APPLICATION OF CEPSTRUM AND NEURAL NETWORK FOR INDUCTION MOTOR FAULT DIAGNOSIS

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Abstract— Induction motors are vulnerable to many faults which results in becoming catastrophic and cause production shutdown, personal injuries and wastage of raw materials. Thus it is important to prevent the faulty conditions at the initial stages so as to avoid any type of failure in the system. This paper is dealing with the rotor bar fault of the induction motor. The possibility of occurrence of rotor bar faults is about 10% of all total induction motor faults and is caused by the rotor winding. Condition monitoring and fault diagnosis of an induction motor is important in the production line. It can reduce the cost of maintenance and risk of unexpected failures by allowing the early detection of failures. This work documents experimental results for broken rotor bar fault detection in induction motors using cepstrum analysis and artificial neural network based approach. It has found that a combination of cepstrum plus neural network analysis is very useful tool for fault diagnosis of induction motor. A feedforward neural network was used for rotor bar fault based on fault features extracted using cepstrum analysis.

Keywords— Cepstrum Analysis, Artificial Neural Network, Induction Motor, Rotor Bar Fault.

I. INTRODUCTION

Induction motors are preferable due to their simple, rugged, very reliable, low cost, less maintenance requirement, easily installed, controlled, and adaptable for many industrial applications. Pulsating load and direct on-line starting are the main reasons behind rotor faults mainly the broken rotor bars. It leads to instconstancy of speed, overheating, torque pulsation, damaging of laminations, arcing and vibration. The electrical and mechanical stresses causes the faults, overloads and abrupt load changes results in mechanical stress leading to bearing fault and rotor bar fault. The other causes are thermal stresses, residual stresses, dynamic stresses, environmental stresses and magnetic stresses. Although the sideband amplitudes are sensitive to motor loading, it has been observed that there is a direct proportionality relation between the rotor bar fault severity and amplitude of the sidebands. Given that we have taken no loads or rather even at light loads, these broken sidebands of motor bar go undetected, the reason is rotor currents are very small under these conditions. Added to the condition is the possibility that a fully or partially broken rotor bar, which can lead from small to even catastrophic failure may as well go undetected even if we consider a full load condition. In order to address these issues there is a need of developing a strong condition monitoring technique.

The major issue concerning machine condition monitoring is machine fault diagnosis. Diagnosis refers to the determination of current ‘health’ status or working condition of the motor. A reliable diagnosis technique along with reducing the risks of unexpected machine breakdowns also helps in prolonging machine’s life. Due to this the current trend in the industry is towards condition-based preventive maintenance. Errors and uncertainties in fault classification can lead to false indication which motivates the researchers to come up with a more robust and reliable condition-monitoring system. Different methodologies based on artificial neural network and cepstrum analysis have been proposed for induction motor broken rotor bar fault. Most methods of condition monitoring and fault diagnosis of induction motor are based on the cepstrum analysis and artificial neural network (M. Aladesaye, 2008 and W.A.F. Justine, 1996). Barrios (1997), Gallardo (1996) and González (1998) have developed a phenomenological model to simulate broken bars in the rotor of an induction motor. An induction motor with broken rotor bar fault the cepstrum gives some extra information about the sidebands associated with broken rotor bar fault (B. Liang, S.D. Iwnicki, Y. Zhao 2013). Both vibration and stator current spectra can identify broken rotor bar fault, provided a certain amount load is exerted on the motor. But, the stator current spectrum demonstrates slightly better performance than vibration power spectrum. (V.A. Kinitsky, N. Rotondale, M. Martelli, and C. Tassoni, 1994)

Neural network can represent complex non-linear relationship and therefore they are extremely useful for fault identification and classification (W.A.F. Justine, 1996). With the development of Artificial Intelligence (AI) systems, expert systems based on neural network, fuzzy logic have been employed in order to assist the fault detection task for correctly interpreting the faulty data (Filippetti, Franceschini, Tassoni, & Vas, 2004; Tung, Yang, Oh, & Tan, 2009; Yang, Han, & Sukin, 2004). Thus, it can be summarized that there are countless techniques for diagnosis of specific induction motor faults, but
cepstrum analysis is an effective tool which can be used for the detection of periodicity in a spectrum and suitable technique for diagnosis of broken rotor bar fault. This paper presents an investigation of cepstrum and neural network analysis for induction motor fault diagnosis. The obtained results demonstrate the suitability of the proposed technique for broken rotor bar fault detection in an induction motor achieving 100% accuracy.

II. CEPSTRUM ANALYSIS

Cepstrum is defined as the Fourier transform of the logarithm of fourier transform of a signal. The name cepstrum was derived by reversing the first four letters of the word ‘spectrum’. Cepstrum gives information about rate of change in different spectrum band. For linear separation it is used to convert signals combined by convolution into sum of their cepstra. There are different types of cepstrum such as, complex cepstrum, real cepstrum, power cepstrum and phase cepstrum. Complex cepstrum is defined as Inverse Fourier transform of logarithm of Fourier transform of signal; this is called as spectrum of a signal. Complex cepstrum uses complex logarithm function for defining complex values whereas Real cepstrum uses logarithm function to define real values. The complex cepstrum gives information about magnitude and phase of the initial spectrum whereas real cepstrum gives only the information of the magnitude of the spectrum.

For a real signal \( x(n) \), different cepstrum forms can be expressed as follows,

The real Cepstrum of a signal \( x(n) \):
\[
c(n) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \log |X(\omega)| e^{j\omega n} d\omega \quad \ldots \ldots \quad (1)
\]

The complex Cepstrum of a signal \( x(n) \):
\[
c(n) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \log|X(\omega)| e^{j\omega n} d\omega \quad \ldots \ldots \quad (2)
\]

The power Cepstrum of a signal \( x(n) \):
\[
c(t)^2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(\omega)| |e^{j\omega n} d\omega|^2 \quad \ldots \ldots \quad (3)
\]

III. NEURAL NETWORK CLASSIFIER

The ANN represents information-processing systems formed by interconnecting simple-processing units called neurons. Each neuron is an independent processing unit that transforms its input data via a function called activation function. The connections between neurons are characterized by weight values that represent the memory of the network. By modifying these weights according to some learning rule, the ANN can be trained to recognize any pattern giving the training data. The network architecture plays a very important role in the performance of ANN and usually depends on the problem at hand. Several types of neural network structures have been proposed in the literature (Filippetti et al., 2004; Tung et al., 2009) for diagnosis purposes, the most popular one is the multilayer perceptron which is used in the present study. This network with a simple architecture may be used. The layers are fully interconnected in one direction from the input layer towards the output layer. The number of neurons in the input and output layers is governed by the number of inputs and outputs of the pattern to be recognized. However, the number of neurons in the middle layer can be selected depending upon the applications. Input patterns are exposed to the network whose output is compared with the target values to calculate the error which is corrected in the next pass by adjusting the weights. In the proposed work, a three-layer feedforward neural network is selected for rotor bar fault diagnosis of an induction motor.

A three-layer feedforward network has proven to have the capability of approximating any function regardless of its complexity. Figure 1 shows the architecture of a feedforward neural network.

IV. EXPERIMENTAL STUDY

The set up used for the experimental purpose consists of 2 Hp, 3 phases; 50 Hz;415 V;1350 rpm;3.6 Amp star connected squirrel cage induction motor. The induction motor is coupled with D.C. generator having 4 poles; 230 volt; 9.6 Amp current rating. For loading the generator resistive load banks are used. The induction motor is loaded from no load to full load. The motor used for experiment has 24 coils, 36 slots in all. The current and voltage signals are captured at sampling frequency of 1 KHz with the help of ADLINK DAQ. The Different experiments are carried out on laboratory bench in healthy and faulty condition such as broken rotorbear fault. The data is captured with the help of ADLINK DAQ. The ADLINK DAQ has 10 input ports and 10 output ports. Each port has maximum voltage rating of 10 volts. Fig.2 shows the experimental set up used.

Figure 2. Experimental Set-up
The purpose of experimentation is to get the current signals in healthy and faulty condition. The different loading conditions such as no-load and full load condition are taken.

**4.1. Healthy Condition**

2 H.P motor is fed by three-phase balanced supply load on the motor is varied from no load to full load. The current signals of healthy induction motor in no load and in full load condition are shown in figure 3 and figure 4 respectively.

![](image1.png)

**Fig 3:** Currents of healthy induction motor at no load condition

![](image2.png)

**Fig 4:** Currents of healthy induction motor at full load condition

**4.2. Broken rotor bars**

The induction motor under test has 32 rotor bars. To carry out the rotor broken bar test; two rotor bars are broken on both sides of end rings and stator current signals are captured at no load and full load conditions. The captured current signal of 3 phase induction motor with broken rotor bar fault in no load condition and full load condition is shown in figure 5 and figure 6 respectively.

![](image3.png)

**Fig 5:** Currents of induction motor with rotor bar fault at no load condition.

![](image4.png)

**Fig 6:** Currents of induction motor with rotor bar fault at full load condition.

**V. FEATURE EXTRACTION USING CEPSTRUM ANALYSIS**

Feature extraction is needed when amount of resources required to describe the data is large. When performing analysis of complex data one of the major problems is number of variable involved. Analysis with a large number of variables generally requires a large amount of memory and computation power. In this paper the different cepstrum analysis is used such as complex cepstrum and real cepstrum. There are observable differences among real cepstrum plots of healthy and faulty motor conditions. Therefore real cepstrum is used for feature extraction. Fig 7 and fig 8 shows real cepstrum of stator current signal for healthy motor and motor with broken rotor bar fault respectively.

![](image5.png)

**Fig 7:** Real cepstrum of healthy motor

![](image6.png)

**Fig 8:** Real cepstrum of motor with rotor bar fault
Certain observations are made from fig 7 and fig 8, for healthy motor and for motor with broken rotor bar fault the cepstrum for current ia and ib shows no variation but for phase c, cepstrum of current ic gives some differentiating feature about healthy and faulty motor condition. Therefore cepstrum for current ic is used for feature extraction. Features like mean, variance and standard deviation of current signal are extracted. The mean is simply the average value of a signal, that means add all the samples together and divide it by number of samples. Standard deviation is a measure of how far the signal fluctuates from the mean and variance represent power of this fluctuation. These parameters can be used to describe the statistical characteristics of a signal. For current ia, ib and ic, the values of these coefficients are computed. The total nine values of mean, variance and standard deviation for current ia, ib and ic are taken and are fed as an input to the ANN for detecting broken rotorbar fault.

VI. RESULT AND DISCUSSION

An ANN with its excellent pattern recognition capabilities can be effectively used for the fault classification of three phase induction motor. In this paper 3 layers fully connected FFANN is used and trained with supervised learning algorithm called back propagation. It consists of one input layer, one hidden layer and one output layer. The values of mean, variance and standard deviation of current signal are fed as an input to neural network. ANN with transfer function Tansigmoid, training method Levenberg Marquardt is used having momentum-0.700, step size - 1.00000 and maximum epochs are 1200 iterations are used to train that network. The training percentage is 50% and testing percentage is 50 % for this the number of processing elements in hidden layers are varied and performance of the network is evaluated. Table 1 and fig 9 shows variation of number of PE with percentage accuracy

<table>
<thead>
<tr>
<th>Number of PE’s</th>
<th>Percentage Accuracy</th>
</tr>
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<tbody>
<tr>
<td>Healthy</td>
<td>Faulty</td>
</tr>
<tr>
<td>1</td>
<td>95</td>
</tr>
<tr>
<td>2</td>
<td>98</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
</tr>
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It is seen that the Tansigmoid transfer function with three processing elements is capable of classifying induction motor broken rotor bar fault with 100% accuracy.

CONCLUSION

This work proposes a real cepstrum-based ANN approach for broken rotor bar fault detection in an induction motor. Real cepstrum analysis is utilized to extract the features like mean, variance and standard deviation that derive rich information from stator current signals and are fed as an input to ANN. Feedforward ANN with the momentum learning rule and Tansigmoid transfer function and with three processing elements is the best network to detect broken rotor bar fault in an induction motor with 100% accuracy.

REFERENCES


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