THE DETECTION OF BROKEN ROTOR BARS IN SQUIRREL CAGE INDUCTION MOTORS BASED ON NEURAL NETWORK APPROACH

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ABSTRACT
The detection of broken rotor bars in three-phase squirrel cage induction motors by means of current signature analysis is presented. In order to diagnose faults, a Neural Network approach is used. At first the data of different rotor faults are achieved. The effects of different rotor faults on current spectrum, in comparison with other fault conditions, are investigated via calculating Power Spectrum Density (PSD). Training the Neural Network discern between "healthy" and "faulty" motor conditions by using experimental data in case of healthy and faulted motor. The test results clearly illustrate that the stator current signature can be used to diagnose faults of squirrel cage rotor.

1. INTRODUCTION
During recent years, intensive research effort has been focused on the motor current signature analysis in order to detect fault condition of induction machines [1-3]. High resistance and different number of broken bars in rotor of squirrel cage induction motors situations and effects on current causing reluctance changes by means of using stator current spectral analysis can be investigated [5-11]. Rotor faults can be detected by using differences in stator current. Rapid developing on computer technology and in addition to this developing on signal processing enables that various methods can be used in these applications. Thus using of data processing methods, such as Genetic Algorithm and especially Neural Network, have been focused in applications for fault detection [11-14].

2. SPECTRAL ANALYSIS
A common approach for extracting the information about the frequency features of periodical signal is to transform the signal to the frequency domain by computing the discrete Fourier transform. For a block of data of length N samples the transform at frequency mΔf is given by;

$$X(m\Delta f) = \sum_{k=0}^{N-1} x(k\Delta t)\exp\left[-j2\pi km/N\right] \qquad (1.1)$$

Where Δf is the frequency resolution and Δt is the data-sampling interval. The auto-power spectral density of X(t) is estimated as;

$$S_{xx}(f) = \frac{1}{N}\left|X(m\Delta f)\right|^2, f = m\Delta f \qquad (1.2)$$

3. ARTIFICIAL NEURAL NETWORKS IN FAULTS DETECTION
An artificial neural networks(ANN) consists of a set of processing elements called neurons that interact by sending signal to one another along weighted connections. The connection weights, which can be determined adaptively, specify the precise knowledge representation. It is not possible to specify the weights beforehand, because the knowledge is distributed over the network. Therefore, a learning procedure is necessary in which the strengths of the connections are modified to achieve the desired form of activation function.

Multilayer feedforward networks are an important class of neural network. Typically, the network consists of a set of source nodes that constitute the input layer, one or more hidden layer of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, on a layer-bylayer basis (as shown from Figure1)[15].

The neural network used in the the diagnostics are of the multilayer perceptron type, trained using the backpropagation algorithm. Training a network by backpropagation involves three stages: the feedforward of the input training pattern, the backpropagation of the associated error, and the adjustment of the weights. During the learning process, the nn weights are adapted in order to create the desired output vectors. For learning process, the symptom-fault map is required.

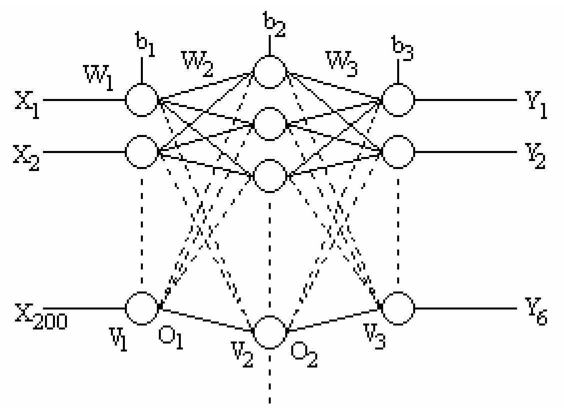

Figure 1. Schematic multilayer feed-forward ANN

Neural network are particularly suitable to link the different variables of a physical system where the relationship between the independent and the dependent variables are not easily quantifiable. Neural network can be applied to a wide variety of problems, such as storing and recalling data or patterns, classifying patterns, performing general mappings from input patterns to output patterns, grouping similar patterns[16].

4. STATOR CURRENT ANALYSIS

In this study the features of used motor is three-phase, 1.3 kW, two pole, eighteen rotor bars, squirrel cage induction motor. Data of stator current are achieved through current transformer, resistance and I/O card. Figure1 shows block diagram. Data was sampled at 5 kHz frequensy.

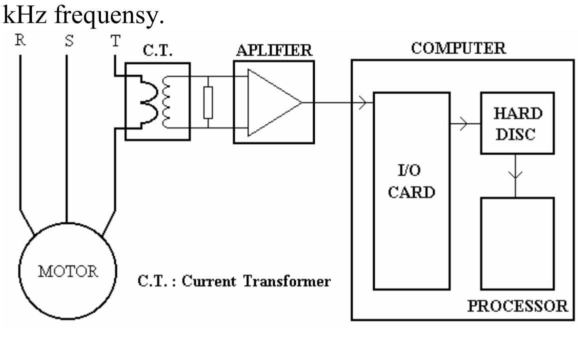

Figure 2. Block diagram of motor current sampling system.

Stator current was initially measured in case of healthy motor without load. Then one of the rotor bars was drilled to simulate high resistance condition. Diameter of hole was half of width of bar. Stator current was measured in case of high resistance of a rotor bar. This drilled hole was wholly scraped through the width of rotor bar to simulate only one broken rotor bar condition. Stator current was measured again in case of a broken bar of rotor bars. Then this cycle was made in case of two broken bars side by side, three broken bars (two bars of which side by side other apart) and three broken bars side by side. Twenty data were achieved for every fault condition. Every data contains two thousand samplings. These data were transformed into 500 sampling data. That is while data for different conditions was compared with each other. And stator currents were started from zero to protect samples from initial destructive effects at sampling. And every data was normalized between -1 and 1. Figure 3 shows current signal in case of healthy motor and Figure 4 shows current signal in case of a broken rotor bar motor. Differences, which these motor conditions caused, can be realized.

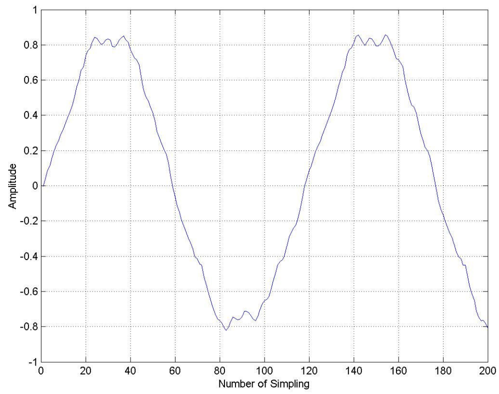

Figure 3. Current of healthy motor.

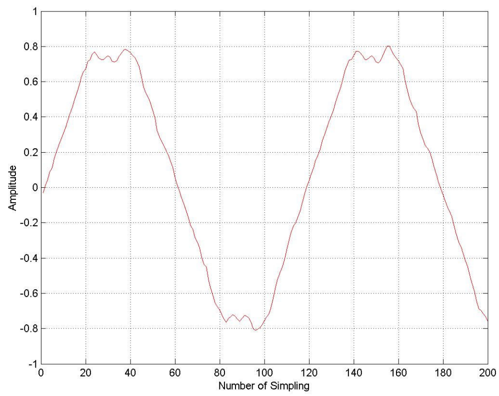

Figure 4. Current of a broken rotor bar motor.

Power Spectral Density (PSD) was calculated to specify harmonics. In calculation Hamming window was used for realizing the differences better. Figure 5 shows current harmonics in case of healthy motor and Figure 6 shows current harmonics in case of a broken rotor bar motor.

The clearest differences were seen at first, second, fifth, seventh harmonics. Therefore data between 0 and 400 Hz was used for training the neural network. And every data was normalized between 0 and 1.

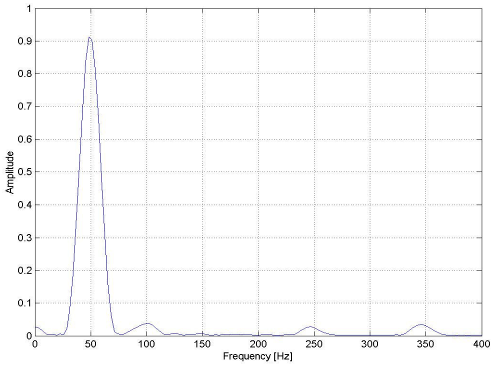

Figure 5. Current spectrum of healthy motor.

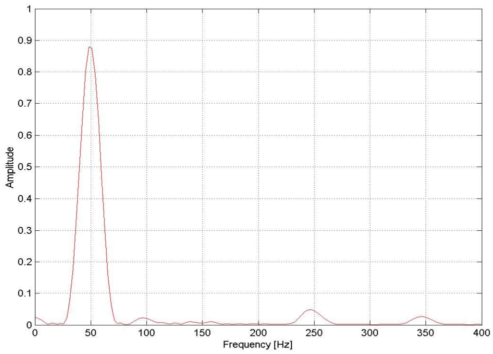

Figure 6. Current spectrum of a broken rotor bar motor.

Ten data of achieved every twenty data for every faulty conditions and healthy condition were used for training and other ten data were used for test. Training and test were processed at different number of hidden layer and iteration to find suitable numbers. Optimization was made by investigating results. As shown from Table1 and Table2 it was determined that the most efficient number of hidden layer was 200 and the most efficient number of iteration was 1500. At the end of the process it was found that the error of training is %3.10^{-12} and the error of test is %1,6.

1000 Iteration			
Hidden Layer	Training Error[%]	Test Error[%]	Diagnosis Error[%]
160	2.17E-06	2.98	10
180	0.278	2.5	13.33
190	3.40E-08	2.82	11.67
200	**1.00E-07**	**2.07**	**8.33**
240	4.70E-09	3.12	15
300	1.57E-08	2.76	13.33

Table 1. Optimization for the number of hidden layer.

200 Hidden Layer			
Iteration Number	Training Error[%]	Test Error[%]	Diagnosis Error[%]
300	7.27E-02	3.15	11.67
400	1.16E-02	2.71	11.67
500	1.80E-03	2.5	11.67
600	3.00E-04	2.4	10
700	4.00E-05	2.3	10
800	5.00E-06	2.23	8.33
900	7.00E-07	2.15	8.33
1000	1.00E-07	2.07	8.33
1100	1.00E-08	1.97	8.33
1500	**3.00E-12**	**1.6**	**5**
2000	8.00E-16	1.45	5
5000	5.00E-16	1.45	5

Table 2. Optimization for the number of Iteration.

Figure 7. Drilled two bars of rotor.

Figure 8. Experiment Mechanism.

CONCLUSION

In this study effect of broken rotor bars on current harmonics was investigated. And the rotor faults via using differences between achieved current spectrums of faults conditions were diagnosed. Dring the study different six conditions(but in this paper healthy and a broken bar were illusrated), healthy motor, a broken rotor bar, two broken rotor bar, three broken rotor bar, three broken rotor bar (two of which is side by side and other is apart), were investigated. By using experimental data, training was made for classification. Finally fault conditions were successfully diagnosed.

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