CHAPTER 1

INTRODUCTION

1.1  MOTIVATION AND GOAL

Rotating machines are essential components in most of the manufacturing and production industries. They are exposed to a variety of environmental conditions. These operating conditions coupled with natural agei

ng cause incipient faults in the machines. The most common incipient faults are winding insulation failure and bearing wear. Almost 40% of rotating machine failures occurs due to winding inter turn faults (Vas 1993 and Chow 1997).

With proper monitoring scheme, if the faults were detected at their early stages, the maintenance cost and down time can be reduced (Mishra et al 1996, Schoen 1995, Chen et al 1994 and Chow et al 1993). Many of the conventional fault detection methods require the need of an expert to evaluate the machine condition. The development of soft computing techniques in the area of computer science motivated the researchers to use these techniques for intelligent problem solving, which exhibits the characteristics of human intelligence.

The soft computing tools like neural network and fuzzy logic have been used in many engineering applications such as fault identification and control of dynamic systems (Wu et al 2004, Ali et al 2001, Park et al 1996 and Narendra et al 1990). The Neural Networks (NN) can be classified as Feed Forward Neural Networks (FFNN) and recurrent
NN according to their structure. It is well known that a feed forward neural network is capable of approximating any continuous function closely.

The use of fuzzy logic in control applications has tremendously increased over the last decades. Theoretically founded by Zadeh and explored by Mamdani in the early 1970s the wide industrial application of fuzzy logic began almost a decade later. With the commercial availability of fuzzy logic control development tools and the better understanding of analysis methods, more and more industrial companies have successfully used this technology for their specific applications (Ross 1997 and Kohonen 1995). The main advantages of fuzzy controllers are simplicity, low cost and possibility to design without knowing the exact mathematical model of the process or system. This motivated the author to investigate the applicability of NN and fuzzy system for fault detection in rotating machines.

1.2 NEURAL NETWORK FOR FAULT DETECTION

1.2.1 Introduction

The NN are simplified models of the biological neuron system. It is a massively parallel distributed processing system made up of highly interconnected neural computing elements that have the ability to learn. Various learning mechanisms exist to enable the neural network to acquire knowledge. Neural network architectures have been classified into various types based on their learning mechanism. The NN can be classified as feed forward and recurrent networks based on its structures. The FFNN can be further classified as single layer and multilayer feed forward networks. The FFNN are widely used since it is capable of approximating any continuous functions closely.
The NN are capable of mapping (learning) input patterns to their associated output patterns. The learning methods in NN can be broadly classified as supervised, unsupervised and reinforced. The supervised learning methods are mostly used in control and fault detection applications since the target is known. Therefore, more attention is given to the FFNN with supervised learning.

The demonstration and limitations of single layer NN was a significant factor in the decline of interest in NN in 1970s. The discovery of an effective general method of training a multilayer NN played a major role in the re-emergence of NN as a tool for solving wide variety of problems.

The FFNN has been a subject of intensive research efforts in the recent years because of their interesting learning and generalization properties and their applicability of classification, approximation and control problems. The key issue is the development of training algorithms that simultaneously improves the convergence ability, learning speed and generalization capability in the real world large scale problems.

1.2.2 The Back Propagation (BP) Network

The BP architecture is a multilayer FFNN in which the weight updating procedure is based on the generalized delta rule. The difference between the actual output and the target is back propagated to the subsequent layers so as to minimize the error.

The BP learning can be applied to any multilayer network that uses differentiable activation function and supervised learning. The weight modification is an optimization procedure based on the gradient descent technique. Learning is carried out by iteratively adjusting the coupling
strengths in the network so as to minimize the difference between the actual output state vector of the network and the target state vector.

The general architecture of a multilayer BP network is shown in Figure 1.1. The network has three layers namely input layer, hidden layer and output layer. Each neuron in the layer is fully interconnected. The additional input neurons called as bias neurons (whose input is always set to 1) are connected in the hidden and output layers to enhance the training process.

Figure 1.1 The general architecture of a two layer BP network

An activation function for a BP network should be continuous, differentiable and monotonically non-decreasing. Furthermore, for computational efficiency, it is desirable that its derivative be easy to compute. For the most commonly used activation functions, the value of the derivative (at a particular value of the independent variable) can be expressed in terms of the value of the function (at the value of the independent variable). Usually, the function is expected to saturate, i.e., approach finite maximum and minimum values asymptotically.
One of the most commonly used typical activation functions is the binary sigmoid function, which has range of (0,1) and is defined as

\[ f(x) = \frac{1}{1+e^{-x}} \text{ with } f^l(x) = f(x)[1-f(x)]. \]

Another common activation function is bipolar sigmoid which has the range of (-1,1) and is defined as

\[ f(x) = \frac{2}{1+e^{-x}} - 1 \text{ with } f^l(x) = 0.5[1+ f(x)][1-f(x)]. \]

### 1.2.3 BP training algorithm

The nomenclature used in the training algorithm of the BP network is as follows:

- **x**: Input training vector, \( x = (x_1, x_2, \ldots, x_i, \ldots, x_n) \)
- **t**: Output target vector, \( t = (t_1, t_2, \ldots, t_k, \ldots, t_m) \)
- **\( \delta_k \)**: Portion of error correction weight adjustment for hidden layer to output layer
- **\( \delta_j \)**: Portion of error correction weight adjustment for input layer to hidden layer
- **\( \alpha \)**: Learning rate
- **\( \mu_i \)**: Momentum factor
- **\( X_i \)**: Input unit
- **\( Z_j \)**: Hidden unit
- **\( Y_k \)**: Output unit
- **\( v_{oj} \)**: Bias on the hidden unit \( j \)
- **\( w_{ok} \)**: Bias on the output unit \( k \)
- **\( v_{ij} \)**: Weight from \( i^{th} \) input unit to \( j^{th} \) hidden unit
The training algorithm for a BP network is as follows:

Step 0: The weights are initialized randomly between $-0.5$ to $+0.5$ and normalized. Initialize the learning parameters.

Setp1: While stopping condition is false, do steps 2-9.

Setp2: For each training pair, do steps 3-8.

Feed forward:

Step3: Each input unit ($X_i, i=1,\ldots,n$) receives input signal $x_i$ and broadcasts this signal to all units in the layer above (the hidden units).

Step4: Each hidden unit ($Z_j, j = 1,\ldots,p$) sums its weighted input signals,

$$Z_{\text{inj}} = v_{oj} + \sum_{i=1}^{n} x_i v_{ij},$$

applies its activation function to compute its output signal,

$$z_j = f(Z_{\text{inj}})$$

and send this signal to all units in the above layer (output layer).

Step5: Each output unit ($Y_k, k=1,\ldots,m$) sums its weighted input signals,

$$Y_{\text{ink}} = w_{ok} + \sum_{j=1}^{p} z_j w_{jk},$$
applies its activation function to compute its output signal,
\[ y_k = f(y_{\text{ink}}) \]

**Back Propagation of Error:**

**Step 6:** Each output unit \((Y_k, k=1,\ldots,m)\) receives a target pattern corresponding to the input training pattern, computes its error information term,
\[ \delta = (t_k - y_k) f'(y_{\text{ink}}), \]

 calculates its weight correction term.
\[ \Delta w_{jk} = \alpha \delta_k z_j \]

 calculates its bias correction term.
\[ \Delta w_{ok} = \alpha \delta_k \]

 and sends \(\delta_k\) to units in the hidden layer below.

**Step 7:** Each hidden unit \((Z_j, j=1,\ldots,p)\) sums its delta inputs
\[ \delta_{\text{inj}} = \sum_{k=1}^{m} \delta_k w_{jk}, \]

 multiplies by the derivative of its activation function to calculate its error information term.
\[ \delta_j = \delta_{\text{inj}} f'(z_{\text{inj}}), \]

 calculates its weight correction term
\[ \Delta v_{ij} = \alpha \delta_j x_i \]
and calculates its bias correction term
\[ \Delta v_{oj} = \alpha \delta_j \]

Update the weights and biases

Setp 8. Each output unit \((Y_k, k=1,\ldots,m)\) updates its bias and weights. \((j=0,\ldots,p)\)
\[ w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk} \]

Each hidden unit \((Z_j, j=1,\ldots,p)\) updates its bias and weights. 
\((i =0,\ldots,n)\)
\[ v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij} \]

Setp 9. Test for stopping condition.

1.2.4 Modified BP algorithm
1.2.4.1 Introduction

Several modifications can be made in the conventional BP algorithm to improve its performance. The modifications may include Immediate Weight Update (IWU) scheme, changing the activation functions, adaptively changing the learning rates and momentum factor etc. Irrespective of the modifications made in the BP algorithm the basic architecture of the network remains the same.

The objective of any NN training is to attain the correct set of weights as early as possible. It can also be stated that the calculated error has to be minimized to a least value (defined as tolerance level) in a minimum time.

In the conventional BP algorithm the weights are updated only after complete learning. That is the change in weights for all the layers have to be calculated in the initial steps. After calculating all the change in weight terms
the new weights are calculated. In this method, as the error term is included only after complete learning, the time taken for the minimum error is a prolonged one.

The effect of error term can be immediately added in back propagating the error by multiplying with the updated weights. In the proposed IWU scheme the weights are updated as soon as the change in error ($\Delta w$) for the corresponding one is calculated.

1.2.4.2 The IWU Scheme

The nomenclature used in this scheme is same as the conventional BP algorithm.

Step0: The weights are initialized randomly between - 0.5 to +0.5 and normalized.

Step1: While the sum squared error is greater than the tolerance level, do steps 2-7.

Step2: For each training pair, do steps 3-6.

Step3: Compute the output signal for the hidden layer units (j=1,…,p)

\[
\begin{align*}
    z_{\text{inj}} & = v_{oj} + \sum x_i v_{ij}, & i = 1, \ldots, n \\
    z_j & = f(z_{\text{inj}})
\end{align*}
\]

Step4: Compute the signal for the output layer units (k=1, …, m)

\[
\begin{align*}
    y_{\text{ink}} & = w_{ok} + \sum z_j w_{jk}, & j = 1, \ldots, p \\
    y_k & = f(y_{\text{inj}})
\end{align*}
\]
Setp 5: Compute
\[ \delta_k = (t_k - y_k) f'(y_{in k}), \quad k=1,\ldots,m \]
\[ \Delta w_{jk} = \alpha \delta_k z_j + \mu_i \Delta w_{jk} \text{ (old)} \]
\[ w_{jk} \text{ (new)} = w_{jk} \text{ (old)} + \Delta w_{jk} \]

Setp 6: Compute
\[ \delta_{inj} = \sum_{k=1}^{m} \delta_k w_{jk}, \]
\[ \delta_j = \delta_{inj} w_{jk} f'(z_{inj}), \quad j = 1,\ldots,p \]
\[ \Delta v_{ij} \text{ (new)} = \alpha \delta_j x_i + \mu_i \Delta v_{ij} \text{ (old)} \]

Setp 7. Test for stopping condition.

From the above scheme it can be noted that the weights from hidden to output layer is updated as soon as the change in weight (\( \Delta w_{jk} \)) is calculated. This updated weight is utilized in the error term, which is back propagated to the subsequent layer. Therefore, the learning time is minimized.

1.3 FUZZY SYSTEM FOR FAULT DETECTION

The fuzzy logic provides a strong framework for achieving robust and simple solutions among different approaches of intelligent computation. Fuzzy model is collection of IF–THEN rules with vague predicates that use a fuzzy reasoning such as Sugeno and Mamdani models. Sugeno type systems can be used to model any inference system in which the output membership functions are either linear or constant whereas Mamdani type produces either linear or nonlinear output. The fuzzy controller consists of four stages; fuzzification of inputs, derivation of rules, inference mechanism and defuzzification.
1.3.1 Fuzzification of input variables

Fuzzification is the process of converting the crisp input variable into corresponding fuzzy values. The most of the engineering problems deal with numerical values. To apply the fuzzy system to the numerical environment, fuzzification and defuzzification procedures are normally employed.

1.3.2 Derivation of rules

The design of fuzzy controller is based on the operators understanding the behaviour of the dynamic system instead of mathematical model. The main advantage of this approach is to implement the heuristic knowledge of the system. Fuzzy rules can be derived in several ways. Some of the methods are listed below:

- Based on the experts experience and experiment data of the system.
- Based on the fuzzy model of the process.
- Based on learning algorithm

1.3.3 Membership functions

The membership functions play an important role in designing fuzzy systems. The membership functions characterize the fuzziness in a fuzzy set whether the elements in the set are discrete or continuous in a graphical form for eventual use in mathematical formalism of fuzzy set theory. The shape of membership function describes the fuzziness in graphical form. The shape of membership functions is also important in the development of fuzzy system. The membership functions can be symmetrical or asymmetrical. A uniform representation of membership functions is desirable. The membership function defines how each point in the input space is mapped to a membership
value in the interval [0,1]. In this section, summary of the popularly used membership functions is given in Table 1.1.

Table 1.1 Summary of commonly used membership functions

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Name of the membership functions</th>
<th>Parameters</th>
<th>Functional form</th>
</tr>
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</table>
| 1     | Triangular shaped Membership Function (TRIMF) | a, b, and c | \( F(x) = \begin{cases} 
  \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\
  \frac{c-x}{c-b} & \text{if } b \leq x \leq c \\
  0 & \text{Otherwise} 
\end{cases} \) |
| 2     | Trapezoidal Membership Function (TRAPMF) | a, b, c and d | \( F(x) = \begin{cases} 
  \frac{x-a}{b-a} & \text{if } a \leq x \leq b \\
  1 & \text{if } b \leq x \leq c \\
  \frac{d-x}{d-c} & \text{if } c \leq x \leq d \\
  0 & \text{Otherwise} 
\end{cases} \) |
| 3     | Gaussian Membership Function (GAUSSMF) | \( \sigma \) and c | \( F(x) = \frac{e^{-\frac{(x-c)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}} \) |
| 4     | Sigmoidally shaped Membership Function (SIGMF) | a and c | \( F(x) = \frac{1}{1+e^{-a(x-c)}} \) |
| 5     | Bell shaped Membership Function | a, b and \( x_o \) | \( F(x) = \frac{a}{a+b(x-x_o)^2} \) |

1.3.4 Defuzzification methods

This section describes the different types of defuzzification procedures for the design of fuzzy system. The influence of defuzzification method on the fuzzy controller performance has been paid very little attention so far. In the literature on fuzzy control, the terms used in describing the
different defuzzification methods vary from author to author. This thesis has paid large attention to the formal definitions of the defuzzification methods rather than to their names.

Defuzzification is a process of converting fuzzy values generated by inference engine into a crisp value that is compatible with output value. The different defuzzification methods such as Center of area (Centroid), Bisector of area (Bisector), Smallest of Maximum (SOM), Mean of Maximum (MOM), Largest of Maximum (LOM) have been used for fuzzy control.

A brief explanation of the most often used defuzzification methods are given below:

1. Centroid method
2. Bisector method
3. MOM method
4. SOM method
5. LOM method

In general, defuzzification is the process of defuzzifying a fuzzy set \( A \) of a universe of discourse \( z \). The fuzzy set \( A \) is usually represented by an aggregated output membership function.

**Centroid of area,** \( z_{\text{COA}} \)

\[
z_{\text{COA}} = \frac{\int_Z \mu_A(z) \, dz}{\int_Z \mu_A(z) \, dz}, \text{ where } \mu_A(z) \text{ is aggregated output membership function.}
\]

**Bisector of area,** \( z_{\text{BOA}} \)

\( z_{\text{BOA}} \) satisfies the following equation
\[ \int_{\alpha}^{\beta} \mu_A(z) \, dz = \int_{\alpha}^{\beta} \mu_A(z) \, dz, \] where \( \alpha = \max \{ z \in Z \} \) and \( \beta = \max \{ z / z \in Z \} \). The vertical line \( z = z_{BOA} \) partitions the region between \( z = \alpha, \beta, y = 0 \) and \( y = \mu_A(z) \) into two regions with same area.

**Mean of maximum, \( z_{\text{MOM}} \)**

\( z_{\text{MOM}} \) is the average of the maximizing \( z \) at which the membership function reaches the maximum \( \mu^* \)

\[ z_{\text{MOM}} = \int z \cdot dz / \int z \cdot dz \] where \( z^1 = \{ z / \mu_A(z) = \mu^* \} \). In particular, if \( \mu_A(z) \) has a single maximum at \( z = z^* \) then \( z_{\text{MOM}} = z^* \).

**Smallest of maximum, \( z_{\text{SOM}} \)**

\( z_{\text{SOM}} \) is the minimum in terms of magnitude of the maximizing \( z \).

**Largest of maximum, \( z_{\text{LOM}} \)**

\( z_{\text{LOM}} \) is the maximum in terms of magnitude of the maximizing \( z \).

The calculation needed to carry out any of the defuzzification operations is time consuming. Furthermore, these defuzzification operations are not easily subject to rigorous mathematical analysis. So, most of the studies are based on experimental results. The various defuzzification schemes are shown in Figure 1.2.
1.4 LITERATURE REVIEW

The rotating electrical machines like induction machines and synchronous machines are extensively used in industries and power plants. It is very essential to monitor these machines online and an effective intelligent fault detection schemes are necessary to improve operational reliability of the machine. The induction machines are widely used because of its rugged construction (Ye et al 2000 and Kilman et al 1996, 1997). The synchronous generator is essential part of the power plant. Therefore, this thesis is focused on these electrical machines.

Bearing wear is the one of the most common faults in rotating machines. As the machine ages, the bearing will change shape due to an imbalance of the machine or fragmentation of bearing itself. These deformations cause vibrations in the machine. These vibrations can contribute failures in other parts of the machine (Stack et al 2004).
Frequency analysis on the vibration signals caused by the bearing wear can be done to evaluate the bearing condition of the machine (Li et al 2000, Nandi et al 1999 and Morel et al 1990). Frequency analysis of machine bearing faults is based upon premise that different types of faults occur in different frequency spectra. This method requires very accurate sensing equipment to capture impulses that occur for short durations over a broad frequency spectrum. Therefore, this method is considered useful for large machines because of high cost of accurate sensing devices.

The direct inspection of determining the bearing wear is less expensive. But, it requires down time for the motor (Sinan Altug et al 1999). The particle analysis of oil that used to lubricate the machine is another method of bearing condition monitoring. This method requires bringing oil samples to a laboratory for chemical analysis. It is very difficult and impractical to implement on a constant basis. Loparo et al (2000) proposed a model based approach for fault detection in rotating machines. This method requires the mathematical model of the machine.

Insulation failure in the machine windings is another common fault in electrical machines. The machine winding is insulated to prevent inter turn faults. This insulation is categorized into several classes, which are rated for different maximum operating temperatures (Sawhney 1993). Often these maximum temperatures are violated due to the operating environment and load requirements. This violation leads to cracks, thinning and eventual loss of insulation at some points on the windings. This decreases the effective stator turns and hence the life of the winding.

The resistance measurement of insulation is a common method used to determine the insulation condition. This method requires the application of a d c voltage to the winding while grounding the core or frame (Schump 1989). The resistance of insulation can be determined based on
measuring the current flowing through the winding. Therefore, this method requires the down time for the motor.

Surge testing of the winding determines the dielectric strength of the insulation. A large sinusoidal voltage is applied to the windings and a comparison of the patterns from the three phases of a motor winding determines the insulation condition. This technique can be implemented online. But, this technique requires the services of an expert to estimate the motor condition (Tavner 1989).

The parameter estimation approach proposed by Chow et al (1993) and Isermann et al (1991, 1997) can provide the information relative to the condition of the insulation and bearing. This method can be applied online but it requires the expensive monitoring equipments. This method relies upon a very accurate mathematical model of the machine. This technique is based on the detailed understanding of the system and how it is effected by the chosen parameters. The parameters can be chosen to reflect the condition of bearing and insulation. Unfortunately, it is very difficult to obtain the accurate mathematical model of the machine.

All the above said methods either require the services of an expert to determine the motor condition and expensive monitoring equipments or accurate mathematical model of the machine. The above methods cannot be applied online except the parameter estimation method. Unfortunately, the need of accurate mathematical model makes this method less attractive.

Chow et al (1991, 1995) have proposed the neural network approach and have demonstrated it to be an effective alternative for motor fault detection because NN can learn any arbitrarily complicated continuous nonlinear functions (Cyberko 1989). It can learn the motor fault detection process, which enables it to give the accurate solution to a particular fault
detection problem. In addition, the neural network can perform fault detection online through the use of inexpensive monitoring devices. These devices obtain the necessary measurements in a noninvasive manner. In addition to this, Keyhani et al (1986) have listed out the detailed merits of using NN instead of using other fault detection techniques.

The FFNN are widely used for fault detection problem. The BP training algorithm is used for learning the fault detection process. In the conventional BP algorithm, several modifications were made in the last two decades to improve the performance of the network.

Pineda (1987) proposed a recurrent generalization of delta rule to adaptively modify the synaptic weights. Jacobs (1988) suggested that every weight of a network should be given its own learning rate and that these rates should be allowed to vary over time. He also proposed two rules namely Delta - Delta learning rule and Delta-Bar-Delta learning rule to change the learning rates adaptively.

Gori et al (1992) analyzed the local minima problem in the BP network and proposed some conditions on the network architecture and leaning environment, which ensures the convergence of BP algorithm. Wessels et al (1991) also tried to avoid local minima and they suggested a new method of initialization, which decreases the probability of local minima.

Van Ooyen et al (1992) proposed a modification in the total error-of-performance function that is to be minimized to accelerate the convergence of BP algorithm. Matsuoka (1992) showed experimentally that the generalization capability could remarkably be enhanced by training the network with the noise injected inputs.
Sakaue (1993) proposed a new algorithm, which is based on overestimation of significant error in order to alleviate underflow and omission of weight updating for correctly recognized patterns. Barnard et al (1993) investigated the ability of neural network classifiers to deal with prior information.

Dimitris et al (1994) presented an efficient constrained algorithm for FFNN. Chen et al (1994) analyzed the function problem and suggested a new algorithm that is resistant to the noise effects and is capable of rejecting the gross errors during the approximation process.

Fu et al (1996) investigated incremental BP networks and proposed a new method, which employs bounded weight modification and structural weight adaptation rules and applies the initial knowledge to constrain the learning process.

Ridella et al (1997) suggested a standardized, uniform representation for the pattern classifiers and introduced a simple modification, which is well suited to cope with pattern classification tasks.

Renato De Leone et al (1998) proposed a variation of the classical BP algorithm to improve the convergence of training. The algorithm is similar to the successive overrelation algorithm for systems of linear equations and linear complementary problems in using the most recently computed values of the weight to update the values on the remaining arcs.

Yamamota et al (2000) proposed a new supervised learning algorithm for multilayer NN. In this method output of each hidden unit is algebraically determined by using an exponentially weighted least squares method.
The BP network is quite expensive computationally, especially during the training process. Many researchers have attempted to modify the basic BP algorithm to speed up the training. Moreover the BP network has the disadvantages such as local minima, instability and high degree of misclassification. It is stated that even a slight improvement in the convergence process will result in saving the time by which a better performance of neural network based system can be achieved.

In this thesis, novel fault detection schemes are proposed for fault detection in induction machines and synchronous machines using conventional BP networks. To minimize the training time of the conventional BP network, the IWU scheme is proposed for fault detection. To illustrate the IWU scheme, the line currents based fault detection scheme for three phase induction motor is demonstrated using this algorithm.

Even though the NN are capable of mapping inputs and its associated outputs correctly for given problem, it cannot perform this function in heuristic manner as humans prefer. To overcome this shortcoming, fuzzy logic can be used. It is well known that fuzzy logic has the capability of transforming expert knowledge and linguistic variables into numerical values for the use of complex machine computations via fuzzy rules and membership functions.

Fuzzy systems have altered the interest of researchers in various engineering applications ranging from consumer products to industrial process control. The necessity of fuzzy control is to build a human like model without thinking in terms of mathematic model. The expert knowledge is transformed into control rules with proper choice of membership functions. Fuzzy rule based modeling is to identify the structures and parameters of a fuzzy if-then rule base so that a desired input and output mapping is achieved (Junhong et al 1998).
Goode et al (1995) proposed the fuzzy system based fault detection scheme and demonstrated its applicability for electric motors. This method requires to define the membership functions and rules for the input and output for fault detection problem. It does not require the machine parameters for fault detection.

Sinan Altug et al (1999) have proposed the fuzzy implemented fault detection scheme for induction machines. This scheme is capable of estimating the bearing condition of the motor. But the accuracy motor fault detection is not discussed.

Mishra et al (1996) presented a fault detection scheme for single phase induction motor. This method makes use of Gaussian membership function for fault detection. The accuracy of fault detection relies upon the choice membership functions. But, the accuracy of the method can be improved further using proper types of membership functions, which not discussed in this work.

Kothari et al (2001) presented a design and investigations on fuzzy logic based power system stabilizer. They presented the detailed investigations on the design of fuzzy controller to improve dynamic response of the system considering different membership functions. But, they have not considered the different defuzzification methods while designing fuzzy controller, because the performance of fuzzy controller also depends on the choice of defuzzification schemes.

The fuzzy fault detection scheme based on stator current Concordia patterns has been presented in Zidani et al (2003). The stator current patterns are measured, recorded and used for Concordia patterns computation
under different load conditions. This scheme can be implemented online and also requires the accurate sensing devices. Therefore this scheme is considered suitable for large machines.

In the literature on fuzzy control, very little attention has been given to the choice of membership functions and defuzzification schemes while designing fuzzy controller. The terms used in describing the membership functions and defuzzification scheme vary from author to author. The type, shape, number of membership functions and the choice of defuzzification methods drastically affect the quality of fuzzy system. Therefore, this thesis is focused on the choices of membership functions and defuzzification schemes for effective fault detection, which is not reported in earlier work. This investigation is carried out for fault detection in single phase induction motor.

The three phase induction motor equivalent circuit model derived in Tallam et al (2002) is useful in extracting fault signature for fault detection. But, it is very difficult to get accurate mathematical model for induction motor including all nonlinearities and motor asymmetry. The supply voltage unbalance, inherent motor asymmetries and measurement errors cause the change in the fault indicator. Therefore these effects must be compensated.

The neural network based turn fault detection method reported in Tallam et al (2003) attempted to detect the change in negative sequence current (I_{sn}) as fault indicator since the inter turn fault causes the unbalance in the motor which, in turn, introduces the negative sequence current. However this method requires large amount of data to be stored for the given machine to avoid false detection.

Turn fault detection methodology proposed in Lee et al (2003) is immune to supply voltage unbalance. The effects due to inherent motor asymmetry are also considered but the fault detection scheme is not included.
In this thesis, three different fault detection schemes are proposed for three phase induction motor. The performances of these schemes are analysed and compared.

Modeling of synchronous machine with shorted turns is the first step in the design of turn fault detection systems (Joksimovic et al 2000). This model exhibits complex relationship between the parameters and exact fault signature extraction is very difficult. The utility of machine model is restricted because it is even theoretically impossible to include all nonlinearities of the machine.

A twin signal sensing method is used for the detection of incipient faults in the windings of turbo generator. The environmental factors such as temperature of machine and operational factors like speed and excitation current can affect the fault signature (Kulkami et al 2000).

Chow et al (2000) have proposed the fault detection scheme based on the monitoring the spectrum of vibration. The accurate sensing devices are required to monitor the vibration spectrum for fault signature and they are expensive.

In this thesis, the online fault detection scheme is proposed to detect the inter turn faults in the armature winding of synchronous generator based on monitoring the negative sequence components of line currents and voltages. The proposed scheme is implemented using NN and fuzzy system. The performance of these schemes is analysed and compared.
1.5 OBJECTIVES OF THE THESIS

This thesis has three major objectives.

1. The first objective is to analyse the different fault detection schemes for induction motors and synchronous generator. The proposed schemes are to be implemented online using NN and fuzzy system. The simulation results of proposed schemes are to be verified experimentally.

2. The second objective is to propose the modifications in conventional design of neural network and to investigate the choice of membership functions and defuzzification methods for effective fault detection.

3. The third objective is to analyse the performance of conventional and modified fault detector.

1.6 ORGANIZATION OF THE THESIS

This thesis is divided into five chapters. Chapter 1 is introductory and it explains the basics of NN and fuzzy system. A brief literature survey of the work done in the area motor fault detection using NN and fuzzy logic is presented. The modified BP algorithm is also presented.

The fuzzy system and NN based fault detection schemes for single phase induction motor are discussed in chapter 2. The mathematical relationship between the motor faults and motor parameters is derived. The laboratory motor is used to obtain the experimental data. The fuzzy fault detector (FFD) is tested in simulated environment with different types of membership functions, defuzzification schemes and hybrid combination of membership functions. The effectiveness of FFD is analyzed in terms of
percentage error between the experimental value and estimated value. The neural network based fault detection scheme is also presented. The performance of the two schemes are compared.

Three different fault detection schemes for three phase induction motor are presented in chapter 3. First scheme is based on monitoring the line currents, the second scheme is based monitoring the negative sequence component of currents and the third scheme is based on monitoring the sequence component impedance as fault indicator. These three schemes are implemented using fuzzy technique. The simulation results of these schemes are compared. The line currents based fault detection scheme is implemented using NN. The modified BP algorithm is used to minimize the training time. The performance of conventional and modified BP algorithms are compared. The hardware implementation of fault detection scheme is also described in this chapter.

Chapter 4 deals with the application of neural network and fuzzy system for fault detection in synchronous generator. The negative sequence components of line voltages and currents are used as fault indicators for inter turn fault detection. The laboratory synchronous generator is used as a test machine to obtain the training data for fault detector. The negative sequence voltage and current are used as inputs for the fault detector. The performance of fault detector is analyzed through simulation and results are presented. The conclusion and the scope for future research are discussed in chapter 5.