

Artificial Intelligent Techniques In Real-Time Diagnosis Of Stator And Rotor Faults In Induction Machines

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ABSTRACT: This work involves the development of an artificial intelligent (AI) scheme in the detection of rotor and stator faults in induction machines. Using discrete wavelet transform technique to process the stator current signals measured from faulty motors with isolated cases of rotor and stator faults, the signals are then matched against known fault signatures for the types of fault. The statistical features of fault signals such as mean, Skewness etc. were then extracted and fed to an Artificial Neural Network (ANN) for training. Different ANN architectures were then compared in terms of their accuracy in classification. The network with the lowest mean squared error was then tested with separate data set and the results found to be satisfactory

1 INTRODUCTION/BACKGROUND OF STUDY

Three-phase induction machines also known as asynchronous machines are the most popular type of rotating electrical machines (Okan Ozgonenel et al., 2011) and widely used in many industrial processes such as automotive, manufacturing, mining, construction etc. Example is the squirrel cage type and has the advantage of being extremely rugged, requiring very low maintenance due to its construction mode. These attributes combined with its relatively low cost makes it an integral component in industrial processes (Jawadekar et al., 2011). Regardless of these advantages, the work by Bellini et al., 2008, illustrates that induction machines are subject to unexpected machine failures especially due to high stresses, which results in reduced productivity, increased production downtime, and damage of related machinery. Thus regular maintenance of the machine is scheduled in order to detect faults early before they result in catastrophic failures. There arise the need for reduction in costs associated with frequent scheduled maintenance while preventing excessive downtime due to machine failure.

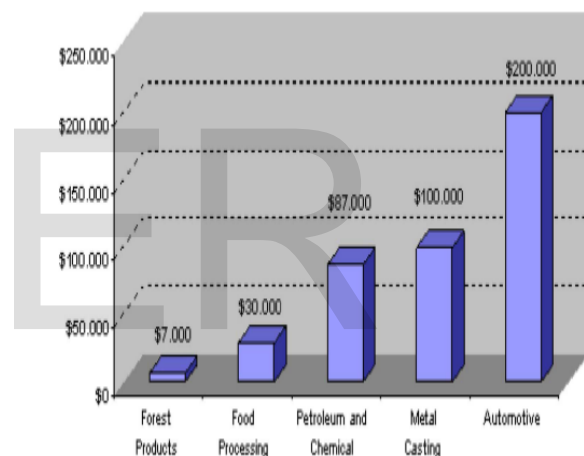


Figure 1.0 Average downtime costs for different industries due to faults (Grubic et al, 2009)

The major faults associated with three-phase induction machines are broadly classified into two (Pandey et al., 2012): Electrical and Mechanical faults. The electrical faults have two main divisions: Stator faults and Rotor faults

The mechanical faults are damaged bearing, Eccentricity, Misalignment and Bent shaft

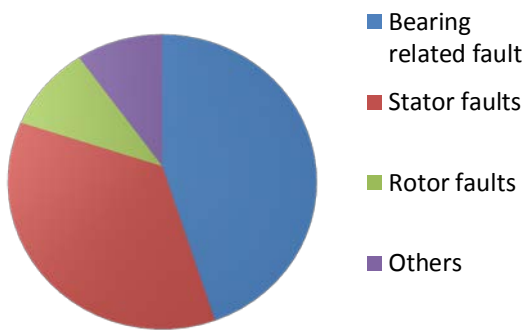


Figure 2.0: Distribution of faults in induction machines (Pandey *et al.*, 2012)

Signals such as motor stator current, voltage, vibration intensity, magnetic flux, temperature, torque etc, are affected by occurrence of faults inside the motor (Shehata *et al.*, 2013), thus resulting in continuous monitoring of these signals to aid in the identification of faults at an early stage. Non-invasive condition monitoring such as with the electrical signals makes monitoring process economical because there is availability of low-cost sensors that can carry out the measurement of these signals (Aroui *et al.*, 2009). Various techniques exist for the diagnosis of faults. These techniques include model-based, signal-based and data-based techniques. Artificial intelligent (AI) techniques which falls in the class of data-based techniques is gradually becoming the de-facto method in the decision or classification stage of fault diagnosis (Aroui *et al.*, 2007) because of their advantages over traditional model-based techniques as the later require detailed modelling of the behaviour of machine under faulty conditions. AI techniques are more reliable and efficient decision method and have been used in diagnosis. These include Artificial Neural Networks (ANN), Genetic Algorithms (GA), Fuzzy Logic (FL) and Expert systems (ES). Hybrid techniques also exist which combines different AI schemes to increase the overall effectiveness and efficiency of the diagnostic system. No single AI-based diagnostic scheme has been able to effectively diagnose all induction machine faults (Bellini *et al.*, 2008). Little progress has been made to achieve extensive fault classification as well as evaluation of fault severity from AI-based schemes. The range of faults that can be diagnosed using AI is limited by the technique employed. Extensive fault diagnosis implies further presentation of specific fault type and extent under a general fault classification. As an instance, the ability to diagnose bearing fault as being inner fault, outer fault or ball fault. ANNs are the dominant AI techniques used in the diagnosis of induction machine faults. Their high accuracy in fault diagnosis makes them preferred to their

fuzzy-logic counterpart. ANNs however require huge effort in the training stage. Convergence which is a measure of efficiency in the training stage depends on the kind of features employed in training the network. A simple algorithm that selects the best features based on a criterion is therefore needed. GAs were tested by Tian Han *et al.*, 2006, and used to select the best features from a general set to train the network. Owing to their complexity and relatively large computation time, they are often considered less of a solution. This paper aim to present an AI-based fault diagnostic scheme to diagnose a wide range of induction motor faults with reduced computation time and complexity. This will involve selecting the best fault distinguishing features, implementation of discrete wavelength transform on the motor stator current signals, utilization of algorithms to implement feature extraction and selection using MATLAB, Design and training of various NN architectures to implement fault classification based on decision making and finally training, cross-validation testing of the proposed AI diagnostic technique to obtain the best performance. This paper will find vast use in optimization of fault diagnosis in production industries as its reliance on non-invasive techniques which results in reduced cost of condition monitoring become advantageous.

2.1 REVIEW OF FAULTS IN INDUCTION MACHINE

According to (Ozgonenel and Yalcin, 2011), bearing failures accounts for more than 40% of all induction machine failures. Contaminants and corrosives are found to accelerate bearing based failures (Onel *et al.*, 2006) especially since induction machines are mostly used in harsh environmental conditions. Induction machines that are controlled by ac drives have higher tendency to fail (Pandey *et al.*, 2012). Bearing faults can generally be detected through vibration and current signals (Filipetti *et al.*, 2008), (Verucchi *et al.*, 2008). There are characteristic frequencies associated with various bearing defects (Benbouzid, 2008).

In the stator currents, frequencies generated are given by:

$$f_{bng} = |f_s \pm m f_{i,o}| \quad (1)$$

$f_{i,o}$ the characteristic vibration frequencies defined by

$$f_{i,o} = \frac{n}{2} f_r \left(1 \pm \frac{D_b}{D_p} \cos \beta \right) \quad (2)$$

$$F_i = \frac{N_B}{2} F_R \left(1 + \frac{D_b \cos \beta}{D_p} \right) \quad (3)$$

$$F_o = \frac{N_B}{2} F_R \left(1 - \frac{D_b \cos \beta}{D_p} \right) \quad (4)$$

$$F_B = \frac{D_p}{D_b} F_R \left[1 - \left(\frac{D_b \cos \beta}{D_c} \right)^2 \right] \quad (5)$$

$$F_c = \frac{1}{2} F_R \left(1 - \frac{D_b \cos \beta}{D_p} \right) \quad (6)$$

Where F_i is inner raceway fault frequency, F_o is outer raceway fault frequency, F_b is ball fault frequency, F_c is cage frequency. D_b is ball diameter, D_c is bitch diameter, β is ball contact angle, N_b is number of rolling elements, F_R is the shaft rotating frequency

2.2 STATOR FAULT

Frequency component in the current due to stator fault is given by

$$F_{short} = f_s \left[k \pm \frac{n}{p} (1 - s) \right] \quad (7)$$

Where $k = 1, 2, 3, \dots, s = \text{slip}$, $f_s = \text{supply frequency}$, $p = \text{number of pole pairs}$

Stator faults are found to account for 25 – 40% of all induction machines. (Clerc and lebaroud, 2008)(Han et al., 2006) and are generally classified into two categories (Ozgonenel and Yalcin, 2011). These include frame/lamination fault and Stator winding fault and occurs in various ways: Abnormal winding connections, phase to ground short circuit fault, phase to phase short circuit fault, turn to turn short circuit and open circuit fault (Lebaroud and Clerc, 2008):

2.3 ROTOR FAULTS

Rotor faults account for 5 – 10% of all induction machine faults. (Han, 2006).

$$f_{brb} = f_s \left[k \left(\frac{1-s}{p} \right) \pm s \right] \quad (8)$$

Where $f_s = \text{supply frequency}$, $p = \text{number of pole pairs}$, $s = \text{per unit slip}$, $k = 1, 2, 3, \dots$ (Bouchikhi et al, 2012). Stresses on the motor are the main reasons for rotor faults (Bhardwaj, 2012). For squirrel cage induction motors (Yeh, 2005), the two main types of faults are: Broken bar fault and cracked end-ring fault.

As with electrical based faults in induction motor, vibration and current measurement are the methods used in the detection of rotor faults. By investigating the sideband components around the fundamental frequency $f_b = (1 \pm 2s)f_s$

(9)

The lower sideband components are specifically due to broken bar

$$f_{lsb} = \left[\frac{k}{p} (1 - s) \pm (1 + 2n)s \right] f_s \quad (10)$$

$$\frac{k}{p} = 3, 5, 7, 9 \dots \quad n = 0, 1, 2, 3 \dots$$

From equation 10, frequency varies with the slip, which is dependent on the loading of the motor. Hence for accurate detection, the motor has to be sufficiently loaded unless the fault frequency components tend to overlap with the fundamental frequency component.

2.4 ANN

ANN mimic the human brain structure and consist of simple arithmetical units connected in complex architecture and are able to represent highly nonlinear functions and to perform multi-input multi-output (MIMO) mapping (Veelenturf, 1995). Figures 3.0 and 4.0

shows simplified configuration of an organic neuron and artificial model of a neuron respectively.

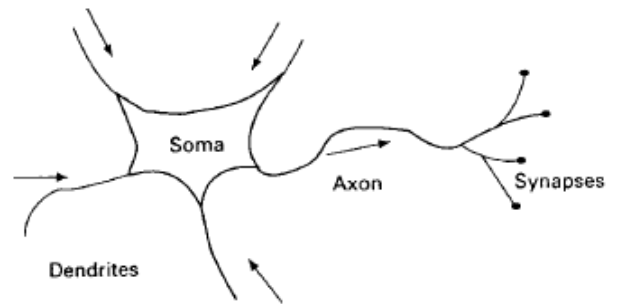


Fig 3.0 Simplified Configuration of an organic neuron (Veelenturf, 1995)

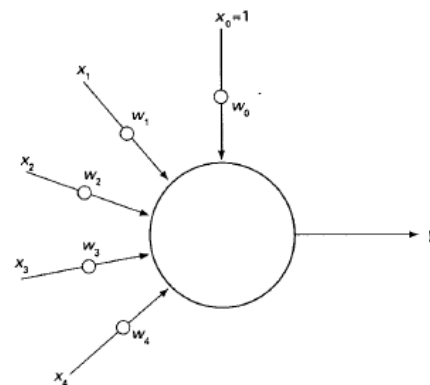


Fig 4.0 Artificial model of a neuron (Veelenturf, 1995)

Through advancement in electronics and computing, NNs are being used in industrial applications (Jain and Martin, 1998) such as pattern recognition, language translation, gaming, transportation, intelligent automated process systems etc. figure 5.0 shows elementary neuron with R inputs and weight w.

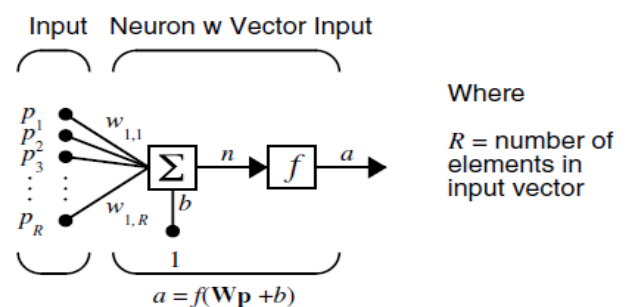


Fig 5.0 elementary neuron with R inputs and weights w (Demuth, 2009)

$$a = \sum_{i=1}^R w_{1i} p_i + b$$

(11)

Where p_i represents an input node, w_{1i} denotes the weights of the connections, b is the bias or offset. $\sum_{i=1}^R w_{1i} p_i$ gives the sum of all scalar products between each input and the weighted value or strength of the connection. NN available models are Feed Forward NN, Recurrent NN, Self-Organising Maps, Radial Basis Function NN and Elman Networks.

NNs learn by updating the weights of the connections and its most popular learning algorithm is back

propagation model (Aroui et al, 2007). In this model, the weights are adjusted by the formula

$$w_{ij}^{k+1} = w_{ij}^k + \Delta w_{ij}^k \quad (12)$$

Where $\Delta w_{ij}^k = \tau \delta_j y_j + \alpha \Delta w_{ij}^{k-1}$, and τ is known as the learning rate, α is known as the momentum term.

2.5 WAVELET TRANSFORM

The wavelet transform is used in the analysis of a signal in the time and frequency domain simultaneously, making it a very important signal processing technique as it can be used in the analysis of time varying signals (Addison, 2002). Wavelets are little waves of short duration with finite energy and decay quickly in time.

3.0 METHODOLOGY

This section gives detailed procedures taken in order to implement AI scheme for diagnosis of faults in induction machines. The project methodology is effectively summarized by the block diagram as shown in figure 1.0

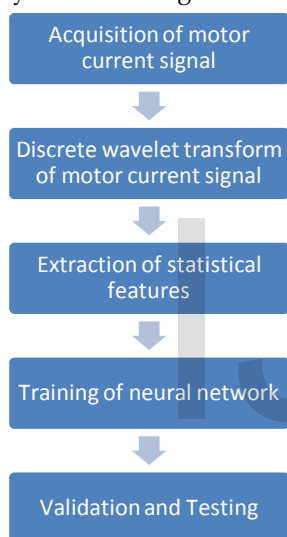


Figure 6.0 Process block

diagram

3.1 ACQUISITION OF MOTOR CURRENT SIGNAL

The first stage involve acquiring current samples from healthy motors and motors with stator and rotor faults. These current data is used as input in the signal processing stage. The healthy and faulty motor current samples used in this study were obtained from experimental results of Fang Duan, 2006. Tables 1.0 and 2.0 shows motor parameters used for both stator and rotor fault analysis.

Table 1.0 Motor parameters used in rotor fault analysis

MOTOR DATA	
Active Power(KW)	0.8
Nominal voltage(V)	380
Rotor speed(rpm)	1400
Nominal current(A)	2.2
Number of rotor bars	22
Power factor	0.74

Table 2.0 Motor parameters used in stator fault analysis

MOTOR DATA	
Active Power(KW)	2.2
Nominal voltage(V)	380-420
Rotor speed(rpm)	1430
Nominal current(A)	4.9
Nominal frequency(Hz)	50
Power factor	0.81

Rotor and stator current samples were acquired using a current transformer connected to a data acquisition board for interfacing with the computer. The stator current for rotor fault analysis was captured at a frequency 5 KHz for 0.8sec at different loading conditions – 80% to 120% full load current equivalent. Stator current was captured at 1 KHz at different loading conditions.

3.2 DISCRETE WAVELET TRANSFORM OF MOTOR CURRENT SIGNALS

Wavelet analysis is implemented using the wavelet toolbox menu on MATLAB. The number of detail levels required to obtain the desired frequency range is given by the formula below

$$L = \frac{\log\left(\frac{f_s}{f}\right)}{\log 2} + 1 \quad (13)$$

Where f_s = the sampling frequency of the signal, f = supply frequency

$$L_{rotor} = \frac{\log\left(\frac{5000}{50}\right)}{\log 2} + 1 = 5 \text{ levels}$$

$$L_{stator} = \frac{\log\left(\frac{1000}{50}\right)}{\log 2} + 1 = 8 \text{ levels}$$

Frequencies bands of sub-band designations at various stator and rotor level analysis is shown in table 3.0 while Figure 7.0 AND 8.0 gives waveform result obtained upon decomposition of signal for stator and rotor fault analysis respectively in matlab environment.

Table 3.0: Showing frequency sub-band designations

Levels (Stator Analysis)	Frequency sub-bands	Levels (Rotor Analysis)	Frequency sub-bands
d_1	[500.0 – 1000.0]	d_1	[2500.0 – 5000]
d_2	[250.0 – 500.0]	d_2	[1250.0 – 2500]
d_3	[125.0 – 250.0]	d_3	[625.0 – 1250.0]
d_4	[64.5 – 125.0]	d_4	[312.5 – 625.0]
d_5	[32.25 – 64.25]	d_5	[125.25 – 312.5]
a_5	[0 – 32.25]	d_6	[78.13 – 125.25]
		d_7	[39.06 – 78.13]
		a_7	[0 – 39.0625]

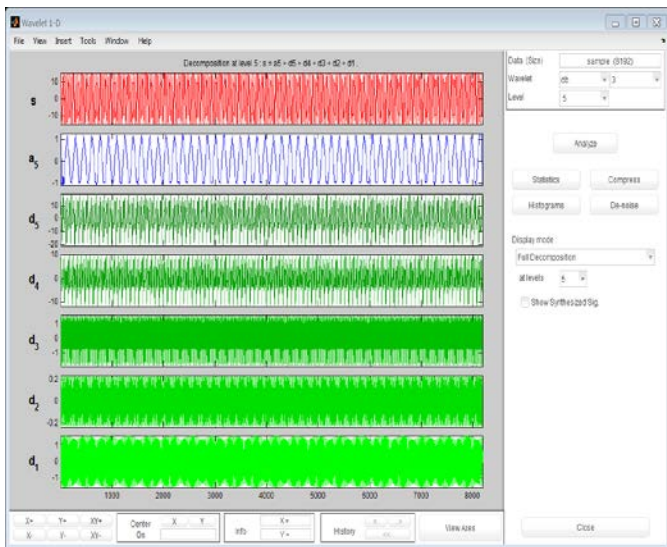


Figure 7.0 decomposition of signal for stator fault analysis

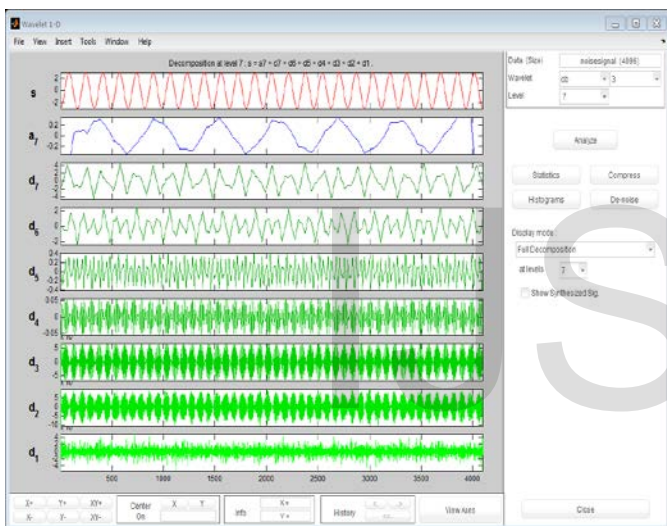


Figure 8.0 wavelet decomposition of the signal for rotor fault analysis

For the rotor fault analysis, as seen in fig 8.0, the debaunche-3 mother wavelet function is used to decompose the current signals into 7 levels. As the dominant frequencies is indicative that the rotor fault lies at detail level 7. For the stator fault analysis, as seen in fig 7.0, db3 mother wavelet is also used to decompose the current signal but into 5 level as the current was sampled at 1000 Hz, hence the dominant fault frequencies lies at detail level 5. Figs 3.2 and 3.3 illustrates the filtering operation of the wavelet transform

3.3 EXTRACTION OF STATISTICAL FEATURES

At the final stage of signal processing, statistical features of current signal are extracted. and used as input to the NN for training in order to classify various signals based on the degree of similarity or disparity of these features. Each type of fault produces a signal with a signature pattern that are reflected in the features of the signal such as mean, standard deviation etc.

The statistical features utilized are

- Mean $= \frac{1}{N} \sum_{i=0}^N x_i = \bar{x}$
- Standard deviation $= \sqrt{\frac{1}{N} \sum_{i=0}^N \bar{x}_i^2 - \bar{x}^2}$
- Skewness $= \frac{1}{N} \sum_{i=0}^N x_i^3 - \frac{3}{N} \bar{x} (\sum_{i=0}^N x_i^2) + 2\bar{x}^3$
- Kurtosis $= \frac{1}{N} \sum_{i=0}^N x_i^4 - \frac{3}{N^2} (\sum_{i=0}^N x_i^2)^2 - \frac{4}{N} \bar{x} (\sum_{i=0}^N x_i^2) + \frac{12}{N} \bar{x}^2 (\sum_{i=0}^N x_i^2) - 6\bar{x}^4$
- Shape factor $= \frac{\sum_{i=0}^N x_i^2}{\sum_{i=0}^N |x_i|}$
- Crest factor $= \frac{x_{peak}}{\frac{1}{N} \sum_{i=0}^N x_i^2}$
- Root mean square $= \sqrt{\frac{1}{N} \sum_{i=0}^N x_i^2}$

A script was written to carry out the statistical analysis .These features were extracted from the highest detail level of the wavelet decomposition.

3.4 DATA PREPROCESSING

In order to improve the NN performance, the input data is preprocessed and properly scaled before feeding it to the NN. The normalization process was carried out to restrict the range of statistical features for input into the NN. In this work, the inputs are normalized between [-1, 1] using the inbuilt MATLAB command, $[xn \ xs] = \text{mapminmax}(\text{input})$

Where xn holds the new processed input variables, xs stores the processing settings

3.5 NN TRAINING

The size of the input training data set used is 43-by-8 matrix and target output data is 43-by-3 matrix whose outputs are binary in nature where a vector output of [1; 0; 0] =healthy motor condition, [0; 1; 0] = presence of broken rotor bar, [0; 0; 1] =presence of stator short circuit. The individual networks weights are initialized randomly using *initiw* command as shown in figure 9.0 and Figure 10.0 is the network sample view

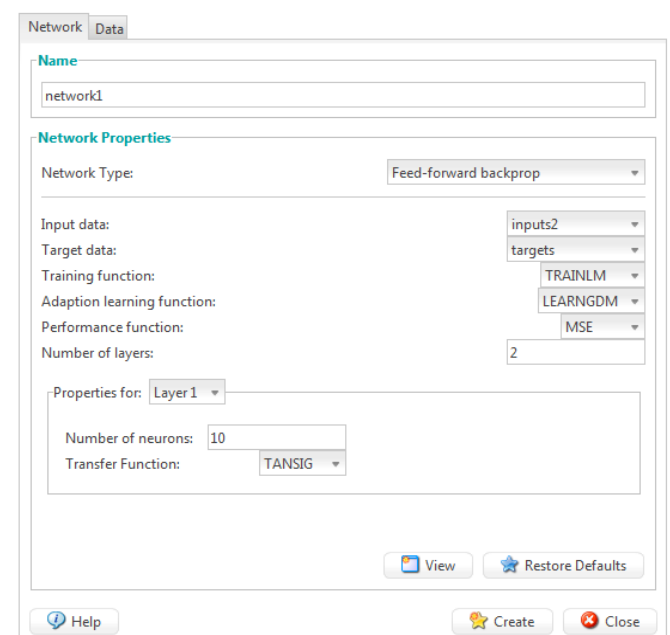


Figure 9.0 NN creation

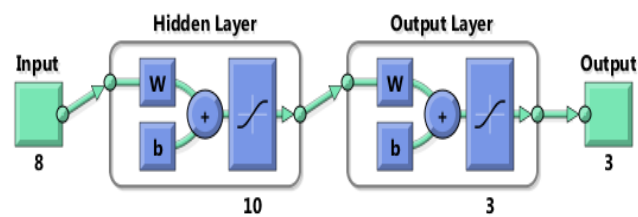


Figure 10.0 Sample View of the Network

4.0 Results and Discussion

The networks investigated include Feed forward, Cascade feed forward, ELMAN and Layer recurrent networks. Each of these networks were trained with the same data set and plot of confusion matrix and mean square error for the training, validation and test stages were obtained. The architecture with the best performance was then chosen. The training functions investigated were Levenberg-Marquardt, Scaled conjugate gradient, Residual propagation and Gradient decent functions. For the selected network, training was done with the same data set with the training function varied after each training process and plots of confusion matrix and mean squared error were obtained in order to pick the training function with the best performance. NN with 10 hidden layer neurons was used after considering the size of data set, number of input features and number of output expected outputs. The training is followed by validation and testing stage. The available data set therefore has to be partitioned accordingly so a certain percentage is allotted to each of these stages. This was achieved by using the MATLAB commands; *net.divideParam.trainRatio* = 70%; ratio of data sets for training, *net.divideParam.valRatio* = 15%; ratio of data sets for validation, *net.divideParam.testRatio* = 15%; ratio of data sets.

The performance plot consists of three graphs as shown in figures 11.0, 12.0 and 13.0 respectively.

- I. The performance plot for training stage
- II. The performance plot for the validation stage
- III. The performance plot for the testing stage

These three plots give a description of how the mean square error varies as network training progresses. The plot of interest is the performance plot, and a good test performance plot is one that constantly decreases with increasing number of epochs. The confusion matrix displays the number of correct and incorrect predictions made by the network compared with the actual classifications in the test data. Since the network has 3 possible output classes of confusion matrix, each row presents the number of actual classifications in the test data. Each column presents the number of predicted classifications made by the model

The confusion matrix plots and validates the performance plots obtained for each network is shown in Figures 11.0.

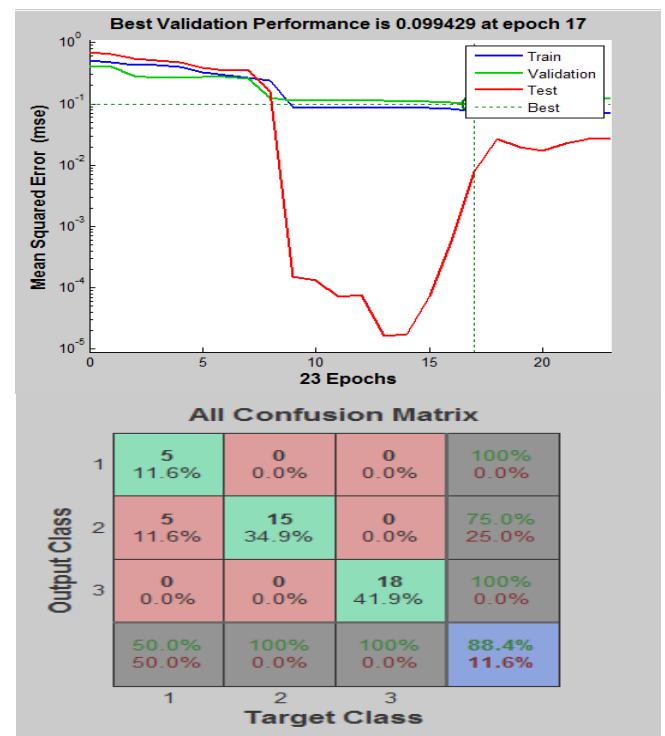


Figure 11 .0 Validation performance plot b) Confusion matrix plot for feed-forward network

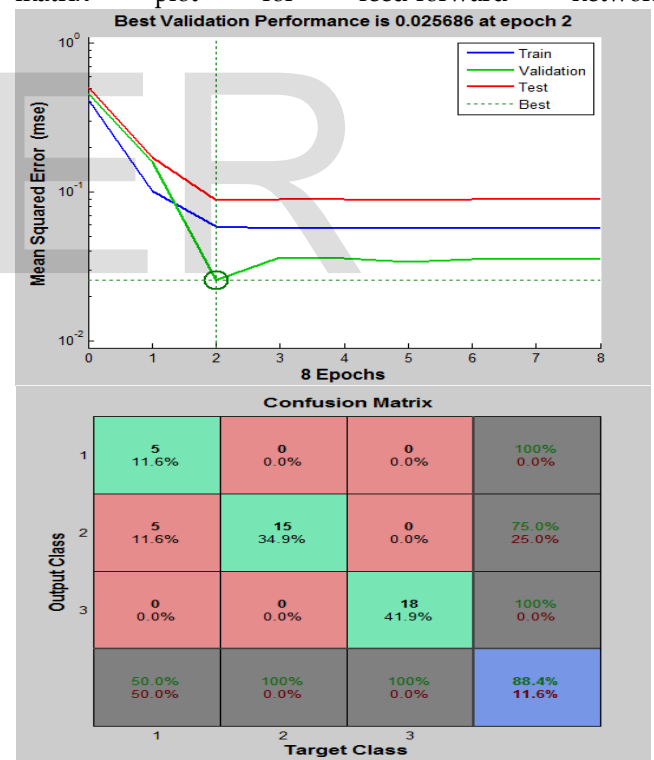


Figure 12 Validation performance plot b) Confusion matrix plot

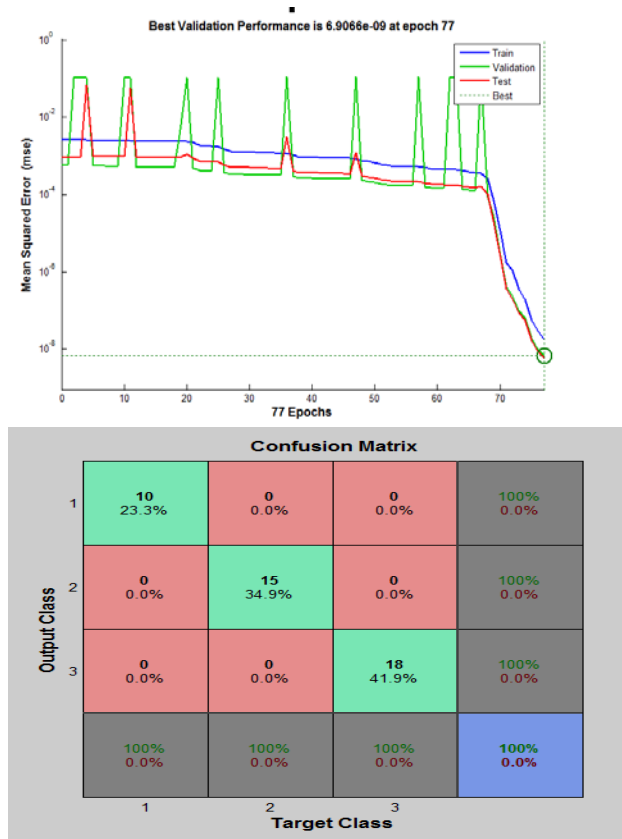


Figure 13.0 Validation b) Confusion matrix for elman

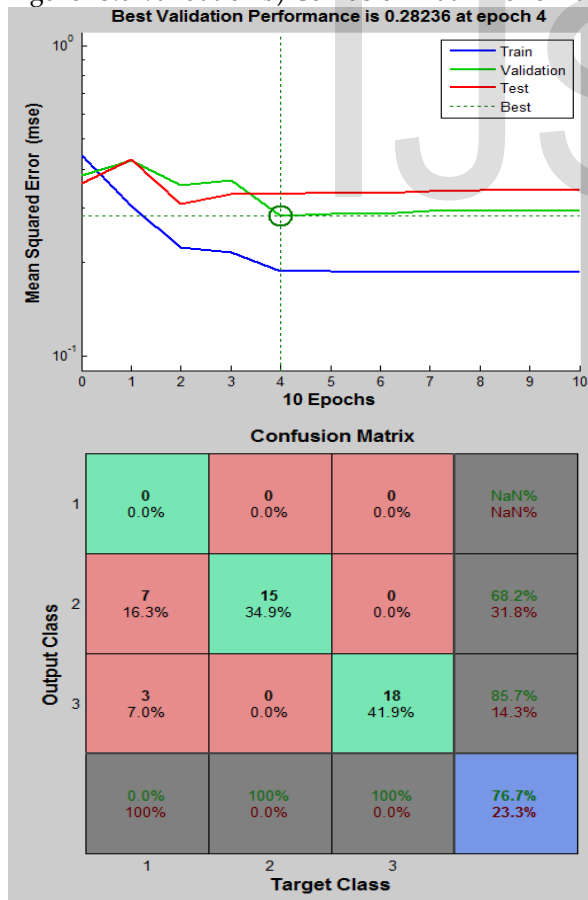


Figure 14 Validation b) Confusion matrix for layer recurrent

By comparison of figures 11.0 to 14.0 above, the confusion and performance plot both show that the elman network carried out the best training as it has the

highest accuracy as shown in its confusion matrix and least MSE in its test performance plot. Hence it becomes the preferred network.

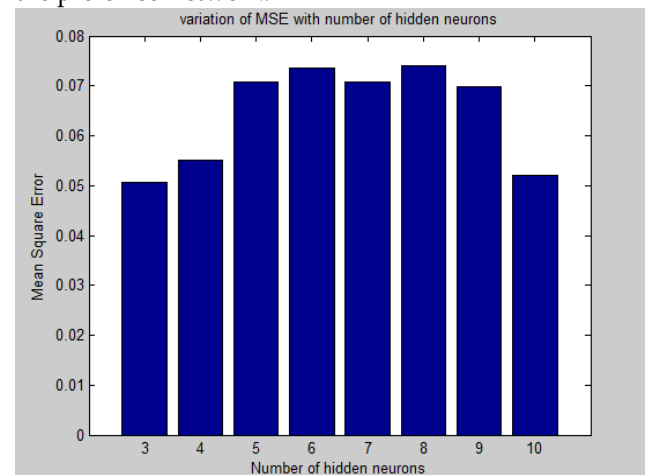


Figure 15.0 Variation of mean square error with number of hidden layer neurons

From figure 15.0, it is seen that the mean square error tends to increase as the number of hidden layer neurons increases, then later decreases until the number of hidden layer neurons is 10, after which the network begins to overfit the data and performance becomes poor on external data. From the analysis of the above results, on the basis of their performance training, the chosen NN topology is feed forward back propagation network with a single hidden layer and 10 hidden layer neurons. The network is then tested off-line with new current data from healthy samples, samples with shorted stator turns and also samples with a broken rotor bar fault.

The results from the test are given in the table 4.0

Table 4.0 Test Classification Results

Test Classification	Accuracy
Healthy	3/4
Stator fault	3/3
Rotor fault	3/3

As can be seen, application of NN is able to correctly classify both rotor and stator faults effectively, 3 out of 3 times in both cases and for healthy condition classification, the NN correctly classified it 3 out of 4 times

4.0 CONCLUSION AND RECOMMENDATION

This paper is relevant to a wide range of production industries such as manufacturing, beverage, chemical, pharmaceutical etc., where profitability depends directly on healthy working condition of induction machines employed. Application of NN helps these industries to detect incipient faults as they occur as early as possible, so as to ensure that the use of the time allocated to preventive maintenance operations is fully optimized by replacing the induction machines before their total breakdown at unsuspecting times; hence preventing extra losses due to unscheduled downtime, though the extent

of fault diagnostic scheme was limited to just stator and rotor fault.

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