fault motor with same training condition.

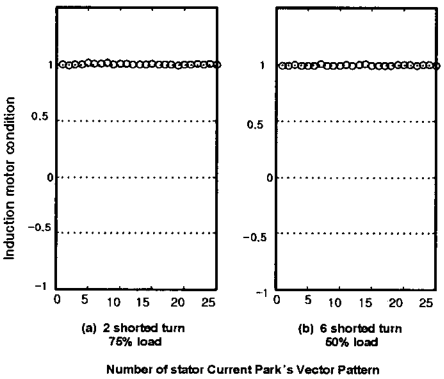

Fig. 6 The results of ANN testing for untrained winding fault motor on ANN train.

B. The more detail diagnosis of stator winding fault

In order to obtain the detail results, this test divided winding fault data into three parts such as healthy motor, slight winding fault with 2 shorted turns and heavy winding fault with 10 to 20 shorted turn. The output layer value '-1' corresponded to the 'healthy motor'. The output layer value '0' and '1' corresponded to the "stator winding motor", respectively, a slight fault, and a heavy fault.

When the ANN has the configuration of 56, 70, 45, 25, 10 and 1 in the ANN training and testing, the ANN has the best results which have total error of 9.25e-06. The Fig. 7 shows the result of ANN test corresponding exactly to each target value.

Fig.8 shows the result of ANN testing for unexpected fault condition such as 2 shorted turn of 75% and 6 shorted turn of 50% load. The output of untrained load condition (2 shorted turn 75%) at ANN train is distributed around '0' indicating the slight winding fault, and the output of untrained turn fault condition (6 shorted turn of 50% load) at ANN train is distributed between '0' and '1' indicating slight winding fault and heavy winding fault. it has been shown that each output layer take a adequate result.

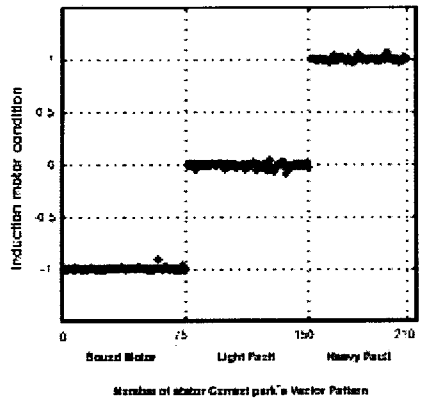

Fig. 7 The results of ANN testing for input data of healthy, slight winding fault and heavy winding fault motor.

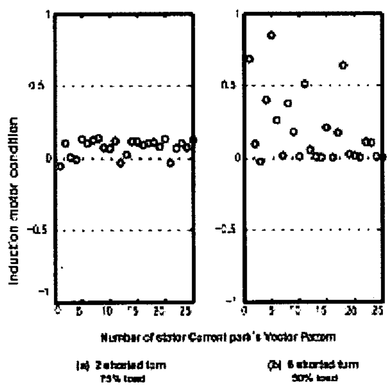

Fig. 8 The results of ANN testing for untrained fault data.

VI. CONCLUSION

This paper presented the effective fault method diagnosis of induction motor winding using neural network.

Experimental results show that it is possible to detect a slight wounding fault such as 2 turn winding fault and obtain a reliable output from untrained load condition(2 turn short 75% load) and untrained shorted turn con-dition (6 turn short 50% load). The proposed Park's vector - neural network approach is very simple and powerful method to diagnose the slight winding fault and untrained winding fault or untrained load condition.

ACKNOWLEDGMENT

This paper was funded by Research Foundation of Engineering College, Sunchon National University.

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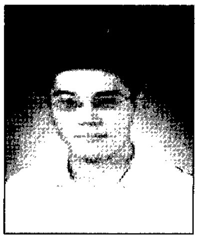

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