Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 12, No. 2, December : 2023

INDUCTION MOTOR FAULT DIAGNOSIS USING CEPSTRUM ANALYSIS AND NEURAL NETWORK TECHNIQUE

Prof. Nutan S. Moghe, **Prof. Priti A. Bhange**, **Prof. Chetan R. Bhale**,
Assistant Professor, Electrical Engineering Department, Govindrao Wanjari College of Engineering & Technology, Nagpur
Prof. Ashwini V. Waghale, Assistant Professor, Electronics & Tele.Engg. Department, Govindrao Wanjari College of Engineering & Technology, Nagpur

Abstract
Due to their numerous moving parts, induction motors can develop catastrophic defects that shut down production, injure people, and waste raw materials. Therefore, in order to prevent any kind of system failure, it is crucial to stop the defective conditions at their beginning. This paper addresses the induction motor's rotor bar fault. About 10% of all induction motor failures have the potential to be rotor bar faults, which are brought on by the rotor winding. An induction motor's condition monitoring and fault diagnosis are crucial on the production line. By enabling the early diagnosis of faults, it can lower the risk of unexpected failures and the cost of maintenance. This work presents experimental findings for malfunctioning. This paper reports on experimental findings for the use of an artificial neural network-based technique and cepstrum analysis for the detection of broken rotor bar faults in induction motors. It has been discovered that an effective method for diagnosing induction motor faults is the combination of cepstrum and neural network analysis. For the rotor bar defect, a feedforward neural network was employed, with fault features retrieved through the use of cepstrum analysis**.**
Keywords: Artificial neural network, rotor bar fault, induction motor, and cepstrum analysis

1. INTRODUCTION
Induction Motors are easy to install, control, simple, robust, dependable, affordable, and suitable for a wide range of industrial applications. The primary causes of rotor problems, mostly broken rotor bars, are pulsating loads and direct on-line starting. It causes arcing, vibration, overheating, torque pulsation, and damage to laminations. It also causes inconsistent speed. Faults are caused by electrical and mechanical strains; overloads and sudden changes in load result in mechanical stress, which causes rotor bar and bearing failures. Thermal stresses, residual stresses, dynamic stressors, environmental stresses, and magnetic stresses are the other reasons. The rotor bar fault severity and sideband amplitude have been found to be directly proportional, despite the sideband amplitudes being sensitive to motor loads. Because the rotor currents are so low in these circumstances, the broken sidebands of the motor bar remain undetected even at light loads or in the absence of any loads at all. Even if we assume a full load condition, there is still a chance that an entirely or partially broken rotor bar, which can cause anything from a minor to a catastrophic failure, will go unnoticed.
A robust condition monitoring method must be developed in order to address these problems. Machine fault diagnosis is the main problem with machine condition monitoring. A diagnosis is an assessment of the motor's current "health" or operational state. In addition to lowering the possibility of unplanned machine breakdowns, a trustworthy diagnosis method also contributes to the machine's lifespan extension. This has led to the industry's current trend toward condition-based preventive maintenance. The potential for false indications resulting from errors and uncertainties in fault classification drives researchers to develop a more robust and trustworthy A robust condition monitoring method must be developed in order to address these problems. Machine fault diagnosis is the main problem with machine condition monitoring. A diagnosis is an assessment of the motor's current "health" or operational state. In addition to lowering the possibility of unplanned machine breakdowns, a trustworthy diagnosis method also contributes to the machine's lifespan extension.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 12, No. 2, December : 2023

This has led to the industry's current trend toward condition-based preventive maintenance. The potential for false indications resulting from errors and uncertainties in fault classification drives researchers to develop a more robust and trustworthy condition-monitoring system. For the problem of an induction motor's broken rotor bar, various approaches based on artificial neural networks and CEPSTRAM analysis have been put forth. The majority of induction motor condition monitoring and fault diagnosis techniques rely on artificial neural networks and cepstrum analysis (M. Aladesaye, 2008 and W.A.F. Justine, 1996). A phenomenological model has been developed by Barrios (1997), Gallardo (1996), and González (1998) to replicate broken bars in an induction motor's rotor. The cepstrum provides additional information about the sidebands connected to a broken rotor bar fault in an induction motor (B. Liang, S.D. Iwnicki, Y. Zhao 2013). As long as the motor is under a specific amount of load, broken rotor bar faults can be detected by both vibration and stator current spectra. However, compared to the vibration power spectrum, the stator current spectrum shows marginally better performance. (Kinitsky, M.A., Rotondale, N., and Tassoni, C., 1994).

According to W.A.F. Justine (1996), neural networks are very helpful for fault identification and classification because they can represent complex non-linear relationships. Fuzzy logic and neural network-based expert systems have been used in conjunction with the advancement of Artificial Intelligence (AI) systems to help with fault detection tasks involving the accurate interpretation of faulty data (Filippetti, Franceschini, Tassoni, & Vas, 2004; Tung, Yang, Oh, & Tan, 2009; Yang, Han, & Sukin, 2004). In summary, there are numerous methods available for diagnosing particular induction motor problems; however, cepstrum analysis is a useful instrument that can be employed to identify periodicity in a spectrum and an appropriate technique for identifying a broken rotor bar fault.

An examination of neural network analysis and cepstrum for the diagnosis of induction motor faults is presented in this paper. The results show that the suggested technique is appropriate for 100% accurate broken rotor bar fault detection in an induction motor.

2. CEPSTRUM ANALYSIS

The Fourier transform of the logarithm of a signal's Fourier transform is known as a cepstrum. The word "spectrum" was given its name cepstrum by flipping its first four letters. Cepstrum provides data on the rate of change in various spectrum bands. It is used to convert signals combined by convolution into the sum of their cepstra for linear separation. There are several varieties of cepstrum, including real, phase, complex, and power varieties. The complex cepstrum, also known as the spectrum of a spectrum, is defined as the inverse Fourier transform of the logarithm of the Fourier transform of a signal. Whereas Real cepstrum uses the logarithm function to define real values, Complex cepstrum uses the complex logarithm function to define complex values. While the real cepstrum only provides information on the spectrum's magnitude, the complex cepstrum provides information on the initial spectrum's phase and magnitude.

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

The real Cepstrum of a signal x(n):

$$c(n) = \frac{1}{2\Pi}\int_{-\Pi}^{\Pi} \log X|e^{j\omega}|e^{j\omega n}\, d\omega \ \ldots\ldots (1)$$

The complex Cepstrum of a signal x(n):

$$c(n) = \frac{1}{2\Pi}\int_{-\Pi}^{\Pi} log X[(\omega)]e^{j\omega n} d\omega \ldots.. (2)$$

The power Cepstrum of a signal x(n):

$$c(t)^2 = \frac{1}{2\Pi}\left|\int_{-\Pi}^{\Pi} log\right| X(\omega)|e^{j\omega n} d\omega|^2 \ldots.. (3)$$

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 12, No. 2, December : 2023

3. NEURAL NETWORK CLASSIFIER

A neural network (ANN) is a representation of an information processing system made up of networked simple processing units, or neurons. Every neuron functions as a separate processing unit and uses an activation function to change the input data. The weight values that characterize the connections among neurons indicate the network's memory. The ANN can be trained to identify any pattern given the training data by adjusting these weights in accordance with a learning rule. An ANN's performance is greatly influenced by its network architecture, which typically varies depending on the issue at hand. The multilayer perceptron, which is employed in this study, is the most widely used neural network structure for diagnosis purposes among those that have been proposed in the literature (Filippetti et al., 2004; Tung et al., 2009). This straightforwardly designed network could be put to use. From the input layer to the output layer, all of the layers are fully connected. The number of inputs and outputs of the pattern that needs to be recognized determines how many neurons are present in the input and output layers. However, based on the applications, the number of neurons in the middle layer can be chosen. The network is exposed to input patterns, and its output is compared to the target values to determine the error. This is then adjusted by changing the weights in the subsequent pass. A three-layer feedforward neural network is chosen in the proposed work to diagnose rotor bar faults in induction motors.

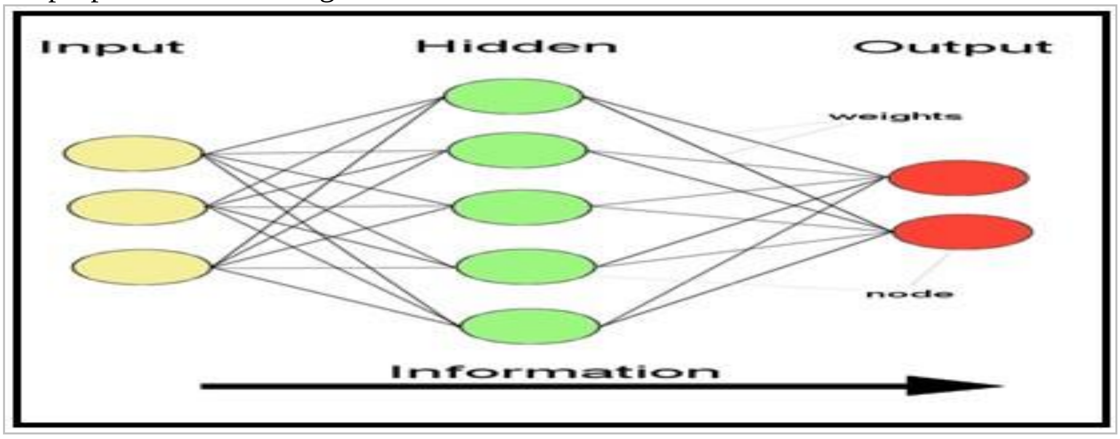

Fig. 1: ANN architecture

It has been demonstrated that a three-layer feedforward network can approximate any function, no matter how complex. The architecture of a feedforward neural network is depicted in Figure 1.

4. EXPERIMENTAL STUDY

A 2 HP, 3 phase, 50 Hz, 415 V, 1350 rpm, and 3.6 amp star connected squirrel cage induction motor makes up the experimental setup. The induction motor is connected to a four-pole, 230-volt DC generator with a 9.6-amp current rating. Resistive load banks are utilized for the generator loading process. From no load to full load, the induction motor is loaded. The experiment's motor has 24 coils totaling 36 slots. With the aid of ADLINK DAQ, the voltage and current signals are recorded at a sampling frequency of 1 KHz. Various experiments, including one with a broken rotorbar fault, are conducted on laboratory test benches in both healthy and defective conditions. ADLINK DAQ is used to help collect the data. There are ten input and ten output ports on the ADLINK DAQ. The maximum voltage rating for each port is 10 volts. The experimental setup is displayed in Fig. 2.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 12, No. 2, December : 2023

Figure 2. Experimental Set-up

Finding the current signals in both healthy and faulty conditions is the aim of experimentation. Different loading conditions are taken into account, such as no load and full load.

4.1. Healthy Condition

A three-phase balanced supply is used to feed a 2 HP motor. The motor's load varies from zero to maximum. Figures 3 and 4 display the current signals of a healthy induction motor when it is not loaded and when it is fully loaded, respectively.

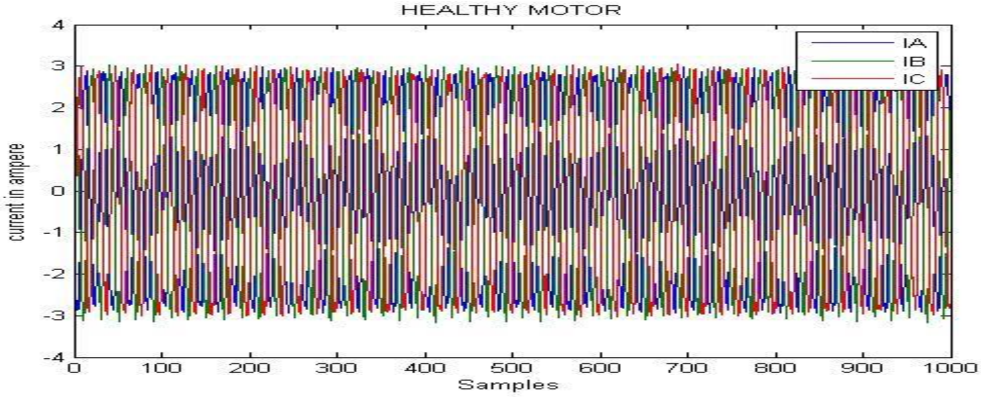

Fig 3: currents of healthy induction motor at no load condition

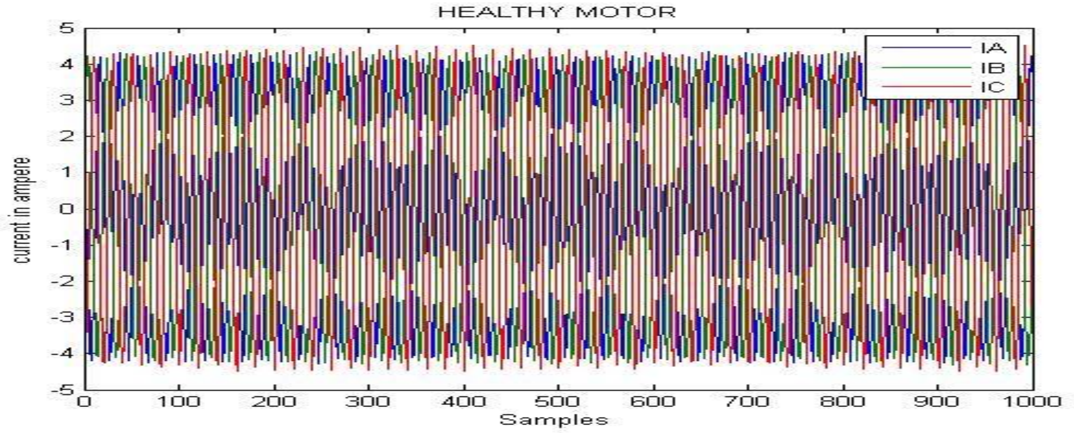

Fig 4: currents of healthy induction motor at full load condition

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 12, No. 2, December : 2023

4.2. Broken rotor bars

There are 32 rotor bars on the induction motor being tested. Two rotor bars are broken on both sides of the end rings to perform the rotor broken bar test. At both no load and full load, stator current signals are recorded. Figures 5 and 6 depict the captured current signal of a three-phase induction motor with a broken rotor bar fault under no load and under full load, respectively.

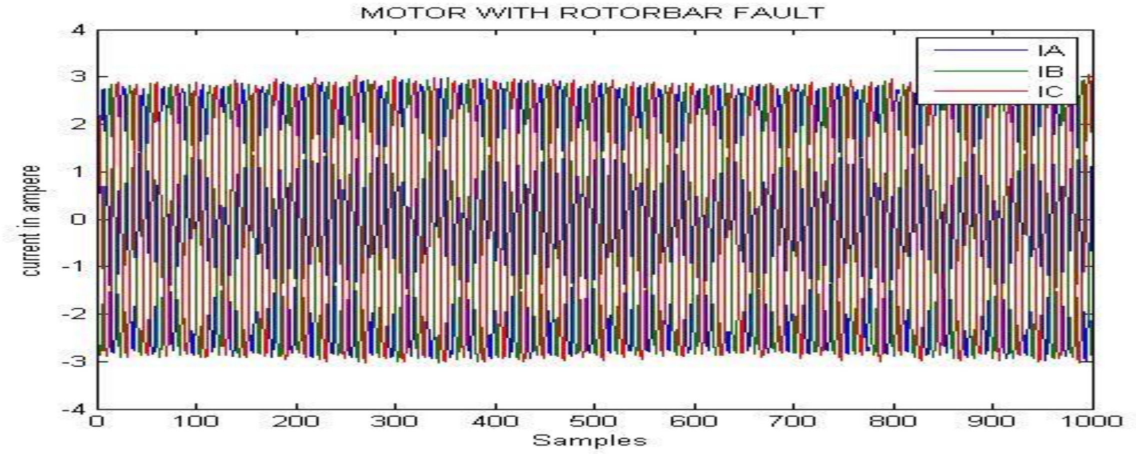

Fig 5: currents of induction motor with rotor bar fault at no load condition.

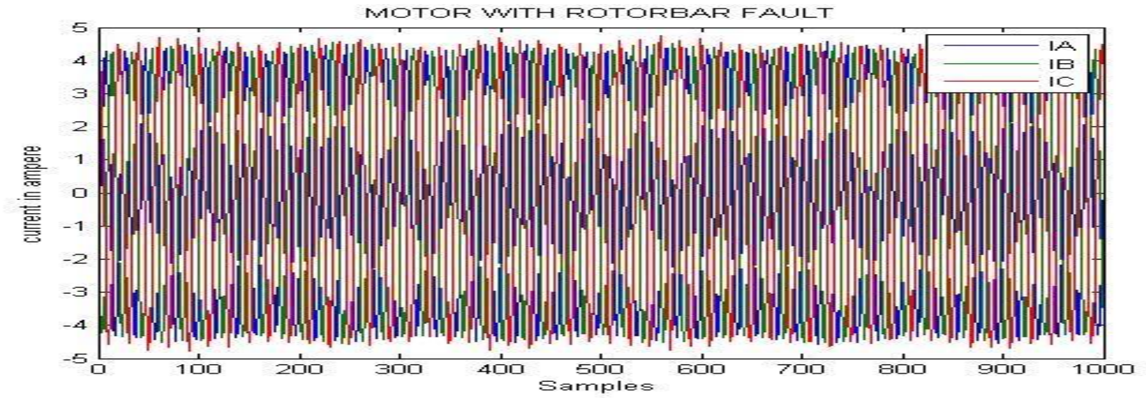

Fig 6: currents of induction motor with rotor bar fault at full load condition.

5. FEATURE EXTRACTION USING CEPSTRUM ANALYSIS

When a significant number of resources are needed to describe the data, feature extraction becomes necessary. One of the main issues with analyzing complex data is the sheer number of variables involved. Large amounts of memory and processing power are typically needed for analyses involving many variables. This paper employs various cepstrum analyses, including real and complex cepstrum. Real cepstrum plots of both healthy and dysfunctional motor conditions differ noticeably. As a result, feature extraction uses real cepstrum. Real stator current signal curves for motors in good condition and those with a broken rotor bar fault are displayed in Figures 7 and 8, respectively.

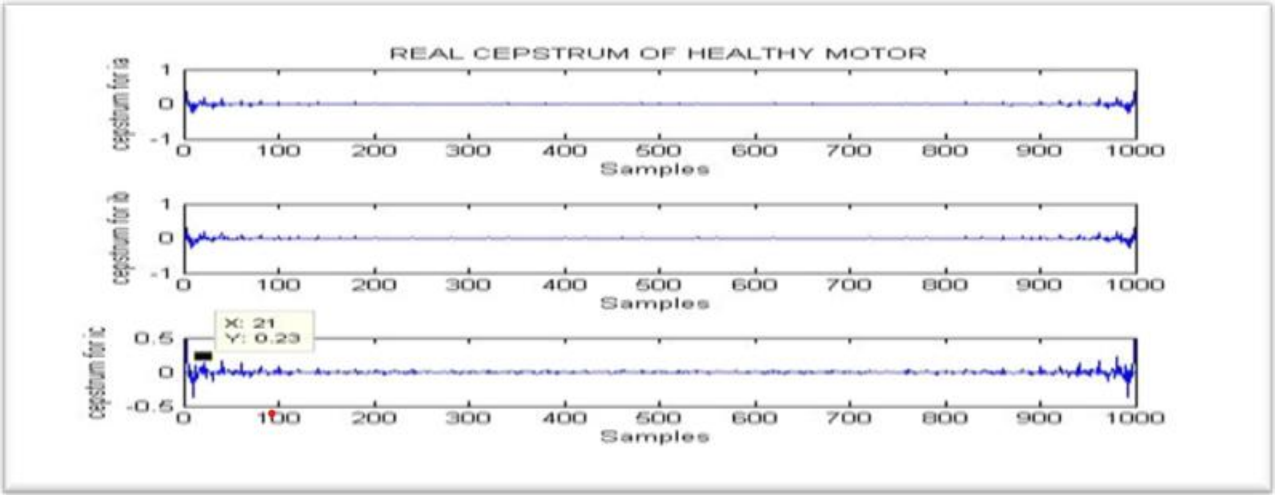

Fig 7: Real cepstrum of healthy motor

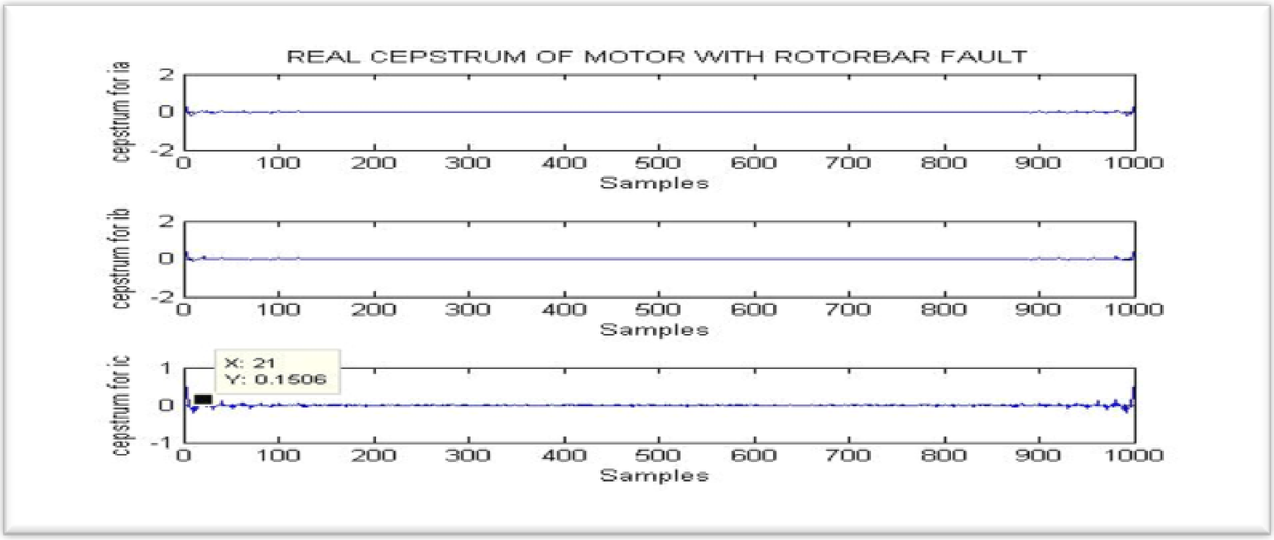

Fig 8: Real Cepstrum of motor with Rotor bar fault

A few observations are drawn from Figures 7 and 8. The cepstrum of current ia and ib for healthy motors and motors with broken rotor bar faults show no variation, but for Phase C, the cepstrum of current ic provides some distinguishing characteristics between the two types of motor conditions. As a result, feature extraction for current ic uses cepstrum.

The current signal's mean, variance, and standard deviation are extracted. A signal's mean can be defined as the sum of all of the samples divided by the total number of samples. The variance indicates the strength of this fluctuation, while the standard deviation measures how far the signal deviates from the mean. These parameters can be applied to characterize a signal's statistical properties. The values of these coefficients are computed for current ia, ib, and ic. To identify a broken rotorbar fault, the ANN receives nine total values for the mean, variance, and standard deviation for the current ia, ib, and ic.

6. RESULT AND DISCUSSION

A three-phase induction motor's fault classification can be efficiently handled by an artificial neural network (ANN) thanks to its superior pattern recognition skills. This paper uses a three-layer fully connected FFANN that is trained using the back propagation supervised learning algorithm. One input layer, one hidden layer, and one output layer make up this structure. The neural network receives the mean, variance, and standard deviation of the current signal as input. Transfer function-equipped ANN Tansigmoid as a training aid to train that network, Levenberg

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 12, No. 2, December : 2023

Marquardt is used, with momentum of 0.700, step size of 1.00000, and maximum epochs of 1200 iterations. In order to vary the number of processing elements in hidden layers and assess the network's performance, 50% is allocated to training and 50% to testing. Variation in the number of PE with percentage accuracy is shown in Table 1 and Figure 9

Table 1: variation of number of PE's and percentage Accuracy

Number of PE's	Percentage Accuracy of classification	
	Healthy	Faulty
1	95	100
2	98	100
3	100	100

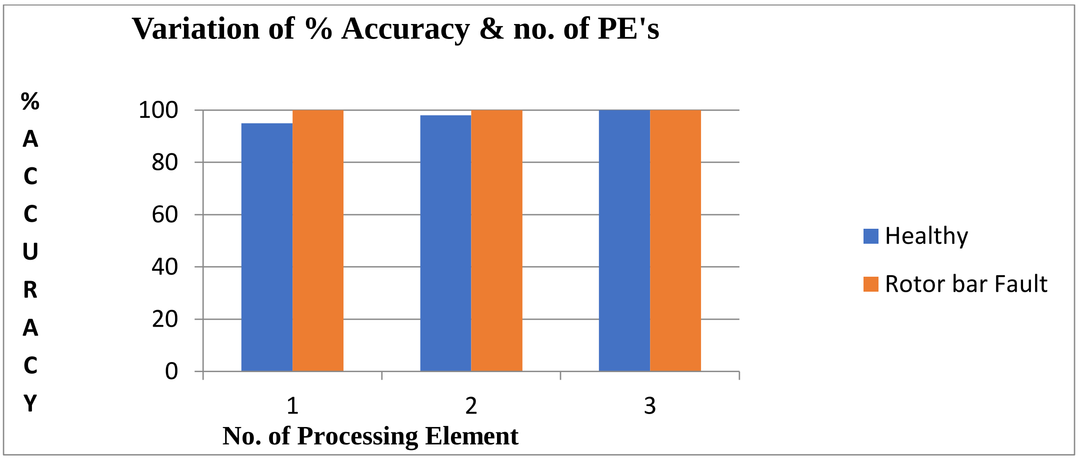

Fig. 9: Variation of number of PE's and percentage Accuracy

With three processing elements, the Tansigmoid transfer function is able to classify induction motor broken rotor bar faults with 100% accuracy.

7. Conclusion

This work suggests an actual cepstrum-based artificial neural network (ANN) method for detecting broken rotor bar faults in induction motors. The features that extract rich information from stator current signals and feed it to an artificial neural network (ANN) are extracted using real cepstrum analysis. These features include mean, variance, and standard deviation. The best network for 100% accurate detection of a broken rotor bar fault in an induction motor is a feedforward artificial neural network (ANN) with three processing elements, the momentum learning rule, and a Tansigmoid transfer function.

8. REFERENCES

[1] Barrios, A. (1997). Diagnosis of incipient failures in induction machines based on multi-resolution analysis and time-frequency decomposition (Electrical Engineer Thesis). Department of Electrical Engineering, University of Chile, Santiago (in Spanish).

[2] B. Liang, S.D. Iwnicki, Y.Zhao, Application of power spectrum, cepstrum,higher order spectrum and nueral network analysis for induction motor fault diagnosis.

[3] Filippetti, F., Franceschini, G., Tassoni, C.,& Vas,P.(2004),Recent development of induction motor drives fault diagnosis using AI techniques. IEEE transactions on Industrial Electronics, 47, 994-1004

[4] Gallardo, E. (1996). Diagnosis of the electromechanical state of induction motors based on acceleration tests (Electrical Engineer Thesis). Department of Electrical Engineering University of Chile Santiagi (in Spanish).

[5] González, D. (1998). Development of patterns for failure recognition in induction motors through recording of transient phenomena (Electrical Engineer Thesis). Department of Electrical Engineering, University of Chile, Santiago, Chile (in Spanish).
[6] M. Aladesaye, Application of Predictive Theory and Application, Ph.D. Thesis, Massey University, France, 2008
[7] V.A. Kinitsky, N. Rotondale, M. Martelli, C. Tassoni, Harmonic analysis of induction motors with stator faults, Electr. Mach. Power Syst. 22(Pt.B) (1994)
[8] W.A.F. Justine, Bispectral Analysis of speech signals, Ph.D. Thesis, The University of Manchester, 2000