DEVELOPMENT OF ANN BASED SYSTEM FOR STABLE AND EFFICIENT POWER DISTRIBUTION SYSTEM

Thesis submitted in partial fulfillment of the requirements for the award of Degree of

Master of Engineering
In
Power Systems & Electric Drives

Thapar University, Patiala

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CERTIFICATE

I hereby certify that the matter which is being presented in the thesis entitled **"Development of ANN based system for Stable and Efficient Power Distribution System"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Power Systems & Electric Drives* submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out by me under the supervision of Ms. Suman Bhullar.

The matter presented in the thesis has not been submitted for the award of any other degree of this or any other university.

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This is to certify that the above statement made by the candidate is correct and true to best of my knowledge.

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ABSTRACT

The electric power system consists of large number of interconnected components that work together to generate and deliver electrical power to many load points scattered over a wide geographical area. In order to satisfy the modem age power needs, it is very much essential to plan ahead for higher power generation and design of efficient transmission and distribution systems. The increasing demand for high power quality has increased the demand for power quality monitoring tools.

The distribution systems are normally configured radially for effective coordination of their protection scheme. Most networks are sectionalized by using switches.

The objective of this study is to develop ANN based system for Evaluation of Stability of Electrical Power Distribution Systems. The will input the parameters of the network branches and train itself whether system is stable and then apply to check stability of other branches of network. Artificial Neural Networks have emerged as a major paradigm for Data Mining applications. Neural nets have gone through two major development periods -the early 60’s and the mid 80’s. They were a key development in the field of machine learning. Artificial Neural Networks were inspired by biological findings relating to the behavior of the brain as a network of units called neurons.

Attempt is made to build a classifier that can identify the stability of a particular electrical distribution system from its characteristics. Six voltage characteristics of the distribution system will be considered. Neural networks have proved themselves as proficient classifiers and are particularly well suited for addressing non-linear problems. This is achieved by presenting previously recorded inputs to a neural network and then tuning it to produce the desired target outputs.

The results are presented for the above using trained ANN.

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CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

The electric power system consists of large number of interconnected components that work together to generate and deliver electrical power to many load points scattered over a wide geographical area. In order to satisfy the modem age power needs, it is very much essential to plan ahead for higher power generation and design of efficient transmission and distribution systems. India is a fast developing country, which has geared itself for globalization process. The structure of Indian power distribution is a large network comprising of various generation, transmission and distribution companies. The generation of power is with the purview of direct Government of India agencies and also provincial state agencies. The transmission and distribution of electric power is the responsibility of companies under different provincial states. Since independence year 1947, the power sector is with the control of Government agencies. The economic reforms, which have been initiated during last decade, have yielded good results in many sectors. The power sector has been identified as a potential area and many improvement steps have been taken in all parts of the country. The measures include installation of large power generation plants, privatization of transmission and distribution sector and implementation of energy efficient management.

The problem of finding the network configuration with minimum line losses, is a mixed integer, non-linear optimization problem has been investigated by branch and bound method. However there is no assurance of convergence and burden on computing resources is extremely high and often impractical. Heuristic rather than analytical methods appear to be more effective for feeder configuration studies. Simulated annealing method can be employed but it is computationally demanding. Recently methodologies based on Genetic Algorithm (GA) are being developed to get appropriate global optimum with less computational burden. The distribution systems are normally configured radially for effective coordination of their protection scheme.

Most distribution networks use sectionalizing switches that are normally closed and tie switches that are normally opened.

Artificial Neural Networks have emerged as as a major paradigm for Data Mining applications. Neural nets have gone through two major development periods -the early 60’s and the mid 80’s. They were a key development in the field of machine learning. Artificial Neural Networks were inspired by biological findings relating to the behavior of the brain as a network of units called neurons. The human brain is estimated to have around 10 billion neurons each connected on average to 10,000 other neurons. Each neuron receives signals through synapses that control the effects of the signal on the neuron. These synaptic connections are believed to play a key role in the behavior of the brain. Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurones) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to software or Hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

1.2 LITERATURE REVIEW

Here is review of some literature that is relevant to carry out this thesis work.

Sharma and Sreedhar proposed an Intelligent approach for efficient operation of electrical distribution automation systems discussed that distribution systems play a vital role in providing an efficient service in terms of power quality, reliability, and economy. Distribution network reconfiguration can be used for planning as well as real time control. The paper presents an efficient approach for network reconfiguration based on artificial neural networks. A package, called "DISTFLOW", is developed adopting the proposed technique. The off-line simulation results and daily load curve data are used for training the neural network. Further, the distribution system operation is optimized by selecting an optimum compensation level computed by genetic algorithms (GA). The proposed integrated approach is applied to a practical 140 bus system in the Surathkal city subdivision of the power utility Mangalore Electricity Supply Company (MESCOM).

Baran and Wu presented that capacitor sizing problem for capacitors placed on a radial distribution system is formulated as a nonlinear programming problem, and a solution algorithm is developed. The object is to find the optimal size of the capacitors so that the power losses will be minimized for a given load profile while considering the cost of the capacitors. The formulation also incorporates the power flow model for the system and the voltage constraints. The solution algorithm developed for the capacitor sizing problem is based on a Phase I and Phase II feasible Directions approach. Novel power flow equations and a solution method, called DistFlow, for radial distribution systems are introduced. The method is computationally efficient and numerically robust, especially for distribution systems with large r/x ratio branches. DistFlow is used repeatedly as a subroutine in the optimization algorithm for the capacitor sizing problem. The test results for the algorithm indicate that the method is computationally efficient and has good convergence characteristics.

Gilbert, Bouchard, and Chikhani suggested that the state of a power system and the methods of calculating this state are extremely important in evaluating the operation of the power system, the control of this system, and the determination of future expansion for the power system. The state of the power system is determined through load flow analysis that calculates the power flowing in the lines of the system. There are several different methods to determine the load flow of a given system. For the purposes of this paper, only three methods of load flow algorithms are evaluated: Gauss-Seidel, optimal load flow, and the DistFlow method.

Sunderland and Conlo presented the role of micro wind generation in Ireland's energy future,This paper defines the current position for micro-generation, with particular reference to the potential for micro-wind units, in the Irish electricity supply system. A network model is developed using the Dist flow method of load flow analysis and is applied to consider the appropriate level of micro-generation penetration.

Mori and Yamada proposed an EPSO-Based Method for State Estimation in Radial Distribution Systems, In this paper, a robust static state estimation method is proposed for radial distribution systems. Distribution automation is of main concern in distribution system operation. Static state estimation plays an important role to provide system operators with reliable data in the framework of distribution automation. In this paper, the state variables at the distribution substation are estimated with the L1-norm estimator that is robust to bad data. Once they are estimated, other state variables are evaluated by the nest structure of radial distribution systems. As the power flow calculation, the DistFlow method is used to constrained nonlinear optimization problem. This paper proposes an EPSO (Evolutionary Particle Swarm Optimization) based method for estimating the state variables at the distribution substation. The proposed method is successfully applied to the 69-node distribution system.

Nanda, Srinivas, Sharma, Dey and Lai proposed new findings on radial distribution system load flow algorithms, In this paper, an attempt has been made to comprehensively compare the two most commonly used distribution load flow (DISTFLOW) models for radial networks to decide the better of the two for practical application. The paper also presents another novel method for radial distribution load flow and demonstrates its superiority over the two said models. Results have been obtained by considering two sample radial distribution networks, one consisting of 33 buses and other consisting of 70 buses.

Chen and Wei-Ming Wang proposed uniqueness of the feasible voltage solutions for radial power networks, The planning and operation of a distribution system depends heavily on the load flow solutions obtained. In this paper, the uniqueness of feasible voltage solution and its stability limit of radial distribution networks is analyzed. The DistFlow method is employed to find the load flow solutions for radial power networks. By this method, an equivalent 2-bus network can be obtained during the solving process. It is proposed that only one feasible voltage solution exists for a radial power network. Moreover, the feasibility can be judged directly from the sign of the Jacobian determinant of the equivalent 2-bus network obtained. A 22-bus practical system was tested to justify the approach.

Rahman and Jasmon proposed a new technique for voltage stability analysis in a power system and improved load flow algorithm for distribution network, Voltage collapse may occur in a power system due to loss in voltage stability in the system. Therefore voltage stability analysis is important in order to identify critical buses in a power system, i.e. buses which are closed to their voltage stability limits and thus enable certain measures to be taken by the control engineer in order to avoid any incidence of voltage collapse. This paper presents a new technique to determine the static voltage stability of load buses in a power system for a certain operating condition and hence identifies load buses which are close to voltage collapse. A voltage stability index with respect to a load bus is formulated from the voltage equation derived from a two bus network and it is computed using a Thevenin equivalent circuit of the power system referred to a load bus. This index indicates how far the load buses are from their voltage stability limits and hence identifies the critical buses. The performance of this index is tested using a 9 bus radial network and the 24 bus IEEE Reliability Test System for its validity. A comparison is also made between this index and the impedance ratio used by Sterling et al. as the voltage collapse indicator. This paper also presents a new load flow technique to compute the power flow solution for a radial network which is found to be more superior than the Second Order Newton Raphson and Distflow since it takes less iterations to give a load flow solution.

Andrei and Chicco proposed identification of the Radial Configurations Extracted from the Weakly Meshed Structures of Electrical Distribution Systems. The electrical distribution systems are typically structured as weakly meshed networks with multiple supply points, but they are operated with radial configurations by opening the redundant branches. The no regular composition of the meshed structure and the constraints imposed by the number and location of the supply points complicate the problem of determining all of the possible radial configurations that can be extracted out of a given structure. This paper illustrates a novel procedure, based on the creation of a reduced network structure, to determine the number of possible radial configurations and the set of open branches corresponding to each radial configuration. The proposed approach is presented and applied to five test distribution systems commonly available in the literature, providing for the first time the information about the number and the layout of the possible radial configurations obtainable for these systems.

Lampley and Glenn presented a fault analysis on electrical distribution system. In paper summarizes the activities conducted at Progress Energy Carolinas (PEC) to investigate electrical faults that occur on the electric distribution system. PEC has developed a series of web tools that are used to analyze data collected by the Feeder Monitoring System (FMS), the Outage Management System (OMS), and Distribution Supervisory Control and Data Acquisition (DSCADA) System. These tools were developed to assist engineers and operations personnel in locating faults and identifying causes of both permanent as well as temporary faults.

Parise and Martirano said that in the last years important improvements are developing in the European Union EU electrical systems: the process of electrical market liberalization, extended to all the customers, small and residential included, and a strong encouragement towards the energy saving and the installation of small renewable power sources. The actual distribution system for low voltage customers appears inadequate to comply with these improvements. The electricity market has to recognize the constitution of union of Customers Bunches. For an actual safety progress, a comparative analysis of international electrical approaches on distribution systems will promote an understanding of their similarities and differences and the design of new integrated common solutions. The authors suggest the eco design of the residential and commercial low voltage distribution for the next future that allows to accomplish the goals about safety, power quality, emergency systems, load shedding and energy management. The eco design requires imagination and intelligence that can reveal opportunities, expose risks and support strategic decision making.

Dionise and Lorch presented evaluation of the proposed retirement of a condensing turbine generator on the paper mill electrical distribution system and utility ties. The problem, as described by this paper mill, is the desire to retire an inefficient condensing steam turbine generator for economic reasons and purchase additional power from the utility. The condensing unit, along with a modern extraction steam turbine generator and two utility ties, presently supply power to this three-bus medium voltage system via sync bus and reactor ties. A power system study commenced to determine the impact of the proposed change on the existing paper mill electrical distribution system as well as the existing utility ties. This paper describes the results of the analytical methods employed: power quality measurements, load flow analysis, short circuit analysis and transient stability simulations. Recommendations included alternatives to accommodate retirement of the condensing steam turbine generator, most significantly, the installation of a new power transformer as a third utility tie and the application of reactive compensation as filters at the three medium voltage busses.

Su and Yeh presented a probabilistic security analysis of shipboard DC zonal electrical distribution systems, Due to significant gains in terms of survivability, weight, manning, and cost obtained from DC zonal electrical distribution systems (DC ZEDS), various practical applications of DC ZEDS to shipboard electric power systems are expected in the foreseeing future. How to ensure whether shipboard DC ZEDS under different power outage events is secure becomes important for real-time operation and planning of the system. This paper proposes a probabilistic AC/DC power flow based security analysis method. The variations in power generation and load are considered in the analysis by using probabilistic load flow computations. Then, a security index that incorporates the stochastic characteristics of contingency and transmission line priority and electrical load importance considerations is proposed for the security analysis. A navy surface combatant shipboard power system with AC/DC network is used to validate and ensure the performance of the proposed method.

Yoon, Yun, Lee and Wiedenbrug, E.J presented an automated Monitoring of High-Resistance Connections in the Electrical Distribution System of Industrial Facilities, Industry Applications Society, High-resistance(R) connections due to poor contacts in the electrical distribution system can cause failures due to overheating, reduce efficiency, and pose safety risks in the industrial facility. The methods currently available for detection of high-R connections such as infrared thermography, resistance or voltage unbalance tests are inconvenient since they are off-line or walk-around type tests that do not provide continuous monitoring. In this paper, an automated technique for detecting high-R connections based on existing voltage and current measurements is proposed. The contact resistance, RHR, of the poor contact is estimated based on the voltage and current variation under startup and/or shutdown of the load for monitoring problems located upstream from the point of voltage measurement. For downstream problems, RHR is estimated based on the negative sequence current under steady state operation of the load. An experimental study on a 10hp induction motor load performed under simulated high-R circuit conditions verifies that poor contacts that exist upstream and downstream can be reliably detected without additional measurements. It is shown that the proposed thetechnique can provide automated monitoring of the existence, location, and severity of high-R contacts for reliable, efficient, and safe operation of the industrial facility.

Adefajo and Todd studied Voltage control on an uninhabited autonomous vehicle electrical distribution system. More-electric vehicle technology is becoming prevalent in a number of transportation systems because of its ability to improve efficiency and reduce costs. This paper examines the specific case of an Uninhabited Autonomous Vehicle (UAV), and the system topology and control elements required to achieve adequate dc distribution voltage bus regulation. Voltage control methods are investigated and a droop control scheme is implemented on the system. Simulation results are also presented.

Smith showed Performing detailed power system studies for designing and analyzing electrical distribution systems - Power system studies for cement plants. The power system studies for designing and analyzing the electrical distribution system for cement plants is detailed. The analysis consists of a short circuit, load flow, motor starting over-current coordination, and arc flash hazard study. There are several load flow solution algorithms used in industry such as Gauss-Seidel, Newton-Raphson, and current injection. It is good engineering practice to have an up-to-date load flow study for every installation.

Donde and Hiskens showed analysis of Tap-Induced Oscillations Observed in an Electrical Distribution System, Slow oscillations, with a period of around 15 min, were observed in an 11-kV electrical distribution system. Initial investigations were unable to reproduce the oscillations. Through the use of hybrid system modeling and analysis concepts, however, it was determined that the oscillations resulted from interactions between tap-changing transformers and switched capacitors. The hybrid systems framework was needed to account for the no smooth (switched) nature of these interactions. Trajectory sensitivities were used to identify influential parameters. It was found that existence of the oscillations was dependent upon factors that included system fault level, capacitor rating, and regulator dead band limits. In all cases, grazing-type conditions separated oscillatory from steady-state behavior. A system of cascaded tap-changing transformers was also investigated, with the hybrid systems framework revealing coexisting limit cycles.

Favuzza, Graditi, Ippolito and Sanseverino proposed optimal Electrical Distribution Systems Reinforcement Planning Using Gas Micro Turbines by Dynamic Ant Colony Search Algorithm, Distribution systems management is becoming an increasingly complicated issue due to the introduction of new energy trading strategies and new technologies. In this paper, an optimal reinforcement strategy to provide reliable and economic service to customers in a given time frame is investigated. In the new deregulated energy market and considering the incentives coming from the political and economical fields, it is reasonable to consider distributed generation (DG) as a viable option for systems reinforcement. In the paper, the DG technology is considered as a possible solution for distribution systems capacity problems, along several years. Therefore, compound solutions comprising the installation of both feeders and substations reinforcement and DG integration at different times are considered in the formulation of a minimum cost distribution systems reinforcement strategy problem. An application on a medium size network, hypothesizing a scenario of reinforcement also using as DG gas micro-turbines, is carried out using a novel optimization technique allowing the identification of optimal paths in trees or graphs. The proposed technique is the Dynamic Ant Colony Search algorithm.

Zamora, Mazon, Sagastabeitia and Zamora showed new Method for Detecting Low Current Faults in Electrical Distribution Systems power in electrical distribution systems, low current faults may be caused by a high impedance fault or by the fault current limitation caused by the neutral to ground connection. In the former case, an indirect contact or insulation degradation give a high value of the fault impedance. In the latter, the neutral grounding may be either isolated or compensated. Nevertheless, these types of faults do not produce enough current so that the traditional over current relays or fuses are not able to detect the fault. This paper presents a new methodology, based on the superposition of voltage signals of certain frequency, for the detection of low current single phase faults in radial distribution systems. The simulation analysis and laboratory tests carried out have proved the validity of the methodology for any type of grounding method.

Caramia and Varilone observed Probabilistic three-phase load flow for unbalanced electrical distribution systems with wind farms. A probabilistic method is proposed to take into account the uncertainties of loads and wind production in electrical unbalanced distribution systems. The proposed method is based on Monte-Carlo simulation applied to the nonlinear three-phase load flow equations including wind farms, thereby taking into account all load and line unbalances that can characterise the distribution systems. The method allows the evaluation of phase-voltage and unbalance factor probability functions and in particular the maximum values and 95th percentiles, being the statistical measures of greatest interest in many international standards for power quality. Numerical applications are presented and discussed with reference to the three-phase unbalanced IEEE 34-bus test distribution system in presence of wind farms connected at different busbars.

Wu, Lee and Lin showed a Rule-Based Genetic Algorithm for the Inter-Feeder Load Transfer in the Multiple Outages of Electrical Distribution Systems. In electrical distribution systems multiple outages are usually occurred in severe weather conditions and the out-of-service areas should be restored as soon as possible. This paper presents an application of evolutionary algorithm that is effectively improved by heuristic rules to find the optimal scheme of multiple-objective problem of inter-feeder load transfer in the cases of multiple outages. Constraints of discrete radial feeder configuration, nonlinear time-variant load patterns, voltage drop, and feeder current rating are considered in the problem. The effectiveness of the proposed approach is demonstrated by conducting the simulation of a practical distribution system in Taiwan power distribution system.

Godoy and Galotto showed voltage estimation in electrical distribution systems, Electrical Power Quality and Utilization, The increasing demand for high power quality has increased the demand for power quality monitoring tools. The voltage performance monitoring for each feeder is one of the needs found by the utility companies. Since it is not economically viable to measure every single node in the system, it is necessary to use estimation techniques in order to get all needed information with a reduced the number of meters. These are basically interpolation techniques. Each interpolation provides different performance of estimations accordingly the application. In this work, it is proposed a non-linear non-parametric method which was found to get the best voltage estimates of feeders in relation to other more usual techniques. Comparative results for different methodologies in a hypothetic system are presented and discussed.

William, Manic and Johnson proposed ANN Relays Used to Determine Fault Locations on Shipboard Electrical Distribution Systems; this paper observes an artificial neural network algorithm (ANN) distance relay solution. It traces the location of the fault on a shipboard power system. The United States Naval Surface Warfare Center has been exploring methods for increasing the reliability for shipboard electrical distribution systems. The electrical distribution system is protected when faults are located and isolated as quickly as possible. The goal is to increase the availability of shipboard electrical distribution systems by locating and isolating faults. Thus, introducing an ANN relay to locate the fault occurrence on the electrical distribution system. Maintaining the integrity of a shipboard power system in the event of multiple simultaneous electrical faults is necessary to achieve continuity of service to all loads under adverse battle conditions.

Mitolo studied Electrical Distribution Systems with Multiple Grounded Neutrals, Industrial and Commercial Power Systems Technical Conference, Multiple grounded neutral systems require that, on most land-based AC current service installations, the bonding conductor used to connect the non-current-carrying metal parts of equipment, the system grounded conductor (neutral), and the grounding electrodes be bonded together at the service entrance box. Users, thus, share their ground with the serving utility's neutral ground. This interconnection, although functional, poses some

Distinctive problems to utility companies as well as to users, which this paper seeks to clarify.

Ahmad, Omar and Sulaiman showed application of ZigZag Transformers to Mitigate Triplen Harmonics in 3 Phase 4 Wire Electrical Distribution System, This paper studies an application of wye-zigzag transforms for reducing harmonics in the neutral conductors of a three phase 415/240 V distribution system. Triple harmonic currents add up in the neutral conductor of the distribution system feeding the non linear loads such as personal computers and electronic office machines with switch mode power supplies. The zigzag transformer is installed between the distribution panel and high harmonics producing loads. This research makes use of a star-zigzag grounded transformer.

Pang and Pong showed DC Electrical Distribution Systems in Buildings, Power Electronics Systems and Applications, with the gaining of popularity of concept of distribution generation (DG) and sustainable development, DG with renewable energy (RE) sources is one of the possible ways for building energy supply in the future. The current "DC-AC-DC" route from DG to DC loads via inverters may not be rational from the viewpoint of system simplicity and energy efficiency, a review on the current electrical distribution systems should be made. This paper reviews and evaluates possibilities of using DC electrical distribution systems with increasing RE resources and DC loads. There is potential of increasing energy efficiency and power quality. Drawbacks and merits are also identified.

Tumilty,Brucoli, Burt and Green presented approaches to network protection for inverter dominated electrical distribution systems. This paper presents a review of the conventional distribution network protection practices and then discusses their limitations when applied to inverter dominated micro-grids. The use of voltage measurement based fault detection is considered and is followed by consideration of how to apply this technique in conjunction with an adaptive form of protection. A potential solution for small micro-grids is presented in the form of voltage controlled over current devices to enable the use of lower current threshold set.

1.3 OBJECTIVES OF THE WORK

The objective of this thesis work is to develop a system for testing stability of Power Distribution System. The neural networks provide artificial intelligence techniques for solution for engineering problems and being flexible in nature allows representation of many types of data for analysis. Since the training in based on the past as well as existing data of different parameters the results obtained can be more reliable. Also the computational difficulty is reduced by considerable extent and recent data. can be obtained for further analysis. Thus it is appropriate to adopt the neural network technique for the load flow analysis and network reconfiguration, to ensure simplicity, reliability and flexibility in modeling process.

The objective of this thesis study is to develop Artificial Neural Network based system for Evaluation of Stability of Electrical Power Distribution Systems. The system will input the parameters of the network branches and train itself whether the system is stable or not and then apply this to evaluate the stability of other unknown branches of network.

1.4 METHODOLOGY

Matlab will be used as the simulation tool. Attempt will be made to build a classifier that can identify the stability of a particular electrical distribution system from its characteristics. Six characteristics of the distribution system will be considered. Neural networks have proved themselves as proficient classifiers and are particularly well suited for addressing non-linear problems. Given the non-linear nature of real world phenomena, like power distribution system stability, neural networks is certainly a good candidate for solving the problem. The six characteristics will act as inputs to a neural network and the stability of Electrical Distribution System will be the target. Given an input, which constitutes the six measured values for the parameters of the electrical distribution system, the neural network is expected to identify if the electrical distribution is stable or not. This is achieved by presenting previously recorded inputs to a neural network and then tuning it to produce the desired target outputs. This process is called neural network training. The samples will be divided into training, validation and test sets. The training set is used to `teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. The trained neural network will be tested with the testing samples. The network response will be compared against the desired target response to build the classification matrix which will provide a comprehensive picture of a system performance.

1.5 ORGANIZATION OF THESIS WORK

Chapter-1 Presents the introduction to Power System, stability and its efficiency, introduction to scope of neural networks and applications in power systems over other conventional methods, literature survey, and objectives of the research, scope and methodology of the work to be carried, organization of the research.

Chapter-2 Presents the architecture details and classifications of neural networks, basic fundamentals of Neurons (single layer and multilayer),Perceptron,Hyperplanes Hebbian Learning.

Chapter-3 Presents the study of power distribution system (i.e Radial distribution) and basics of Power Stability.

Chapter-4 Presents the work done by designing, training and analysis of neural networks for desired inputs to check stable or unstable efficient operation of power system.

Chapter-5 Results and discussions.

Chapter-6 Conclusion and Future scope of the work

References present the list of previous papers published by researchers in power system stability analysis, conventional and adaptive designs that have been surveyed by the author and also the books in this area.

CHAPTER 2

NEURAL NETWORKS

2.1 ANN-BASIC CONCEPTS

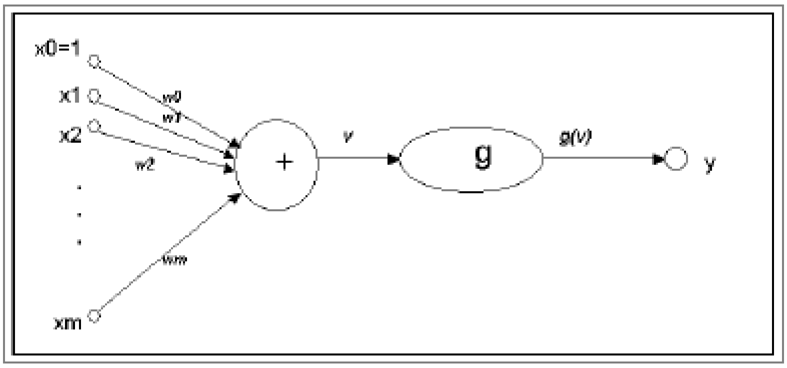
The fundamental building block in an Artificial Neural Network is the mathematical model of a neuron as shown in Figure

The three basic components of the (artificial) neuron are:

1. The synapses or connecting links that provide weights, wj , to the input values, xj for j = 1, ...m;

2. An adder that sums the weighted input values to compute the input to the activation function v, where w0 is called the bias (not to be confused with statistical bias in prediction or estimation) is a numerical value associated with the neuron. It is convenient to think of the bias as the weight for an input x0 whose value is always equal to one.

3. An activation function g (also called a squashing function) that maps v to g(v) the output value of the neuron. This function is a monotone function.



While there are numerous different (artificial) neural network architectures that have been studied by researchers, the most successful applications in data mining of neural networks have been multilayer feedforward networks. These are networks in which there is an input layer consisting of nodes that simply accept the input values and successive layers of nodes that are neurons as depicted (in Figure 2.1). The outputs of neurons in a layer are inputs to neurons in the next layer. The last layer is called the output layer. Layers between the input and output layers are known as hidden layers.

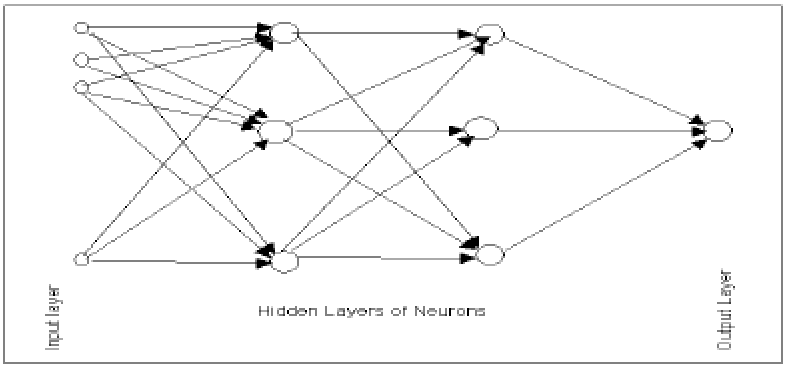


Figure 2.2 : Diagram for the Architecture of Neuron Layers

In a supervised setting where a neural net is used to predict a numerical quantity there is one neuron in the output layer and its output is the prediction. When the network is used for classification, the output layer typically has as many nodes as the number of classes and the output layer node with the largest output value gives the network's estimate of the class for a given input. In the special case of two classes it is common to have just one node in the output layer, the classification between the two classes being made by applying a cut-off to the output value at the node.

2.1.1 Single Layer Networks

Let us begin by examining neural networks with just one layer of neurons (output layer only, no hidden layers). The simplest network consists of just one neuron with (figure 2.1) the function g chosen to be the identity function, $g(v) = v$ for all v. In this case notice that the output of the network is linear function of the input vector x with Components x_j . If we are modeling the dependent variable y using multiple linear regression, we can interpret the neural network as a structure that predicts a value _y for a given input vector x with the weights being the coefficients. If we choose these weights to minimize the mean square error using observations in a training set, these weights would simply be the least squares estimates of the coefficients. The weights in neural nets are also often designed to minimize mean square error in a training data set. There is, however, a different orientation in the case of neural nets: the weights are ”learned”. The network is presented with cases from the training data one at a time and the weights are revised after each case in an attempt to minimize the mean square error. This process of incremental adjustment of weights is based on the error made on training cases and is known as ’training’ the neural net. The almost universally used dynamic updating algorithm for the neural net version of linear regression is known as the Widrow-Hoff rule or the least-mean-square (LMS) algorithm. It is simply stated. Let x(i) denote the input vector x for the ith case used to train the network, and the weights before this case is presented to the net by the vector w(i). The updating rule is w(i+1) = w(i)+η(y(i)_y(i))x(i) with w(0) = 0. It can be shown that if the network is trained in this manner by repeatedly presenting test data observations one-at-a-time then for suitably small (absolute) values of η the network will learn (converge to) the optimal values of w. Note that the training data may have to be presented several times for w(i) to be close to the optimal w. The advantage of dynamic updating is that the network tracks moderate time trends in the underlying linear model quite effectively.

If we consider using the single layer neural net for classification into c classes, we would use c nodes in the output layer. If we think of classical discriminant analysis in neural network terms, the coefficients in Fisher’s classification functions give us weights for the network that are optimal if the input vectors come from Multivariate Normal distributions with a common covariance matrix. For classification into two classes, the linear optimization approach that we examined in class, can be viewed as choosing optimal weights in a single layer neural network using the appropriate objective function. Maximum likelihood coefficients for logistic regression can also be considered as weights in a neural network to minimize a function of the residuals called the deviance. In this case the logistic function g(v) is the activation function for the output node. i.e g(v) = $\left(\frac{e^{v}}{1+e^{v}}\right)$

2.1.2 Multilayer Neural Net

Multilayer neural networks are undoubtedly the most popular networks used in applications. While it is possible to consider many activation functions, in practice it has been found that the logistic (also called the sigmoid) function as the activation function (or minor variants such as the tanh function) works best. In fact the revival of interest in neural nets was sparked by successes in training neural networks using this function in place of the historically (biologically inspired) step function (the ”perceptron”}. Notice that using a linear function does not achieve anything in multilayer networks that is beyond what can be done with single layer networks with linear activation functions. The practical value of the logistic function arises from the fact that it is almost linear in the range where g is between 0.1 and 0.9 but has a squashing effect on very small or very large values of v. In theory it is sufficient to consider networks with two layers of neurons–one hidden and one output layer–and

this is certainly the case for most applications. There are, however, a number of situations where three and sometimes four and five layers have been more effective. For prediction the output node is often given a linear activation function to provide forecasts that are not limited to the zero to one range. An alternative is to scale the output to the linear part (0.1 to 0.9) of the logistic function. Unfortunately there is no clear theory to guide us on choosing the number of nodes in each hidden layer or indeed the number of layers. The common practice is to use trial and error, although there are schemes for combining optimization methods such as genetic algorithms with network training for these parameters. Since trial and error is a necessary part of neural net applications it is important to have an understanding of the standard method used to train a multilayered network: back propagation. It is no exaggeration to say that the speed of the backprop algorithm made neural nets a practical tool in the manner that the simplex method made linear optimization a practical tool. The revival of strong interest in neural nets in the mid of the 80s was in large measure due to the efficiency of the backprop algorithm. In many real- world applications, we want our
Computers to perform complex problems such as pattern recognition, we therefore take inspiration from the structure of the brain in order to produce new models of processing, we call this new approach Artificial Neural Systems (ANS) technology or simply Neural Networks. How do we define this new approach? At one extreme we may say that these are synthetic networks that emulate the biological neural networks found in living organisms, but the correspondence between our artificial networks and real neural systems is still rather weak, as knowledge about the brain and the neurons that it is composed of is still rather limited. A better approach to adopt is to say that our new approach takes inspiration from the brain in order to produce new computational properties, but is not a strict emulation of how the brain works. As more knowledge is gleaned about the workings of the brain by Neurophysiologists and Psychologists, then perhaps we will be able to make use of this knowledge and adapt our models.

2.1.3 Biological Neurons

A human brain consists of approximately 1011 computing elements called neurons, they communicate through a network of long fibers called axons, each of these axons splits up into a series of smaller fibers , which communicate with other neurons via junctions called synapses that connect to small fibers called dendrites attached to the main body of the neuron (Figure 2.3).

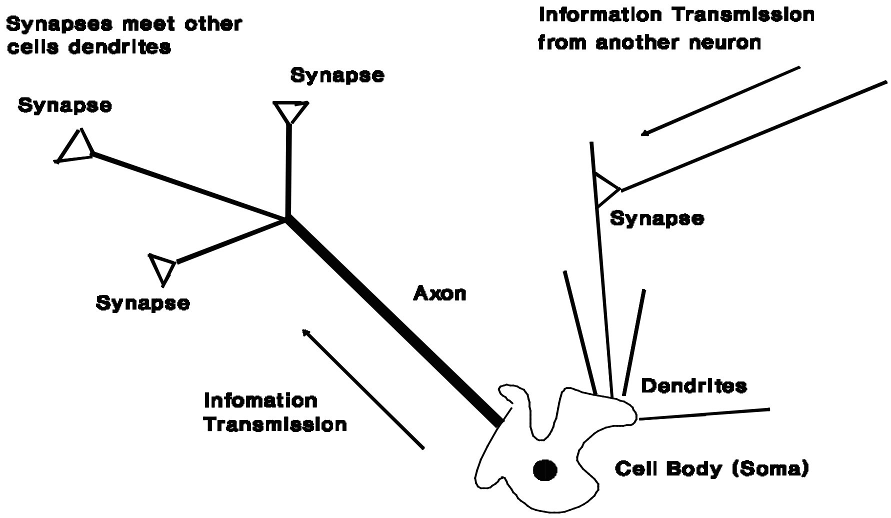


Figure 2.3: Diagram of the body of Biological Neurons

The synapse is rather like a one-way valve where one neuron transmits its signal to another neuron. An electrical signal is generated by the neuron, passes down the axon, and is received by the synapses that join onto other neurons dendrites. On reaching a synapse the electrical signal causes the release of transmitter chemicals which flow across a small gap in the synapse (the synaptic cleft) and meet the dendrite of the neuron that the signal is being transmitted to. These chemicals can have an excitatory effect on the receiving neuron (making it more likely to fire) or an inhibitory effect (making it less likely to fire). When deciding whether to fire, the total inhibitory and excitatory connections to a particular neuron are summed, and if this value exceeds a particular amount (the neurons threshold) the neuron fires, if the threshold is not exceeded the neuron does not fire. If a neuron does fire, and generate a signal down its axon, there is a period where the neuron is unable to fire called the refractory period, for this time period the axon cannot conduct any signals, regardless of the intensity of excitation. Thus we can divide the time scale of the neurons operation into discrete time periods, each the length of the refractory period. This allows a discrete time description of the all the neurons in a systems performance in terms of their states at particular time instances, for example we can specify which neurons will fire at time t + 1 based on the conditions at time t. The above discussion is extremely simplified when seen from a neurobiological point of view, but is valuable for gaining insights into attempting to model neural systems. This highly simplified model was used as inspiration for the following historically significant neural network model.

The McCulloch-Pitts Model

This first formal definition of a synthetic neuron was formulated in 1943, is shown in figure 2.4, and has these main features:

a) The neuron has binary inputs (0 or 1) labelled xi where i = 1,2, ...,n.

b) These inputs have weights of +1 for excitatory synapses and -1 for inhibitory synapses labelled wi where i = 1,2, ...,n.

c) The neuron has a threshold value T which has to be exceeded by the weighted sum of signals if the neuron is to fire.

d) The neuron has a binary output signal denoted by o.

The superscript k = 0, 1, 2, ... denotes discrete time instants.

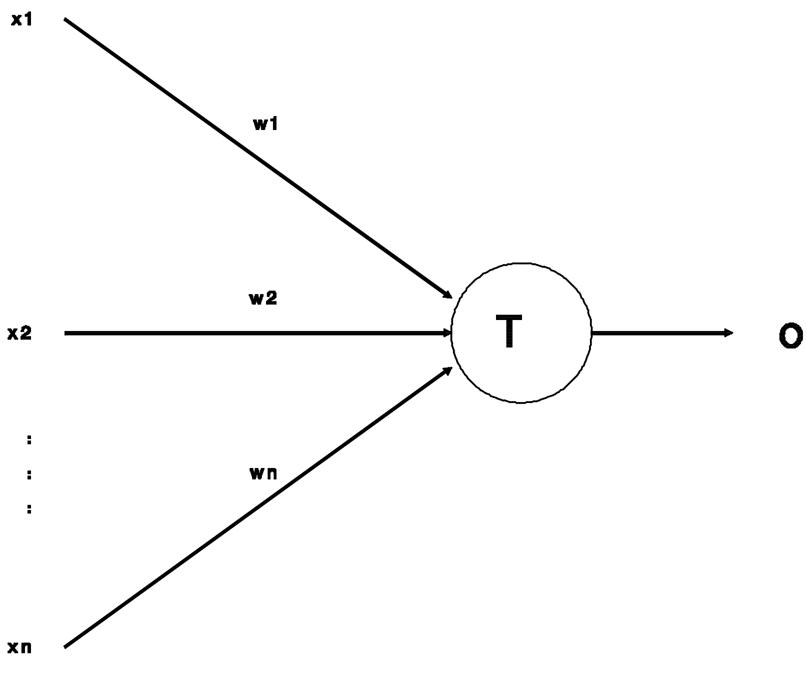


Figure 2.4: McCulloch-Pitts Model

The output o at a time k+1 can be defined in terms of the conditions at time k by the following equation:

$$o^{k+1} = 1 \text{ if } \sum_{i=1}^{n} w_i x_i^k \geq T$$

$$o^{k+1} = 0 \text{ if } \sum_{i=1}^{n} w_i x_i^k < T$$

i.e. the output o of the neuron at time k+1 is 1 if the sum of all the inputs x at time k multiplied by their weights w is greater than or equal to the threshold T, and 0 if the sum of all the inputs x at time k multiplied by their weights is less than the threshold T. Although this neuron model is very simplistic, it has substantial computing potential. Providing its weights and thresholds are appropriately selected it can perform the basic logic operations NOT, OR and AND. As any multivariable combinational function can be constructed using these operations, digital computer hardware of great complexity can be constructed using these simple neurons as building blocks.

The above network has its knowledge pre-coded into the network when the network when it is first constructed, this is obviously not true of all biological neural systems, which are not born pre-programmed with all the knowledge and abilities they will eventually have. In biological systems a learning process takes place over time which somehow modifies the network to incorporate new information.

2.1.4 Hebbian Learning

This basic learning law was first stated in 1949, and was originally stated as:

"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes place in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

To illustrate this kind of learning, consider an example from Pavlovian conditioning, where two neurons A and C are stimulated by the sensory inputs of sound and sight respectively, and the third neuron B triggers salivation. The two synaptic junctions are labeled Sba and Sbc respectively (Figure 2.5). Suppose that the excitation of C, caused by the sight of food, is sufficient to excite B, causing salivation. Also suppose that the excitation of A resulting from hearing a bell is not sufficient to cause the firing of B. If we allow C to cause B to fire by showing food to the subject and while B is still firing stimulate A by ringing a bell. Because B is still firing, A is now participating in the excitation of B, even though by itself A would be insufficient to cause B to fire. In this situation Hebb's law dictates that some change should occur between A and B, so that A's influence on B is increased.

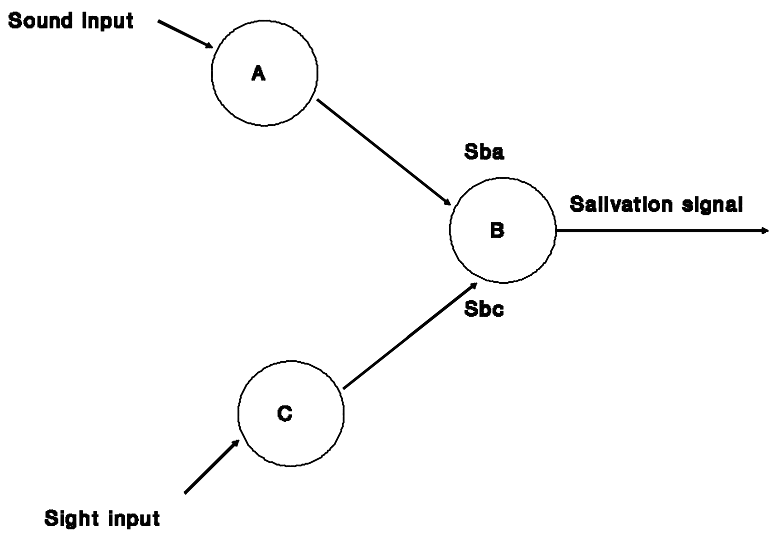


Figure 2.5: Hebbian Learning

If the experiment is repeated often enough, A will eventually be able to cause B to fire even in the absence of stimulation from C, i.e. if the bell is rung but no food is shown salivation will still occur. Because the connection between neurons is through the synapse, it is reasonable to assume that whatever changes occur during learning take place there. Hebb theorized that the area of the synaptic junction changed during learning, but more recent research indicates that a change in the rate of neurotransmitter release in the synapse is responsible for learning.

2.1.5 The Perceptron

The next historically significant neural network model was invented by the psychologist Frank Rosenblatt in the late 1950's. Rosenblatt believed that the connectivity that develops in biological networks contains a large random element, and took exception to previous models such as McCulloch and Pitts where symbolic logic was used to produce rather idealized structures. One of the models he developed was the photoperceptron, used to analyze and classify optical patterns; this model had three areas of units, a sensory area, an association area and a response area. Each sensory point responds in an all-or-nothing manner to incoming light, impulses generated by the sensory points are transmitted to the units in the association layer, each association layer unit being connected to a random set of units in the sensory layer, the connections may be either excitatory or inhibitory and can have the possible values +1, 0 and -1. When a pattern appears on the sensory layer, an association layer unit becomes active if the sum of its inputs exceeds a threshold value; if that association layer becomes active it produces an output which is sent to the next layer of units, the response units. The response units are connected randomly to the association layer units, in addition there is inhibitory feedback from the response layer to the association layer, and also inhibitory connections between the response layer units. A simplified section of a photoperceptron is shown in Figure; please note that there are in fact usually many more units in the three areas in a complete perceptron.

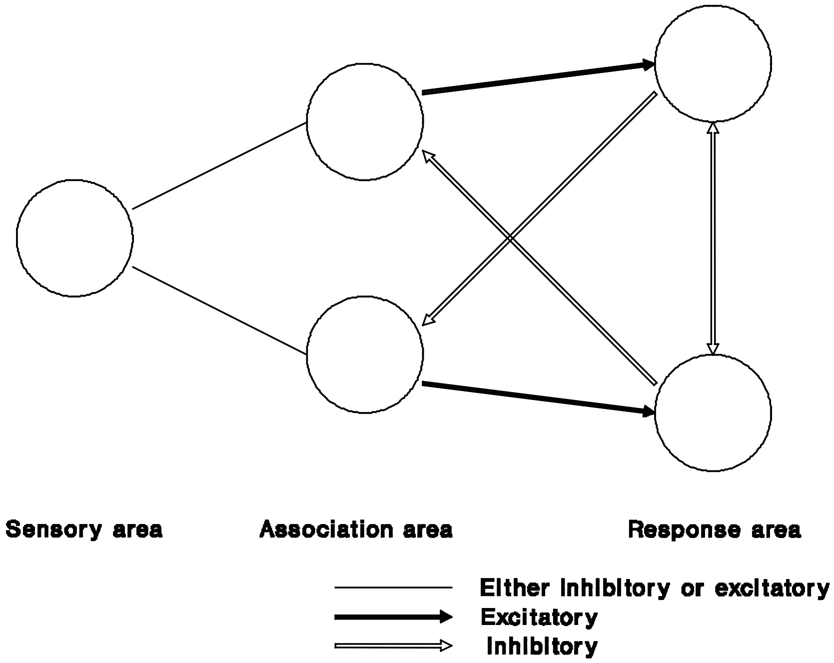


Figure 2.6: Perceptron Model

The response layer units respond in a similar way to the association layer units, if the sum of their inputs exceeds a threshold they give an output value of +1, otherwise their output is -1. It can be seen that each response unit inhibits the association layer units in the complement to its own source set, and in addition each response layer unit inhibits all the others in its layer. These factors aid in the establishment of a single winning response unit for each stimulus pattern presented to the sensory area. In this way such a system can be used to classify patterns appearing on the retina into Categories, according to the number of response units in the system. Patterns that are sufficiently similar should excite the same response unit, different patterns should excite different response units. How we distinguish between classes of patterns will be discussed later. The perceptron is a learning device, in its initial configuration it is incapable of distinguishing patterns, but can learn this capability through a training process. During training a pattern is applied to the sensory area, and the stimulus is propagated through the layers until a response layer unit is activated. If the correct response layer unit is activated the output of the corresponding association layer units is increased, if the incorrect response layer unit is active the output of the corresponding association layer units is decreased. Using this training scheme Rosenblatt was able to show that the perceptron would classify patterns correctly in what he called a differentiated environment, where each class consisted of patterns that in some way similar to one another, but its accuracy diminished as the number of patterns that it attempted to learn increased. Rosenblatt's work resulted in an important proof known as the perceptron convergence theorem, which states that if a pattern can be learned by the perceptron then it will be learned in a finite number of training cycles.

Problems with perceptrons - the end of neural networks research?

In 1969 a book appeared that some people considered to have sounded the death knell for neural networks, called Perceptrons: An introduction to Computational Geometry by Marvin Minsky and Seymour Papert of MIT, who produced a detailed analysis of the perceptron and its limitations. Whether their intention was to defuse popular support for neural-network research remains a matter for debate, but the result was that the field of artificial neural networks was almost entirely abandoned, except for a few die-hard researchers. One of the main points of their book was that there are restrictions on the class of problems for which the perceptron is suitable; in particular perceptrons can differentiate patterns only if they are linearly separable, and as many classification problems do not possess linearly separable classes, this condition places a severe restriction on the applicability of the perceptron.

2.1.6 Linear Separability

One of the simplest examples of a problem that is not linearly separable and therefore cannot be solved by the perceptron is the XOR problem:

Inputs		Output
x1	x2	
0	0	0
0	1	1
1	0	1
1	1	0

A simplified perceptron, with x1 and x2 representing inputs from the sensory area, two units in the association layer and one in the response layer is shown (figure 2.7)

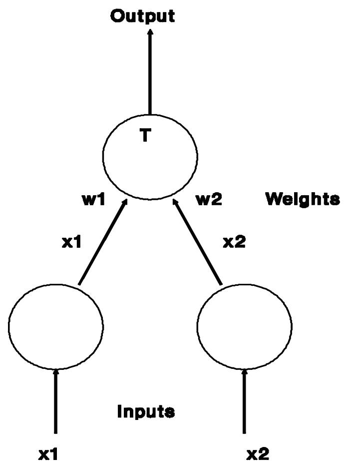


Figure 2.7 : Simplified Perceptron

The output function of the output unit is 1 if its net input is greater than the threshold T, and 0 if it is less than this threshold, this type of node is called a linear threshold unit.

$$f(net) = 1 \quad net \geq T$$

$$f(net) = 0 \quad net < T$$

The net input to the output node is

$$net = w_1 x_1 + w_2 x_2$$

The problem is to select values of the weights such that each pair of input values results in a proper output value, if we refer to figure 2.8, we see that this cannot be done.

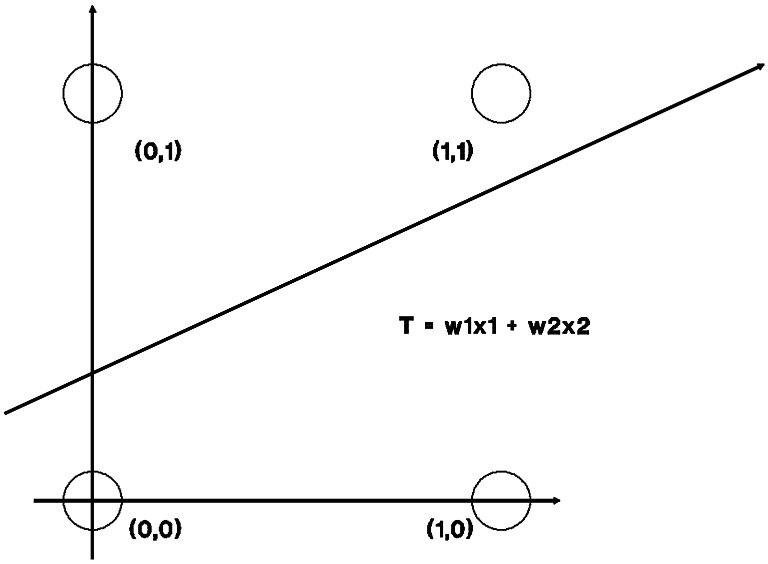


Figure 2.8: Output Plane

Looking at the equation of the line T = w1x1 + w2x2, this is an equation of a line in the x1, x2 plane. The four points marked are the possible inputs to the network. We can think of the classification problem as being one of subdividing this space into regions that correspond to the right answer for points in that region. The line that

represents the above equation can separate the plane into at most two distinct regions, we can then classify points in one region as belonging to the class having an output of 1, and those in the other region as belonging to the class having an output of 0. There is no way to arrange the position of the line so that the correct two points for each class both lie in the same region, so this simple arrangement of linear threshold units cannot correctly perform the XOR function, and in general perceptrons cannot solve problems that are not linearly separable.

2.1.7 Hyper Planes

In three-dimensional space a plane is an object of two dimensions, which can separate this space into two distinct regions, two planes can separate the space into three or four distinct regions, depending on their orientation. In an n-dimensional space (a hyperspace), hyperplanes are objects of n-1 dimensions. Suitable arrangements of hyperplanes allow an n-dimensional space to be partitioned into various distinct regions, it may seem difficult to select these hyperplanes so that they produce the correct partitioning, but fortunately (as we shall see later) neural networks can learn the correct partitioning. Returning to our XOR problem, looking at Figure 2.7 we can see that we could partition the space correctly if we had three regions, one region would belong to one output class, and the other two would belong to another output class (there is no reason why disjoint regions cannot belong to the same output class) as in Figure 2.9.

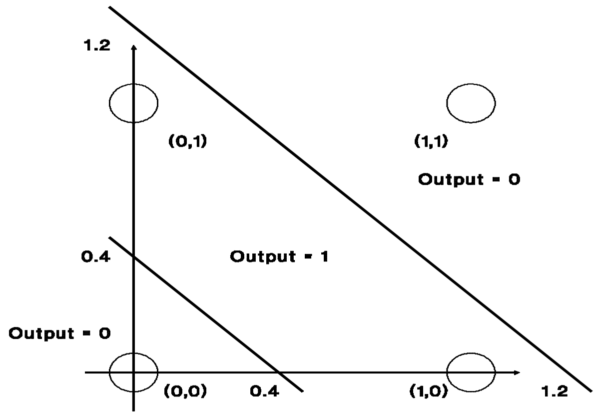


Figure 2.9: Hyper Planes

We can achieve this by adding an extra layer to the network, which has the effect of expanding the dimensionality of the space that the XOR problem is being represented in and allowing us to produce a hyper plane which correctly partitions the space, an example with an appropriate set of connection weights and thresholds is shown in Figure 2.10.

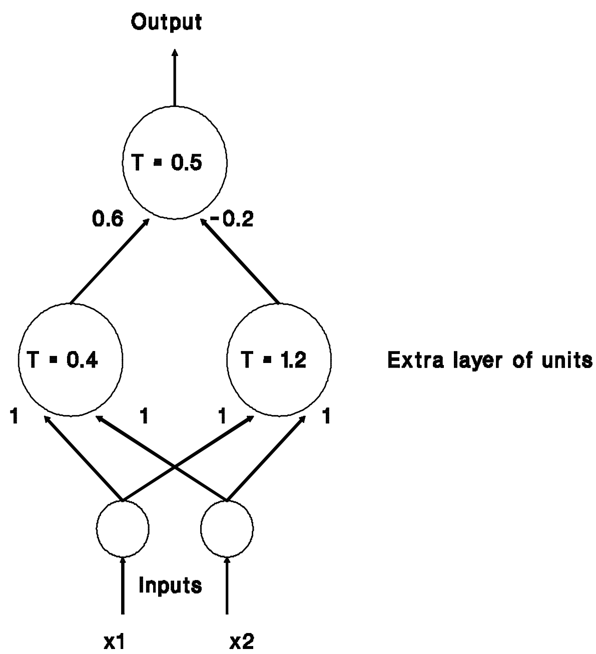


Figure 2.10: XOR Representation in Hyperplane

By summing the connection weights for all four patterns involved in the XOR problem, it can be seen that this network gives correct results for them all, there are however other equally valid solutions. Three layers of perceptron units can form arbitrarily complex hyperplanes in a hyperspace, and are capable of separating any classes. The complexity of shapes formed is limited by the number of units in the network as these define the complexity of the hyperplanes involved, but the arbitrary complexity of the shapes that can be created means that we never need more than three layers in a network to represent any problem (this is referred to as Kolmogorov's theorem).

CHAPTER 3

DISTRIBUTION SYSTEM AND STABILITY

3.1 DISTRIBUTION SYSTEM

Electrical Distribution is the final stage in the delivery of electricity to end users. A distribution system's network carries electricity from the transmission system and delivers it to consumers. Typically, the network would include medium-voltage (less than 50 kV) power lines, electrical substations and pole-mounted transformers, low-voltage (less than 1000 V) distribution wiring and sometimes electricity meters. So that the part of power system used for distribution of electric power for local use is known as distribution system.

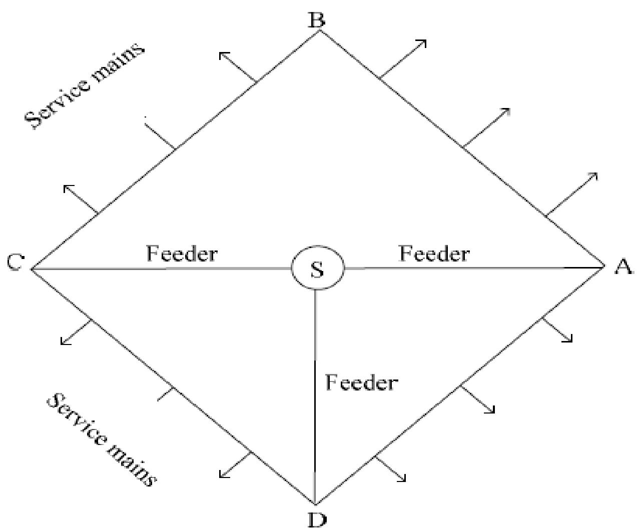


Figure 3.1: Single line diagram of Distribution System

In general, the distribution system is the electrical system between the substation fed by the transmission system and the consumers' meters. It generally consists of feeders, distributors and the service mains figure 3.1 shows the single line diagram of a typical low tension distribution system.

a) **Feeders -** A feeder is a conductor, which connects the sub-station (or localized generating station) to the area where power is to be distributed. Generally, no tappings are taken from the feeder so that the current in it remains the same throughout. The main consideration in the design of a feeder is the current carrying capacity.

b) **Distributor -** A distributor is a conductor from which tappings are taken for supply to the consumers. In Figure 2.10 AB, BC, CD, and DA are the distributors. The current through a distributor is not constant because tapping are taken at various places along its length. While designing a distributor, voltage drop along its length is the main consideration since the statutory limit of voltage variations is 10% of rated value at the consumer's terminals.

c) **Service mains -** A service mains is generally a small cable which connects the distributor to the consumer's terminals.

3.1.1 Requirement of Distribution System

A considerable amount of effort is necessary to maintain an electric power supply within the requirements of various types of consumers. Some of the requirements of a good distribution system are: proper voltage, availability of power on demand, and reliability

a) **Proper Voltage:** One important requirement of a distribution system is that voltage variations at consumers' terminals should be as low as possible. The changes in voltage are generally caused due to the variation of load on the system. Low voltage causes loss of revenue, inefficient lighting and possible burning out of motors. High voltage causes lamps to burn out permanently and may cause failure of other appliances. Therefore, a good distribution system should ensure that the voltage variations at consumers' terminals are within permissible limits. The statutory limit of voltage variations is $\pm 10\%$ of the rated value at the consumers' terminals. Thus, if the declared voltage is 230 V, then the highest voltage of the consumer should not exceed 244 V while the lowest voltage of the consumer should not be less than 216 V.

b) **Availability of Power Demand:** Power must be available to the consumers in any amount that they may require from time to time. For example, motors may be started or shut down, lights may be turned on or off, without advance warning to the electric supply company. As electrical energy cannot be stored, therefore, the distribution system must be capable of supplying load demands of the consumers. This necessitates that operating staff must continuously study load patterns to predict in advance those major load changes that follow the known schedules.

c) **Reliability:** Modern industry is almost dependent on electric power for its operation. Homes and office buildings are lighted, heated, cooled and ventilated by electric power. This calls for reliable service. Unfortunately electric power, like everything else that is man-made, can never be absolutely reliable. However, the reliability can be improved to a considerable extent by (a) inter-connected system, (b) reliable automatic control system and (c) providing additional reserve facilities.

3.1.2 Classification of Distribution System

Nature of current:- According to nature of current, distribution system may be classified as (a) d.c. distribution system and (b) a.c. distribution system. Now-a-days a.c. system is universally adopted for distribution of electric power as it is simpler and more economical than direct current method.

Type of construction:- According to type of construction, distribution system may be classified as (a) overhead system and (b) underground system. The overhead system is generally employed for distribution as it is 5 to 10 times cheaper than the equivalent underground system. In general, the underground system is used at places where overhead construction is impracticable or prohibited by the local laws.

Scheme of connection:- According to scheme of connection, the distribution system may be classified as (a) radial system, (b) ring main system and (c) inter-connected system.

3.1.3 Essential Parts of Distribution System

Various types of distribution systems have identical subsystems and components. These components can be connected and configured in various alternative ways that depends upon the area covered, load density, type and importance of consumer, reliability and freedom from interruption desired, cost of land and right of way available.

A. Sub-transmission Circuits

B. Distribution Substations.

C. Primary Distribution Circuit.

D. Distribution Transformers

E. Secondary Distribution System

3.1.4 Radial Distribution System

A radial system has only one power source for a group of customers. A power failure, short-circuit, or a downed power line would interrupt power in the entire line which must be fixed before power can be restored. The figure of Radial Distribution System is shown as

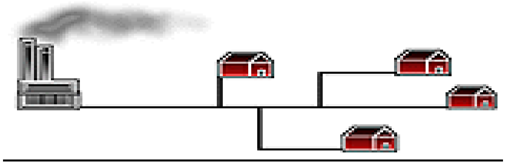


Figure 3.2 : Radial Distribution System

In this system, separate feeders radiate from a single sub-station and feed the distributors at one end only. Figure 3.3 **(a)** shows a single line diagram of a radial system for d.c. Distribution where a feeder OC supplies a distributor AB at point A. Obviously, the distributors are fed at one point only i.e. point A in this case. Figure 3.3 (b) shows a single line diagram of radial system for a.c. distribution. The radial system is employed only when power is generated at low voltage and the sub-station is located at the centre of load. This is the simplest distribution circuit and has the lowest initial cost.

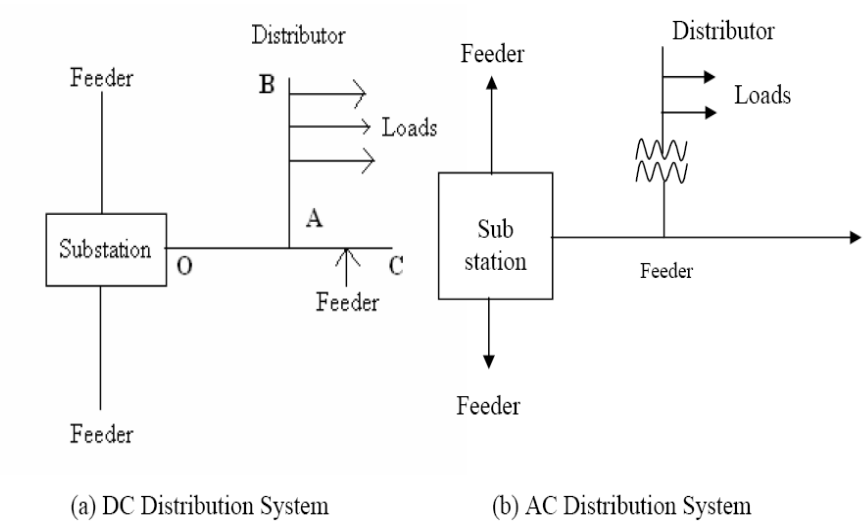


Figure 3.3 : Single line diagram of Radial System.

3.1.4.1 Node Radial Distribution Network

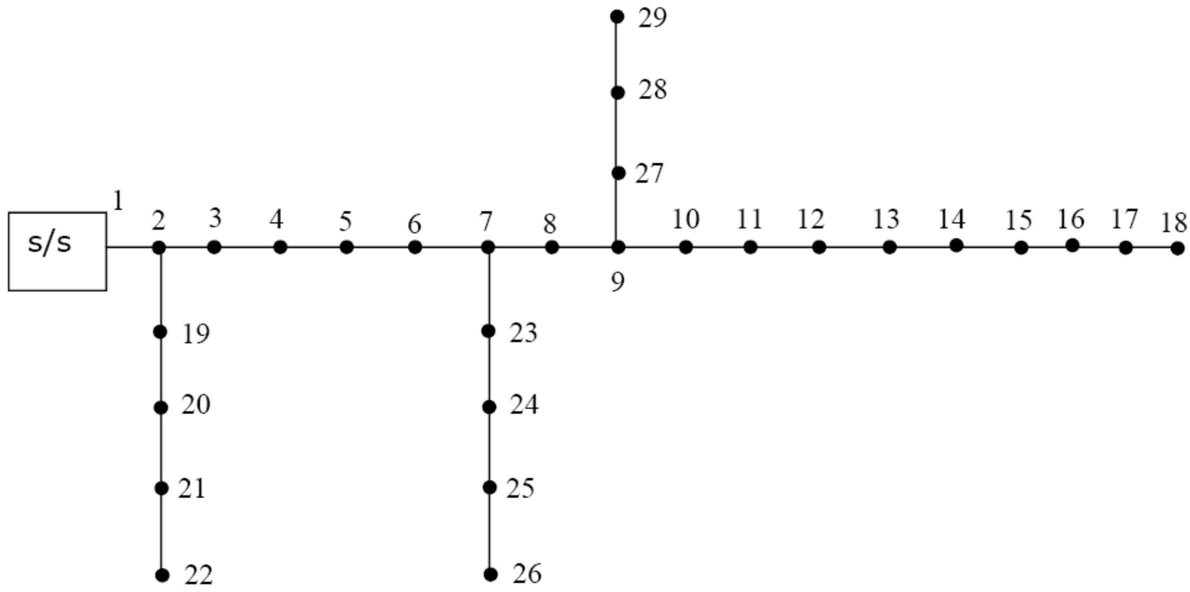


Figure 3.4: 29 -Node Radial Distribution System

3.1.4.2 Objectives of Radial Distribution System:

1. Planning, modernisation and automation.
2. To provide service connection to various urban, rural and industrial consumer in the allocated area.
3. Maximum security of supply and minimum duration of interruption.
4. Safety of consumers, utility personnel.
5. To provide electricity of accepted quality in terms of :-
   - (a) Balanced three phase supply.
   - (b) Good power factor.
   - (c) Voltage flicker within permissible limits.
   - (d) Less voltage dips.
   - (e) Minimum interruption in power supply.

3.1.4.3 Advantages of Radial Distribution System

(a) Radial distribution system is easiest and cheapest to build.

(b) The maintenance is easy.

(c) It is widely used in sparsely populated areas.

3.2 POWER SYSTEM STABILITY

Power system stability may be broadly defined as that property of a power system that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance.

From this general definition, two categories of stability are derived: small-signal and Transient stability. Small-signal stability is the ability of the system to return to normal operating state following a small disturbance. Investigations involving this stability concept usually involve the analysis of the linearized state space equations that define the power system dynamics. Transient stability is the ability of the system to return to a normal operating state following a severe disturbance, such as a single or multi-phase short-circuit or a generator loss. Under these conditions, the linearized power system model does not usually apply and the nonlinear equations must be used directly for the analysis. A third term, dynamic stability has been used to describe a separate class of stability. However, this term has represented different concepts for different authors, and there has also been a difference between groups of analysts in North America and Europe.

CHAPTER 4
WORK DONE

4.1 SCOPE

The objective of this thesis work is to develop a system for testing stability of Power Distribution System. The neural networks provide artificial intelligence techniques for solution for engineering problems and being flexible in nature allows representation of many types of data for analysis. Since the training in based on the past as well as existing data of different parameters the results obtained can be more reliable. Also the computational difficulty is reduced by considerable extent and recent data can be obtained for further analysis. Thus it is appropriate to adopt the neural network technique for the load flow analysis and network reconfiguration, to ensure simplicity, reliability and flexibility in modeling process. The system inputs the parameters of the network branches and train itself whether the system is stable or not and then applies this to evaluate the stability of other unknown branches of network.

4.2 PROBLEM FORMULATION

Matlab has been used as the simulation tool. Attempt has been made to build a classifier that can identify the stability of a particular electrical distribution system from its characteristics. Six characteristics of the distribution Instantaneous Voltage of the system have been considered. Neural networks have proved themselves as proficient classifiers and are particularly well suited for addressing non-linear problems. Given the non-linear nature of real world phenomena, like power distribution system stability, neural networks is certainly a good candidate for solving the problem. The six characteristics will act as inputs to a neural network and the stability of Electrical Distribution System will be the target. Given an input, which constitutes the six measured values for the parameters of the electrical distribution system, the neural network is expected to identify if the electrical distribution is stable or not. This is achieved by presenting previously recorded inputs to a neural network and then tuning it to produce the desired target outputs. This process is called neural network training. The samples will be divided into training, validation and test sets.

The training set is used to teach the network. Training continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. The trained neural network will be tested with the testing samples. The network response will be compared against the desired target response to build the classification matrix which will provide a comprehensive picture of a system performance.

4.3 TRAINING DATA

The training data set includes a number of cases, each containing values for a range of input and output variables. The first decisions you will need to make are: which variables to use, and how many (and which) cases to gather. The choice of variables (at least initially) is guided by intuition. Expertise in the problem domain will give you some idea of which input variables are likely to be influential. As a first pass, you should include any variables that you think could have an influence - part of the design process will be to whittle this set down.

Neural networks process numeric data in a fairly limited range. This presents a problem if data is in an unusual range, if there is missing data, or if data is non-numeric. Fortunately, there are methods to deal with each of these problems. Numeric data is scaled into an appropriate range for the network, and missing values can be substituted for using the mean value (or other statistic) of that variable across the other available training cases.

Handling non-numeric data is more difficult. The most common form of non-numeric data consists of nominal-value variables such as *Outcomer*={Success, *Failure*}. Nominal-valued variables can be represented numerically. However, neural networks do not tend to perform well with nominal variables that have a large number of possible values.For example, consider a neural network being trained to estimate the value of houses. The price of houses depends critically on the area of a city in which they are located. A particular city might be subdivided into dozens of named locations, and so it might seem natural to use a nominal-valued variable representing these locations. Unfortunately, it would be very difficult to train a neural network under these circumstances, and a more credible approach would be to assign ratings (based on expert knowledge) to each area; for example, you might assign ratings for the quality of local schools, convenient access to leisure facilities, etc.

Other kinds of non-numeric data must either be converted to numeric form, or discarded. Dates and times, if important, can be converted to an offset value from a starting date/time. Currency values can easily be converted. Unconstrained text fields (such as names) cannot be handled and should be discarded.

The number of cases required for neural network training frequently presents difficulties. There are some heuristic guidelines, which relate the number of cases needed to the size of the network (the simplest of these says that there should be ten times as many cases as connections in the network). Actually, the number needed is also related to the (unknown) complexity of the underlying function which the network is trying to model, and to the variance of the additive noise. As the number of variables increases, the number of cases required increases nonlinearly, so that with even a fairly small number of variables (perhaps fifty or less) a huge number of cases are required. This problem is known as "the curse of dimensionality," and is discussed further later in this chapter.

For most practical problem domains, the number of cases required will be hundreds or thousands. For very complex problems more may be required, but it would be a rare (even trivial) problem which required less than a hundred cases. If your data is sparser than this, you really don't have enough information to train a network, and the best you can do is probably to fit a linear model. If you have a larger, but still restricted, data set, you can compensate to some extent by forming an ensemble of networks, each trained using a different resampling of the available data, and then average across the predictions of the networks in the ensemble.

Many practical problems suffer from data that is unreliable: some variables may be corrupted by noise, or values may be missing altogether. Neural networks are also noise tolerant. However, there is a limit to this tolerance; if there are occasional outliers far outside the range of normal values for a variable, they may bias the training. The best approach to such outliers is to identify and remove them (either discarding the case, or converting the outlier into a missing value). If outliers are difficult to detect, a city block error function may be used, but this outlier-tolerant training is generally less effective than the standard approach.

4.4 PRE- AND POST-PROCESSING

All neural networks take numeric input and produce numeric output. The transfer function of a unit is typically chosen so that it can accept input in any range, and produces output in a strictly limited range (it has a squashing effect). Although the input can be in any range, there is a saturation effect so that the unit is only sensitive to inputs within a fairly limited range. The illustration below shows one of the most common transfer functions, the logistic function (also sometimes referred to as the sigmoid function, although strictly speaking it is only one example of a sigmoid - S-shaped - function). In this case, the output is in the range (0,1), and the input is sensitive in a range not much larger than (-1,+1). The function is also smooth and easily differentiable, facts that are critical in allowing the network training algorithms to operate (this is the reason why the step function is not used in practice).

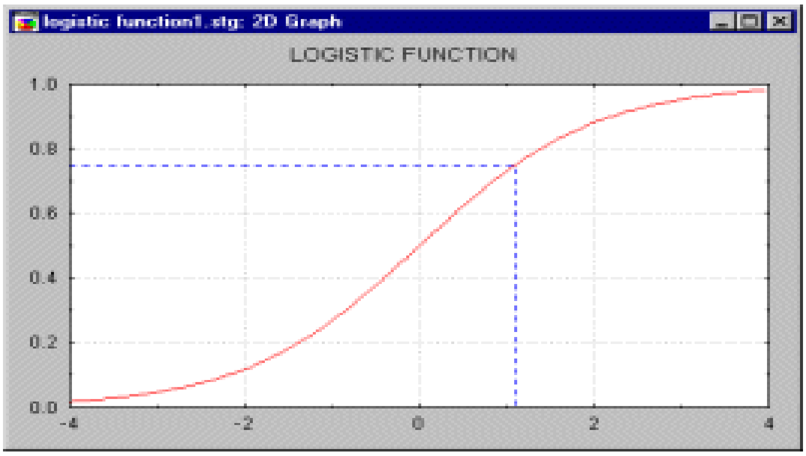


Figure 4.1 : Logistic Function

The limited numeric response range, together with the fact that information has to be in numeric form, implies that neural solutions require preprocessing and post-processing stages to be used in real applications (see Bishop, 1995). Two issues need to be addressed:

4.4.1 Scaling. Numeric values have to be scaled into a range that is appropriate for the network. Typically, raw variable values are scaled linearly. In some circumstances, non-linear scaling may be appropriate (for example, if you know that a variable is exponentially distributed, you might take the logarithm). Non-linear scaling is not supported in ST Neural Networks. Instead, you should scale the variable using STATISTICA's data transformation facilities before transferring the data to ST Neural Networks.

4.4.2 Nominal Variables. Nominal variables may be two-state (e.g., Outcome ={Success ,Failure }) or many-state (i.e., more than two states). A two-state nominal variable is easily represented by transformation into a numeric value (e.g., Success =0, Failure =1). Many-state nominal variables are more difficult to handle. They can be represented using an ordinal encoding but this implies a (probably) false ordering on the nominal. A better approach, known as one-of-N encoding, is to use a number of numeric variables to represent the single nominal variable. The number of numeric variables equals the number of possible values; one of the N variables is set, and the others cleared. ST Neural Networks has facilities to convert both two-state and many-state nominal variables for use in the neural network. Unfortunately, a nominal variable with a large number of states would require a prohibitive number of numeric variables for one-of-N encoding, driving up the network size and making training difficult. In such a case it is possible (although unsatisfactory) to model the nominal variable using a single numeric ordinal; a better approach is to look for a different way to represent the information.

Prediction problems may be divided into two main categories:

a) Classification. In classification, the objective is to determine to which of a number of discrete classes a given input case belongs. Examples include credit assignment (is this person a good or bad credit risk), cancer detection (tumor, clear), signature recognition (forgery, true). In all these cases, the output required is clearly a single nominal variable. The most common classification tasks are (as above) two-state, although many-state tasks are also not unknown.

b) Regression. In regression, the objective is to predict the value of a (usually) continuous variable: tomorrow's stock price, the fuel consumption of a car, next year's profits. In this case, the output required is a single numeric variable.

Neural networks can actually perform a number of regression and/or classification tasks at once, although commonly each network performs only one. In the vast majority of cases, therefore, the network will have a single output variable, although in the case of many-state classification problems, this may correspond to a number of output units (the post-processing stage takes care of the mapping from output units to output variables). If you do define a single network with multiple output variables, it may suffer from cross-talk (the hidden neurons experience difficulty learning, as they are attempting to model at least two functions at once). The best solution is usually to train separate networks for each output, then to combine them into an ensemble so that they can be run as a unit.

4.5 TRAINING MULTILAYER PERCEPTRONS

This is perhaps the most popular network architecture in use today, due originally to Rumelhart and McClelland (1986) and discussed at length in most neural network textbooks (e.g., Bishop, 1995). This is the type of network discussed briefly in previous sections: the units each perform a biased weighted sum of their inputs and pass this activation level through a transfer function to produce their output, and the units are arranged in a layered feed forward topology. The network thus has a simple interpretation as a form of input-output model, with the weights and thresholds (Biases) the free parameters of the model. Such networks can model functions of almost arbitrary complexity, with the number of layers, and the number of units in each layer, determining the function complexity. Important issues in Multilayer Perceptrons (MLP) design include specification of the number of hidden layers and the number of units in these layers. The number of input and output units is defined by the problem (there may be some uncertainty about precisely which inputs to use, a point to which we will return later. However, for the moment we will assume that the input variables are intuitively selected and are all meaningful). The number of hidden units to use is far from clear. As good a starting point as any is to use one hidden layer, with the number of units equal to half the sum of the number of input and output units. Again, we will discuss how to choose a sensible number later. Once the number of layers, and number of units in each layer, has been selected, the network's weights and thresholds must be set so as to minimize the prediction error made by the network. This is the role of the training algorithms. The historical cases that you have gathered are used to automatically adjust the weights and thresholds in order to minimize this error. This process is equivalent to fitting the model represented by the network to the training data available. The error of a particular configuration of the network can be determined by running all the training cases through the network, comparing the actual output generated with the desired or target outputs. The differences are combined together by an error function to give the network error. The most common error functions are the sum squared error (used for regression problems), where the individual errors of output units on each case are squared and summed together, and the cross entropy functions (used for maximum likelihood classification).

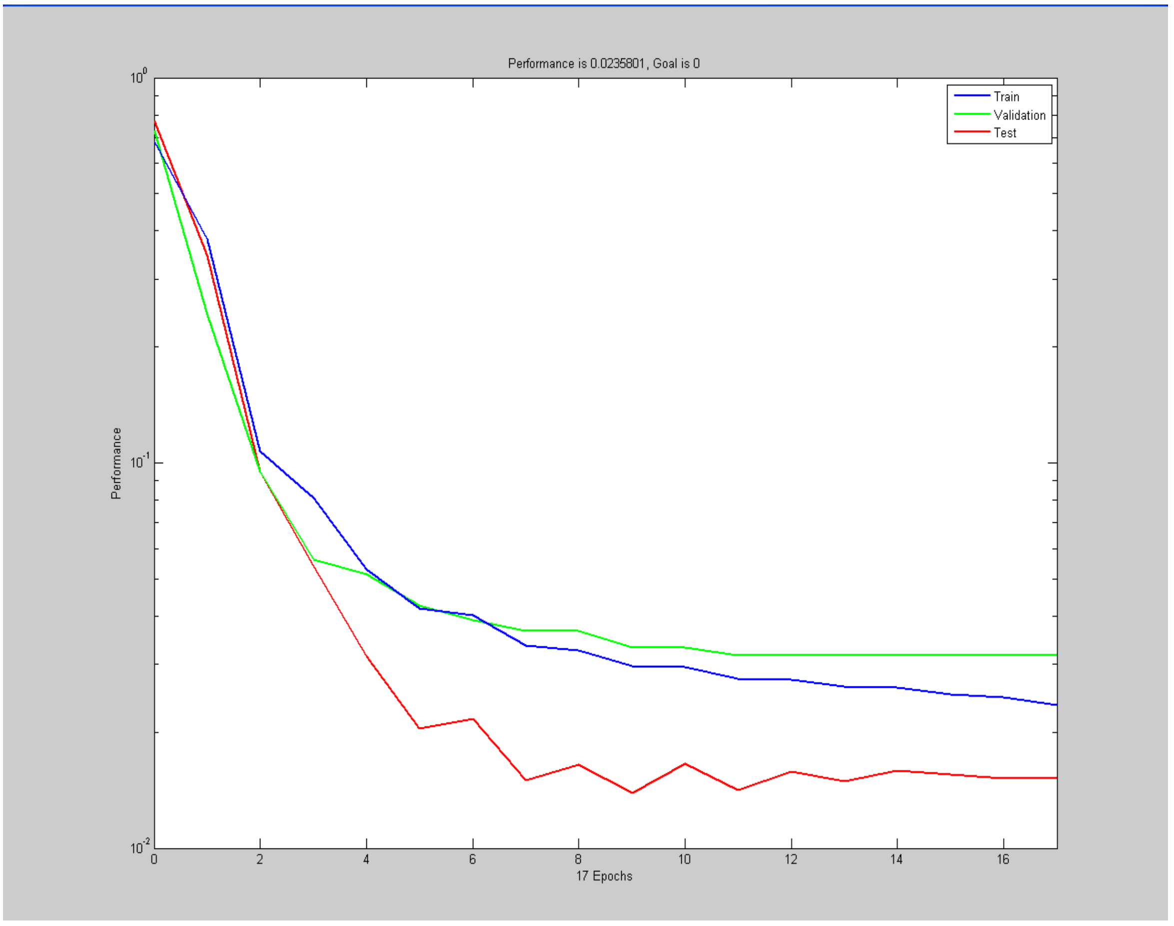
In traditional modeling approaches (e.g., linear modeling) it is possible to algorithmically determine the model configuration that absolutely minimizes this error. The price paid for the greater (non-linear) modeling power of neural networks is that although we can adjust a network to lower its error, we can never be sure that the error could not be lower still. A helpful concept here is the error surface. Each of the N weights and thresholds of the network (i.e., the free parameters of the model) is taken to be a dimension in space. The N+1th dimension is the network error. For any possible configuration of weights the error can be plotted in the N+1th dimension, forming an error surface. The objective of network training is to find the lowest point in this many-dimensional surface. In a linear model with sum squared error function, this error surface is a parabola (a quadratic), which means that it is a smooth bowl-shape with a single minimum. It is therefore "easy" to locate the minimum.

Neural network error surfaces are much more complex, and are characterized by a number of unhelpful features, such as local minima (which are lower than the surrounding terrain, but above the global minimum), flat-spots and plateaus, saddle-points, and long narrow ravines.

CHAPTER 5

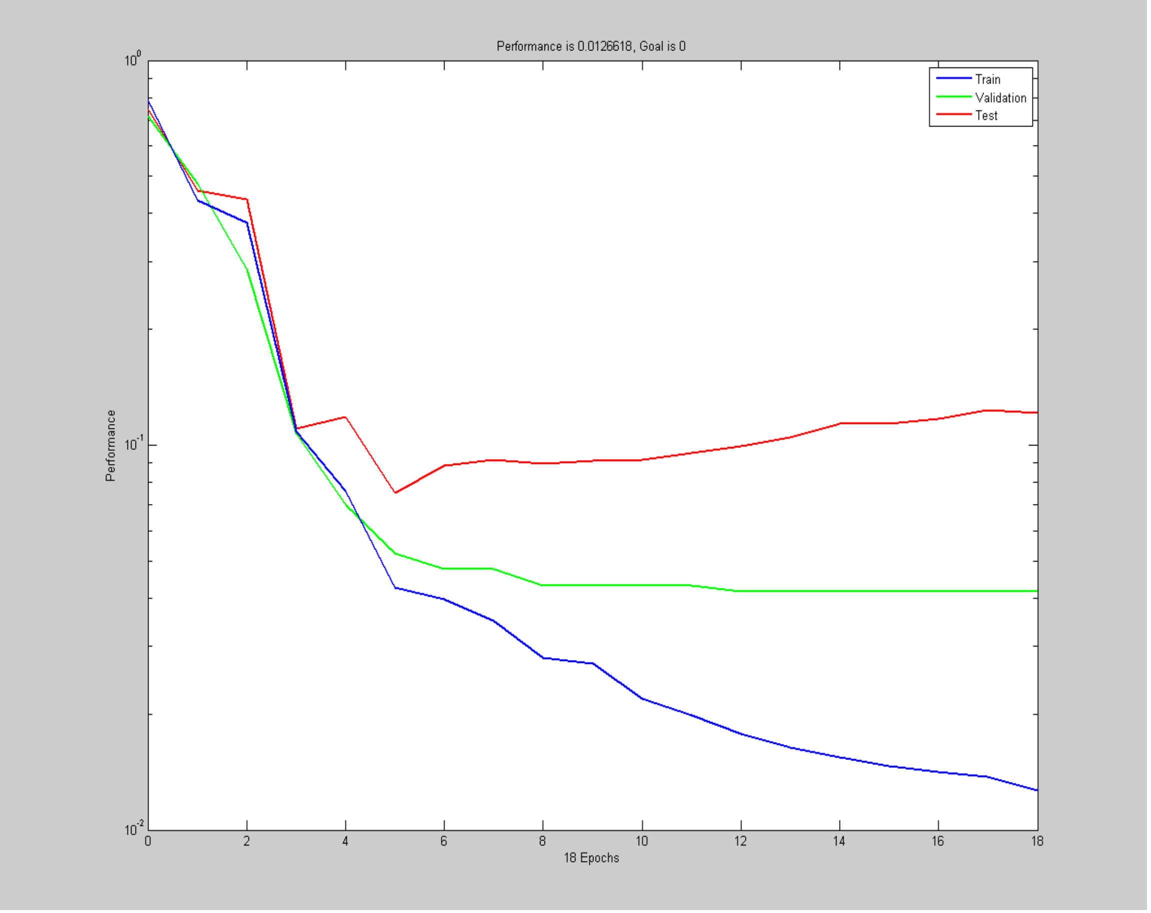
RESULTS AND DISCUSSIONS

The results of the simulation are in the form of graphs of performance of system v/s epochs. The first iteration shows the output of the system with 1-hidden layer feed forward network with 10 neurons in the hidden layer



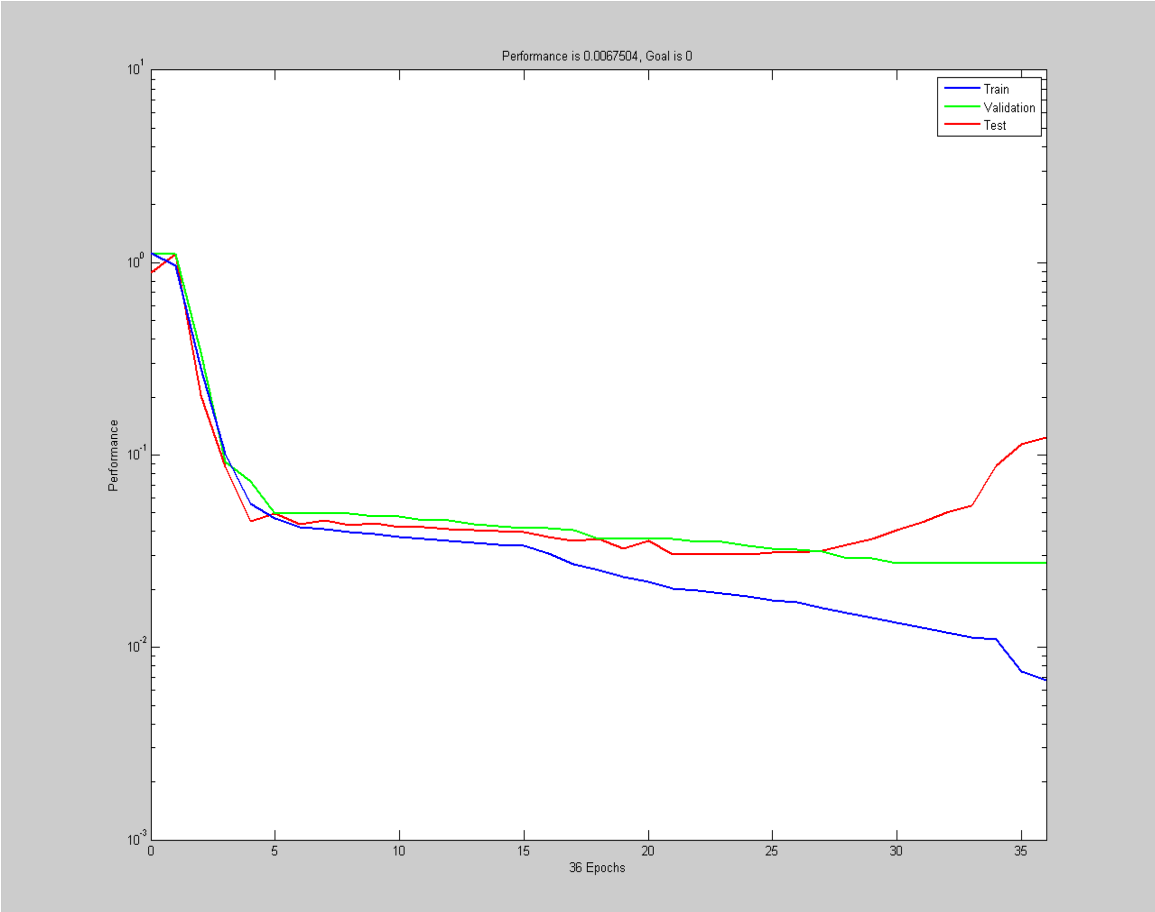
TRAINLM-calcjx, Epoch 0/100, MSE 0.683164/0, Gradient 0.808662/1e-010
TRAINLM-calcjx, Epoch 17/100, MSE 0.0235801/0, Gradient 0.0163509/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 100.000000,
Percentage Incorrect identification: 0.000000%

The 2nd iteration shows the output of the system with 1-hidden layer feed forward network with 11 neurons in the hidden layer



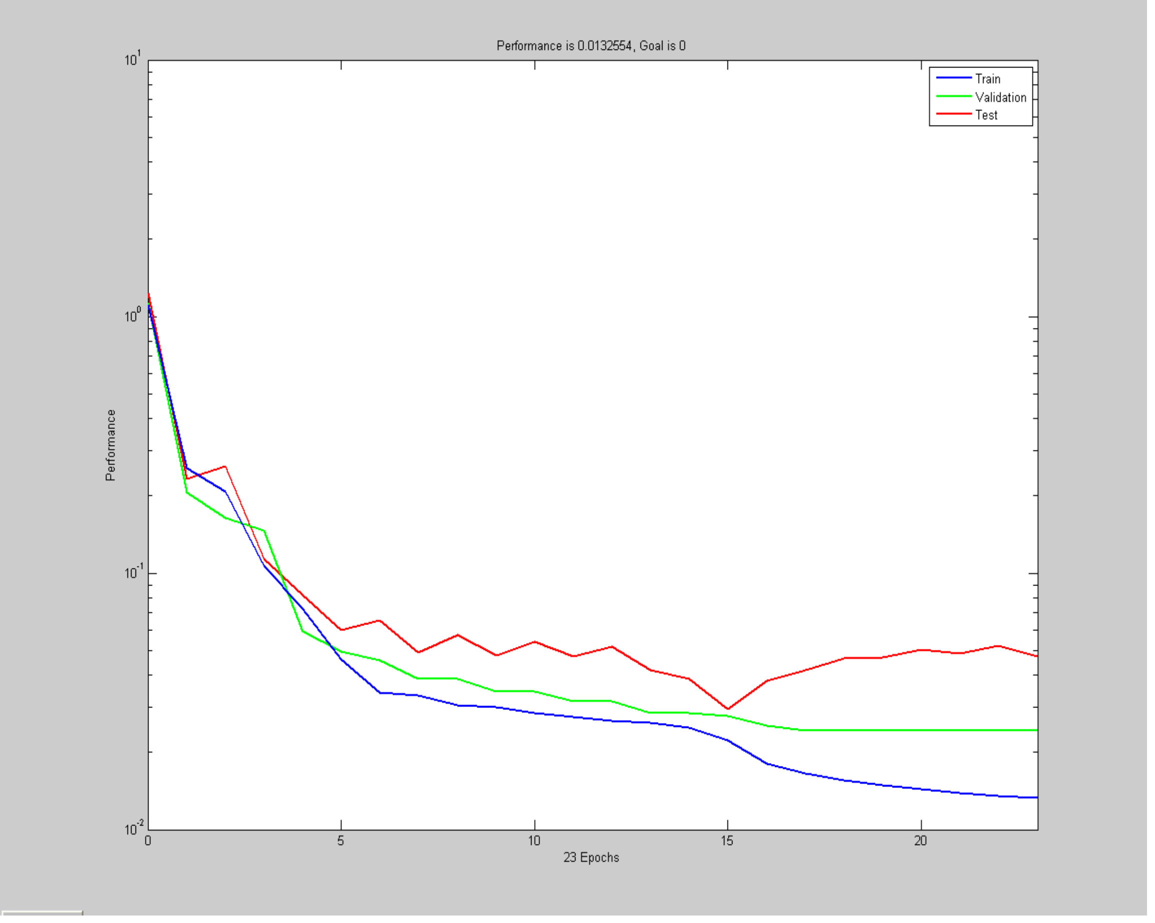
TRAINLM-calcjx, Epoch 0/100, MSE 0.786652/0, Gradient 1.05701/1e-010
TRAINLM-calcjx, Epoch 18/100, MSE 0.0126618/0, Gradient 0.0123547/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 92.500000%
Percentage Incorrect identification: 7.500000%

The 3rd iteration shows the output of the system with 1-hidden layer feed forward network with 12 neurons in the hidden layer



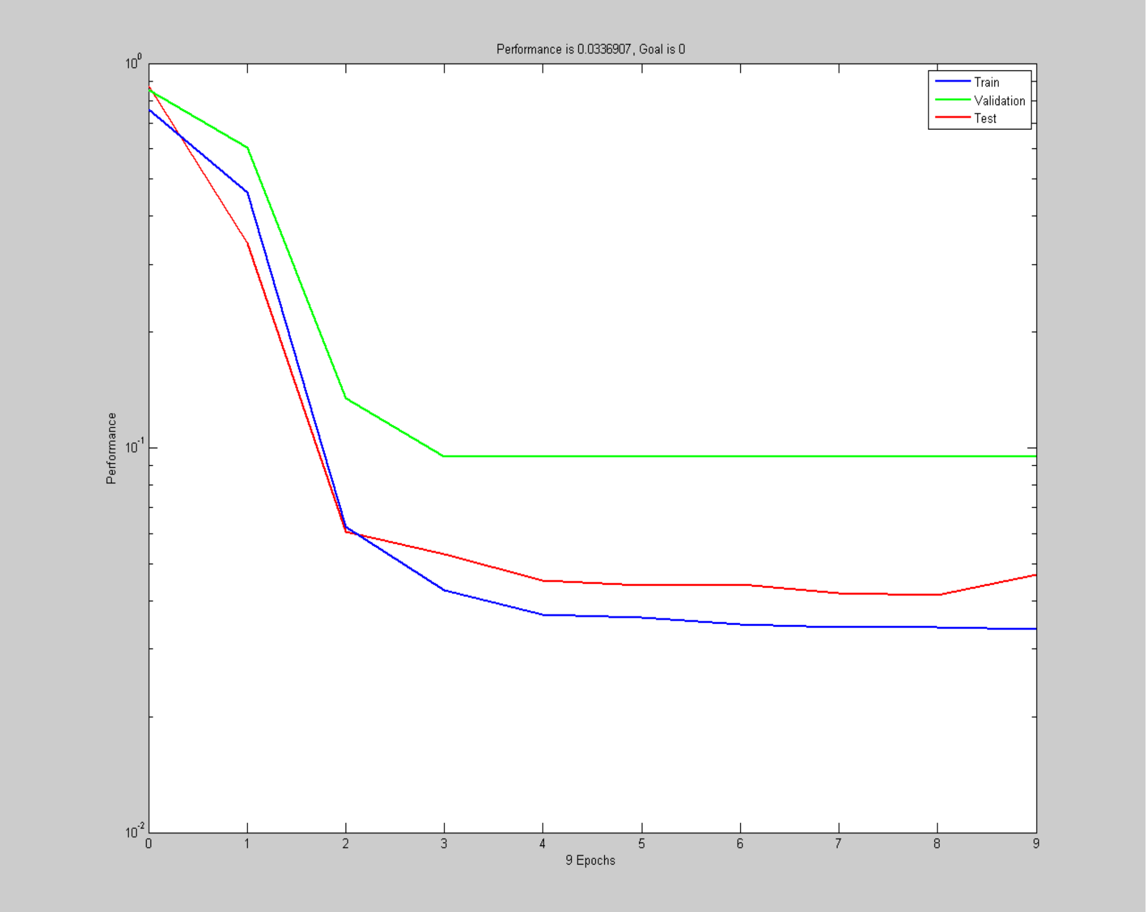
TRAINLM-calcjx, Epoch 0/100, MSE 1.11442/0, Gradient 1.30094/1e-010
TRAINLM-calcjx, Epoch 25/100, MSE 0.017549/0, Gradient 0.0222404/1e-010
TRAINLM-calcjx, Epoch 36/100, MSE 0.0067504/0, Gradient 0.0181246/1e-010
TRAINLM, Validation stop
Total testing samples: 40
Percentage Correct identification : 97.500000,
Percentage Incorrect identification: 2.500000%

The 4th iteration shows the output of the system with 1-hidden layer feed forward network with 13 neurons in the hidden layer



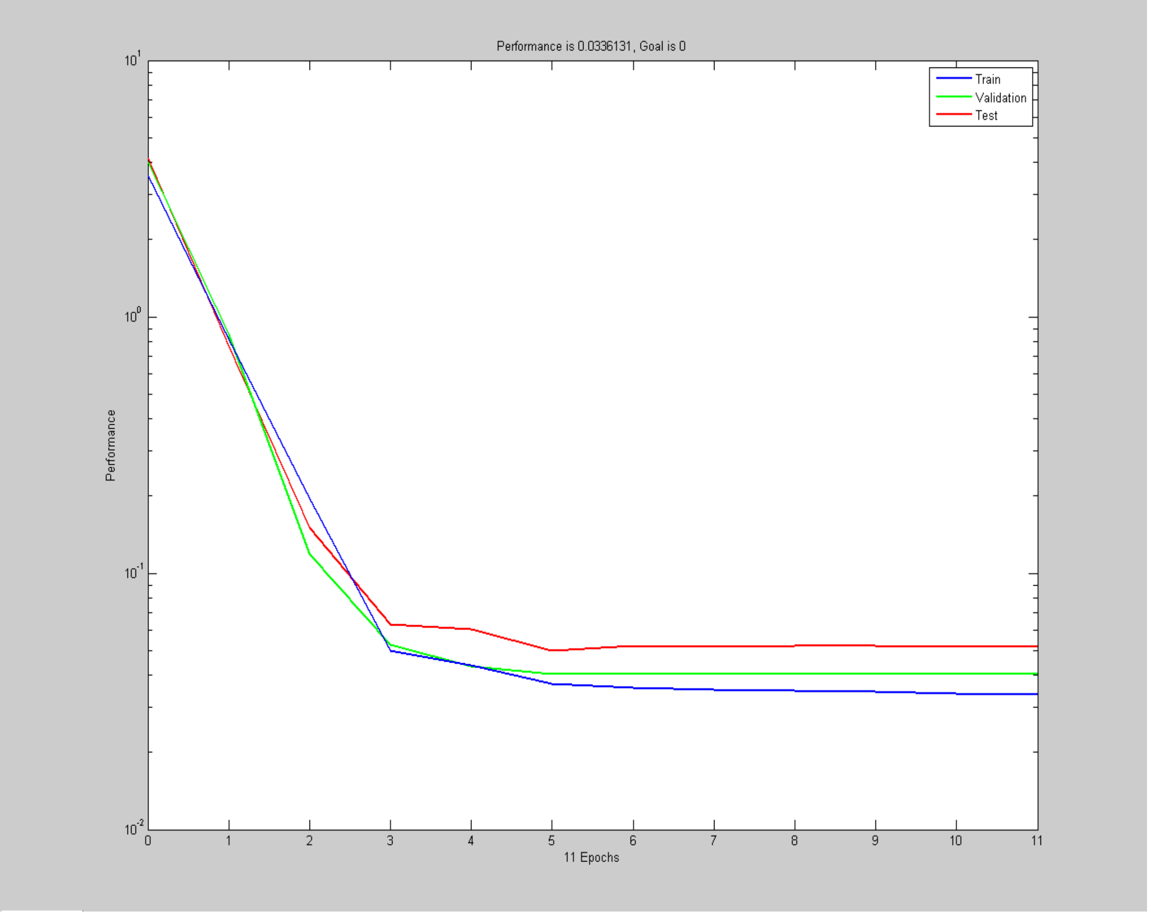
TRAINLM-calcjx, Epoch 0/100, MSE 1.10928/0, Gradient 1.45153/1e-010
TRAINLM-calcjx, Epoch 23/100, MSE 0.0132554/0, Gradient 0.0147554/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 95.000000%
Percentage Incorrect identification: 5.000000%

The 5th iteration shows the output of the system with 1-hidden layer feed forward network with 14 neurons in the hidden layer



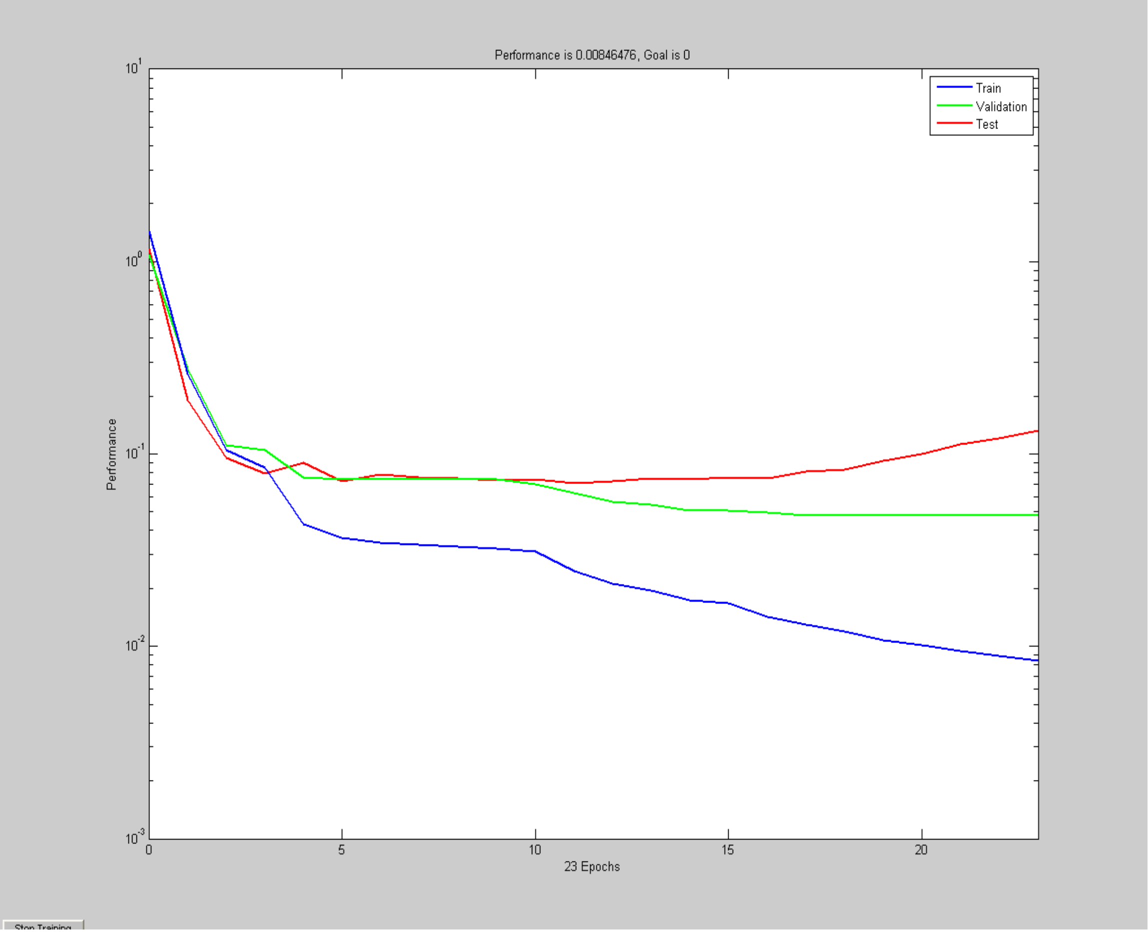
TRAINLM-calcjx, Epoch 0/100, MSE 0.758789/0, Gradient 1.16007/1e-010
TRAINLM-calcjx, Epoch 9/100, MSE 0.0336907/0, Gradient 0.0601881/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 97.500000%
Percentage Incorrect identification: 2.500000%

The 6th iteration shows the output of the system with 1-hidden layer feed forward network with 15 neurons in the hidden layer



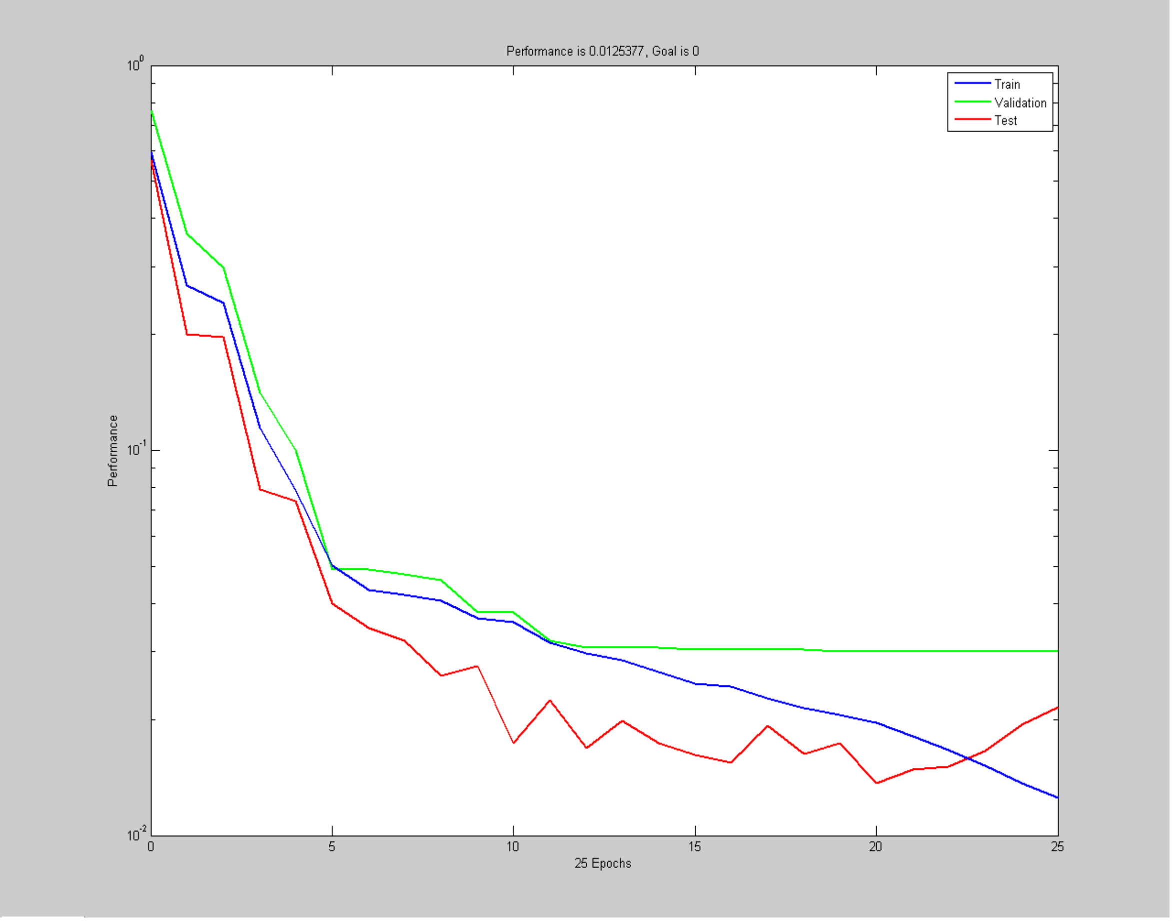
TRAINLM-calcjx, Epoch 0/100, MSE 3.52908/0, Gradient 3.53553/1e-010
TRAINLM-calcjx, Epoch 11/100, MSE 0.0336131/0, Gradient 0.0039927/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 90.000000%
Percentage Incorrect identification: 10.000000%

The 7th iteration shows the output of the system with 1-hidden layer feed forward network with 16 neurons in the hidden layer



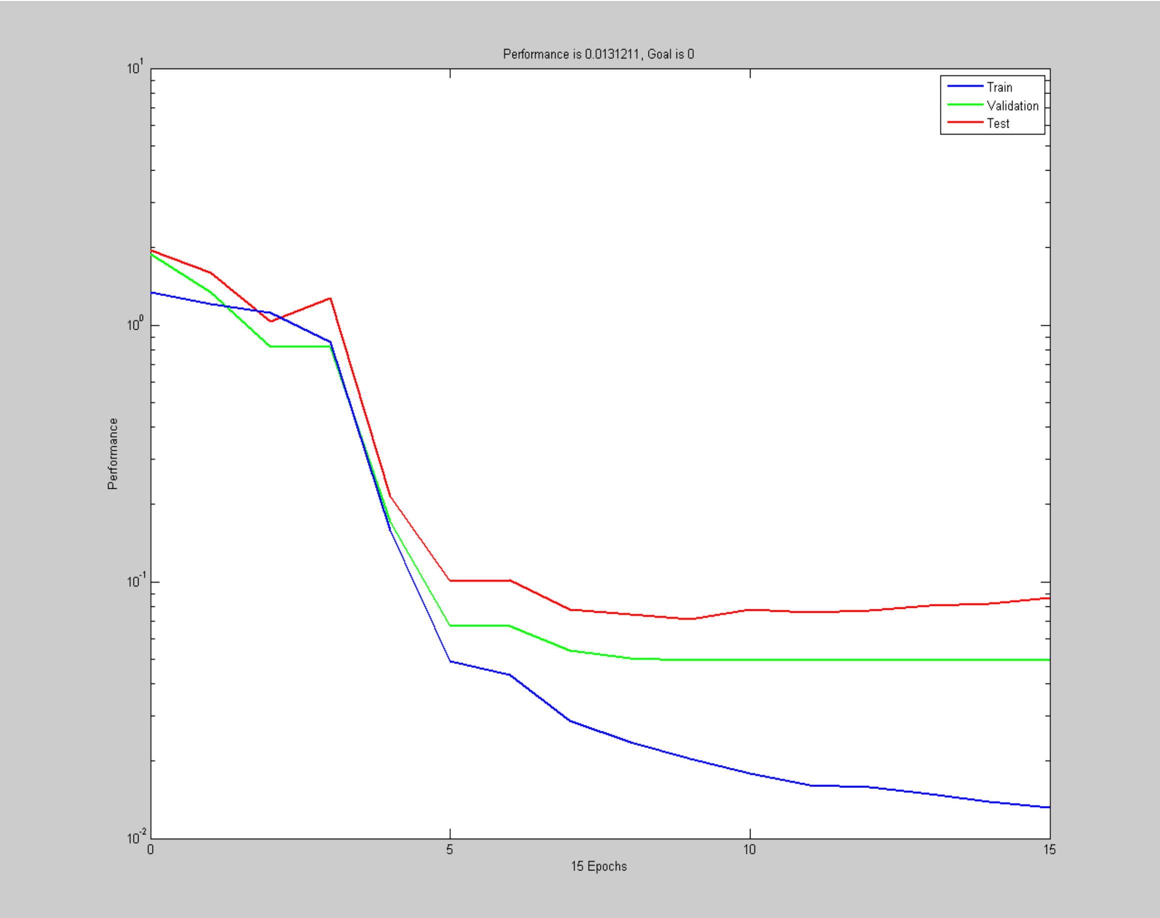
TRAINLM-calcjx, Epoch 0/100, MSE 1.43298/0, Gradient 1.70158/1e-010
TRAINLM-calcjx, Epoch 23/100, MSE 0.00846476/0, Gradient 0.0145398/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 90.000000%
Percentage Incorrect identification: 10.000000%

The 8th iteration shows the output of the system with 1-hidden layer feed forward n etwork with 17 neurons in the hidden layer



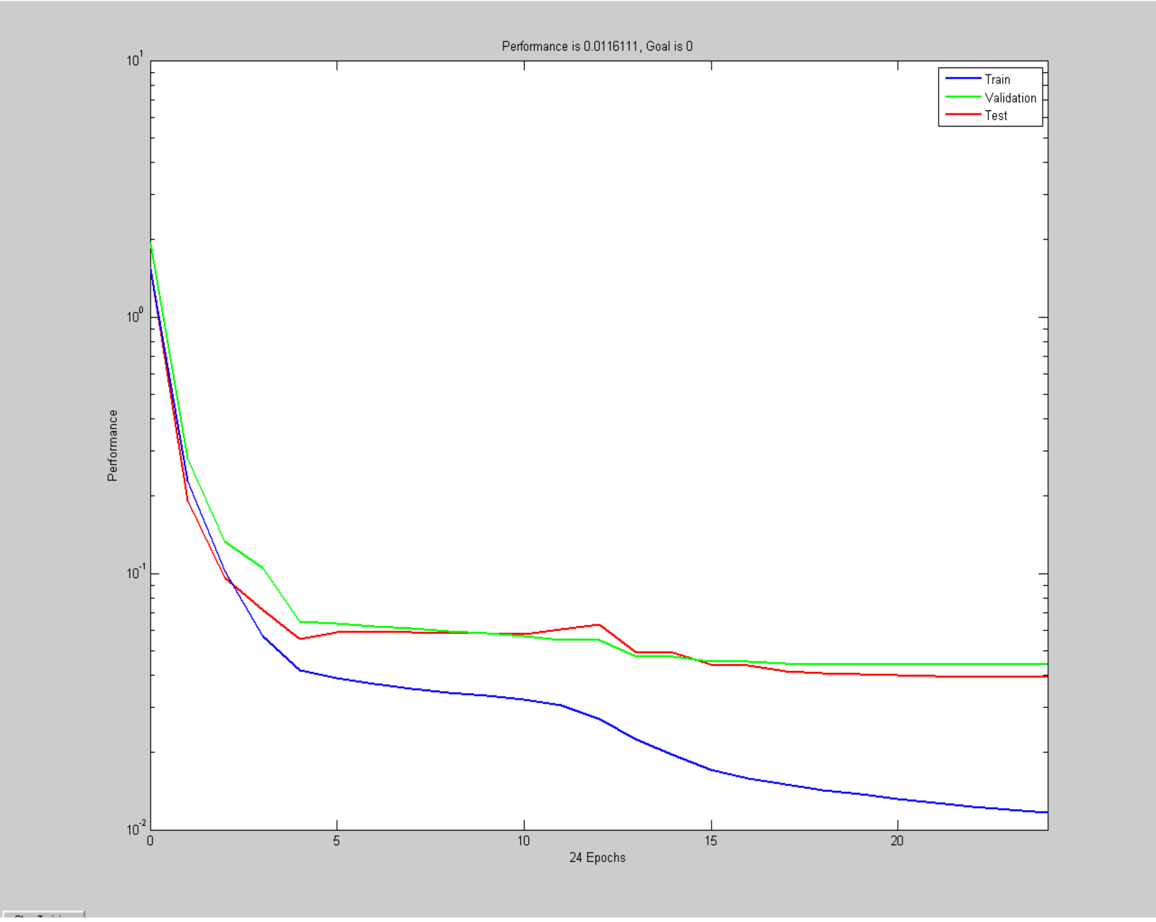
TRAINLM-calcjx, Epoch 0/100, MSE 0.592254/0, Gradient 0.746683/1e-010
TRAINLM-calcjx, Epoch 25/100, MSE 0.0125377/0, Gradient 0.0256221/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 100.000000%
Percentage Incorrect identification: 0.000000%

The 9th iteration shows the output of the system with 1-hidden layer feed forward network with 18 neurons in the hidden layer



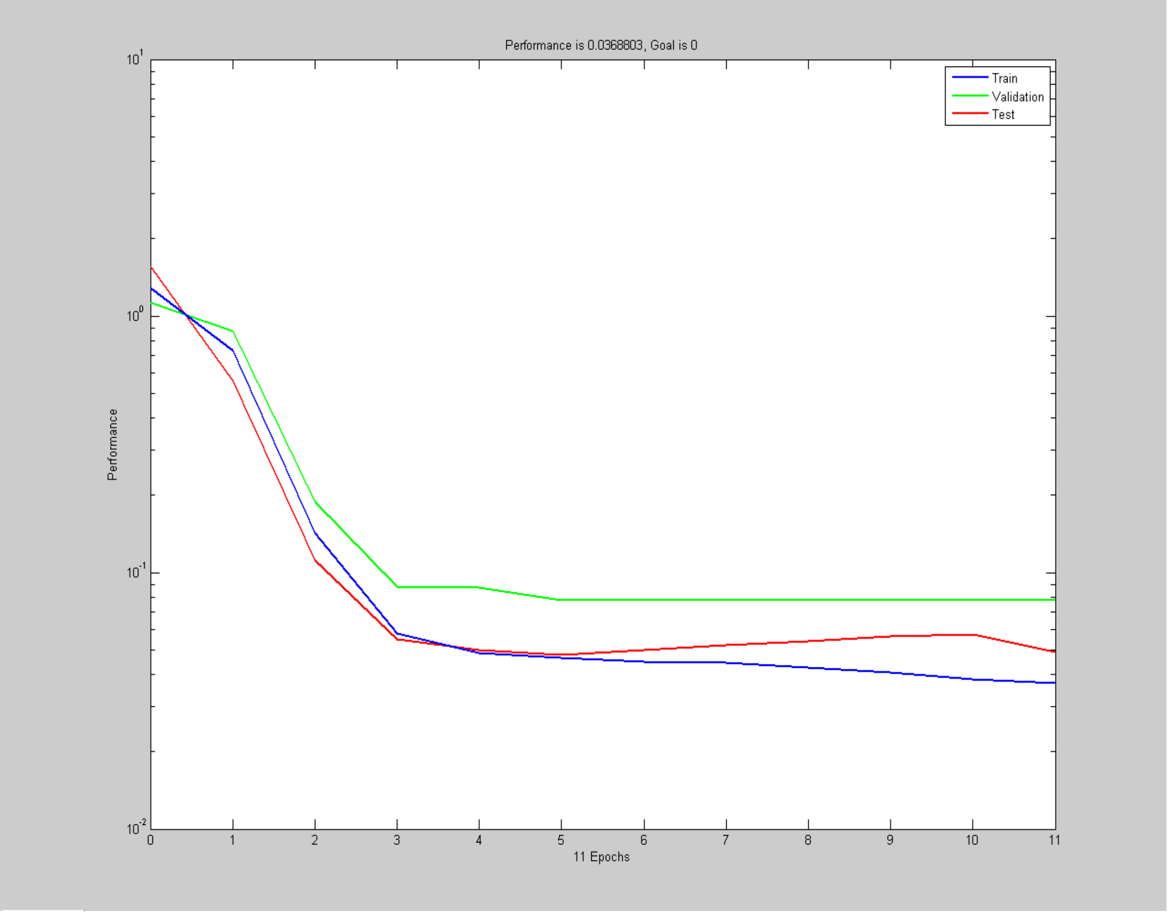
TRAINLM-calcjx, Epoch 0/100, MSE 1.33641/0, Gradient 1.42396/1e-010
TRAINLM-calcjx, Epoch 15/100, MSE 0.0131211/0, Gradient 0.0286172/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 90.000000%
Percentage Incorrect identification: 10.000000%

The 10th iteration shows the output of the system with 1-hidden layer feed forward network with 19 neurons in the hidden layer



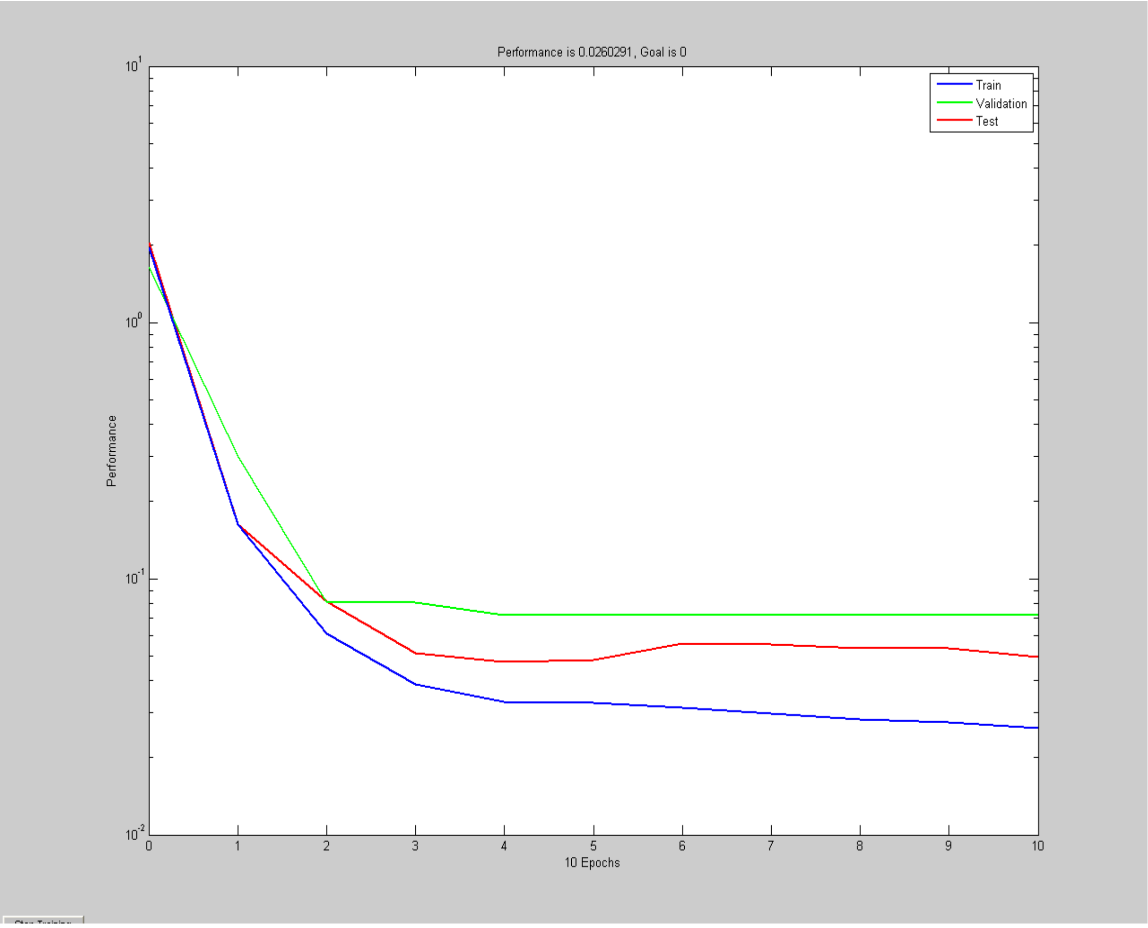
TRAINLM-calcjx, Epoch 0/100, MSE 1.52269/0, Gradient 2.09262/1e-010
TRAINLM-calcjx, Epoch 24/100, MSE 0.0116111/0, Gradient 0.00675582/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 95.000000%
Percentage Incorrect identification: 5.000000%

The 11th iteration shows the output of the system with 1-hidden layer feed forward network with 20 neurons in the hidden layer



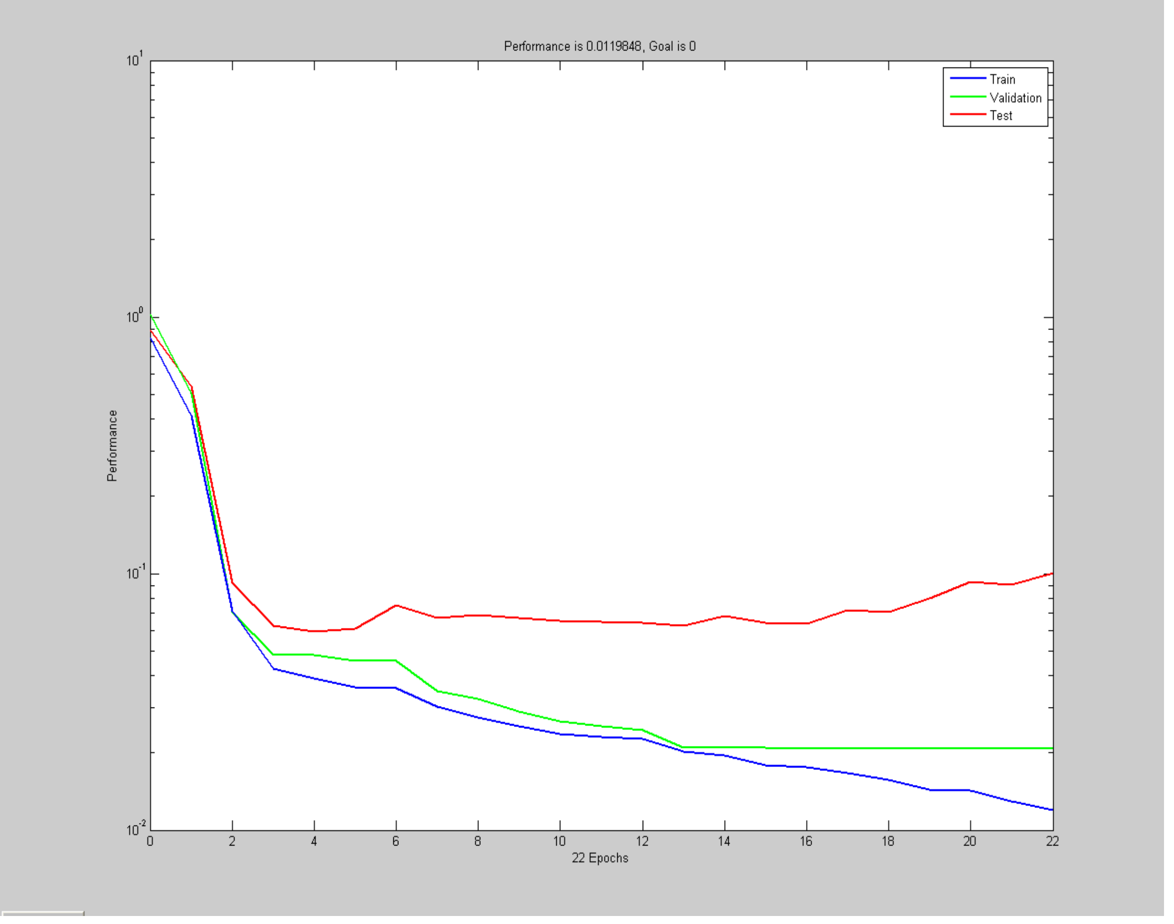
TRAINLM-calcjx, Epoch 0/100, MSE 1.28405/0, Gradient 1.91348/1e-010
TRAINLM-calcjx, Epoch 11/100, MSE 0.0368803/0, Gradient 0.154867/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 97.500000%
Percentage Incorrect identification: 2.500000%

The 12th iteration shows the output of the system with 1-hidden layer feed forward network with 21 neurons in the hidden layer



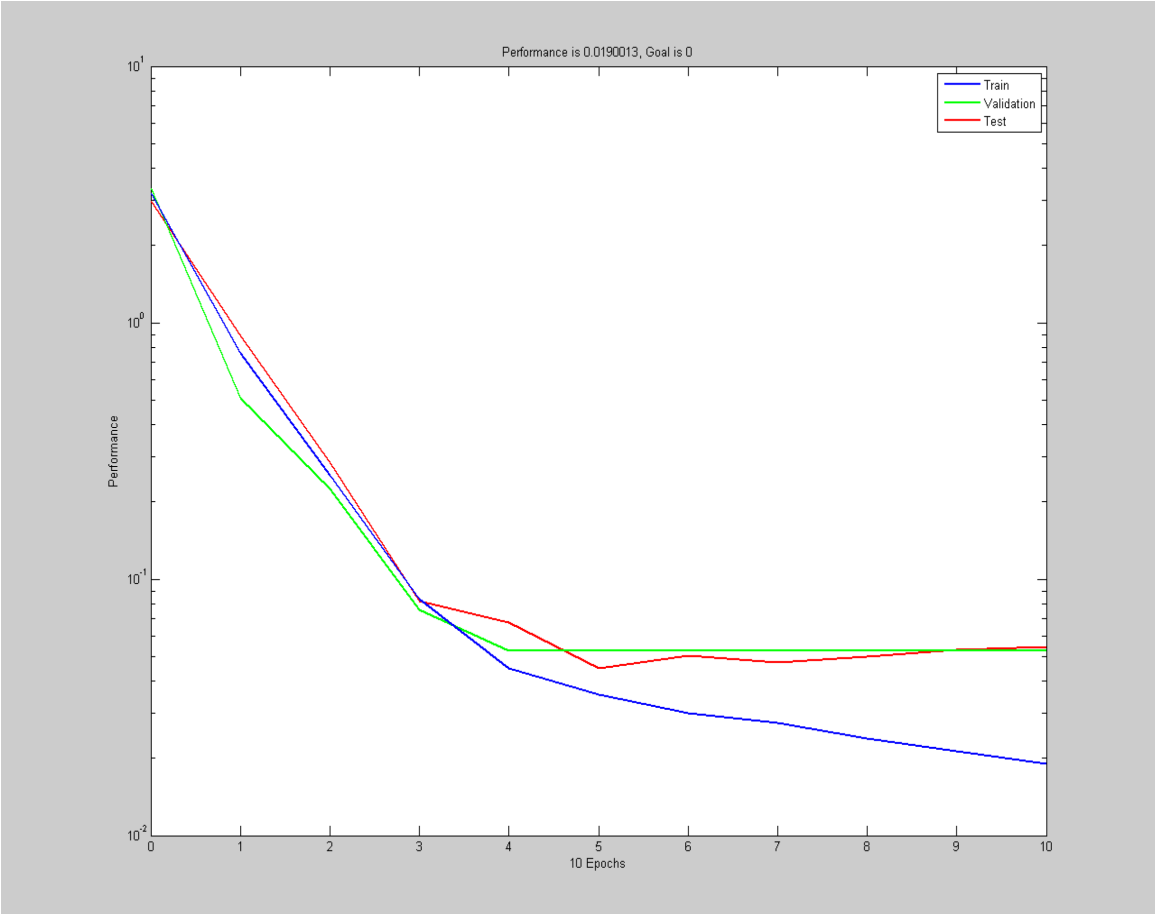
TRAINLM-calcjx, Epoch 0/100, MSE 1.95688/0, Gradient 3.02517/1e-010
TRAINLM-calcjx, Epoch 10/100, MSE 0.0260291/0, Gradient 0.029368/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 97.500000%
Percentage Incorrect identification: 2.500000%

The 13th iteration shows the output of the system with 1-hidden layer feed forward network with 12 neurons in the hidden layer



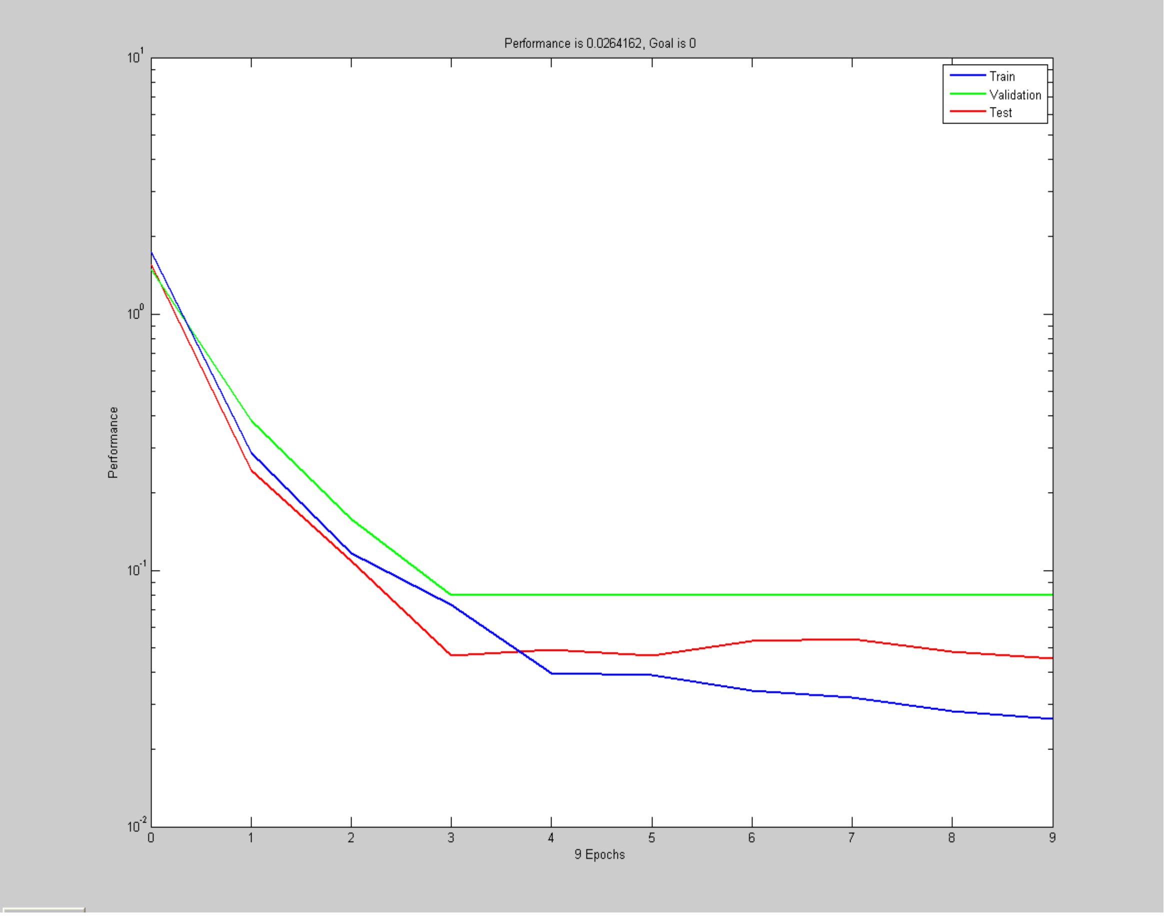
TRAINLM-calcjx, Epoch 0/100, MSE 0.829539/0, Gradient 1.84412/1e-010
TRAINLM-calcjx, Epoch 22/100, MSE 0.0119848/0, Gradient 0.0194297/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification   : 95.000000%
Percentage Incorrect identification: 5.000000%

The 14th iteration shows the output of the system with 1-hidden layer feed forward network with 13 neurons in the hidden layer



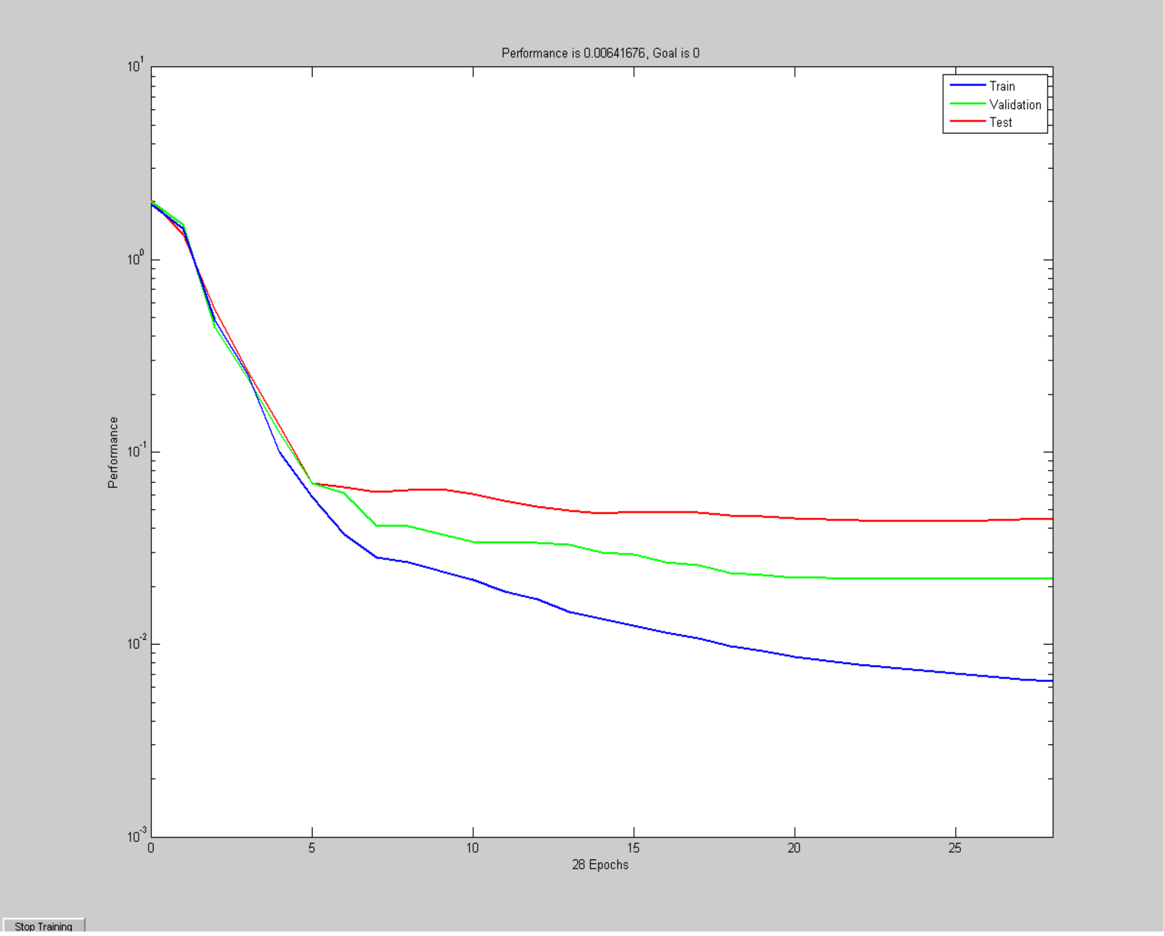
TRAINLM-calcjx, Epoch 0/100, MSE 3.18446/0, Gradient 4.25571/1e-010
TRAINLM-calcjx, Epoch 10/100, MSE 0.0190013/0, Gradient 0.0224126/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 97.500000%
Percentage Incorrect identification: 2.500000%

The 15th iteration shows the output of the system with 1-hidden layer feed forward network with 14 neurons in the hidden layer



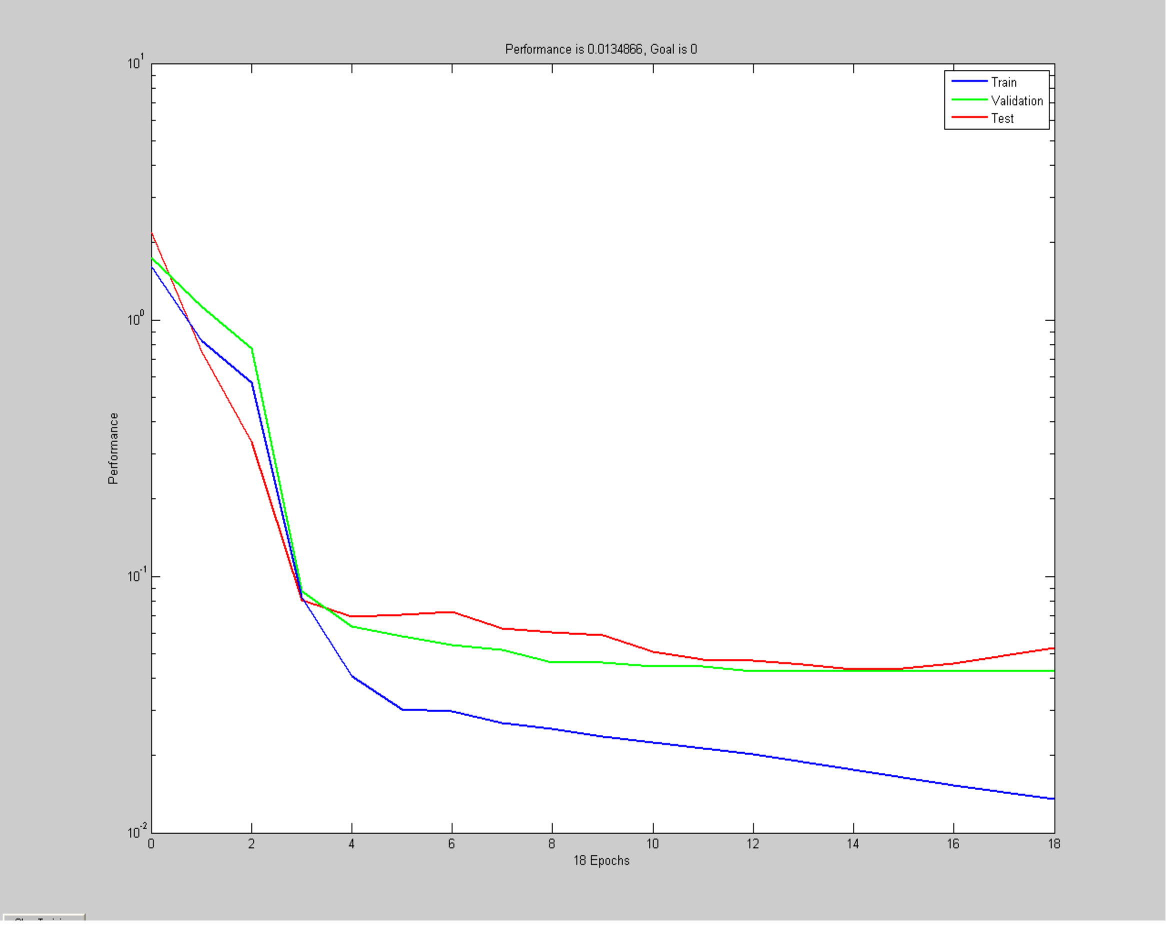
TRAINLM-calcjx, Epoch 0/100, MSE 1.74063/0, Gradient 2.71404/1e-010
TRAINLM-calcjx, Epoch 9/100, MSE 0.0264162/0, Gradient 0.0182176/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 100.000000%
Percentage Incorrect identification: 0.000000%

The 16th iteration shows the output of the system with 1-hidden layer feed forward network with 15 neurons in the hidden layer



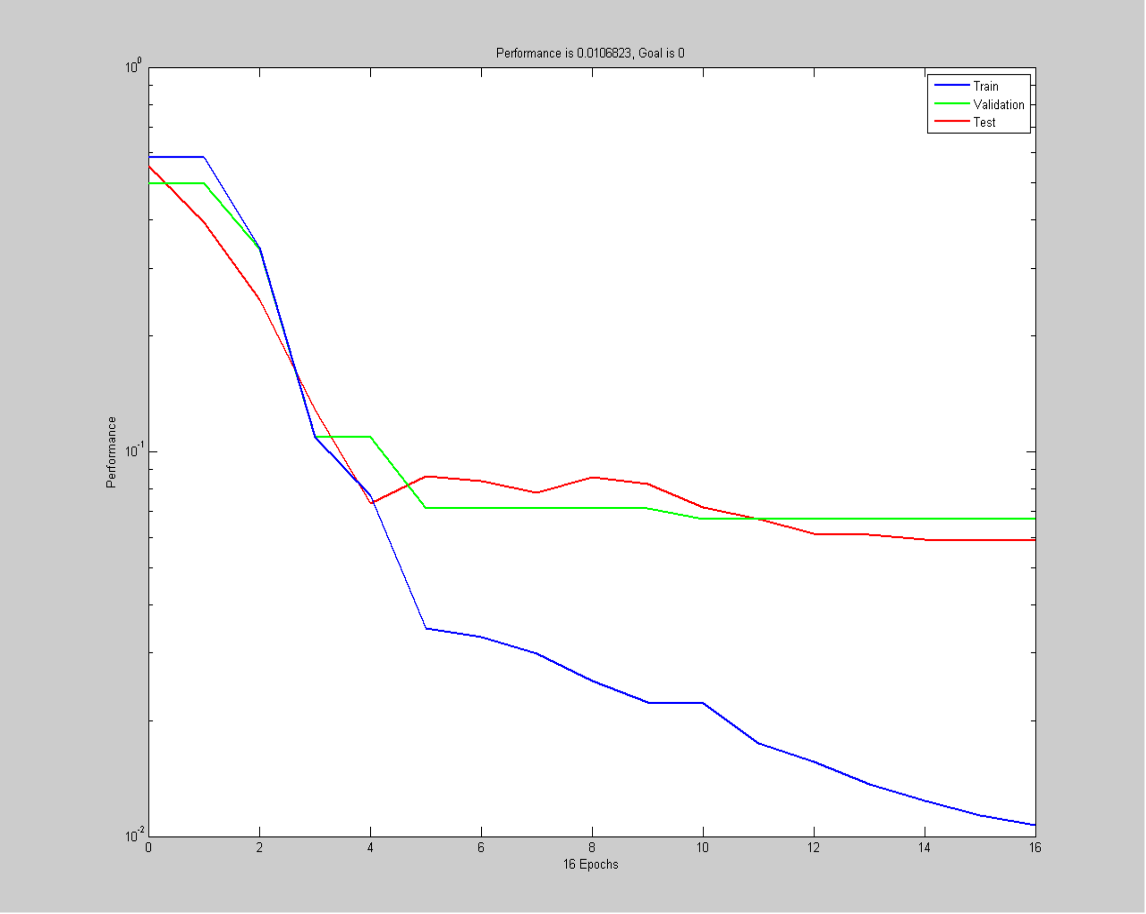
TRAINLM-calcjx, Epoch 0/100, MSE 1.92923/0, Gradient 2.86712/1e-010
TRAINLM-calcjx, Epoch 25/100, MSE 0.00705224/0, Gradient 0.00542461/1e-010
TRAINLM-calcjx, Epoch 28/100, MSE 0.00641676/0, Gradient 0.00365777/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 95.000000%
Percentage Incorrect identification: 5.000000%

The 17th iteration shows the output of the system with 1-hidden layer feed forward network with 16 neurons in the hidden layer



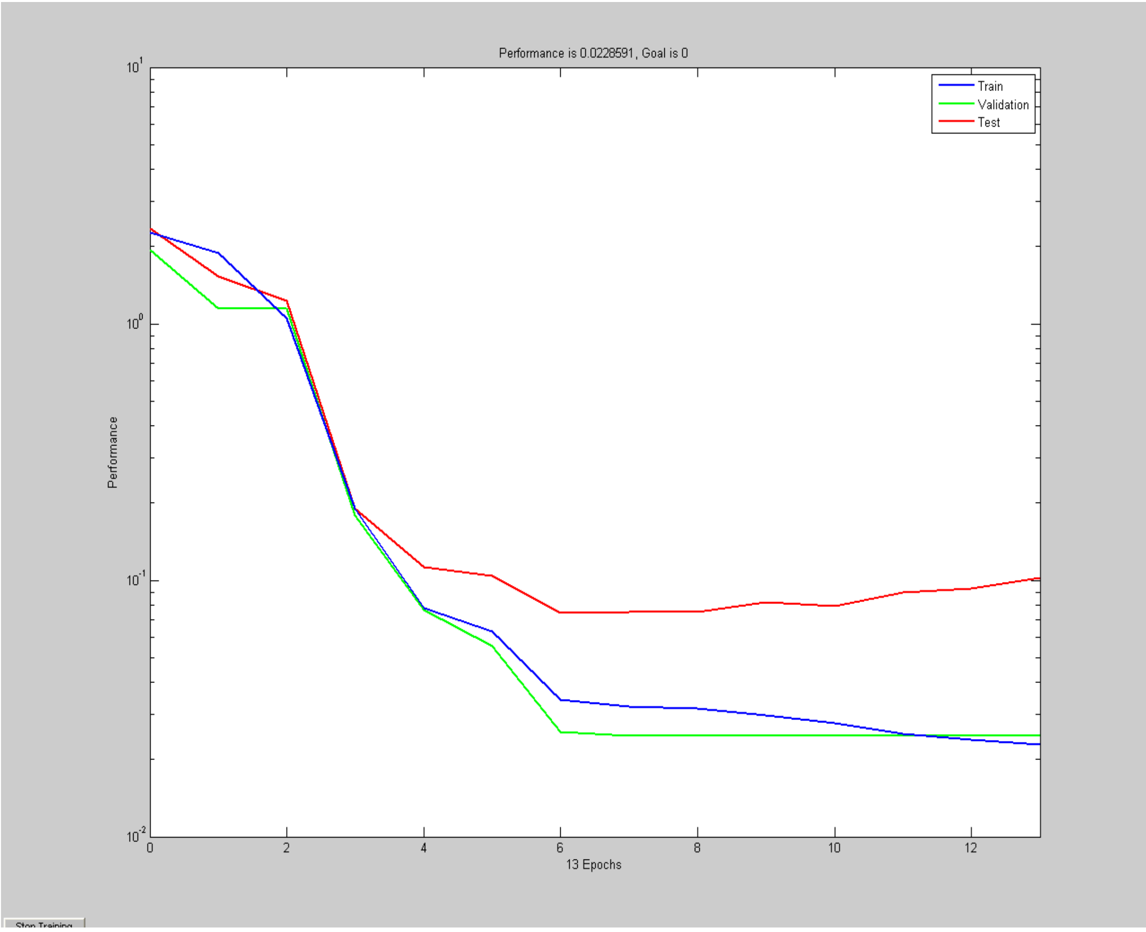
TRAINLM-calcjx, Epoch 0/100, MSE 1.60728/0, Gradient 2.6478/1e-010
TRAINLM-calcjx, Epoch 18/100, MSE 0.0134866/0, Gradient 0.0146145/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 95.000000%
Percentage Incorrect identification: 5.000000%

The 18th iteration shows the output of the system with 1-hidden layer feed forward network with 17 neurons in the hidden layer



TRAINLM-calcjx, Epoch 0/100, MSE 0.585598/0, Gradient 1.28187/1e-010
TRAINLM-calcjx, Epoch 16/100, MSE 0.0106823/0, Gradient 0.0602643/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 92.500000%
Percentage Incorrect identification: 7.500000%

The 19th iteration shows the output of the system with 1-hidden layer feed forward network with 18 neurons in the hidden layer



TRAINLM-calcjx, Epoch 0/100, MSE 2.25799/0, Gradient 3.06468/1e-010
TRAINLM-calcjx, Epoch 13/100, MSE 0.0228591/0, Gradient 0.117323/1e-010
TRAINLM, Validation stop.
Total testing samples: 40
Percentage Correct identification : 92.500000%
Percentage Incorrect identification: 7.500000%

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

It has been found that the output of the system with 1-hidden layer feed forward network with 14 neurons in the hidden layer gives the best results in predicting whether the system is stable or not.

The performance of the electrical system can be improved by efficient and reliable distribution network. This thesis discusses a neural network technique for network restructuring and determines stable or unstable state in distribution automation systems. The classification of loads, their variation in load curve are considered to be input for training the ANN and optimum feeder configuration is arrived at.

5.2 **FUTURE SCOPE OF THESIS**

Results of this work tell that neural networks can be trained according to input but still further work is needed to confirm their use for their automatic training.

Testing using more complex network models must be carried out.

Moreover same work can be carried out under transient stability conditions of the power system. Different training technique can be used for training purpose of neural networks.

Other methods can be practiced such as Genetic Algorithm, to get appropriate global optimum with less computational burden.

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Appendix A

Voltage Input Data (In KVs)

V1	V2	V3	V4	V5	V6	Output
0	20.6	14.4	42.8	46.5	19.6	Stable
1	13.3	11.1	27.8	32.3	11.3	Stable
0	16.7	14.3	32.3	37	14.7	Unstable
1	9.8	8.9	20.4	23.9	8.8	Unstable
0	15.6	14.1	31	34.5	13.8	Unstable
1	9.1	8.1	18.5	21.6	7.7	Unstable
0	14.1	10.5	29.1	31.6	13.1	Stable
1	11.1	9.9	23.8	27.1	9.8	Stable
1	12.8	12.2	27.9	31.9	11.5	Unstable
0	19.9	16.6	39.4	43.9	17.9	Unstable
0	17.5	14.7	33.3	37.6	14.6	Unstable
0	20.1	17.2	39.8	44.1	18.6	Unstable
0	19.9	17.9	40.1	46.4	17.9	Unstable
1	21.3	15.7	47.1	54.6	20	Stable
1	16.4	13	35.7	41.8	15.2	Stable
0	19.7	16.7	39.9	43.6	18.2	unstable
1	12.8	12.2	26.7	31.1	11.1	Unstable
0	14	11.5	29.2	32.2	13.1	Stable
0	17.4	12.8	36.1	39.5	16.2	Stable
0	10.2	8.2	20.2	22.2	9	Stable
1	15.7	12.6	35.8	40.3	14.5	Stable
1	15	14.2	32.8	37.4	14	Unstable
0	18.8	13.8	39.2	43.3	17.9	Stable
0	17.6	14	34	38.6	15.5	Unstable
0	15.4	11.1	30.2	33.6	13.5	Stable
1	11.2	10	22.8	26.9	9.4	Unstable
0	18	14.9	34.7	39.5	15.7	Unstable
1	17.1	12.6	36.4	42	15.1	Stable
1	9	8.5	19.3	22.7	7.7	Unstable
0	18.9	16.7	36.3	41.7	15.3	Unstable
1	10.4	9.7	21.7	25.4	8.3	Unstable
0	13.7	11	27.5	30.5	12.2	Stable
0	19.4	14.4	39.8	44.3	17.9	Stable
1	16.6	13.5	38.1	43.4	14.9	Stable
1	12.2	10.8	27.3	31.6	10.9	Stable
1	15.8	15	34.5	40.3	15.3	Unstable
0	14.2	10.7	27.8	30.9	12.7	Stable
1	12	10.7	24.6	28.9	10.5	Unstable
0	14.3	12.2	28.1	31.8	12.5	Unstable
1	8.1	6.7	16.1	19	7	Stable

1	13.1	10.6	28.2	32.3	11	Stable
0	13.4	10.1	26.6	29.6	12	Stable
1	11.9	11.4	26	30.1	10.9	Unstable
0	17.9	12.9	36.9	40.9	16.5	Stable
1	9.1	8.2	19.2	22.2	7.7	Unstable
0	17.1	14.5	33.1	37.2	14.6	Unstable
1	16.2	13.3	36	41.7	15.4	Stable
1	9.5	8.2	19.6	22.4	7.8	Unstable
0	14.6	11.3	29.9	33.5	12.8	Stable
0	11.4	9.2	21.7	24.1	9.7	Unstable
0	13.2	11	27.1	30.4	12.2	Stable
0	17.5	12.7	34.6	38.4	16.1	Stable
0	12.5	9.4	24.2	27	11.2	Stable
0	18.4	13.4	37.9	42.2	17.7	Stable
1	16.4	14	34.2	39.8	15.2	Unstable
0	15.7	12.2	31.7	34.2	14.2	Stable
0	14.2	10.6	28.7	31.7	12.9	Stable
1	11.6	11.4	23.7	27.7	10	Unstable
1	19.3	13.5	41.6	47.4	17.8	Stable
1	9.8	8	20.3	23	8.2	Stable
1	13.4	11.8	28.4	32.7	11.7	Unstable
1	19.2	16.5	40.9	47.9	18.1	Unstable
1	15.4	13.3	32.4	37.6	13.8	Unstable
1	17.1	12.7	36.7	41.9	15.6	Stable
0	15.7	13.6	31	34.8	13.8	Unstable
1	17.7	13.6	38.7	44.5	16	Stable
0	15.1	11.4	30.2	33.3	14	Stable
1	12.8	10.2	27.2	31.8	10.9	Stable
0	12.6	11.5	25	28.1	11.5	Unstable
0	23.1	15.7	47.6	52.8	21.6	Stable
1	14.3	11.6	31.3	35.5	12.7	Stable
0	21.9	17.2	42.6	47.4	19.5	Unstable
0	16.3	11.6	31.6	34.2	14.5	Stable
1	15.2	14.3	33.9	38.5	14.7	Unstable
1	13.1	10.9	28.3	32.4	11.2	Stable
1	15.1	13.5	31.9	37	13.8	Unstable
0	18.4	15.7	36.5	41.6	16.4	Unstable
0	12.9	11.2	25.8	29.1	11.9	Unstable