A

Project Report

On

"ANALYZING EFFECT OF SYSTEM INERTIA ON GRID FREQUENCY FORECASTING USING TWO STAGE NEURO FUZZY SYSTEM "

Submitted to

CHHATTISGARH SWAMI VIVEKANAND TECHNICAL UNIVERSITY

BHILAI

In partial fulfilment of requirements for award of degree

Of

Bachelor of Engineering

In

Electrical and Electronics Engineering

By

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We acknowledge with the sense of obligation and gratitude to **Dr. Arun Arora**, Principal, for infusing his interminable enthusiasm into all of us and installing a spirit of dynamism in us.

Last, but by no means to least, we owe our gratitude to the teaching and non-teaching staff and also to our parents and friends.

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CERTIFICATE

This is to certify that the report of the project submitted is an outcome of project entitled **"ANALYZING EFFECT OF SYSTEM INERTIA ON GRID FREQUENCY FORECASTING USING TWO STAGE NEURO FUZZY SYSTEM"** carried out by Divyansh Chourey,Himanshu Gupta,Amit Kumar,Anand Kumar,Jitesh Kumar under my guidance and supervision for the award of Degree of Bachelor Of Engineering in Electrical And Electronics Engineering of Chhattisgarh Swami Vivekanand Technical University, Bhilai (C.G.), India.

To the best of my knowledge and belief, the thesis:

1. Embodies the work of the candidate herself,
2. Has duly been completed,
3. Fulfils the requirement of the Ordinance relating to B.E. degree of the university,
4. Is up to the desired standard for the purpose of which is submitted.

The project work as mentioned above is here by being recommended and forwarded for examination and evaluation.

(Signature of supervisor)

Dr. ANUP MISHRA
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<u>CERTIFICATE BY THE EXAMINERS</u>

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DECLARATION

We the undersigned solemnly declare that the report of project work entitled **"ANALYZING EFFECT OF SYSTEM INERTIA ON GRID FREQUENCY FORECASTING USING TWO STAGE NEURO- FUZZY SYSTEM"** is based on our own work carried out during the course of our study under the supervision of **Dr. ANUP MISHRA**, Professor & Head of Department, Electrical & Electronic Engineering Department, Bhilai Institute of Technology, Durg.

We assert that the statements made and conclusions drawn are an outcome of the project work. We further declare that to the best of our knowledge and belief that the report does not contain any work which has been submitted for the award of any other degree/diploma/certificate in this university/deemed university.

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TABLE OF CONTENTS

ABSTRACT

Significant involvement of soft computing techniques like neural network and neuro-fuzzy system lead the computation of different parameter in advance for the purposes like safety, operation, expansion, risk management, market analysis etc. A wide variety of approaches has been developed in load and electricity price forecasting using the neural network techniques with appreciable accuracy. Yet, the frequency is the parameter of the power grid which is to be forecasted. Significant attention has been given by the world in load forecasting to make electricity price forecasting, hence profit forecasting to facilitate industry like power transmission and generation companies. And also believe that the frequency is somewhat the constant parameter, never attracted the attention of research analysts. Random and fast switching of load faced by the grid in a typical practice cause the frequency disturbance and this disturbance is quite dangerous even in small amount with respect to grid operation and safety. A small percentage change (about 1 Hz) in frequency may lead to even grid failure. In this paper, Artificial Neural Network is used to make frequency forecast. Artificial neural network is trained by Levenberg - Marquadt training method and has two generalized inputs and one output with hidden layers. The grid is first modelled and based on that model, artificial neural network is trained. The grid selected for the forecasting is the western regional grid of Power Grid Corporation of India Ltd.

Frequency forecasting is an important aspect of power system operation. The system frequency varies with load-generation imbalance. Frequency variation depends upon various parameters including system inertia. System inertia determines the rate of fall of frequency after the disturbance in the grid. Though, inertia of the system is not considered while forecasting the frequency of power system during planning and operation. This leads to significant errors in forecasting. In this paper, the effect of inertia on frequency forecasting is analysed for a particular grid system. In this paper, a parameter equivalent to system inertia is introduced. This parameter is used to forecast the frequency of a typical power grid for any instant of time. The system gives appreciable result with reduced error.

LIST OF FIGURES

LIST OF GRAPHS

LIST OF TABLES

ABREVIATIONS USED

ANN	Artificial Neural Network
MLP	Multi-layer Perceptron
BPA	Back Propagation Algorithm
PCA	Principal Component Analysis
NEM	National Electricity Market

Chapter 1

ARTIFICIAL NEURAL NETWORKS

What are ANNs?

Why do we use ANN?

History of ANN

Benefits of ANN

Biological Model

WHAT ARE ANNs?

Work on artificial neural network has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear and parallel information processing system. It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations many times faster than the fastest digital computer in existence today. The brain routinely accomplishes perceptual recognition tasks, e.g. recognizing a familiar face embedded in an unfamiliar scene, in approximately 100-200 ms, whereas tasks of much lesser complexity may take days on a conventional computer.

A neural network is a machine that is designed to model the way in which the brain performs a particular task. The network is implemented by using electronic components or is simulated in software on a digital computer. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:

1. Knowledge is acquired by the network from its environment through a learning process.
2. Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective.

WHY DO WE USE NEURAL NETWORKS?

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

Other advantages include:

1. Adaptive learning**:** An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization**:** An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation**:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

HISTORY OF ANN

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback in several eras.

Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding.

The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much.

BENEFITS OF ANN

1. They are extremely powerful computational devices.
2. Massive parallelism makes them very efficient.
3. They can learn and generalize from training data – so there is no need for enormous feats of programming.
3. They are particularly fault tolerant – this is equivalent to the "graceful degradation" found in biological systems.
4. They are very noise tolerant – so they can cope with situations where normal symbolic systems would have difficulty.
5. In principle, they can do anything a symbolic/logic system can do, and more

.

BIOLOGICAL MODEL

The human nervous system can be broken down into three stages that may be represented as follows:

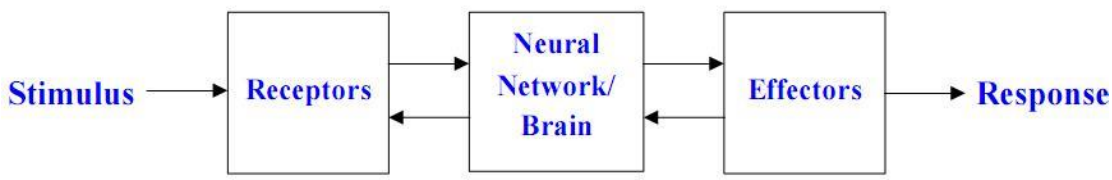


Fig 1.1 Block Diagram of a Human Nervous System.

The receptors collect information from the environment. The effectors generate interactions with the environment e.g. activate muscles. The flow of information/activation is represented by arrows.

There is a hierarchy of interwoven levels of organisation:

1. Molecules and Ions
2. Synapses
3. Neuronal microcircuits
4. dendritic trees
5. Neurons
6. Local circuits
7. Inter-regional circuits
8. Central nervous system

There are approximately 10 billion neurons in the human cortex. Each biological neuron is connected to several thousands of other neurons. The typical operating speed of biological neurons is measured in milliseconds.

The majority of neurons encode their activations or outputs as a series of brief electrical pulses. The neuron‟s cell body processes the incoming activations and converts the into output activations. The neurons nucleus contains the genetic material in the form of DNA. This exists in most types of cells. Dendrites are fibres which emanate from the cell body and provide the receptive zones that receive activation from other neurons. Axons are fibres acting as transmission lines that send activation to other neurons. The junctions that allow signal transmission between axons and dendrites are called synapses. The process of transmission is by diffusion of chemicals called neurotransmitters across the synaptic cleft.

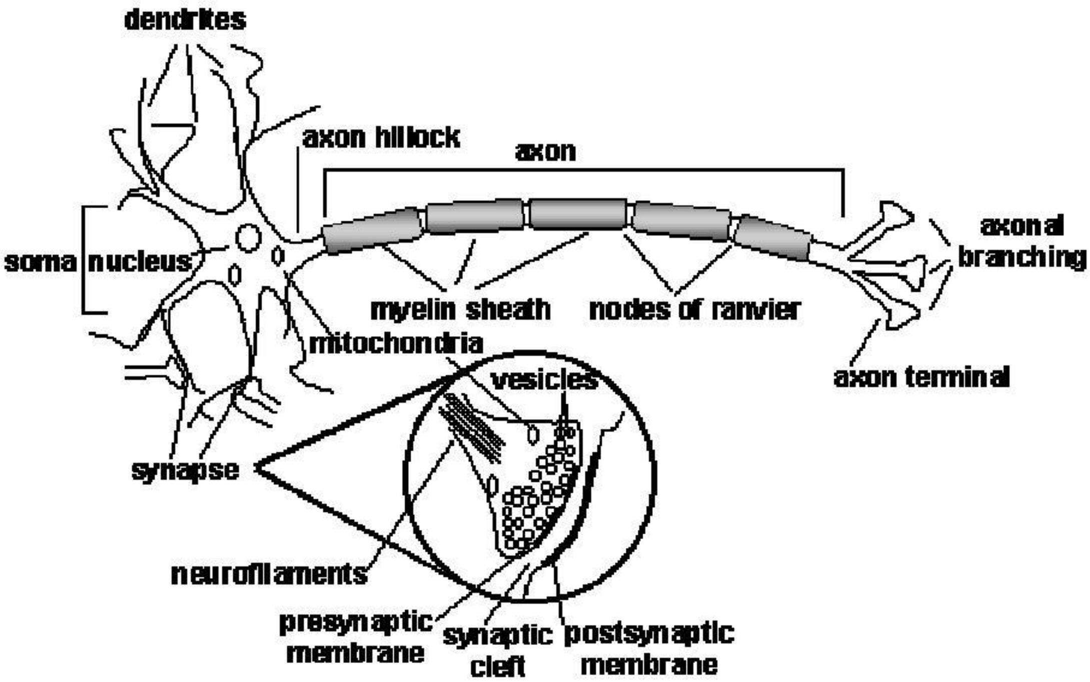


Fig 1.2 Schematic diagram of a Biological Neuron

Chapter 2

STRUCTURE OF ANN

Mathematical Model of a Neuron

Network Architecture

Learning Process

MATHEMATICAL MODEL OF A NEURON

A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are:

1. A set of weights, each of which is characterized by a strength of its own. A signal x_j connected to neuron k is multiplied by the weight w_{kj}. The weight of an artificial neuron may lie in a range that includes negative as well as positive values.
2. An adder for summing the input signals, weighted by the respective weights of the neuron.
3. An activation function for limiting the amplitude of the output of a neuron. It is also referred to as squashing function which squashes the amplitude range of the output signal to some finite value.

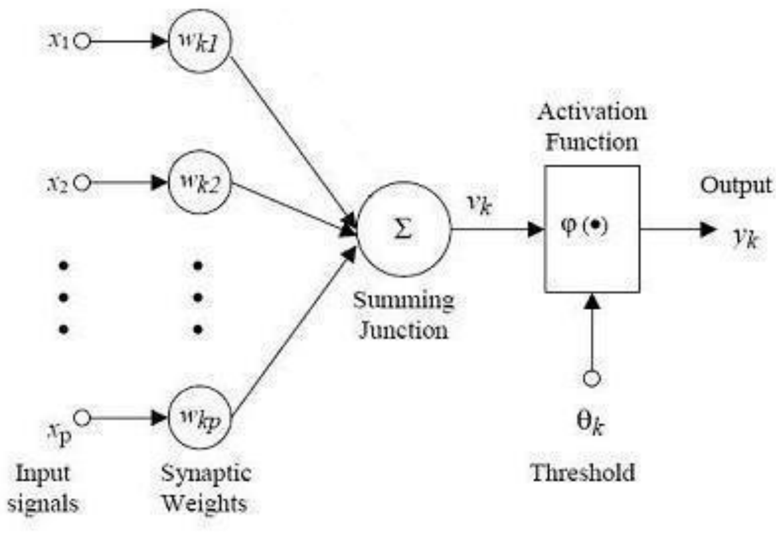


Fig 2.1 Model of an ANN

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \tag{2.1}$$

and

$$y_k = \varphi(v_k + \theta_k) \tag{2.2}$$

NETWORK ARCHITECTURES

There are three fundamental different classes of network architectures [5]:

1) Single-layer Feedforward Networks

   In a layered neural network the neurons are organized in the form of layers. In the simplest form of a layered network, we have an input layer of source nodes that projects onto an output layer of neurons, but not vice versa. This network is strictly a Feedforward type. In single-layer network, there is only one input and one output layer. Input layer is not counted as a layer since no mathematical calculations take place at this layer.

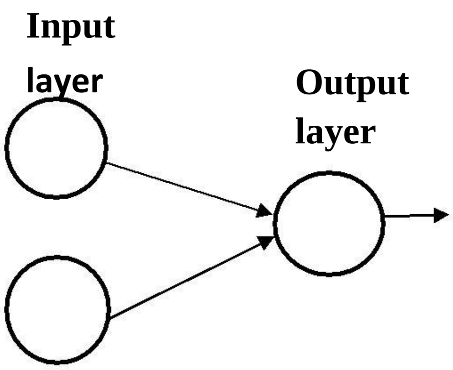


Fig 2.2 Single-layer Feedforward Network

2) Multilayer Feedforward Networks

The second class of a Feedforward neural network distinguishes itself by the presence of one or more hidden layers, whose computational nodes are correspondingly called hidden neurons. The function of hidden neuron is to intervene between the external input and the network output in some useful manner. By adding more hidden layers, the network is enabled to extract higher order statistics. The input signal is applied to the neurons in the second layer. The output signal of second layer is used as inputs to the third layer, and so on for the rest of the network.

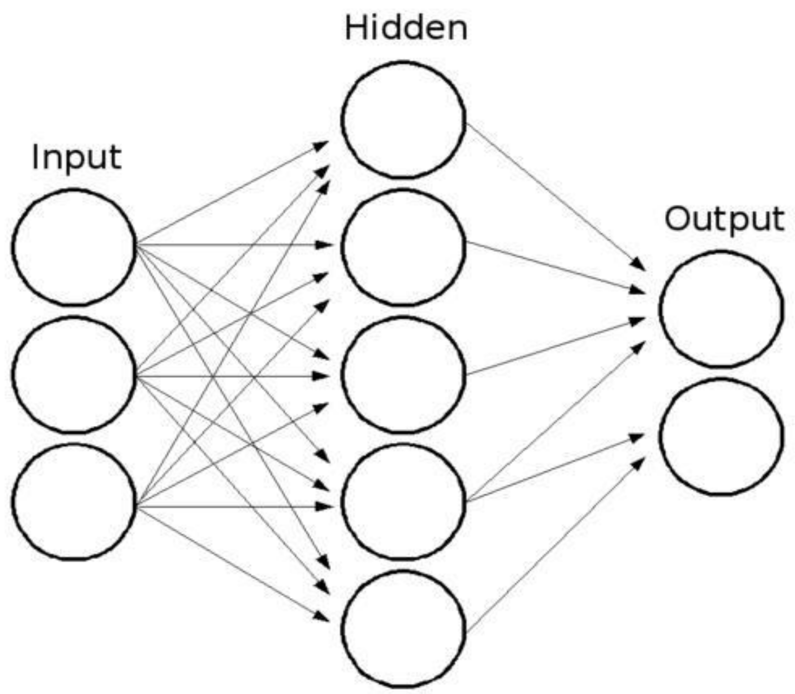


Fig 2.3 Multi-layer Feedforward Network

3) Recurrent networks

A recurrent neural network has at least one feedback loop. A recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Self-feedback refers to a situation where the output of a neuron is fed back into its own input. The presence of feedback loops has a profound impact on the learning capability of the network and on its performance.

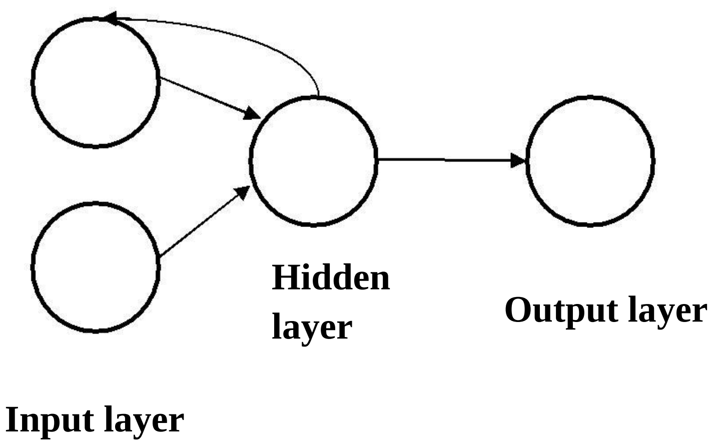


Fig 2.4 Recurrent Network

LEARNING PROCESSES

By learning rule we mean a procedure for modifying the weights and biases of a network. The purpose of learning rule is to train the network to perform some task. They fall into three broad categories:

1. Supervised learning

   The learning rule is provided with a set of training data of proper network behavior. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

2. Reinforcement learning

   It is similar to supervised learning, except that, instead of being provided with the correct output for each network input, the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs.

3. Unsupervised learning

   The weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categorize the input patterns into a finite number of classes.

Chapter 3

BACK PROPAGATION ALGORITHM

INTRODUCTION

Multiple layer perceptrons have been applied successfully to solve some difficult diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. This algorithm is based on the error-correction learning rule. It may be viewed as a generalization of an equally popular adaptive filtering algorithm- the least mean square (LMS) algorithm.

Error back-propagation learning consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an input vector is applied to the nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the weights of the networks are all fixed. During the backward pass, the weights are all adjusted in accordance with an error correction rule. The actual response of the network is subtracted from a desired response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections. The weights are adjusted to make the actual response of the network move closer to the desired response.

A multilayer perceptron has three distinctive characteristics:

1. The model of each neuron in the network includes a nonlinear activation function. The sigmoid function is commonly used which is defined by the logistic function:

$$y = \frac{1}{1+\exp(-x)} \tag{3.1}$$

Another commonly used function is hyperbolic tangent.

$$y = \frac{1-\exp(-x)}{1+\exp(-x)} \tag{3.2}$$

The presence of nonlinearities is important because otherwise the input-output relation of the network could be reduced to that of single layer perceptron.

2. The network contains one or more layers of hidden neurons that are not part of the input or output of the network. These hidden neurons enable the network to learn complex tasks.
3. The network exhibits a high degree of connectivity. A change in the connectivity of the network requires a change in the population of their weights.

LEARNING PROCESS

To illustrate the process a three layer neural network with two inputs and one output,which is shown in the picture below, is used.

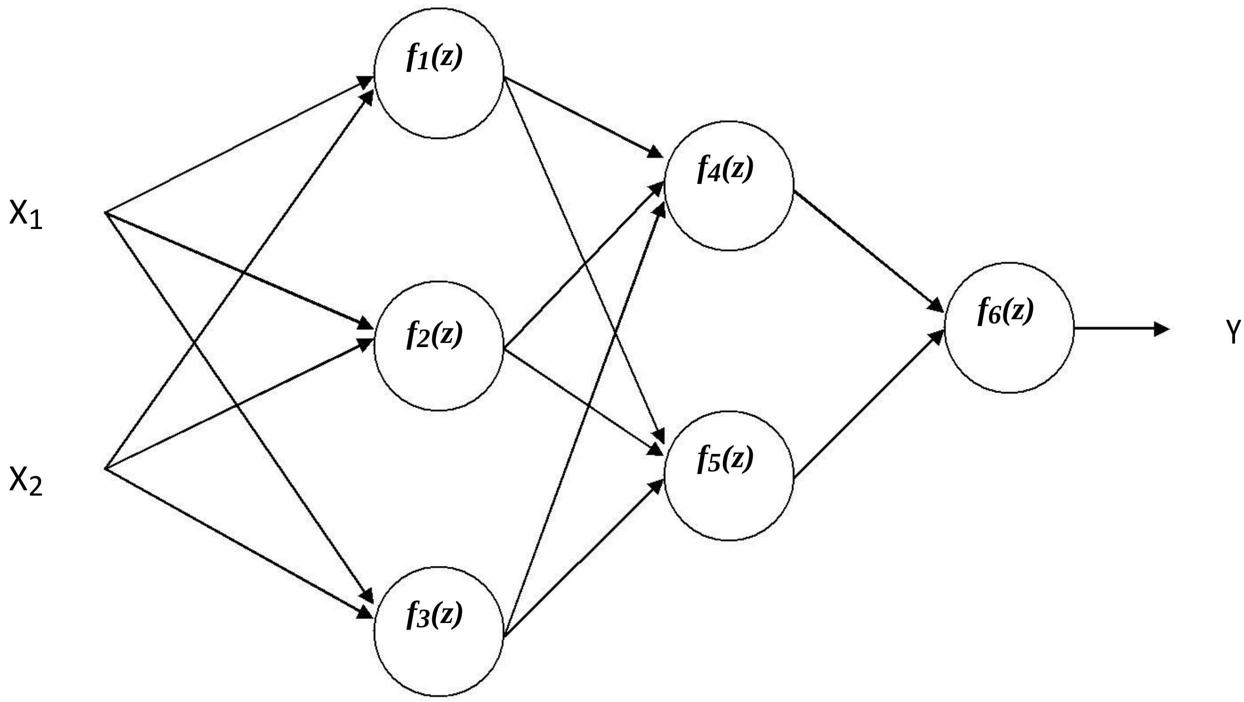


Fig 3.1 Three layer neural network with two inputs and single output

Signal z is adder output signal, and $y = f(z)$ is output signal of nonlinear element. Signal y is also output signal of neuron. The training data set consists of input signals (x_1 and x_2) assigned with corresponding target (desired output) y'. The network training is an iterative process. In each iteration weights coefficients of nodes are modified using new data from training data set. Symbols w_{mn} represent weights of connections between output of neuron m and input of neuron n in the next layer. Symbols y_n represents output signal of neuron n.

$$y_1 = f_1(w_{11} x_1 + w_{21} x_2) \quad (3.3)$$

$$y_2 = f_2(w_{12} x_1 + w_{22} x_2) \quad (3.4)$$

$$y_3 = f_3(w_{13} x_1 + w_{23} x_2) \quad (3.5)$$

$$y_4 = f_4(w_{14} y_1 + w_{24} y_2 + w_{34} y_3) \quad (3.6)$$

$$y_5 = f_5(w_{15} y_1 + w_{25} y_2 + w_{35} y_3) \quad (3.7)$$

$$y_6 = f_6(w_{46} y_4 + w_{56} y_5) \quad (3.8)$$

The desired output value (the target), which is found in training data set. The difference is called error signal δ of output layer neuron.

$$\delta = y'' - y \quad (3.9)$$

$$\delta_4 = w_{46} \delta \quad (3.10)$$

$$\delta_5 = w_{56} \delta \quad (3.11)$$

$$\delta_3 = w_{34} \delta_4 + w_{35} \delta_5 \quad (3.12)$$

$$\delta_2 = w_{24} \delta_4 + w_{25} \delta_5 \quad (3.13)$$

$$\delta_1 = w_{14}\,\delta_4 + w_{15}\,\delta_5 \tag{3.14}$$

When the error signal for each neuron is computed, the weights coefficients of each neuron input node may be modified. In formulas below *df(z)/dz* represents derivative of neuron activation function.

The correction $w_{ij}(n)$ applied to the weight connecting neuron *j* to neuron *i* is defined by the delta rule:

Weight correction = learning rate parameter*local gradient*i/p signal of neuron *i*

$$\Delta w_{ij}(n) = \eta \,.\, \delta_i(n) \,.\, y_j(n) \tag{3.15}$$

The local gradient $\delta_i(n)$ depends on whether neuron i is an output node or a hidden node:

1. If neuron *i* is an output node, $\delta_i(n)$ equals the product of the derivative $df_i(z)/dz$ and the error signal $e_i(n)$, both of which are associated with neuron i.
2. If neuron *j* is a hidden node, $\delta_i(n)$ equals the product of the associated derivative $df_i(z)/dz$ and the weighted sum of the *δs* computed for the neurons in the next hidden or output layer that are connected to neuron *j*.

FLOW CHART

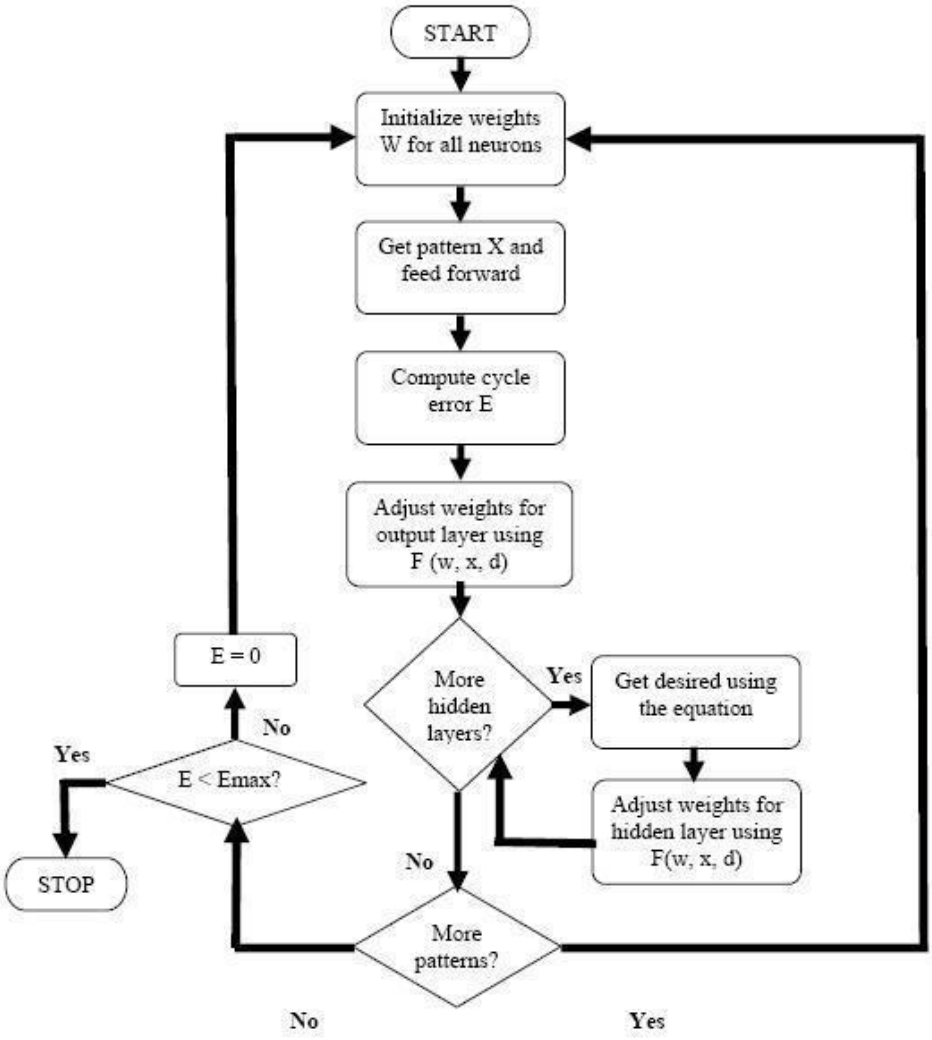


Fig 3.2 Flowchart showing working of BPA

Chapter 4

FUNCTION APPROXIMATION

What is Function Approximation?

Approximation of a Linear Function

Approximation of a Sinc Function

WHAT IS FUNCTION APPROXIMATION?

Function approximation takes examples from a desired function (e.g., a value function) and attempts to generalize from them to construct an approximation of the entire function. Function approximation is an instance of *supervised learning*, the primary topic studied in machine learning, artificial neural networks, pattern recognition, and statistical curve fitting. In principle, any of the methods studied in these fields can be used in reinforcement learning.

The need for function approximations arises in many branches of applied mathematics, and computer science in particular. In general, a function approximation problem asks us to select a function among a well-defined class that closely matches ("approximates") a target function in a task-specific way.

One can distinguish two major classes of function approximation problems: First, for known target functions approximation theory is the branch of numerical analysis that investigates how certain known functions (for example, special functions) can be approximated by a specific class of functions (for example, polynomials or rational functions) that often have desirable properties (inexpensive computation, continuity, integral and limit values, etc.).

Second, the target function, call it g, may be unknown; instead of an explicit formula, only a set of points of the form $(x, g(x))$ is provided. Depending on the structure of the domain and codomain of g, several techniques for approximating g may be applicable. For example, if g is an operation on the real numbers, techniques of interpolation, extrapolation, can be used

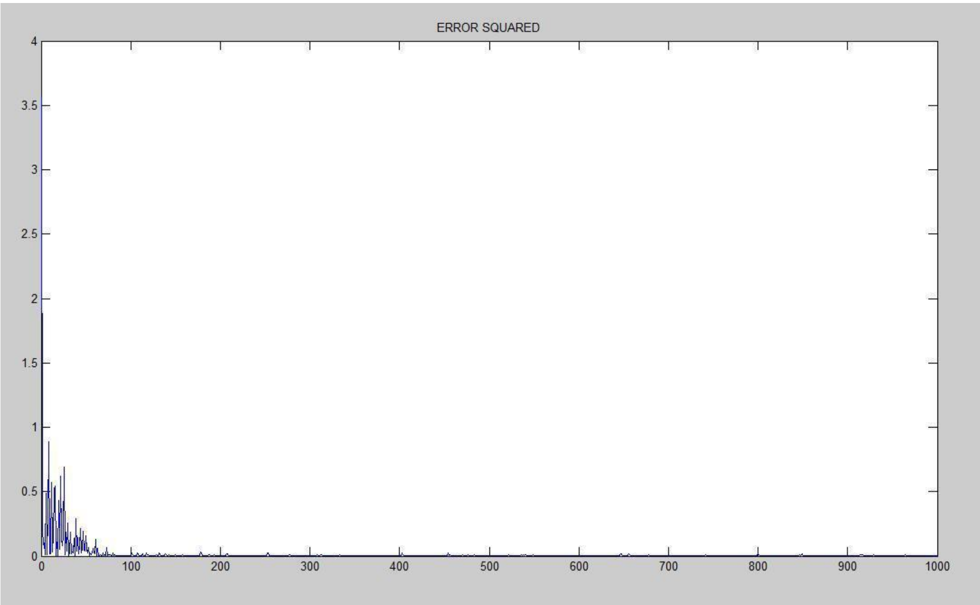
APPROXIMATION OF A LINEAR FUNCTION

The linear function taken was:

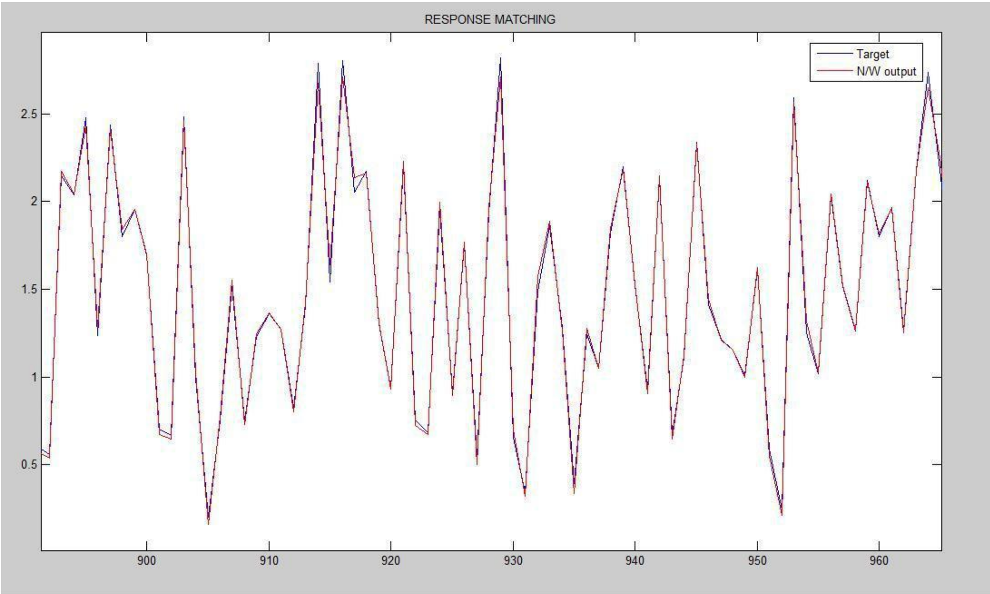
$$Y = 2X_1 + X_2 \tag{4.1}$$

The network used was a Multi-layer Perceptron (MLP) network with a single hidden layer consisting of 6 neurons. The activation function for the hidden layer was “tan-sigmoid” while that of the output layer was “pure-linear”. We used a learning rate of 0.01.

The results obtained are shown below:



Graph 4.1 Error Squared graph of Linear Function



Graph 4.2 Response Matching of Linear Function

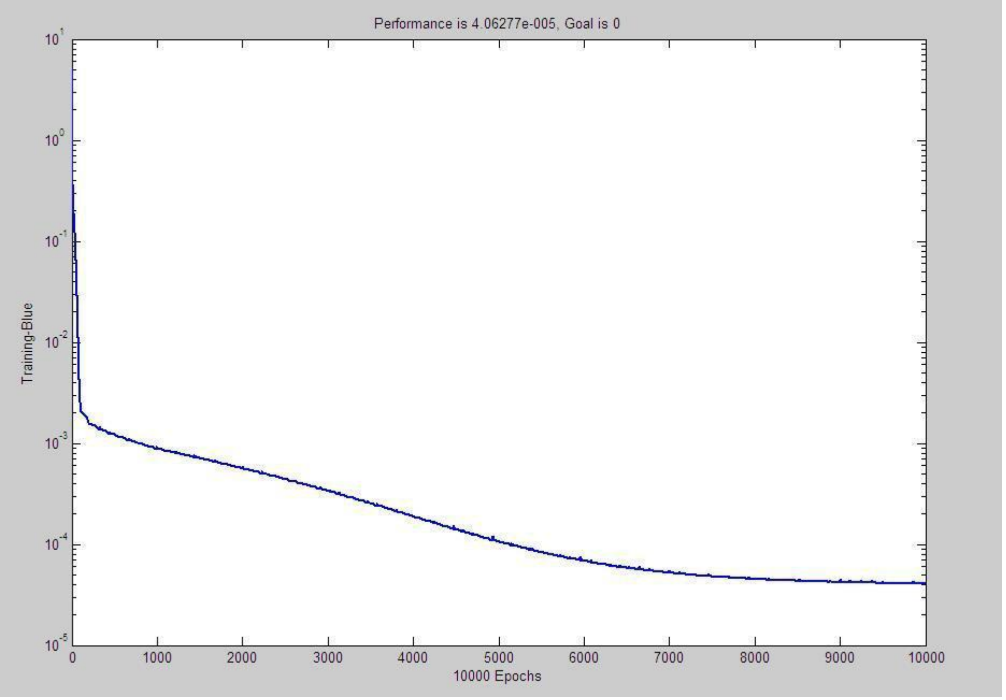
APPROXIMATION OF A SINC FUNCTION

The sinc function is defined by:

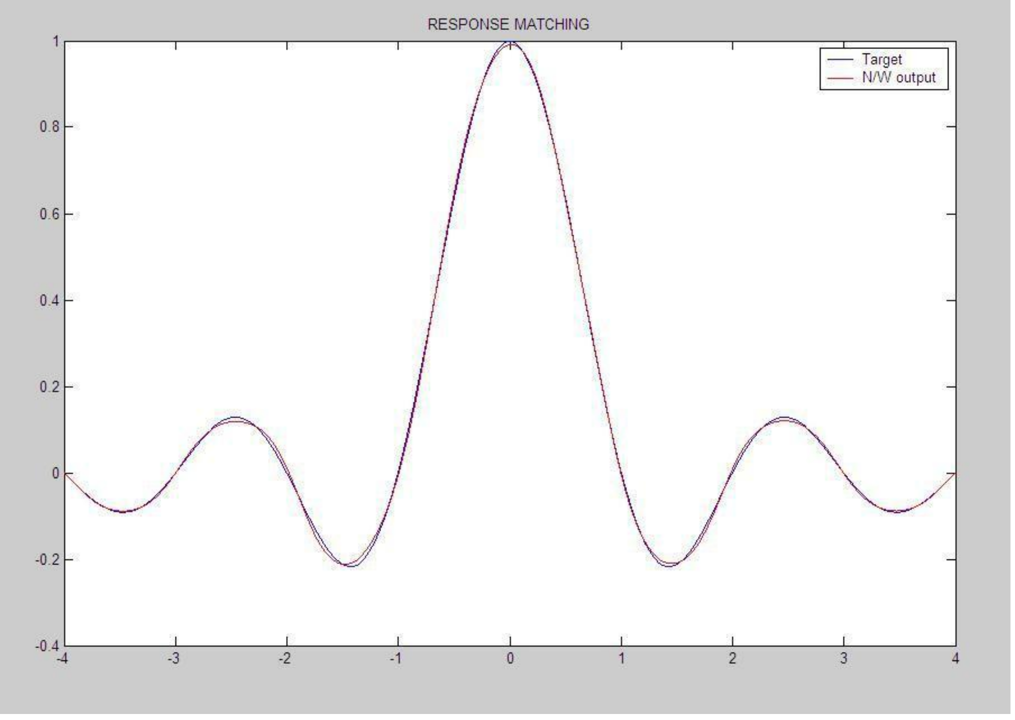
Sinc x = Sin(π x)/π x (4.2)

The network used was a Multi-layer Perceptron (MLP) network with a single hidden layer consisting of 11 neurons. The activation function for the hidden layer was “log-sigmoid” while that of the output layer was “pure-linear”. We used a learning rate of 0.069

The results obtained are shown below:



Graph 4.3 Error Square graph of Sinc Function.



Graph 4.4 Response matching of the Sinc Function.

Chapter 5

FREQUENCY FORECASTING USING ANN

Frequency Forecasting

Approach

ANN Model

Data Recording System

Flowchart

Program

FREQUENCY FORECASTING

A planning tool that helps management in its attempts to cope up with the uncertainity of the future relying mainly data from the past and present analysis of trends is termed as Forecasting .forecasting starts with certain assumptions based on management's experience ,knowledge & judgement. These estimates are projected into coming months or years using one or more techniques like box Jenkins models, Delphi model,exponential smoothing,moving averages,regression analysis,trend projection.Since any error in assumption will result in similar or magnified error in forecasting, the technique of sensitive analysis is used which assigns a range of values to the uncertain factors (variables).

As frequency is the major system parameter of power grid which has tremendous effect on working i.e. even if frequency reaches to 49Hz , whole power grid can fail and shut down happens.so the frequency forecasting must be a key issue for power system operation and grid security. Significant involvement of soft computing techniques like neural network and neuro-fuzzy system lead the computation of different parameter in advance for the purposes like safety, operation , expansion, risk management, market analysis etc. [1]. It is also very much important for those grids which adopted deviation settlement mechanism or unscheduled interchange mechanism for frequency stabilization. Frequency forecasting will be surely very much helping tool for this type of grids and its entities in economic point of view.

Following are the causes of frequency disturbance in grid:

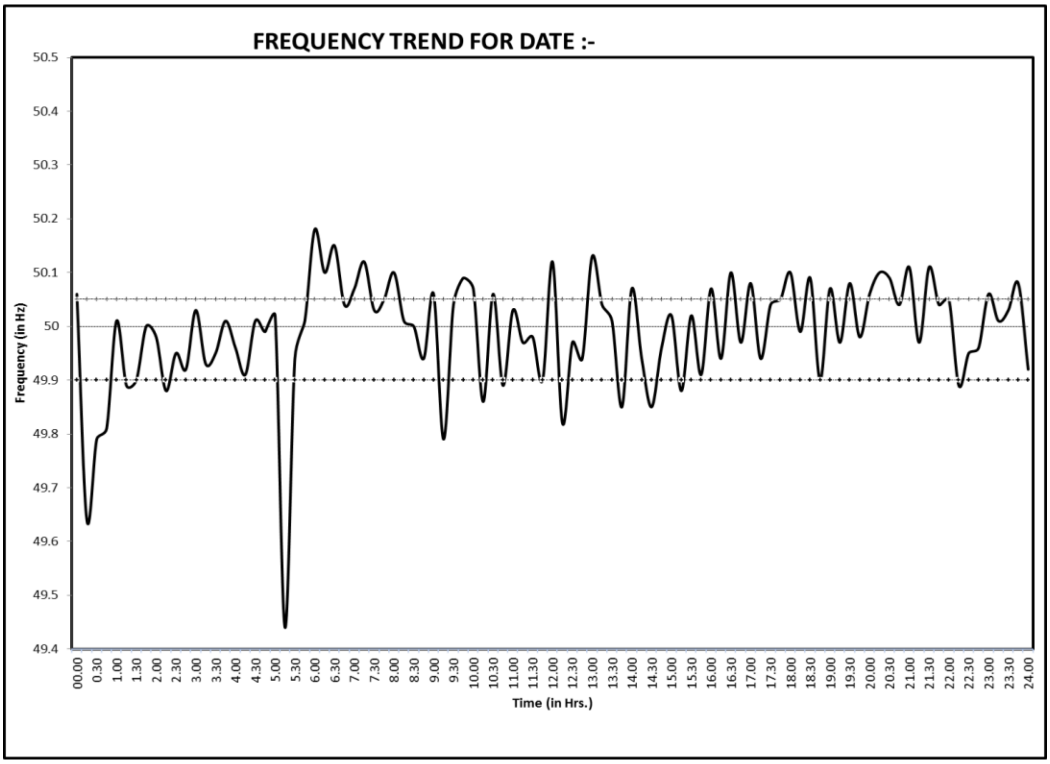
- Fast and random switching of load [4]
- Transients in steam inlet and prime-mover rotational transients. [5]
- Contingencies (loss of load block or generating block) [5]
- Power harmonics in grid due to various types of load(mainly non-linear loads)

This paper deals with the main and continuously observed reason of frequency disturbance i.e. fast and random switching of load as well as steam inlet transient that causes transient in prime mover rotational speed.

APPROACH

In this approach, frequency of grid is considered to be purely time independent and generators connected directly to grid have same inertial constant. In a single alternator system, the frequency response can be obtained from its prime-mover characteristics which shows that as load (MW) increases, the prime-mover slows down and hence frequency of alternator decreases. Similarly, for ideal infinite bus systems, the frequency is strictly constant and independent of the load But the practical power system is neither belongs to first case nor to second case but belongs in between the two.

A typical frequency characteristics/profile of an Indian utility system is shown in Fig. 5. This grid has allowable frequency deviation band of 0.15 Hz and since the bandwidth for frequency is very low and deviation from its fixed value (in this case 50Hz) of order 1-2% is very critical and may lead to grid failure.



Graph 5.1 Frequency response on random day

ANN Model

As earlier declared that frequency is considered as time independent, hence there will be no time component input to ANN. The value of input vector [V] can be easily forecasted using load forecasting techniques and Prg can be taken from scheduling chart of generators.

Since forecasting of frequency requires forecasting of load first, it is independent of the type of model designed for specific period of forecast [9]. For example, if load forecasting is done for entire 24 hours, frequency profile can be forecasted and if load forecasting system is designed to forecast next minute load, next minute frequency can be estimated [8]. Hence, using this forecasting system any type of forecast can be attempted that is from next minute frequency to 24 hour profile. Since various methods and techniques are already available to make load forecast it would be very easy to use load forecasting system and already power industries use them for scheduling there generators [10].

The typical indian grid has allowable frequency deviation band of 0.15 Hz and since the bandwidth for frequency is very low and deviation from its fixed value (in this case 50Hz) of order 1-2% is very critical and may lead to grid failure. So, first difficulty in forecasting the grid frequency is its accuracy, as the bandwidth itself is very small so the forecasting accuracy must be very high (more than 94%).

Second difficulty encountered in frequency forecasting is its very random characteristics and time independence. Although, the mutual disturbance is considered as zero in this project, which is caused by grid connected by corridor of that grid whose frequency is to be forecasted.

So, due to this fast and random switching, the frequency will not be a linear function of load for alternator and not be a linear function of chock power for grid. Switching and prime-mover transients make the frequency characteristics to be non-linear. As we know the powerful tool to analyse any non-linear function is Artificial Neural Network, so in this paper this technique is discussed to make frequency forecasting.

To make frequency forecasting, entire grid needs to be converted into model form as shown in Fig.4 , the given grid model is developed based on assumption that frequency is time independent & only fast switching is the major cause in change of frequency in system

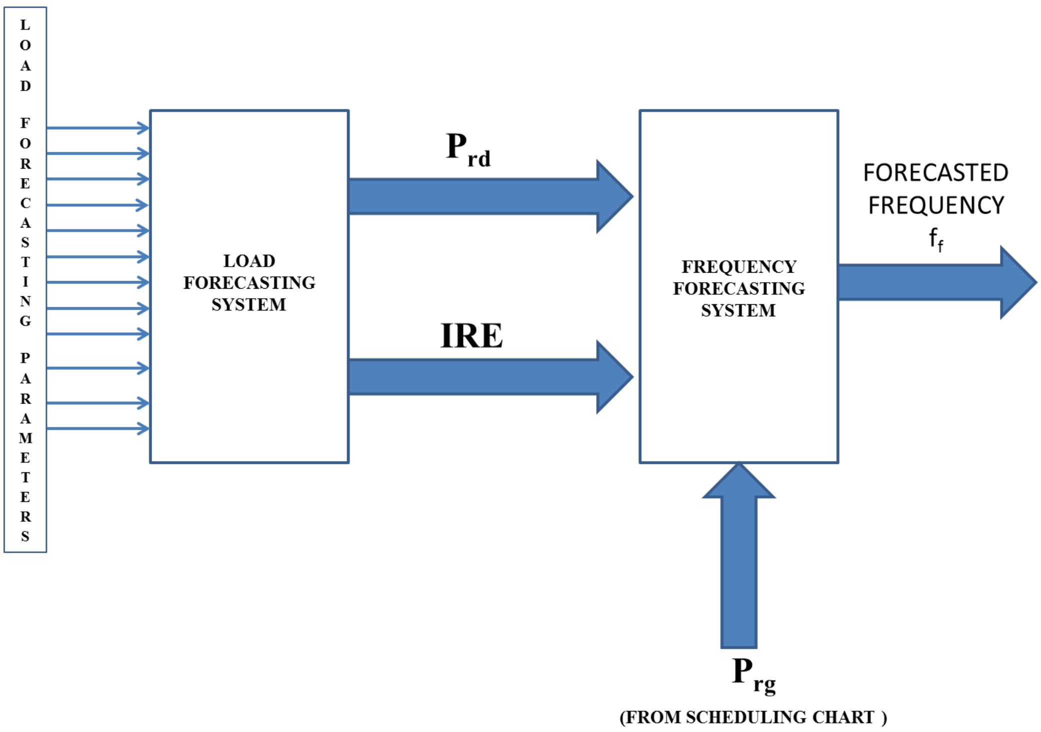


Fig 5.1 Frequency Forecasting System Complete Structure

The ANN was implemented using MATLAB 7. The recorded data set is used to train Backpropagation feed-forward network using MATLAB NEURAL NETWORK TOOLBOX. The training rule used is Levenberg-Marquat.

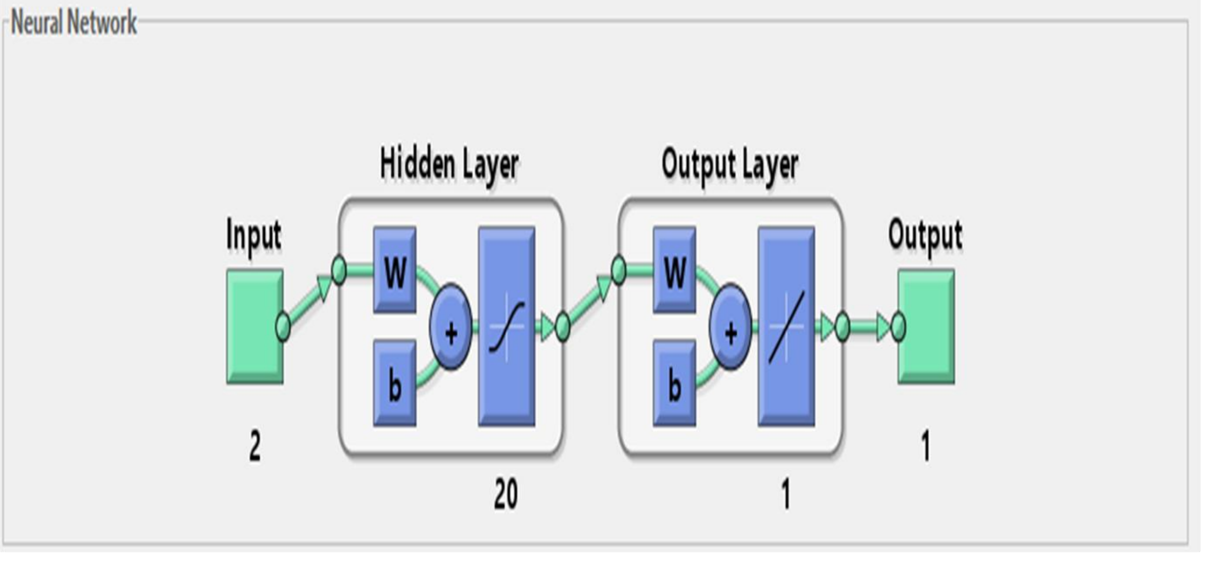


Fig 5.2 Network Structure for frequency Forecasting

Data Recording System

The data employed for training and testing the neural network were obtained from the Wrldc website for the period septemember 2016.

The forecast is performed on the western regional grid of PGCIL, India considering it to be central grid. Data are recorded from 1’st SEP 2016 in every minute to record about 5000 training sets for ANN, which is further divided into *training, validation* and *testing sets* to avoid overfitting [6][7]. Central grid considered for forecast is one of the 5 regional grids of India with all regions connected via inter-regional corridor. This grid has 7 regional entities (Gujrat, Madhya-Pradesh, Chhattisgarh, Maharashtra, Goa, Daman- Diu, and Dadra Nagar Haveli).

Desired features of Data Recording System are:-

- Should be capable of handling large data sets
- Should connect to source server automatically
- Should have timing arrangement & easy control
- Should filter the data easily
- Should process the data effeciently

Use of Macro

To record data from every minute , we have used MACRO RECORDER in MS EXCEL The MACRO RECODER, a very useful tool included in Excel VBA, records every task you perform with Excel. All you have to do is record a specific task once. Next, you can execute the task over and over with the click of a button. The Macro Recorder is also a great help when you don't know how to program a specific task in Excel VBA. Simply open the Visual Basic Editor after recording the task to see how it can be programmed.It almost completes all the basic requirement for the satisfactory working in our project .

Fig 5.3 Wrldc website with data of demand & generation

FLOWCHART

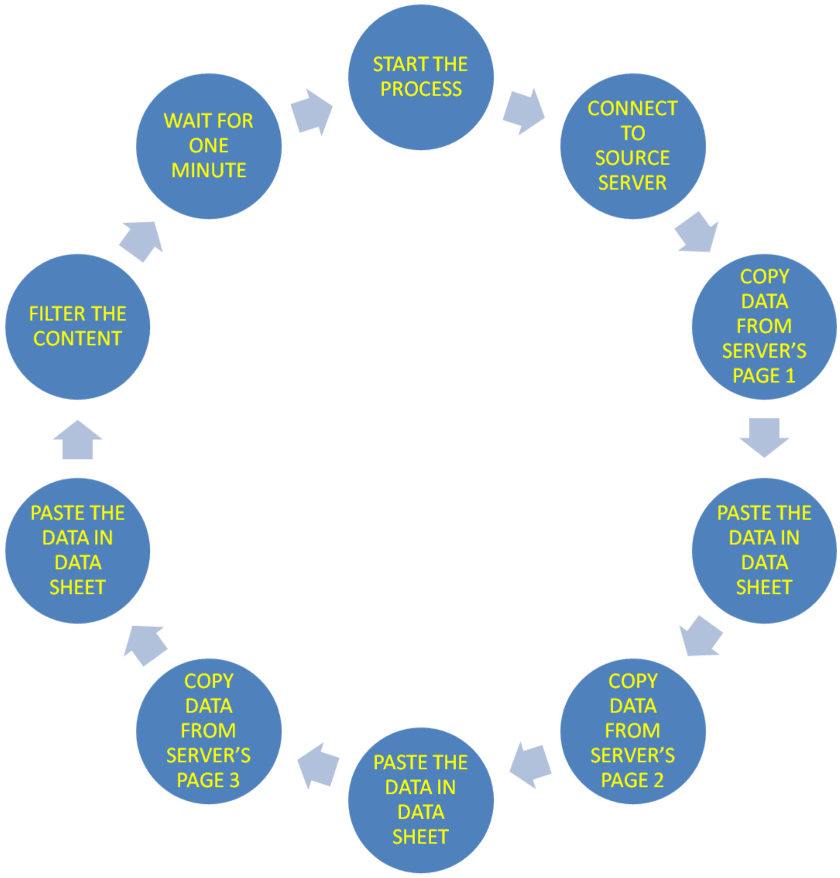


Fig 5.4 Data Recording System

PROGRAM USED

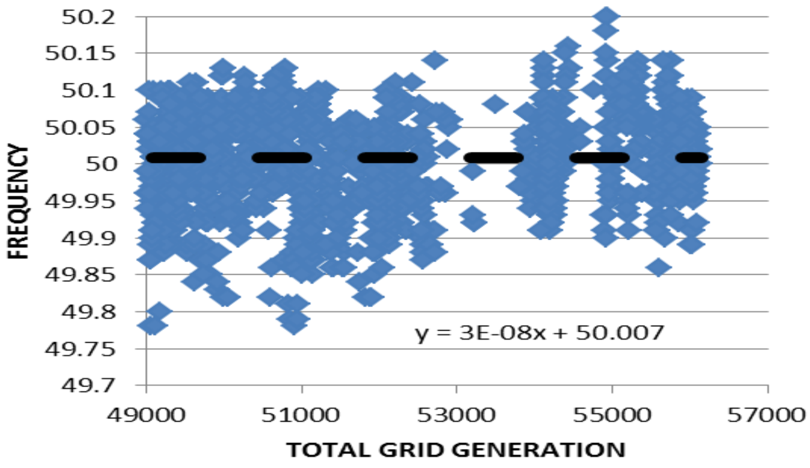
In Excel file we coded following:-

```
Sub wrldc()
'
' wrldc Macro
'

'
Do
    With ActiveSheet.QueryTables.Add(Connection:= _
        "URL;http://www.wrldc.in/onlinestate.aspx", Destination:=Range("$A$1"))
        .Name = "onlinestate"
        .FieldNames = True
        .RowNumbers = False
        .FillAdjacentFormulas = False
        .PreserveFormatting = True
        .RefreshOnFileOpen = False
```

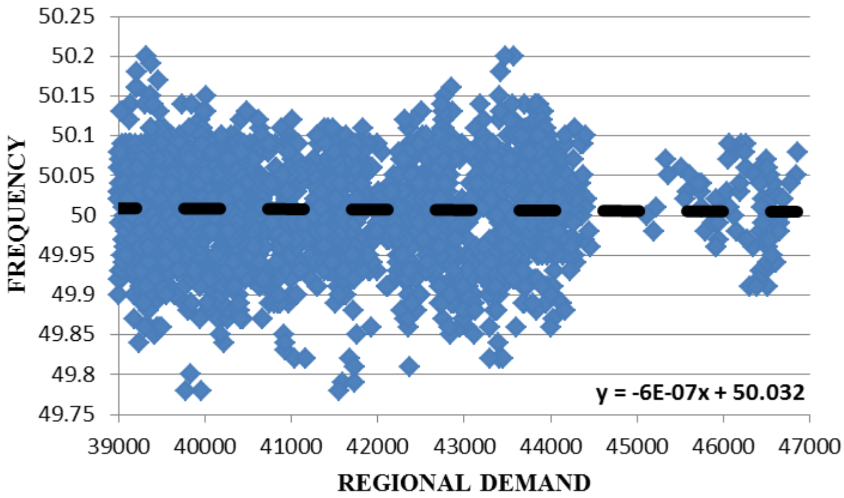
```
     BackgroundQuery = False
    .RefreshStyle = xlInsertDeleteCells
    .SavePassword = False
    .SaveData = True
    .AdjustColumnWidth = True
    .RefreshPeriod = 0
    .WebSelectionType = xlSpecifiedTables
    .WebFormatting = xlWebFormattingNone
    .WebTables = "184,""Table1"""
    .WebPreFormattedTextToColumns = True
    .WebConsecutiveDelimitersAsOne = True
    .WebSingleBlockTextImport = False
    .WebDisableDateRecognition = False
    .WebDisableRedirections = False
    .Refresh BackgroundQuery:=False
End With
Columns("A:A").ColumnWidth = 6.14
Range("A16:B16").Select
With Selection
    .HorizontalAlignment = xlCenter
    .VerticalAlignment = xlBottom
    .WrapText = False
    .Orientation = 0
    .AddIndent = False
    .IndentLevel = 0
    .ShrinkToFit = False
    .ReadingOrder = xlContext
    .MergeCells = False
End With
Selection.Merge
ActiveCell.FormulaR1C1 = "total"
Range("C16").Select
ActiveCell.FormulaR1C1 = "=SUM(R[-7]C:R[-1]C)"
Range("C16").Select
Selection.AutoFill Destination:=Range("C16:G16"), Type:=xlFillDefault
Range("C16:G16").Select
Range("A1:G16").Select
Selection.Borders(xlDiagonalDown).LineStyle = xlNone
Selection.Borders(xlDiagonalUp).LineStyle = xlNone
With Selection.Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ColorIndex = 0
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Selection.Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ColorIndex = 0
    .TintAndShade = 0
    .Weight = xlMedium
```

```
     End With
    With Selection.Borders(xlEdgeBottom)
        .LineStyle = xlContinuous
        .ColorIndex = 0


.TintAndShade = 0
        .Weight = xlMedium
    End With
    With Selection.Borders(xlEdgeRight)
        .LineStyle = xlContinuous
        .ColorIndex = 0
        .TintAndShade = 0
        .Weight = xlMedium
    End With
    Selection.Borders(xlInsideVertical).LineStyle = xlNone
    Selection.Borders(xlInsideHorizontal).LineStyle = xlNone
    Range("A1").Select
Application.Wait (Now + TimeValue("00:01:00"))
Loop
End Sub
```

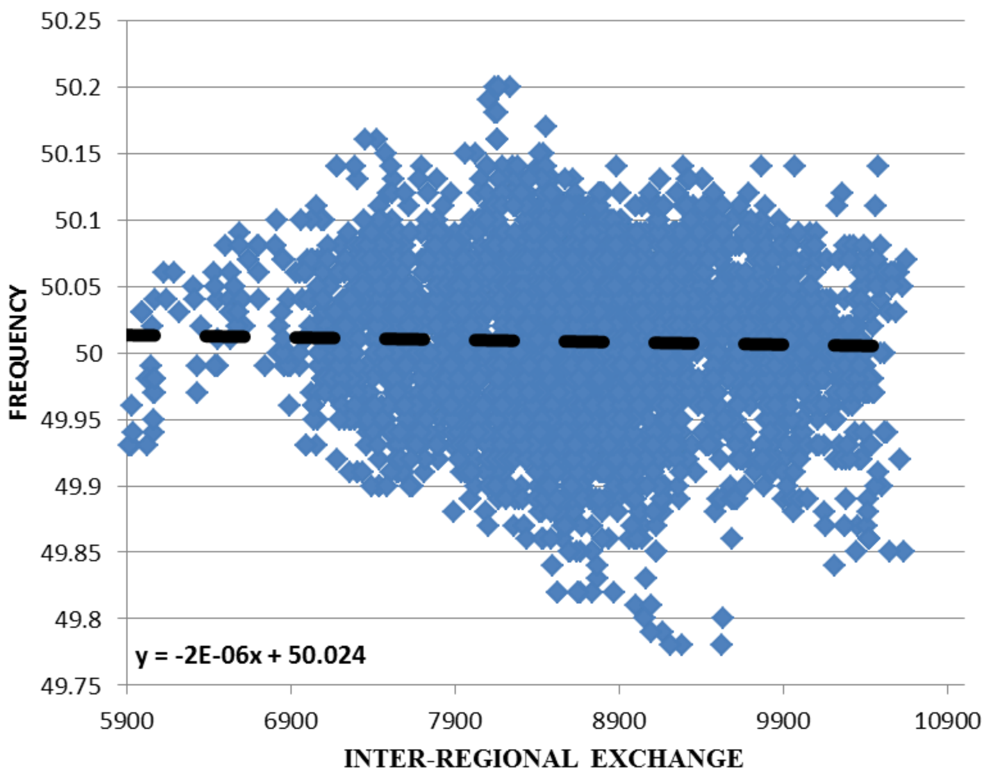
Scattered Plot Between Ann Input Parameter And Frequency



Graph 5.2 Frequency Response of Generation



Graph 5.3 Frequency Response of Demand



Graph 5.4 Frequency Response of Inter Regional Exchange

Chapter 6

EFFECT OF SYSTEM INERTIA ON FREQUENCY FORECASTING

Introduction to system inertia

Types of load & their inertia

Inertia Profile of loads

INTRODUCTION TO SYSTEM INERTIA

From the beginning of the soft computing era of system analysis and operation, lots of parameters of different systems have been forecasted and used for system planning and operation. In power system analysis, load forecasting is used for almost every system for schedule preparation on daily basis. But frequency is the most critical parameter among all the other parameters and its forecasting is equally important. The frequency decides the system's health and instantaneous operating condition in much accurate way then demand, generation and other parameters.

Frequency forecasting requires load or demand to be forecast first, so the result of frequency forecast incorporates the load forecasting errors along with frequency forecasting errors [18]. In this paper, to analyze only the frequency forecasting system, instantaneous real time frequency is forecasted. As the performance of artificial neural network (ANN) based forecasting system is subjected to training data sets [19][20]; hence every system has different outputs and errors. ANN is first trained without considering the parameter equivalent to system inertia (Hn) and then another network is trained with same training sets along with the inertia parameter (Hn). The grid is first generalized and then generation, demand and exchanges with other regions or control areas are recorded to train the system [21]. Among all the parameters over which frequency is dependent, most critical parameters are chock or lapse power within the grid [22]. Frequency deviation depends upon the system inertia. Hence, deviation in frequency is time dependent as inertia changes over the time. As the inertia of generators installed in the grid is a constant value (since the number of generators do not change for long period), so only the load inertia will affect the frequency deviation [23].

ANALYZING EFFECT OF SYSTEM INERTIA ON GRID FREQUENCY FORECASTING USING TWO STAGE NEURO FUZZY SYSTEM

TYPES OF LOAD & THEIR INERTIA

The inertia of system changes at every moment of time as a result of the random and fast switching of load. The inertia equivalent parameter cannot be determined directly by the time. But using the fuzzy logic based system, the load can be classified among domestic, industrial, commercial and agricultural [24]. The inertia depends upon percentage of this load and their profile. This percentage also depends upon weather parameters. The inertia of load changes with the percentage of load connected to the grid. Hence, inertia profile for this entire load will follow the same pattern as their load profile follows over the time. So, inertia variation for 24-hour, individual type of load profile is studied for the whole year.

TYPES OF LOAD

INERTIA OF RESISTIVE,INDUCTIVE & CAPACITIVE LOAD

Nearly all light load are resistive, motor load are inductive and electronic load are capacitive in nature. The inertia of load is not mechanical inertia but electrical inertia which is directly proportional to change in output power per unit change in frequency;

$$H = k \cdot \frac{dP}{df} \qquad (6.1)$$

Where K is constant

Using (6.1) , inertia obtained for resistive load is given by

$$P = V.I.\cos\phi \qquad (6.2)$$

$$H = 0 \qquad (6.3)$$

Similarly for inductive or motor load;

$$H = 2K.\sin^2\phi.\frac{P}{f} \qquad (6.4)$$

For capacitive or electronic load;

$$H = -2K.\mathrm{Sin}^2\phi.\frac{P}{f} \qquad (6.5)$$

Where P is power consumed, f is frequency and ø is power factor angle.

From (6.3), (6.4) and (6.5) it is clear that;

HCapacitive < HResistive < HInductive (6.6)

From (6,6), the inertia offered by inductive or motor load is highest & capacitive or electronic load is lowest. The net system inertia will be proportional to the percentage of resistive, inductive and capacitive load connected. In other words, the inertia will be proportional to the number of motor load, light load and electronic load connected [25][26][27].

In this paper, a parameter equivalent to system inertia is calculated by using two stage fuzzy inference system and this parameter changes with the system inertia [28][29][30]. The inertia obtained from practical real-time data is plotted in fig.2. The system inertia does not vary with high frequency and is constant for long duration of day [31][32][33].

INERTIA PROFILE OF LOAD TYPE

1.Inertia profile for domestic load

On a casual winter day, the load demand in India is often low as compare to the general summer day. But the load pattern is still the same irrespective of the season. That clearly suggested that the main sections of load profile curve remain same and only the amplitude changes with season, e.g. the evening peak occur for every season but their amplitude changes with the season. It should also be noted that the load profile may shift with the time i.e. if evening peak is seen in winter season at 18:00, then this peak may appear in winter at 17:00 with changed amplitude [24].

The inertia does not depend on the magnitude of the load connected to the grid but depends on the type of loading connected at that time i.e. resistive or lighting loading, inductive or motor loading and capacitive or non-ohmic loading. The domestic load in a summer season is almost inductive or motor load throughout the day except for the evening period. Similarly, for winter period, they are all lighting load and capacitive or non-ohmic load (electronic load).

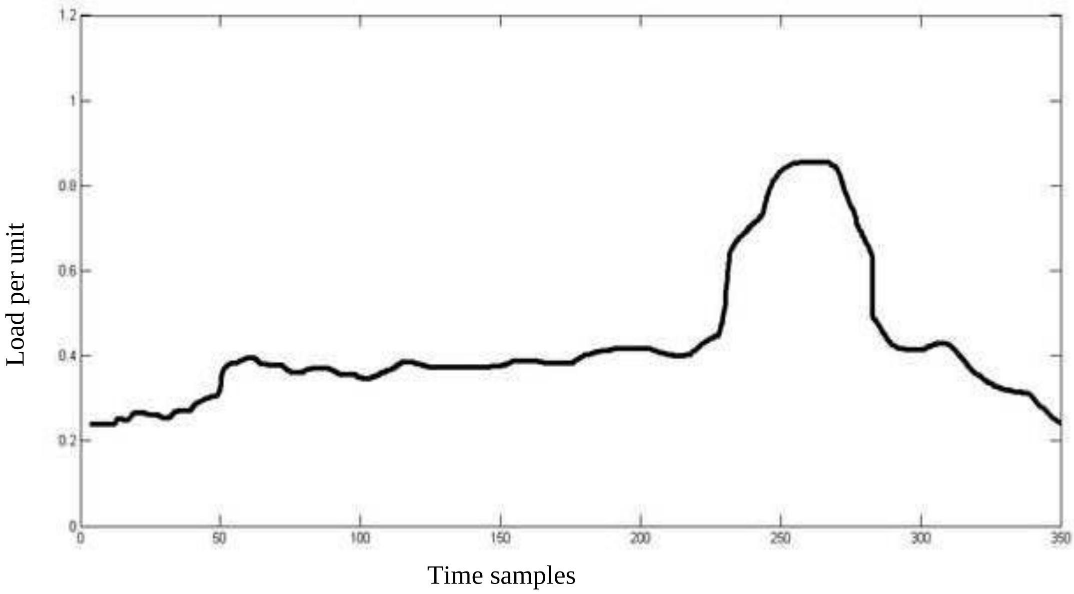


Figure 6.1 Load profile for domestic load

2. Inertia profile for industrial load

Industrial load are mainly constant and do not change with season. This classification includes big industries that work for 365 days on 24-hour basis. Hence, the load percentage throughout the day for industrial demand is constant. For the sake of easy computing, this paper assumes that change in production does not change the demand of industry. The industrial load involves mainly motor load. Also, it is assumed that only 50% of installed industrial load is connected at any time of the day because in large industries all the machines do have an auxiliary standby machine for emergency [24][26].

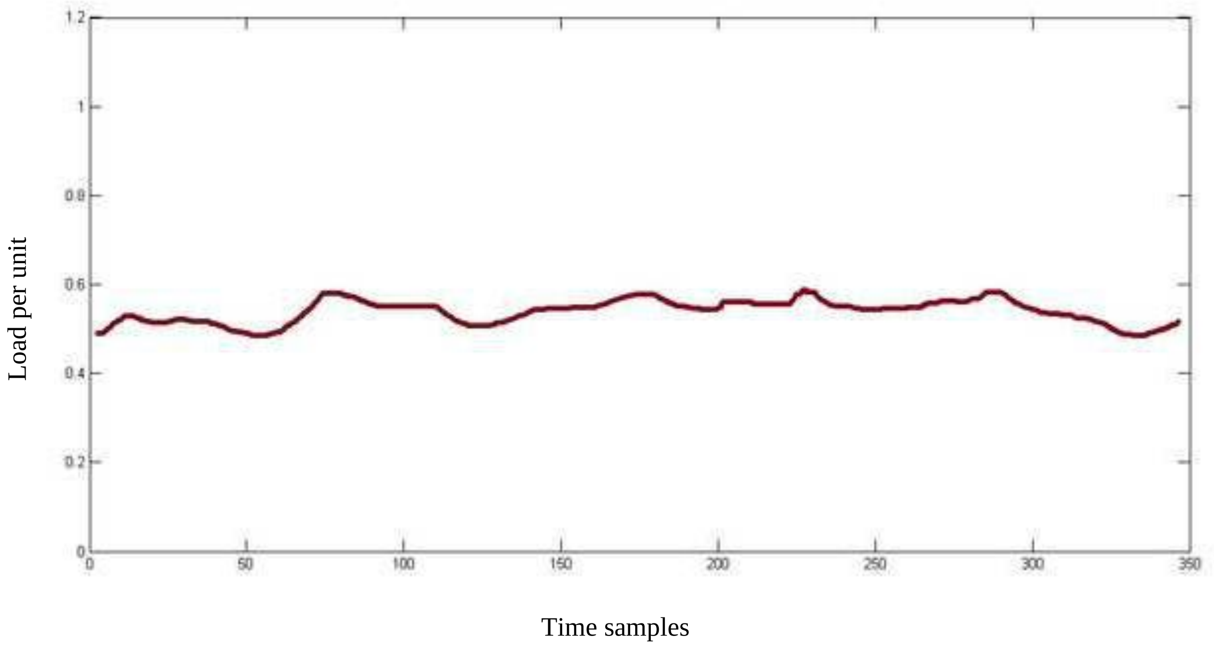


Figure 6.2 Load profile of industrial load

3. Inertia profile for commercial load

The commercial load includes all commercial shops and small industry that work on daily schedule. The load profile of commercial load is same as the domestic load with exception of peak time. Normally the commercial peak occurs after 19:00 to 22:00 whereas the domestic peak occurs in between 17:00 to 19:00. Commercial load during morning hours are mainly motor load but during peak hours, they are lighting loads and sometimes they are electronic load [24][26].

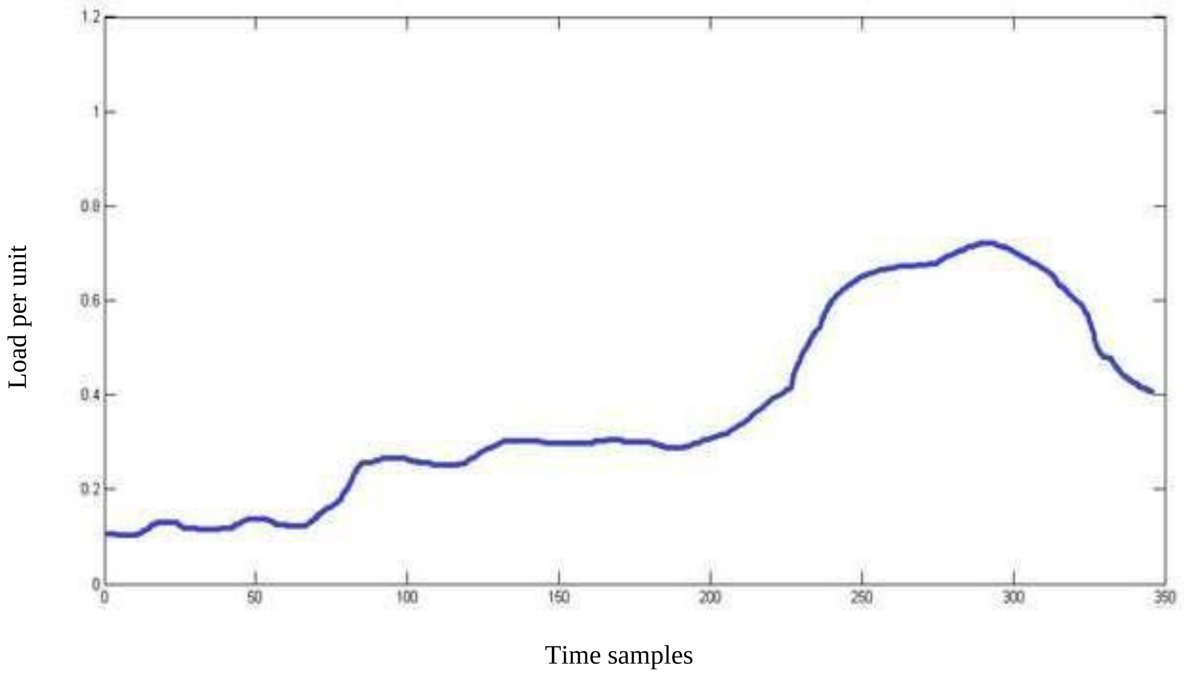


Figure 6.3 Load profile for Commercial Load

4. Inertia profile for agricultural load

Load profile for agricultural load changes for different regions and with the method of irrigation. The profile obtained for typical day of agricultural load in western part of India is shown in fig.6.5

The agricultural load starts simultaneously in night and continuous for whole night. It is disconnected from the grid in morning hours. In western part of India, agricultural supply lines are isolated from domestic supply lines. Agricultural load are highly inductive load and proportion of light load and electronic load are zero [24].

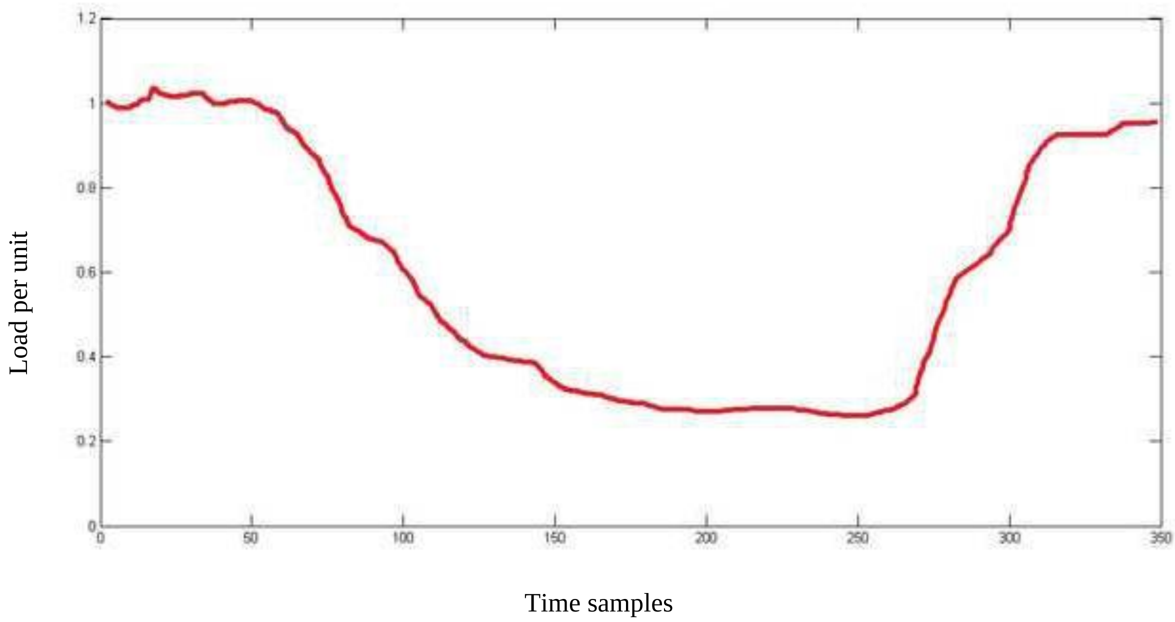


Figure 6.4 Load profile for Agricultural Load

Calculation of percentage of load types from fuzzy system

The time is divided into 96 blocks of 15 minute each. The blocks are numbered from 1 to 96. A fuzzy system is designed for each season i.e. summer, rainy, winter and spring and denoted as season equivalent (Seq). These are shown in table 6.2. The proportion of domestic, commercial, industrial and agricultural load for western region of India as per Dept. of Power and Energy, Govt. of India (2015), are shown in table 6.1.

Table 6.1 Distribution of load in Western India

S. No.	LOAD	PERCENTAGE
1.	Domestic	48%
2.	Industrial	25%
3.	Commercial	20%
4.	Agricultural	07%

Table 6.2 Duration for all linguistic variable of time for all seasons

S. No.	Linguistic Variable	Duration (Summer Seq = 1)		Duration (Rainy Seq = 2)		Duration (Winter Seq = 3)		Duration (Spring Seq = 4)	
1	Night	00:00	04:00	00:00	06:00	00:00	07:00	00:00	05:00
2	Morning	04:00	08:00	06:00	10:00	07:00	11:00	05:00	09:00
3	Afternoon	08:00	16:00	10:00	15:30	11:00	15:00	09:00	16:00
4	Evening	16:00	20:00	15:30	17:30	15:00	19:00	16:00	19:30
5	Night	20:00	24:00	17:30	24:00	19:00	24:00	19:30	24:00

INERTIA PROFILE FOR 24 HOURS

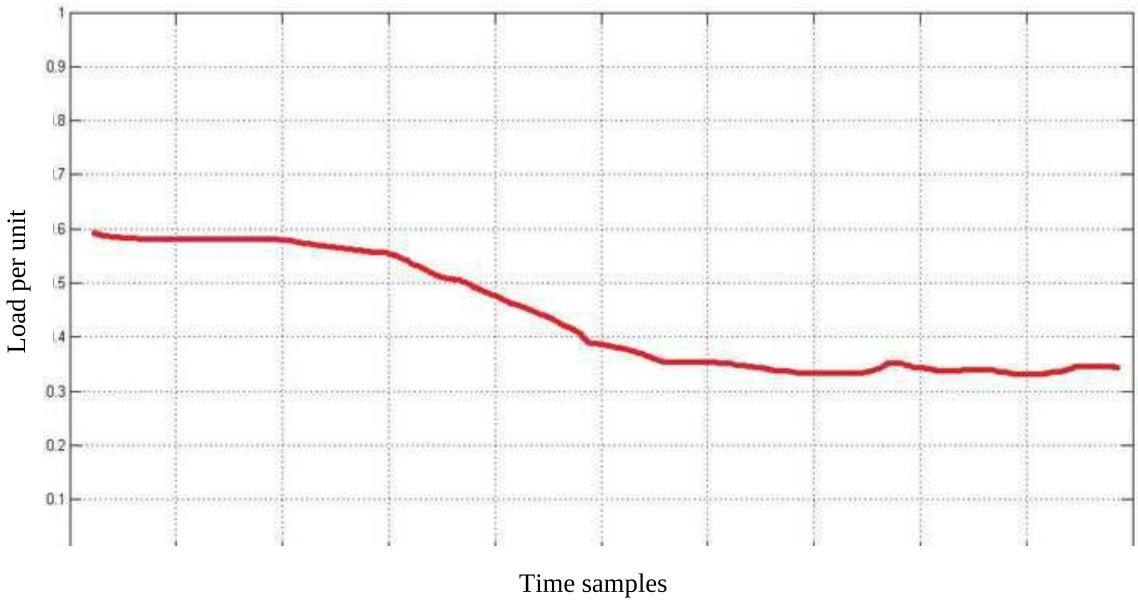


Figure 6.5 Inertia profile for 24 hour

Chapter 7

FUZZY LOGIC MODEL AND IMPLEMENTATION

Fuzzy logic systems

Neuro-Fuzzy system

Design of Fuzzy A stage

Design of Fuzzy B stage

Forecasting Algorithm

Simulation

FUZZY LOGIC SYSTEM

Fuzzy Logic Systems (FLS) produce acceptable but definite output in response to incomplete, ambiguous, distorted, or inaccurate (fuzzy) input. Fuzzy Logic (FL) is a method of reasoning that resembles human reasoning. The approach of FL imitates the way of decision making in humans that involves all intermediate possibilities between digital values YES and NO.

On an engineering level, fuzzy logic provides a platform for easily encoding human knowledge into the control of a system. Fuzzy logic is a method of characterizing knowledge in terms of fuzzy sets and a rule base. A fuzzy system has one or more inputs that are fuzzified, a rule base that is evaluated according to the inputs, and one or more outputs that are defuzzified into "crisp" values. A fuzzy system structure is illustrated in figure 7.1. Bringing fuzzy logic to control problems is a way to use a human expert's knowledge about an analog process in a digital computer.

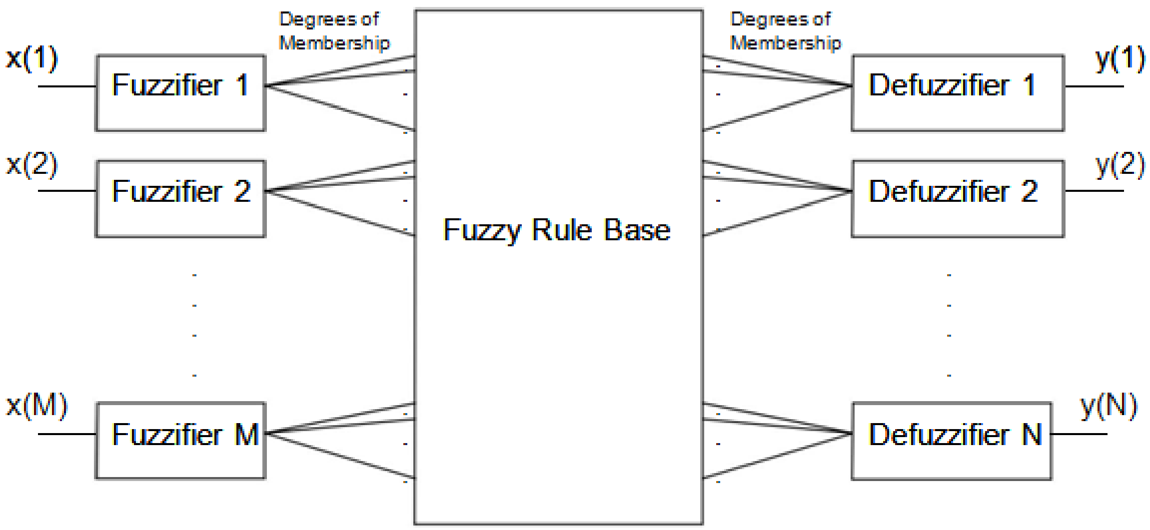


Fig. 7.1 A typical Fuzzy System

Fuzzy sets are values to which a variable can belong. Fuzzy control involves describing the control procedure in terms of subjective descriptions like "very low","low", "just right", "high", and "very high". Suppose a human were to describe the operation of an elevator. If the elevator did not stop exactly on the desired floor, he might describe the elevator's error in terms of a fuzzy variable like the one above. If the elevator stopped three feet too high, the position of the elevator would definitely be "very high". Six inches too high might just be "high." The question is, "At what height did the elevator go from just being 'high' to being 'very high'?" Fuzzy logic avoids this problem by its multivalent nature. A fuzzy variable can have a certain degree of membership to "high" and a degree of membership to "very high." Often times these fuzzy sets are graphed as shown in figure 7.2

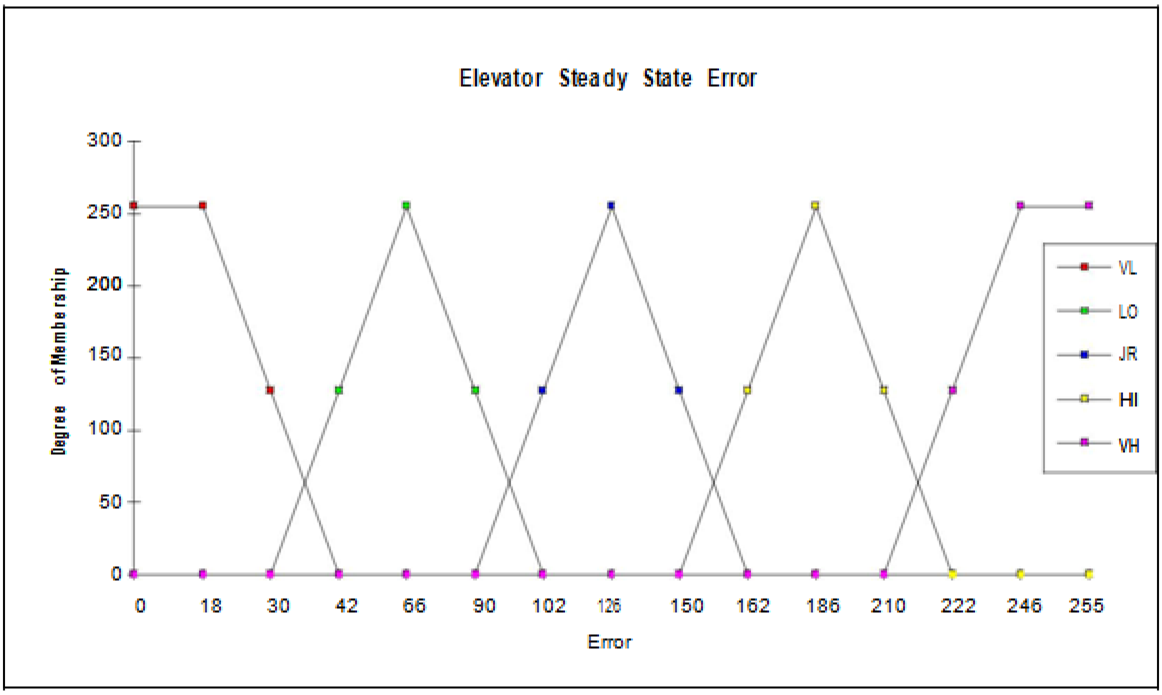


Fig. 7.2 A sample fuzzy set

NEURO-FUZZY SYSTEM

Hybrid systems combining fuzzy logic, neural networks, genetic algorithms, and expert systems are proving their effectiveness in a wide variety of realworld problems. Every intelligent technique has particular computational properties (e.g. ability to learn, explanation of decisions) that make them suited for particular problems and not for others. For example, while neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions. These limitations have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques.

Determining the fuzzy membership functions from sample data using a neural network is the most obvious method of using the two fuzzy & neural networks together. The definition of the membership function has a huge impact on the system response. Often, the programmer must use trial and error to find acceptable values.

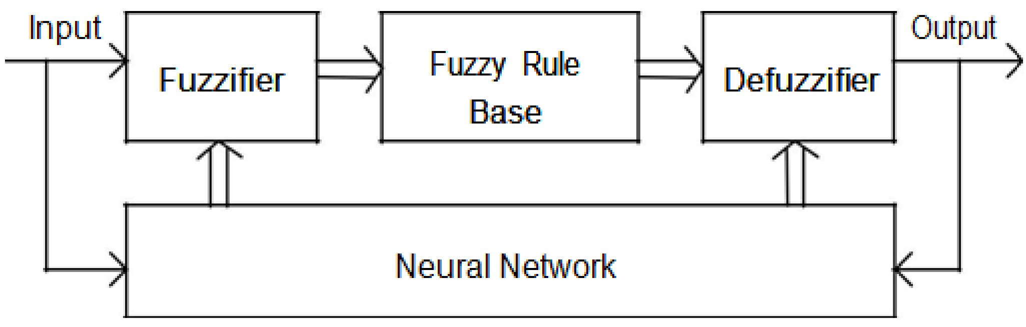


Fig. 7.3 A fuzzy system whose membership functions are adjusted by a neural network.

The idea of fuzzification of control variables into degrees of membership in fuzzy sets has been integrated into neural networks. If the inputs and outputs of a neural network are fuzzified and defuzzified, significant improvements in the training time, in the ability to generalize, and in the ability to find minimizing weights can be realized. Also, the membership function definition gives the designer more control over the neural network inputs and outputs. It is this technique that is implemented in this thesis for the frequency forecasting of the power grid to achieve optimal frequency stabilisation.

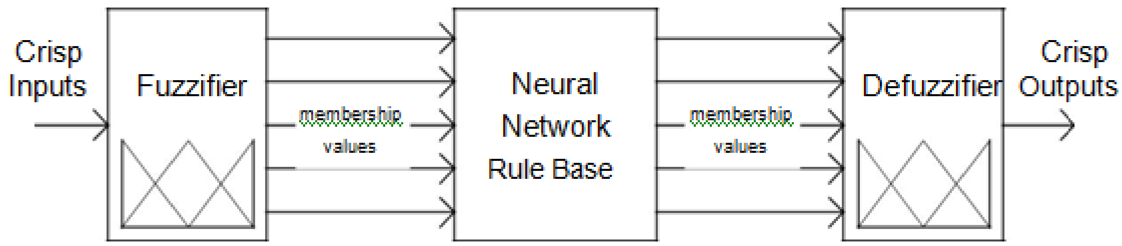


Fig. 7.4 A fuzzy system with neural network rule base

DESIGN OF FUZZY A STAGE

The fuzzy system designed to obtain load type percentage from time specification is termed as FUZZY A. The rules of this fuzzy system are decided such that the individual output of load type resembles its own load profile. The membership function of time equivalent (Teq block number) is divided into five parts which are shown in table 6.2 with their durations. These durations change with season in accordance to load.

For example, during summer, the morning hours will start from 05:00 and go till 08:00 but in winter season this period is 07:00 to 11:00. The membership function used for the time (Teq) is double sided trapezoidal function. As these durations are not strictly bounded, so to minimize the error trapezoidal membership function is used. The membership plot is shown in fig7.5.

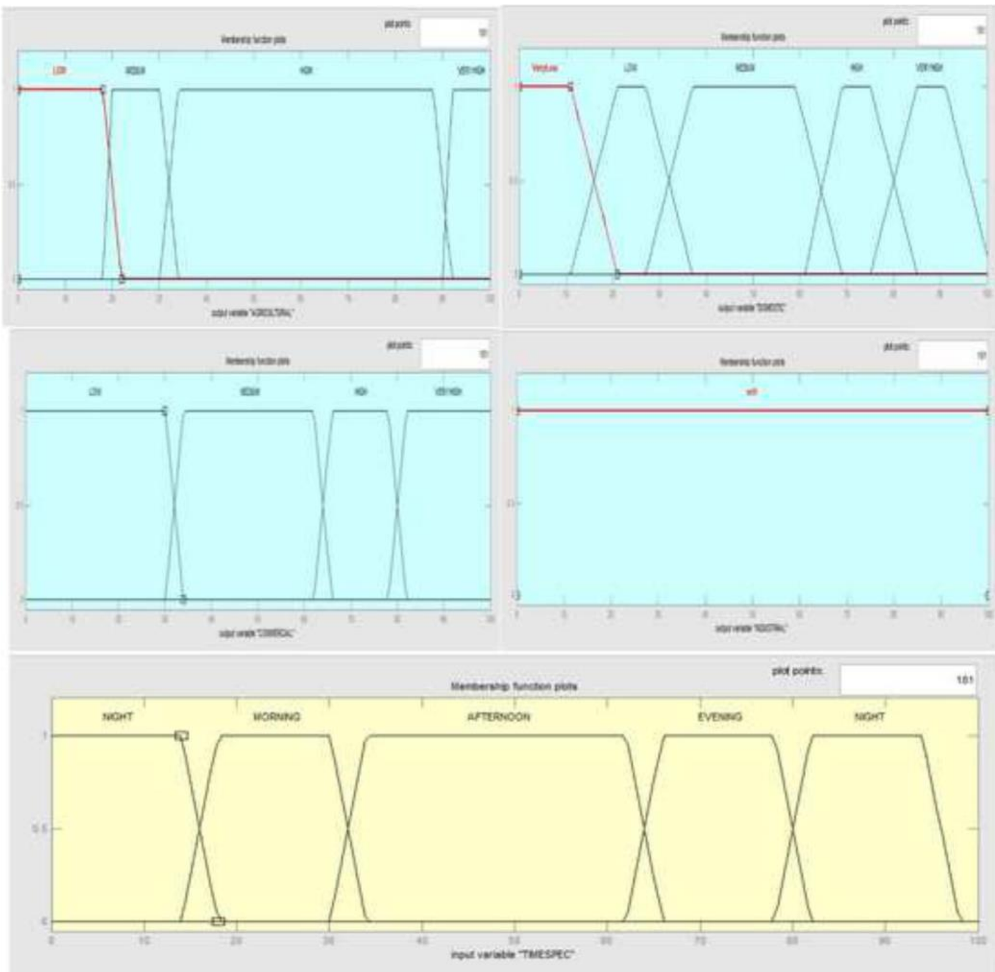


Figure 7.5 Membership function plots for output and input of fuzzy A system

The output of FUZZY A system consist of 4 outputs each corresponding to domestic, industrial, commercial and agricultural load. The membership function corresponding to the outputs are also double sided trapezoidal function and are shown in fig7.5. Membership function range of block number of output parameters is mentioned in table 7.1. The industrial membership function is taken constant as the industrial load is almost constant throughout the period. Rules of the FUZZY A system is decided based on the proportion of these load in western region of India and load pattern of individual output. Total five rules are defined and weight assigned to them will be proportional to the strength of individual in grid.

Table 7.1 Time slot number assigned to membership functions of linguistic variable for Seq = 1 for FUZZY A stage

S. No.	Time	Domestic		Industrial		Commercial		Agricultural	
1.	Very Low	0	21	-	-	-	-	-	-
2.	Low	11	37	-	-	0	34	0	22
3.	Medium	27	69	-	-	30	66	18	34
4.	High	61	85	-	-	62	82	30	92
5.	Very High	75	96	-	-	78	96	90	96

DESIGN OF FUZZY B STAGE

Second stage is designed to calculate the inertia equivalent parameter (Hn) from percentage of the load obtained from the FUZZY A system. There are 4 inputs of the FUZZY B system, each corresponding to the domestic, industrial, commercial and agricultural percentage. The membership function of this stage is also double sided trapezoidal function. The ranges for each of these inputs are mentioned in table 7.2 and fig7.6 shows the membership functions. The output of the FUZZY B system is inertia equivalent and is divided into three parts which are low, medium and high inertia. Ranges of these functions are decided as per the percentage of installed load. The rules were formed by looking the individual load profile with the time range where they are light load, motor load and electronic load; total 11 rules formed. For every season equivalent (Seq), these fuzzy stages are designed. For 4 seasons, total 8 stage sets are designed. The output of each stage sets is input to artificial neural network (ANN) which is trained to forecast the frequency of grid. The defuzzification is done by centroid method and fuzzy inference system is MAMDANI processor.

Table 7.2 Percentage and normalized value assigned to membership function of linguistic variable of load and inertia equivalent respectively for seq = 1 for FUZZY B stage

S. No.	Level	Domestic (%)		Industrial (%)		Commercial (%)		Agricultural (%)		Inertia Equivalent	
1.	Low	0	22	-	-	0	22	0	28	0	0.4
2.	Medium	18	62	-	-	18	62	24	62	0.3	0.8
3.	High	56	100	-	-	56	100	58	100	0.7	1.0

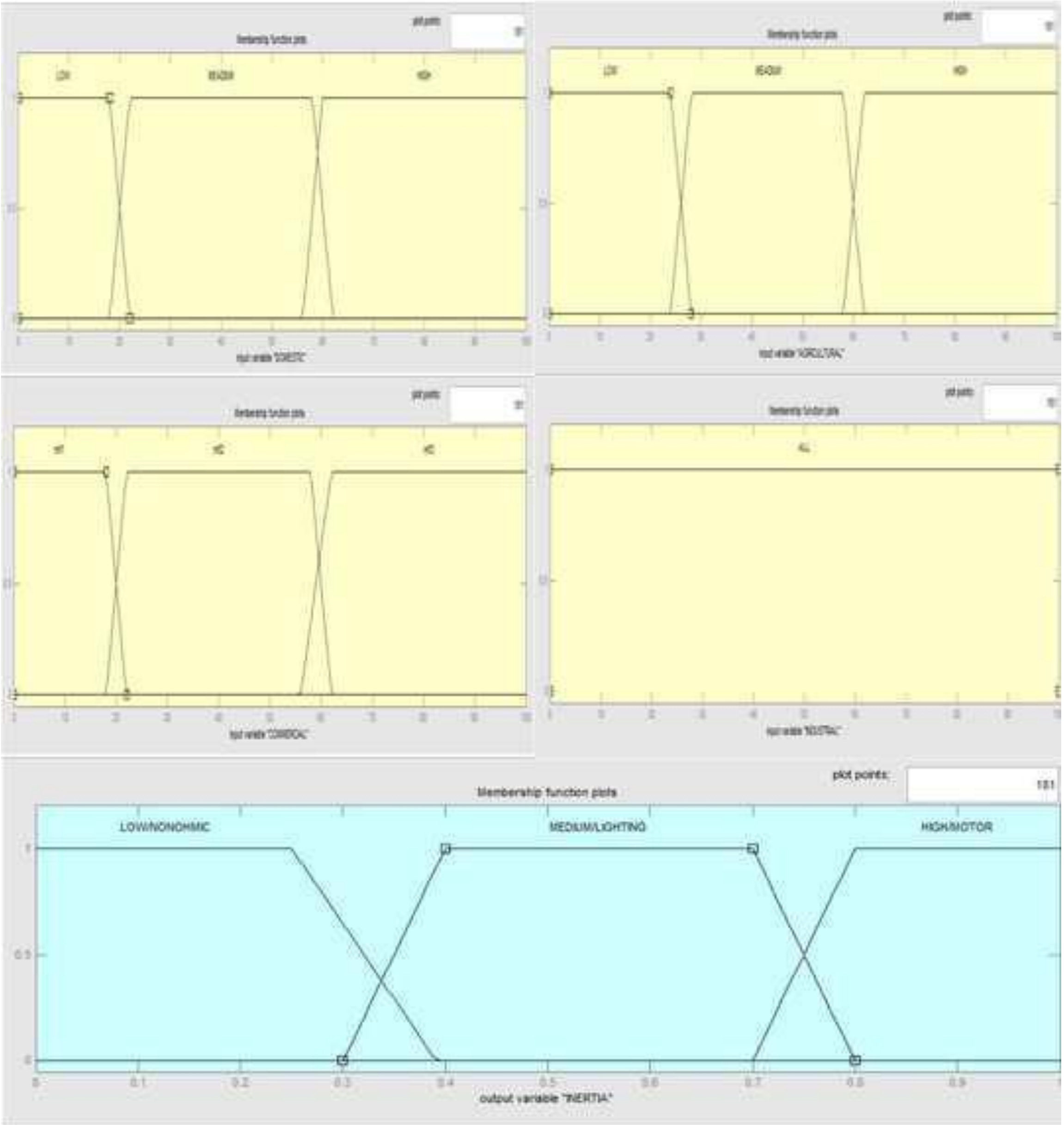


Figure 7.6 Membership function plots for output and input of fuzzy B system

ALGORITHM FOR FREQUENCY FORECASTING

The algorithm is designed on MATLAB 2007 platform. The input to the system is time block number (Teq), total generation (Pg), total demand (Pd) of grid and power exchanges with other control centre (en). The ANN has (n+2) input if n is the number of grids with which exchanges are made by control centres of main grid. Algorithm flowchart is shown in fig.5.

The algorithm consists of mainly three parts. The first part includes operation of parameter related to the inertia equivalent parameter and its calculation. The second part includes operation related to the power parameters such as generation, demand and exchanges and their normalization. The third part involves the artificial neural network and frequency forecast. The power parameters can be obtained from schedule chart and load forecast. Since the inertia parameter equivalent is already in range of 0-1, so its normalization is neglected. The input vector for ANN will be normalized and is given by;

$$[V] = [P_{dn} \;\; e_{1n} \;\; e_{2n} \;\; e_{3n} \;\; H_n\,] \qquad (7.1)$$

Normalization is done by dividing each power parameter by total generation [34]. Inertia equivalent is obtained by dividing load inertia equivalent parameter with the generator equivalent parameter. Since generator equivalent parameter is constant and considered as one. The inertia equivalent parameter is just a representation of the system inertia. The value of frequency fall in different time blocks, for same chock or lapse power will be different due to different value of the inertia. For example, for a system with a high value of inertia, a power lapse of 100MW will decrease the frequency by 0.02 Hz. But for a low inertia system, decrement in frequency for 100MW will be 0.5 Hz.

FLOWCHART FOR FREQUENCY FORECASTING

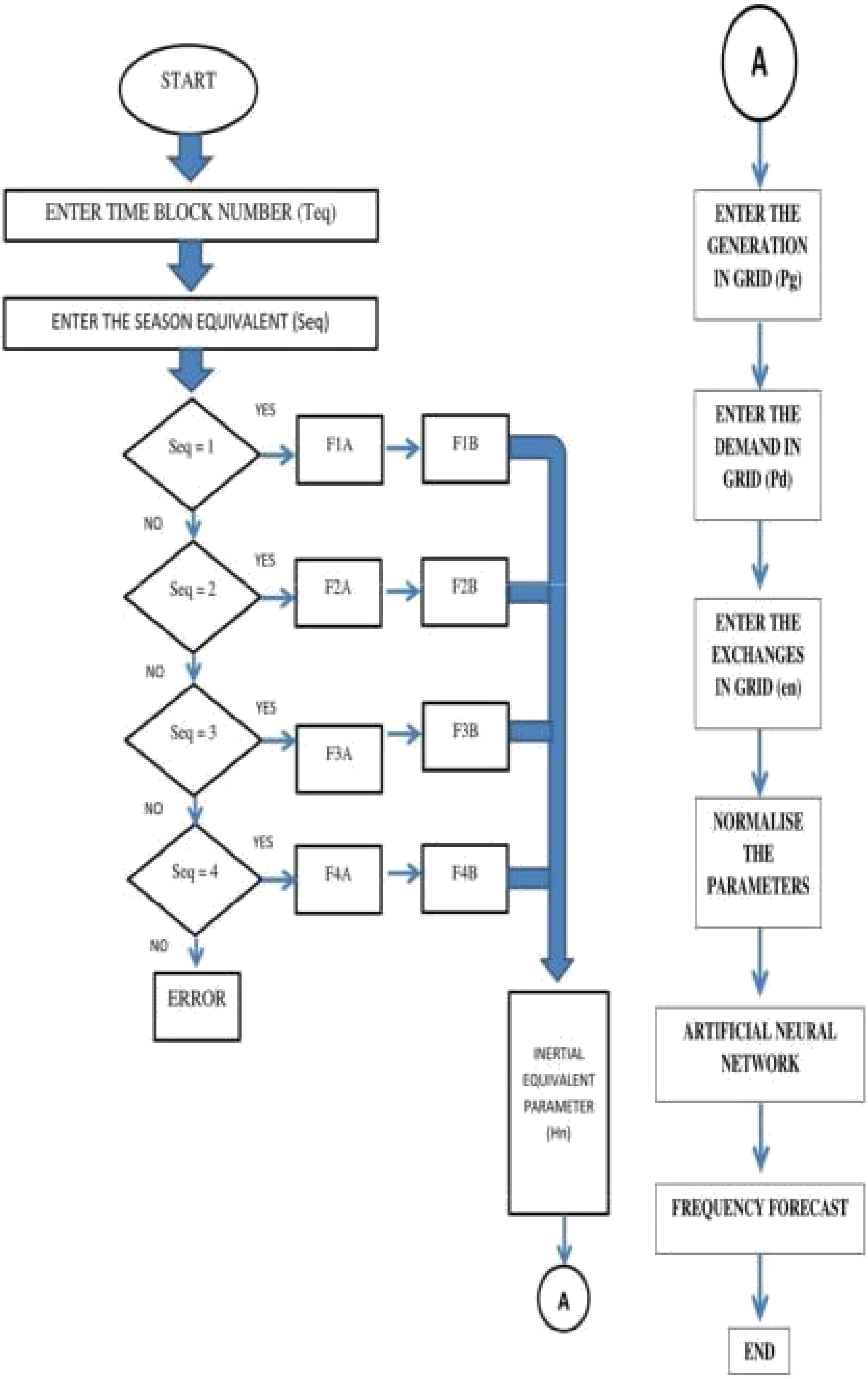


Fig. 7.7 flowchart of frequency forecasting

SIMULATION AND RESULTS

The system is first analyzed without considering the system inertia. The same set of training data were used to train another ANN but with the inertia equivalent parameter as part of input vector. The data were taken from the western regional load dispatch centre and frequency is forecasted for the western regional grid. It consists of seven entities (Gujrat, Madhya-Pradesh, Chhattisgarh, Maharashtra, Goa, Daman Diu, and Dadra Nagar Haveli). The total 7000 datasets were used in this process. These data sets were further divided into training, validation and testing sets [35]. The average error of 10% is considered to acknowledge load forecasting error [36][37]. The fig7.8 shows the frequency forecast for both the ANN. The performance specifications of both the networks are given in table 7.3.

Table 7.3 ANN performance specifications for both conditions

S. No.	Specifications	ANN Specification (Inertia is excluded)	ANN Specification (Inertia is included)
1.	Network	Feedforward Backpropagation Network	Feedforward Backpropagation Network
2.	Learning Mechanism	Levenberg-Marquat	Levenberg-Marquat
3.	Input	4	5
4.	Output	1	1
5.	Hidden Layers	20	80
6.	Training Data Sets	1500	1500
7.	Convergence Time (sec)	0.6	1.3
8.	Regression	0.55	0.87
9.	Mean Absolute Error	4.39 %	2.1%
10.	Mean Square Error	0.28 %	9.21e-4 %
11.	Mean Absolute Percentage Error	0.0878 %	0.04 %

RESULTS WITH AND WITHOUT INERTIA CONSIDERATION

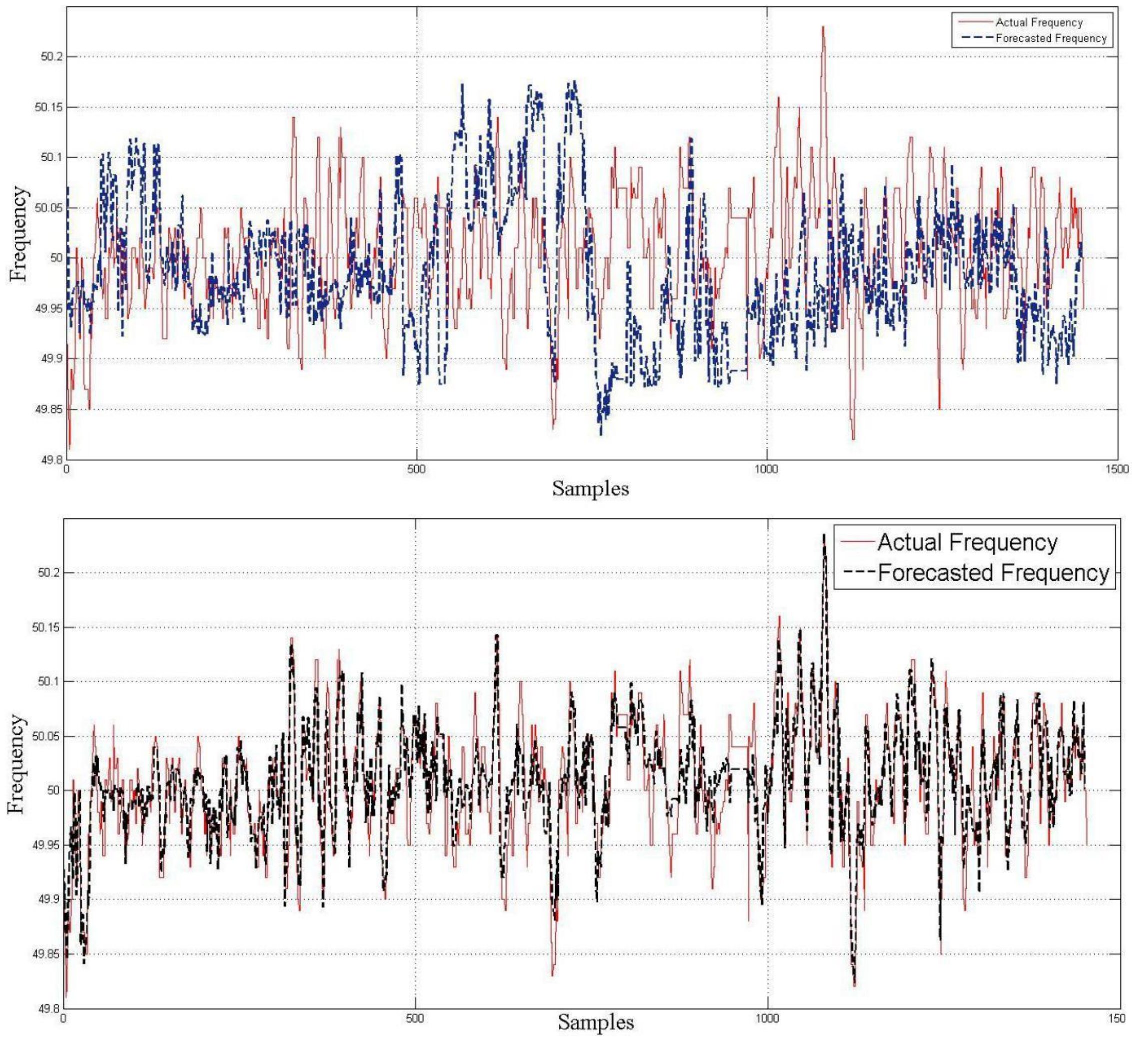


Figure 7.8 Results; when Inertia is neglected (above), when inertia is considered (below)

DISCUSSION

It is observed from fig.7.8 that accuracy of frequency forecasting system increases when inertia is considered. The ANN designed in the second case has lesser number of hidden layers and better regression.The system involves inertia equivalent parameter which represents system inertia during the forecasting process. It is impossible to calculate actual load inertia for large grid like western regional grid of India. Hence, it is better option to adopt this approach of representing load inertia in form of equivalent parameter. Higher the inertia of system, lower will be the effect of disturbance on the frequency of power grid. This method of frequency forecasting can be used as indirect method of scheduling the generators of grid. all the membership function data introduced in table 7.1 and 7.2 are user defined and can be redefined as per regional conditions and environment.

CONCLUSION

This thesis represents the importance of frequency forecasting for power grid and bring the frequency response of grid system in practical scenario. The grid is generalized to make model that was reduced to get frequency forecasting input vector of ANN. This approach is an elementary and effective way to forecast frequency at grid level. Still system has several limitation and initial consideration over which further research is expected.

This thesis introduces an advance two stage neurofuzzy system for forecasting the frequency of a typical power grid. The frequency forecasting also involves effect of system inertia. A new parameter which is equivalent to system inertia is introduced to involve effect of inertia on frequency deviation due to fast and random switching of load. The parameter gives an approximate analysis of system inertia and follows the same profile as system inertia does. Effect of mutual disturbance of interconnected grid is neglected over which further research is expected.

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