ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

IJESRT
INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

SOFT-COMPUTING TECHNIQUES FOR FAULT DIAGNOSIS OF ELECTRICAL DRIVES

Sulekha Shukla*, Manoj Kumar Jha, Shilpa Sharma
Ph.D. Scholar, Computer Science Department, Dr. C.V. Raman University, Bilaspur, India.
Department of Applied Mathematics, Rungta Engg. College, Raipur, India.
Department of Applied Chemistry, Rungta Engg. College, Raipur, India.

ABSTRACT
A method of using fuzzy logic to interpret current sensors signal of induction motor for its stator condition monitoring was presented. Correctly processing theses current signals and inputting them to a fuzzy decision system achieved high diagnosis accuracy. There is most likely still room for improvement by using an intelligent means of optimization. Fault Detection Scheme using Neuro-Fuzzy Approach ANFIS had gained popularity over other techniques due to its knowledge extraction feasibility, domain partitioning, rule structuring and modifications. The artificial neural network (ANN) has the capability of solving the motor monitoring and fault detection problem using an inexpensive, reliable procedure. However, it does not provide heuristic reasoning about the fault detection process. On the other hand, fuzzy logic can easily provide heuristic reasoning, while being difficult to provide exact solutions. By merging the positive features of ANN and fuzzy logic, a simple noninvasive fault detection technique is developed. By using a hybrid, supervised learning algorithm, ANFIS can construct an input-output mapping. The supervised learning (gradient descent) algorithm is used here to train the weights to minimize the errors.
.

KEYWORDS: Fault diagnosis, soft computing

INTRODUCTION
A fuzzy logic approach may help to diagnose induction motor faults. Fuzzy logic is reminiscent of human thinking process and natural language enabling decisions to be made based on vague information.

The induction motor condition is diagnosed using a compositional rule of fuzzy inference as shown in Fig.1. The obtained results indicate that the proposed fuzzy logic approach is capable of highly accurate diagnosis. The stator current signal contains the information about faults in the motor. Fuzzy systems rely on a set of rules. These rules, allow the input to be fuzzy, i.e. like an electrical machine referred as "somewhat secure", "little overloaded". This linguistic input can be expressed directly by a fuzzy system.

$$I_a = \{\mu(f_a(I_{aj})\epsilon)I_a\}$$
$$I_b = \{\mu(f_b(I_{bj})\epsilon)I_b\}$$
$$I_c = \{\mu(f_c(I_{cj})\epsilon)I_c\}$$
$$CM = \{\mu_{cm}(cm_j)\ \epsilon\ CM\}$$

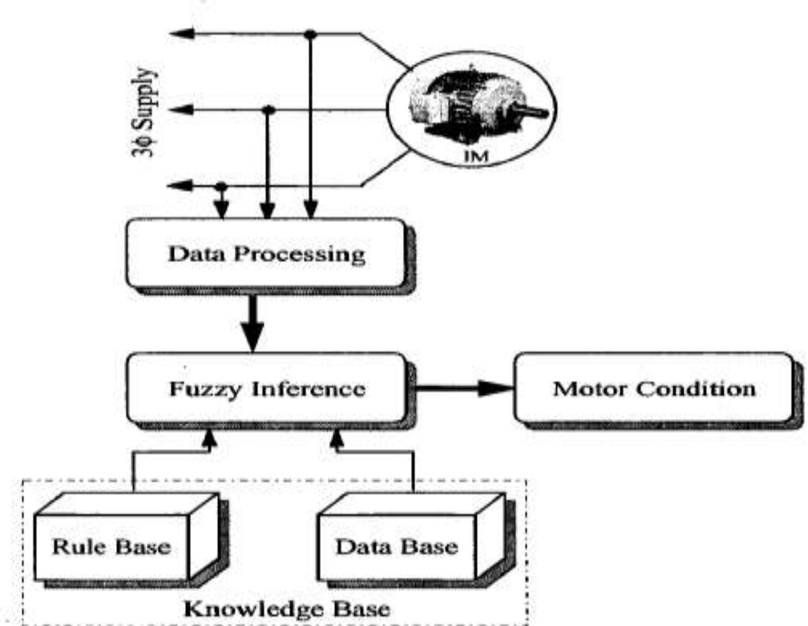


Fig.1 Block Diagram of Induction Motor Condition Monitoring System

FUZZY INFERENCE SYSTEM

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if-then rules. There are two types of fuzzy inference systems that can be implemented in the Fuzzy Logic Toolbox. They are Mamdani-type and Sugeno-type. In this setup Mamdani-type fuzzy inference system is used. The fuzzy inference system is shown in Fig.2.

MEMBERSHIP FUNCTIONS

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.The input space is sometimes referred to as the universe of discourse. There are two types of membership functions. They are input membership function and output membership function.

Input Membership Function

The input membership function consists of three input variables. They are Ia, Ib and Ic nothing but the stator current signals. Here trapezoidal and triangular membership function is used. The input variables are interpreted as linguistic variables, with Zero (Z), Small(S), Medium (M) and Big (B). The input membership function is shown in Fig.3. The range of input membership function varies from 0 to 3.

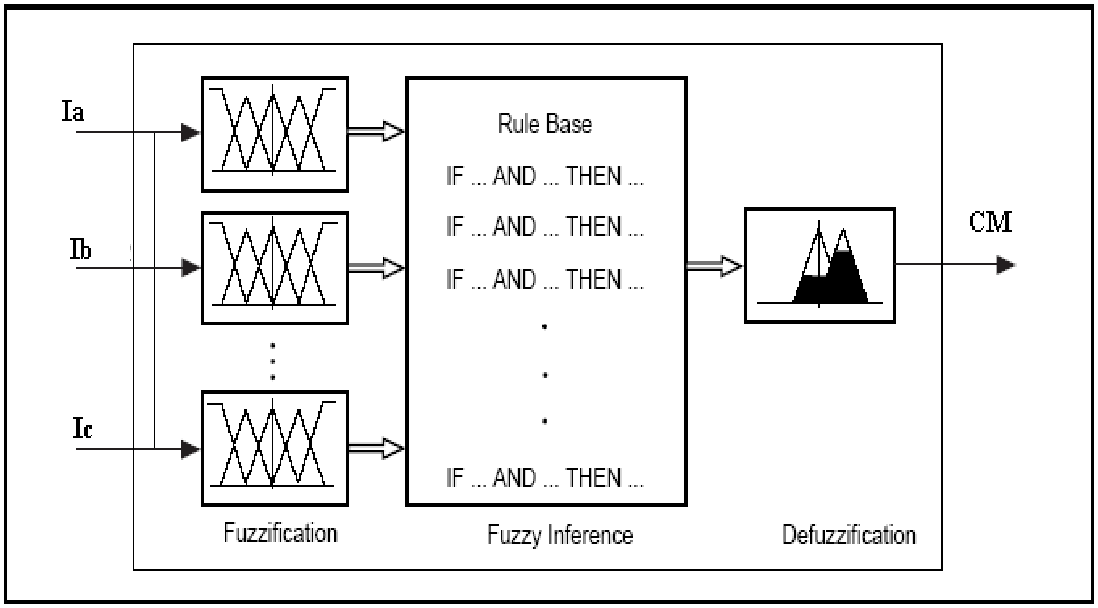


Fig.2 Internal Structure of Fuzzy Logic Controller

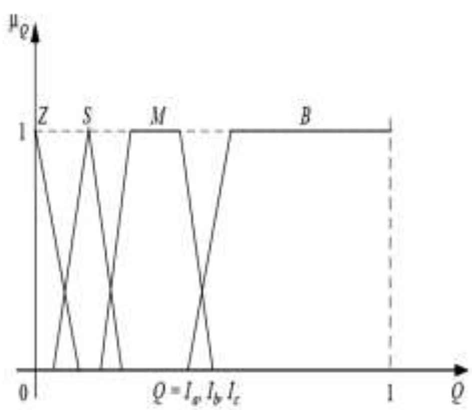


Fig.3 Fuzzy Membership functions for stator currents (Z: Zero, S: Small, M: Medium and B: Big)

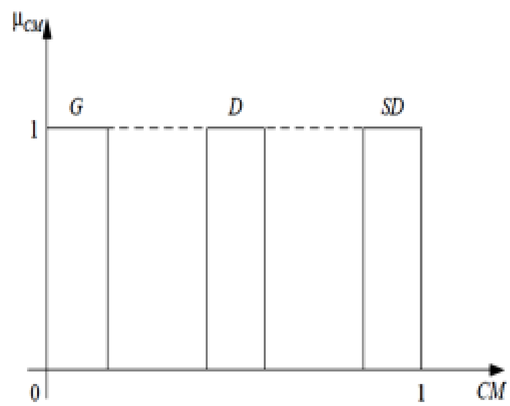


Fig.4 Fuzzy membership functions for the stator condition (G: Good, D: Damaged and SD: Seriously Damaged)

Output Membership Function

The Output membership consists of one variable. The variable is the condition of the motor. The output variables are interpreted as linguistic variable with Good, Damaged and Seriously Damaged. Here also trapezoidal membership function is used. The output membership function is shown in Fig. 4. The range of output membership function varies from 0 to 100.

DEFUZZIFICATION AND FUZZY RULES

Defuzzification is defined as the conversion of fuzzy output to crisp output. There are many types of defuzzification methods available. Here we used Center of Area (COA) method for defuzzification. Despite its complexity it is more popularly used because, if the areas of two or more contributing rules overlap, the overlapping area is counted only once.

Rule (1): If *Ia* is *Z* Then *CM* is *SD*
Rule (2): If *Ib* is *Z* Then *CM* is *SD*
Rule (3): If *Ic* is *Z* Then *CM* is *SD*
Rule (4): If *Ia* is *B* Then *CM* is *SD*
Rule (5): If *Ib* is *B* Then *CM* is *SD*
Rule (6): If *Ic* is *B* Then *CM* is *SD*
Rule (7): If *Ia* is S and *Ib* is S and *Ic* is *M* Then *CM* is *D*
Rule (8): If *Ia* is *S* and *Ib* is *M* and *Ic* is *M* Then *CM* is *D*
Rule (9): If *Ia* is *M* and *Ib* is *S* and *Ic* is *M* Then *CM* is *D*
Rule (10): If *Ia* is *M* and *Ib* is *M* and *Ic* is *M* Then *CM* is *G*
Rule (11): If *Ia* is *S* and *Ib* is *S* and *Ic* is *S* Then *CM* is *G*
Rule (12): If *Ia* is *S* and *Ib* is *M* and *Ic* is *S* Then *CM* is *D*
Rule (13): If *Ia* is *M* and *Ib* is *S* and *Ic* is *S* Then *CM* is *D*
Rule (14): If *Ia* is *M* and *Ib* is *M* and *Ic* is *S* Then *CM* is *D.*

MODELING AND SIMULATION OF INDUCTION MOTOR FAULT DETECTION

Modeling here refers to the process of analysis and synthesis to arrive at a suitable mathematical description that encompasses the relevant dynamic characteristics of the component, preferably in terms of parameters that can be easily determined in practice. In mathematical modeling, we try to establish functional relationships between entities that are important. A model supposedly imitates or reproduces certain essential characteristics or conditions of the actual – often on a different scale. Here the three-phase induction motor model has been derived instead of two phase model (d-q representation), which is very commonly used. So, in order to gain an understanding of problems that does not comply directly with balanced operating conditions and for which d-q methods of analysis are inappropriate, three-phase representation becomes essential.

Induction Motor Performance Parameter Analysis for Stator Fault

When induction machines are expressed in three-phase axes, many of the inductances are function of the rotor displacement and therefore functions of rotor speed and time as shown in the following Stator Inductances: It is assumed that the air gap of the induction machine is uniform and the stator and rotor windings are sinusoidally distributed, all the stator self-inductances are identical.

$$L_{AA} = L_{BB} = L_{CC} = L_{is} + L_{ms}$$

The mutual inductance between any two stator windings is the same due to symmetry

$$L_{AB} = L_{BA} = -0.5L_{ms}$$
$$L_{BC} = L_{CB} = -0.5L_{ms}$$
$$L_{CA} = L_{AC} = -0.5L_{ms}$$

Rotor Inductances: In the same manner to that given for the stator, the rotor self-inductances and mutual inductances are:

$$L_{aa} = L_{bb} = L_{cc} = L_{lr} + L_{mr}$$
$$L_{ab} = L_{ba} = -0.5L_{mr}$$
$$L_{bc} = L_{cb} = -0.5L_{mr}$$
$$L_{ca} = L_{ac} = -0.5L_{mr}$$
$$L_{Aa} = L_{Bb} = L_{Cc} = L_{msr}\cos\theta_r$$
$$L_{Ac} = L_{Ba} = L_{Cb} = L_{msr}\cos(\theta_r - 120^0)$$
$$L_{Ab} = L_{Bc} = L_{Ca} = L_{msr}\cos(\theta_r + 120^0)$$

The mutual inductance between a stator winding and any rotor winding varies sinusoidally with rotor position. The Fig. 5 Shows the two dimensional diagram of three-phase induction motor with stator and rotor windings.

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

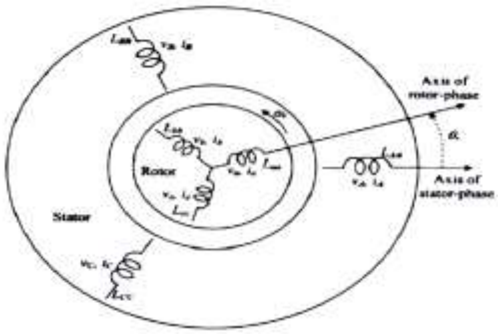


Fig. 5 Three Phase Induction Motor

The voltage equations for a three-phase induction machine can be expressed as:

Stator Equation is $V_A = R_A i_A + \frac{d\lambda_A}{dt}$

$$V_B = R_B i_B + \frac{d\lambda_B}{dt}$$

$$V_C = R_C i_C + \frac{d\lambda_C}{dt}$$

Rotor equation is $V_a = R_a i_a + \frac{d\lambda_a}{dt}$

$$V_b = R_b i_b + \frac{d\lambda_b}{dt}$$

$$V_c = R_c i_c + \frac{d\lambda_c}{dt}$$

The parameters inside the induction motor three-phase model and the three phase source can be set by executing a m-file which stores the all parameters used in the model. By running the m-file all the values of the parameters can be accessed by the model from the workspace.

Machine Parameters: The parameters of the machine used for simulation are listed below:
Rated Voltage V = 380V,
Frequency f= 50 Hz,
Stator Resistance R_{stator} = 15.3Ω,
Rotor Resistance R_{rotor} = 7.46Ω,
The stator and rotor self-inductances are equal to
$L_{stator} = L_{rotor} = L_{leakage}+L_{mutual}$ = .035+.55 = 0.585H,
The mutual inductance between any two stator and any tow rotor windings is equal to
Lss, mutual = Lrr, mutual = -0.5L_{mutual} = -0.275H,
The mutual inductance between a stator winding and any rotor winding is equal to Lsr, mutual = L_{mutual} =0.55H,
Number of Poles P = 4,
Inertial constant J = 0.023kg.m2.

Sub Models and Equations Governing the Subsystem of Induction Motor

1) Mechanical Model

The dynamic load equation is: $T_e - T_L = J\frac{d\omega_r}{dt} + D\omega_r$

$$\frac{d\omega_r}{dt} = \frac{T_e - T_L}{J}$$

$$\omega_r = \frac{1}{J}\int (T_e - T_L)dt$$

2) Torque Model

The electromechanical torque equation is: $\left[i_A\left\{i_a[L_{Aa}+L_{aA}]\sin(\theta_r)+i_b[L_{Ab}+L_{bA}]\sin\left(\theta_r+\frac{2\pi}{3}\right)+i_c[L_{Ac}+L_{cA}]\sin\left(\theta_r-\frac{2\pi}{3}\right)\right\}+i_B\left\{i_a[L_{Ba}+L_{aB}]\sin(\theta_r)+i_b[L_{Bb}+L_{bB}]\sin\left(\theta_r+\frac{2\pi}{3}\right)+i_c[L_{Bc}+L_{cB}]\sin\left(\theta_r-\frac{2\pi}{3}\right)\right\}+i_C\left\{i_a[L_{Ca}+L_{aC}]\sin(\theta_r)+i_b[L_{Cb}+L_{bC}]\sin\left(\theta_r+\frac{2\pi}{3}\right)+i_c[L_{Cc}+L_{cC}]\sin\left(\theta_r-\frac{2\pi}{3}\right)\right\}\right]$

3) Flux Linkages Model

The flux linkages associated with the interactions between stator and rotor windings are represented by:

Stator:

$$\lambda_A = L_{AA}i_A + L_{AB}i_B + L_{AC}i_C + L_{Aa}\cos(\theta_r)\,i_a + L_{Ab}\cos\left(\theta_r+\frac{2\pi}{3}\right)i_b + L_{Ac}\cos\left(\theta_r-\frac{2\pi}{3}\right)i_c$$
$$\lambda_B = L_{BA}i_A + L_{BB}i_B + L_{BC}i_C + L_{Ba}\cos\left(\theta_r-\frac{2\pi}{3}\right)i_a + L_{Bb}\cos(\theta_r)\,i_b + L_{Bc}\cos\left(\theta_r+\frac{2\pi}{3}\right)i_c$$
$$\lambda_C = L_{CA}i_A + L_{CB}i_B + L_{CC}i_C + L_{Ca}\cos\left(\theta_r+\frac{2\pi}{3}\right)i_a + L_{Cb}\cos\left(\theta_r-\frac{2\pi}{3}\right)i_b + L_{Cc}\cos(\theta_r)\,i_c$$

Rotor:

$$\lambda_a = L_{Aa}i_a + L_{Ab}i_b + L_{Ac}i_c + L_{aA}\cos(\theta_r)\,i_A + L_{aB}\cos\left(\theta_r+\frac{2\pi}{3}\right)i_B + L_{aC}\cos\left(\theta_r-\frac{2\pi}{3}\right)i_C$$
$$\lambda_b = L_{ba}i_a + L_{bb}i_b + L_{bc}i_c + L_{bA}\cos\left(\theta_r+\frac{2\pi}{3}\right)i_A + L_{aB}\cos(\theta_r)\,i_B + L_{aC}\cos\left(\theta_r-\frac{2\pi}{3}\right)i_C$$
$$\lambda_c = L_{ca}i_a + L_{cb}i_b + L_{cc}i_c + L_{bA}\cos\left(\theta_r-\frac{2\pi}{3}\right)i_A + L_{cB}\cos\left(\theta_r+\frac{2\pi}{3}\right)i_B + L_{bC}\cos(\theta_r)\,i_C$$

Symmetrical Component Analysis

The occurrence of shorted turns and phase imbalanced in the stator winding of induction motors cause predictable harmonics to appear in the spectrum of line currents and in the axial leakage flux. By analyzing the relation of the positive and negative-sequence currents to that of torque and slip, when the machine is subjected to various operating conditions, the faults can be diagnosed.

An unbalanced system of related phasors can be resolved into n systems of balanced phasors called the symmetrical components of the original phasors. The per phase impedance of the positive-sequence network will be different from those of negative and zero-sequence networks. The expression for the three unbalanced phasors as a function of the balanced phasor components are as given below:

$$V_A = V_{A0} + V_{A1} + V_{A2}$$
$$V_B = V_{B0} + V_{B1} + V_{B2}$$
$$V_C = V_{C0} + V_{C1} + V_{C2}$$

The positive, negative and zero sequence vector components of any phase always have the angular relationship with respect to one another.

$$V_{A0} = (V_A + V_B + V_c)/3$$
$$V_{A1} = (V_A + aV_B + a^2V_c)/3$$
$$V_{A2} = (V_A + a^2V_B + aV_c)/3$$
$$\begin{pmatrix} V_{A0} \\ V_{A1} \\ V_{A2} \end{pmatrix} = \frac{1}{3}\begin{pmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{pmatrix}\begin{pmatrix} V_a \\ V_b \\ V_c \end{pmatrix}$$
$$a = exp\left({}^{2\pi}/_{3}\right)$$

If suppose C phase is lost and the motor is running at a steady speed. Then Va and Vb are the remaining voltages and they produce equal and opposite line currents Ia and Ib, which increase to around 1.73 to 2.00 times that of the normal. The negative-sequence voltages produce currents which are limited by impedance that closely approximate those that apply when the motor is started. This negative-sequence current results in the production of counter torque. To compensate negative torque produced the positive-sequence current increases. The motor slip increases to allow the additional positive torque to develop.

FAULT DIAGNOSIS OF ELECTRICAL DRIVES USING ANFIS

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

This section introduces a brief idea about the architecture and learning procedure of the ANFIS which uses a feed-forward multilayer perceptron neural network (MLP) with supervised learning capability. An ANFIS, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, part or all of the nodes are adaptive, which means their outputs of the ANFIS structure depend on the weights connected to the nodes, and the learning rule (gradient descent) specifies how these parameters should be changed to minimize a prescribed error measure.

ANFIS Architecture

For simplicity, we assume the fuzzy inference system under consideration has two inputs x and y and one output z. suppose that the rule base contains two fuzzy if then rules of Takagi and Sugeno's type.

Rule 1: if x is A1 and y is B1, then f1 = p1x + q1y + r1,

Rule 2: if x is A2 and y is B2, then f2 = p2x + q2y + r2.

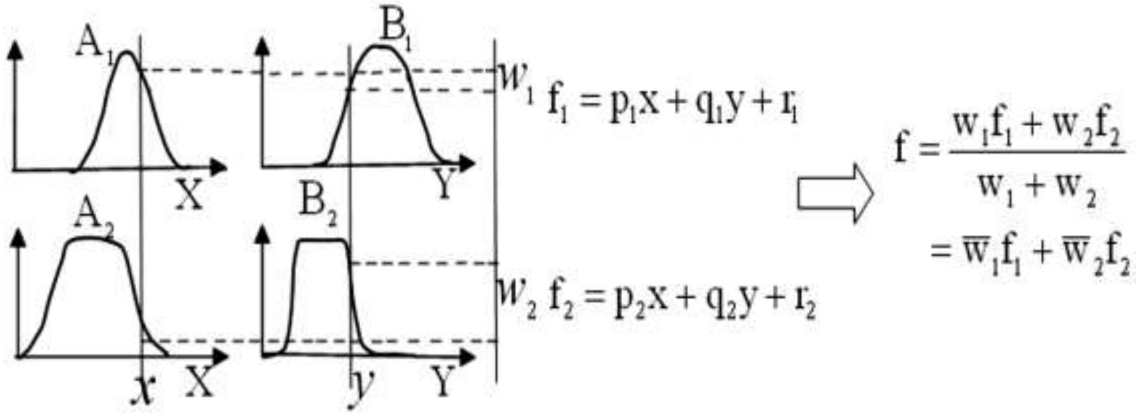


Fig.6 Type-3 fuzzy reasoning

Then the type-3 fuzzy reasoning is illustrated in Fig.6, and the corresponding equivalent ANFIS architecture is shown in Fig.7. The node functions in the same layer are of the same function family as described below:

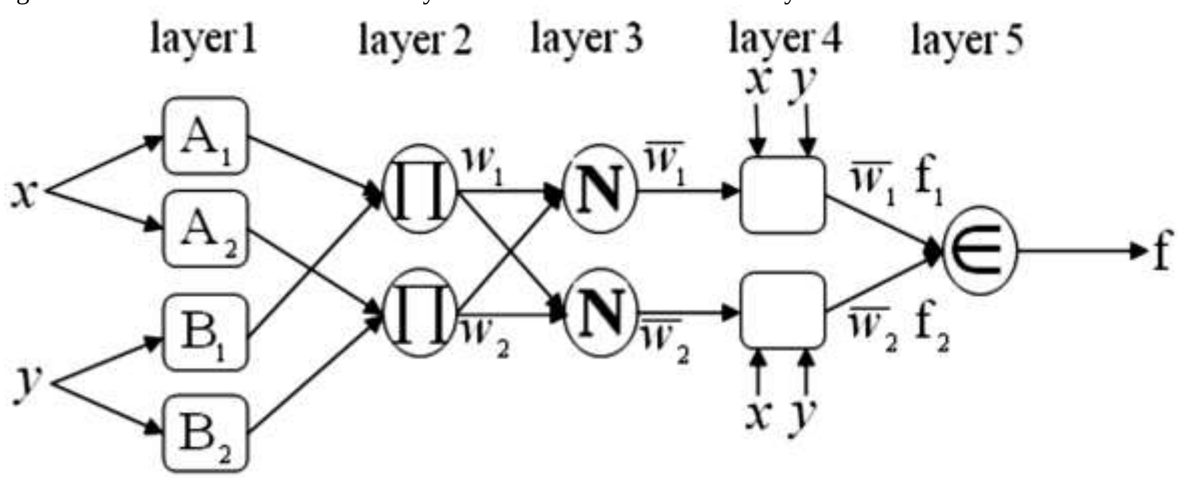


Fig.7 Equivalent ANFIS architecture

Layer 1: Every node I in this layer is a square node with a node function $O_i^1 = \mu_{Ai}(x)$

Where

x = input to node i

Ai= linguistic label (small, large, etc) associated with this node function.

1 =*i O* Membership function of Ai and it specifies the degree to which the given x satisfies the quantifier Ai. A bell-shaped membership function $\mu_{Ai}(x)$ with maximum equal to 1 and minimum equal to 0 is chosen for the ANFIS architecture

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x-c_i}{a_i}\right)^2\right] b_i}$$

Or

$$\mu_{Ai}(x) = exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\}$$

Where {a_i, b_i, c_i} is the parameter set. As the values of these parameters change, the bell shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label Ai. In fact, any continuous and piecewise differentiable functions, such as commonly used Gaussian, trapezoidal or triangular shaped membership functions are also qualified candidates for node functions in this layer.

Layer 2: Every node in this layer is a circle node labeled Π which implies the incoming signals and sends the product out. For instance,

$$W_i = \mu_{Ai}(x) X \mu_{Bi}(x)$$

Where i = 1, 2.

Each node output presents the firing strength of a rule (in fact, other T-norms operators that perform generalized and can be used as the node function in this layer).

Layer 3: Every node in this layer is a circle node labeled N. the i^{th} node calculates the ratio of the i^{th} rules firing strength to the sum of all rules firing strengths:

$$\overline{W}_i = \frac{W_i}{W_1 + W_2}$$

Where i = 1, 2.

For convenience, outputs of this layer will be called normalized firing strengths.

Layer 4: Every node I in this layer is a square node with a node function

$$O_i^4 = \overline{W}_i f_i = \overline{W}_i (P_i x + q_i y + r_i)$$

Where

$$\overline{W}_i = Output\ of\ the\ layer\ 3$$

And $\{p_i, q_i, r_i\} = the\ parameter\ set$

Layer 5: The single node in this layer is a circle node labeled Σ that computes the overall output as the summation of all incoming signals i.e.

$$Overall\ output = O_1^5 = \sum_i \overline{W}_i f_i$$

Fuzzy Inference Systems with Simplified Fuzzy if-then Rules

Though the reasoning mechanisms as shown in Fig.8 are commonly used each of them have inherent draw backs. For Type-1 reasoning, the membership functions on the consequence part are restricted to monotonic functions which are not compatible with linguistic terms such as “medium” whose member ship function should be bell-shaped. To cope with these disadvantages, simplified fuzzy if-then rules of the following form are introduced.

If x is big and y is small, then z is d.

Most of all, with this simplified fuzzy if-then rule, it is possible to prove that under certain circumstances, the resulting fuzzy inference system has unlimited approximation power to match any nonlinear functions arbitrarily well on a compact set. We will proceed this in a descriptive way by applying the stone-weierstrass theorem. Suppose we have two fuzzy inference systems s and š: each has two rules and the output of each system can be expressed as

$$S: Z = \frac{W_1 f_1 + W_2 f_2}{W_1 + W_2}$$

$$\tilde{S}:\tilde{Z}=\frac{\widetilde{W}_1\tilde{f}_1+\widetilde{W}_2\tilde{f}_2}{\widetilde{W}_1+\widetilde{W}_2}$$

Where $f_1, f_2, \tilde{f}_1, \tilde{f}_2$ are constant output of each rule. Then $az+b\tilde{z}$ and $z\tilde{z}$ can be calculated as follows,

$$az+b\tilde{z}=a\frac{W_1f_1+W_2f_2}{W_1+W_2}+b\frac{\widetilde{W}_1\tilde{f}_1+\widetilde{W}_2\tilde{f}_2}{\widetilde{W}_1+\widetilde{W}_2}$$

$$=\frac{W_1\widetilde{W}_1\left(af_1+b\tilde{f}_1\right)+W_1\widetilde{W}_2\left(af_1+b\tilde{f}_2\right)}{W_1\widetilde{W}_1+W_1\widetilde{W}_2+W_2\widetilde{W}_1+W_2\widetilde{W}_2}+\frac{W_2\widetilde{W}_1\left(af_2+b\tilde{f}_1\right)+W_2\widetilde{W}_2\left(af_2+b\tilde{f}_2\right)}{W_1\widetilde{W}_1+W_1\widetilde{W}_2+W_2\widetilde{W}_1+W_2\widetilde{W}_2}$$

$$z\tilde{z}=\frac{W_1\widetilde{W}_1f_1\tilde{f}_1+W_1\widetilde{W}_2f_1\tilde{f}_2+W_2\widetilde{W}_1f_2\tilde{f}_1+W_2\widetilde{W}_2f_2\tilde{f}_2}{W_1\widetilde{W}_1+W_1\widetilde{W}_2+W_2\widetilde{W}_1+W_2\widetilde{W}_2}$$

Apparently the ANFIS architectures that compute $az+b\tilde{z}$ and $z\tilde{z}$ are of the same class of s and $\tilde{s}$ if and only if the class of membership functions are invariant under multiplication. This is loosely true if the class of membership functions is the set of all bell-shaped functions, since the multiplication of two bell-shaped functions is almost always still bell-shaped. Another more highly defined class of membership functions satisfying these criteria, as pointed out by Wang, is the scaled Gaussian membership function:

$$\mu_{Ai}(x)=a_i\,exp\left\{-\left(\frac{x-c_i}{a_i}\right)^2\right\}$$

Therefore by choosing an appropriate class of membership functions, we can conclude that the ANFIS with simplified fuzzy if-then rules satisfy the criteria of the stone Weierstrass theorem. Consequently for any given ε > 0, and any real valued function g, there is a fuzzy inference system such that $|g(\overline{x})-s(\overline{x})|<\varepsilon$ for all $\overline{x}$ in the underlying compact set. Moreover, since the simplified ANFIS is a proper subset of all three types of ANFIS in Fig.8, we can draw the conclusion that all the three types of ANFIS have unlimited approximation power to match any given data set.

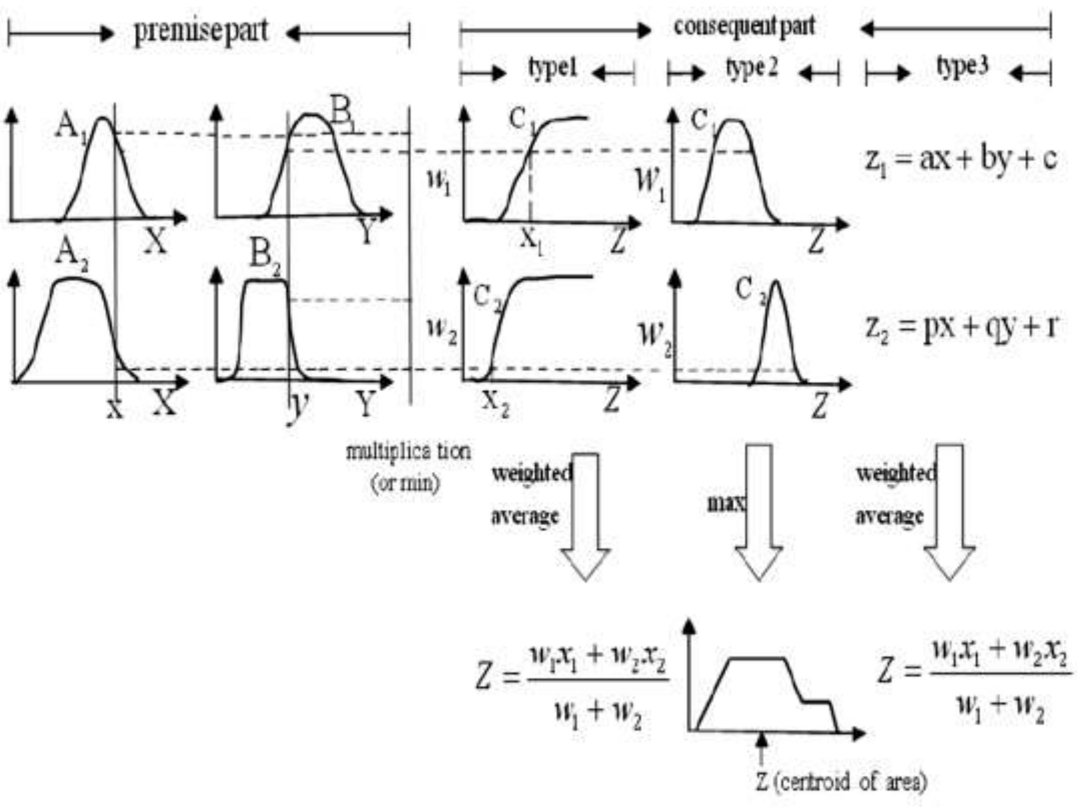


Fig.8 commonly used fuzzy if-then rules and fuzzy reasoning mechanism

Proposed ANFIS Approach for Induction Motor Fault Detection

The proposed work consists of detection and location of an inter-turn short circuit fault in the stator windings of a three phase induction motor by using the combination of the positive features of neural networks and fuzzy logic.

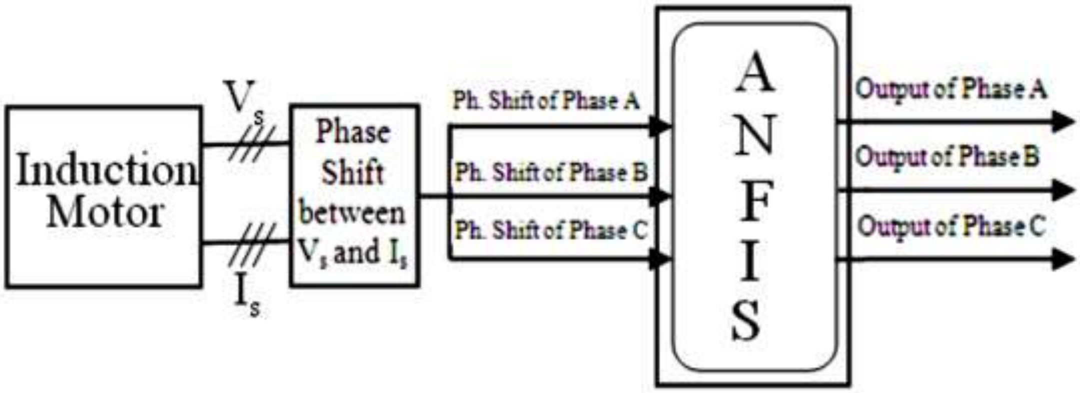


Fig.9 Block diagram of the fault location procedure

Fig.9 shows the block diagram of the procedure to detect and locate inter-turn fault in the stator winding of an induction motor. The first step of in this procedure is the acquisition of the three line currents and phase voltages from the induction motor in order to extract the three phase shift between the line currents and the phase voltages. The three phase shifts are fed to the ANFIS network. ANFIS has to learn the relationships between the fault signature i.e the three phase shifts between the line currents and phase voltages under different load conditions (ANFIS inputs) and the corresponding operating condition (ANFIS outputs) to be able to locate correctly the faulty phase.

Fig.9 shows the ANFIS has three inputs namely, the three phase shifts and three outputs corresponding to the three phases of the induction motor, where the fault can occur. If a short circuit is detected and located in one of the three phases, the corresponding ANFIS is set to 'one', otherwise it is 'zero'.

Selection of a Suitable ANFIS Structure

The neural-fuzzy architecture takes into account both ANN and fuzzy logic technologies. The system is a neural network structured upon fuzzy logic principles, which enables the neural fuzzy system to provide qualitative descriptions about the motor condition and fault detection process. This knowledge is provided by the fuzzy parameters of membership functions and fuzzy rules. The fault detector based on ANFIS, which is a fuzzy inference system implemented on five layers feed-forward network.

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

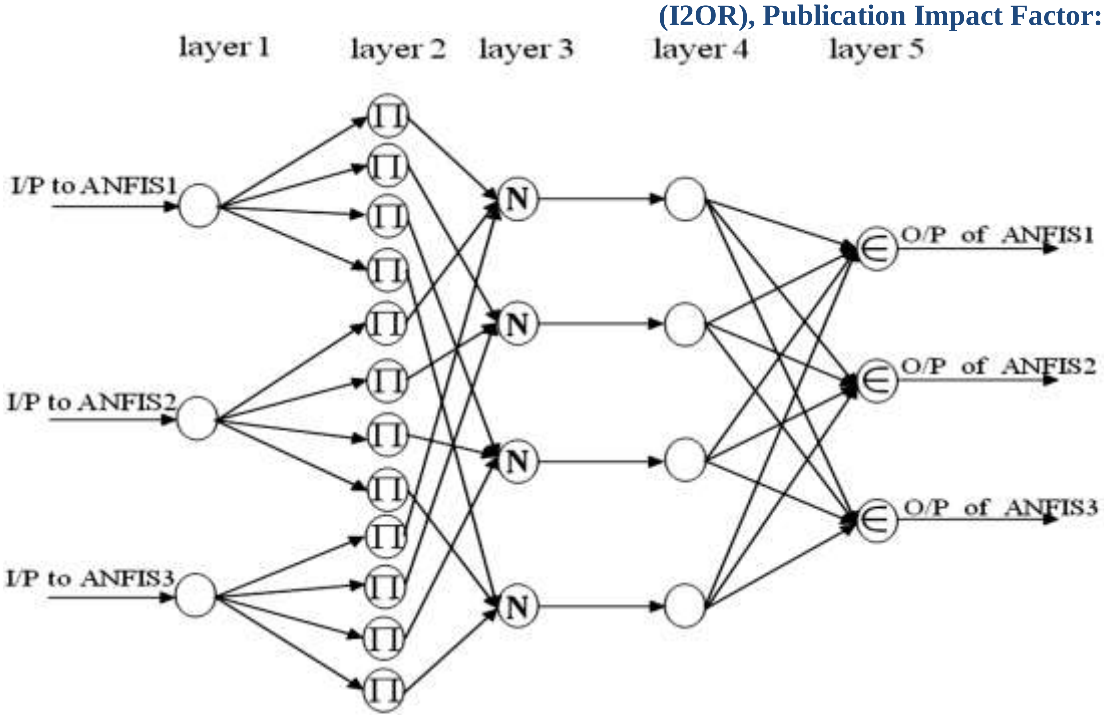


Fig.10 ANFIS fault detector

The ANFIS architecture enables a change in rule structure during the evaluation of fuzzy inference system. The ANFIS optimized itself in given the number of iterations by providing a change in rules, by discarding unnecessary rules, and by changing shapes of membership functions, this is called modifications. It is an inherent characteristic of ANFIS architecture. The use of least square estimation is due to the fact that the network output is linear function of the consequence parameters. Once the system is trained for specific data over a wide range, it can be applicable to similar types of motor use in plants, and thus there is no need to train the model for each and every motor.

Testing Results for ANFIS

The performance of ANFIS on the testing data set represents its generalization ability. The data set is divided into two. One set is used for training and the other for testing. In fact a generalized neural network will perform well for both training and testing data. The test procedure is conducted by a test data set that is different from the training data set to assess the generalization capacity of the adopted network.

The test data set are presented to the neural networks under three load torques ($\tau 1$ = 3 N-m, $\tau 2$ = 5 N-m, $\tau 3$ = 7 N-m) and represent the following different operating cases of the induction motor: healthy (three points) and fault of an even number of shorted turns (2, 4, 6, 8, 10, and 12) on each stator phase [18 (6 × 3) points]. Thus, a total of 21(18 + 3) testing samples has been collected testing the each phase stator inter-turn fault.

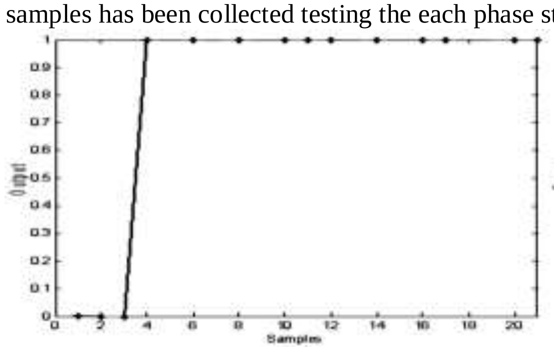


Fig.11 Test Output of phase A for fault on phase A

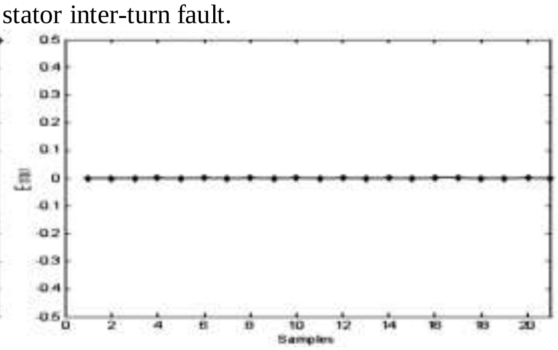
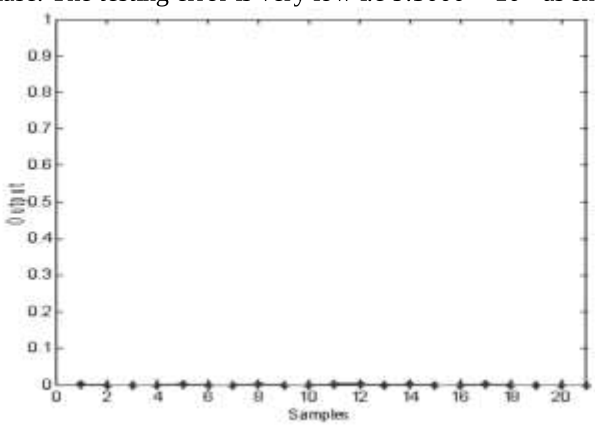


Fig.12 Test Error of phase A for fault on phase A

Figs.11 and 12 show the ANFIS test output and error of phase A when an inter-turn fault occurs on phase A inside the stator of an induction motor. From Fig.11 the ANFIS test output is equal to zero for first three samples and is equal to one for the faulty condition from 4 to 21 samples with good accuracy. This shows that the ANFIS is able to locate correctly the fault occurring on phase A. The testing error is 1.5045×10^{-7} as shown in Fig.12.

The ANFIS test output and error of phase B when an inter-turn short circuit fault occurs on phase A inside the stator of an induction motor as shown in Figs.13 and 14. From Fig.13 it is clear that the ANFIS well learn the test data with good accuracy. Hence the ANFIS is able to locate correctly the stator inter-turn short circuit fault occurring on A phase. The testing error is very low i.e 9.5000×10^{-8} as shown in Fig.14.



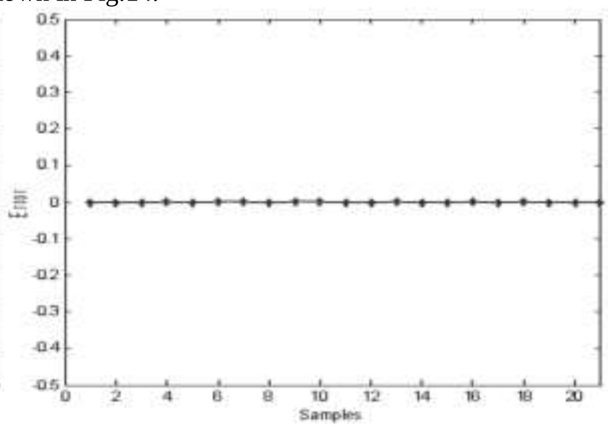
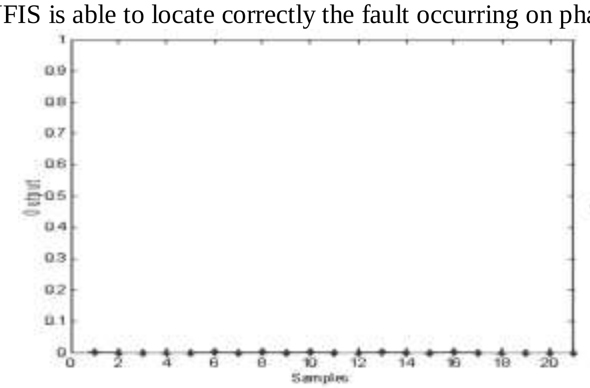


Fig.13 Test Output of phase B for fault on phase A *Fig.14 Test Error of phase B for fault on phase A*

Figs.14 and 15 shows the ANFIS test output and test error of phase C when an inter-turn short circuit fault occurs on phase A inside the stator of an induction motor. Fig.14 shows that the ANFIS well learn the test data and gives the test output with good accuracy. The testing error is 4.0909×10^{-8} as shown in Fig.15. Hence we conclude that the ANFIS is able to locate correctly the fault occurring on phase A.



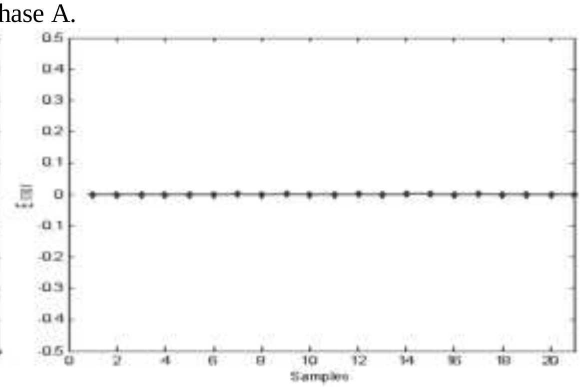


Fig.14 Test Output of phase C for fault on phase A *Fig.15 Test Error of phase C for fault on phase A*

Identification of motor parameters and application AI techniques for fault detection

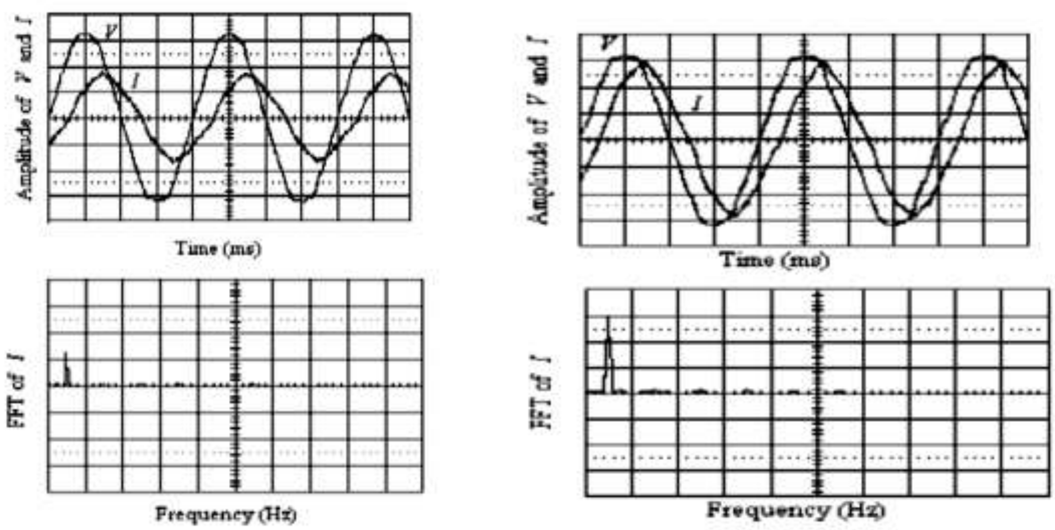
The non-linear relation between the five input measurable parameters of the induction motor $(I, \omega, \tau_w, \tau_b, db)$ with the motor insulation condition (*Nc*) and bearing condition (*Bc*) is explained in literatures. From previous analysis, the motor intake current (*I*), rotor speed (ω), winding 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. it was shown that there exists a mapping *m* between $(I, \omega, \tau_w, \tau_b, db)$ to (*Nc* , *Bc*) such that;

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

$$m = (I, \omega, \tau_w, \tau_b, db) \rightarrow (Nc\ , Bc)$$

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. 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.

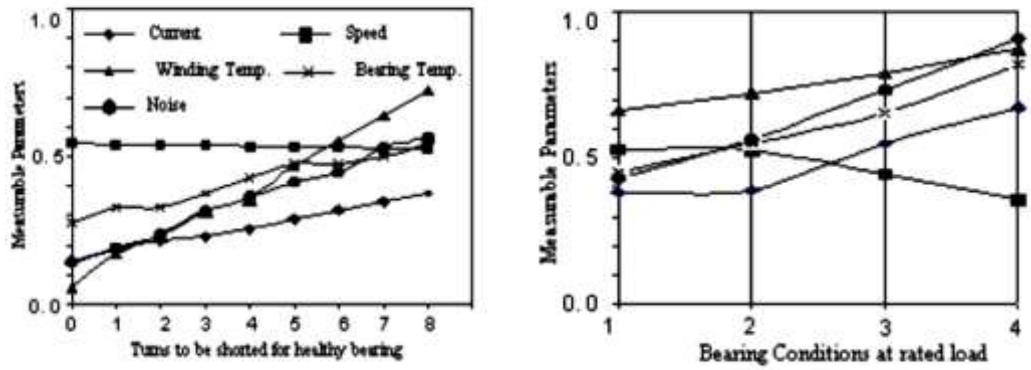
The ANFIS is a neural network structured upon fuzzy logic principles, which enable the neural fuzzy system to provide the motor condition and fault detection process. The AI based inter turn insulation and bearing wear fault detectors are developed in real time. The experimental stator currents waveforms and their respective Fast Fourier Transforms (FFTs) are shown in Fig.16. 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 few samples of noise waveforms and corresponding FFTs obtained from the DSO are shown in Fig.17. It is observed from Fig.16 and 17 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 one hundred and eight patterns are used for training the systems and the thirty-six patterns are used for testing the systems.



a. ***b.***

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

Fig.16 Motor intake current and their respective FFTs
(a) Rated load, healthy bearing, two turns shorted,
(b) Rated load, damaged bearing, all turns shorted



0: Healthy condition – No turns shorted

8: Fault condition – All turns shorted

(a) Insulation Fault

1. Healthy, 2. Less lubricated,

3. Dry and 4. Damage bearings

(b) Bearing Fault

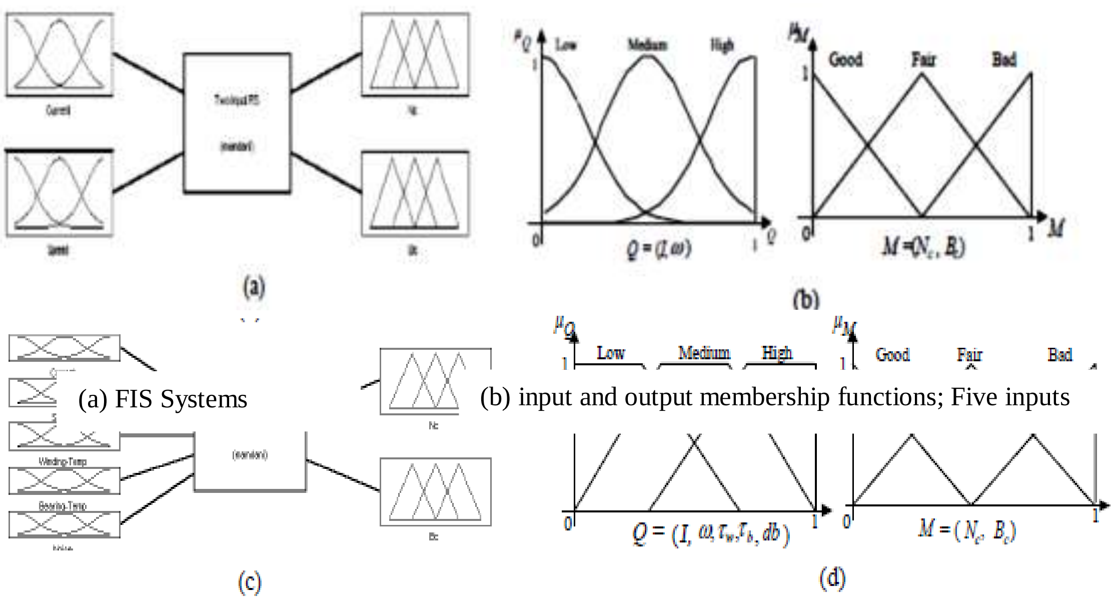
Fig.17 Experimental Results in pu. at rated load

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. Later the



(a) FIS Systems

(b) input and output membership functions; Five inputs

(c) FIS System, Two inputs

(d) input and output membership functions

Fig.18 consistency of these rules is verified using experimental results.

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

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.

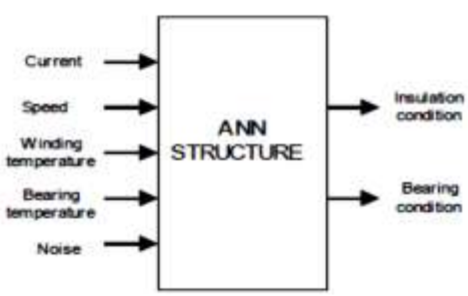
Fig.18 shows the two different types of Fuzzy Inference Systems (FISs) and their corresponding optimized membership functions. The accuracy of the fault detection is improved sequentially by adding the new input parameter in the earlier system. It is observed that the response time is considerably increased 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

S.No.	No. of Input	% Accuracy N_c	% Accuracy B_c
1.	Two	93.24	77.32
2.	Three	94.65	87.34
3.	Four	97.23	95.32
4.	Five	99.24	97.56

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. 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 *Nc* and *Bc* 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.



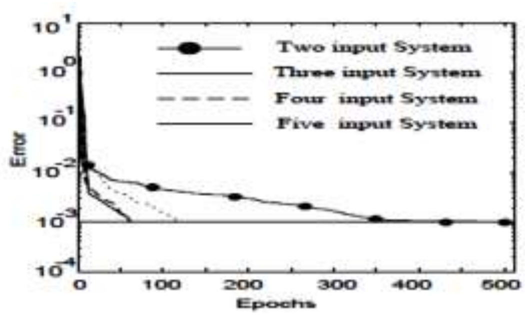


Fig.19 ANN structure ***Fig.20 Error reducing with epochs for two to five input system***

ANN based faults detection systems were developed as shown in Fig.19. 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.

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.20. It is observed that the epochs (iterations) required for training the system reduces as the number of input increases.

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 (*Nc*) and bearing wear (*Bc*). It was observed that the system having the five input parameters produced the highest accuracy.

Table 2 Artificial Neural Network System results

S.No.	No. of Input	% Accuracy N_c	% Accuracy B_c
1.	Two	89.24	83.32
2.	Three	92.65	88.34
3.	Four	96.23	93.32
4.	Five	99.64	98.56

***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.

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.

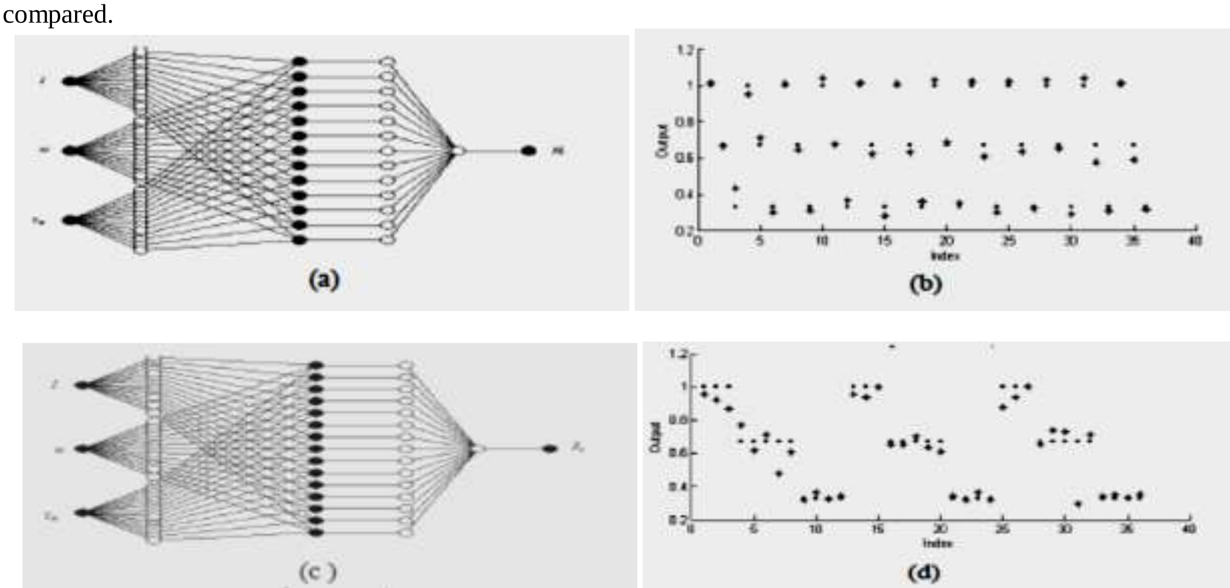


Fig.21 Three inputs (a) ANFIS Systems for insulation condition, (b) Testing performance for insulation condition (c) ANFIS Systems for bearing condition, (d) Testing performance for bearing condition

The three inputs ANFIS fault detectors are shown in Fig.21 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.

Table 3 Adaptive Neural Fuzzy Inference System results

S.No.	No. of Input	% Accuracy N_c	% Accuracy B_c
1.	Two	94.04	90.32
2.	Three	96.04	91.34
3.	Four	96.43	95.35
4.	Five	96.67	98.56

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, 220v). 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.

A method of using fuzzy logic to interpret current sensors signal of induction motor for its stator condition monitoring was presented. Correctly processing theses current signals and inputting them to a fuzzy decision system achieved high diagnosis accuracy. There is most likely still room for improvement by using an intelligent means of optimization. Fault Detection Scheme using Neuro-Fuzzy Approach ANFIS had gained popularity over other techniques due to its knowledge extraction feasibility, domain partitioning, rule structuring and modifications. The artificial neural network (ANN) has the capability of solving the motor monitoring and fault detection problem using an inexpensive, reliable procedure. However, it does not provide heuristic reasoning about the fault detection process. On the other hand, fuzzy logic can easily provide heuristic reasoning, while being difficult to provide exact solutions. By merging the positive features of ANN and fuzzy logic, a simple noninvasive fault detection technique is developed. By using a hybrid, supervised learning algorithm, ANFIS can construct an input-output mapping. The supervised learning (gradient descent) algorithm is used here to train the weights to minimize the errors.

In this chapter, application of ANFIS architecture takes into account the positive features of both the ANN and fuzzy logic technology for detection of stator winding inter-turn fault of an induction motor has been proposed. This system is a neural network structured upon fuzzy logic principles, which enables the neural fuzzy system to provide qualitative descriptions about the motor condition and fault detection process. Here we have used the three phase shifts between the line currents and phase voltages of the induction motor as inputs to the ANFIS.

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

A diagnosis method using fuzzy logic to determine the state condition of the induction motor was presented. In order to make an efficient diagnosis at low slip, the stator current envelope obtained via Hilbert transform has been used as diagnostic signal. The amplitude of the dc and 2sf components of the spectrum stator current envelope are intended as inputs to the fuzzy system which are converted to variables linguistic by fuzzy subsets and their corresponding membership functions. The output of this system represents the rotor condition. The system was tested under different load and for different number of broken bars. The results obtained with this system are good and is capable to detect the correct number of broken bar.

REFERENCE

[1] Annette Muetze, and Andreas Binder, "Calculation of Circulating Bearing Currents in Machines of Inverter-Based Drive Systems," IEEE Transaction on Industrial Electronic, Vol. 54, No. 2, pp. 932-938, April 2007.

[2] Antonino-Daviu, J. A.; Riera-Guasp, M.; Folch, J. R. & Palomares, M. P. M. (2006). Validation of a new method for the diagnosis of rotor bar failures via wavelet transform in industrial induction machines, *IEEE Transactions on Industry Applications*, Vol. 42, No. 4, pp. 990- 996.

[3] Arfat Siddique, G. S. Yadava, and Bhim Singh, "A Review of Stator Fault Monitoring Techniques of Induction Motors," IEEE Transactions on Energy Conversion, Vol. 20, No. 1, pp 106 – 115, March 2005.

[4] Arfat siddique, member, ieee, g. S. Yadava, and bhim singh, senior member, IEEE ,"a review of stator fault monitoring techniques of induction motors", IEEE transactions on energy conversion, Vol. 20, No. 1, March 2005.

[5] Awadallah, M.A. and Morcos, M. M., "ANFIS-based diagnosis and location of stator inter. faults in PM brushless DC motors", IEEE Trans. Energy Conversion, Vol. 19, No. 4, pp. 795–796, 2004.

[6] B. Ayhan, J. Trussell, M.Y. Chow, (2008) "On the use of a lower sampling rate for broken rotor bar detection with DTFT and AR-based spectrum methods", IEEE Transaction on Industrial Electronics, Vol. 55, Issue 3, pp. 1421-1434.

[7] Behrooz Mirafzal and Nabeel A. O. Demerdash, "On Innovative Methods of Induction Motor Interturn and Broken-Bar Fault Diagnostics," IEEE Transactions on Industry applications, Vol. 42, No. 2, pp. 405-410, March/April 2006.

[8] Benbouzid M. E. H., (Jan. 2001) "A Simple Fuzzy Logic Approach for induction Motor Stator Condition Monitoring," IEMDC 2001. IEEE International, pp. 634-639.

[9] Benbouzid, M. E. H. & Kliman, G. B. (2003). "What stator current processing-based technique to use for induction motor rotor faults diagnosis ?," *IEEE Transactions on Energy Conversion*, Vol. 18, No. 2, pp. 238-244

[10] Benbouzid, M.E.H., "A review of induction motors signatures analysis as a medium for fault detection", IEEE Transactions on Industrial Electronics, Vol. 47, pp. 984–993, 2000.

[11] Bonnett, A.H. and Soukup, G.C., (1992) "Cause and analysis of stator and rotor failures in three phase squirrel cage induction motors", IEEE Transaction on Industry Applications, pp. 921–937.

[12] C. Lynch. H. Hagras and V. Callaghan; (July 2006) "Embedded Interval type-2 Neuro-Fuzzy Speed Controller for Marine Diesel Engines"; Proceedings of the 2006 Information Processing and Management of Uncertainty in Knowledge-based Systems conference, pp. 1340-1347, Paris, France.

[13] C. Yeh, A. Sayed, R. Povinelli, (3-5 May 2007)"A reconfigurable motor for experimental emulation of stator winding inter-turn and broken bar faults in poly phase induction machines", Electric Machines & Drives Conference, 2007. IEMDC '07. IEEE International. Vol.2, pp. 1413 – 1419.

[14] Cohen, L. (1989). "Time-frequency distributions – A review", *Proceedings of the IEEE*, Vol. 77, No. 7, , pp. 941-981.

[15] Culbert, I. M. & Rhodes, W. (2007). "Using Current Signature Analysis Technology to Reliably Detect Cage Winding Defects in Squirrel-Cage Induction Motors", *IEEE Transactions on Industry Applications*, Vol. 43, No. 2, pp. 422-428.

[16] Culbert, I. M. & Rhodes, W. (2007). "Using Current Signature Analysis Technology to Reliably Detect Cage Winding Defects in Squirrel-Cage Induction Motors", *IEEE Transactions on Industry Applications* Vol. 43, No. 2, pp. 422-428.

[17] Culbert, I.M. & Rhodes, W. (2007). "Using Current Signature Analysis Technology to Reliably Detect Cage Winding Defects in Squirrel-Cage Induction Motors", *IEEE Transactions on Industry Applications* Vol. 43, No. 2, pp. 422-428.

[18] D. E. Rumelhart, B. Widrow and M.A. Lehr, "The basic ideas in neural networks," Communication of ACM, Vol.37, No.3, pp. 87-92, March 1994.

[19] D. Wu and W.W. Tan; (May 2005) "type-2 FLS modeling capability analysis"; Proceedings of the 2005 IEEE International Conference on Fuzzy Systems, pp. 242-247; Reno, USA.

[20] Dorrell, D. G. (1996). "Calculation of Unbalanced Magnetic Pull in Small Cage Induction Motors with Scewed Rotors and Dynamic Rotor Eccentricity", *IEEE Transactions on Energy Conversion*, pp. 483-488.

[21] Dorrell, D.G., Thomson, W.T., and Roach, S. (1997). "Analysis of Airgap Flux, Current, and Vibration Signals as a Function of the Combination of Static and Dynamic Airgap Eccentricity in 3-Phase Induction Motors", *IEEE Transactions on Industry Applications*, Vol. 33, No. 1, (January/February) pp. 24-34.

[22] F. Filippeti, G. Franceschini, C. Tassoni, and P. Vas, (Oct. 2000) "Recent Developments of Induction Motor Drives Fault Diagnosis Using AI Techniques", IEEE Trans. Ind. Electron., Vol.47, No. 5, pp. 994-1004.

[23] F. Filippetti, G. Franceschini, and C. Tassoni, "Neural networks aided on-line diagnostics of induction motor rotor faults," IEEE Trans. on Industrial Applications, Vol. 31, No. 4, pp. 892-899, July/August 1995.