www.ijrream.in Impact Factor: 2.9463

INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)

Tamilnadu-636121, India

Indexed by

Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610

ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

A COMPARATIVE STUDY AND AN OPTIMIZED SOLUTION FOR DETECTING FAULTS IN INDUCTION MOTOR DRIVES

Dr.V.S.Chandrika,

Professor/EEE,

Priyadarshini Engineering College,

Vaniyambadi, Vellore district ,Tamilnadu , India

E-Mail: mailchandrika@gmail.com

Abstract

The use of induction motors in industry is extensive. These motors are exposed to a wide variety of environments and conditions which age the motor and make it subject to incipient faults. These incipient faults, if left undetected, contribute to the degradation and eventual failure of the motors. With proper monitoring and fault detection schemes, the incipient faults can be detected; Thus, maintenance and down time expenses can be reduced while also improving safety. Unfortunately, many of the conventional methods used to determine these faults are either very extensive to implement or impractical for small machines. Hence, this paper presents Artificial intelligence techniques to detect insulation and bearing faults in an induction motor. Initially, the general design consideration for error back propagation feed forward Artificial neural networks to perform motor fault detection is presented. Secondly, the application of Fuzzy logic to detect the faults in an induction motor is given. A Neuro/Fuzzy controller in fault detection is then presented. The detection/diagnosis structures are analyzed and compared regard to their learning algorithms, initial knowledge requirements, extracted knowledge. Finally, a comparative study on all these techniques is presented.

Index Terms— **Induction motors**, **Incipient faults, Artificial neural network, Fuzzy logic, Neuro/Fuzzy controller**

I. INTRODUCTION

Induction motors are the workhorses of industry because of their roughness and reliability. They enjoy inherent advantages like simplicity, low cost and virtually maintenance free electrical drives. However, the use of the induction motors in today's industry is extensive, and the motors can be exposed to different hostile environments, mis-operation, manufacturing defects, etc. Different internal motor faults like short-circuit of motor leads , interturn short circuits, ground faults, worn out /broken bearings, broken rotor bars along with external motor faults like phase failure, asymmetry of mains supply, mechanical overload, blocked rotor, under load are expected to happen sooner or later[1]. Further more the wide variety of environments and conditions that the motors are exposed to can age the motor and make it subject to incipient faults. These types of faults usually refer to the gradual deterioration in the motor that can lead to motor failure if left undetected. Motor problems can cause crisis that are expensive and are quite annoying, in particular, if the problem could have been prevented. Actually, many motor faults can be avoided if the application, environment, and the cause-effect of motor faults were understood. Therefore, reliability demands for electric motors are constantly increasing due to some of the important motor applications, and the advancement in technologies[2].

Many engineers and researchers have focused on incipient fault detection and preventive maintenance, which aim at preventing motor faults from happening. Usually, devices such as fuses, overload relays, and circuit breakers protect induction motors. Research has focused on different motor failure mechanisms, causes of stator and rotor failures, analyses of these failures, methodologies to determine whether a motor is suitable for extended service, test methods, the test equipment needed, application and limitations of these test procedures, data gathering, specific benefits, and costs[3]. In addition to developing motor protection schemes in reaction to faults due to misoperation, disturbances, sudden failure, etc., motor incipient fault detection problems have also been attracting significant attention and interest. Different researchers have addressed the importance and economic benefits of fault detection approaches. General methods of cost benefit analysis have been applied to investigate the financial viability of such systems.

With proper monitoring and fault detection/diagnosis schemes, the incipient faults can be detected in their early stages, thus, maintenance and downtime expensive can be reduced, and reliability can be improved. System identification and parameter estimation have previously been proposed for fault detection/diagnosis in motors[4]. As opposed to conventional techniques,

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

where expensive equipment or accurate mathematical models are required, fuzzy logic and neural network technologies can be used to provide inexpensive but effective fault detection mechanism alternatives. This paper discusses fault detection using advanced techniques like ANN, Fuzzy and Neuro-Fuzzy approach. A brief analysis on these three approaches is carried out, compared and finally, an optimized solution for detection of faults in IM is obtained

II. PROBLEM FORMULATION ON INCIPIENT FAULT DETECTION OF IM

In order to successfully perform fault detection, different sets of criteria are needed to define a motor's condition at different operating conditions. Two of the most common incipient faults in motors are bearing wear and winding insulation failure. The occurrence of these two faults in induction motor will be used to illustrate the motor fault detector[5]. To determine the measurements necessary for detecting the faults in a noninvasive manner, the dynamics of the induction motor will be briefly discussed.

The stator and rotor flux linkages of an induction motor represented as

$$\lambda_a = [\lambda_{as}\ \lambda_{bs}]^T$$

$$\lambda_b = [\lambda_{ar}\ \lambda_{br}]^T$$

where a and b represent the phases a and b of the motor when s and r denote the stator and rotor, respectively. This notion allows for representation of the induction motor dynamics by the following state equations

$$\dot{\lambda}_s = R_s i_s - V_s$$

$$\dot{\lambda}_r = R_r i_r - V_r$$

The variables Rs and Rr represent the stator and rotor resistance. These are both diagonal matrices with $i_s = [i_{as}\ i_{bs}]^T$

$i_r = [i_{ar}\ i_{br}]^T$

$\mathbf{v}_s = [v_{as}\ v_{bs}]^T$ $\mathbf{v}_r = [v_{ar}\ v_{br}]^T$

nonnegative elements. The variable represents the stator winding currents while represents the rotor winding currents. The stator

$$\begin{bmatrix} \lambda_s \\ \lambda_r \end{bmatrix} = \begin{bmatrix} L_s(\theta) & L_{sr}(\theta) \\ L_{sr}(\theta) & L_r(\theta) \end{bmatrix} \begin{bmatrix} i_s \\ i_r \end{bmatrix}$$

and rotor winding voltages are denoted by and , respectively. For steady-state conditions, the flux linkages can be approximated by a linear relationship with respect to the currents. This relationship can be expressed as

where Ls and Lr represent the stator and rotor inductances while the mutual inductance between the stator and the rotor is Lsr. θ indicates the rotor position.

From electromagnetic theory, the flux linkage is a function of the equivalent turns of the winding[6]. The equivalent turns for phases a and b can be represented by Ns = $[Nas\ Nbs]^T$ and Nr = $[Nar\ Nbr]^T$ the stator and rotor windings, respectively. As the equivalent number of turns changes, motor parameters such as winding resistance and inductance will also change.

www.ijrream.in Impact Factor: 2.9463

INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)

Tamilnadu-636121, India

Indexed by

IJRREM

Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610

ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

$f = [f_1\ f_2]^T$

Therefore, the transient and steady-state performance of the motor can be expressed in terms of the resistance and inductances of the stator and rotor. Nr is generally assumed to be constant because of the robustness of the rotor. The deterioration of the stator windings will cause Ns to change, thus making the stator resistance, stator inductance, and mutual inductance functions of Ns.

$$T_e = i_s^T (\partial/\partial\theta) L_{sr} i_r.$$

The electrical torque for the motor, Te, is a function of the motor parameters and state variables. This torque can be expressed as

$$T_e(N_s) = j\dot{\omega} + B\omega + T_l$$

Therefore, the electrical torque is a function of the equivalent number of stator turns and is expressed as Te(Ns). This electrical torque can represent the mechanical dynamic equation of the motor as follows: where j represents the inertia of the rotor and the connected load and Tl is the load torque which is assumed to be known and constant[7]. B represents the damping coefficient of the motor.

The induction motor is started with the stator windings of both phases energized. Once the motor has reached 60%-80% synchronous speed, the auxiliary winding, b, is disconnected and no longer used. Therefore, in steady state operation, only the main winding, a, is used. Because Nbs makes no contribution to the detection of faults which occur in steady-state, Nas can be represented as N for ease of notation. Likewise, I can be used to represent the steady–state root mean square value of the stator current, ias. The average steady-state rotor speed is expressed as ω. By combining and manipulating above equations with N and B as variables, the steady-state current and rotor speed ω can be represented by a system of nonlinear algebraic equations of the form,

These nonlinear algebraic equations are functions of the main winding equivalent turns, N, and the damping coefficient, B

$$f(I, \omega, B, N) = 0$$

$$f = [f_1 \ f_2]^T$$

Equation suggests that the condition of the bearing and winding insulation can be obtained from the stator current and rotor speed[8]. Because of this, and their easy accessibility, stator current and rotor speed are used as noninvasive inputs for the motor fault detector.

III. NON LINEAR RELATION OF MOTOR PARAMETERS

From the induction motor dynamics analysis, there exists a relationship R1 between (I, ω) to (N, B) as shown

$$R1: (I, \omega) \rightarrow (N, B)$$

R1 is highly nonlinear due to the nonlinearities present in the induction motor. An accurate mathematical model of R1 is difficult to obtain. As stated before, conditions of the main winding and bearings of the motor are reflected in the numerical values of the main winding equivalent turns N and the damping coefficient B, respectively. For our application, the values of N and B which quantitatively describe the motor, a re quantized into three condition levels (good, fair, bad) to yield Nc and Bc, respectively, which qualitatively describe the motor's condition[9]. This qualitative description of the motor's condition the quantitative description of the motor's condition is more suitable for fault detection purposes.

A second relationship R2 is used to denote the relationship from the quantitative description (N,B) to qualitative description (Nc,Bc).

$$R2: (N, B) \rightarrow (Nc, Bc)$$

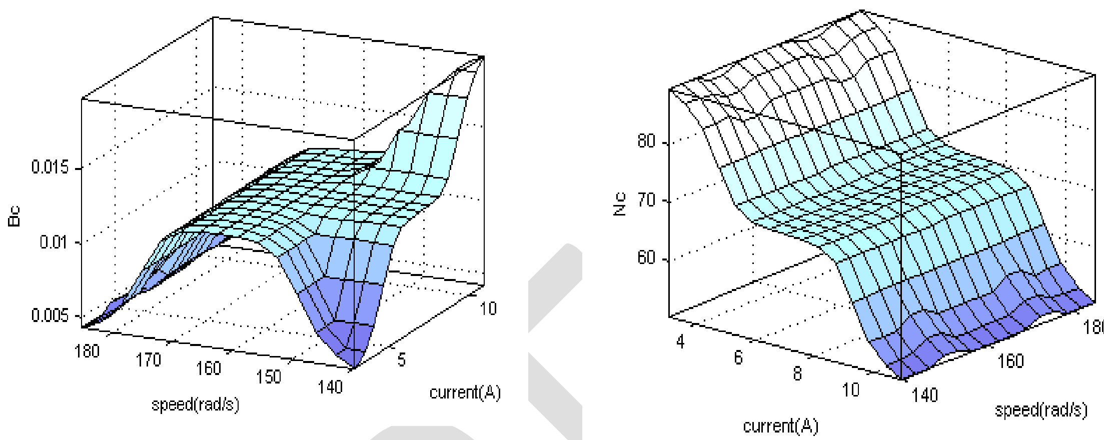
As a result, the relationship R from (I, ω) to (Nc, Bc) can be written as a composition of R1 and R2:

$$R = R1*R2: (I, \omega) \rightarrow (Nc, Bc)$$

Using the notations defined above, the parameter estimation approach can be summarized as follows. First, it estimates the values of N and B based on R1, then it determines the motor's conditions based on the model R2 and on the estimated values of N and B, which are denoted as N and B, respectively. The qualitative motor condition (Nc,Bc) is then predicted based on (N, B) and R2. The performance of the parameter estimation technique heavily depends on the accuracy of R1and R2 to reflect the actual situation[10]. R is very complex due to the high degree of nonlinearity of the motor dynamics (R1) and the discretization (R2); thus, obtaining an accurate analytical expression R for a given induction motor is rather difficult.

The relationship between the four variables of above equation can be conceptually viewed as shown below in Fig.1(a) and 1(b). The figure is a graphical view of the Bearing and Insulation conditions of the induction motor depending on the motor current and rotor speed values. These figures were obtained by simulating the bearing and insulation conditions using the MATLAB/Fuzzy Logic Toolbox.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794



(a)

Fig. 1. Graphical view of (a) Bearing (b) Insulation

Fig. 1(a) and 1(b) illustrate the bearing condition and insulation condition as a function of the motor current and rotor speed. The shaded regions are rough heuristic estimated of good, fair and bad conditions of the motor bearing and insulation windings, respectively. In Fig.1, the darker regions represent a bad condition and the lighter regions represent a good condition. For example, when a bearing is bad, it will impede the turning of the rotor. This will cause a decrease in rotor speed while increasing the amount of input current to the motor. This condition is reflected in the darker region of Fig.1(a), where a high value of input motor current and a low value of rotor speed occur when the bearing coefficient is large in value. Likewise, when the insulation condition is bad, the effective number of stator turns will decease, causing an increase in the input motor current. Therefore, a bad winding condition will occur when the input current to the motor is high. This condition is reflected in the darker region of Fig.1(b), where a high value of current and a high value of speed occur when the number of stator turns is low in value. In actual practice, however, these regions are determined through the knowledge of experts in this field Simulated motor data, rather than experimentally obtained motor data is used in this paper because it provides a more controlled set of data by which to demonstrate the technique proposed in this paper.

IV. ARTIFICIAL NEURAL NETWORK FOR IM FAULT DETECTION

As stated previously, the interpretation of a motor's condition based on numerical value is usually a difficult task because fault interpretation is a fuzzy concept and usually requires experience. Therefore, in many cases, a heuristic interpretation of the results which only humans are capable of doing becomes necessary. An experienced engineer can diagnose the motor's conditions based on its operating conditions and measurements, without knowing the exact mathematical model of the motor[11]. The approach is simple and reliable, and the complicated relation R is implicitly embedded in the engineer's knowledge about the motor. However, an experienced engineer may not be able to give detailed explanations regarding his reasoning and logic used to make the decisions simply because experience belongs to the fuzzy logic realm and is difficult to describe accurately in exact mathematical terms.

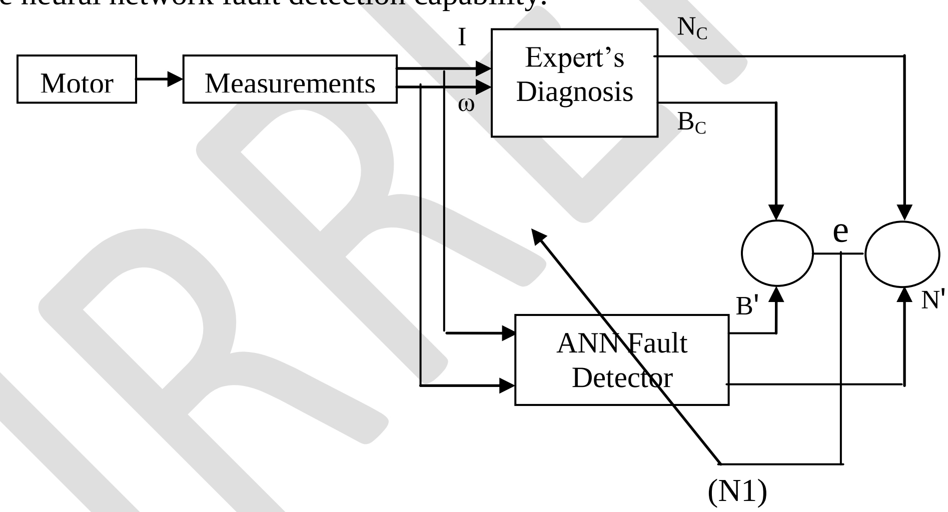
A. Learning Skills of ANN

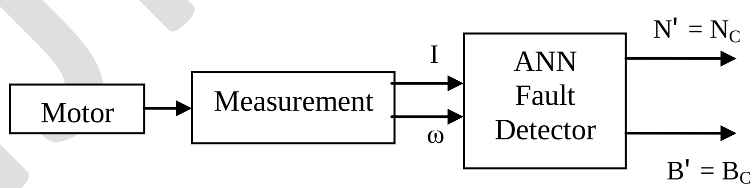
The emerging technology of ANN has been successfully used in a variety of areas such as fault detection, control, signal processing and many others. With this emergence, the human expertise approach can be mimicked and automated. ANN can be trained to perform motor fault detection by learning expertise knowledge using a representative set of motor data. Such a scheme is depicted in Fig.N1.

At the beginning of a neural network's learning session, the detection and diagnosis of the motor's condition N' and B' for our specific application made by the neural network fault detector will be incorrect. Based on the difference between the correct decision $y' = [Nc,Bc]^T$ made by the expert and $y = [N',B']^T$ made by the neural network and error quantity $e = (Nc-N')^2+(Bc-B')^2$ is generated and used to adjust the neural network's internal parameters (called network weights) to give a better y' that is closer to the correct decision[12]. By training a neural network to learn the fault detection based solely on input-output examples without the need of mathematical models, the complexity of the parameter estimation approach can be avoided. Once the neural network is trained appropriately, the network weights will contain the knowledge needed to perform fault detection in Fig.N2.

B. Stator Current and Rotor Speed Cost Functions

For many applications, the qualitative condition of the motor, rather than the numerical values of its parameter. The qualitative condition of the motor is generally based on some cost function of the required operating condition. Excess heat generated by over-current is the major cause of insulation failure[13]. An appropriate thermal model is used to relate the stator current and the heat generated in the stator winding. Thus the life expectance of the stator winding based on the heat generated by the current is used as a cost function to determine the condition of the winding. Similarly, the bearing condition is determined by another cost function related to the motor efficiency. The cost function mappings are highly nonlinear and are chosen to demonstrate the feasibility of the neural network fault detection capability.





www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

(N2)

Fig.(N1) Training of ANN fault detector (N2) ANN fault detection process

Since the classification of faults is very subjective and depends on many factors such as operating condition and economic factors. In many cases, the data can be supplied by an expert in the area, based on his heuristics and experience. Again the neural network does not need to know how the cost functions are chosen. It only needs to know the training patterns, which contain the winding and bearing condition (output) for the corresponding stator current and rotor speed measurements (input).Based on the relationship between the turn-to-turn insulation fault and bearing wear with respect to eh number of equivalent turns, N, and the damping coefficient, B, the condition of the motor can be quantified in to three condition levels- good, fair and bad. The resulting mapping is (0.9, 0.5, 0.1) is the condition space which represents good, fair and bad motor condition respectively, according to the degree of turn-to – turn insulation fault and bearing wear. Very accurate measurements, such as measurement of motor speed to are solution of better that 1 RPM, is difficult to achieve with inexpensive equipment. However, accurate measuring and expensive devices are not needed if the proposed neural network fault detection schemes used.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

C. Size of Training Data Set

The number of training examples used to train a neural network is some times critical to the success of the training process. If the number of training examples is not sufficient, then the network cannot correctly learn the actually input-output relation μ of the system. If the number training examples is too large, then the network training time will be longer. So, learning theory is used to estimate the number of training examples that is sufficient to train a network for fault detection. For training the network to perform fault detection, the training can be performed off-line and more training data are preferred over using insufficient training data to achieve greater network accuracy.

V. Fuzzy Logic in Fault Detection

Fuzzy logic, unlike Boolean or crisp logic, deals with problems that have vagueness, uncertainty, or imprecision, and uses membership functions (MF) with values varying between 0 and1. Fuzzy logic tends to mimic human thinking that is often fuzzy in nature. In conventional set theory based on Boolean logic, a particular object or variable is either a member (logic 1) of a given set or it is not (logic 0). On the other hand, in fuzzy set theory based on fuzzy logic, a particular object has a degree of membership in a given set that may be anywhere in the range of 0 to 1 .This property allows fuzzy logic to deal with uncertain situations in a fairly natural way. A process control algorithm that is based on fuzzy logic is called fuzzy control[14]. A fuzzy control essentially embeds the intuition and experience of a human operator, and some times those of a designer and researcher. The conventional control is normally based on mathematical model of a plant. If an accurate mathematical model of a plant is available with known parameters, it can be analyzed for example, by Bode or a Nyquist plot, and a controller can be designed for the specified performance. Often, the plant model is unknown or ill-defined. Even if the plant model is known, there may be parameter variation problem. It can be shown that fuzzy control is basically adaptive in nature, and can give improved robustness in such problems.

A. *Fuzzy in Fault Detection*

Fig.F1. shows the layout of the fuzzy fault diagnosis system.

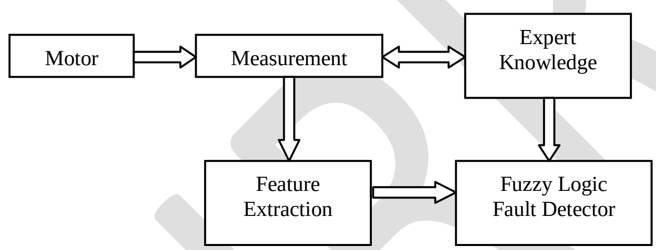


Fig.F1.FLFD in a System

For fault detection in induction motor fuzzy logic can be applied with a wide heuristic knowledge of the motor.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

B. Steps of the Training Phase

The training phase consists of the following steps:

1) Dividing the input and output domains into Fuzzy Regions:

To determine the fuzzy regions, the variable spaces of speed ω (140 to 185) rad/s, current I (3 to 13 A), and Nc (40 to 100) insulation condition and Bc(0 to 0.024) bearing wear condition were divided into N1, N2, N3 and N4 regions respectively. In the next stage, each region was then assigned a fuzzy membership function. Depending on the data, bell shaped membership function is chosen for this application. Each fuzzy set is denoted by fuzzy linguistic terms like (low, med, high) for speed and current and (bad, fair, good) for Nc and Bc

2) Generating Fuzzy Rules from Input Data of Speed, Current, Bearing and Insulation:

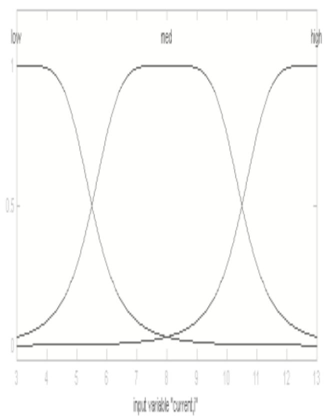
After the fuzzy membership functions in each of the input and output domains are defined, measured training data can be used to generate fuzzy rules in order to create the fuzzy rule base model. During the training phase, each input output data pair, which consists of a crisp numerical value of measured current, speed, Nc and Bc is used to generate the fuzzy rules which model the system.

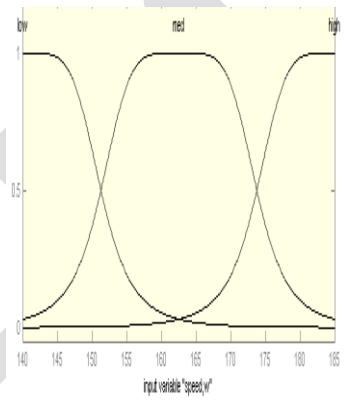
Fig.F2 Membership Functions for (a)current (b)speed (c)Bearing (d)Insulation

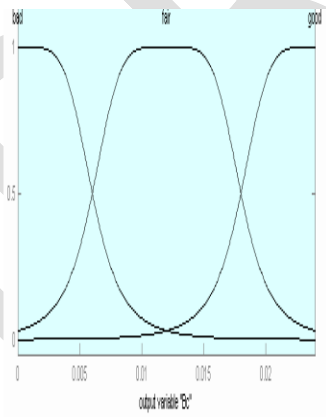
To determine a fuzzy rule from each input-output data pair, the first step is to find each data value (current, speed, insulation, bearing) in every membership region of its corresponding fuzzy domain. The variable is then assigned to the region with the maximum degree.

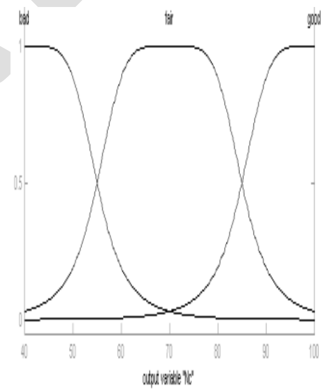
3) Assigning Rule Degrees:

When each new rule is generated from the input-output data pairs, a rule degree or truth is assigned to that rule, where this rule degree is defined as the degree of confidence that the rule does in fact correlate to the function relating speed and current to insulation and bearing condition. In the developed method, a degree is assigned which is the product of the membership function degree of each variable in its respective region. The purpose of this assignment is to choose between datasets that produce the same antecedents but different consequents. This would arise because when there is a large amount of measured data, some data pairs will produce rules that have the same antecedent but a different consequent (Due to errors or noise in the measured data). This would mean that there are conflicting rules in the system. Conflicting rules are resolved by choosing the conflicting rule that has the highest degree. This rule is the one that is placed in the fuzzy rule base.


low
med
high
1
0.5
0
3
4
5
6
7
8
9
10
11
12
13
input variable "current,I"


low
med
high
1
0.5
0
140
145
150
155
160
165
170
175
180
185
input variable "speed,w"


bad
fair
good
1
0.5
0
0
0.005
0.01
0.015
0.02
output variable "Ec"


bad
fair
good
1
0.5
0
40
50
60
70
80
90
100
output variable "Nc"

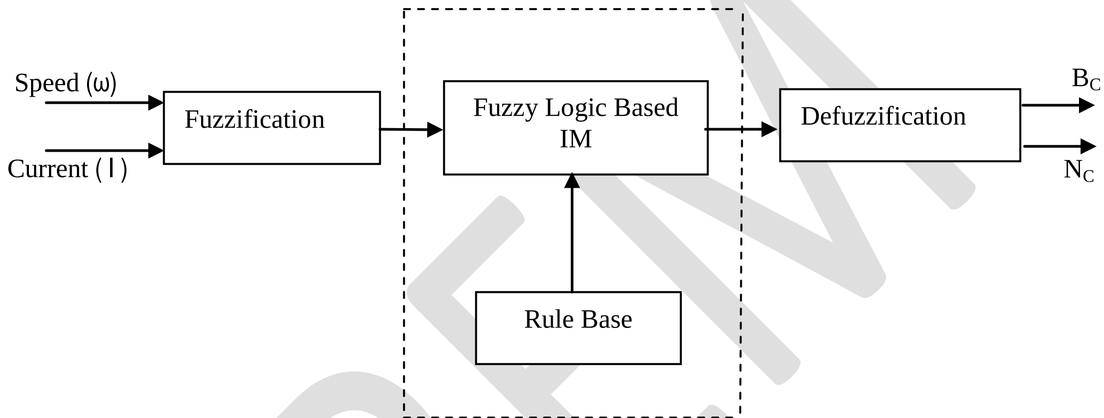


Fig.F3.Fuzzy logic fault detection scheme

4) Create the Fuzzy Rule Base:

As it can be seen from the above, every training data set produces a corresponding fuzzy rule which is stored in the fuzzy rule base. Therefore, as each input-output data pair is processed, and the rules are generated, a fuzzy rule or knowledge base is in the form of a two dimensional table, which can be looked up by the fuzzy reasoning mechanism. The current and speed fuzzy sets, which are the antecedents, are the axes of a two dimensional look-up table, and the stored table values are the output sets. After training the system with all the points, the rule table is generated.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

C. Fuzzy Fault Detection Scheme:

A block diagram of the complete fuzzy fault diagnosis system is shown in Fig.F3. The algorithm has the steps of: Initialization, Read Data, Find Fuzzy Regions, Calculate Membership Value, Determine Rule Outputs, and Defuzzify.

The fault diagnosis system essentially operates as follows:

The fuzzy fault diagnosis is designed to monitor the current, speed, Nc, and Bc. The prediction algorithms are implemented using fuzzy logic, and their purpose is to predict future values, so that if a measurement inaccuracy occurs, the predicted value may be used to lower the error. To achieve this, a comparison between estimated and predicted Nc and Bc values are made during each iteration. Then, some combination of these is chosen in order to lessen the effect of errors.

VI. Neural/Fuzzy Fault Detection Scheme

The neural/fuzzy architecture takes into account both fuzzy logic and neural network 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 the fault detection process. This knowledge is provided by the fuzzy parameters of membership functions and fuzzy rules[15]. This is done by constructing the fault detector using two modules; the fuzzy membership function module (module1) and the fuzzy rule module (module 2).The neural/fuzzy motor fault detector is shown in Fig.NF1.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

The use of these modules for the motor fault detection problem is discussed below.

A. Module I- The Fuzzy Membership Function Module

The fuzzy membership function module is composed of two independent subnetworks. One of these networks takes normalized motor current, I as an input while the other takes normalized motor speed, ω as an input. This measurement is achieved by noninvasive devices. The function of the subnetwork is to partition the normalized values into fuzzy membership function space and provide these as outputs of the module[16]. Subnetworks are used because they allow for representation of very complex membership functions which are more flexible to adaptation for decision classification. The fuzzy membership functions of motor current and rotor speed do not need to be known because the neural/fuzzy system will adaptively determine these membership functions.

B. Module II- The Fuzzy Rule Module

The fuzzy rule module provides the antecedent-consequent statements of fuzzy logic. These statements provide the condition of the fault being monitored, given the linguistic operating range of the inputs. The fuzzy rule represents a combination of the qualitative heuristic knowledge of the operating systems and the quantitative descriptions of the motor conditions[17]. The antecedents are the second half of the qualitative heuristics by telling us what types of conditions can exist. The consequence provides the quantitative information about

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

the condition of the motor by using the descriptions of good, fair, and bad. The structure of the module is a two-layer feed forward ANN. The nodes of the input layer of this module are antecedent nodes which represent the conditional part of the antecedent-consequence rules of fuzzy logic. These conditional statements are based upon combinations of the fuzzy membership functions.

C. Bearing Wear Fault Detection

The first step of the training requires initialization of the fuzzy membership function module. The fuzzy membership function module consists of two independent subnetworks, one for motor current and one for rotor speed. Each subnetwork is initialized with the generalized heuristics of low, med, and high. This initialization gives the module a better starting point for classification. The best guess of the fuzzy rules is made from whatever minimal heuristic knowledge available. If no minimal heuristic knowledge is available a simple guess is made this initial rule base is shown in table 2., where Bc represents bearing condition.

Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

I	ω	Bc
Low	Low	Good
Low	Med	Fair
Low	High	Good
Med	Low	Fair
Med	Med	Fair
Med	High	Fair
High	Low	Bad
High	Med	Fair
High	High	Good

The neural/fuzzy bearing fault detector was trained while allowing the weights of the rule module to change. The membership functions were extracted by evaluating the output nodes of the membership function module. The initial rule base is suspected of having an incorrect rule .It is these incorrect rules that are forcing the membership functions to change in this heuristically unacceptable fashion. The network is trained again while allowing the weights of the rule module to change. After the training criterion was reached, the weights ere analyzed to determine if any incorrect rules were present in the initial rule base. The weight analysis is shown below in table.NF2..If the cell is marked with a √, then the weight changed correctly. Or if the cell contained negative group, then it indicated that is decreasing in strength. Likewise if a cell contains a positive value, then it indicates a consequent attempting to become a rule.

Antecedent	Good	Fair	Bad
LL	-2.4	√	4
LM	0.6	√	√
LH	√	√	√
ML	√	-1.1	√
MM	0.9	√	√
MH	5.9	-0.3	√
HL	√	√	√
HM	√	-0.1	1.5
HH	√	√	5.5

Although Table.NF2 reflects several cases of rule weights changing in the incorrect direction, two cases demand immediate attention. These are case1, low current, low speed and case2, medium current, high speed. Both of these cases exhibit large change in amplitude and a change in more than one weight. Because one of these weights in each case is a rule weight the change indicates that the rule is trying to change from one consequent to another. Of these two

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

candidates for an incorrect rule, case 2 will be addressed first. This case is chosen over case 1 because case 1 does not have training data in its regions. Case 2 does have training data in its region, thus making case2 a more important candidate. Therefore, the rule base is modified to reflect the attempted change through training. This attempted change increased the weight connecting to the good consequence while decreasing the weight connecting to the fair consequence. Therefore, the rule for medium current, high speed is changed from having a consequence of fair to having a consequence of good. The new rule base is reflected in Table.NF3. The rule that changed is shaded.

I	ω	Bc
Low	Low	Good
Low	Med	Fair
Low	High	Good
Med	Low	Fair
Med	Med	Fair
Med	High	Good
High	Low	Bad
High	Med	Fair
High	High	Good

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

The neural/fuzzy system is trained while holding this new rule base constant. This training is done to determine if any other fuzzy rules are candidates for being incorrect rules. Now that the incorrect true analysis has been done the new rule base is examined for unnecessary rules by once again reinitializing the neural/fuzzy system and allowing the weights of the rule module to change. The rule weights of this module are examined for unnecessary rules after the neural/fuzzy fault detector reaches the training criterion.

An antecedent-consequent rule is a candidate for an unnecessary rule if its weight changes sign. TableNF4. reflects the weights which changed sign by a shaded X. The weights marked with a √ did not change sign and are not candidates for unnecessary rule nodes. The three shaded weights indicated by an X changed sign, thus causing those antecedents to have two consequences. Because this is impossible, this antecedent –consequence rules are candidates for unnecessary rules and are therefore eliminated form module2.Module 2 node has only six antecedent nodes. The new rule base reflects this in Table NF4

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

Antecedent	Good	Fair	Bad
LL	√	√	X
LM	√	√	√
LH	√	√	√
ML	√	√	√
MM	√	√	√
MH	√	√	√
HL	√	√	√
HM	√	√	X
HH	√	√	X

This action can be verified in two ways. The first verification is done by analyzing the rule weights of the rule module after training the neural/fuzzy system with the reduced rule base. If all the weights change appropriately, then the rule base is considered reduced and correct.

The second verification is done by comparing the resulting membership functions of module 1 trained with the rule base before and after reduction. If the two sets of membership functions are

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

nearly identical, it supports the claim that the rules were unnecessary and not needed for proper classification.

These results make heuristic sense if they are compared to the actual training data used. It can be observed that the bearing condition is more dependent on motor speed than motor current, but is still a function of both inputs. As bearing wear increases, the rotor speed is reduced. This reduction in rotor speed causes an increase in Slip, thus increasing motor current. Therefore, it is physically impossible for the motor to maintain a low current while decreasing rotor speed. This condition nullifies the possibility of data belonging to a low-current, low–speed region. Furthermore, the motor cannot maintain a high speed with increased bearing wear. As mentioned, the rotor speed will decrease and the motor current will increase. This condition excludes the possibility of data belonging to a high-current, high-speed region. This data verifies the resulting rules and membership functions obtained through training.

D. Insulation Wear Fault Detection using the Neural/Fuzzy system

The neural/fuzzy motor fault detector is also trained to learn insulation failure. The insulation condition was classified into three categories: good, fair, and bad. These classifications were made based upon life expectancy of the insulation as the stator winding temperature increases. The insulation condition is heavily depending on motor current. This dependence is due to the Arrhenius life relation. The insulation condition is determined by the expected life given by the Arrhenius relation, which is dependent on the temperature of the stator windings. The temperature of the windings is a direct result of the operating environment and the current going through the windings. Because this work assumes an average operating environment, the motor current becomes the major contributing factor. The neural/fuzzy motor fault detector will be used to verify that rotor speed is not a necessary input.

The first step of the training requires initialization of the fuzzy membership function module, which was initialized in the same manner as was done for the motor bearing wear problem. The" best guess" of the fuzzy rules for the insulation wear is made. From the general knowledge of insulation wear dependence on current. If a best guess rule base was made then some of the rules would be incorrect and the training procedure would determine these. To avoid presenting this procedure twice, this best guess rule base is chosen to illustrate the ability of the neural/fuzzy motor fault detector to identify unnecessary inputs. This initial rule base is shown in Table. NF5, where Nc represents the winding insulation condition.

The neural/fuzzy insulation fault detector was trained while not allowing the weights of the rule module to change. The membership functions were extracted by evaluating the output nodes of the membership function module.

I	ω	Nc
Low	Low	Good
Low	Med	Good
Low	High	Good
Med	Low	Fair
Med	Med	Fair
Med	High	Fair
High	Low	Bad
High	Med	Bad
High	High	Bad

According to Table.NF5. The speed has no effect or the classification of the insulation condition. As a result, no further training is necessary and the membership functions of are assumed to be correct. The rules of Table.NF5 now become those shown in Table NF6.

www.ijrream.in Impact Factor: 2.9463

INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)

Tamilnadu-636121, India

Indexed by

Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610

ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

I	Nc
Low	Good
Med	Fair
High	Bad

VII. Results

A. Neuro Fuzzy and ANN

The neural/fuzzy systems are shown to have an initial error much less than the standard ANN while comparing the bearing wear fault conditions of IM. This is because it has a better starting point, the correct rule base and general membership functions. In the end, however, the two are proven to be almost equal in performance with the standard ANN obtaining a sum squared error of 0.0091 after 5000 iterations. The ANN also classifies 100% of the training and testing data.

The performance of the neural/fuzzy fault detector for the insulation problem is compared to a standard feed forward ANN using back propagation algorithm. It can be seen that the neural/fuzzy system has better starting point than the ANN. Although the NN learns faster than the neural/fuzzy system, the two are almost equal after 2000 iterations of training. The ANN also classifies 100% of the training and testing data.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

B. Neuro Fuzzy and FLFD

Here both fuzzy logic and neuro fuzzy structure provide good fault detection under varying load torque. But the results of the neuro fuzzy technique is being slightly more accurate. Consistent heuristic information can be extracted in terms of fuzzy-if-then rules from FLFD. This is the main advantage of the structure. However, the fault detection scheme is slower in convergence when compared to the neuro-fuzzy fault detection. Furthermore neurofuzzy provider better results when applied without any pretraining.

Conclusion

Artificial intelligence techniques for motor fault detection are briefly analyzed in this paper. The neural, fuzzy and Neuro/fuzzy motor fault detection systems were heuristically analyzed to determine the optimized solution for properly detecting motor bearing and insulation faults. The results of this analysis suggest that Neuro/fuzzy systems provide better results when compared to other two. Hence Neuro/fuzzy systems can be suggested as a better utilizing system for new and promising research areas in induction motor fault detection.

References

[1] Bo Li, Mo-yuen Chow, Yodyium, Tipsuwan, "Neural –Network-Based Motor Rolling Bearing Fault Diagnosis", IEEE Trans. On Industrial Electronics, Vol.47, No.5, Oct-2010.

[2] Fiorenzo Filippetti, Giovanni Franceschni and Carla Tassoni, "Neural Networks Aided On-line Diagnostics of IM Rotor Faults"' IEEE Trans. On Industrial Electronics, Vol.31, No.4, Jul-Aug 2015.

[3] Chow M.Y., Yee S.0. "Methodology for On-line Incipient Fault Detection in Single-phase Squirrel-cage Induction Motors Using Artificial Neural Networks", IEEE Trans.Ener. Convers. vol.6, no.3, Sep. 2011.

[4] Chow M.Y., Sharpe R.N., Hung, J.C., "On the Application and Design of Artificial Neural Networks for Motor Fault Detection-Part 1", IEEE Trans. Ind. Electron. Apr.2013

[5] Chow M.Y., Sharpe R.N., Hung, J.C., "On the Application and Design of Artificial Neural Networks for Motor Fault Detection-Part2", IEEE Trans. Ind. Electronics. Apr.2013.

[6] Subhasis Nandi, Hamid A.Toliyat, "Fault Diagnosis of Electricalmachines -A Review" IEEE Trans Sep 2009.

[7] Subhasis Nandi, Hamid A.Toliyat, "Condition Monitoring and Fault Diagnosis of Electricalmachines A- Review" IEEE Trans Sep 2009.

[8] Rangarajan M.Tallam, Sang-Bin Lee, Greg Stone, Gerald B.Kilman, Jiyoon Yoo, G.Harley," A Survey of Methods for Detection of Stator Related Faults in Induction Machines "Symposium on Diagnostics for Electric Machines Power Electronics and Drives, Aug 2016.

[9] Jyh-Singh, and Rogerjang, "ANFIS-Adaptive Network Based Fuzzy Inference System"', IEEE Trans. Systems Man and Cyber, Vol23, No.3, May-June 2014.

www.ijrream.in Impact Factor: 2.9463
INTERNATIONAL JOURNAL OF RESEARCH REVIEW IN ENGINEERING AND MANAGEMENT (IJRREM)
Tamilnadu-636121, India
Indexed by
IJRREM
Scribd impact Factor: 4.7317, Academia Impact Factor: 1.1610
ISSN NO (online) : Application No : 19702 RNI –Application No 2017103794

[10] Paul V. Goode, Mo-Yuen Chow, "Using a Neural/Fuzzy System to Extract Heuristic Knowledge of Incipient Faults in IM Part-1-Methodolgy", IEEE Trans. On Industrial Electronics, Vol.42, No.2, Apr-2015.

[11] Paul V. Goode, Mo-Yuen Chow, "Using a Neural/Fuzzy System to Extract Heuristic Knowledge of Incipient Faults in IM Part-1I Application", IEEE Trans. On Industrial Electronics, Vol.42, No.2, Apr-2015.

[12] V.Duraisamy, N.Devarajan, "Comparative Study of Membership Functions for Design of Fuzzy Logic Fault Diagnosis System for Single Phase IM", Academic Open Internet Journal Vol-13, 2014.

[13] R. N. Dave and R. Krishnapuram, "Robust clustering methods: A unified view," IEEE Trans. Fuzzy Syst., vol. 5, pp. 270–293, May 2017.

[14] L. X. Wang and J. Mendel, "Generating fuzzy rules by learning from examples," IEEE Trans. Syst., Man, Cybern., vol. 22, pp. 1414–1427, July 2012.

[15] Cao S.G., Rees N.W. and Feng G. (2009): Analysis and design of fuzzy control systems using dynamic fuzzy state space models.—IEEE Trans. Fuzzy Syst., Vol. 7, No. 2, pp. 192–199.

[16] Hunt K.J. and S.Barbaro D. (2011): Neural networks for nonlinear model control. — IEE Proc., Part D, Vol. 138, pp. 431–438.

[17] H.N. Kolvo, Artificial Neural Networks in Fault Diagnosis and Control, Control Eng. Practice, vol 2. No. 1, pp. 89-101, 2014.