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Layer Recurrent Neural Network Based External Fault Diagnosis Model for Three Phase Induction Motor Using Current Signature Analysis

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Chapter 1

INTRODUCTION

1.1 GENERAL

In this modern era of technology, from all the inventions that have been done till present, some of them have made our life totally dependent upon them and Motors are one of those. These are used in most of the instruments that we have in this world whether the instruments are big machines in the industries or small home appliances ,electric motors are fixed everywhere. Among. all the electric motors like DC motors, universal motors, synchronous motors, induction motors and many more ; IMs are most widely used because of their self-starting property means they don't need any external force for their running. IMs possess several basic characteristics such as low maintenance, high starting torque, high efficiency, robustness, reliability etc which form IM a desirable tool for applications. [1]

IM are commonly known as work horses. These are planted everywhere around us. They are placed in the water pumps and in wind power plants and many more. Due to regular use and while operating under heavy loads these may suffer from breakdowns. Losses like resources loss, schedule delays etc can be caused due to these breakdowns which are intolerable regarding industries & home applications. Hence many condition monitoring techniques have been used in order to prevent induction motors from the losses.

In recent years, for the faults diagnosis and identification purpose various conventional and microcontroller based fault identification systems have been proposed. Among all these AI techniques proved to be best and extremely successful instead of the

Conventional methods which were less accurate and more time consuming and hence it was concluded that AI techniques are better than conventional methods. [42],[43]

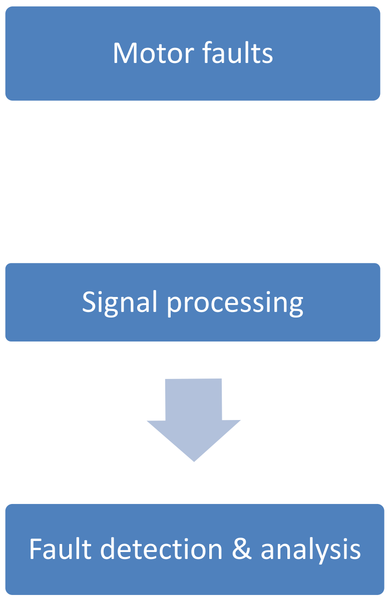


Fig 1.1 Fault detection scheme in three phase IM

IM experiences faults which are majorly classified as mechanical faults and electrical faults. Electrical faults can further be classified into internal and external faults. Internal faults are of two types stator and rotor faults while the external faults are of six types i.e. single phasing(SP), under voltage (UV), over voltage(OV), unbalanced voltage (UB), overload (OL) &locked rotor (LR) fault. In this paper our main focus will be only on external faults experienced by IM. Initially an AI based MPLNN model has been applied for the fault identification but this method has drawbacks as in MLP method calculation of local minima is required and this methods requires an optimal neural network structure but both of these are time consuming. To overcome these problems, we use LRNN technique for fault detections.[3]

Artificial neural networks are the systems or structures which works like nervous system in humans. Here the variables are arranged in same way as in a nervous system in a human brain

AI networks are represented as systems of interconnected 'neurons' that exchanges the messages from one neuron to another. There are various classes of Artificial Neural Networks, some important ones are:

1. Feed forward Neural Network (FNN)
2. Recurrent Neural Network (RNN)
3. Probabilistic Neural Network (PNN)
4. Time Delay Neural Network (TDNN) and many more in this list.

In this project, we have used the AI Technique "Recurrent Neural Network (RNN)" or more commonly known as "Layered Recurrent Neural Network (LRNN)"

Recurrent Neural networks are the dynamic systems which can be linear on non-linear in nature. They can be formed in hardware (whether it be analog or digital) or can be simulated via using a software. These systems can be classified broadly into two groups:

i) CONTINOUS SYSTEMS

ii) DISCRETE SYSTEM

RNN networks have a special property that they possess internal memory which can be used to control the forward directed paths means they can be used to control arbitrary sequences of input. Each of the hidden layer has a context layer which is used to do this work in an RNN network . Its general architecture with three inputs and two outputs is shown below.[46]

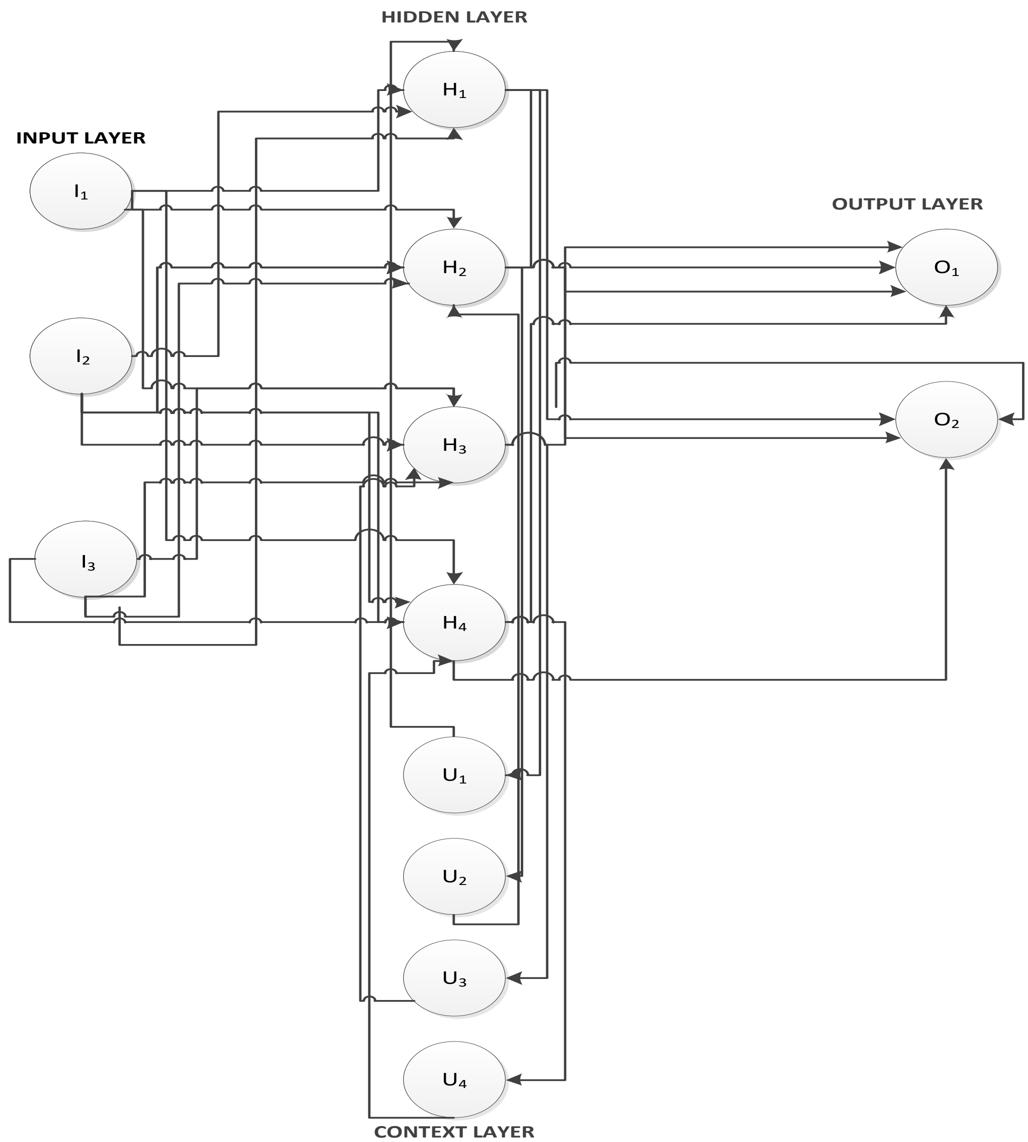


Fig. 1.2 Architecture of Layered Recurrent neural network

These systems are based on supervised learning technique. On the basis of state space models RNN can have 3 types' architectures:

a) Fully Recurrent Neural Networks (FRNN)- The networks in which output of all the N neurons are interconnected through N delay elements and N^2 weighted feedback connections. These networks can be used to simulate or identify nonlinear systems.

b) Partially Recurrent Neural Networks(PRNN)- The networks in which state and output units are separate and the key point distinguishes this types is the all the feedback connections from the neurons are removed here .These network systems can be used to simulate N dimensional linear systems.

c) Simple Recurrent Neural Networks (SRN)- These network systems have their network structures much more simpler than those of FRNN or PRNN. They only have simple one to one recurrent connections. Only the recurrent connections have a time delay as well as forward connections are instantaneous.

Apart from these networks, RNN has some special architecture which are most commonly used in AI techniques. The important ones among them are:

a) Recursive Neural Networks- These networks can be obtained by applying same weights sets repeatedly or recursively over a differentiable graph like structure by changing that particular structure in a topological order. These networks are trained by the method of reverse mode of automated differentiation.

b) Hope field Networks: This is not a general RNN as it has stationary inputs but if this network is trained by hebbian learning then this network can an perform as robust content-addressable memory.

c) Elman networks and Jordan networks-It is a special network which uses a three layer network as shown.

Multi-Layer Perceptron (MLP) is a type of Feed forward Neural Network systems which maps input data set on to the output data set with several layers of dependent variables (also termed as nodes) called hidden layers with each node in a layer is connected to the every node of successive layer and a giant network on interconnected nodes is formed which is called a neural network. This technique uses supervised learning philosophy and based upon back propagation algorithm and hence successive weight modification is done in this algorithm to minimise the error between the actual plant output and the output came from the neural network.

1.2 The scope of this dissertation

1.2.1 Areas of interest

This dissertation addresses two areas. Initially, the discussion is about the method use by human experts and their representation in machine language. The other is to use machine intelligence to extract expertise directly from raw data.

1.2.2 Contributions through the research

The major contribution of this dissertation is the development of Layer Recurrent Neural Network (LRNN), and Artificial Neural Network (ANN) tool for external fault identification experienced by 3–phase induction motor. In this modern era of technology, a vast area can be seen where three phase induction motors is used, so their safe operations are desired. Hence we have to detect and eliminate the external faults experienced by three phase induction motors that are occurring during operation. Although there are many methods present in modern science .Many computational methods have been used for the diagnosis of various faults in an induction motor.

Additional contributions include the development of a knowledge-based external fault identification inference engine for IM condition assessment and maintenance recommendations. Finally, techniques are presented for IM fault identification process.

These contributions can be seen from the contents of the chapters and will be summarized in the final conclusions.

1.2.3 Arrangement of this dissertation

This project thesis is represented in six chapters. First chapter contains the introductory portion of the topic. All the mandatory theoretical aspects along with the objective of the project is discussed in this chapter.

Second chapter of this thesis gives the information about all theory regarding the topic. The description about three phase induction motor is explained in this unit and all the faults which can occur in IM are fully explained in this unit along with all the AI techniques which can be used in condition monitoring of the faults. A new technique has been introduced which has never been used till present and the name of this technique is 'LRNN' and a brief review of all the research papers of different directories like IEEE, Elsivier , Mtech thesis , Phd Thesis are presented in tabular form.

Third chapter of this thesis accounts for the methodology used to operate RNN and to diagnose faults. The division of dataset into training and testing components is introduced in this unit and after that the MATLAB code for the RNN is provided here.

Fourth chapter accounts for the 'FAULTS INDENTIFICATION USING LRNN'. In this chapter all the output plots of LRNN which includes both training and testing outputs are show in this chapter and after that the results obtained by using MLP technique using same data seta are obtained and plotted and the detailed division of data set has been explained in this chapter.

Fifth chapter gives the "Result" of the project. LRNN outputs are compared with MLP outputs and Errors are calculated in this section and it is shown in this chapter that LRNN technique gives more optimal result than MLP technique.

Sixth chapter concludes the thesis. The summary of the whole thesis is provided in this section. And at last references are added from where the manual helps are taken to write this thesis.

1.3 Conclusion

In this chapter, an introduction about the dissertation work has been presented. The conventional methods under MCSA analysis were discussed. The working of each of these methods will be discussed in detail in chapter-2 along with related state of art.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, the literature on faults identification of induction motors is reviewed. This review cover some important topics such as induction motor types of faults in induction motors, faults diagnosis methods i.e. AI techniques and conventional & computational methods. In addition, this review also covers the major developments in this field from previous researches.

2.2 Literature review

Diagnosis means identification of errors or faults in any plant in its service life. Induction motors are widely used in transportation, mining, petrochemical, manufacturing and almost in every other field dealing with electrical power & failure of induction may cause lot of financial loss, no optimization in maintenance, delay in manufacturing etc.so the faults identification is very necessary & important.

This thesis is focused on the diagnosis of external fault experienced by induction motors. The diagnosis of faults gives a great business environment due to these reasons:

- Prediction of equipment failure
- Optimisation of equipment
- Time consumption is less
- Protection of the plant

2.2.1 Types of faults in induction motors

In recent years, there is significant progress in the field of fault diagnosis of induction motors with the help of controlling techniques, computer techniques, Artificial

Intelligence techniques and advanced intelligence algorithms. There are many types of faults in induction motors. Fig 2.1 has shown a flow chart. [3], [42]

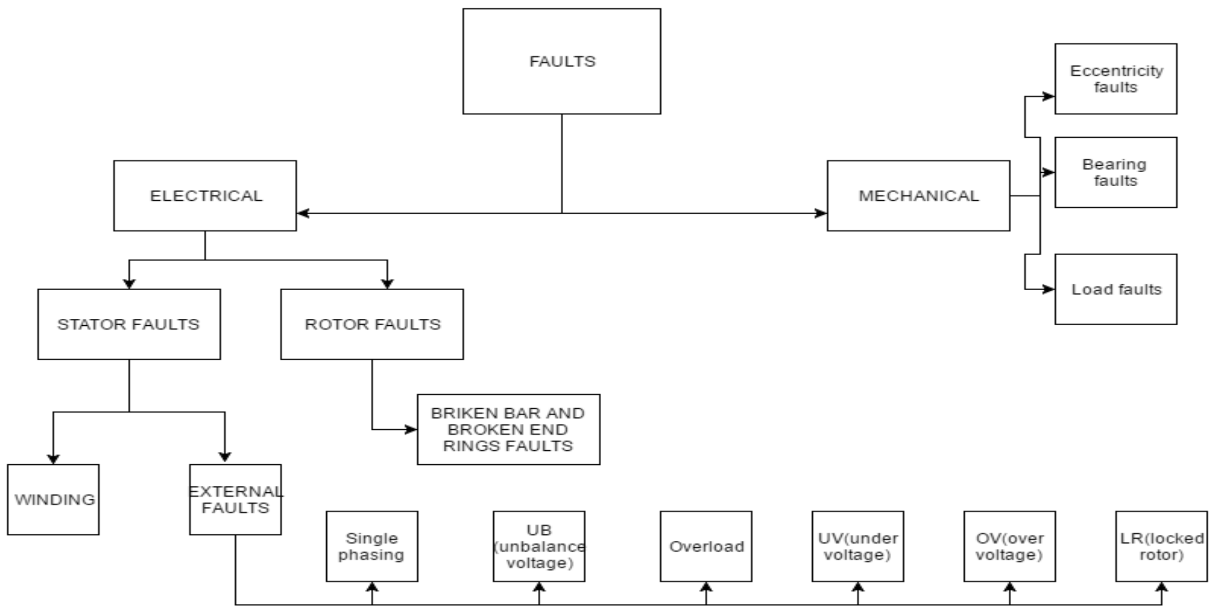


Fig 2.1 Types of Faults experienced by IMs.

The classification of faults in induction motors are :

(a) Mechanical Faults

(b) Electrical Faults

2.2.1.1 Mechanical Faults*:* About 40-50% of induction motor faults are related to mechanical defects. Classification of these faults includes the following.

2.2.1.1.1 Eccentricity Faults

Unequal air gap between stator and rotor results in eccentricity of induction motor. In general, air-gap eccentricity can be of two types: the static air-gap eccentricity and the dynamic air-gap eccentricity. A mixture of both forms, called mixed eccentricity and the axial non uniformity of air gap, known as inclined eccentricity have also been accounted. The minimal radial air-gap length is fixed in space for static air-gap eccentricity. On the contrary, the center of rotor and the center of rotation do not coincide for dynamic eccentricity. In this case, the position of minimum air gap is not fixed in space but rotates with the rotor. An erroneous positioning of the rotor or stator during the commissioning phase may give rise to static eccentricity. It may also be caused by stator core ovality. A cause of dynamic eccentricity can be a bent shaft, bearing wear and movement, or mechanical resonances at critical speeds[2],[43].

Air gap e ccentricity is one of the common failure conditions in an induction motor. For static eccentricity, the Centre of rotation is displaced from the original Centre, for dynamic eccentricity, the Centre of rotation is at origin while the cylinder is displaced .Finally, for mixed eccentricity, both the cylinder and Centre of rotation are displaced from their respective origin. An eccentricity may be caused by many problems such as bad bearing positioning during the motor assembly, worn earing's, bent rotor shaft or operation under a critical speed creating rotor whirl. The eccentricity causes extensive stressing on the machine and greatly increases the bearing wear. Also, the radial magnetic field owing to the eccentricity can act on the stator core exposing the stator windings to potentially harmful vibrations. More recently, the rotor eccentricity was evaluated through different signal analysis such as vibration, flux and current.

2.2.1.1.2 Bearing Faults

Most electrical machines use either ball or rolling element bearings which consists of outer and inner rings. Balls or rolling elements rotate in tracks inside the rings. Bearing faults may be reflected in defects of outer race, inner race, ball or track. Vibrations, internal stresses, inherent eccentricity, and bearing currents have effective influence on the development of such faults.

Fault in the load part of the drive system, load imbalance, shaft misalignment, gearbox faults, or bearing faults, gives rise to a periodic variation of the induction machine load torque. Torque oscillations already exist in a healthy motor owing to space and harmonics of the air-gap field but fault-related torque oscillations are present at particular frequencies often related to the shaft speed[13].

2.2.1.1.3 Unbalanced Load

Load unbalances were implemented by placing a steel bolt and nut on a balanced metal disk at different radial distances from the motor shaft. The change in the trend in the current is mainly caused by the metal disk that is used for creating the unbalance.

2.2.1.4 Shaft misalignment

Shaft misalignment is a frequent fault in rotating machinery, for which the shafts of the driving and the driven parts are not in the same centerline. The most general misalignment is a combination of angular misalignment (shaft centerlines do meet, but are not parallel) and offset misalignments (shaft centerlines are parallel, but do not meet). This type of fault generates reaction forces and torques in the coupling, and finally torque oscillations and dynamic air gap eccentricity in the driving machine.

2.2.1.2 Electrical Faults

There are two types of electrical faults. (i) Internal Faults (ii) External Faults

2.2.1.2.1 Internal Faults

2.2.1.2.1.1 Stator Winding Short Circuit

There is a consensus that 35-40 % of induction motor breakdowns are attributed the stator short circuit. It is assumed that a significant part of stator winding-connected failures are initiated by insulation failures in multiple turns of a stator coil within one phase. Asymmetrical Inter-turn short circuits in stator windings constitute a category of faults that is most common in induction motors. Typically, short circuits in stator windings occur between turns of one phase, or between turns of two phases, or between turns of all phases. Moreover, short circuits between winding conductors and the stator core also occur.

2.2.1.2.1.2 Rotor Broken Bar/Broken End Ring

Broken rotor bars represent 10% to 20% of the whole Faults. Broken rotor bar is one of the commonly encountered induction motor faults that may cause serious motor damage to the motor if not detected timely. Broken bar or end ring may refer to removal of resistance or inductor attached to it. Wavelet transform methods require accurate slip estimation to localize fault-related frequency. Numerical and experimental studies have confirmed that the proposed approach is effective in diagnosing broken rotor bar faults for improved induction motor condition monitoring and damage assessment.

2.2.1.2.2 External Faults

2.2.1.2.2.1 Single Phasing

In single phasing protection to 3 phase induction motor, if other two phases is faulted and only one protection of motor section starts functioning. Generally in single phase supply voltage is lower value than specified value. On this value of voltage motor is unable to start. Comparator which compares single phasing supply voltage and rated specified voltage, and single sends to microcontroller and microcontroller generates single which stop the motor if motor is running and does not allow to motor start in case of standstill. Sometimes single phasing protection looking much motor important when the motor is tight which important function like furnishing, pump driving and crane driving etc. A loose wire, a bad connection, bad starter contacts, overload relay problems, a bad breaker, a blown fuse, and other things can cause this destructive condition. Obvious signs are a louder than normal humming from the motor and/or shaft that vibrates rather than rotating.

2.2.1.2.2.2 Under Voltage

Low voltage is normally not the direct cause of motor overheating since the overload relays will kick the motor off line when the current exceeds rated amps. As a result, the motor will not generate rated HP. The motor slip also increases proportionally to the square of the voltage drop. As a result, the motor will be running slower with a lower output and the process would not be producing as expected. Low voltage during start can create additional problems. When specifying the motor, it is important to understand what the true voltage at the motor terminals is during starting. This is not the power system voltage, or the tap on the autotransformer. To determine this voltage, one must take into account the total line drop to the motor terminals during the high current draw, which is present while the motor is starting. On designs which are subject to reduced voltage start and have a high risk of not properly starting, it is recommended that the voltage at the motor terminals be measured on the first couple of starts, after this motor or any other machinery is added to the power system, to eliminate concerns or problems in the future.

2.2.1.2.2.3 Over Voltage

It is normally true that motors tend to run cooler at rated horsepower at voltages exceeding rated voltage by up to 10%,but the current draw is only controlled by the load and at rated current and 10% overvoltage the motor will be overloaded by approximately 10%. The core loss is 20 to 30% greater than normal and could cause the machine to overheat. If it is verified that the motor will see an overvoltage, the overload current relay must be adjusted downward to compensate, or stator temperature detectors should be used to monitor temperature.

2.2.1.2.2.4 Unbalanced voltage

Unbalanced voltage will produce negative sequence currents that will produce excess heating in the stator winding and rotor bars, but will not produce useful power output. Derating of the motor is necessary when unbalanced voltages exceed 1%. This condition produced increased heating, increased energy consumption and lower efficiency. Note, a 2% voltage unbalance can produce as much as 10% increased losses in the machine.

2.2.1.2.2.5 Locked Rotor

Failure of a motor to accelerate when its stator is energized can be caused by:

- Mechanical failure of the motor or load bearings.
- Low supply voltage

  When a motor stator winding is energized with the rotor stationary, the motor performs like a transformer with resistance-loaded secondary winding. During starting, the skin effect due to slip frequency operation causes the rotor resistance to exhibit a high locked-rotor value, which decreases to a low running value at rated slip speed. Using a typical locked-rotor current of six times the rated current and a locked-rotor resistance of three times the normal running value: Consequently, an extreme temperature must be tolerated for a limited time to start the motor. To provide locked-rotor or failure-to-accelerate protection, the protective device must be set to disconnect the motor before the stator insulation suffers thermal damage, or the rotor conductors melt or suffer damage from repeated stress and deformation.

2.2.1.2.2.6 Overload

If the motor is drawing more than rated current at full load, the most likely cause is excessive load or under voltage. The full load amps on motors with efficiencies in the high 90's can be predicted very accurately, and normally are within 2% of the required amp draw for the load, whereas the load equipment which may have efficiencies less than 50% can easily be off by 5-10%. The voltage also plays an important part. If the voltage were down by 10%, it would require 10% overcurrent to provide rated torque. Also, the load will vary as the material being processed changes temperature. Liquid and air handling equipment requires more horsepower to process cold material than it does when the material reaches its designed operating temperature.

In this thesis, we have diagnosed the external faults of induction motors using AI techniques**.** There are many conventional and AI techniques which are used for faults identification in induction motors. In our project work, we have used Layer Recurrent Neural Network for the identification of external faults.[12]

2.2.2 Computational Methods used for the faults identification in induction motor:

There are many ways for the identification of faults computational methods. There are the many graphical and artificial intelligence based which are used for the detection of faults before the revolution of Artificial Intelligence techniques in faults detection. Flowchart of the techniques used for the identification of faults has been shown in the fig. 2.

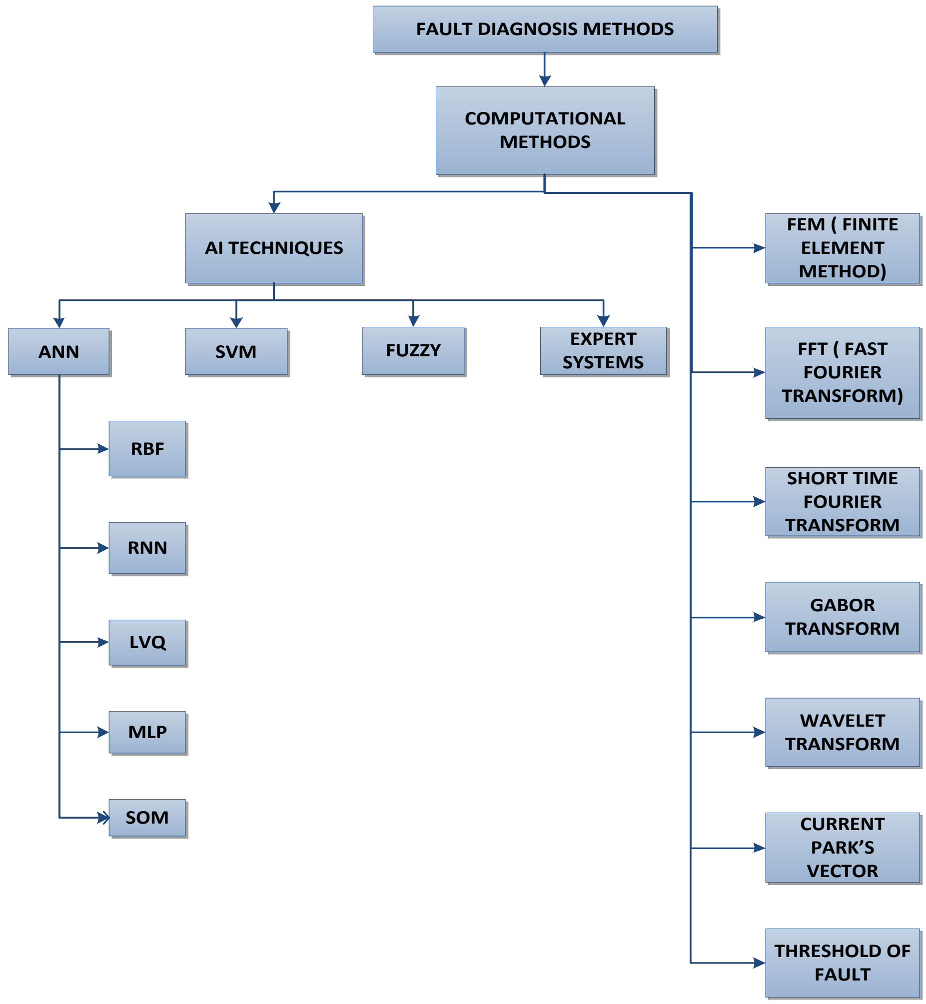


Fig 2.2 Computational methods of fault detection

The following techniques have been discussed as follows:

2.2.2.1 Model Based Approaches: Finite Element Method (FEM)

Model based approaches are used for analyzing the effect of particular faults on parameters such as current and voltage. One of most popular method is Finite Element Method [22]. FEM is most accurate technique for diagnosis because it includes all the characteristics of faulty and healthy motor. In finite element application steady state values are used for operation. For the diagnosis of faults in induction motors, there electrical and magnetic behaviors are taken into account. All the physical system are represented by partial difference equations. FEM allows the representation of equation converting them into algebraic equation. For example, if the magnetic field is time varying, eddy currents can be induced in materials with non zero conductivity so, the time varying field equation can be used for modeling the induction motors which has eddy current. FEM gives information of machine more than other analytical analysis, which uses magnetic linearized parameters. With the help of machine dimension and material, in FEM magnetic field is calculated which gives precious information about machine. The machines parameters such as magnetic flux density, inductances and torques can be measured by calculating magnetic field distribution. Therefore, it can be used in monitoring and analysis of faults and unbalanced condition of induction motors.

2.2.2.2 Trending

In this method, the parameters of faulty conditions are observed over a period of time so it will be able to detect sudden changes which are associated with presence of faults. This method is used very rarely because it is very difficult to determine the very slight change in parameters. This is used where very large change observed in machine parameters due to occurrence of faults.[28]

2.2.2.3 Thresholds of Faults

This method is simplest method used for detecting faulty condition of induction motors. In this method, a threshold value is set for any given parameter and according to that threshold value it variation are measured. For instance, there are tables which show the vibration acceptable levels of mechanical vibration amplitude which is depending on size of machine.one of example is thumb rule for broken bars sidebands in current spectrums. Experimentally it is measured if sidebands are more than -54dB than motor is faulty and if it is less than +54dB with respect to peak then the motor is healthy. This method mainly used for detection of mechanical faults such as broken bars, bearing faults in induction motors.

2.2.2.4 Fast Fourier Transform

In frequency domain, Discrete Fourier Transform (DFT) is most straight mathematical method for determining frequency content of time domain sequence. But it is very tough to calculating higher number of points when increases to hundreds or thousands. In 1965,[32] this technique is modified and that is known as Fast Fourier Transform (FFT). FFT is new way to calculate & compute DFT. By using periodicity in sine's, FFT reduce the calculation required. Functionally, the FFT decomposed the set of data to be transformed then it composes to those smaller sets into even smaller sets. Finally it calculates the DFT of each small data set.[32]

FFT algorithm is also used for detecting various types of faults in induction motors. The power spectrum is computed from the basic function of FFT. Power spectrum shows power as the mean squared amplitude at each frequency line. With the help of Lab VIEW a two sided spectrum in complex form is observed. The scale of spectrum is converted into polar form to obtain magnitude and phase. The amplitude of FFT represents the no of points in the time domain signal.

In FFT, the input single is passed through sampling circuit then it is a power spectrum is observed and that spectrum is converted into frequency domain. The last step is to search the fault frequencies in spectrum. FFT mainly used to detect broken rotor faults, stator winding fault, Air gap Eccentricity fault & Bearing & Gear box faults.

2.2.2.5 Short Time Fourier Transform (STFT)

To study the properties of signal at time t, one emphasizes the signal at that time and suppresses the signal at other times. To achieve this signal is multiplied by window function, h (t), centered at t, to produce a modified signal. To analyze the signal around time t, window function has chosen that is peak around t. The modified signal is short and its Fourier transform is called short-time Fourier transform (STFT).

$$s(w) = \frac{1}{\sqrt{2\pi}} \int e^{-jwt} s_i(\tau) h(\tau - t) d\tau \qquad (2.1)$$

FFT analysis is not suitable for analyzing transient signals so STFT can be used to analyze transient signals using a time frequency representation but it gives output for fixed size window for all frequencies, which leads to poor frequency resolution

2.2.2.6 Gabor Transform

It is a linear time frequency analysis method that computes a linear time-frequency representation of time domain signals. [23]Gabor transform gives better time frequency resolution than STFT spectrum method. Gabor spectrograph is used to estimate the frequency content of a signal. It helps to develop a visual understanding of frequency content of one speech while a particular sound is being vocalized.

Gabor transform is used to diagnose the short winding fault and Lab VIEW software is used for observing the spectrum.

2.2.2.7 Wavelet Transform

Wavelets are those functions which can be used to decompose signals & it is very similar to how to use complex sinusoids in Fourier transform [6]to decompose signals. The wavelet transform computes the inner products of analyzed signal and a numbers of wavelets. The difference between wavelet transform and sinusoid wavelets is that in WT, wavelets are localized in both the time and frequency domain, so wavelet signal processing is suitable for those signals whose signal content changes over time. The adaptive time-frequency resolution of wavelet signal processing is used as multi resolution analysis[9].

Wavelets signal processing is different from other signal processing methods because of the unique properties of wavelets. In WT, wavelets are irregular in shape and finite in length. [1]Wavelet signal processing can represent signals sparsely, capture the transient features of signals, and enable signal analysis at multiple resolutions.

Wavelet transform is used for the detection of rotor faults, stator winding, gear-box & eccentricity faults. And it is best technique, because with the help this technique we can diagnose all the mechanical faults.

2.2.2.8 Current Park's vector Approach

In three phase induction motors, the connection to the mains does not usually use the neutral. Therefore, the main current has no homo-polar component. A two dimensional representation can be used to describing three phase induction motor phenomena, a suitable one based on the current Park's Vector.

As a function of mains phase variable (i_1, i_2, i_3) the current Park's vector components (i_p, i_q) are

$$i_p = \sqrt{\frac{2}{3}} i_1 - \frac{1}{\sqrt{6}} i_2 - \frac{1}{\sqrt{6}} i_3 \tag{2.2}$$

$$i_q = \frac{1}{\sqrt{2}} i_2 - \frac{1}{\sqrt{2}} i_3 \tag{2.3}$$

Under ideal conditions, these current becomes as follows :

$$i_p = \frac{\sqrt{6}}{2} I \sin \omega t \tag{2.4}$$

$$i_q = \frac{\sqrt{6}}{2} I \sin\left(\omega t - \frac{\pi}{2}\right) \tag{2.5}$$

Where

I = maximum value of supply phase current

ω_s = supply frequency

t = time variable

the representation of the currents is a circular pattern which is centered at origin of the coordinators. And the circular graph allows the detection of abnormal conditions by monitoring the deviations of acquired pattern.

Park vector approach is generally used for finding the stator winding faults. In this, stator current is visualized. If the vector is perfect circle then the motor is healthy & if the vector representation is elliptical then the motor is faulty.

After the revolution of artificial intelligence, many techniques are found for the detection of faults in induction motors. Many AI techniques have been used for finding faults such as neural networks (ANN), Support Vector Machine, Fuzzy Logic & Expert systems.

2.2.2.9 Artificial Neural Network (ANN)

Artificial neural networks are family of models which have been tries to simulate the biological brain neural network in a mathematical model [12]. In this system, a set of neurons connected to each other and weights are assigned to the connections. According to learning rule, the weights are updated by training the ANN using training data. An ANN generally consists of input layer, hidden layer and output layer. Any number of hidden layers can be used. The neuron is combination of input, a summation and a activation function. Activation function is generally sigmoid or tanh function which limits the output in range (0, 1) or (-1, 1) respectively. There are many types of neural networks which are discussed below.

2.2.2.9.1 Feed forward neural network: Single layer perceptron (SLP and Multilayer perceptron (MLP)

Generally all neural networks which are used in application are feed forward neural network. The feed forward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes.[3] There are no cycles or loops in the network. Basically two types of feed-forward network are used which are explained below: (a) SLP & (b) MLP

Perceptron's with more than one layer of variably weighted connections are referred to as multilayer perceptron's (MLP). An n-layer or n-stage perceptron has thereby exactly n variable weight layers and (n + 1) neuron layers with neuron layer 1 being the input layer. For the training of data, back propagation method is used. Multi-layer networks use a variety of learning techniques, the most popular being back propagation. In this technique, the output values are compared with the correct answer to compute the value of predefined error-function.

A single layer perceptron (SLP) is a perceptron having only one layer of variable weights and one layer of output neurons i.e. the inputs are fed directly to the outputs via a series of weights.

Perceptron is an type of function for supervised learning which decide whether input belongs to one class or another class. So these perceptron are used for identification of faults. In a feed forward network information always moves in one direction, it never goes backwards. MLP generally used for the identification of external faults occur in induction motors.

2.2.2.9.2 Radial Basis Function (RBF) Network

A radial basis function network is defined as the network which has exactly three layers; input layer consists of input neurons, hidden layer (also known as RBF layer) consists of RBF neurons & output layer consisting of output neurons [13]. RBF use the radial basis function as activation functions. The output taken from the network is linear combination of radial basis functions of inputs and neurons parameters.

RBF function is a real valued function whose values depends only on the distance from the origin, so that $\phi(x) = \phi(\| x \|)$. Any function which satisfies this equation is radial function. Generally Gaussian function is used for the training in RBF.

$$\varphi(x) = \sum_{i=1}^{N} b_i \phi(\| x - c_i)$$

Where $\phi(\| x - c_i) = e^{-\alpha \| x - c_i \|^2}$ & c_i is the center vector

RBF networks are typically trained by a two-step algorithm. In first step, the center vectors of RBF functions in the hidden layer are chosen. Second step is simply fits a linear model with some coefficient to hidden layer outputs w.r.t. to some objective function. Generally this technique used for interpolation & also used for classification. In classification problems the output layer is typically a sigmoid function of a linear combination of hidden layer values, representing a posterior probability. For classification of the faults it is rarely used because it has limited number of hidden layers due to which the number of iteration will not be effective.

RBF networks have the advantage of not suffering from local minima. This is because the only parameters that are adjusted in the learning process are linear mapping from hidden layer to output layer. RBF networks have the disadvantage of requiring good coverage of input space by radial basis functions.[18]

2.2.2.9.3 Kohonen self-organized network or Self-Organized Mapping (SOM)

SOM is a type of unsupervised learning type network where the output is the state of network, which learns completely unsupervised i.e. without teacher. This neural network is trained by unsupervised learning to produce a low dimensional discretized representation of input space of the training samples, called a map. These networks are useful for the visualizing low dimensional views of high dimensional data. The neurons are interconnected by neighborhood relationships. These neighborhood relationships are called topology. The training of a SOM is highly influenced by the topology. Topology function h (i, k, t) describes the neighborhood relationships in the topology. It can be any uni modal function that reaches its maximum when $i = k$ gilt. Time-dependence is optional, but often used.

SOM operate in two modes: training and mapping. "Training" generally builds the map & mapping classifies a new vector. SOM consists of components called nodes or neurons. Associated with each node are a weight vector of same dimension as input data vectors, and a position in map space. These networks typically depend on arrangements and motivation of the architecture.

There are several learning things which are linked with SOM. The goal of learning in SOM is to cause different parts of the networks to respond similarly to certain input patterns. The weights of neurons are initialized either to small random values of sampled evenly from subspace spanned by two principal component eigenvectors. Applications of SOM are meteorology and oceanography, project prioritization and selection, seismic faces analysis for oil and gas exploration. This is rarely used in faut identification because of its structure is depend on arrangement and it gives very less accuracy ranging 80-85 percent[37].

Self-organized map approach for mechanical & rotor faults in IM. Two neural network-based schemes for fault diagnosis and identification on induction motors The first scheme uses the information of the motor phase current for feeding the network, in order to perform the diagnosis of load unbalance and shaft misalignment faults. The second scheme is based on the motor's active and reactive instantaneous powers, in order to detect and diagnose faults whose characteristic frequencies are very close each other, such as broken rotor bars and oscillating loads.

2.2.2.9.4 Learning Vector Quantization (LVQ)

Learning Vector Quantization is a learning procedure with the aim to represent the vector training sets divided into predefined classes as well as possible by using a few representative vectors. If this has been managed, vectors which were unknown until then could easily be assigned to one of these classes. Quantization means Separation of a continuous space into discrete sections. An LVQ system is representation of prototypes which are defined in feature space of observed data. An LVQ network has a competitive layer and a second linear layer. The competitive layer learns to classify input vectors in much the same way as the competitive layers of self-organizing features map. The linear layer transforms the competitive layer's classes into target classification defined by user. The classes learned by the competitive layer are referred to as sub classes and classes to linear layer as target classes.

There are many ANN techniques which are based on Back Propagation (BP) &can be used for distribution & training of data set. But, these techniques have several disadvantages like slow convergence of dataset, hampering the adaptive capability & determination of the hidden layers & no. of neurons. So, to overcome these drawbacks, the modeling of LVQ becomes very important. LVQ structure consists of input layer, hidden layer & output layer. Input layer each neuron is connected to each and every neurons of hidden through a weight while output neurons are connected to a particular group of hidden layer neurons. LVQ is widely used for the identification of faults in induction motors because it gives best accuracy and minimal error[14].

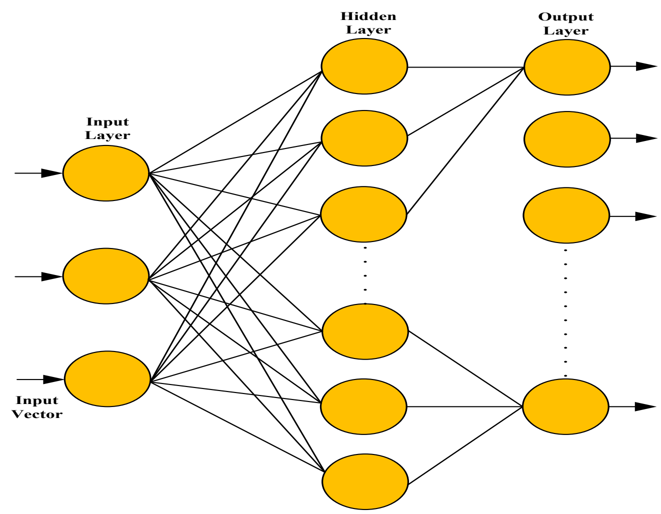


Fig 2.3 LVQ model

2.2.2.9.5 Recurrent Neural Network

A RNN is a class of ANN where connections between units form a directed cycle. This creates an internal state of network which allows it to exhibit dynamic temporal behavior. RRNs can use their internal memory to process arbitrary sequences of inputs. RNN uses supervision based learning system algorithm for testing and training of kohonen layer (hidden layer). The structure of LRNN consists of input layer, context layers, hidden layers and output layer. Each neuron of input layer is connected to each and every neurons of hidden through a weight and output neurons are connected to each neuron of hidden layer while a context layer is connected to both the ends of hidden layer. The advantage of context layer is to modified the with less no. of epochs, hence the accuracy of model increases & the time consumption will be less. In the RNN, there is a feedback loop, with a single delay, around each layer of the network except for the last layer. The original Elman network had only two layers, and used a tan sigmoid activation function for the hidden layer and a purely activation function for the output layer. The original Elman network was trained using an approximation to the back propagation algorithm[36].

There are many Types of RNN networks which are discussed below:

- Fully Recurrent Network – A network of neuron-like units, each with directed connection to every other unit. Each unit has a time varying real valued activation. For supervised learning in discrete time settings, training sequences of real valued input vectors become sequences of activations of input nodes, one input at a time.
- Jordon Network & Elman Network - A Jordan network is a multilayer perceptron with one context neuron per output neuron. The set of context neurons is called *K*. The context neurons are completely linked toward the input layer of the network. An Elman network is an MLP with one context neuron per information processing neuron. The set of context neurons is called *K*. This means that there exists one context layer per information processing neuron layer with exactly the same number of context neurons. Every neuron has a weighted connection to exactly one context neuron while the context layer is completely linked towards its original layer.
- Hopfield network – It is not a general RNN because it is not designed to process sequences of patterns. It is a RNN in which all the connections are symmetric and its dynamic will converges for sure.
- Recursive neural networks – it is created by applying the same set of weight recursively over a differentiable structure, by traversing the structures in topological order. These networks were invented to learn distributed representations of structure such as logical terms.

- Echo state network – it is RNN type network which is connected sparsely to random hidden layer. The weights of outputs are trained only and that weight can only be changed. These are very in time series production.
- Bi-directional RNN [14]– This method use a finite sequence to predict or label each element of sequence based on the past and the future context of the element. In BRNN, from two outputs one output is processed from left to right & other one from right to left.
- Continuous time RNN – A continuous time RNN is a dynamical systems model of biological neural networks. A CTRNN use a system of ordinary differential equations to model the effects on a neuron of the income spike train.

2.2.2.10 Support Vector Machine (SVM)

Support vector machine is a statistical learning theory based machine learning method used for classification and regression. The main principle of SVM is that it classifies the input data into different classes by learning the training data. It separates the data by linear separable method. To classify the data, a classifier namely hyper plane is used. An optimised solution is calculated for the hyper plane with the help of mathematical modelling of SVM.

We can use a SVM when we have exactly two classes. An SVM classifies data by finding the best hyper plane for an SVM that separates all data points of one class from other class. The best hyper plane for SVM means that maximal width of the slab parallel to the hyper plane that has no interior data points.[8] The disadvantage of SVM is that it takes two inputs at single time so the training of SVM takes lot of time and also takes very large memory. For the inseparable data SVM use a soft margin means a hyper plane that separates many, but not all the data points. For the nonlinear inseparable data a kernel function is used for classification of data.

An SVM model is representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. For unlabelled data, it is not possible to learn supervised data so a unsupervised learning is required. The clustering algorithm which gives improved results to SVM is known as Support vector clustering and it is used in industrial application. SVM has been used for monitoring and identifying mechanical faults in power systems machinery; for example, ball bearing faults in induction motors, bearing faults detection of induction motors.

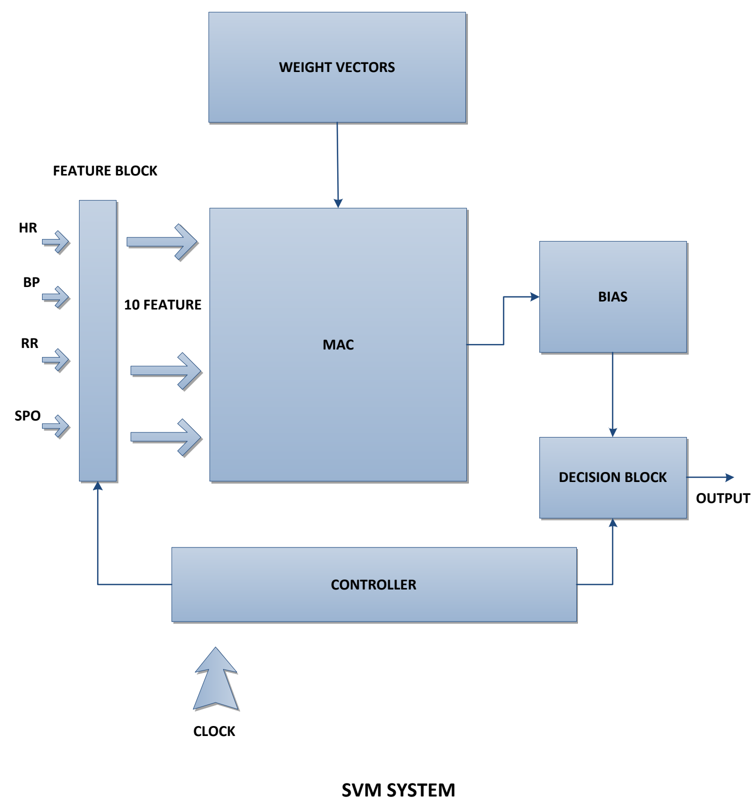


Fig 2.4 Block diagram of a SVM system

SVM can be used to solve these types of problems:

1. They can be used to categorized text and hypertexts as there application can significantly reduce the need for labelled training.

2. Classification of images

3. in medical science for the classification of different compounds.

4. for the classification of faults in induction motors.

2.2.2.11 Fuzzy Logic technique

Fuzzy logic is used for diagnosis of short-circuit and open stator phase faults in induction motors. For induction motors RMS current linguistic variables, fuzzy subsets and the membership functions are describe for diagnosis. [1]To support fuzzy inference a fuzzy system compromising rules and data base is established. To find the state of motor, a rule is composed for fuzzy execution. Generally linguistic variable like small, medium, large, very large etc. are assigned for inputs. Complete data is observed to build the fuzzy rules of membership function. Fuzzy inference method established the relation between symptoms and fault reasons.

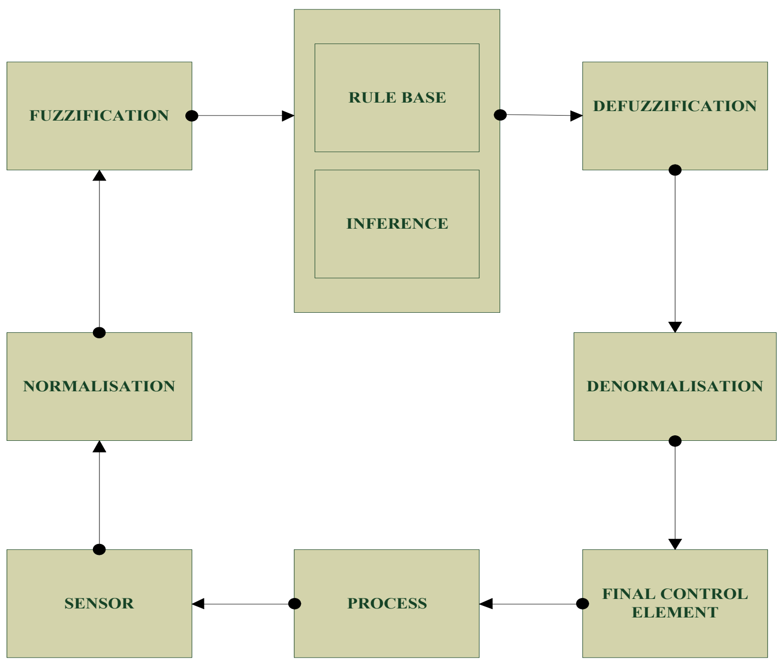


Fig 2.3 Block diagram of a Fuzzy system

Fuzzy systems are learned by Natural language, Linguistic hedges, fuzzy rule based systems, Graphical technique of inference. Natural language is perhaps the most powerful form of conveying information that humans possess for any given problem or situation that requires solving or reasoning. This power has largely remained untapped in today's mathematical paradigms; not so anymore with the utility of fuzzy logic. Our natural language consists of fundamental terms characterized as atoms in the literature. A collection of these atoms will form the molecules, or phrases, of our natural language. The fundamental terms can be called *atomic* terms. Examples of some atomic terms are *slow*, *medium*, *young*, *beautiful*, etc. are the collection of individual elements and sets that represent the cognitive patterns and mental images. These interpretations would be rather vague, and they might best be represented as fuzzy sets so a linguistic variable, can be interpreted using fuzzy sets. In linguistics, fundamental atomic terms are often modified with adjectives (nouns) or adverbs (verbs) like very, low, slight, more or less, fairly, slightly, almost, barely, mostly, roughly, approximately etc. these modifiers are called as linguistic hedges[14].

Most easy method is graphical techniques of inference. Graphical methods that emulate the inference process and that make manual computations, involve a few simple rules straight forward. There are basically three models for graphical method. (1) Mamdani systems, (2) Sugeno models, and (3) Tsukamoto models. In these methods mamdani is most widely used because it is easy to measure.

Fuzzy model introduces the time as an important factor or variable that plays an important role either in fault detection. Generally fuzzy logic technique is mainly used for the diagnosis of stator winding faults. It gives very high accuracy.

2.2.2.12 Expert systems

Expert systems are sophisticated computer programs that manipulate knowledge to solve problems efficiently and effectively in a narrow problem area. Like real human being, these systems use symbolic logic and heuristics- rule of thumb- to find solutions. Expert systems have advantages over human being: it is permanent, consistent, easy to transfer and document, and cheaper. Expert systems enhance the value of expert knowledge by making it readily and widely accessible.

Features of expert systems are training facility, high level expertise, predictive modeling and institutional memory. The most important feature is high level expertise because these systems provide best thinking of the top experts in field. Another useful feature is its predictive modeling power & institutional memory.

Expert systems are widely used in diagnosis in different areas like computer systems, electronics systems, engineering, chemistry, geology, process control systems etc. There are many computer programs for the identification of fault in electrical and electronic systems: ACE, IN-ATE, NDS etc.

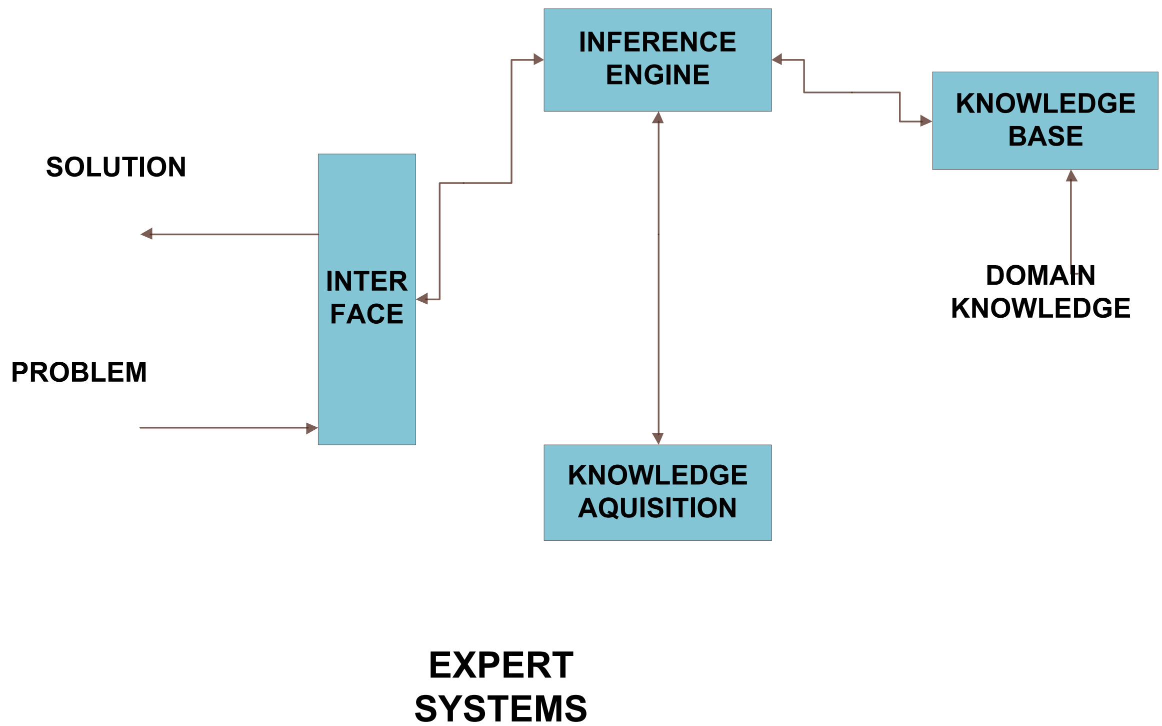


Fig 2.6 Block diagram of an Expert System

Below is the review of the previous research papers published in the field of diagnosis of faults experienced by three phase induction motors

Table 2.1 Review Table of IEEE research papers

Reference No.	Authors	Major Findings	Technique Used	Accuracy	Comparison
1	J. Stein et al [1988]	faults in Squirrel cage	a computer	Highly accurate	Not given

		rotors of induction motor	based instrument		
2	John C Salman and Barry R Williams [1990]	Stator windings for 3-phase induction motor	Not given	3-layer wound motor gives an efficiency droop of 0.2%	the unipolar winding efficiency droop of 3%.
3	Debaprasad Kastha, and Bimal K. Bose [1994]	Fault diagnosis	open loop volts/hertz speed control method.	Highly reliable and accurate	Not given
4	Debaprasad Kastha, and Bimal K. Bose [1994]	Operation of faulty 3-phase inverter into single phase variable frequency mode	pulsating torque suppressio n algorithm	Highly accurate	Not given
5	Paul V. Goode and MO-pen [1994]	Extraction of Heuristic Knowledge of Incipient Faults in Induction motor	ANN	Highly accurate	Not given
6	Andrea Bernier et al [1995]	Fault detection	IFDI	correct fault detection and isolation higher than 94%.	Not given
7	Debaprasad	on-line search	C language	Not given	Not given

	Kastha and Bimal K. Bose [1995]	algorithm for neutralization of low-frequency harmonic torques for fault mode single-phase operation of a variable frequency variable voltage induction motor drive	on a TMS320C30 digital signal processor board.		
8	Randy R. Schoen et al [1995]	Fault detection	Computer based simulation	Highly accurate	Not given
9	John S. Hsu [1995]	Monitoring of Defects in Induction Motors	Air-Gap Torque Observation	Not given	Present wave form compared with previous records
10	David G. Dorrell et al [1997]	on- line diagnosis of airgap eccentricity	Vibration analysis	Not given	Not given
11	Chang-Eob Kim et al [1997]	Fault diagnosis	the time stepping finite element method	Not given	Not given
12	A. Bentounsi and A. Nicolas [1998]	Fault diagnosis	FEM	Highly accurate	Not given

13	Giovanni Betta et al [1998]	Fault detection and isolation	ANN	isolation percentages higher than 98%	Compared with reference to a measurement station for induction motor
14	Sinan Altug et al [1999]	IMPLEMENTATION TECHNIQUES FOR CONSTRAINT ENFORCEMENT METHODS	Fuzzy/Neural logic	Not given	Not given
15	M.E.H. Benbouzid et al [1999]	Fault diagnosis	FFT	-	-

Table 2.2 Review Table of Elsevier Research Paper

References	Technique used	Major finding	Performance measure	Comparison
[1] Hasmat Malik et al.	ELM (External Learning Machine)	External electrical faults (overloading, under-voltage etc.)	99.3	MLP
[2] Abbas Rezaei et al	ANN, ANFIS	External faults	98.5	ANFIS
[3] R. Osornio-Rios et al	Fused Empirical Mode Decomposition(EMD) and MUSIC Algorithms	Rotor faults	97.9	FFT
[4] Vishwanath Hegde et al	current signature analysis and vibration analysis	eccentricity fault	96.4	MEMS (vibration analysis)
[5] LIU Hao	Intelligent fuzzy	Rotor faults	97.4	---

et al	technique			
[6] Tahar Bahi et al	Fuzzy Technique	Stator faults, Rotor faults	98.8	----
[7] B. Bessam et al	DWT & Hilbert Transform	Broken rotor faults	94.7	
[8] Li Qin et al	Advance filtering technique , ES(expert system) algorithm Wiener filtering algorithms, the Kalman filtering algorithms and the novel self-adaptive filtering algorithms	Stator and rotor faults	96.4	ANN
[9] Xin Wang et al	LABVIEW variable step size LMS algorithm	Broken rotor bar	97.3	ANN
[10] Yihua Liu	SWPT & Hilbert Transform	ROTOR bar faults	95.2	FFT

Table 2.3 Review Table of Springer Research Paper

References	Technique used	Major finding	Performance Measure	Comparision
[1] Guillermo A. Jim´enez et al	Hilbert Transform, Wavelet Transform	broken bars, bearing malfunctioning, rotor slot effects, saturations, and dynamical and static eccentricities	99.99%	MRA
[2] Osman bilgin et. al.	ANN	Rotor faults	96.4%	FFT

[3] Jose´ M. Bossio et al	Self-organizing map (SOM)	Broken rotor faults	92%	ANN
[4] Manjeevan seera et al	Fuzzy networks	Eccentricity	98.7%	MLP
[5] Hyeon bea et al	Wavelet analysis	Rotor faults	99.2%	MLP
[6] Erhan Akın et al	Combined intelligent methods based on wireless sensor networks & fuzzy logic	Bearing faults, stator faults, rotor faults	97.4%	Fuzzy logic
[7] Manjeevan Seera et al	Hybrid FMM-CART	Rotor faults	100%	ANN
[8] Ridha Kechida et al	Fast Fourier Transform	Broken rotor Faults	98%	ANN
[9] Abderrahim ALLAL et al	Park’s vector approach(PSVM)	Rotor faults	100%	FFT
[10] Yishan HUANG et al	Observer method	Internal Fault detection	99.9%	Basic conventional method
[11] SONG Jung-il et al	FFT, WVT	Stator faults	98.3%	Fuzzy model
[12] JUNG D Y et al	principal component analysis (PCA) and linear discriminant analysis (LDA)	bearing fault, coupling and rotor bar faults, air gap, rotor, end ring and stator faults	100% (LDA) , 92.6%(PCA)	Conventional methods

2.3. Conclusion

In this chapter, all the computational techniques as well as conventional techniques have been explained in detail and the superiority of computational techniques over conventional approaches is shown and at the end, the reviews of the research papers of various conferences has been shown in tabular form.

Chapter 3

MATERIAL AND METHODOLOGY

3.1 Introduction

Methodology is the branch of philosophy that analyzes the principles and procedures of assumption in a particular field. In this research process, LRNN technique is used to diagnose the faults experienced by three phase IM.

In this chapter, initially the dataset or the input material of the model has been described followed by the general architecture of LRNN and MLP techniques which are used in this project and in the end step by step procedure of the process has been shown.

3.2 Material used

Fault diagnosis of external faults in three phase induction motor using RNN is done in this project work. Here we have used the online publically available dataset for squirrel cage induction motor (SCIM) which has 788 samples and divided this datasets into two parts out of which one is used for training of the neural network and other is used for the testing purpose. Out of 788 samples we have arranged this data set as follows:[3]

Out of total 788 samples,

- 154 samples are used for training and testing conditions to check healthy character of motor and out of 154 samples , 16 samples are used for the testing purpose while the rest 138 samples are used for the training purpose.
- 85 samples are assigned to detect the variation in the response of "single phase" fault. Out of 85 samples, 9 samples are allotted in training dataset while rest 76 samples are allotted in training dataset.
- 450 samples are assigned to detect the variation in the response of "unbalanced voltage" fault. Out of 450 samples, 45 samples are allotted in training dataset while rest 405 samples are allotted in training dataset.

- 49 samples are assigned to detect the variation in the response of "under voltage" fault. Out of 49 samples, 7 samples are allotted in training dataset while rest 42 samples are allotted in training dataset.
- 10 samples are assigned to detect the variation in the response of "over voltage" fault. Out of 10 samples, 3 samples are allotted in training dataset while rest 7 samples are allotted in training dataset.
- 10 samples are assigned to detect the variation in the response of "Locked Rotor" fault. Out of 10 samples, 3 samples are allotted in training dataset while rest 7 samples are allotted in training dataset.
- 30 samples are assigned to detect the variation in the response of "overload" fault. Out of 30 samples, 5 samples are allotted in training dataset while rest 25 samples are allotted in training dataset.

In this by Electrical department of MIT for the analysis of faults in the squirrel cage induction motor model (SCIM).This dataset is available on the internet for the public use and we have used the same data set in our project work to diagnose the faults using a technique which has never been used in the world by anybody to diagnose the electrical faults in a three phase induction motor.

3.3 Methodology

3.3.1 Layered Recurrent Neural Network (LRNN)

Many AI techniques have been proposed which are based upon the back propagation algorithm and which can be used for the classification and training of available dataset but due to several disadvantages of these techniques like hampering the adaptive capability convergence of dataset & determination of the hidden layers & no. of neurons these techniques fail and LRNN comes into action. In figure shown below, general architecture of LRNN is shown. This is a two input two output model with a hidden layer containing three neurons and a context layer containing equal number of neurons as in the hidden layer.

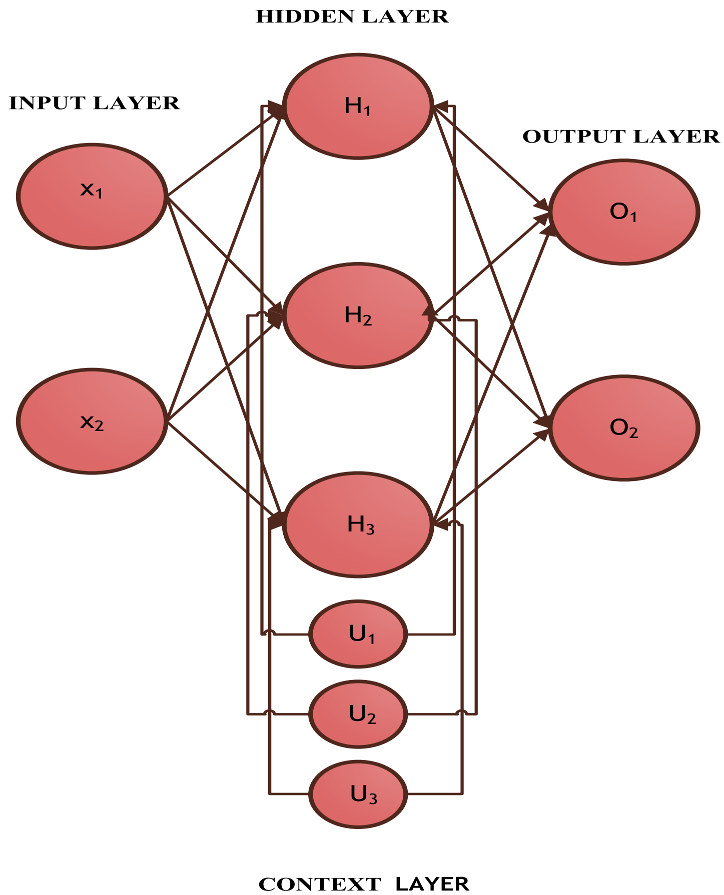


Fig 3.1 LRNN architecture

3.3.2 MULTI LAYERED PERCEPTRON(MLP)

Perceptron with more than one layer of variably weighted connections are referred to as multilayer perceptron (MLP). An *n*-layer or *n*-stage perceptron has thereby exactly *n* variable weight layers and (*n* + 1) neuron layers with neuron layer 1 being the input layer. For the training of data, back propagation method is used. Multi-layer networks use a variety of learning techniques, the most popular being back propagation. In this technique, the output values are compared with the correct answer to compute the value of predefined error-function. Perceptron is an type of function for supervised learning which decide whether input belongs to one class or another class. So these perceptron are used for identification of faults. In a feed forward network information always moves in one direction, it never goes backwards. MLP generally used for the identification of external faults occur in induction motors. Below is the architecture of MLP

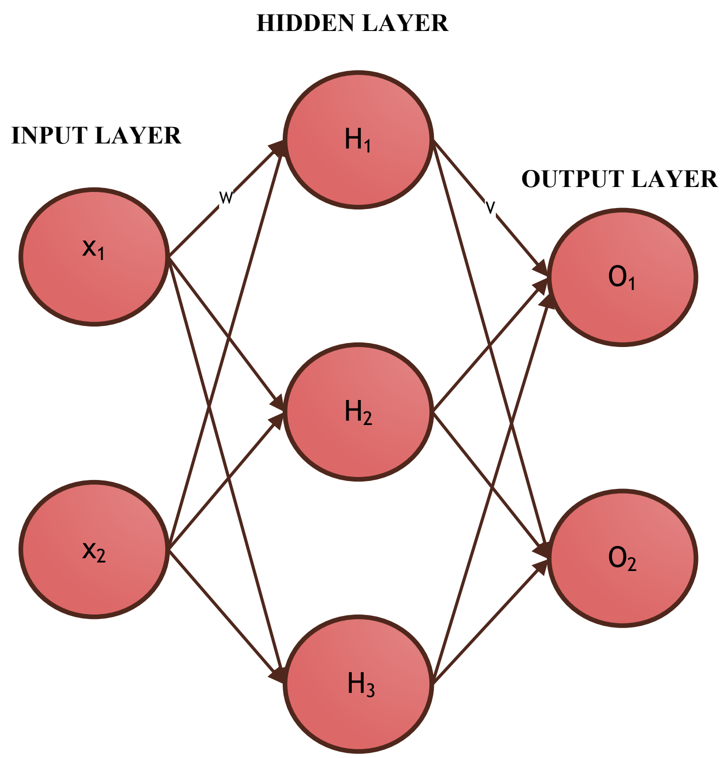


Fig 3.2 MLP model

3.2.3 METHODOLOGY

Following steps have been followed for the LRNN learning & modelling (Testing):

Step1: First prepare the training data. Convert the data in matrix form W_x.

$$W_x = \begin{pmatrix} w_{11} & \cdots & w_{1k} \\ \vdots & \ddots & \vdots \\ w_{l1} & \cdots & w_{lk} \end{pmatrix} \tag{3.1}$$

Step2. Convert the data from concurrent matrix to sequential form.

Step3. The input of the hidden layer is the sum of intial weight W_x & the modified weight coming from the context layer W_u.

$$W_u = \begin{pmatrix} u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{l1} & \cdots & u_{lk} \end{pmatrix} \tag{3.2}$$

Net weight coming in the hidden layer $W_H = W_u + W_x$ (3.3)

Step4. Multiply the weights coming from hidden layer W_H with activation function matrix $F(s)$.

$$F(s) = \begin{pmatrix} F_1(s) \\ F_2(s) \\ . \\ . \\ . \\ . \\ F_n(s) \end{pmatrix} \tag{3.4}$$

The net output matrix O of the model is, $O = W_H * F(s)$ (3.5)

Step5. Repeat steps 2-4 until desired output is obtained.

On applying these steps in a sequential order, we gets the desired output of various characteristics which is shown in the results section and hence then compared with the outputs obtained by using MLP method and then the results have been compared. After comparison it is found that the newly applied LRNN method is a good method to diagnose the faults in a three phase induction motor which gives the results with a better accuracy as compared to MLP.

3.3 SUMMARY

In this chapter, firstly we have discussed about the datasets and its division. After this, mathematical representation of LRNN model is shown and the implementation of the MATLAB code of LRNN model is discussed here. The MATLAB code governing model of LRNN is provided in APPENDIX section.

Chapter 4

EXTERNAL FAULT IDENTIFICATION USING LRNN

4.1 Introduction

In this chapter, the steps of algorithm used for development of artificial intelligence (AI) model using LRNN and MLP has been discussed and then developed AI model has been applied to diagnose the external faults experienced by 3-phase induction motor.

4.2 Training and Testing Data

The dataset of 788 samples is divided into two parts. The first dataset has 700 samples for training and second dataset has 88 samples for testing. Entire data sets is related to 7 states of induction motor & samples are divided for each state i.e. 154 samples for Normal State, 85 samples for single phasing(SP), 49 samples for under voltage (UV), 10 samples for over voltage(OV), 450 samples for unbalanced voltage (UB), 30 samples for overload (OL) & 10 samples for locked rotor (LR) fault. The proposed model is using these samples for faults identification in SCIM.

Fault	NS	SP	UB	OV	UV	OL	LR	Total
Training	138	76	405	7	42	25	7	700
Testing	16	9	45	3	7	5	3	88
Total	154	85	450	10	49	30	10	788

Table 4.1 Dataset of input for training and testing for LRNN

4.3 Proposed Method

In the proposed method, a MATLAB based model is developed for Layer Recurrent Neural Network (LRNN) and Multilayer Perceptron (MLP). The algorithm for the models has shown in fig 4.1. For the identification of seven states namely, Normal State (NS), single phasing (SP), under voltage (UV), over voltage(OV), unbalanced voltage (UB),overload (OL) & locked rotor (LR) fault [4]. LVQ model will proceed in 6 steps which are discussed in chapter-3.

LRNN model for fault identification of IMs have used 6 inputs i.e. RMS voltage & RMS currents. The LRNN model has been designed for 788 samples which are generated for IM fault conditions. From the 788 samples, 700 samples are used for training of LRNN model while 88 samples are used for testing of model.

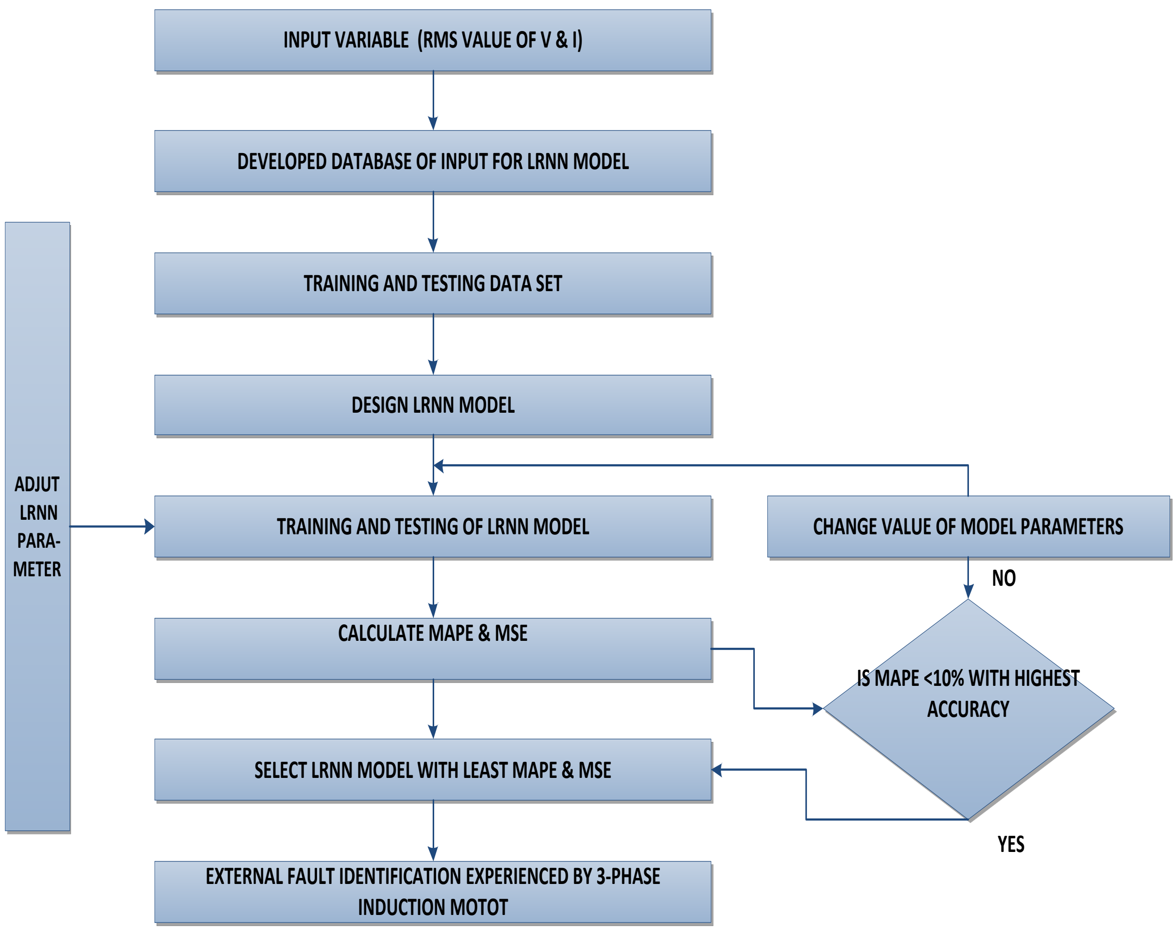


Fig.4.1 Proposed algorithm for external fault classification

For the performance measurement of LRNN network error histogram & ROC are used. Performance parameters are following:

- Identification accuracy (IA):

$$\text{IA}=\frac{\text{total samples}_{correctly\ classified}}{\text{total samples}_{data\ set}} \tag{4.1}$$

- Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{k-1}^{n} E_c{}^2\ ,\ \mathrm{E}_c = \left| \mathrm{O_d} - \mathrm{O_a} \right| \tag{4.2}$$

Where n = total no of cases in data set, O_d = desired output and O_a = actual output by training of LRNN model.

4.4 Conclusion

In this chapter, models for the LRNN and MLP have been generated & then the inputs are given to the models for finding output graphs and the parameters accuracy error, MAPE, MSE, RMSE and rate of success.

Chapter 5

RESULTS AND DISCUSSION

5.1 Introduction

The fault diagnosis is very necessary for machine for industrial purpose. The main external faults experienced by induction motors are single phasing, unbalanced voltage, under voltage, overvoltage, locked rotor and overload. These faults degrade the operating condition of motors so their diagnosis is important. In previous chapter, a model of LRNN and MLP is generated for the diagnosis of faults. The model has been applied to given data set and their output graphs have been generated for the analysis.

5.2 Result and Discussions

Databases of 788 numbers of samples given in chapter-3 as presented by Rama [43] The results of both the algorithms have been shown in this section and their respective comparison is done as follows:

5.2.1 LRNN Model Outputs

LRNN model for fault identification of IMs have used 6 inputs i.e. RMS voltage & RMS currents. The LRNN model has been designed for 788 samples which are generated for IM fault conditions. From the 788 samples, 700 samples are used for training of LRNN model while 88 samples are used for testing of model.

Firstly the training data has been fed to training model and in this manner the model network has been trained[38]. Then the dataset of 88 samples has been given to the trained model and the output has been observed and represented in this section. The comparison is also done for the given techniques and it is concluded that LRNN is better than MLP. The graph which are obtained for the futher analysis are regression, model vs target value etc. The output graph for MLP are also obtained.

The graphical result of training samples (700 samples) of LRNN model using MATLAB is represented in Fig 5.1 to Fig 5.8.

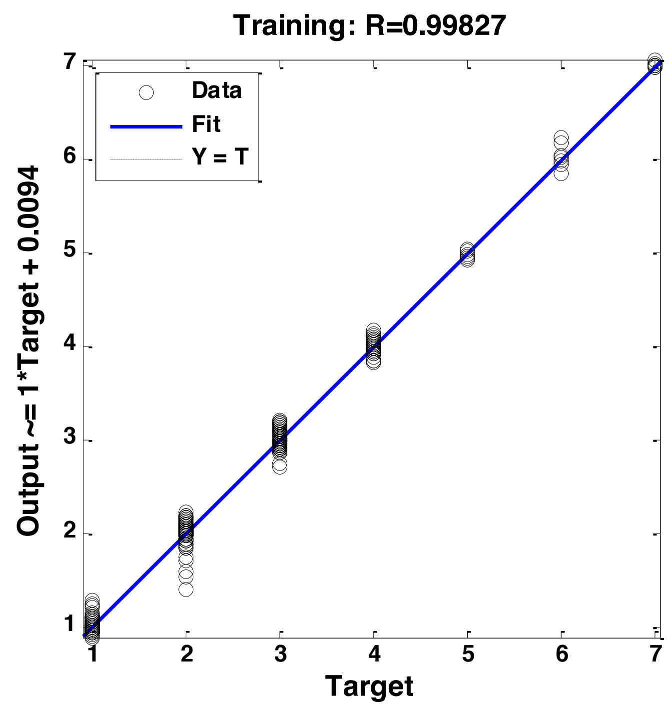


Fig 5.1 Regression of LRNN

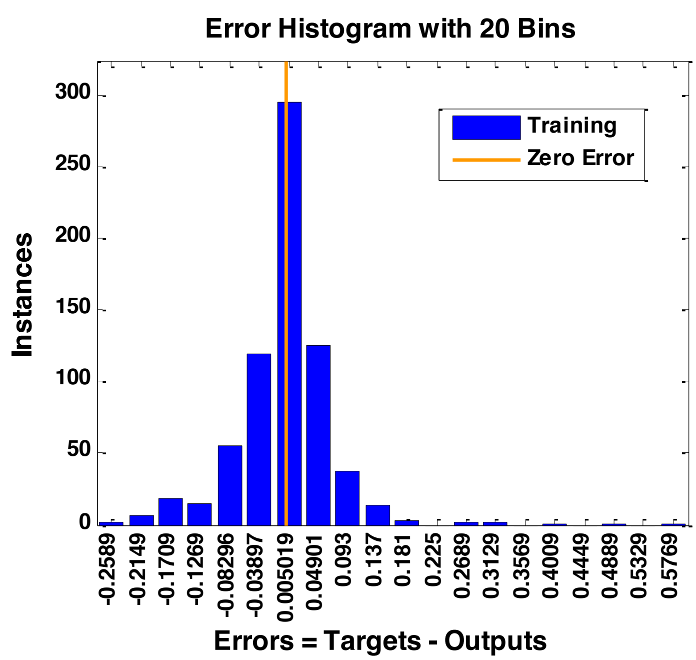


Fig 5.2 Error Histogram of LRNN

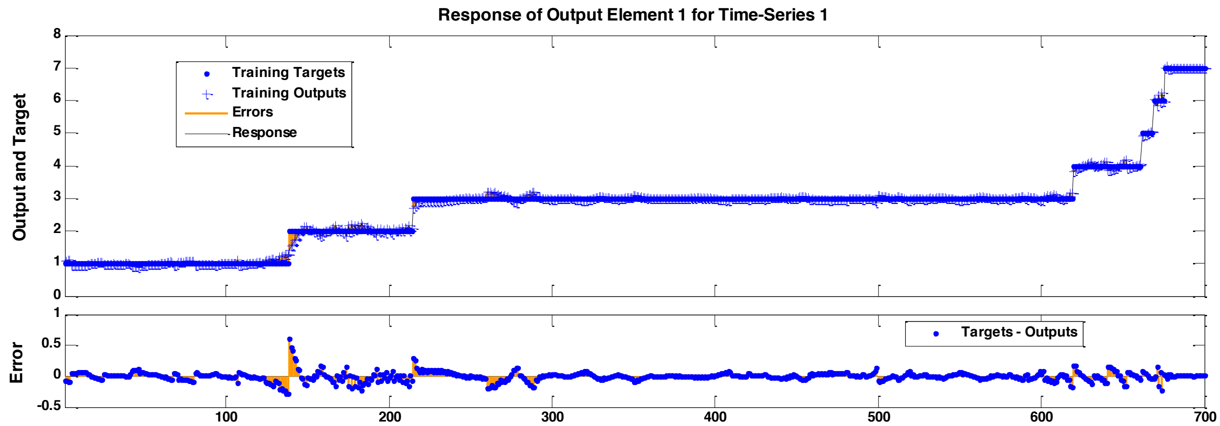


Fig 5.3 Time series response of LRNN

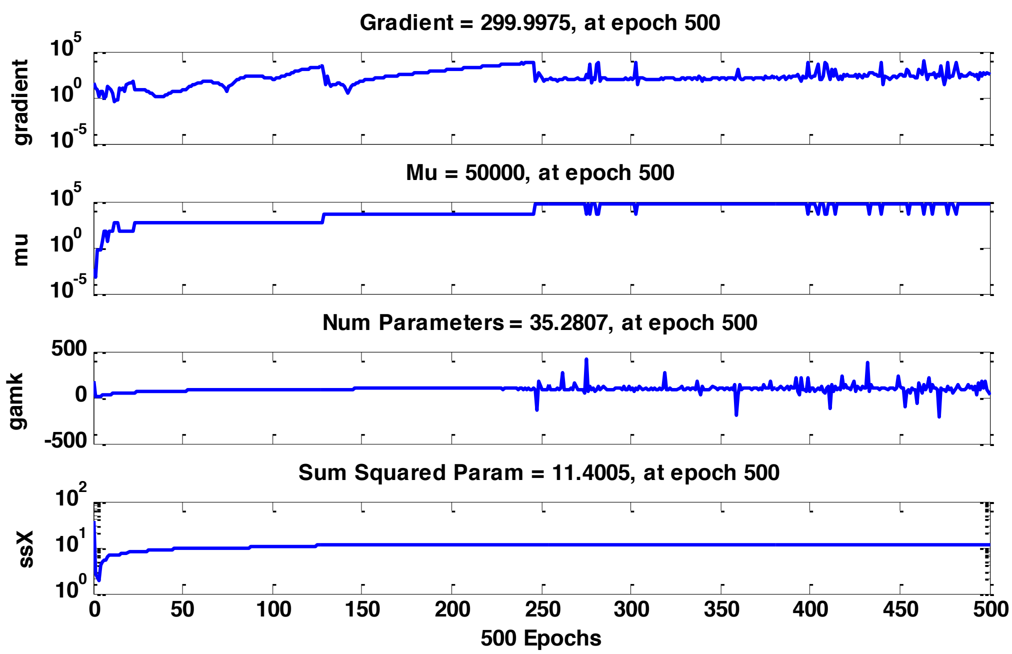


Fig 5.4 Training state of LRNN

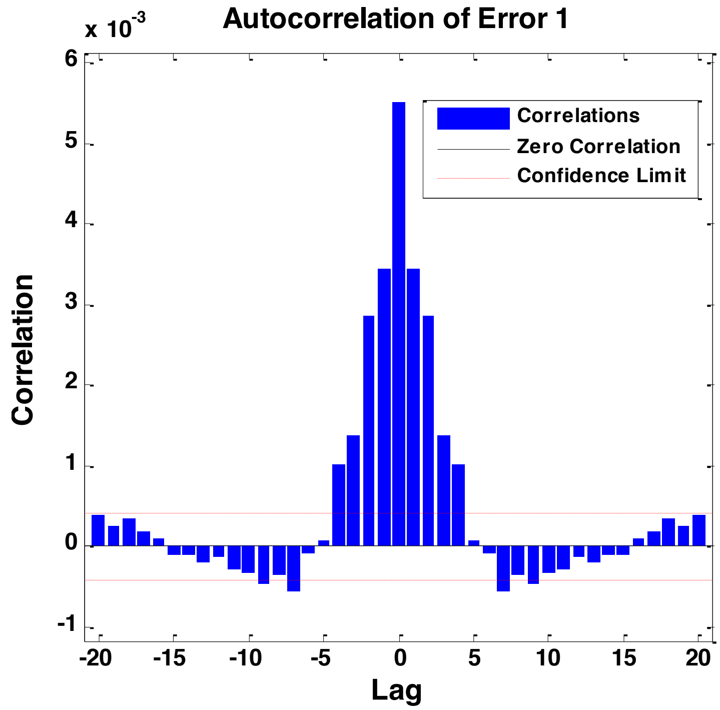


Fig 5.5 Autocorrelation of LRNN

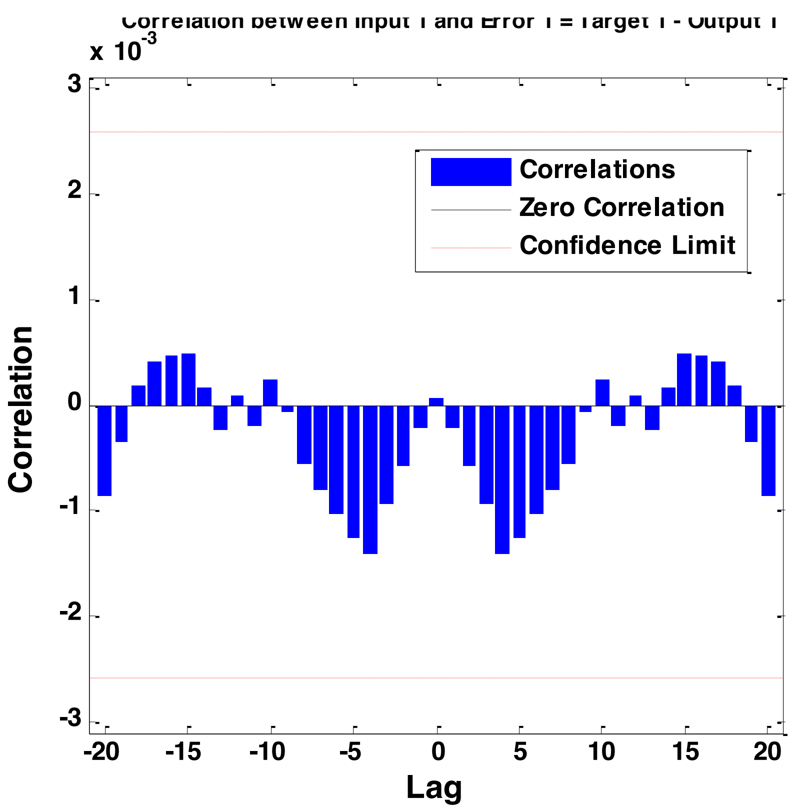


Fig 5.6 Cross correlation of LRNN

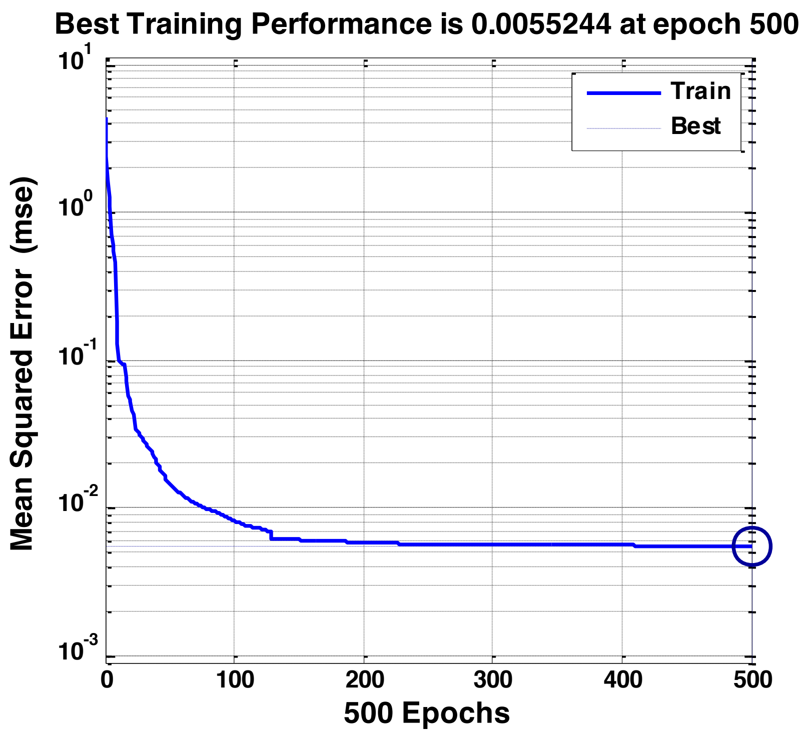


Fig 5.7 Performance of LRNN

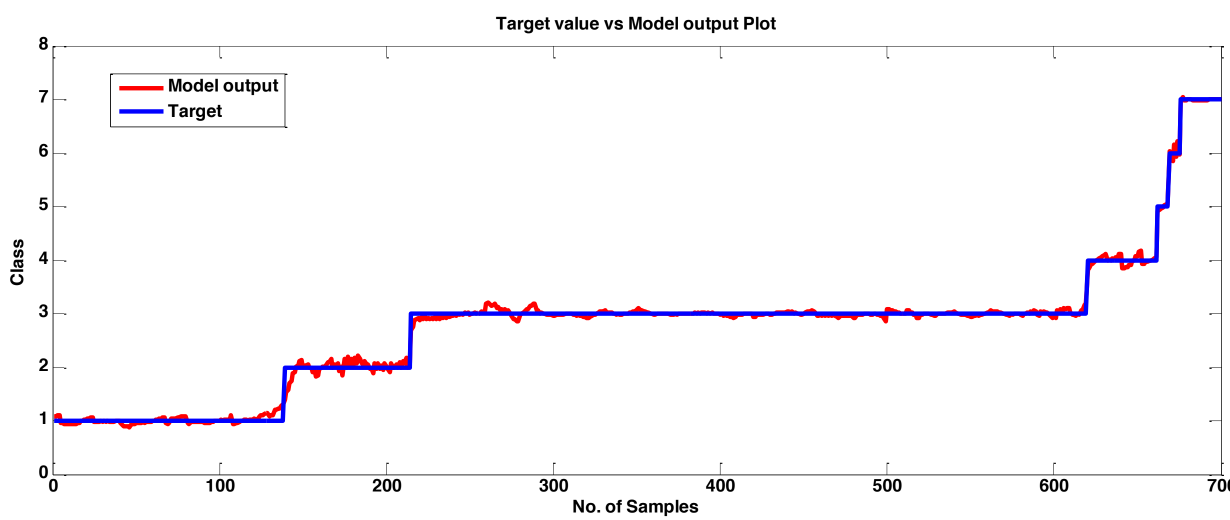


Fig 5.8 Target value vs model output

Graphical results of testing samples (88 samples) using MATLAB have been shown in fig.5.9 and fig. 5.10.

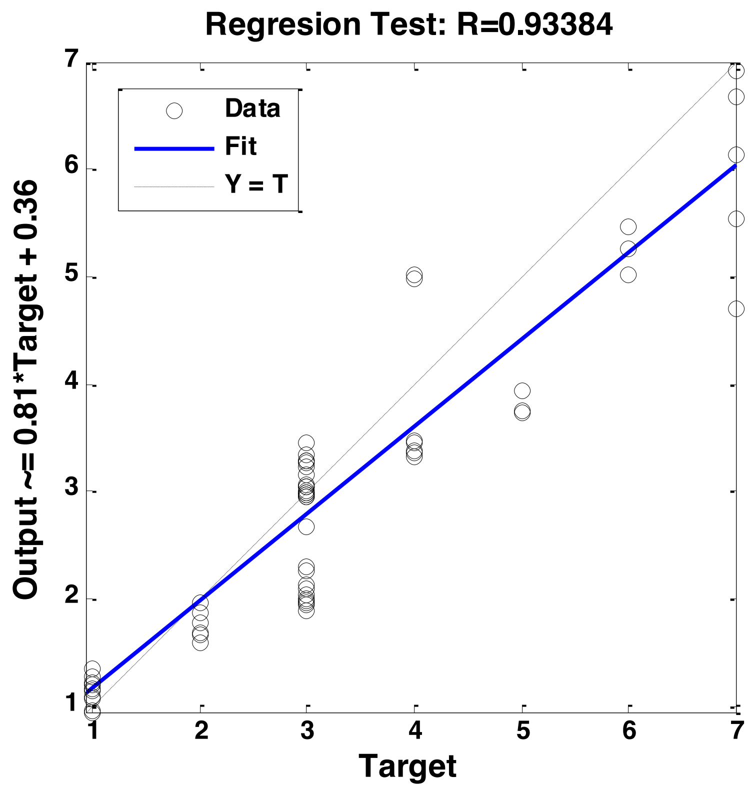


Fig 5.9 Regression of testing of LRNN

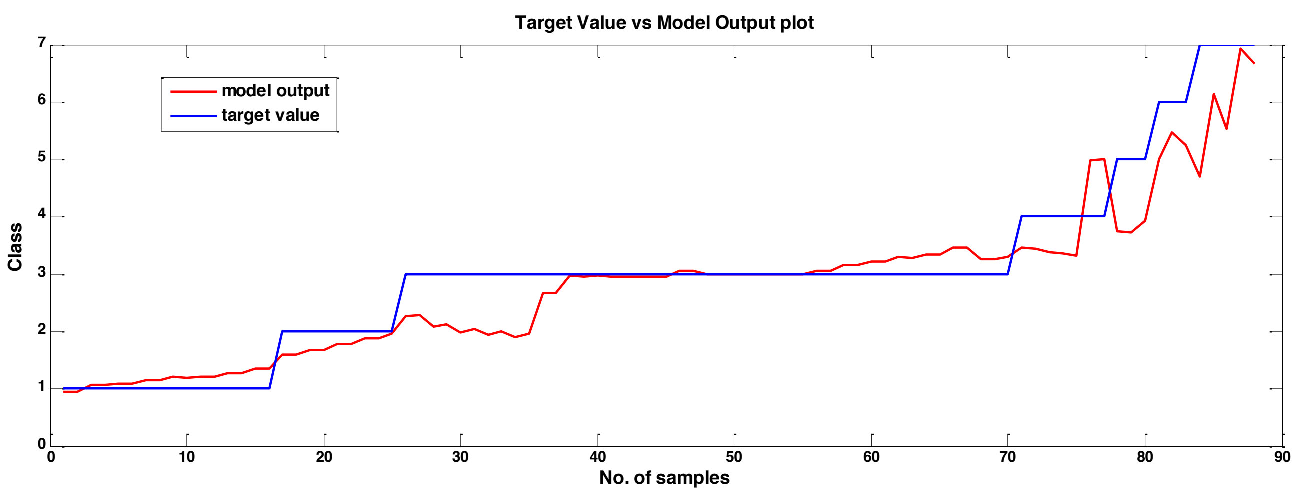


Fig 5.10 Target value vs Model output plot

A MATLAB [6] based code is designed for LRNN approach & then training was done, the efficiency of training phase for fault identification using LRNN was approx 99.827 % (Table 1) & the efficiency of testing was 93.384 % (Table 1).

Identification accuracy & mean square error is calculated using Eq.(5.1) & Eq (5.2). The values of IA & MSE are presented in Table 1 for both training and testing phase of the model.

Model operation	**Mean Square Error**	**Root Mean Square Error**	**Rate of success (%)**
Training Phase	0.00173	0.041593	99.827
Testing Phase	0.06616	0.257215	93.384

Table 5.1 Accuracy measurement of LRNN model during training and testing.

5.2.2 MLP model output plots

For the comparison of LRNN with MLP (Multilayer Perceptron), MLP model is run for same dataset of inputs (rms current & rms voltage) and target (faults). In Fig 5.11 to Fig. 5.14 training & testing output is represented.

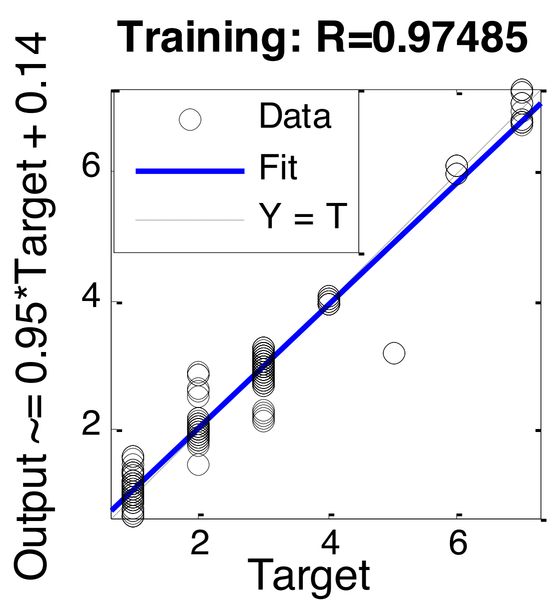


Fig 5.11 (a) Regression of Training of MLP

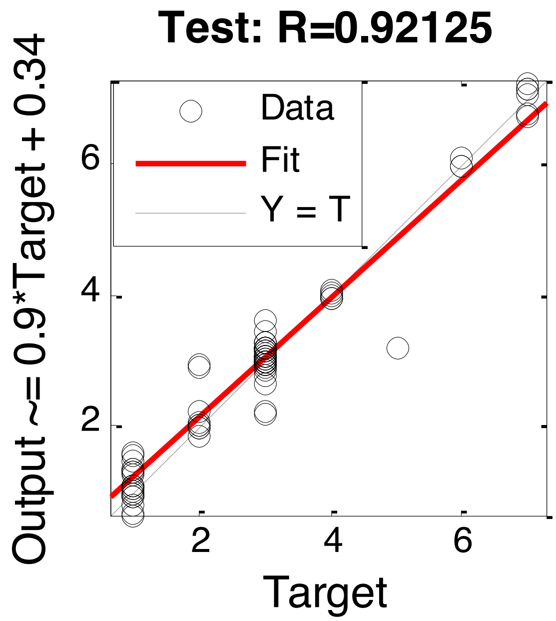


Fig 5.11 (b) Regression of Testing of MLP

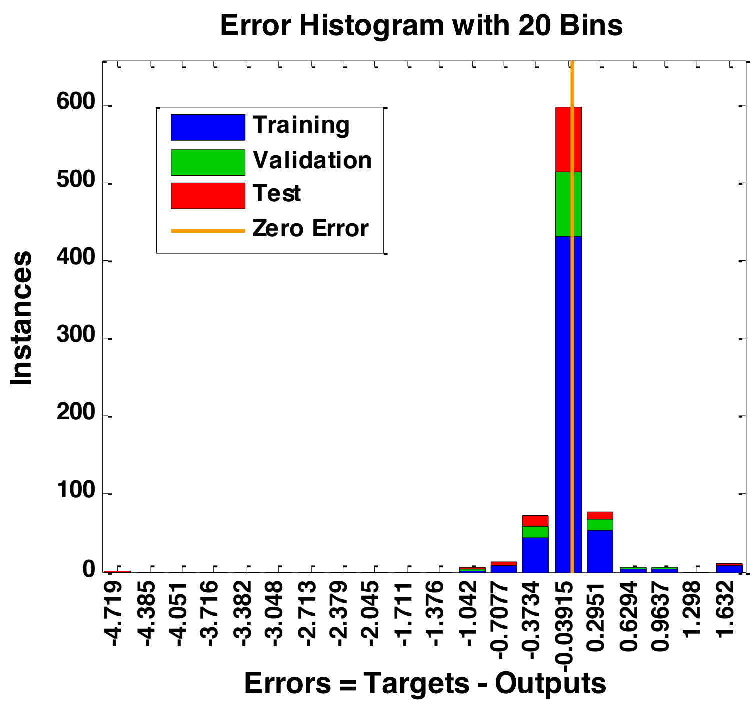


Fig 5.12 Error Histogram

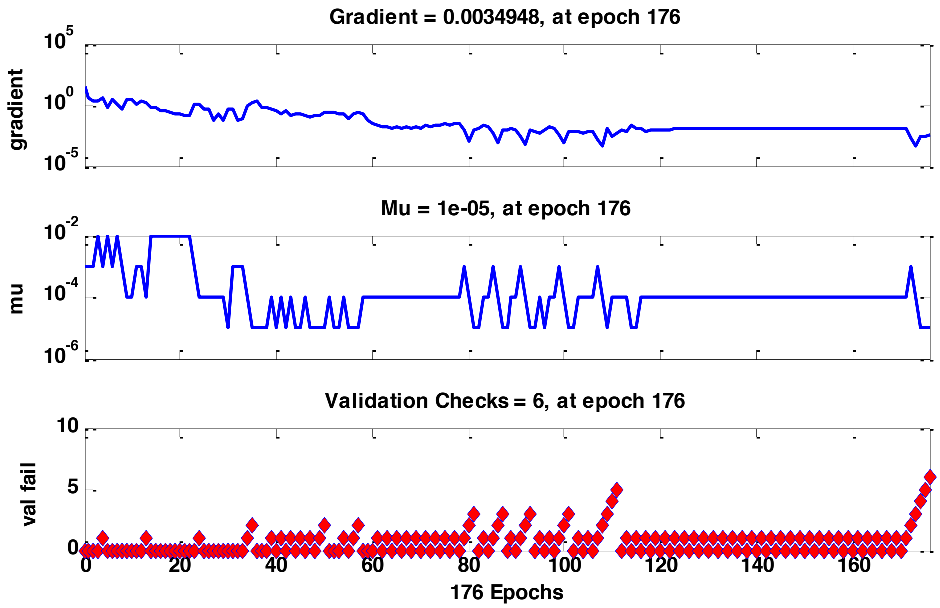
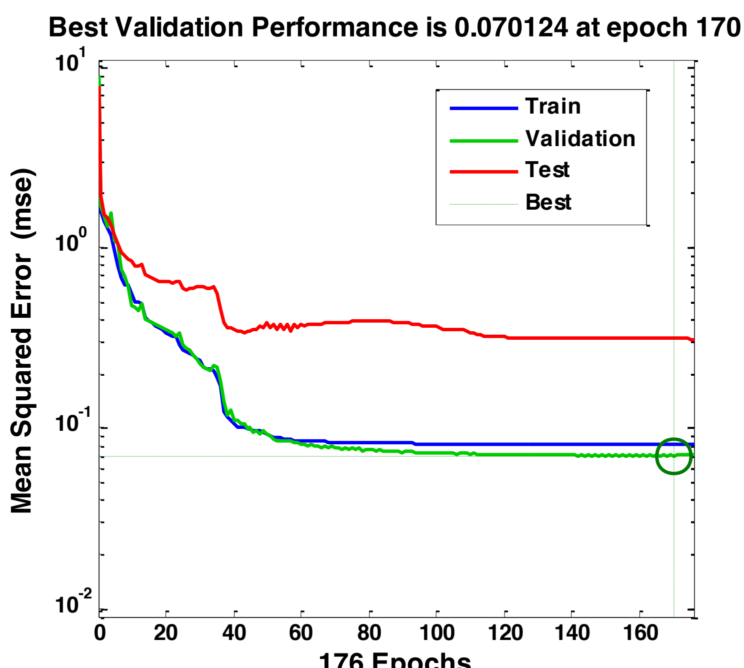


Fig 5.13 Training state of MLP



s

Fig 5.14 Plot Performance

Identification accuracy & mean square error is calculated using Eq. (5.1) & Eq(5.2). The values of IA & MSE are presented in Table 5.2 for both training and testing phase of the MLP model.

Model operation	Mean Square Error	Root Mean Square Error	Rate of success (%)
Training Phase	8.0554 e-2	2.83 e-1	97.485
Testing Phase	3.126 e-2	1.768 e-1	92.125

Table 5.2 Accuracy measurement of MLP model during training and testing phase.

A MATLAB based code is designed for LRNN approach & then training was done, the efficiency of training phase for fault identification using LRNN was approx 97.485 % (Table 1) & the efficiency of testing was 92.125 % (Table 5.2).

5.2.3 Comparison between LRNN and MLP

In the thesis, a BP based MLP neural network is used for comparing with the LRNN approach. MLP is also implemented by taking RMS voltage & RMS current as input variable & then accuracy of fault identification is compared with LRNN model. Table 5.3 is showing MLP output layer faults coding in binary form.

Fault	NS	SP	UV	OV	UB	OL	LR
Binary code	0000001	0000010	0000100	0001000	0010000	0100000	1000000

Table 5.3 The output layer faults in binary form of MLP model.

In Table 5.4, the results of some testing samples have been shown and its diagnosis results are presented in Table 5.5.

S.no.	Actual fault condition	v_1	v_2	v_3	i_1	i_2	i_3

1.	NS	2.6498	2.6498	2.6954	0.4267	0.4281	0.4323
2.	SP	2.6389	2.59280	2.6669	0.0067	0.6451	0.6409
3.	UV	2.3824	2.3606	2.4226	0.3529	0.3529	0.3416
4.	OV	2.8853	2.8800	2.8636	0.4835	0.4995	0.4969
5.	UB	0.9182	2.8949	2.9650	0.2731	0.9540	0.5640
6.	OL	2.642	2.6051	2.6789	0.8492	0.8297	0.8431
7	LR	2.6571	2.6134	2.6873	1.6713	1.6505	1.6687

Table 5.4.Simulated test patterns.

In Table 5.4, the comparision of MLP and LRNN is done & from there it is obtained that LRNN is much more better than MLP.

S.No.	Actual fault condition	Diagnosis results	
		MLP	LRNN
1	NS	NS	NS
2	SP	**NS**	SP
3	UV	**UB**	UV
4	OV	OV	OV
5	UB	UB	UB
6	OL	OL	OL
7	LR	LR	LR

Table 5.5 Diagnosis results using MLP and LRNN methods.

5.3 CONCLUSION

In this chapter, the results of LRNN techniques are first calculated and plotted using MATLAB and then the results of the MLP technique are plotted . The results of LRNN outputs have been compared with MLP outputs. From the result it has been concluded that LRNN is better technique than MLP.

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Chapter 6

CONCLUSIONS

6.1 Conclusion and Importance of dissertation work

An optimal and efficient artificial intelligence (AI) model based upon Layered Recurrent Neural Network Technique has been developed and implemented in this dissertation which has been used for the external fault diagnosis experienced by 3-phase IM.

The following conclusions are derived out of this dissertation work:

- In the first chapter an introduction of the project work was presented. Conventional as well as AI techniques which has been used in the previous times for the faults diagnosis process were explained in brief and then the technique which was used first time for the faults diagnosis was explained in this unit
- After introduction, the literature review on the basic conventional methods as well as modern AI techniques was presented in Chapter-2. In this unit after the introduction about the induction motors and AI as well as conventional techniques used for the faults diagnosis process, The limitations of the conventional methods or the superiority of the AI methods over the conventional methods were explained. After that portion, A review of the previous work which has been done in this field by scholars across the world was done and the techniques used by the for the diagnosis of faults were understood and explained and in the end the contributions given by scholars in the field of diagnosis of faults experienced by three phase induction motors were presented in the tabular form.
- After literature review, AI based methodology (i.e. multilayer perceptron neural network MLP and layer recurrent neural network LRNN) is presented in chapter-3 which has been used for external fault identification experienced by 3-phase IM .

  Initially a description of the dataset division for the training in accordance to the seven states, one is no fault condition and six fault types condition (i.e. single phasing-SP, unbalanced voltage-UB, under-voltage-UV, over-voltage-OV, locked rotor-LR and overload-OL) as presented in the data base.

  After this, working algorithm for the proposed technique has been presented in this unit and using that working algorithm, the model obtained from the proposed technique was initially trained from the testing data and then in testing phase, model was fed with testing data and with the proposed LRNN code, the results were obtained and plotted in the MATLAB software. Results from the both the techniques (i.e. LRNN as well as MLP) were presented and from the results obtained from the proposed AI based models, it can be concluded that

1. The results coming from the newly implemented LRNN technique are better than MLP technique
2. LRNN technique gives more optimal solutions with less time consumption

6.2 Future scope

As we have seen this dissertation that the results coming from LRNN technique are better than the MLP technique and the results are highly accurate, the following future works can be done

- The first recommended for future work would be to a the real-time implementation system for the three-phase induction motor faults identification based on the proposed LRNN technique which was used in this project.
- Another work which can be done in future is to implement this technique to diagnose the faults experienced by other power system components like generators and synchros.
- As this algorithm was only for the RMS values of currents and voltages , this technique can be modified to any kind of signal input
- Future work can be done to build such a system which can detect multiple faults at one time.

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Appendix A

MATLAB BASED CODE FOR LRNN MODEL

A1: MATLAB based LRNN code.

```
clc; clear all
tic
load('TrainData.mat')
y=training';
t=trainingS1';

%yy=testing';
pp = con2seq((testing)');
tt = con2seq((testingS1)');

p = con2seq(y);
t = con2seq(t);
lrn_net = layrecnet(1,3);
lrn_net.trainFcn = 'traincgb';
lrn_net.trainParam.show = 5;
lrn_net.trainParam.epochs = 100;
lrn_net = train(lrn_net,p,t);
%after training the model
y = lrn_net(p);
%Train output plot
figure(1)
plot(cell2mat(y))
hold on
plot(cell2mat(t))
hold off

%% Test the Model
Y_test = sim(lrn_net,pp);
YY_test=cell2mat(Y_test);
YY_testT=cell2mat(tt);
% plot(cell2mat(Y_test))

% Testing output plot
figure(2)
plot(cell2mat(Y_test))
hold on
plot(cell2mat(tt))
hold off

figure(3)
plotregression(YY_testT,YY_test,'Regresion Test')
```

```
YY_test=cell2mat(Y_test);
YY_testT=cell2mat(tt);
error_test=YY_testT-YY_test;
%MSE_test=mse(error_test)
%plotregression()
Toc
```

A2: Graphical Representation for LRNN Model validation

For LRNN model with classification accuracy of 99.827% :