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Detection of Incipient Faults in Induction Motors using FIS, ANN and ANFIS Techniques

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ABSTRACT

The task performed by induction motors grows increasingly complex in modern industry and hence improvements are sought in the field of fault diagnosis. It is essential to diagnose faults at their very inception, as unscheduled machine down time can upset critical dead lines and cause heavy financial losses. Artificial intelligence (AI) techniques have proved their ability in detection of incipient faults in electrical machines. This paper presents an application of AI techniques for the detection of inter-turn insulation and bearing wear faults in single-phase induction motors. The single-phase induction motor is considered a proto type model to create inter-turn insulation and bearing wear faults. The experimental data for motor intake current, rotor speed, stator winding temperature, bearing temperature and noise of the motor under running condition was generated in the laboratory. The different types of fault detectors were developed based upon three different AI techniques. The input parameters for these detectors were varied from two to five sequentially. The comparisons were made and the best fault detector was determined.

Keywords: Induction motor, Winding insulation, Inter-turn short circuit, Bearing wear, FIS, ANN, ANFIS.

1. Introduction

Three-phase, as well as, singe-phase induction motors are used due to their advantages like quick start, less maintenance, etc. Therefore, the application of induction motors is advancing daily. Additionally, the tasks performed by them grow increasingly complex. Like other types of electrical machines, these motors are exposed to a wide variety of environments and conditions. They are also apt to develop various types of incipient faults, like the deterioration of winding insulation, bearing wear, broken rotor bar, eccentricity, etc. [1].

Work on induction motor fault diagnostics and protection dates back to the time when the manufacturers and the users of these motors initially relied on simple protection such as over-current, over-voltage or earth faults, to ensure safe and uninterrupted operation. If these incipient faults are not detected and diagnosed at an early stage, they may cause gradual deterioration of the motor

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which results in down time and financial losses. The frequency of scheduled maintenance increases the cost and decreases the productivity of a system. Therefore, it is always desirable to provide prevention of motor failure rather than protection. This is achieved by continuous condition monitoring. Condition monitoring of induction motors is a fast emerging technology for online detection of incipient faults. It avoids unexpected failure of a critical system. Concepts and functions of condition monitoring (CM) are explained in [2], with a description of the popular monitoring methods and research status of CM on transformer, generator, and induction motor. The potential benefits through the utilization of advanced signal processing and artificial intelligence techniques in developing novel CM schemes is also pointed out.

The stator current is analyzed via wavelet packet decomposition to detect bearing defects is explained in [3]. This method enables the analysis of frequency bands that can accommodate the rotational speed dependence of the bearing defect frequencies. In [4] a comprehensive review of various stator faults, their causes, detection parameters/ techniques, and latest trends in the condition monitoring technology is presented. Sensor less drive control has been widely studied in recent years due to the numerous advantages regarding potential failures of position sensors, especially in automotive or aerospace applications.

The parameter estimation is carried out using lumped-parameter models and is explained in [5]. The control scheme is modified and is able to account for static friction, and the over current protection improves the performance allowing transient currents over the rated value. A fault indicator, the so-called swing angle, for broken-bar and inter-turn faults is investigated in [6]. This fault indicator is based on the rotating magnetic-field pendulous-oscillation concept in faulty squirrel-cage induction motors. In [7], a comparative analysis involving several fault-tolerant operating strategies, applied to three-phase induction-motor drives is elaborated. The advantages and the inconveniences of several fault-tolerant drive structures, under different control techniques, such as the field-oriented control and the direct torque control, etc. are discussed. In [8], the performance of the three-phase induction motor, based on the analysis of some key parameters, like induction-motor efficiency, motor power factor, and harmonic distortion of both motor line currents and phase voltages is described.

A synchronous machine internal faults model based on the actual winding arrangement is also described. Based on the winding function approach, the machine inductances are calculated directly from the machine winding distribution, thereby the space harmonics produced by the machine windings are taken into account. The calculation of inductances is derived from the waveforms of the winding functions of the machine winding distribution.

In [9], an online induction motor diagnosis system using motor current signature analysis (MCSA) with signal-and-data-processing algorithms is used. MCSA is a method for motor diagnosis with stator-current signals. Induction motors having four types of faults such as breakage of rotor bars and end rings short-circuit of stator windings, bearing cracks, and air-gap eccentricity are considered.

In [10], an algorithm based on an unsupervised neural network for on-line diagnostics of a three-phase induction motor stator fault is developed. This algorithm uses the stator currents to distinguish the two parts as input variables after that an unsupervised method is applied in which a Hebbian-based unsupervised neural network is used to extract the principal components of the stator current data. This data is used to decide the severity of the faults.

In [11], an analytical redundancy method using neural network modeling of the induction motor in vibration spectra is proposed for machine fault detection and diagnosis. The faults are detected from changes in the expectation of vibration spectra modeling error. The high-frequency circulating bearing current that may occur in machines of inverter-based drive systems is described by an eddy-current mode in [12]. The parameters of an equivalent circuit are derived from the model. The ratio between the bearing current and common-mode current amplitudes for different machines is calculated. In [13], a simulation model is used to investigate the internal fault currents of large synchronous generators with parallel-connected windings. This model is based on a modified winding function theory that takes into account all space harmonics. The calculation of the machine inductances is made easier by the use of the machine electrical parameters instead of the geometrical ones. The existence of different currents in parallel windings in the case of internal faults is simulated.

Information on the various conventional methods is available with their pros and cons. In literature [14]-[17], the ANN is used for the detection of two types of incipient faults viz. inter-turn insulation failure and bearing wear with only two input parameters i.e. motor intake current and speed. However, in [18], the ANN method is applied successfully for the detection of these two types of faults with consideration of the five measurable input parameters. These five measurable parameters are motor intake current (I), rotor speed (ω), winding temperature (τ_w), bearing temperature (τ_b) and noise of the motor (db) under running condition. The Fuzzy Inference System (FIS) and Adaptive Neural Fuzzy Inference System (ANFIS) are applied for the detection of these two types of faults with consideration of the same five measurable input parameters as explained in [19] and [20] respectively. Whenever, an incipient fault develops in a motor, it exhibits a considerable change in these five measurable parameters. For example, if an inter-turn short circuit occurs, the intake current rises, I^2R loss increases, this causes a rise in the winding temperature and it weakens the insulation strength. Similarly, if a bearing fault develops, the bad bearing causes more friction, thus it causes an increase in bearing temperature and a reduction in speed. These types of faults also alter the noise of the motor.

In this article, the review of techniques explained in [18]-[20] is carried out to determine the best methodology for the detection of stator winding and bearing wear incipient faults. A comparison of all three methods *viz.* ANN, FIS and ANFIS is made with their results obtained with five measurable parameters. It was observed in all the three systems that as the number of input parameters increases, the accuracy of incipient fault detection also improved. The accuracy of the results is more than 97% of all the three systems with maximum inputs. All these techniques will lead to an improvement in the reliability of online condition monitoring of induction motors.

2. Identification of motor parameters and application AI techniques for fault detection

The non-linear relation between the five input measurable parameters of the induction motor (I, ω, τ_w, τ_b, db) with the motor insulation condition (N_c) and bearing condition (B_c) is explained in [18]-[20]. From previous analysis, the motor intake current (I), rotor speed (ω), winding temperature (τ_w), bearing temperature (τ_b) and noise of the motor (db) were found to be very sensitive to the changing conditions of the stator winding and bearings. In [20], it was shown that there exists a mapping m between ($I, \omega, \tau_w, \tau_b$, db) to (N_c, B_c) such that;

$$m = (I,\ \omega, \tau_w, \tau_b,\ db) \rightarrow (N_c, B_c) \tag{1}$$

where m is complex it has a high degree of non-linearity. Because of the non-linearity, an accurate result is rather difficult. However, this complexity can be avoided using different kinds of AI techniques.

Basic definitions relating to ANN, FIS and ANFIS are given in literature [21]-[27]. The FISs are based on a set of rules. These rules allow the input to be fuzzy, i.e. more like the natural way that humans express knowledge. A reasoning procedure, the compositional rule of inference, enables conclusions to be drawn by extrapolation or interpolation from qualitative information stored in the knowledge base. ANN can capture domain knowledge from examples. It can readily handle both continuous and discrete data and has a good generalization capability as with FISs. An ANN is a computational model of the brain. ANNs assume that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel thus known as parallel distributed processing systems. The error between the actual and expected output is used to strengthen the weights of the connection between neurons. The neural fuzzy architecture takes into account both the ANN and FIS. It incorporates positive features of ANN and FIS. The ANFIS is a neural network structured upon fuzzy logic principles, which enables the neural fuzzy system to

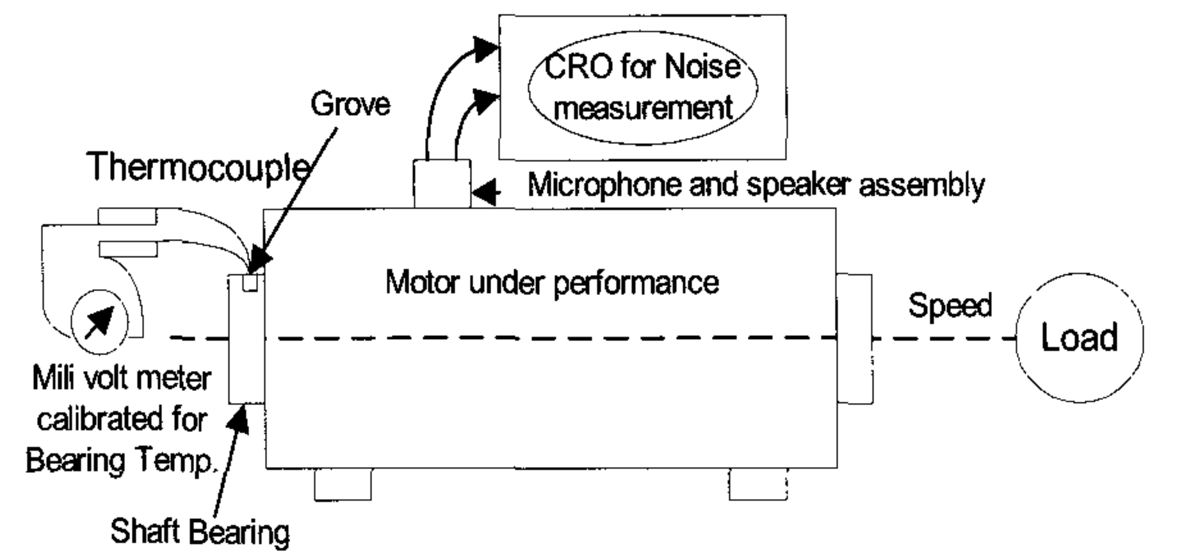


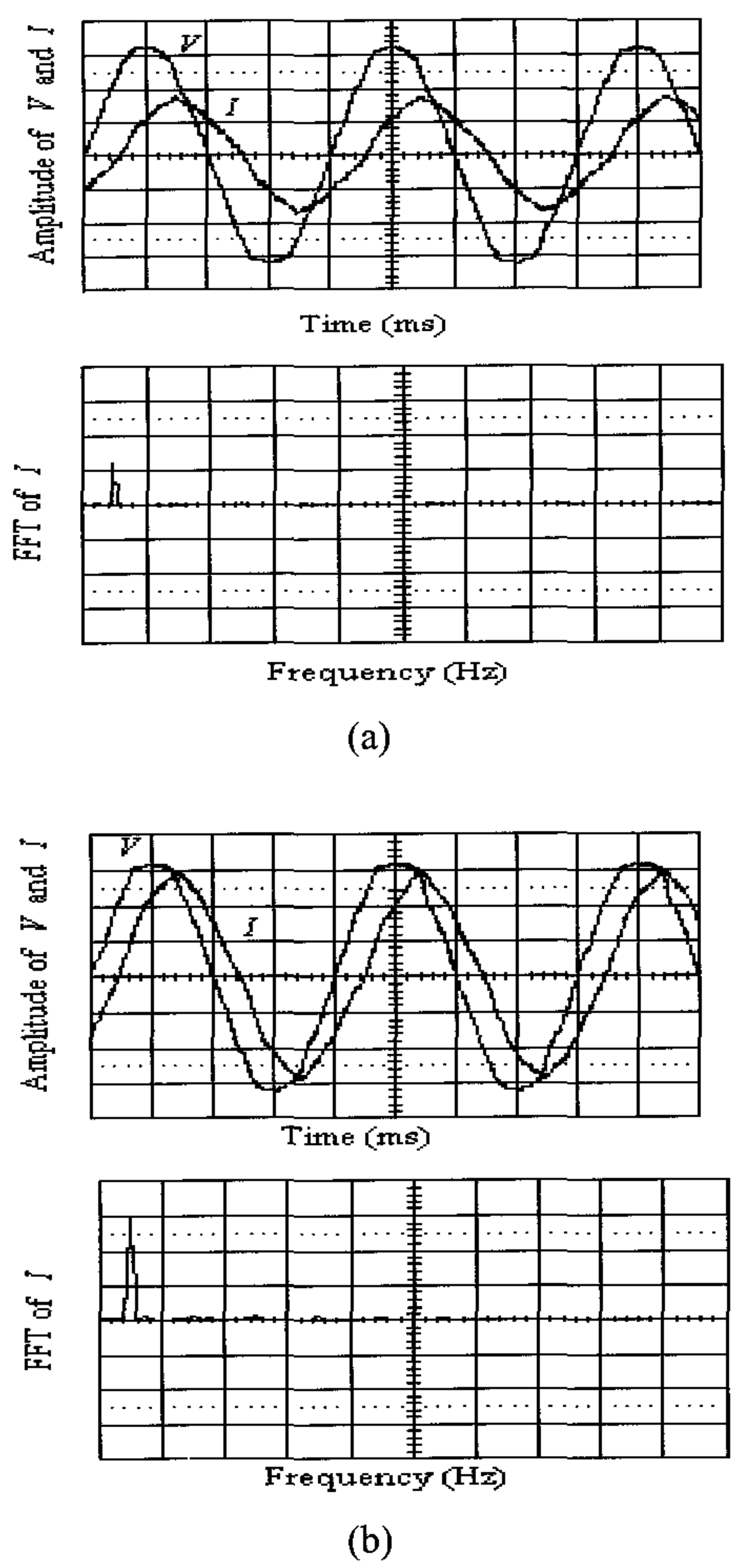
Fig. 1 Experimental setup for data collection

provide the motor condition and fault detection process. This knowledge is provided by the fuzzy parameters of membership functions and fuzzy rules.

The AI based interturn insulation and bearing wear fault detectors are developed in real time. Experimental data was obtained after performing experiments on a specially designed single-phase induction motor of 0.5-hp, 220 volts. The induction motor with associated components under test is shown in Fig. 1. Four turns of one of the North and South Poles (a total of eight turns) are taken out on the panel to reduce the number of turns in the steps. The experimental data is recorded by shortening all these turns in steps and also by replacing healthy bearing by less lubricated, dry and damaged bearings for no-load, rated load and more than rated load conditions [18]-[20].

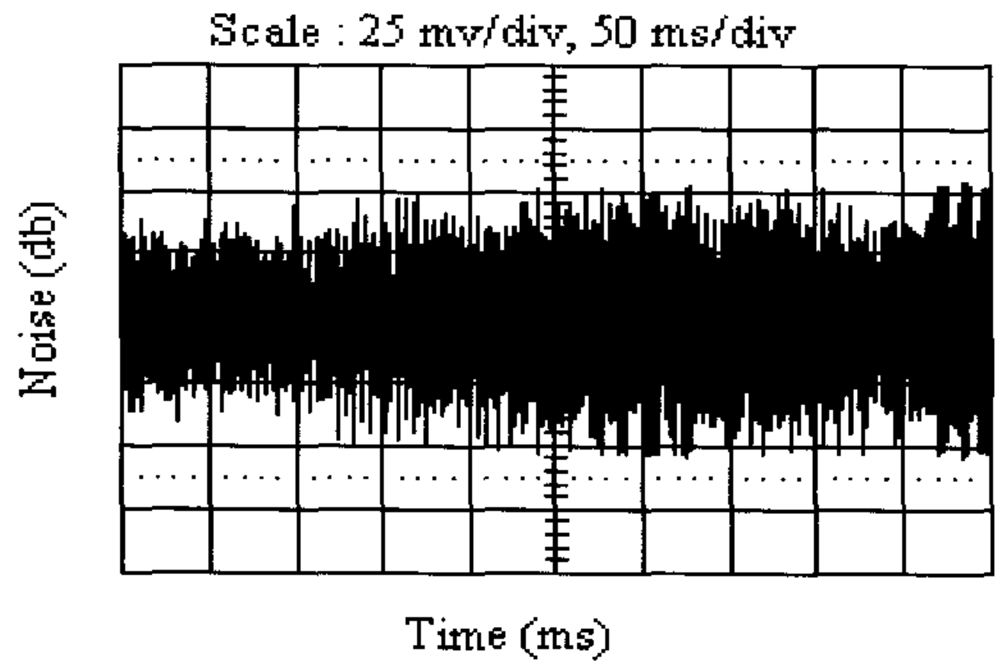
The experimental stator currents waveforms and their respective Fast Fourier Transforms (FFTs) are shown in Fig.2. The minimum motor intake current recorded was 3.51 Amps and the maximum current under fault condition when the motor was heavily loaded was 10.72 amps. The speed drops from 1480 rpm to 894 rpm corresponding to results when a no-load healthy machine is changed to heavily loaded faulty machine. The corresponding winding temperature rises from 41°C to 88°C. The variation for the motor bearing temperature is between 46 °C to 50 °C or in terms of a calibrated mili-voltmeter it is in the range of 0.6-mv to 5.1-mv . The noise level peak value is between 50-mv to 250-mv. These values correspond to a healthy no load condition to a severe fault with heavily loaded condition. The few samples of noise waveforms and corresponding FFTs obtained from the DSO are shown in Fig. 3. It is observed from Fig. 2 and 3 that the FFTs of the current and noise waveforms increase with the severity of faults. The harmonics contents get introduced and continuously rise with the type of faults. The losses in the motor continuously rise as the intensity of faults increases and it reduces motor efficiency. The experimental data for all the five measurable parameters (I, ω, τ_w, τ_b, db) under different conditions for insulation fault and bearing fault is normalized for the training and testing of fault detection systems and it also gives the numerical stability. The experimental data is illustrated in Fig. 4 for the rated load condition [18]-[20].

One hundred and forty four training and testing data patterns have been generated according to uniform distribution over the operating conditions on the laboratory test stand. The one hundred and eight patterns are used for training the systems and the thirty-six patterns are used for testing the systems.

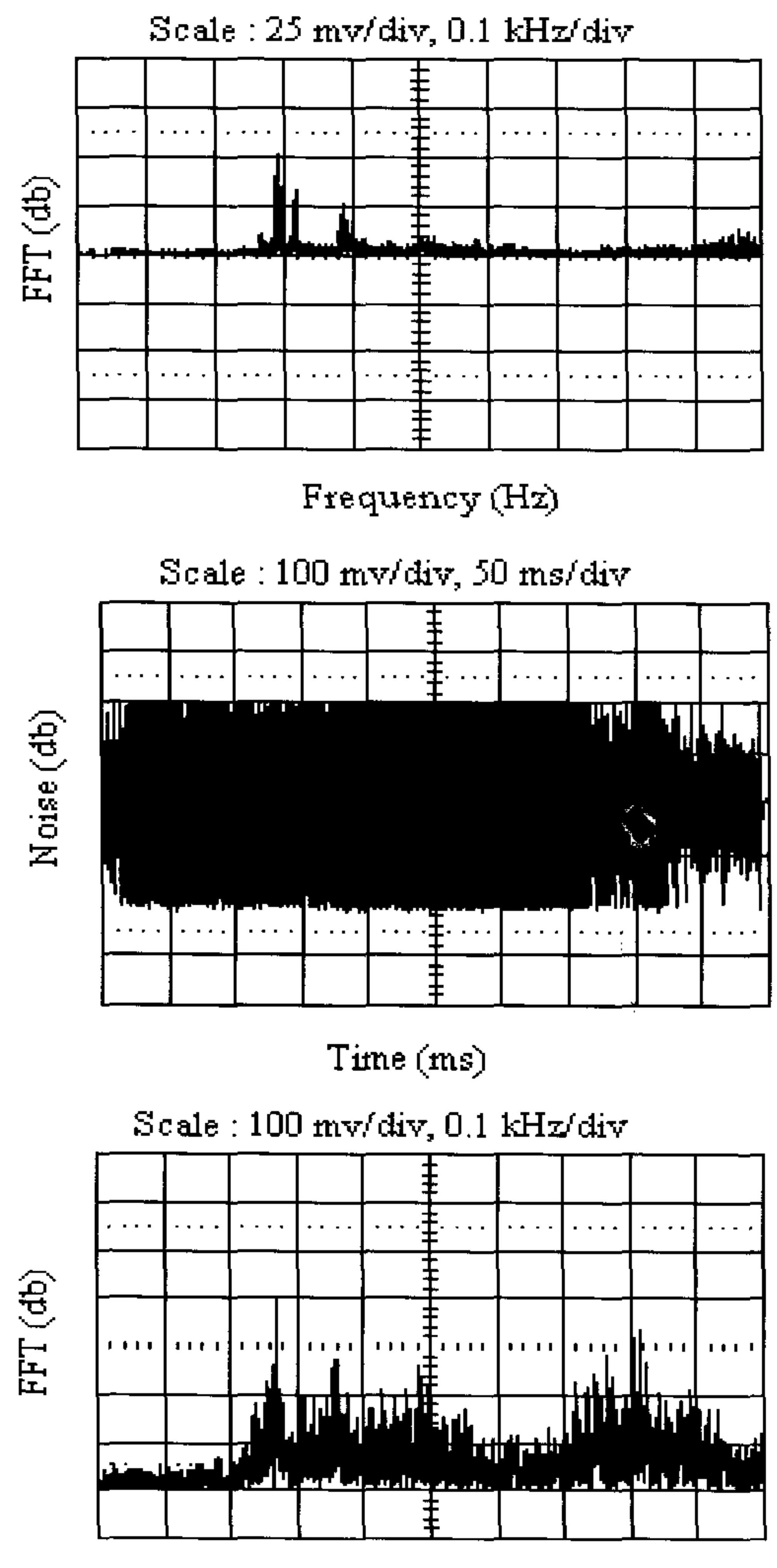


Scale: 100 volts/ div, 4 Amps. /div, 10 ms/ div, 100Hz/ div.

Fig. 2 Motor intake current and their respective FFTs (a) Rated load, healthy bearing, two turns shorted, (b) Rated load, damaged bearing, all turns shorted

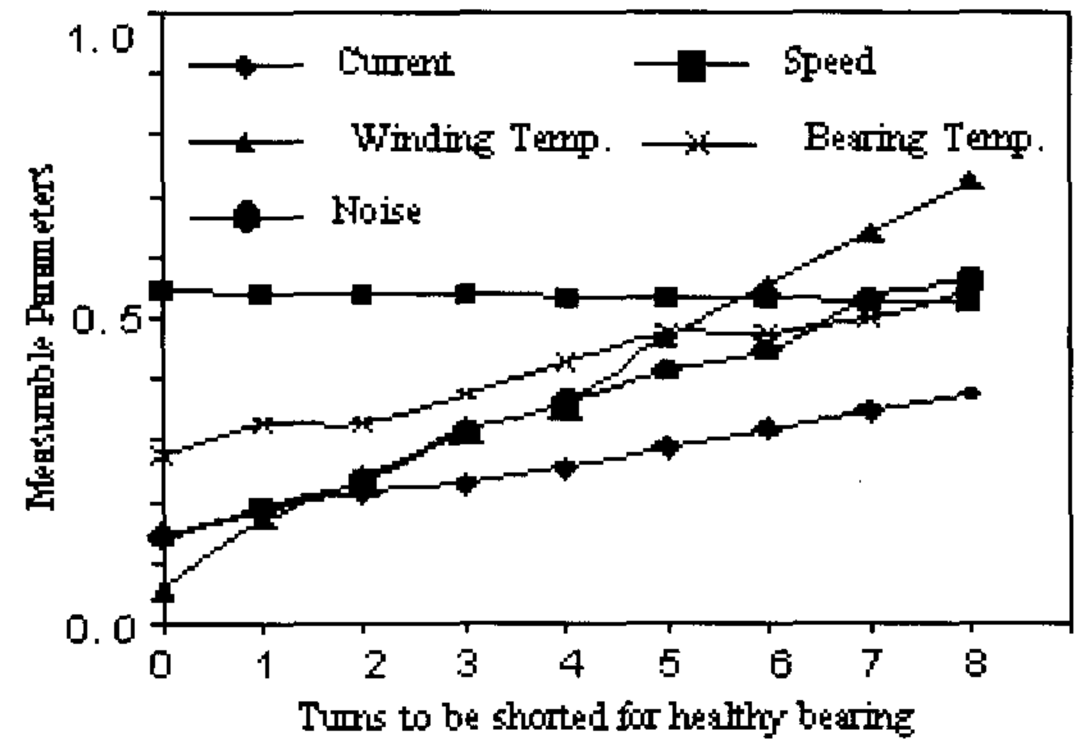


(a)



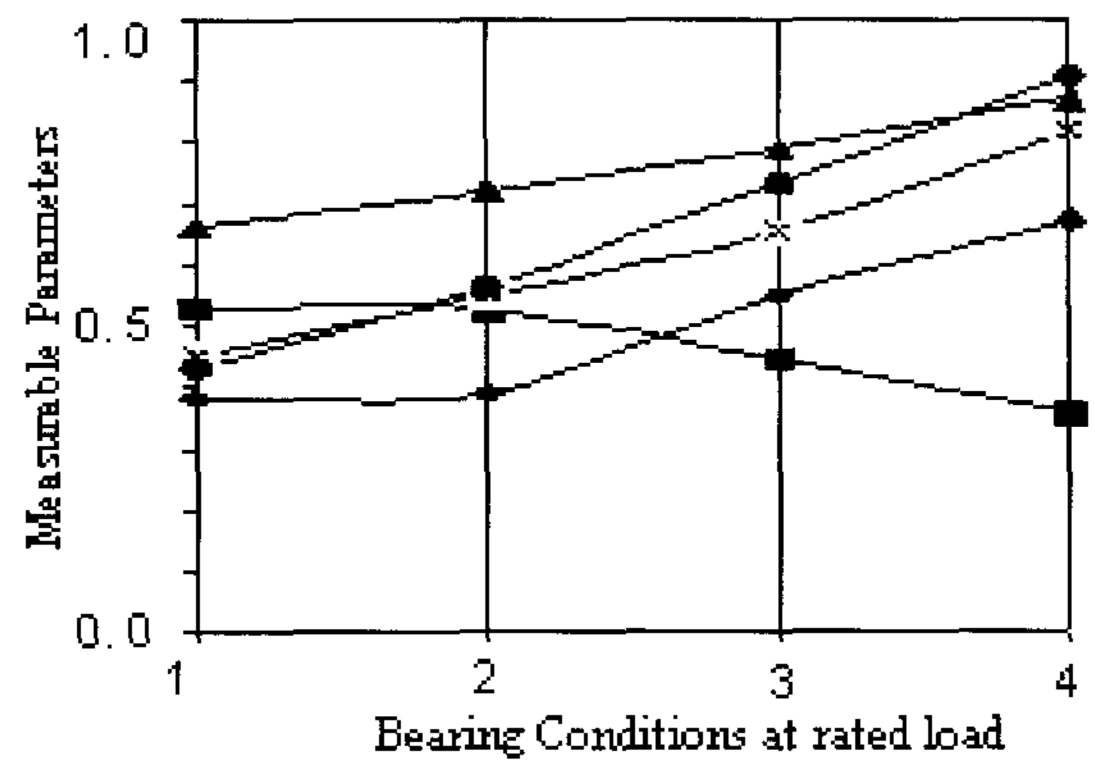
(b)

Fig. 3 Audible noise and their respective FFTs (a) No load, healthy bearing, no turns shorted, (b) Rated load, dry bearing, all turns shorted



0: Healthy condition – No turns shorted
8: Fault condition – All turns shorted

(a)



Bearing Condition: 1. Healthy, 2. Less lubricated, 3. Dry and 4. Damage bearings

(b)

Fig. 4 Experimental Results in pu. at rated load (a) Insulation Fault (b) Bearing Fault

3. Comparative results and their analysis

The three AI systems based upon FIS, ANN and ANFIS are applied to detect the inter-turn insulation and bearing wear faults in a single-phase induction motor. The results obtained and their analyses are as follows:

A: Fault Detection Fuzzy Inference System (FIS)

The main advantage of this approach is that it is easy to implement "rule of thumb", experiences and heuristics. The expert knowledge and the experimental data are used to form the fuzzy rules [25]. Later the

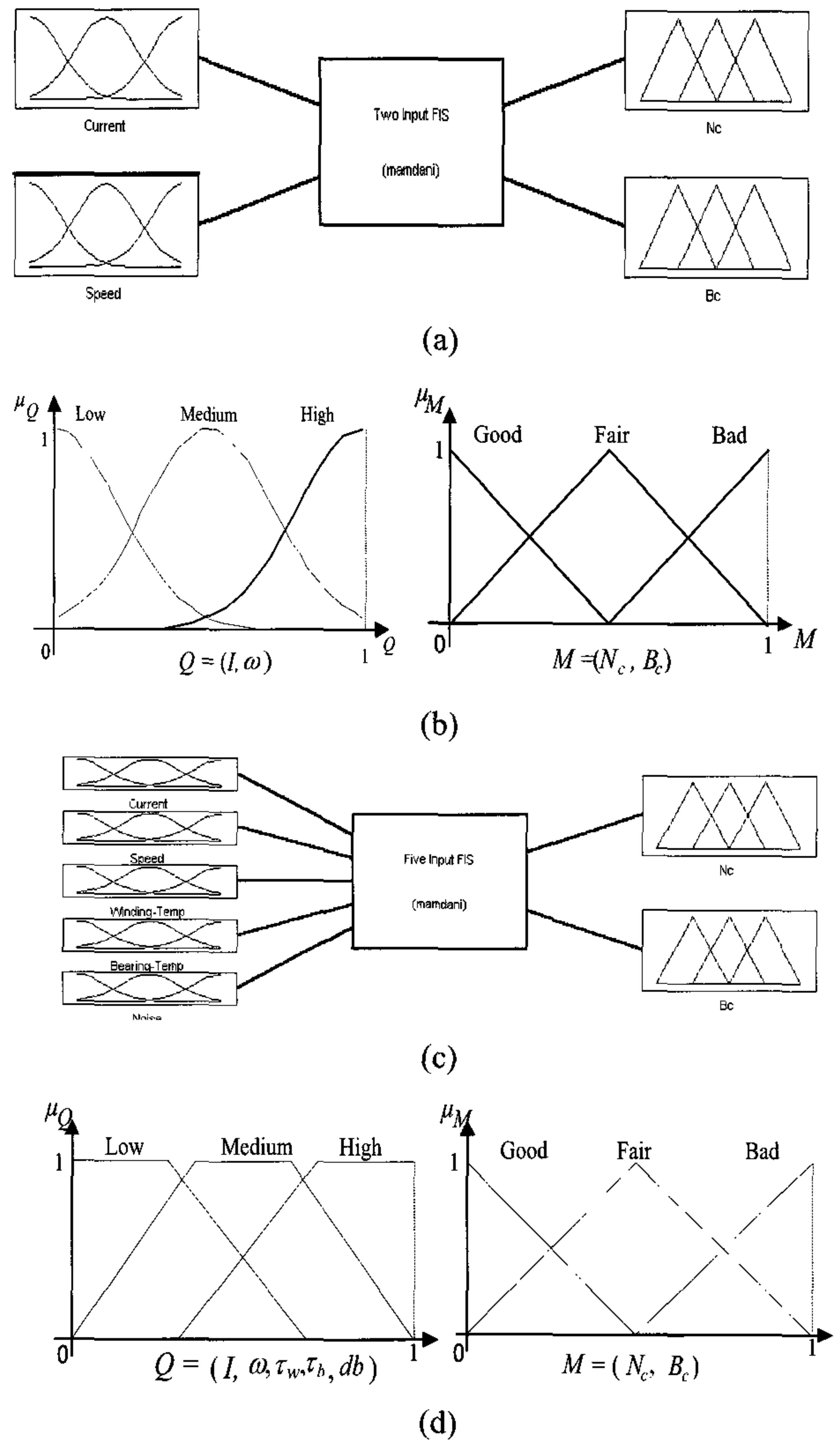


Fig. 5 Two inputs (a) FIS Systems, (b) input and out put membership functions; Five inputs (c) FIS System, (d) input and out put membership functions

consistency of these rules is verified using experimental results. Fuzzy systems provide qualitative description about the motor condition and performance. This knowledge is provided by fuzzy parameters of membership functions and fuzzy rules. The fuzzy systems are developed for two input parameters (I, ω) and in later steps the remaining three parameters (τ_w, τ_b, db) are added sequentially. The performance is tested by varying the types of membership functions and their percentage of overlapping. The universe of discourse represents the operating range of the inputs.

The experimental data presents variation of the five parameters (I, ω, τ_w, τ_b, db) from the healthy condition of the motor to the severe fault condition of the motor. This data at the two extreme conditions is used to define the range of inputs in the proposed fuzzy system. Hence for checking the motor performance, the motor current operating range is chosen from 3 to 11 amps and the drooping speed range from 1480 to 890 rpm. The operating range is between 40°C to 90°C for the stator main winding temperature and 46 °C to 50°C for the motor bearing temperature. The operating range for the noise wave form in terms of the peak value is between 50-mv to 250-mv. Initially, the performance of this detector was tested with the two inputs (I, ω) and later the remaining three inputs (τ_w, τ_b, db) were added sequentially and again the fault detectors were tested. Fig 5 shows the two different types of Fuzzy Inference Systems (FISs) and their corresponding optimized membership functions.

The accuracy of the fault detection is improved sequentially by adding the new input parameter in the earlier system. All the results presented are after optimization by applying different types of membership functions and varying their percentage of overlapping. It is observed that the response time is considerably increased with the addition of input parameters. The performance, as shown in Table 1, is quite good. In fact, it indicates that the fuzzy system is capable to provide good detection.

Table 1 Fuzzy Inference System results

SN	No. of Inputs	% Accuracy N_c	% Accuracy B_c
1	Two	93.61	78.32
2	Three	94.24	89.78
3	Four	97.42	95.88
4	Five	99.01	97.76

B: Fault Detection by ANN system

The neural network is appropriately trained so that the network weights will contain the non-linearity of the desired mapping. Therefore, the difficulties of mathematical modeling can be avoided [10].

In order to use ANN for identifying induction motor faults and no fault condition, it is necessary to select proper inputs and outputs of the network, structure of the network, and train it with appropriate data. The neurons detecting the winding insulation fault can be separated from the neurons detecting the bearing wear. This is because, all the hidden neurons are not fully connected to the output neurons, which decode the condition of N_c and B_c from the information obtained from the hidden neurons. The sigmoid function is used as the nonlinear activation function for all neurons (except the ones in the input layer), and the network is trained.

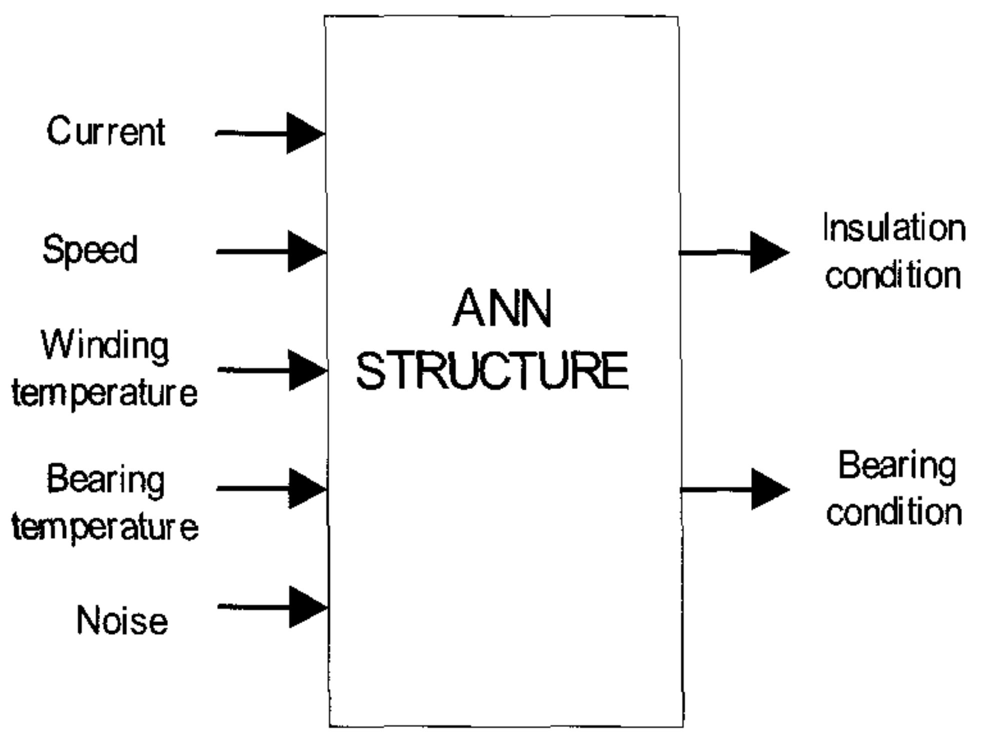


Fig. 6 ANN structure

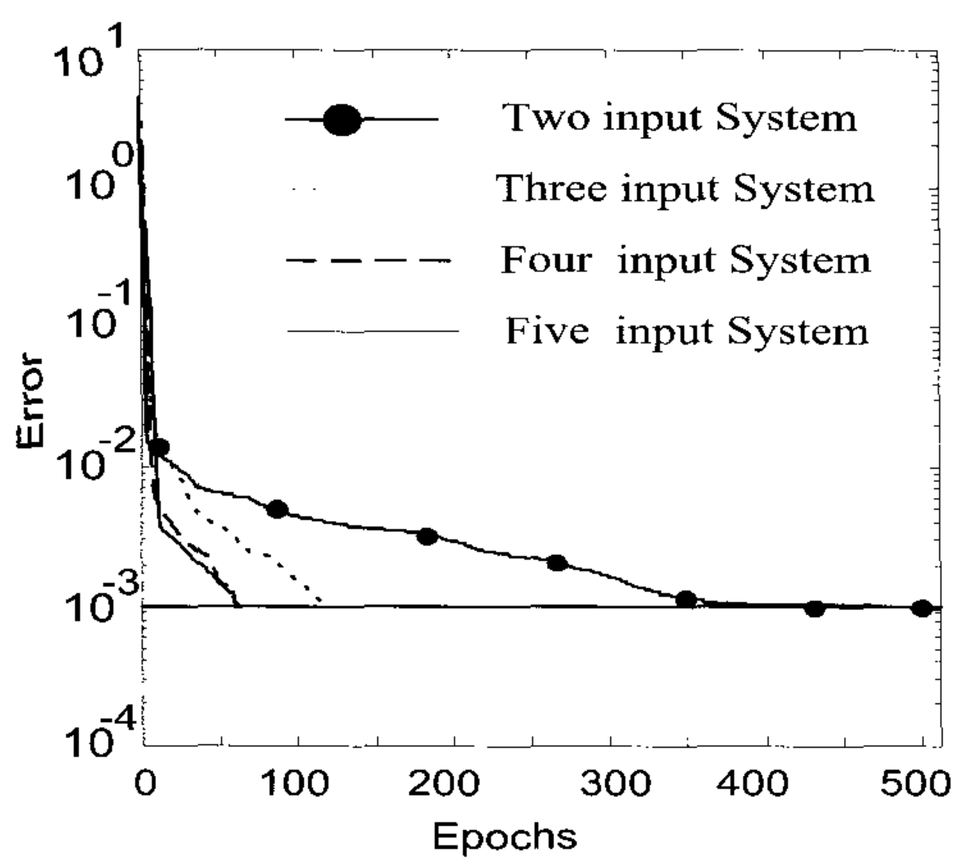


Fig. 7 Error reducing with epochs for two to five input system

ANN based faults detection systems were developed as shown in Fig 6. The inputs to these systems vary from two to five, while the outputs are two in number and they predict the stator winding and motor bearing conditions respectively. The ANN is a multi-input and multi-output system consisting of 10 hidden neurons.

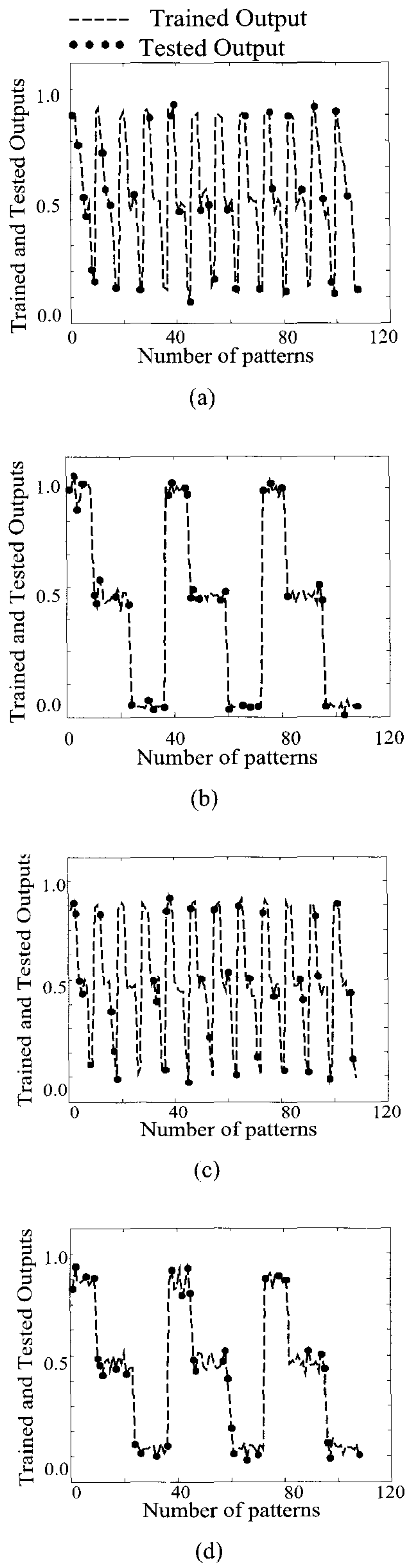


Fig. 8 Training and testing results for two inputs (a) N and (b) B_c, and for five inputs (c) N_c and (d) B_c

The popular back propagation training algorithm is used for training [6], [10]. The learning factor and momentum are 0.1 and 0.9 respectively. Out of the one hundred and forty four training and testing data patterns generated, one hundred and eight patterns were used for training and thirty six patterns were used for testing the system.

The training data sets present discrete target values of 1, 0.67 and 0.33 to the neural network, which correspond to relative conditions of good, fair and bad respectively. An ANN was trained until the average two-norm error of the entire training data set was less than or equal to 0.001 or until the absolute values of the total networks weights was less than 0.0001. The four systems were trained and optimized with the two, three, four and five inputs and two outputs respectively. The data patterns applied for training and testing purposes were (108 x 2, 36 x 2), (108 x 3, 36 x 3) (108 x 4, 36 x 4) and (108 x 5, 36 x 5) respectively.

The training error against iterations graph is given in Fig. 7. It is observed that the epochs (iterations) required for training the system reduces as the number of input increases. Fig. 8 illustrates the training and testing performance for the stator winding insulation condition (N_c) and bearing wear (B_c) for two and five inputs respectively. Table 2 indicates the comparison among all these four systems. All the four systems are optimized by varying the number of neurons in the hidden layer, the learning factor and the momentum. It is found that the accuracy improved with the addition of every input parameter for winding insulation condition (N_c) and bearing wear (B_c). It was observed that the system having the five input parameters produced the highest accuracy.

C: Fault Detection by Adaptive Neural Fuzzy Inference System (ANFIS)

The neural-fuzzy architecture takes into account both neural network and fuzzy logic technologies. The ANFIS tool box in MATLAB environment is used for the fault detection purpose [20] .

Table 2 Artificial Neural Network System results

SN	No. of Inputs	% Accuracy N_c	% Accuracy B_c
1	Two	89.73	83.47
2	Three	92.56	88.12
3	Four	96.49	93.94
4	Five	99.64	98.39

Table 3 Adaptive Neural Fuzzy Inference System results

SN	No. of Inputs	% Accuracy N_c	% Accuracy B_c
1	Two	94.03	90.5
2	Three	96.02	91.39
3	Four	96.42	95.35
4	Five	96.67	98.77

The limitation of this tool box is that the output parameter should be limited to one despite the input parameters. Therefore, two independent ANFIS fault detectors were developed. They were: (i) ANFIS insulation condition detector and (ii) ANFIS bearing condition detector. Each detector was trained and tested individually. Initially, both the detectors were developed with two input parameters speed and current. Afterwards, the remaining three parameters (winding temperature, bearing temperature and noise of the motor) were included sequentially and the results were compared.

The three inputs ANFIS fault detectors are shown in Fig. 9 along with their corresponding testing performances. The performance results were tabulated as shown in Table 3. It was observed from the table that the percentage accuracy also increased with the addition of input parameters.

4. Conclusion

Three AI techniques were applied and five input parameters were used sequentially to develop fault detection systems for the detection of inter-turn short circuits and bearing wear faults. The results of this paper are as follows.

1. The percentage accuracy of incipient faults detection with respect to winding insulation condition and bearing condition was improved with the additional input parameters in all the above fault detection systems.
2. The Fuzzy Inference System (FIS) provides accuracy of more than 97%. However, the response time is poor to predict the conditions.
3. The five inputs ANN based detector provides the highest accuracy in the prediction of winding condition. Also the response time (iterations) reduces with the addition of input parameters.

4. An ANFIS based detector provides the highest accuracy in prediction of bearing condition. However, ANFIS has its unique advantages and these are applicable for fault detection.
5. In comparing Tables 1 to 3, the best system for the prediction of insulation and bearing condition is a five inputs ANN based system as the percentage accuracy after testing is more than 98% for the prediction of insulation condition as well as bearing condition.
6. All these techniques were applied to the actual faulty motor of the same capacity (0.5 hp, 220 v). The performance obtained is quite good with accuracy of more than 96%. The fault detection results were found to be satisfactory.
7. Once the system is trained for specific data over a wide range it can be applicable to similar types of motors used in plants and thus there is no need to train the model for each and every motor.

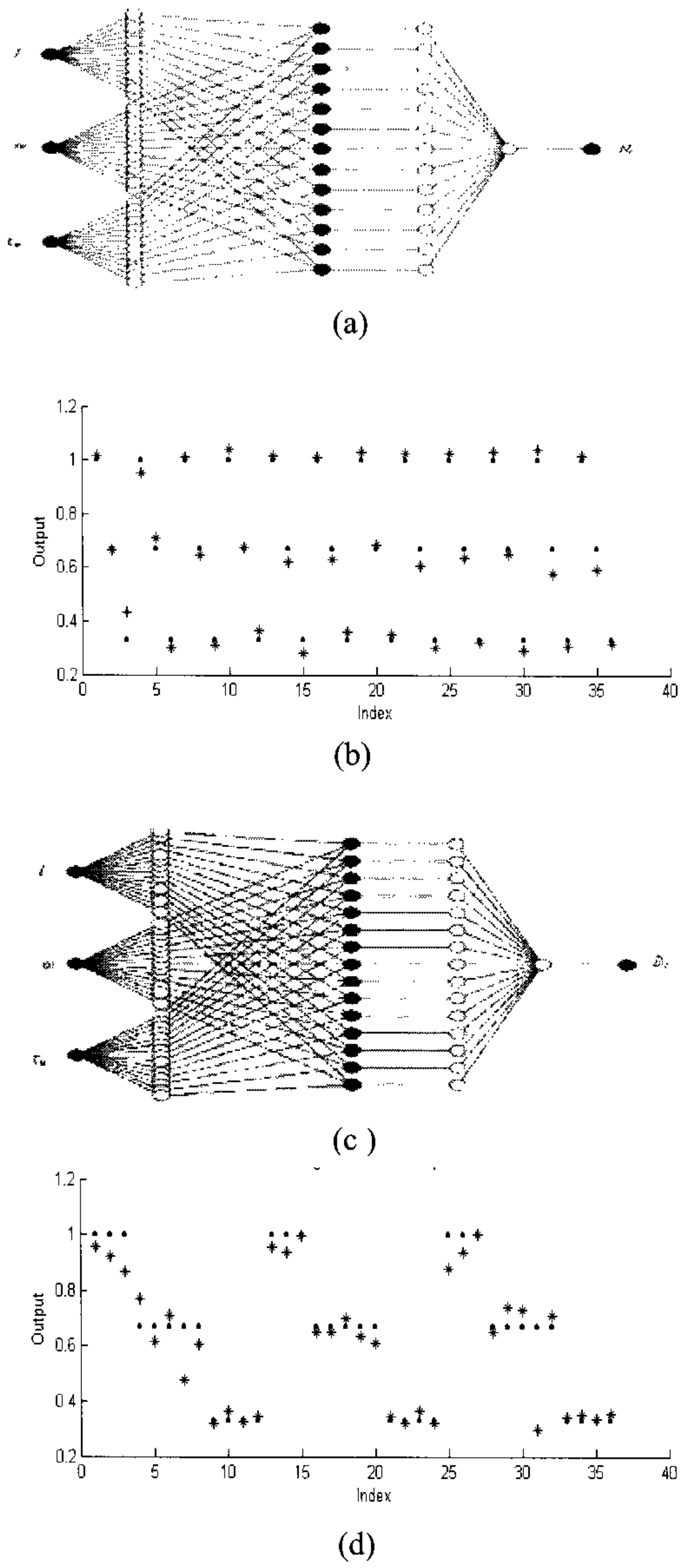


Fig. 9 Three inputs (a) ANFIS Systems for insulation condition, (b) Testing performance for insulation condition (c) ANFIS Systems for bearing condition, (d) Testing performance for bearing condition

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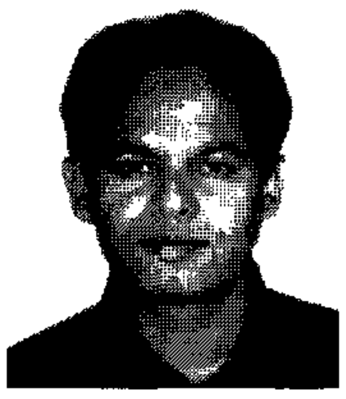

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