To Identify Fault Location in Transmission Line using Artificial Neural Network

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

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CANDIDATE'S DECLARATION

We hereby declare that the project entitled **"To Identify Fault Location in Transmission Line Using Artificial Neural Network"** submitted in partial fulfillment for the award of the degree of **Bachelor of Technology** in **Electrical Engineering** is an authentic work.

The project was supervised by **Dr. Trapti Jain, Assistant Professor, Electrical Engineering, IIT Indore**.

Further, we declare that we have not submitted this work for the award of any other degree elsewhere.

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CERTIFICATE
by BTP Guide

It is certified that the declaration made by the students is correct to the best of my knowledge and belief.

Dr. Trapti Jain,
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PREFACE

This report on “To identify fault location in transmission line using Artificial Neural Network” is prepared under the guidance of Dr. Trapti Jain. Through this report we have tried to give a detailed method of fault location detection and try to cover every aspect of the new methodology, so as to make the detection fast, accurate and economic.

We have tried to the best of our abilities and knowledge to explain the content in a lucid manner. We have also added graphs and relevant codes to make it more illustrative.

ACKNOWLEDGEMENTS

We wish to thank **Dr. Trapti Jain** for her constant support and invaluable guidance. We would also like to thank her for giving us the opportunity to work under this subject of our liking. I am greatly indebted to **Mr. Karthik Thirumala** and **Mr. Venkatesh T.**, PhD Scholars for guiding us along all issues regarding neural networks .Their sound advice and insights helped us put our best step forward.

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ABSTRACT

Aim of this project is to implement a reliable, efficient technique "To identify fault location in power transmission line using Artificial Neural Network". In this project a Neural Network based approach has been proposed capable of finding fault location accurately thus reducing time consumption. As a result the manual effort to find fault will be greatly reduced.

To design such method two major steps are carried out: first, a power system model is simulated to generate data for analysis. In second step, Wavelet decomposition is applied to generate training features for the neural network. Finally a neural network is trained using the generated features. Feedforward networks have been employed along with backpropagation algorithm for each of the three phases in the Fault location process. Analysis on neural networks with varying number of hidden layers and neurons per hidden layer has been provided to validate the choice of the neural networks in each step. All the steps have been validated by performing detailed simulation studies.

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Chapter 1

Introduction

1.1 Introduction

A transmission line is a vital component of the electric power system. The transmission line is exposed to the environment and the possibility of experiencing faults on the transmission line is generally higher than that on other main components of power system. Actually any abnormal flow of current in a power system's components is called as a fault. These faults cannot be completely avoided since a portion of these faults also occur due to natural reasons which are way beyond the control of mankind like lightning strokes, trees may fall across lines, fog and salt spray on dirty insulators may cause the insulator strings to flash over, and ice and snow loadings may cause insulator strings to fail mechanically.

When a fault occurs on an electrical transmission line, it is very important to find its location in order to make necessary repairs and to restore power as soon as possible. The time needed to determine the fault point along the line will affect the quality of the power delivery.

Therefore, it is very important to have a well-coordinated protection system that accurately locates the position of the fault in the power system.

Existing fault location techniques can be broadly classified into the following categories:

1. Impedance measurement based methods
2. Traveling-wave phenomenon based methods
3. High-frequency components of currents and voltages generated by faults based methods
4. Intelligence based method

From quite a few years, intelligent based methods are being used in the process of fault detection and location. Three major artificial intelligence based techniques that have been widely used in the power and automation industry are:

1. Expert System Techniques
2. Artificial Neural Networks
3. Fuzzy Logic Systems

Among these available techniques, Artificial Neural Networks (ANN) have been used extensively in this project for fault location on electric power transmission lines.

These ANN based methods do not require a knowledge base for the location of faults unlike the other artificial intelligence based methods.

1.2 Motivation

The prime motive behind this project was the significant impact a very accurate fault locator could make if employed in a power transmission and distribution system, in terms of the amount of money and time that can be saved. The main goal of Fault Location is to locate a fault in the power system with the highest practically achievable accuracy. When the physical dimensions and the size of the transmission lines are considered, the accuracy with which the designed fault locator locates faults in the power system becomes very important. One of the important aspects that this report concentrates on is the analysis of the transmission line's phase currents during various fault conditions and how they can be effectively utilized in the design of an efficient fault locator. The main objective of this research is to study and successfully design a fault locator that can locate faults in power transmission lines. This report drew its initial motivation from which demonstrates a method that could be used for location of faults in transmission lines using neural fuzzy logic. However, when extensively studied, it can be noted that a fault locator with satisfactorily high accuracy can be easily achieved with the help of artificial neural networks by the use of a large amount of data set for training and the learning process. This eliminates the need for proficiency in power systems which is a necessity when working with expert fuzzy systems. Hence this report focuses on the design of a fault locator that can be even used by people who aren't experts in the field of power systems.

1.3 Outline of the report

The second chapter deals with the several problems that hinder the protection of a typical transmission line system. The various kinds of faults and the protection techniques that are currently available and employed are briefly discussed. Some important results from the research on the existing transmission line protection techniques are also provided in this chapter.

The third chapter introduces the concept behind Wavelet Transform. A few mother wavelets that are usually employed are discussed.

The fourth chapter describe the concept behind artificial intelligence and neural networks. A few ANN architectures that are usually employed are discussed and the various learning strategies employed in the training process of the neural networks along with the critical factors that affect the size and output of a trained network are discussed in this chapter.

The fifth chapter deals with the actual implementation and development of the neural networks and their architectures proposed for the fault location process. An overview of the training and testing processes employed with neural networks in this work has been outlined in this chapter.

The sixth chapter presents series of simulation results that have been obtained using MATLAB, Sim Power Systems and the Artificial Neural Networks Toolboxes in Simulink in detail to emphasize the efficiency and accuracy factors of the proposed fault locator. Several neural networks with varying configurations have been trained, tested and their performances have been analysed in this chapter.

The seventh chapter concludes the entire research work and the report. It discusses the results obtained in the previous chapters. Moreover, the scope for future work and possible extensions to this work has been outlined briefly in this chapter.

Chapter 2

Literature Review

This chapter tells about the state of the art research going on in the field of fault location in power transmission lines using artificial neural networks. Sections 2.2.1 –2.2.2 talk about the different techniques being used for fault location in transmission lines. The section 2.2.3 talks about the various artificial intelligence based methods that are being researched upon in the field of fault location in power transmission lines.

2.1 Power protection systems

One of the most important components of a power protection system is the relay which is a device that trips the circuit breakers when the input voltage and current signals correspond to the fault conditions designed for the relay operation. Relays in general can be classified into the following categories:

1. Directional Relays: These relays respond to the phase angle difference between two inputs to the relay.
2. Differential Relays: These relays respond to the magnitude of the algebraic sum of two or more of its inputs.
3. Magnitude Relays: These relays respond to the magnitude of the input quantity.
4. Pilot Relays: These relays respond to the input signals that are communicated to the relay from a remote location.
5. Distance Relays: These relays respond to the ratio of two input phasor signals.

Among the various relays that are used for the protection of power lines distance relays are the most relevant to fault locators. Usually a pair of these distance relays is used for the protection of a two-terminal transmission line.

2.2 Transmission line fault location technique

The transmission line fault location process, as mentioned before, has been researched for a while and several innovative and efficient techniques have been proposed and analysed by several authors. These techniques can be broadly classified as Impedance based methods, Travelling wave based methods and Artificial Intelligence based methods. Each of these methods is discussed briefly in the following subsections.

2.2.1 Impedance based methods

In the case of Impedance based methods, the operation of the distance relay greatly relies on the fault resistance and is not successful in cases with very high fault resistance. Impedance based methods can be classified into single-ended methods and two-ended methods depending upon the number of terminals at which the voltage and current data are collected.

The basic logic behind a single-ended impedance based fault locator is to calculate the location of the fault from the apparent impedance seen looking into the line from one end. The various impedance based methods available in literature are discussed in the upcoming subsections.

Simple reactance method

The measured voltage and current values at the terminal are used to calculate the impedance of the line to the fault position as shown in equation 2.1. Once the line impedance per unit length has been determined, the fault distance can be calculated accordingly as illustrated by equations 2.2 and 2.3.

$$V_{\mathrm{A}} = x.Z_{\mathrm{L}}.l_{\mathrm{A}} + V_{\mathrm{f}} \tag{2.1}$$

where V_{A} is the voltage at terminal A, x is the distance to the fault from the terminal A, I_{A} is the current flowing out of the terminal A, V_{A} is the fault voltage and Z_{L} is the line impedance.

$$V_{\mathrm{A}} = x.Z_{\mathrm{L}}.l_{\mathrm{A}} + R_{\mathrm{f}}.I_{\mathrm{f}} \tag{2.2}$$

where I_{f} is the fault current and R_{f} is the fault resistance as shown in Fig 2.1.

$$x = \frac{(V_{\mathrm{A}}/I_{\mathrm{A}})}{Z_{\mathrm{L}}} - \frac{R_{\mathrm{f}}}{Z_{\mathrm{L}}(\frac{I_{\mathrm{A}}}{I_{\mathrm{f}}})} \tag{2.3}$$

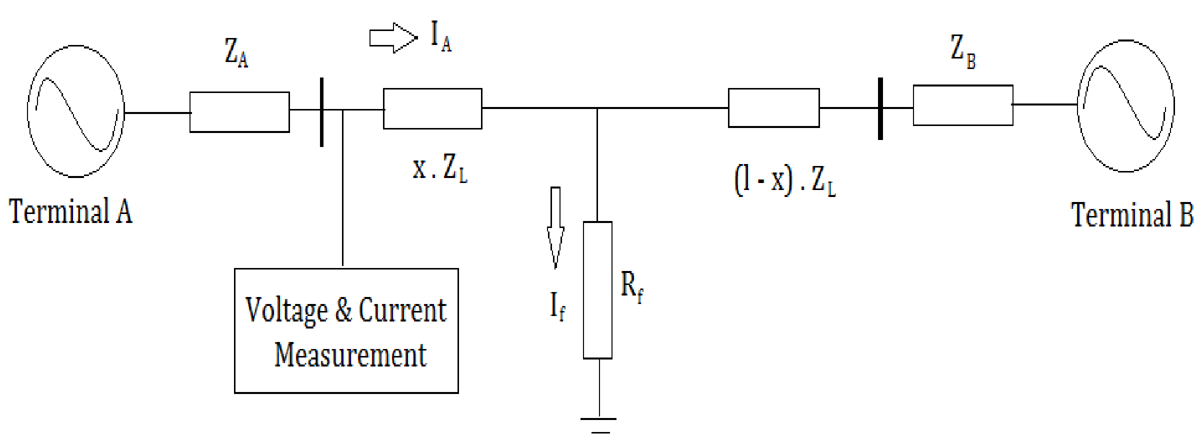

FIGURE 2.1: Faulted Transmission Line illustrating simple-reactance method

Takagi method

The Takagi method is a very simple yet innovative single-ended impedance based Fault location technique and is illustrated by Fig 2.2. It requires both the pre-fault and fault data and enhances the simple reactance method by minimizing the effect of fault resistance and reducing the effect of load flow.

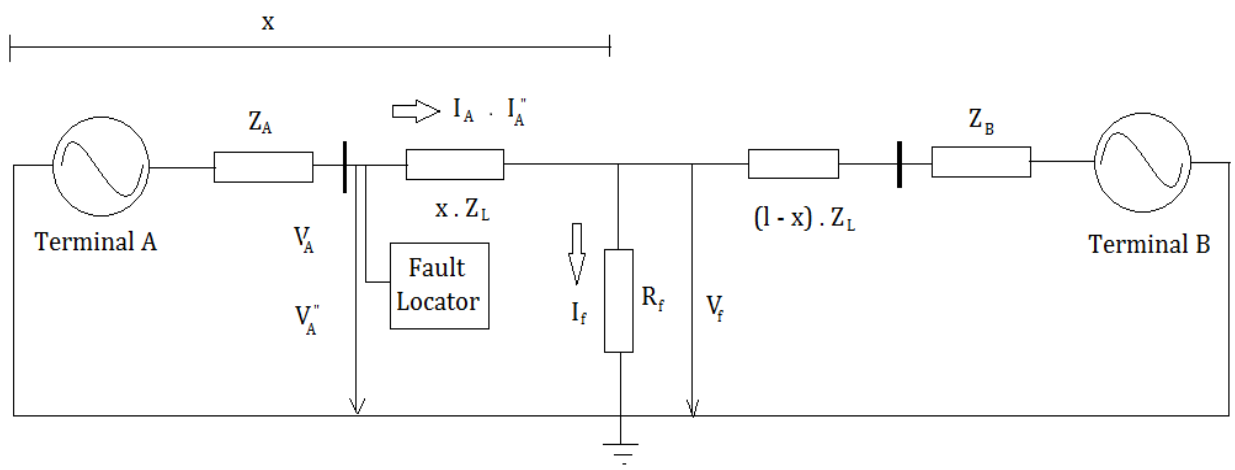

FIGURE 2.2: A single-phase circuit illustrating Takagi method

The Fault Resistance is given by

$$R_{\mathrm{f}} = \frac{V_{\mathrm{A}} - Z_{\mathrm{C}} I_{\mathrm{A}} \tanh \gamma x}{(\frac{V''_{\mathrm{A}}}{Z_{\mathrm{C}}} \tanh \gamma x - I''_{\mathrm{A}}) \phi E^{\mathrm{j}\theta}} \tag{2.4}$$

where V_{A} is voltage measured at terminal A, I_{A} is the flowing out of terminal A, γ is the propagation constant, Z_{C} is the characteristic impedance, Z_{L} is the line impedance, I''_{A} is the superposition current which is the difference between the fault current and the prefault current. And

$$x = \frac{lm(V_{\mathrm{A}}.I''_{\mathrm{A}})}{lm(Z_{\mathrm{L}} I_{\mathrm{A}}.I''_{\mathrm{A}})} \tag{2.5}$$

is the distance to the fault from terminal A, Where $Z_{\mathrm{L}} = \gamma Z_{\mathrm{C}}$

Modified Takagi method

The modified Takagi method also called the Zero Sequence current method does not require pre-fault data because it uses zero-sequence current instead of the superposition current for ground faults. The location of the fault in this method is given by x in equation 2.6.

$$x = \frac{lm(V_{\mathrm{A}}.I^{*}_{\mathrm{A}}.e^{\text{-j}\beta})}{lm(Z_{1\mathrm{L}}.I_{\mathrm{A}}.I^{*}_{\mathrm{A}}.e^{\text{-j}\beta})} \tag{2.6}$$

where I_{R} is the zero-sequence current and β is the zero-sequence current angle. The position of the fault 'x' is given by equation 2.6; V_{A} is voltage measured at terminal A, I_{A} is the flowing out of terminal A and $Z_{1\mathrm{L}}$ is the positive sequence line impedance.

2.2.2 Traveling wave based methods

Traveling wave based methods have been widely used for the purpose of fault location and are usually based on the correlation between the forward and backward waves traveling along the transmission line as shown in Fig 2.3. The basic idea is to successively identify the fault initiated by high-frequency traveling waves at the fault locator.

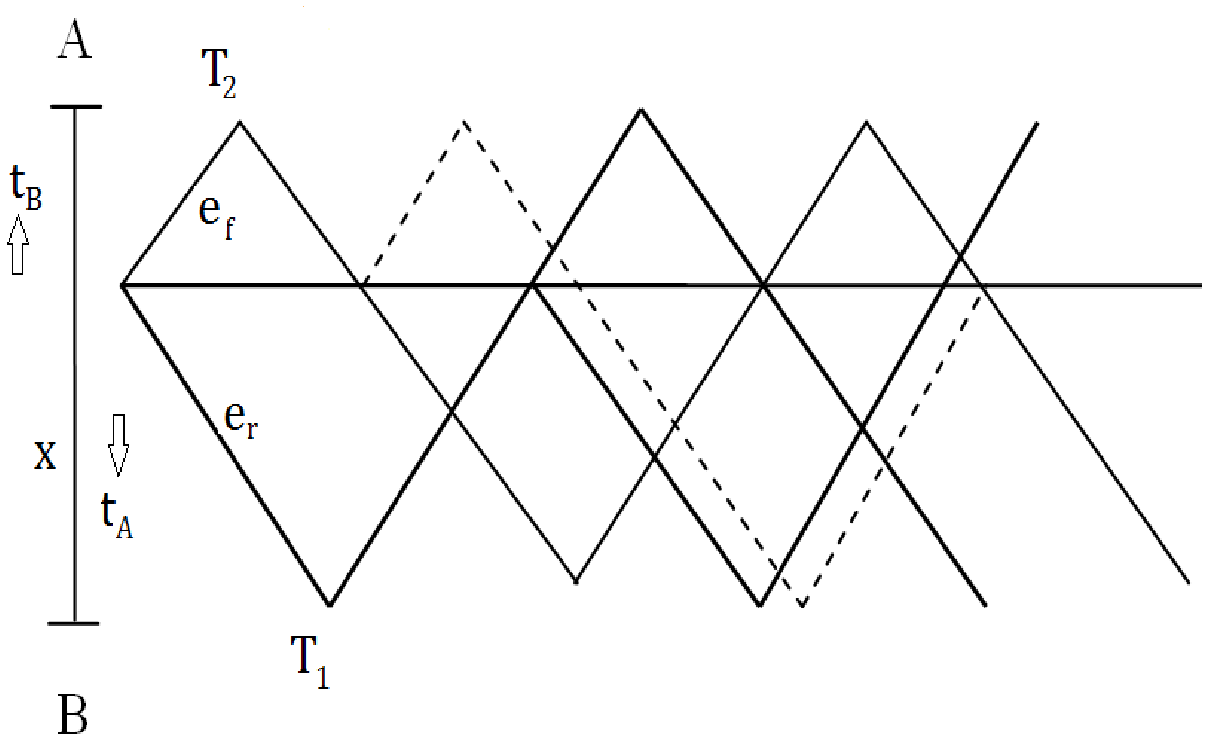

FIGURE 2.3: Illustration of Travelling wave based Fault Location

The time taken by the high frequency components for propagation is used for the location of fault. In Fig 2.3, a single phase lossless transmission line of length 'l' is considered with a travelling wave velocity of v, capacitance and inductance per unit length L' and C' and a characteristic impedance of Z_{C}. Assuming the occurrence of a fault at a distance of 'x' from the terminal A, the voltage and current values are given by 2.7 and 2.8.

$$\frac{\partial u}{\partial x} = -L' \frac{\partial i}{\partial t} \tag{2.7}$$

$$\frac{\partial u}{\partial x} = -C' \frac{\partial i}{\partial t} \tag{2.8}$$

whose solutions are given by 2.9 and 2.10.

$$e(x,t) = e_{\mathrm{f}}(x - vt) + e_{\mathrm{r}}(x + vt) \tag{2.9}$$

$$i(x,t) = \frac{1}{Z_{\mathrm{C}}}{}_{\mathrm{f}}(x - vt) - \frac{1}{Z_{\mathrm{C}}} e_{\mathrm{r}}(x + vt) \tag{2.10}$$

The times taken for the waves to travel from the fault to the discontinuity τ_{A} and τ_{B} are to be determined using GPS technology. Once this is done, the fault location (x) can be readily determined by the following equation 2.11.

$$x = \frac{l - c(\tau_{\mathrm{A}} - \tau_{\mathrm{B}})}{2} \tag{2.11}$$

where c is the wave propagation speed of 299.79 m/sec.

2.2.3 Neural networks based mathods

Neural networks have been put in use for fault location quite recently and have gained significant importance. Wide usage of neural networks started by late eighties and during early nineties. Neural networks are usually used to achieve greater efficiency in fault detection, classification and location. A lot of research has been done and abundant literature has been published in the field of fault location using neural networks. A majority of the work made use of feed-forward multilayer perceptron technique. Artificial neural networks also be used for the detection of faults on transmission lines and also differentiated between arcing and no arcing faults. Neural network based single ended fault location techniques have been widely researched and also for fault location on series compensated lines.

Chapter 3

Wavelet transform

Wavelet transform (WT) is a mathematical technique used for many application of signal processing. Wavelet is much more powerful than conventional method in processing the stochastic signals because of analysing the waveform time-scale region. In wavelet transform, the band of analysis can be adjusted so that low frequency and high frequency components can be windowing by different scale factor. Recently WT is widely used in signal processing applications, such as de-noising, filtering, and image compression.

Many pattern recognition algorithms have been developed based on the wavelet transforms. It also has been used widely by the power system researchers. According to scale factor, wavelet categorized different section. In this paper the wavelet which is named *Continuous Wavelet Transform (CWT)* by two scale factor was used. For any function /f(x), CWT is written as,

$$[W_\phi f](a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} \phi \frac{(x-b)}{a} f(x) dx \tag{3.1}$$

where $\phi(x)$ is the mother wavelet, $f(x)$ is the input signal and a is scaling factor and b is the translating factor.

We used db4 as mother wavelet during our whole work

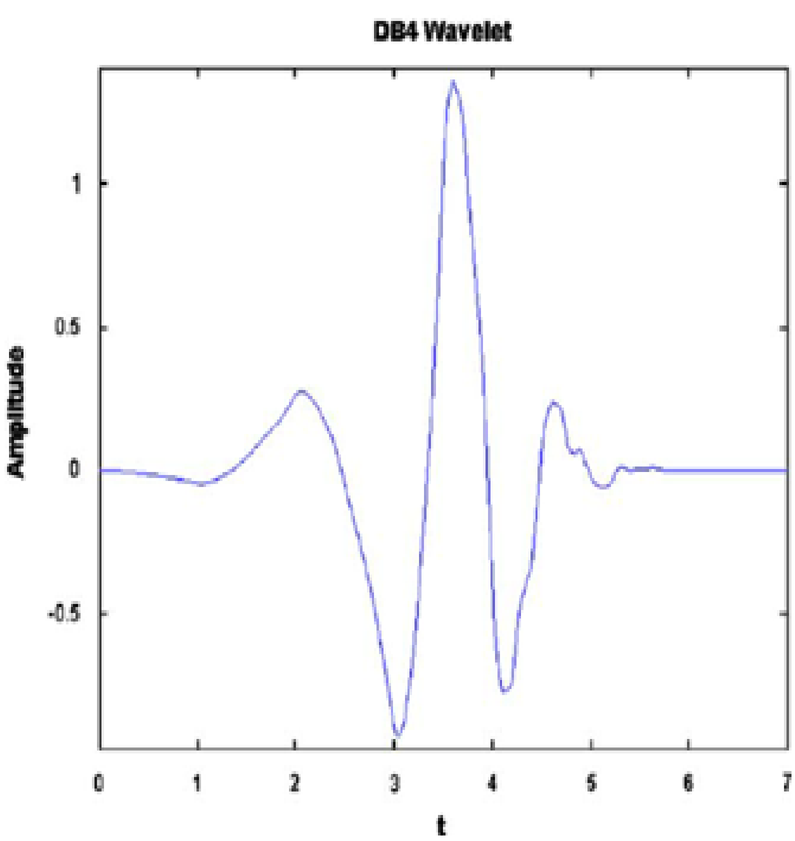

FIGURE 3.1: *db*4 mother wavelet

Basics of wavelet is given below:

Why we need any transform

- obtain a further information from a signal that is not readily available in the raw signal (time-domain signal).

Why wavelet transform

- For frequency analysis we have Fourier Transform so why we need W.T at all.

Fourier Transform

- It breaks down a signal into constituent sinusoids of different frequencies. In other words it transform the signal time-base to frequency-base

What's wrong with Fourier Transform?

- In case of Fourier Transform, we lose the time information: When did a particular event take place.
- Fourier Transform can't locate abrupt changes in the signal.

Short Time Fourier Transform (STFT).

- In order to study small section of a signal we use STFT which is based on FT and Windowing.
- It is a compromise between Time-domain and Frequency–domain views of a signal.
- Time and Frequency both are represented in limited precision.
- The precision is determined by the size of the window.
- Once we choose a particular size for the time window it will be the same for all frequencies.

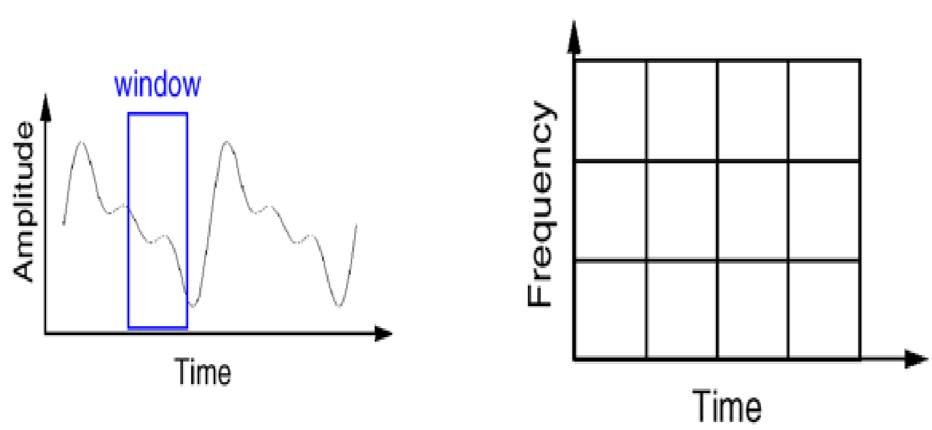

FIGURE 3.2: Short wave Fourier transform

What's wrong with STFT?

- Unchanged Window
- Dilemma of Resolution
- Narrow window ⇒ poor frequency resolution
- Wide window ⇒ poor time resolution
- Heisenberg Uncertainty Principle
- Cannot know what frequency exists at what time intervals

Wavelet Transform

- An alternative approach to the short time Fourier transform to overcome the resolution problem
- Similar to STFT: signal is multiplied with a function

Multiresolution Analysis

- Analyze the signal at different frequencies with different resolutions
- Good time resolution and poor frequency resolution at high frequencies
- Good frequency resolution and poor time resolution at low frequencies
- More suitable for short duration of higher frequency; and longer duration of lower frequency components

How wavelet Transform Works

- Split Up the Signal into a Bunch of Signals
- Representing the Same Signal, but all Corresponding to Different Frequency Bands
- It Provides What Frequency Exists at What Time Intervals

Multi-level Decomposition

- Iterating the decomposition process, breaks the input signal into many lower-resolution components

Wavelet decomposition

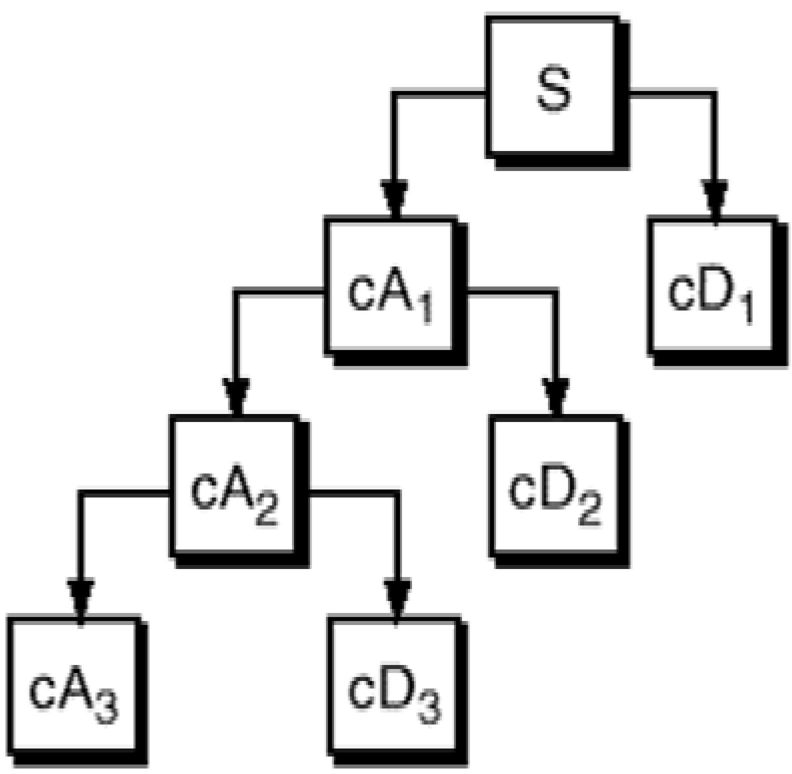

FIGURE 3.3: Signal Decomposition Using Wavelet

Chapter 4

Artificial neural network

4.1 Introduction to neural networks

An Artificial Neural Network (ANN) can be described as a set of elementary neurons that are usually connected in biologically inspired architectures and organized in several layers. The structure of a feed-forward ANN, also called as the perceptron is shown in Fig 4.1. There are Ni numbers of neurons in each i^{th} layer and the inputs to these neurons are connected to the previous layer neurons. The input layer is fed with the excitation signals. Simply put, an elementary neuron is like a processor that produces an output by performing a simple non-linear operation on its inputs. A weight is attached to each and every neuron and training an ANN is the process of adjusting different weights tailored to the training set. An Artificial Neural Network learns to produce a response based on the inputs given by adjusting the node weights. Hence we need a set of data referred to as the training data set, which is used to train the neural network.

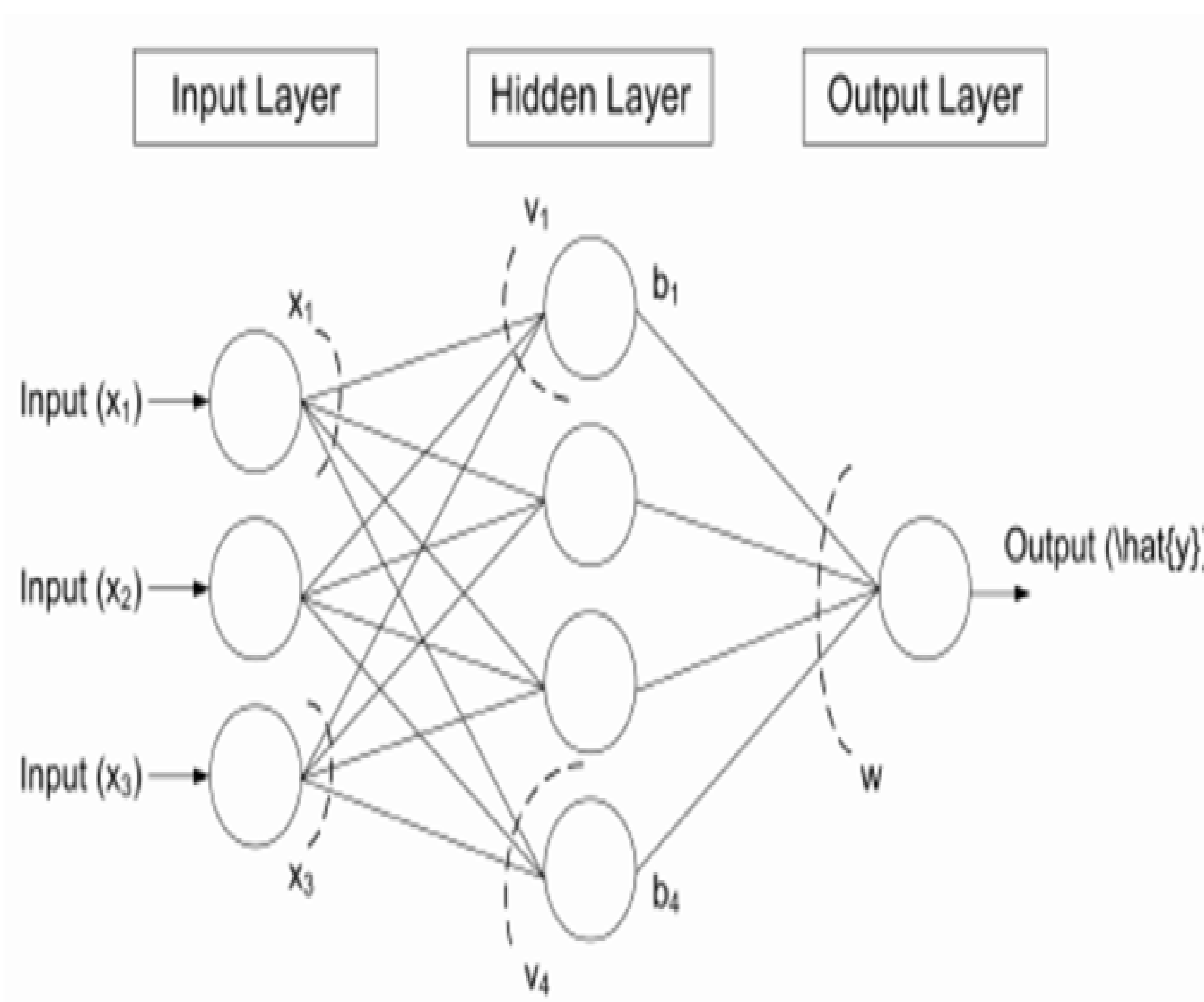

FIGURE 4.1: A basic three-layer architecture of a feedforward ANN

In Fig 4.1, x_1, x_2, x_3 is the set of inputs to the ANN. Due to their outstanding pattern recognition abilities ANNs are used for several purposes in a wide variety of fields including signal processing, computers and decision making. Some important notes on artificial neural networks are:

- Either signal features extracted using certain measuring algorithms or even unprocessed samples of the input signals are fed into the ANN.
- The most recent along with a few older samples of the signals are fed into the ANN.
- The output provided by the neural network corresponds to the concerned decision which might be the type of fault, existence of a fault or the location of a fault.
- The most important factor that affects the functionality of the ANN is the training pattern that is employed for the same.
- Pre-processing and post-processing techniques may be employed as well to enhance the learning process and reduce the training time of the ANN.

One of the biggest drawbacks of applications that make use of artificial neural networks is that no well-defined guide exists to help us choose the ideal number of hidden layers to be used and the number of neurons per each hidden layer. From a different perspective, it is advantageous considering the ability to generalize. A vital feature of ANN is its dedication to parallel computing. Hence it can produce a correct output corresponding to any input even if the concerned input was not fed into the ANN during the training process. Another challenge in the ANN based application development was to synthesize the algorithm for the adaptive learning process. The back-error-propagation algorithm is the basic algorithm in which the neuron weights are adjusted in consecutive steps to minimize the error between the actual and the desired outputs. This process is known as supervised learning.

4.2 Model of a neuron

Any basic neuron model as shown in Fig 4.2 can be described by a function that calculates the output as a function of N_0 inputs to it.

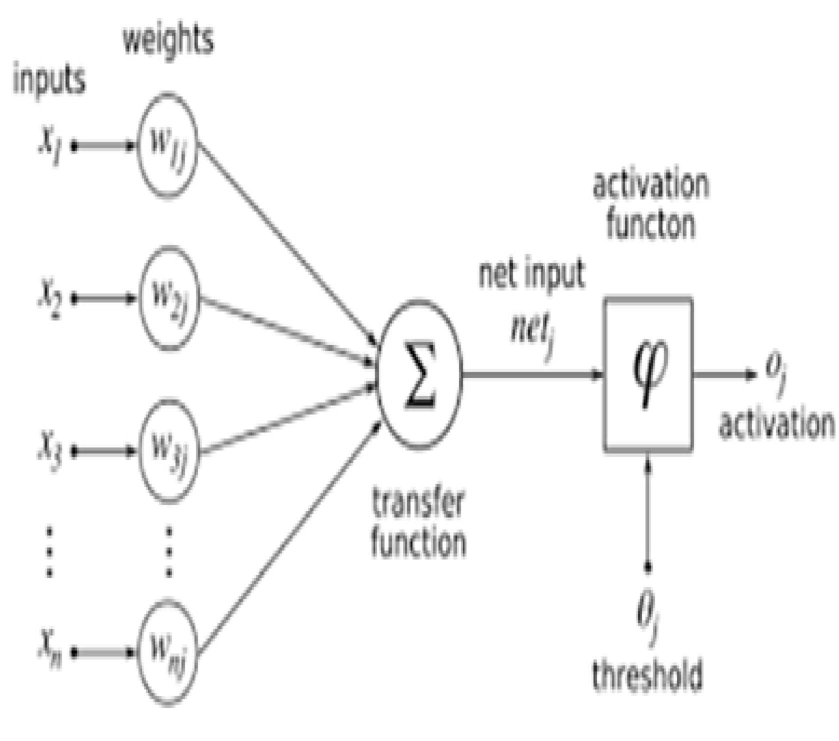

FIGURE 4.2: Typical model of a neuron

The output of the neuron is given by

$$y = f(\phi) = f(\sum_{i=0}^{N_0} W_{\mathrm{i}} a_{\mathrm{i}}) \tag{4.1}$$

where $w_0 a_0$ is the threshold value (polarization), $f(\phi)$ is the neuron activation function, ϕ is the summation output signal and y is the neuron output.

$$\phi = W_{\mathrm{T}} X \tag{4.2}$$

where W=$[W_0 W_1 W_2 W_3]^{\mathrm{T}}$, X=$[x_0 x_1 x_2 x_3]^{\mathrm{T}}$. An activation function decides how powerful the output from the neuron should be, based on the sum of its inputs. Depending upon the application's requirements, the most appropriate activation function is chosen.

The activation function $f(\phi)$ can be in different forms a few of which are described in Fig. 4.3.

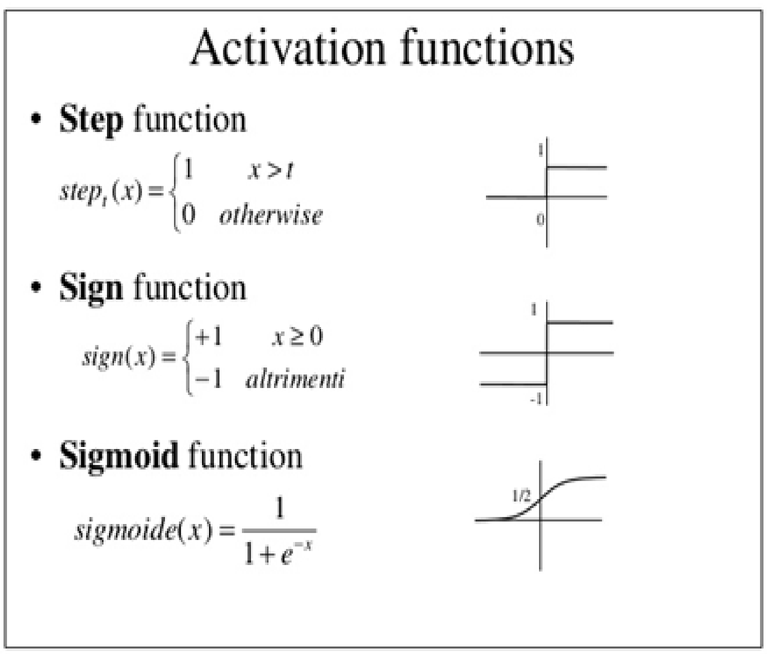

FIGURE 4.3: Commonly used Activation Functions

Based on the way the neurons are interconnected in a model, neural networks can be broadly classified into two types namely feedforward and feedback networks. As the name suggests, feedback networks unlike feedforward networks have a feedback connection fed back into the network along with the inputs. Due to their simplicity and the existence of a well-defined learning algorithm, only feedforward networks have been used in this thesis for the simulation and hence are discussed briefly in the upcoming sections.

4.2.1 Feedforward networks

Feedforward networks are the simplest neural networks where there is no feedback connection involved in the network and hence the information travel is unidirectional.

A feedforward network with N_0 input and K_{R} output signals is shown in Fig 4.4.

The computation process in the i^{th} layer can be described by the following equation 4.3.

$$p^{\text{i}} = f^{\text{i}}(W^{(\text{i})} g^{(\text{i-1})}) \tag{4.3}$$

where $p^{\text{i}} = [{p_0}^{(\text{i})} {p_1}^{(\text{i})} {p_2}^{(\text{i})} ......{p_{\text{n}}}^{(\text{i})}]^{\text{T}}$ is the signal vector at the output of the i^{th} layer.

And $\begin{pmatrix} {w_{10}}^{(\text{i})} & {w_{11}}^{(\text{i})} & {w_{12}}^{(\text{i})} & ... & {w_{1\text{n}}}^{(\text{i})} \\ {w_{20}}^{(\text{i})} & {w_{21}}^{(\text{i})} & {w_{22}}^{(\text{i})} & ... & {w_{2\text{n}}}^{(\text{i})} \\ {w_{30}}^{(\text{i})} & {w_{31}}^{(\text{i})} & {w_{32}}^{(\text{i})} & ... & {w_{3\text{n}}}^{(\text{i})} \\ & & .... & & \\ {w_{\text{n}0}}^{(\text{i})} & {w_{\text{n}1}}^{(\text{i})} & {w_{\text{n}2}}^{(\text{i})} & ... & {w_{\text{nn}}}^{(\text{i})} \end{pmatrix}$ is the weighing matrix between the $(i-1)^{\text{th}}$ and i^{th} layer.

$$g^{(\text{i-1})} = \begin{cases} A & \text{for } i = 1 \\ \begin{bmatrix} 1 \\ p^{(\text{i-1})} \end{bmatrix} & \text{for } i = 2, 3, 4... \end{cases}$$

A is the vector containing the input signals, $f^{(\text{i})}(.)$ is the activation function of the neurons in the i^{th} layer and R is the number of processing layers. All the neurons in a particular layer are assumed to be similar in all aspects and the number of hidden layers can be more than one and is usually determined by the purpose of the neural network. The output of the processed neural network is represented by the output vector:

$$y = p^{(\text{R})} = \begin{bmatrix} y_1 & y_2 & ... & y_{\text{N}_\text{R}} \end{bmatrix}^{\text{T}} \tag{4.4}$$

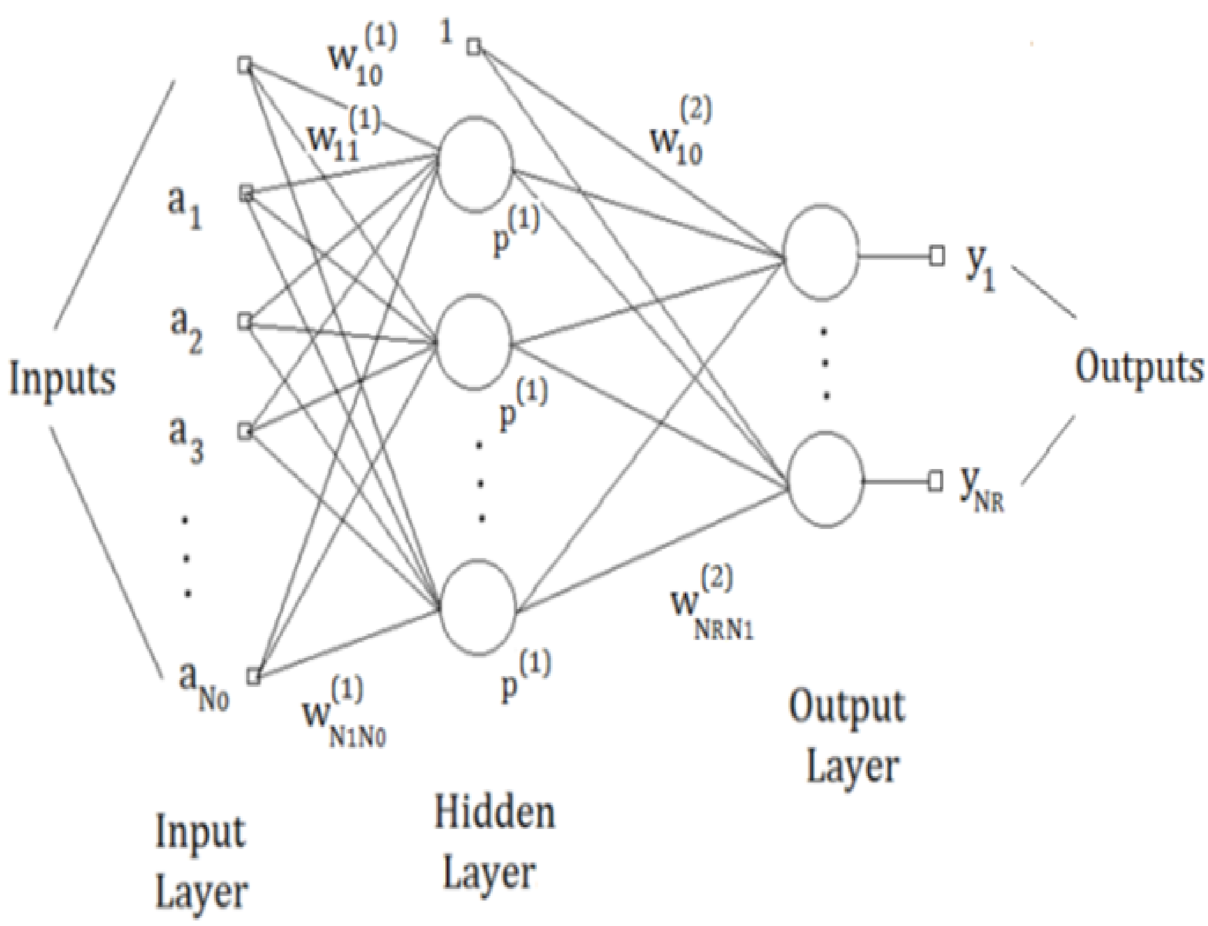

FIGURE 4.4: Structure of a two-layered feedforward network

4.2.2 Learning Strategies

The basic concept behind the successful application of neural networks in any field is to determine the weights to achieve the desired target and this process is called learning or training. The two different learning mechanisms usually employed are supervised and unsupervised learning. In the case of supervised learning the network weights are modified with the prime objective of minimization of the error between a given set of inputs and their corresponding target values. Hence we know the training data set which is a set of inputs and the corresponding targets the neural network should output ideally. This is called supervised learning because both the inputs and the expected target values are known prior to the training of ANN.

On the other hand, in the case of unsupervised learning, we are unaware of the relationship between the inputs and the target values. We train the neural network with a training data set in which only the input values are known. Hence it is very important to choose the right set of examples for efficient training. These examples are usually chosen using some sort of a similarity principle. The most commonly used unsupervised learning algorithms are the Self-Organizing Map (SOM) and the Adaptive Resonance Theory (ART). The learning strategy employed depends on the structure of the neural network. Feedforward networks are trained using the supervised learning strategy. The supervised learning strategy for a feedforward neural network has been shown in the Fig 4.5.

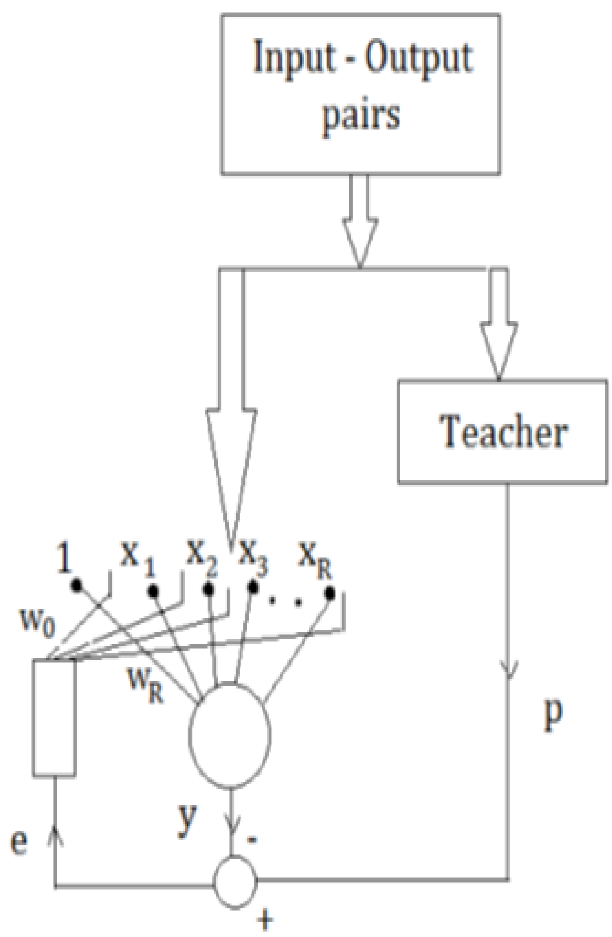

FIGURE 4.5: Scheme of supervised learning

The set of input-output pairs (shown in Fig 3.8) that are used to train the neural network are obtained prior to the training process either by using physical measurements or by performing some kind of simulations. Fig 3.8 shows that the teacher teaches the neural network to modify its weights according to the error 'e' between the outputs and the targets. The weights of the neural network are then modified iteratively according to equation 4.5.

$$W_{\mathrm{ji}}(n+1) = W_{\mathrm{ji}}(n) + \delta W_{\mathrm{ji}}(n) \tag{4.5}$$

where $W_{\mathrm{ji}}(n)$ and $W_{\mathrm{ji}}(n+1)$ are the previous and the modified weights connected between the i_{th} and the j_{th} adjoining layers. $\delta W_{\mathrm{ji}}(n)$ Stands for the correction or modification factor and n stands for the number of the iteration. If we consider the j_{th} neuron in a single layer neural network, the training efficiency is enhanced by minimizing the error between the actual output of the j_{th} neuron and the output that has been dictated by the teacher. Let $y_{\mathrm{j}}(n)$ and $p_{\mathrm{j}}(n)$ be the actual and the teacher-requested outputs for the j_{th} neuron in the nth iteration.

$$e_{\mathrm{j}}(n) = p_{\mathrm{j}}(n) - y_{\mathrm{j}}(n) \tag{4.6}$$

The vector $e(n)$ that stores the values of all the errors is also a function of the weights $W(n)$ for the corresponding layers' inputs. The value by which the weighing coefficients change (also called the correction factor) is given by the following equation 4.7.

$$\delta W_{\mathrm{ji}}(n) = \eta e_j(n) x_j(n) \tag{4.7}$$

where xi is the i^{th} input signal and η is the rate at which the learning process takes place. As mentioned earlier, learning process aims at the minimization of the error function. The same criterion can also be achieved by the usage of a Least Squares Method (LSM). Hence, if there are L neurons in a particular network, the cost function to be ultimately minimized is given by 4.8.

$$S_2(w) = \frac{1}{2}\sum_{j=1}^{L}(p_j - y_i)^2 \tag{4.8}$$

If the number of learning pairs with an input vector $x(n)$ and an output vector $d(n)$ of the form $(x(n), d(n))$ are P in the training set, then during the nth iteration of the learning process, we have:

$$S_2(w(n)) = \frac{1}{2}\sum_{n=1}^{p}\sum_{j=1}^{L}(p_j(n) - y_i(n))^2 \tag{4.9}$$

Since the activation functions that are employed are more than often non-linear, minimization of the above equation 4.9 is a non-linear problem. Several numerical methods that can handle non-linear functions effectively are available and are based on the steepest-decent method. The steepest-decent method is an extension to the Laplace's method of integral approximation where the contour integral in a complex plane is deformed to approach a stationary point in the direction of the steepest decent. The back-error propagation learning technique is based on the steepest-decent method and is usually widely applied in a version known as the Levenberg-Marquardt algorithm.

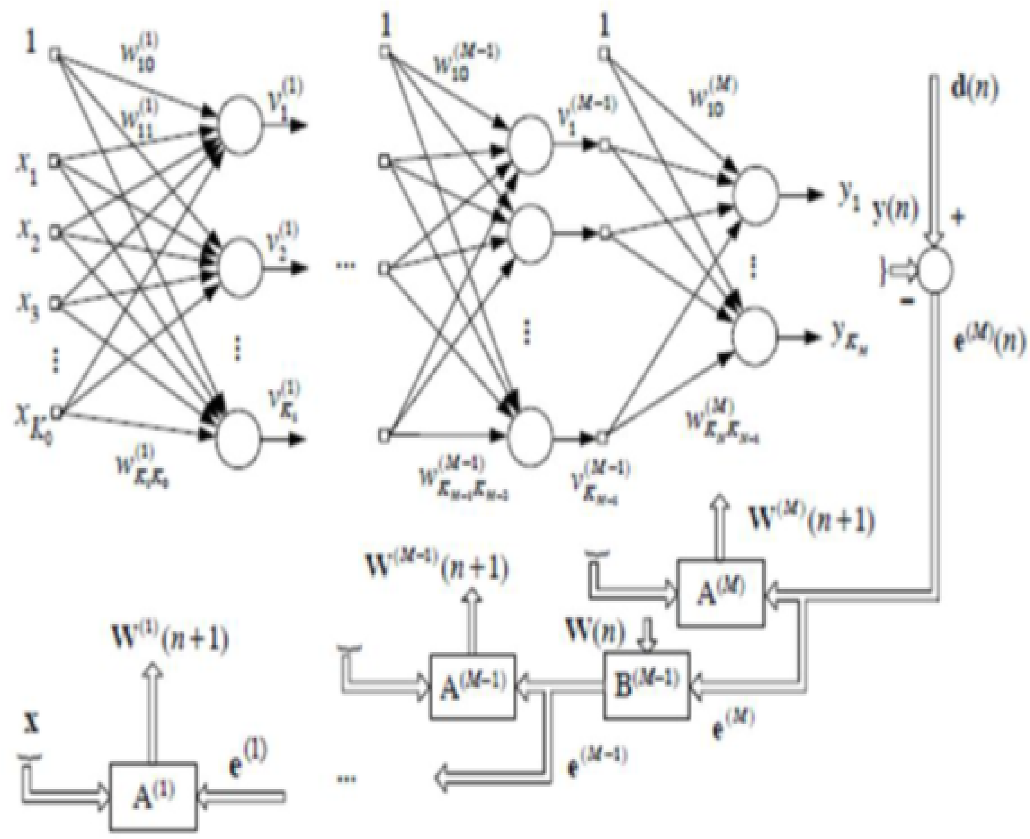

FIGURE 4.6: Structure of back-error-propagation algorithm

The back-error-propagation algorithm chooses random weights for the neural network nodes, feeds in an input pair and obtains the result. Then we calculate the error for each node starting from the last stage and by propagating the error backwards. Once this is done, we update the weights and repeat the process with the entire set of input output pairs available in the training data set. This process is continued till the network converges with respect to the desired targets. The back-error-propagation technique is widely used for several purposes including its application to error functions (other than the sum of squared errors) and for the evaluation of Jacobian and Hessian matrices. The correction values are calculated as functions of errors estimated from the minimization of equation 4.9. This process is carried out layer by layer throughout the network in the backward direction. This algorithm is pictorially depicted in Fig 4.6.

The corresponding weighing vectors are shown in blocks $A^{(M)}, A^{(M-1)}, \ldots, A^{(1)}$ and the errors that are propagated to the lower layers are calculated and stored in the blocks $B^{(M-1)}, B^{(M-2)}, \ldots, B^{(2)}$. The back-error-propagation algorithm has been implemented in many ways but the basic idea remains the same. The only thing that changes in each of these implementations is the method used for the calculation of the weights that are iteratively upgraded when passed backward from layer to layer in the neural network. The modifications involved are also used in the training process of recurrent networks. The rate at which the learning process takes place can be estimated by keeping a check on the correction values in successive stages. The total number of iterations required to achieve satisfactory convergence rate depends on the following factors

- size of the neural network
- structure of the network
- the problem being investigated
- the learning strategy employed

- size of the training/learning set

The efficiency of a chosen ANN and the learning strategy employed can be estimated by using the trained network on some test cases with known output values. This test set is also a part of the learning set. Hence the entire set of data consists of the training data set along with the testing data set. The former is used to train the neural network and the latter is used to evaluate the performance of the trained artificial neural network.

Chapter 5

Experimentation and results

5.1 Introduction

As discussed in the previous chapters, artificial neural networks have been used for the protection of power transmission lines. The excellent pattern recognition and classification abilities of neural networks have been cleverly utilized in this thesis to address the issue of transmission line fault location.

In this chapter, a complete neural-network based approach has been outlined in detail for the location of faults on transmission lines in a power system. To achieve the same, the original problem has been dealt with in namely fault location.5.2

5.2 Modelling the power transmission line system

A 400 kV transmission line system has been used to develop and implement the proposed strategy using ANNs. The system consists of two generators of 400 kV each located on either ends of the transmission line along with a three phase fault simulator used to simulate faults at various positions on the transmission line. The line has been modelled using distributed parameters so that it more accurately describes a very long transmission line.

This power system was simulated using the SimPowerSystems toolbox in Simulink by The MathWorks. A snapshot of the model used for obtaining the training and test data sets is shown in Fig 5.1. In Fig 5.1, two loads are there of 100MW. The three phase V-I measurement block is used to measure the voltage and current samples at the terminal A. The transmission line (line 1 and line 2 together) is 300 km long and the three-phase fault simulator is used to simulate various types of faults at varying locations along the transmission line with different fault resistances.

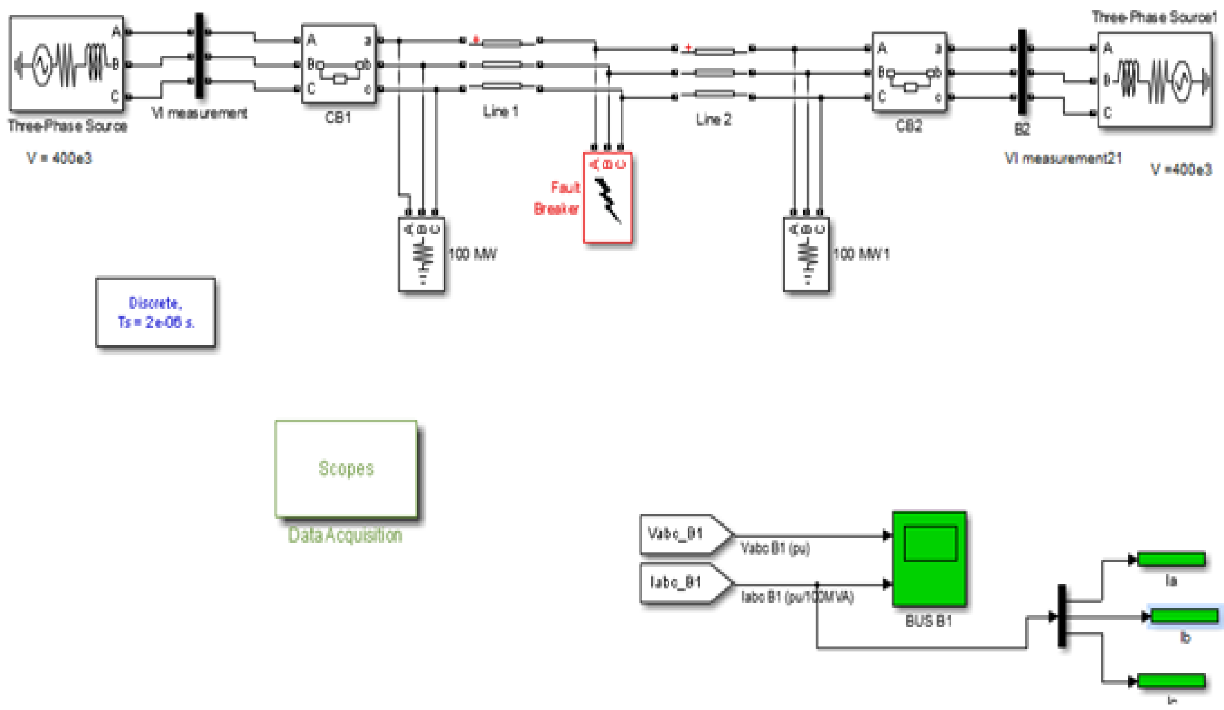

FIGURE 5.1: Circuit Diagram of the studied model in SimPowerSystems

The values of the three-phase currents are measured and modified in terms of summation of ninth level detailed coefficient(mother wavelet 'db4') accordingly and are ultimately fed into the neural network as inputs. The SimPowerSystems toolbox has been used to generate the entire set of training data for the neural network in all kind of fault cases.

5.3 Outline of the proposed scheme

The goal of this project is to propose an integrated method to identify fault location using artificial neural networks. A back-propagation based neural network has been used for the purpose of fault location. For each of the different kinds of faults, separate neural networks have been employed for the purpose of fault location. Each of these steps has been depicted in the flowchart shown in Fig 5.2.

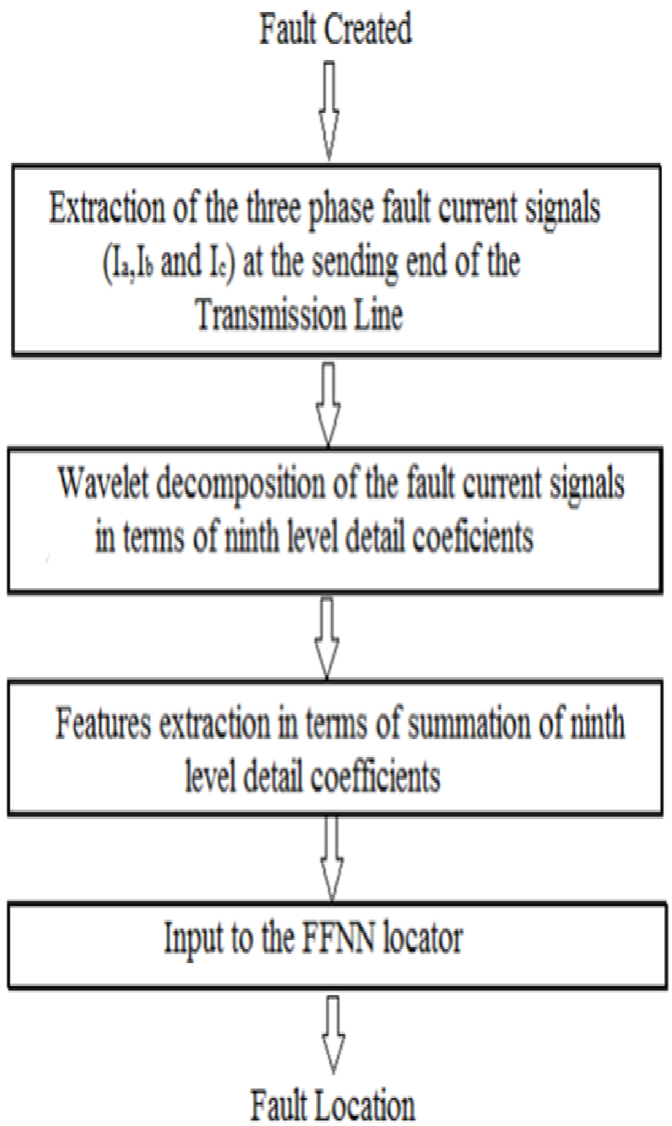

FIGURE 5.2: Flowchart depicting the outline of the proposed scheme

5.4 Data pre-processing

To obtain the features for training of neural network we first simulate the power system model at different locations along with different fault resistance. By this we record the three phase currents and then we apply the wavelet decomposition (using the "db4" as mother wavelet) on the recorded current data.

In decomposition we mainly decompose the faulted signal in nine different signals which have different- different frequencies and amplitudes. Out of them we take the highest frequency signal and sum up the magnitudes of this sampled signal. That's how we got three numbers corresponding to the $I_a, I_b and I_c$. To recoded the current data we use this code

```
for L = 1:1:299
    R = .5;
   sim('C:\Users\PACL-SERVER\Desktop\kkk\mketan.slx')
if case_num==1
   Sig_Ia_total1=Sig_Ia(:,2);
   Sig_Ib_total1=Sig_Ib(:,2);
   Sig_Ic_total1=Sig_Ic(:,2);
```

```
else
    Sig_Ia_total1=[Sig_Ia_total1 Sig_Ia(:,2)];
    Sig_Ib_total1=[Sig_Ib_total1 Sig_Ib(:,2)];
    Sig_Ic_total1=[Sig_Ic_total1 Sig_Ic(:,2)];
end
case_num=case_num+1
end
```

after recording this current we apply the wavelet decomposition

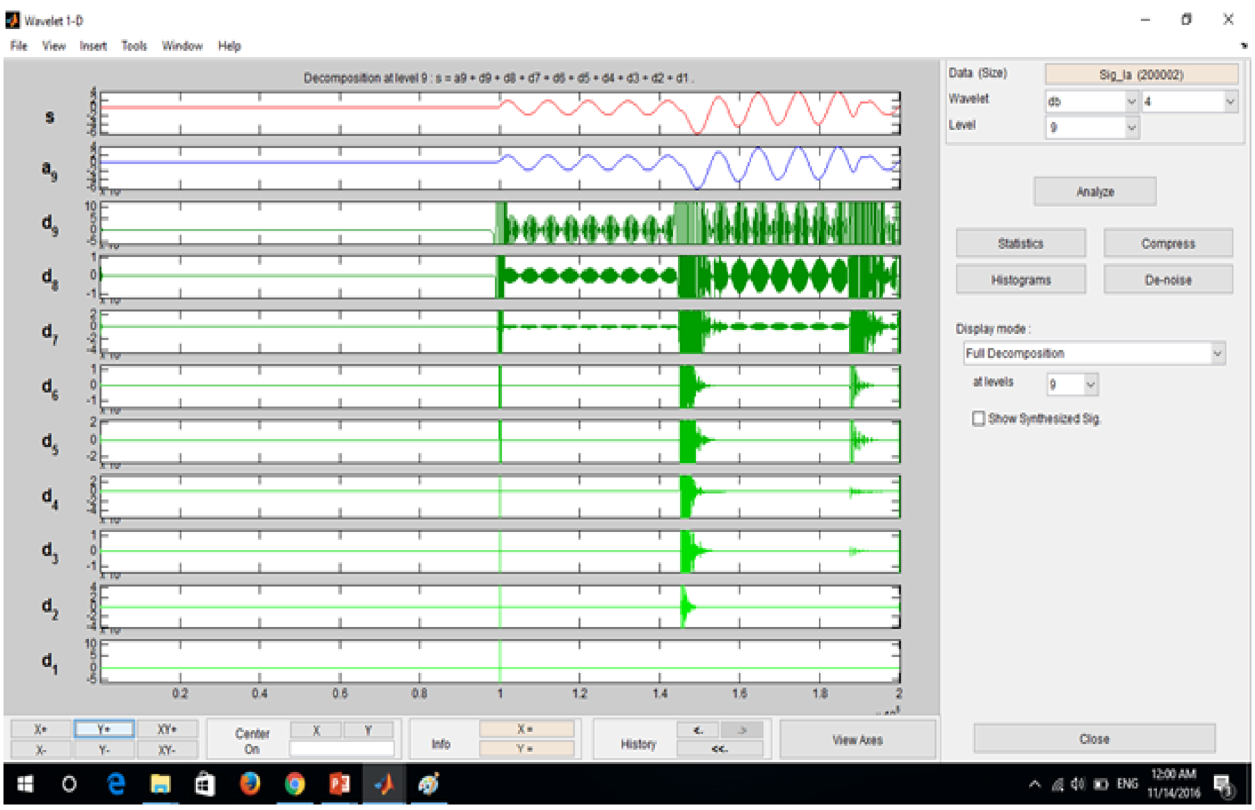

FIGURE 5.3: Decomposition of current in nine different signal

After summing the d_9 coefficients we got the features for the training of neural network.

5.5 Overview of the training process

The important part in the application of neural networks for any purpose is the training. Training is the process by which the neural network learns from the inputs and updates its weights accordingly. In order to train the neural network we need a set of data called the training data set which is a set of input output pairs fed into the neural network. Thereby, we teach the neural network what the output should be, when that particular input is fed into it. The ANN slowly learns the training set and slowly develops an ability to generalize upon this data and will eventually be able to produce an output when a new data is provided to it. During the training process, the neural network's weights are updated with the prime goal of minimizing the performance function. This performance function can be user defined, but usually feedforward networks employ Mean Square Error as the performance function and the same is adopted throughout this work.

As already mentioned in the previous chapter, summation of ninth level detail coefficient (using 'db4') of currents fed into the neural network. The outputs of the neural network is the location of the fault on the transmission line.

For the task of training the neural networks for different stages, sequential feeding of input and output pair has been adopted. In order to obtain a large training set for efficient performance, each of the eleven kinds of faults has been simulated at different locations along the considered transmission line. In view of all these issues, about 2990 different fault cases for each of the 11 kinds of faults have been simulated.

Apart from the type of fault, the phases that are faulted and the distance of the fault along the transmission line, the fault resistance also has been varied to include several possible real-time fault scenarios.

- The fault resistance has been varied as follows: 0.5 ohm, 0.75 ohm, 5 ohm, 10 ohm, 15 ohm, 25 ohm, 35 ohm, 45 ohm, 55 ohm, 70 ohm.
- Fault distance has been varied at an incremental factor of every 1 km on a 300 km transmission line.

5.6 Training and testing the neural network for different faults

Feed forward back - propagation neural networks have been surveyed for the purpose of fault location, mainly because of the availability of sufficient relevant data for training. In order to train the neural network, all faults have been simulated on the transmission line model. For each of the faults have been simulated at every 1 Km on a 300 Km long transmission line. Along with the fault distance, the fault resistance has been varied as follows: 0.5 ohm, 0.75 ohm, 5 ohm, 10 ohm, 15 ohm, 25 ohm, 35 ohm, 45 ohm, 55 ohm, 70 ohm. Hence, a total of 2990 cases have been simulated for each kind of fault. In each of these cases, the current samples for all three phases (features got by wavelet decomposition and summing) are given as inputs to the neural network. The output of the neural network is the distance to the fault from sending end which we considered left source.

We divide the 2990 features as given below

- Training - 70%
- Validation - 15%
- Testing - 15%

Which is also the default ratio of Levenberg - Marquardt training algorithm.

For discerning fault location, employed ANN had 3 neurons in the input layer, 1 hidden layer with 30 neurons, and 1 neuron in the output layer (3-30-1). The Levenberg - Marquardt algorithm alongside 'mean square error' performance function was chosen for the training process.

Firstly, a few of the various neural networks (with varying combination of hidden layers and number of neurons per hidden layer) has been trained out of which performed reasonably well is presented along with its respective ANN configuration ,error performances, gradient and validation performance, error histogram and also the regression plots depicted in detail. Efficiency of each of the trained networks is analysed based on their regression performance and their performance in the testing phase.

The ANN performances were observed for the AG faults. The results determined can be used as a trend for the other 10 faults viz. –

➢ **BG**	➢ **ABG**
➢ **CG**	➢ **ACG**
➢ **AB**	➢ **BCG**
➢ **BC**	➢ **ABC**
➢ **CA**	➢ **ABCG**

AG Fault

For discerning fault location, employed ANN had 3 neurons in the input layer, 1 hidden layer with 30 neurons, and 1 neuron in the output layer (3-30-1). The Levenberg - Marquardt algorithm alongside 'mean square error' performance function was chosen for the training process.

- 3 neurons in the input layer
- 1 hidden layer with 30 neurons
- 1 neuron in the output layer

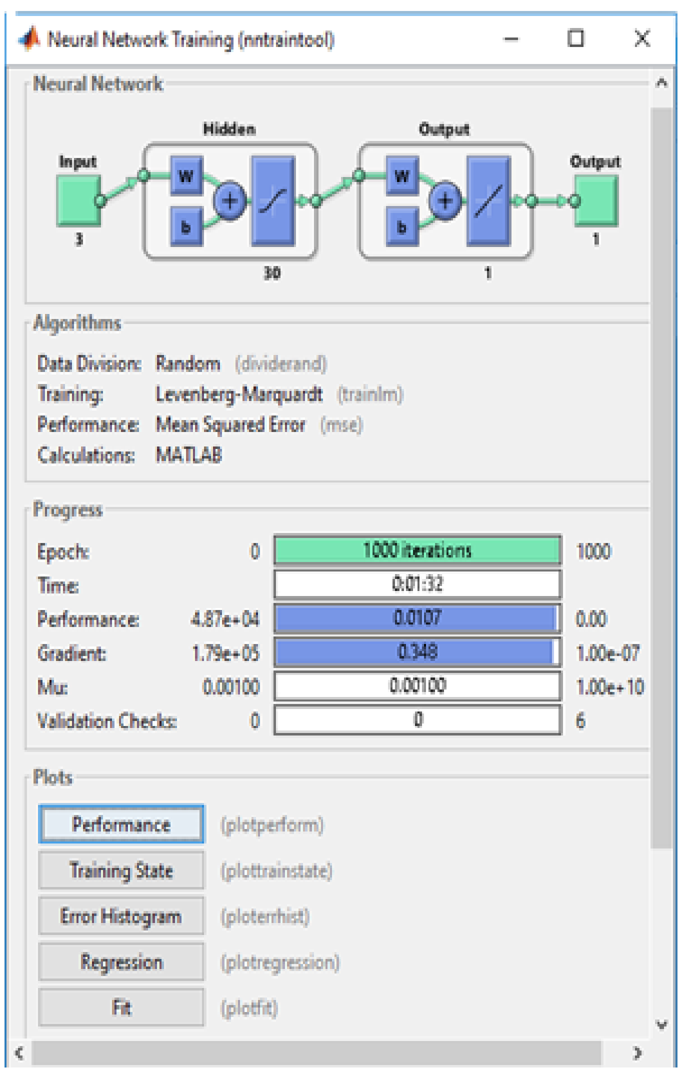

FIGURE 5.4: Overview of the chosen ANN with configuration (3-30-1)

Fig 5.5 plots the mean-square error as a function of time during the learning process and it can be seen that the achieved MSE is about 0.010541 which is way below the MSE goal of 0.01.

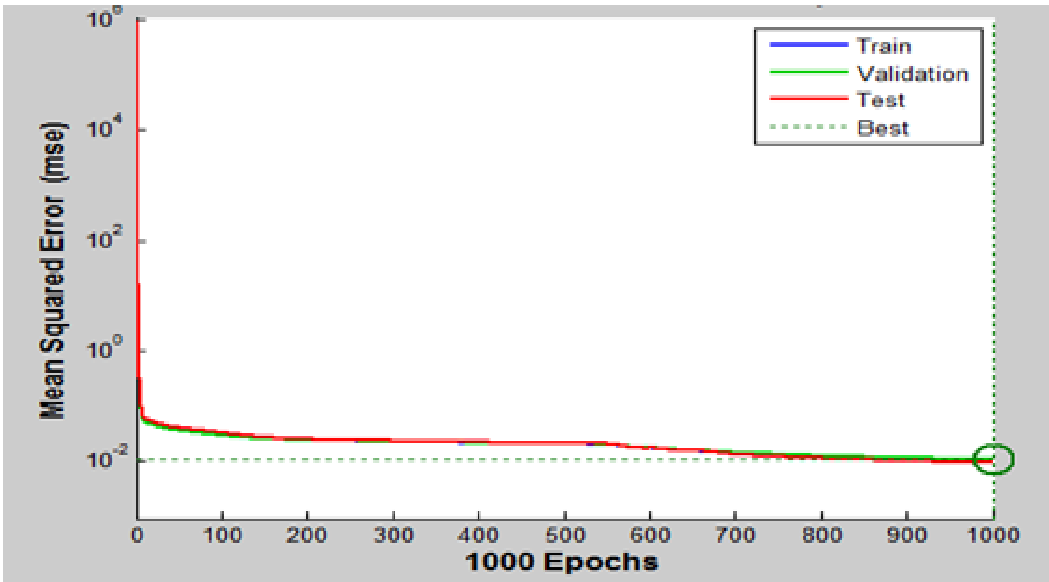

FIGURE 5.5: Mean-square error performance of the network with configuration (3-30-1).

Several factors have been considered while testing the performance of the neural networks. One prime factor that evaluates the efficiency of the ANN is the test phase performance already illustrated in Fig 5.5. Another form of analysis is provided by Fig 5.6, which is the gradient and validation performance plot. It can be seen that there is a steady decrease and then constant in the gradient and also that the number of validation fails are 0 during the entire process which indicates smooth and efficient training.

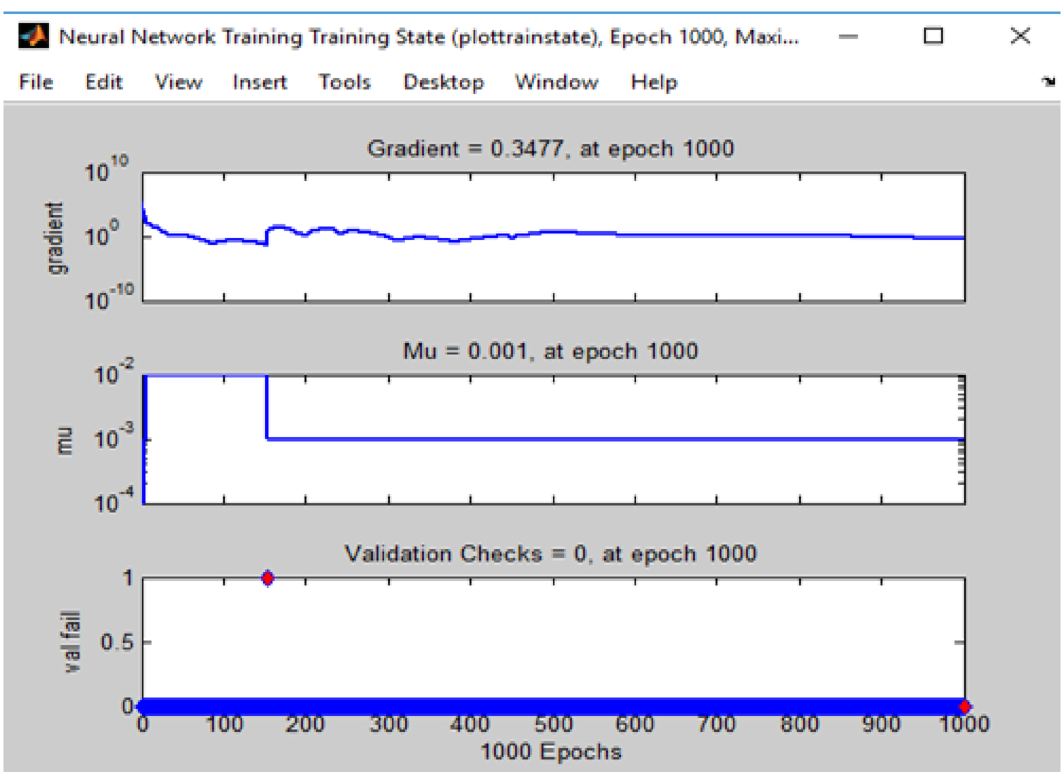

FIGURE 5.6: Gradient and validation performance of the network with configuration (3-30-1)

Another aspect evaluating the performance of the trained neural network is the error histogram. As we describe above we take 2990 feature for training, testing and validation. This actually tells how many of them is trained at which error. As we can see from the Figure 5.7 that maximum and minimum error are respectively 0.288 and 0.1789, which is very good for the in our case.

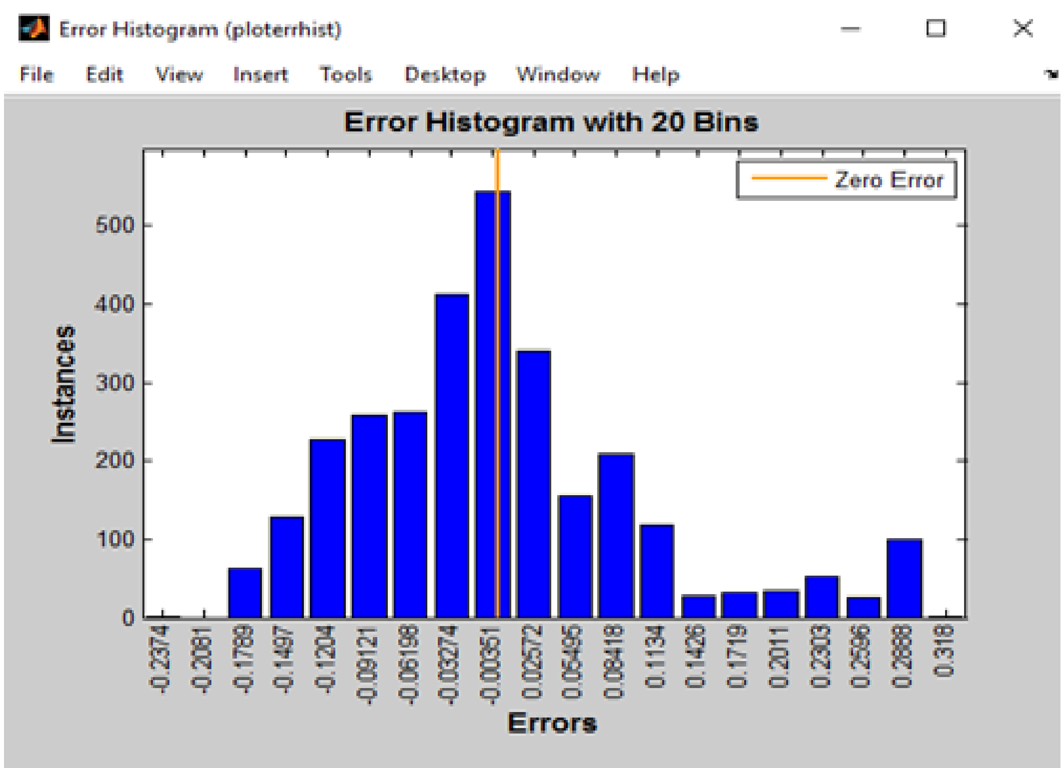

FIGURE 5.7: Error Histogram of learning of the ANN with configuration (3-30-1)

Another factor that is considered while evaluating the performance of the network is the correlation coefficient of each of the various phases of training, validation and testing. Fig 5.8 shows the regression plots of the various phases such as training, testing and validation. It can be seen that the best linear fit very closely matches the ideal case with an overall correlation coefficient of 1.

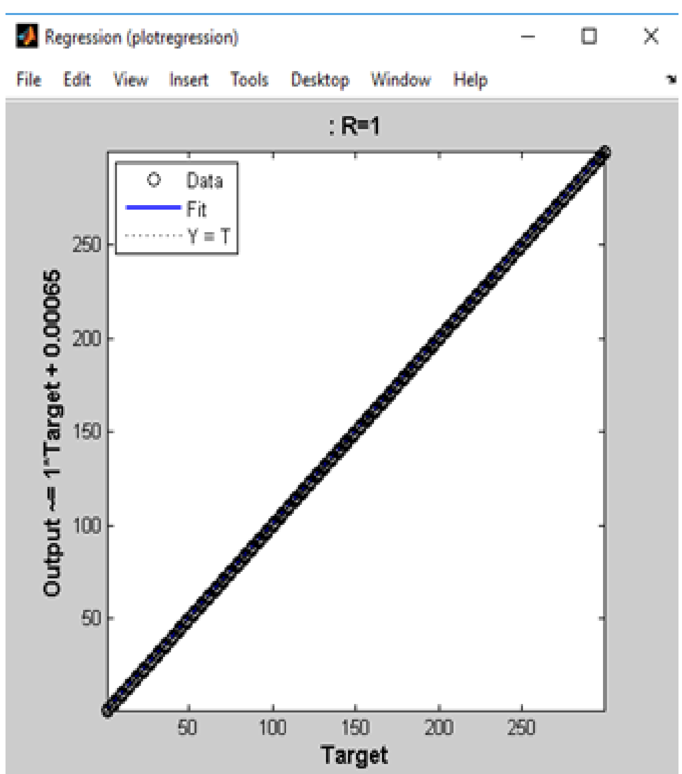

FIGURE 5.8: Regression plots of learning of the ANN with configuration (3-30-1)

5.7 Results

- Table 5.1 illustrates the percentage errors in Fault location as a function of Fault distance and Fault resistance.
- Two different cases have been considered (shown in adjacent columns), one with a fault resistance of 5 ohms and another with a fault resistance of 50 ohms.
- Each of the cases also were subdivided into further two sections – one where the fault locations (D) belonged to the training data set and another where it didn't.
- The network performed best in the case when both fault resistance and fault location belonged to the training data set. However, observations from other sets also confirm that the paradigm can be used for those cases as well. Therefore, the ANN performed adequately in all the subcases and hence can be utilised for physical fault detection.

TABLE 5.1: Percentage errors as a function of fault distance and fault resistance for the ANN chosen for three phase fault location

Type of Fault	**R & D in Training Data Set, R = 5**			**R in Training Data set, D not in Training Data set, R = 5**			**D in Training Data set, R not in Training Data set, R = 50**			**R& D not in Training Data Set, R = 50**		
	D	**Y**	**%Error**	**D**	**Y**	**%Error**	**D**	**Y**	**%Error**	**D**	**Y**	**%Error**
AG	50	49.759	0.481	41.67	41.425	0.587	80	79.705	0.368	225.68	225.34	0.1511
BG	10	10.0003	0.003	107.75	107.7516	0.0015	180	179.9987	0.000718	210.5	210.4975	0.0012
CG	5	4.9923	0.1547	290.53	290.5010	0.0100	75	75.0063	0.0084	2.75	2.6689	2.9492
ABG	100	99.9979	0.0021	177.79	177.7928	0.0016	295	294.9268	0.0248	29.535	29.5923	0.1938
ACG	1	0.9989	0.1071	2.787	2.7874	0.0128	278	278.0074	0.0027	298.999	298.9215	0.0229
BCG	290	289.9996	.00013	243.36	243.3599	5.3761e-05	10	10.0072	0.0722	7.78	7.7873	0.0941
ABCG	170	169.9991	5.5714e-04	145.52	145.5193	4.8551e-04	25	25.1477	0.5908	18.73	18.8944	0.8778
AC	17	16.9955	0.0267	7.53	7.5358	0.0766	165	165.0103	0.0062	123.33	123.3384	0.0068
AB	213	213.0078	0.0037	189.78	189.7630	0.0090	56	56.5639	1.0069	60.5	60.6113	0.1840
ABC	1	1.0006	.0574	215.5	215.4999	3.4520e-05	**R,=12**			**R,= 12**		
							286	286.8645	0.3023	111.5	111.7878	0.2581

Chapter 6

Conclusions

This report has studied the usage of neural networks as an alternative method for the location of faults on transmission lines. The methods employed make use of the phase currents (features got by wavelet decomposition and summing) as inputs to the neural networks. All kind of faults which can occur on transmission line have been taken into consideration into this work and separate ANNs have been proposed for each of these faults.

All the neural networks investigated in this report belong to the back-propagation neural network architecture. A fault location scheme for the transmission line system has been devised successfully by using artificial neural networks.

The simulation results obtained prove that satisfactory performance has been achieved by all of the proposed neural networks in general. As further illustrated, depending on the application of the neural network and the size of the training data set, the size of the ANN (the number of hidden layers and number of neurons per hidden layer) keeps varying. The importance of choosing the most appropriate ANN configuration, in order to get the best performance from the network, has been stressed upon in this work. The sampling frequency adopted for sampling the voltage and current waveforms in this thesis is just 2 kHz.

To simulate the entire power transmission line model and to obtain the training data set, MATLAB R2014 a has been used along with the SimPowerSystems toolbox in Simulink. In order to train and analyse the performance of the neural networks, the Artificial Neural Networks Toolbox has been used extensively.

Some important conclusions that can be drawn from this thesis are:

- Neural Networks are indeed a reliable and attractive scheme for an ideal transmission line fault location scheme especially in view of the increasing complexity of the modern power transmission systems.
- It is very essential to investigate and analyse the advantages of a particular neural network structure and learning algorithm before choosing it for an application because there should be a trade-off between the training characteristics and the performance factors of any neural network.
- Back Propagation neural networks are very efficient when a sufficiently large training data set is available and hence Back Propagation networks have been chosen for all the fault location.

As a possible extension to this work, it would be quite useful to analyse all the possible neural network architectures and to provide a comparative analysis on each of the architectures and their performance characteristics. The possible neural network architectures that can be analysed apart from back propagation neural networks are radial basis neural network (RBF) and support vector machines (SVM) networks.

Bibliography

[1] *Das R, Novosel D, "Review of fault location techniques for transmission and sub – transmission lines". Proceedings of 54th Annual Georgia Tech Protective Relaying Conference, 2000.*

[2] *IEEE guide for determining fault location on AC transmission and distribution lines. IEEE Power Engineering Society Publ., New York, IEEE Std C37.114, 2005.*

[3] *Saha MM, Das R, Verho P, Novosel D, "Review of fault location techniques for distribution systems", Proceedings of Power Systems and Communications Infrastructure for the Future Conference, Beijing, 2002, 6p.*

[4] *Eriksson L, Saha MM, Rockefeller GD, "An accurate fault locator with compensation for apparent reactance in the fault resistance resulting from remote-end feed", IEEE Trans on PAS 104(2), 1985, pp. 424-436.*

[5] *Saha MM, Izykowski J, Rosolowski E, Fault Location on Power Networks, Springer publications, 2010.*

[6] *Magnago FH, Abur A, "Advanced techniques for transmission and distribution system fault location", Proceedings of CIGRE – Study committee 34 Colloquium and Meeting, Florence, 1999, paper 215.*

[7] *Tang Y, Wang HF, Aggarwal RK et al., "Fault indicators in transmission and distribution systems", Proceedings of International conference on Electric Utility Deregulation and Restructuring and Power Technologies – DRPT, 2000, pp. 238-243.*

[8] *Reddy MJ, Mohanta DK, "Adaptive-neuro-fuzzy inference system approach for transmission line fault classification and location incorporating effects of power swings", Proceedings of IET Generation, Transmission and Distribution, 2008, pp. 235 – 244.*

[9] *Alessandro Ferrero, Silvia Sangiovanni, Ennio Zappitelli, "A fuzzy-set approach to fault-type identification in digital relaying", Transmission and Distribution conference, Proceedings of the IEEE Power Engineering Society, 1994, pp. 269-275.*

[10] *Cook V, Fundamental aspects of fault location algorithms used in distance protection, Proceedings of IEE Conference 133(6), 1986, pp. 359-368.*

[11] *Cook V, Analysis of Distance Protection, Research Studies Press Ltd., John Wiley & Sons, Inc., New York, 1985.*

[12] *Network Protection & Automation Guide, T&D Energy Automation & Information, Alstom, France.101*

[13] *Wright A, Christopoulos C, Electrical Power System Protection, Chapman & Hall publications, London, 1993.*

[14] *Ziegler G, Numerical Distance Protection, Principles and Applications, Siemens AG, Publicis MCD Verlag, Erlangen, 2006.*

[15] *Djuric MB, Radojevic ZM, Terzija VV, "Distance Protection and fault location utilizing only phase current phasors", IEEE Transactions of Power Delivery 13(4),1998, pp. 1020-1026.*

[16] *Eriksson L, Saha MM, Rockefeller GD, "An accurate fault locator with compensation for apparent reactance in the fault resistance resulting from remote-end feed", IEEE Trans on PAS 104(2), 1985, pp. 424-436.*

[17] *Kasztenny B, Sharples D, Asaro V, "Distance Relays and capacitive voltage transformers – balancing speed and transient overreach", Proceedings of 55th Annual Georgia Tech Protective Relaying Conference, 2001.*

[18] *Zhang Y, Zhang Q, Song W et al., "Transmission line fault location for double phaseto- earth fault on non-direct-ground neutral system", IEEE Transactions on Power Delivery 15(2), 2000, pp. 520-524.*

[19] *Girgis AA, Hart DG, Peterson WL, "A new fault location techniques for two and three terminal lines", IEEE Transactions on Power Delivery 7(1), 1992, pp. 98-107.*

[20] *Saha MM, Izykowski J, Rosolowski E, "A method of fault location based on measurements from impedance relays at the line ends", Proceedings of the 8th International Conference on Developments in Power Systems Protection – DPSP, IEE CP500, 2004, pp. 176-179.*

[21] *Wanjing Xiu, Yuan Liao, "Accurate transmission line fault location considering shunt capacitances without utilizing line parameters", Electric Power components and Systems, 2012.*

[22] *Yuan Liao, "Generalized fault location methods for overhead electric distribution systems", IEEE Transactions on Power Delivery, vol. 26, no. 1, pp. 53-64, Jan 2011.*

[23] *Yuan Liao, Ning Kang, "Fault Location algorithms without utilizing line parameters based on distributed parameter line model", IEEE Transactions on Power Delivery, vol. 24, no. 2, pp. 579-584, Apr 2009.*

[24] *Karl Zimmerman, David Costello, "Impedance-based fault location experience", Schweitzer Engineering Laboratories, Inc. Pullman, WA USA.*

[25] *T. Takagi, Y. Yamakoshi, M. Yamaura, R. Kondou, and T. Matsushima, "Development of a New Type Fault Locator Using the One-Terminal Voltage and Current Data," IEEE Transactions on Power Apparatuand Systems, Vol. PAS-101, No. 8, August 1982, pp. 2892-2898.*

[26] *Edmund O. Schweitzer, III, "A Review of Impedance-Based Fault Locating experience," Proceedings of the 15th Annual Western Protective Relay Conference, Spokane, WA, October 24-27, 1988.*

[27] *Aurangzeb M, Crossley PA, Gale P, "Fault location using high frequency travelling waves measured at a single location on transmission line", Proceedings of 7th International conference on Developments in Power System Protection – DPSP, IEE CP479, 2001, pp. 403-406.*

[28] *Bo ZQ, Weller G, Redfern MA, "Accurate fault location technique for distribution system using fault-generated high frequency transient voltage signals", IEEE Proceedings of Generation, Transmission and Distribution 146(1), 1999, pp. 73-79.*

[29] *Silva M, Oleskovicz M, Coury DV, "A fault locator for transmission lines using travelling waves and wavelet transform theory", Proceedings of 8th International conference on Developments in Power System Protection – DPSP, IEE CP500, 2004, pp. 212-215.*

[30] *El-Sharkawi M, Niebur D, "A tutorial course on artificial neural networks with applications to Power systems", IEEE Publ. No. 96TP 112-0, 1996.*

[31] *Pao YH, Sobajic DJ, "Autonomous Feature Discovery of Clearing time assessment", Symposium of Expert System Applications to Power Systems, Stockholm – Helsinki, Aug 1988, pp. 5.22-5.27.*

[32] *Dalstein T, Kulicke B, "Neural network approach to fault classification for high speed protective relaying", IEEE Transactions on Power Delivery, vol. 4, 1995, pp. 1002 – 1009.*

[33] *Kezunovic M, Rikalo I, Sobajic DJ, "Real-time and Off-line Transmission Line Faulyt Classification Using Neural Networks", Engineering Intelligent Systems, vol.10, 1996, pp. 57-63.*

[34] *S.M. El Safty and M.A. Sharkas, "Identification of Transmission line faults using Wavelet Analysis", IEEE Transactions on Industrial Applications, ID: 0-7803-8294-3/04, 2004.*

[35] *Fernando H. Magnago and Ali Abur, "Fault Location Using Wavelets", IEEE Transactions on Power Delivery, Vol. 13, No. 4, pp.1475-1480,1998.*

[36] *Amara Graps, "An Introduction to Wavelets", IEEE Computational Science & Engineering, pp.50-61, 1995.*

[37] *Mattew N.O. Sadiku, Cajetan M. Akujuobi and Raymond C.Garcia, "An Introduction to Wavelets in Electromagnetics", IEEE microwave magazine, pp.63-72, 2005*

[38] *Shyh-Jier Huang and Cheng-Tao Hsieh Ching-Lien Huang, "Application of Morlet Wavelets to Supervise Power System Disturbances", IEEE Transactions on Power Delivery, Vol.14, No. 1, pp.235-243, 1999.*

[39] *R.N.Mahanty,P.B.Dutta Gupta, "A fuzzy logic based fault classification approach using current samples only",EPSR,pp.501-507 ,14 Feb 2006.*