Monitoring and Detecting Health of a Single Phase Induction Motor Using Data Acquisition Interface (DAI) module with Artificial Neural Network

AINUL ANAM SHAHJAMAL KHAN[1], ADITTYA RANJAN CHOWDHURY[2], MD. SHAHRIAR HAQUE[3]
Department of Electrical and Electronic Engineering
Chittagong University of Engineering and Technology
Chittagong-4349
BANGLADESH
khanshahjamal@yahoo.com[1], adittya.cuet@gmail.com[2], shahriarhaque77@hotmail.com[3]

Abstract: - This paper deals with the problem of detection of induction motor incipient faults and usefulness of Artificial Neural Network (ANN) in this respect. The research work diagnoses the three major faults such as stator inter-turn faults, bearing faults and misalignment faults using some measurable parameters (motor intake current, speed and body temperature). The experimental data for three measurable parameters were generated in the laboratory on specially connected single phase induction motor. The measurable parameters were obtained by a Data Acquisition Interface (DAI) module and neural network algorithm was achieved by using MATLAB programming language. Experimental results show that it is a very good choice to detect incipient faults in single phase induction motor using an ANN algorithm.

Key-Words: - Monitoring, Detecting, Single phase induction motor, Data Acquisition Interface (DAI) module, Artificial Neural Network

1 Introduction

Single phase induction motors are most commonly used electrical machines because of their low cost, small size, ruggedness, low maintenance and operation with an easily available power supply. Although these are very consistent, they may be subjected to different modes of faults. It is necessary to observe whether the detected faults are inherent to the machine itself or electrical forces performing on the machine. If a fault is not detected early stage or it is approved to develop further it may lead to a failure. Condition monitoring is used for achieving good operation of machinery by reducing consequential damage and thus increasing machine lifetime. An efficient condition monitoring method is one that gives warning and predicts the faults at early stages [1], [2]. Monitoring system obtains information about the machine in the form of primary data. Through the use of modern signal processing techniques it is possible to give necessary diagnosis information to equipment operator before it disastrously fails. Several fault identification methods have been effectively applied to detect machine faults at early stages by using different machine variables. Among them artificial neural network has gained its popularity in the field of fault detection [3]. The neural network can present any non-linear model without knowledge of its genuine structure and can present result in a short time. This research work addresses the three major faults such as stator inter-turn fault, bearing fault and misalignment fault. Three measurable parameters such as current, speed and temperature were measured from Data Acquisition Interface (DAI) module and used as inputs in artificial neural network. All the parameters were measured in constant voltage and constant load.

2 Previous Works

Various schemes have been proposed for the detection of induction motor faults. Fillippetti has presented a comprehensive study of artificial intelligence in a machine monitoring and fault detecting [4]. Tan and Huo have recommended a generic neuro-fuzzy model approach for the detection of rotor broken bar faults in an induction motor [5]. Here, the data for training the neuro-fuzzy system to model the generic static torque-speed relationship of the class of induction motors was used in the realistic evaluation of the fault detector. Chow applied ANNs for the identification of incipient faults in single phase induction motor [6]-[10]. He detected stator winding faults and bearing wear using ANNs. The motor intake current and speed of motor were used as input parameters for the fault detection. Makarand, Zaffer, Hirallal and Ram used adaptive neural fuzzy interference system for the detection of inter-turn insulation faults and bearing wear faults in induction motor [11]. Abiyev has incorporated both fuzzy logic system with a wavelet neural network for identification and control of an uncertain system [12]. In his research, he used the gradient decent algorithm for weight updating. Bouzid has proposed a neural network approach for the detection of an inter-turn short circuit fault in the stator windings of an induction motor [13]. He used a feed forward multilayer perceptron neural network and it was trained by the back-propagation technique. Research has been made since long ago to detect faults that occur mostly in three phase induction motor. But this paper is concerned with single phase induction motor and an attempt is made in the present work to detect the faults in single phase induction motor using some measurable parameters externally without disintegrating the motor. Here, a multilayer feed forward network with Levenberg-Marquardt algorithm has been used as a tool for the fault diagnosis. The validity of using neural network for fault identification and easy detection of the condition of single phase induction motor are shown by the authors in this research.

3 Methodology

For this experiment, a 0.5-hp, 220-240V, 3.95A, 1420 r.p.m., 50 Hz, squirrel cage single phase induction motor was selected. A Data Acquisition Interface (DAI) module (LVDAM-EMS, LABVOLT, model 9062-15) was used for data collecting and recording. For measuring the speed with DAI module a dynamometer (LABVOLT, model 8960-15) was also added. The LVDAM-EMS system and the LVVL softwares were installed for Data Acquisition Interface (DAI) module and neural network computation was done by MATLAB programming language (MATLAB R-2009a). The block diagram of the proposed method is shown in Fig.1. This diagram gives a simplified idea of the research work. At first a dynamometer is coupled with a single phase induction motor. This combined arrangement sends information to a DAI module to measure and record the necessary parameters (current, speed and temperature) of motor in healthy and different faulty conditions. Next step is extraction and analysis of the feature of these parameters. These parameters are then fed into a neural network for training and testing purposes. After training and testing the network is capable of detecting different faults. The complete procedure of this experiment takes a several steps. These steps are described in the following sections.

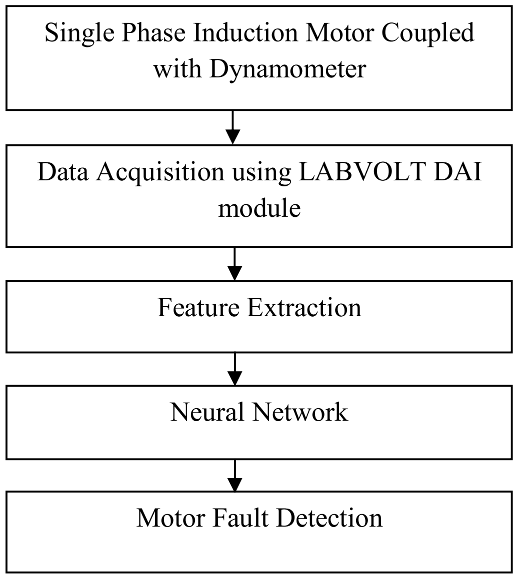


Fig.1 Block diagram of fault detection of motor

3.1 Experimental Setup for Data Collection

In order to diagnose the fault of single phase induction motor with higher accuracy, a modern laboratory test bench was set up as shown in Fig.2.

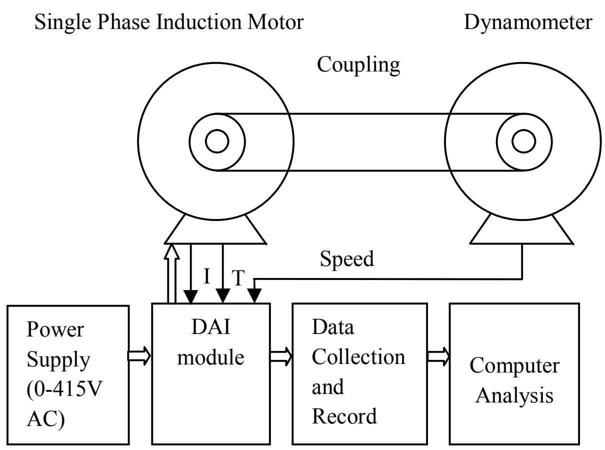
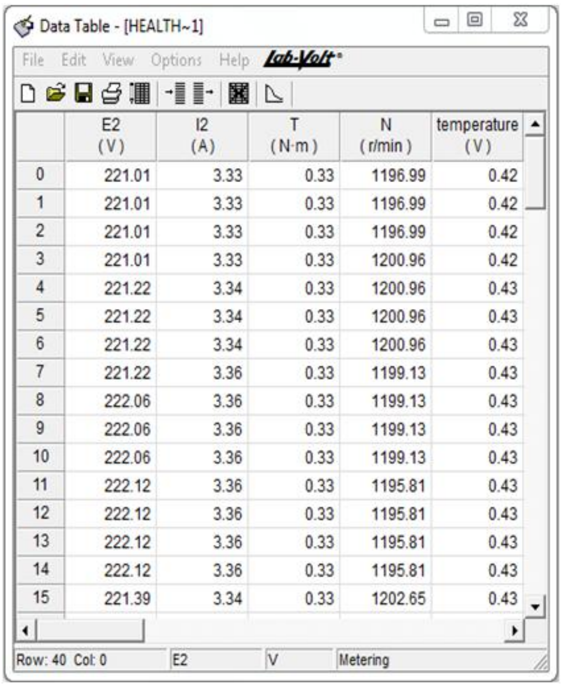


Fig.2 Connection diagram for the experiment

A single phase induction motor after coupling with a dynamometer is seen connected to a DAI module. The three thin arrows indicate three parameters i.e. current, speed and temperature. After measuring and recording data by DAI module, faults were detected by computer analysis. The dynamometer was used to measure the motor speed and the LM 35 was for the measurement of body temperature. The output from LM35 was fed into the data acquisition card as an analog input to measure the equivalent voltage of corresponding temperature.

Fig.3 displays a complete setup of necessary equipment for the experiment. The power supply, DAI module, single phase induction motor, dynamometer, computer, connecting cables and USB cable are all seen in this figure.

Fig.3 Experimental setup for data collection



Data Table - [HEALTH~1]

File Edit View Options Help Lab-Volt

	E2 (V)	I2 (A)	T (N·m)	N (r/min)	temperature (V)
0	221.01	3.33	0.33	1196.99	0.42
1	221.01	3.33	0.33	1196.99	0.42
2	221.01	3.33	0.33	1196.99	0.42
3	221.01	3.33	0.33	1200.96	0.42
4	221.22	3.34	0.33	1200.96	0.43
5	221.22	3.34	0.33	1200.96	0.43
6	221.22	3.34	0.33	1200.96	0.43
7	221.22	3.36	0.33	1199.13	0.43
8	222.06	3.36	0.33	1199.13	0.43
9	222.06	3.36	0.33	1199.13	0.43
10	222.06	3.36	0.33	1199.13	0.43
11	222.12	3.36	0.33	1195.81	0.43
12	222.12	3.36	0.33	1195.81	0.43
13	222.12	3.36	0.33	1195.81	0.43
14	222.12	3.36	0.33	1195.81	0.43
15	221.39	3.34	0.33	1202.65	0.43

Row: 40 Col: 0 | E2 | V | Metering

Fig.4 Data table of different parameters

The parameters (current, speed and temperature) were measured in constant voltage (approximately 220V) and constant torque (0.33 N-m). Fig.4 indicates a dataset which was recorded in healthy condition. The last Colum in the data table indicates the equivalent voltage of real temperature, which was converted into temperature for final calculation. The value of the mentioned parameters are changed during faulty conditions and these parameters can be externally measured. That is why, these parameters were selected for the diagnosis of faults by the authors.

3.2 Artificial Fault Creation in Single Phase Induction Motor

Though induction motor may be subjected to different faults, our concern is limited to the major three internal faults such as stator inter-turn fault, bearing fault and misalignment fault.

3.2.1 Stator Inter-turn Fault

According to an IEEE and Electric Power Research Institute motor reliability study, stator faults are mostly responsible for 37% of the failures in an induction motor [14]. The stator inter-turn fault was developed using a variable resistance. Firstly, the impedance of motor winding per turn was measured. Then, a variable resistance was adjusted shown in Fig.5 and combined value of impedance was set to the previous value of impedance. Finally, the combined value of impedance was decreased with the variable resistance.

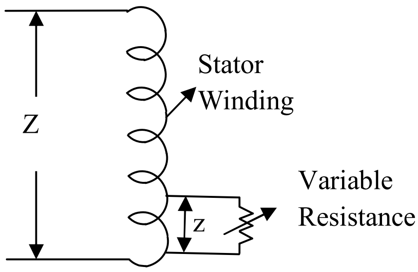


Fig.5 Stator inter-turn fault

From Fig.5 it clearly indicates how stator inter-turn fault was artificially created. Let, the impedance of complete stator winding having N number of turns is Z. Therefore, the impedance of motor winding per turn z is defined as,

$$z = Z/N \tag{1}$$

The winding impedance Z depending upon the number of shorted turns. As more number of turns gets shorted, Z decreases [15]. At constant load and voltage conditions, the decrease in magnitude of Z increases the stator current and it is expressed by the following equation in terms of instantaneous value.

$$\mathrm{i} = \mathrm{V}/\mathrm{Z} \tag{2}$$

The increased stator-winding current cause increased heating due to I^2R losses.

3.2.2 Bearing Fault

The results of various studies show that bearing problems account for over 40% of all machine failures [16]. The bearing consists mainly of the outer and inner raceway, the balls and the cage which assures equidistance between the balls. For the intentional bearing fault, the original bearing was replaced by a defective bearing making sure that its balls were displaced from the original position. Also, the bearing was not freely movable which results frictional losses. The continuous stress results the displacement of bearing balls. Whenever, the bearings of the machine deteriorate, it affects the damping coefficient and thereby the load increases. Consequently, the motor slip increases and this causes the increase in rotor current. If the increased rotor current is obtained from stator there is a rise in motor intake current to fulfill the required load demand. The bearing temperature and speed are also disturbed from bearing defects.

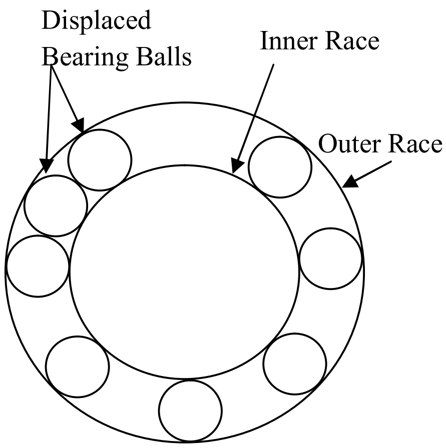


Fig.6 Bearing fault

Fig.6 shows the displaced bearing balls in the defective bearing. It indicates that two balls are displaced from their original position where the other six balls remain in their original position.

3.2.3 Misalignment Fault

The misalignment in induction motor occurs when the motor load pulleys are not aligned. To make calculated misalignment fault, the rotor shaft was displaced from its original position. This type of fault generates reaction forces and torques in the coupling, and finally torque oscillations in the motor and these oscillations changes the parameters of the motor [17].

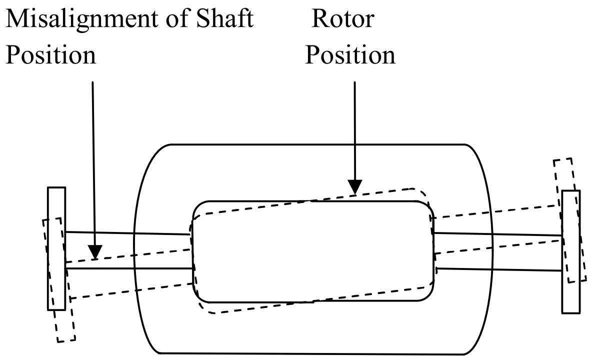


Fig.7 Misalignment fault

Fig.7 shows the shaft misalignment fault in single phase induction motor.

3.3 Back-propagation Algorithm (LM)

The generalized delta rule, also known as back propagation algorithm is explained here briefly for feed forward Neural Network (NN) [18]. The NN contains three layers. These are input, hidden and output layers shown in Fig.8. During the training phase, the training data is fed in to the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the forward pass of the back propagation algorithm. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with appropriate weights and then summed. The output of the hidden node is the non-linear transformation of this resulting sum. Similarly, each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights then summed. The output of this node is the non-linear transformation of the resulting sum. The output values of the output layer are compared with the target output values. The target output values are those that we attempt to teach our network. The error between actual output values and target output values is calculated and propagated back toward hidden layer. This is called backward pass of the back propagation algorithm. The error is used to update the connection strengths between nodes, i.e. weight matrices between input-hidden layers and hidden-output layers are updated. During the testing phase, no learning takes place i.e., weight matrices are not changed. Each test vector is fed into the input layer. The feed forward of the testing data is similar to the feed forward of the training data.

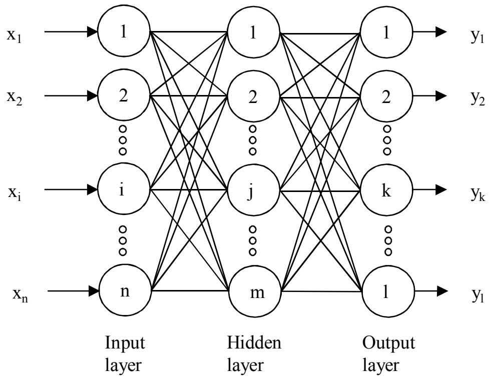


Fig.8 A Multilayer feed forward network

Levenberg-Marquardt algorithm is specially designed to minimize sum of square error functions [19].

$$E = \left(\frac{1}{2}\right)\sum k(e_k)^2 = \frac{1}{2} \parallel e \parallel^2 \tag{3}$$

Where e_k is the error in the k^{th} pattern and e is a vector with element e_k. If the difference between the previous weight vector and the new weight vector is small, the error vector can be expanded to first order by means of a Taylor series.

$$e_{(j+1)} = e_{(j)} + \frac{\partial e_k}{\partial w_i}(w_{(j+1)} - w_{(j)}) \tag{4}$$

As a consequence, the error function can be expressed as

$$E = \frac{1}{2} \parallel e_{(j)} + \frac{\partial e_k}{\partial w_i}\left(w_{(j+1)} - w(j)\right) \parallel^2 \tag{5}$$

Minimizing the error function with respect to the new weight vector, gives

$$w_{(j+1)} = w_{(j)} - \left(Z^T Z\right)^{-1} Z^T e_{(j)} \tag{6}$$

Where, $(Z)_{ki} = \frac{\partial e_k}{\partial w_i}$

Since the Hessian for the sum of error function is

$$(H)_{ij} = \frac{\partial^2 e_k}{\partial w_i \partial w_j} = \sum\left\{\left(\frac{\partial e_k}{\partial w_i}\right)\left(\frac{\partial e_k}{\partial w_i}\right) + e_k\left(\frac{\partial^2 e_k}{\partial w_i \partial w_j}\right)\right\} \tag{7}$$

Neglecting the second term, the Hessian can be written as

$$H = Z^T Z \tag{8}$$

Updating of the weights therefore involves the inverse Hessian or an approximation thereof for nonlinear networks. The Hessian is relatively easy to compute, since it is based on first order derivatives with respect to the network weights that are easily accommodated by the back propagation. Although the updating formula could be applied iteratively to minimize the error function, this may result in a large step size, which would invalidated the linear approximation on which the formula is based. In the Levenberg-Marquardt algorithm, the error function is minimized, while the step size is kept small in order to ensure the validity of the linear approximation. This is accomplished by the use of a modified error function of the form

$$E = \left(\frac{1}{2}\right) \parallel e_{(j)} + \frac{\partial e_k}{\partial w_i}\left(w_{(j+1)} - w(j)\right) \parallel^2 + \lambda \parallel w_{(j+1)} - w_{(j)} \parallel^2 \tag{9}$$

Where, λ is a parameter governing the step size. Minimizing the modified error with respect to $w_{(j+1)}$ gives

$$w_{(j+1)} = w_{(j)} - \left(Z^T Z + \lambda I\right)^{-1} Z^T e_{(j)} \tag{10}$$

If the value of λ is large then it is gradient descent method and if the value of λ is small it is Newton method.

3.4 Preparation of Suitable Training Data Set for the NNs

The collected parameters (current, speed and temperature) in healthy condition and different faulty conditions were needed to be prepared for training.

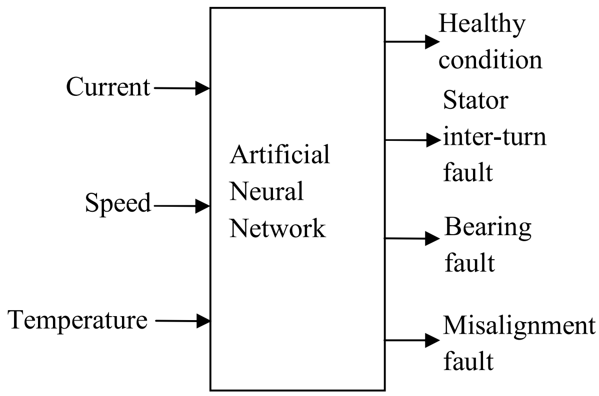


Fig.9 ANN structure

These parameters were used as inputs in artificial neural network for the detection of motor fault condition shown in Fig. 9. A training data set constituted by input and target data sets was applied to the network. The input data set contains 1000 sample values composed by a successive range of several examples in different operating conditions of the induction motor. First 250 samples contains information from healthy condition, second 250 samples from stator inter-turn fault, third 250 from bearing fault and remaining 250 from misalignment fault. All these examples are presented to NNs under load torque 0.33 N-m. The target values (T_i) of the neural network are described as below:

T_1=1 for a healthy condition; otherwise, T_1=0
T_2=1 for a stator inter-turn fault condition; otherwise, T_2=0
T_3=1 for a bearing fault condition; otherwise, T_3=0
T_4=1 for a misalignment fault condition; otherwise, T_4=0
Therefore, the target values are set according to the Table 1.

Table 1
Preparation of Target Dataset

Healthy dataset (0-250)	**Inter-turn fault dataset (251-500)**	**Bearing fault dataset (501-750)**	**Misalignment fault dataset (751-1000)**
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

3.5 Formation of Network
The Levenberg-Marquardt algorithm is the fastest method for training moderate sized feed-forward neural networks. It also has an efficient implementation in MATLAB software, since the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment [20]. The measured data of current, speed and temperature were placed as input of the network and target values were also set accordingly. The network was trained with Levenberg-Marquardt back propagation algorithm (*trainlm*). The network *trainlm* can train any network as long as its weight, net input, and transfer functions have derivative functions. The network used is a feed-forward network as illustrated in Fig.10. The transfer function used between hidden and output layer is hyperbolic tangent sigmoid and transfer function in the output layer is linear. The number of neurons in hidden layer was set with trial and error method.

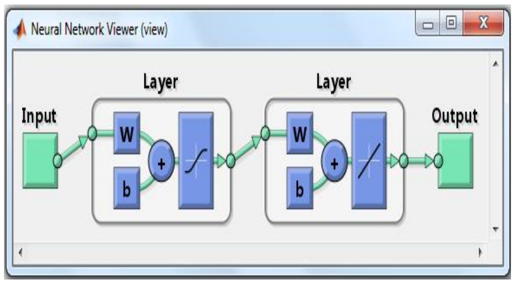


Fig.10 Formation of feed forward network in MATLAB window

3.6 Training and Testing the Network
Once the network was formed, it was ready for training. During training the weights and biases of the network were iteratively adjusted to minimize the error. The default performance function for feed-forward networks was chosen Mean Square Error (MSE). The *train* command was used for training.

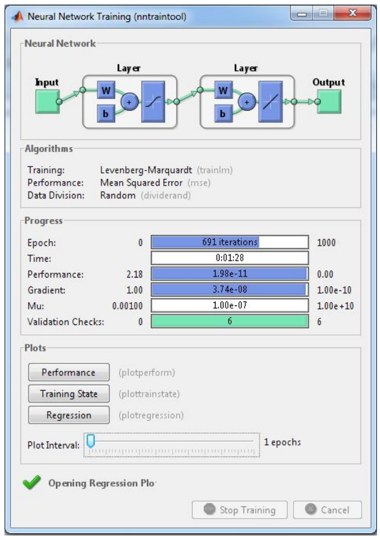


Fig.11 Neural network training window in MATLAB

Fig. 11 shows the training window in MATLAB environment. It clearly indicates that the training algorithm is Levenberg-Marquardt (*trainlm*). The performance function and data division are Mean Square Error (*mse*) and Random (*dividerand*) respectively. When the training was completed, the network was capable of testing. For the testing purpose, a random dataset was chosen from healthy and different faulty datasets and placed in the input of the network. For a proper diagnosis, some unseen data were presented; those were not used in the training purposes.

4 Results

For performance evaluation of the proposed method, the results are divided in two sections: the training result and the testing result. The training result indicates whether the network is properly trained or not. The testing result on the other hand tests the network and investigates the motor conditions.

Fig. 12 shows the Mean Square Error (MSE) which is the difference between outputs and targets. The plot shows the mean squared error of the network starting at a large value and decreasing to a smaller value. In other words, it shows that the network is learning. The plot has three lines, because the 1000 inputs and targets vectors were randomly divided into three sets. 60% of the vectors were used to train the network, 20% of the vectors were used to validate how well the network generalized. Training on the training vectors continues as long the training reduces the network's error on the validation vectors. After the network memorizes the training set, training was stopped. This technique automatically avoids the problem of overfitting, which plagues many optimization and learning algorithms. Finally, 20% of the vectors provide an independent test of network generalization to data that the network has never seen. Lower values of MSE are better while zero means no error. From Fig. 12 it is observed that the best validation performance 2.9079e-007 at epoch 82 is obtained. It clearly indicates that error tends to zero which is very good result.

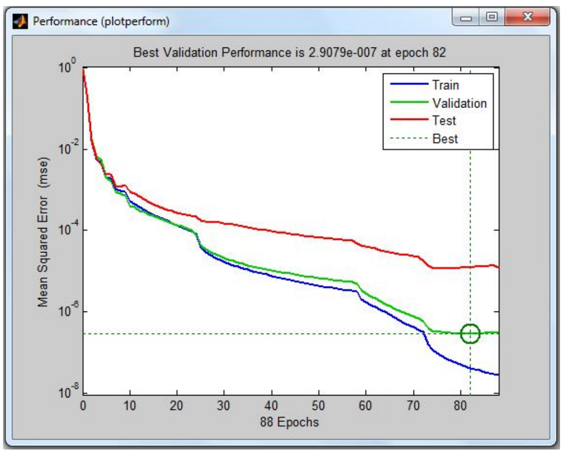


Fig.12 Training performance with Mean Square Error

Fig. 13 denotes the Regression R analysis to measure the correlation between targets and outputs. If the value of R is 1, it indicates a close relationship between target and output. On the other hand, if the value of R is 0, it denotes a random relationship between target and output. The Regression plot shown in Fig. 13 indicates the perfect correlation between outputs and targets.

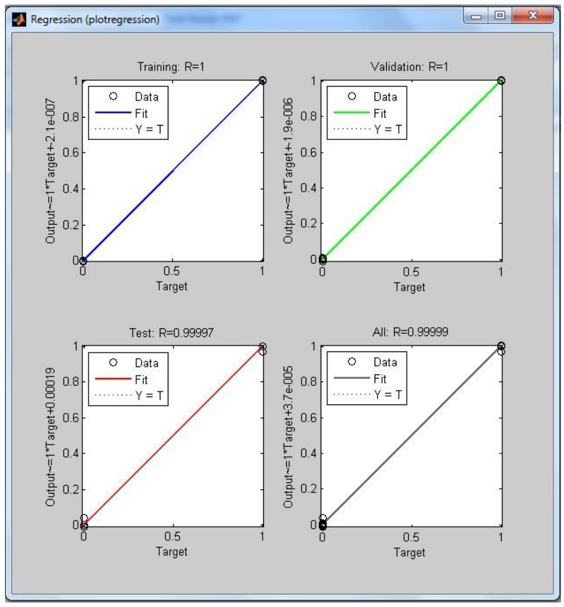


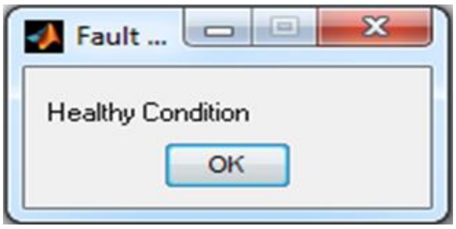
Fig.13 Regression analysis of training result

The network was trained by changing the number of neurons in hidden layer. It was estimated that with the increase of neurons in hidden layer, the number of iterations was decreased but the value of error was increased to some extent. The several training results are summarized in the Table 2.

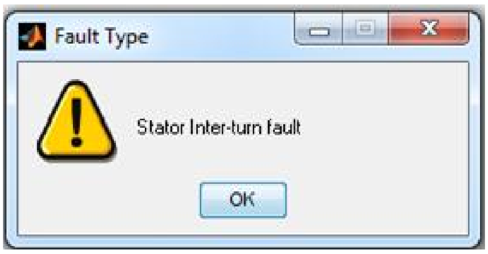
Table 2
Summarized Training Result

Number of neurons	**Number of Iterations**	**MSE**	**Regression**
20	625	2.44e-14	1
25	52	1.83e-06	1
30	18	0.000185	1

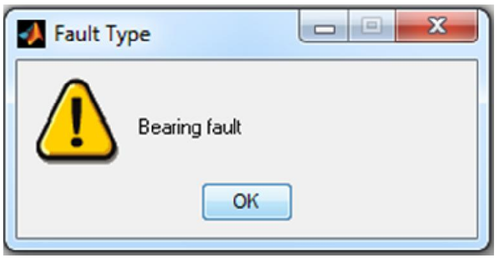
After completing training program, the network was tested with various datasets from healthy and different faulty datasets. The combined result was displayed in a message box. The function of message box was to display the name of healthy or different faulty conditions. In Fig. 14 the final testing result is shown. If the motor remains in healthy condition, the message box displays healthy condition. When fault conditions arise, it indicates the particular fault name. For example, Stator inter-turn fault is displayed in message box when a stator inter-turn fault dataset is presented in the input.



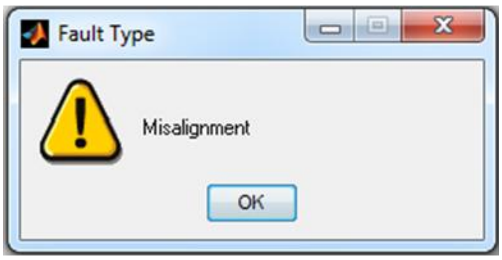
(a)



(b)



(c)



(d)

Fig.14 Testing result of the network in a message box (a) Healthy condition, (b) Stator Inter-turn fault condition, (c) Bearing fault condition, (d) Misalignment fault condition

5 Conclusion

The paper aimed to evaluate the artificial neural network in detecting the conditions of a single phase induction motor. The feed-forward back-propagation neural network with supervised learning is proposed to diagnosis the faults in motor. Back-propagation learning algorithm was used to train the feed-forward neural network to execute the task based on Levenberg-Marquardt algorithm and the performance was analyzed. The proposed diagnosis based on neural network showed significant results in identifying the faults. In future, more faults will be analyzed and detected both in single phase and three phase induction motors for which the proposed method is believed to be similarly effective.

References:

[1] G. B. Kliman, W. J. Premerlani, B. Yazici, R. A. Koegl and J. Mazereeuw, Sensorless Online Motor Diagnosis, *IEEE Comput. Applications Power,* Vol. 10, No. 2, Apr. 1997, pp. 39-43.

[2] N. M. Burnstein et al., Case Histories of Rotating Equipment Condition Assessment by Electric Signal Analysis, *P/PM Technol.*, Vol. 9, No. 6, Dec. 1996, pp. 36-39.

[3] I. E. Alguindigue, A. Loskiewicz-Buczak and R. E. Uhrig, Monitoring and Diagnosis of Rolling Element Bearings Using Artificial Neural Networks, *IEEE Trans. Industrial Electronics*, Vol. 40, No. 2, Apr. 1993, pp. 209–217.

[4] F. Filippetti, G. Franceschini, C. Tassoni and P. Vas, Recent Developments of Induction Motor Drives Fault Diagnosis Using AI Techniques, *IEEE Trans. Industrial Electronics*, Vol. 47, No.5, Oct. 2000, pp. 994–1003.

[5] W. W. Tan and H. Huo, A Generic Neuro-Fuzzy Model-Based Approach for Detecting Faults in Induction Motors, *IEEE Trans. Industrial Electronics*, Vol. 52, No. 5, Oct. 2005, pp. 1420-1427.

[6] M. Y. Chow, R. N. Sharpe and J. C. Hung, On the Application and Design of Artificial Neural Networks for Motor Fault Detection, *Part I and II, IEEE trans. Industrial Electronics*, Vol. 40, No.2, Apr. 1993, pp. 181 - 196.

[7] M. Y. Chow, P. M. Mangum and S. O. Yee, A Neural Network Approach to Real Time Condition Monitoring of Induction Motors, *IEEE trans. Industrial Electronics*, Vol.38, No.6, Dec. 1991, pp.448 – 453.

[8] P. V. Goode and M. Y. Chow, Using A Neural/Fuzzy System to Extract Heuristic Knowledge of Incipient Faults in Induction Motors: Part I and II, *IEEE Trans. Industrial Electronics*, Vol.42, No.2, Apr. 1995, pp.131-146.

[9] M. Y. Chow and P. V. Goode, Adaptation of Neural/Fuzzy Fault Detection System, *in Proceedings of IEEE conference on Decision and Control*, Dec. 1993, pp.1733-1738.

[10] M. Y. Chow and S. O. Yee, Methodology for On-line Incipient Fault Detection in Single-phase Squirrel Cage Induction Motors Using Artificial Neural Networks, *IEEE Trans. Energy Conversation*, Vol.6, No.3, Sep. 1991, pp.536-545.

[11] M. S. Ballal, Z. J. Khan, H. M. Suryawanshi and R. L. Sonolikar, Adaptive Neural Fuzzy Inference System for the Detection of Inter-Turn Insulation and Bearing Wear Faults in Induction Motor, *IEEE Trans. Industrial Electronics*, Vol. 54, No. 1, Feb. 2007, pp. 250–258.

[12] R. H. Abiyev and O. Kaynak, Fuzzy Wavelet Neural Networks for Identification and Control of Dynamic Plants- A Novel Structure and a Comparative Study, *IEEE Trans. Industrial Electronics*, Vol. 55, No. 8, Aug. 2008, pp. 3133–3140.

[13] M. B. K. Bouzid, G. Champenois, N. M. Bellaaj, L. Signac and K. Jelassi, An Effective Neural Approach for the Automatic Location of Stator Inter-Turn Faults in Induction Motor, *IEEE Trans. Industrial Electronics*, Vol. 55, No. 12, Dec. 2008, pp. 4277-4289.

[14] A. Siddique and G. S. Yadava, A Review of Stator Fault Monitoring Techniques of Induction Motors, *IEEE Trans. Energy Conversion*, Vol. 20, No. 1, Mar. 2005, pp. 106–114.

[15] A. J. M. Cardoso, S. M. A. Cruz and D. S. B. Fonseca, Inter-turn Stator Winding Fault Diagnosis in Three-phase Induction Motors by Park's Vector Approach, *IEEE Trans. Energy Conversation*, Vol. 14, No. 3, Sept. 1999, pp. 595-598.

[16] R. R. Schoen, T. G. Habetler, F. Kamran and R. Bartheld, Motor Bearing Damage Detection Using Stator Current Monitoring, *IEEE Trans. Industrial Applications*, Vol. 31, No. 6, Nov./Dec. 1995, pp. 1274–1279.

[17] M. Xu and R. D. Marangoni, Vibration Analysis of a Motor-flexible Coupling-rotor System Subject to Misalignment and Unbalance, part ii: Experimental Validation, *Journal of Sound and Vibrations*, Vol. 176, No. 5, Oct. 1994, pp. 681–691.

[18] D. E. Rumelhart and J. L. McClelland, *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, MIT Press, Cambridge Massachusette, 1986.

[19] C. Aldrich, Exploratory Analysis of Metallurgical Process Data with Neural Networks and Related Methods, *Elsevier Science, British Library Cataloguing in Publication Data*, Netherlands, Vol. 1, 2002, pp. 56-57.

[20] C. Charrier, G. Lebrun and O. Lezoray, Selection of features by a machine learning expert to design a color image quality metrics, *3rd Int. Workshop on Video Processing and Quality Metrics for Consumer Electronics (VPQM)*, Scottsdale, Arizona, 2007, pp. 113-119.