NANYANG TECHNOLOGICAL UNIVERSITY

VOLTAGE STABILITY ASSESSMENT USING NEURAL NETWORKS IN THE OPEN MARKET ENVIRONMENT

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TABLE OF CONTENTS

Certificate

This is to certify that AnIsm research project titled ***"Voltage stability assessment using Neural Networks in the deregulated market environment"*** for the award of Master of science (Power engineering) degree by Diponkar Paul, Matric no: G0601406D has been carried out under my supervision.

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Summary

Artificial neural network is a method of synthesizing a mapping between input and output variables by learning a set of arc weights and node thresholds of a connectionist model based on training examples. They have been developed in a wide variety of configurations with some common underlying characteristics. They all attempt to achieve good performance through massive interconnection of simple computational elements.An artificial neural network can be defined as a loosely connected array of elementary processors or neurons. Algorithms are then crafted about this architecture. Neurons are linked with interconnects analogous to the biological synapse. This highly connected array of elementary processors defines the system hardware. Commonly used neural networks such as the layered perception, are used to be trained rather than programmed in the conventional sense. Neural networks have been found to be effective systems for learning functional mappings from a body of examples. This is done by adjusting are weights and node thresholds of a set of interconnected neurons according to a specific learning rule. The high degree of connectivity brings about desirable properties such as generation, fault tolerance and noise rejection that are useful in any model. Computationally neural networks have the advantage of massive parallelism and are not restricted in speed by the von Neumann bottle neck characteristic of conventional computation. Neural networks, in most cases are significantly fault tolerant.

At this writing the layered perceptron is receiving the most attention as a viable candidate for application to power system. The layered percceptron is taught by example, as opposed, for example to an expert system, which is taught by rules,. The preponderance of data typically available from the power industry, coupled with the ability of the layered perceptron to learn significantly nonlinear relationships, reveals it as a viable candidate in the available plethora for solving significant power system engineering problems.

A layered perceptron can be used as either a classifier or a regression machine. As a classifier, the layered perceptron categorizes the input into two or more

categories. In power system security assessment, for example, the trained perceptrons categorizes the system as either secure or insecure in accordance to the current system states. For regression applications, the output of the layered perceptron takes a continuous value. Electric load forecasting is an example of regression application.

Chapter 2 states that in static voltage stability assessment, the steady states corresponding to a number of parameters including the loading conditions are examined. One important concept in static assessment is that of the transfer limit surface. The transfer limit is the upper limit from the generator node and is defined as a hyper surface in load parameter space. Here the load parameter space is the multi dimensional space spanned by model loads. A steady state corresponds to a point in this load parameter space. If a loading scenario is given and the maximum loading point is calculated, a point on the transfer limit surface is obtained. Here a loading scenario is a mapping from the total load to the power of each load node. The maximum loading point is the operating point corresponding to the right hand end of the well known nose curve. In other words, the transfer limit surface is the set of maximum loading points under a range of scenarios. The transfer limit surface is the upper limit of the transfer power., hence it divides load parameter space into two regions, one in which operation is possible (hereafter the inside) and one in which operation is possible(the outside). If the operating point reaches the transfer limit through gradual increase of the load, voltages collapse may result. The transfer limit surface holds information about how the maximum loading will change when the scenario changes. For this reason, the normal vector to the transfer limit surface is useful for calculation of preventive control and stability indices as they relates to voltage stability. Representation inequality constraints in power system are the constraints on capacity of equipment and facilities. Of these, the reactive power limit of generators is known to greatly affect voltage stability. If the reactive power reaches its upper limit as the result of gradual increase in load demand, the system stability may change discontinuously. In the worst case, a stable system may suddenly become unstable. This case is referred to as a saddle limit-induced bifurcation. However cases of saddle node bifurcation have long been familiar and both direct methods and continuation methods for the computation of saddle node bifurcation points are known.

Chapter 3 states that unless the notion of learning in a network, we will consider a process of forcing a network to yield a particular response to a specific input. A particular response may or may not be specified to provide external correction. Learning is necessary when the informations about inputs /outputs is unknown or incomplete a priority so that no design of a network can be performed in advance. The majority of the neural network covered requires training in a supervised or nsupervised learning mode. Some of the network however can be designed without incremental training they are designed by batch training rather than stepwise training Back training takes place when the network weights are adjusted in a simple training step. In this mode of learning, the complete set of inputs/output learning data is needed to determine weights and feedback information produced by the network itself is not involved in developing the network. This learning technique is called recording. Learning with feed back either from the teacher or from the environmental rather than a teacher, however, is more typical for normal networks. Such learning is called incremental and is usually performed in steps.In supervised learning , we assume that at each instant of time when the input is applied, the desired response of the system is possible by the system. In learning without supervision, the desired response is not known, thus explicit error information can not be used to improve network behavior. Unsupervised learning is some times called learning without a teacher. The terminology is not more appropriate because leaning without a teacher is not possible at all. Un-supervised learning algorithms are patterns that are typically redundant new data. The techniques of unsupervised learning is often used to perform clustering. Some information about the number of clusters or similarity versus dissimilarity of patterns can be helpful for this mode of learning.

Chapter 4 states that the static method is widely used to provide the static voltage stability margin indexes and the sensitivity information to the state variables because of its advantages of simplification and visualization. However the static voltage stability has been neglected all the dynamic elements and considered that the voltage instability is caused by the active power or reactive unbalance. It takes the inflection point of P-V curve as the point of voltage collapse. But the P-V curve has neglected the system load characteristic influence and its reflection point reflects the electric power network transmission power limit and corresponding running voltage. While the instability or voltage collapse is a dynamic phenomenon under large or small disturbance easily influenced by the load restore characteristic and generator system the maximum power transfer point is not necessarily the voltage instability point. Therefore the P-V curve inflection cannot completely reflects the state of the actual electrical network voltage instability point, it is relative optimistic to judge the system voltage stability using the above result. Many papers have been making great efforts to find the relationship between the nature of Jacobian matrix and voltage stability matrix and state equation from different point of view. But they did not give the error when taking the singular point of the static power flow Jacobian matrix as the critical point of the voltage stability. As far as ANNs are concerned, the area is not new, but has long binary. However the important breakthrough of recess ANNs stern from the following:

1. Development of multi layer perceptrons.
2. Use of the sigmoid function.

Chapter 5 states that it should be noted that only small inroads have been made to solve the contingency problem due to line and generator outages (i.e. change in network configuration which is one of the key problems in SA and SE. This is probably why not many ANNs are presently used in SA and SE. This problem cannot be solved by ANN technology alone, since it basically is the problem of the selecting the type of input data for the ANN.

Chapter 6 states that an alternative to the back-error-propagation is the genetic algorithm (GA) which is an evolutionary algorithm based on the concept of neural selection and genetics. As the genetic algorithm can prevent the local minimum when guided by the parallel evolution, the learning stagnation in neural network can thus be avoided. The features of genetic algorithms are different from either search techniques in several aspects. First, the algorithm works with a population of strings. Thus searching many peaks in parallel which reduces the possibility of becoming trapped into a local minimum, a comparison between single and multiple path search is only a single path in the single search. On the contrary, in genetic search, the multiple path searches have various routes in each iteration. Secondly, GA works with a coding of parameters instead of the parameters themselves. The coding of parameter helps the genetic operator to evolve the current state into the next state with minimum computations. Thirdly, GA evaluates the fitness of each string to guide its search instead of the explicit optimization function. There is no need for computations of derivatives or other auxiliary knowledge. Finally GA explores the search space where the probability of finding improved performance is high. Since our main goal is to enhance the neural network performance, the emphasis is put on the ancillary role of genetic algorithm in neural network computations

List of Figures

List of Tables

Chapter 1: Introduction

1.1. Motivation

The liberalization of electric market has generated the unbundling of large utilities into separated generation, Transmission and Distribution companies with subsequent changes in the operating condition at electric power systems. Most of the breakdowns in the electric power systems are caused by unfavorable dynamic response of the networks following system disturbances. In addition, environmental and economic consideration are forcing power systems to be operated closer to their limits of stability . Therefore dynamic security assessment of power systems is becoming increasingly important. Voltage collapse is one of the instability which occurs when the system is heavily loaded. In addition, the mechanism of voltage collapse is due to the load reacting to the voltage changed which leads to further voltage changes.

In this project, indicators utilizing the generator-load mismatch and active/reactive power margins, for on-line assessment of proximity of voltage instability of power system will be developed. The proposed approach will utilize an artificial neural networks(ANN) function approximator. In the area of Power systems, problems may be expressed in different ways depending upon their nature. The problem formulation may be expressed in terms of complex systems, say nonlinear, large scale, dynamical, discrete, stochastic, ransom like quasi-periodical, time-variant parameter systems etc. Among these factors, the nonlinear and the large scale systems make power system problems more hard to solve. Apart from linear systems, no good analytical system are available for the complicated problems. ANN is a good promising candidate for dealing with them.

1.2. Objectives

Power system is a complex nonlinear dynamic system which can be described with differential-algebraic equation (DAE). All the voltage problems can be analyzed based on the DAE. Mathematic models are simplified according to different purposes and various kind of analysis methods for voltage stability were proposed including static and dynamic methods, non-linear dynamic methods and probability analysis methods etc. The static method is widely used to provide the static voltage stability margin indexes and the sensitivity information to the state variables because of its advantages of simplification and visualization. However the static voltage stability has been neglected all the dynamic elements and considered that the voltage instability is caused by the active power or reactive unbalance. It takes the inflection point of P-V curve as the point of voltage collapse. But the P-V curve has neglected the system load characteristic influence and its reflection point reflects the electric power network transmission power limit and corresponding running voltage. While the instability or voltage collapse is a dynamic phenomenon under large or small disturbance easily influenced by the load restore characteristic and generator system the maximum power transfer point is not necessarily the voltage instability point. Therefore the P-V curve inflection cannot completely reflects the state of the actual electrical network voltage instability point, it is relative optimistic to judge the system voltage stability using the above result. Many papers have been making great efforts to find the relationship between the nature of Jacobian matrix and voltage stability matrix and state equation from different point of view. But they did not give the error when taking the singular point of the static power flow Jacobian matrix as the critical point of the voltage stability. As far as ANNs are concerned, the area is not new, but has long binary. However the important breakthrough of recess ANNs stern from the following:

1. Development of multi layer perceptrons.
2. Use of the sigmoid function.

Regarding item (1) the traditional perceptron consists of two layers which means it has only input and output layers. As a result it has a limitations of coping with nonlinear problems. Introducing the hidden layer between the input and output ones, the perceptron becomes general. According to the Kolmogorov theorem, the three layer perceptron allows to approximate any nonlinear function. Thus the multi layer perceptron is an universal approximater. In conjunction with item (1), item (2) is quite important for a couple of reasons. Firstly, the sigmoid function that is a smooth function can be differentiated by the cost function with respect to weights in order to evaluate the optimum weights. The fact is used to develop the back propagation algorithm for determining the optimal weights of Multi Layer Perceptron (MLP). Secondly, the sigmoid function is used to develop the Hopfield net (HN) with continuous variables. Therefore HN converges to an optimal solutions in a local area of Lyapnov stability.

1.3. Major contribution of the Thesis:

The voltage stability has already become a serious concern to power system operators. It is willing to find out a fast assessment method to estimate the static voltage stability level. To the dispatcher, the most practical index for analyzing the voltage security is power margin. So it is necessary to determine the critical point of the steady state voltage collapse accurately. There are important parameters to access the capability of each node to maintain the voltage stability, i.e. the critical voltage and the power limit at the loading point.

The static voltage stability analysis has been widely used in the analysis for the real life power system. But theoretically, static analysis is not restrict because there is certainly some error to take the maximum power transfer point as the critical point of the voltage stability, it is necessary to find out how much the error is and whether it is still meaningful to use the static analysis method in the analysis of the voltage stability. The error of the load power value and the critical voltage taking the inflection point of the P-V curve as the static voltage stability limit in the static voltage can be calculated. Standard IEEE9 system is analyzed and explained as an example. Finally draw the following facts:-

1. It is reasonably and feasible to take the P-V inflection point as the system voltage instability.
2. Taking the P-V inflection point as the critical point of system voltage instability in static voltage analysis, the error is different for different load model. It is the biggest under the load model of the “permanent power”. The less advantage of the content power in the load model, the smaller the error is.
3. Avoid selecting “the permanent power” load model as far as possible in order to reduce the analysis error in the static voltage stability analysis.

In the actual analysis application, it is definitely acceptable for the errors of system critical load power within 2% and the critical voltage within 0.05%. So it reasonable and feasible to take the P-V inflection point as the system voltage instability point.

While the system reaches to the limit of the steady state stability, Jacobian matrix becomes singular, and there is a zero eigenvalue. During the transient period from the normal operating node to the stability limit, Jacobian will tend to be singular and the corresponding minimum eigenvalue is then considered as the measure to the steady-state voltage margin.

Chapter 2: Literature Survey

2.1. Background

From the book reference [29], the function of an electric power system is to convert energy from one of the naturally forms to the electrical form and to transport it to the points of consumption. A properly designed and operated power system should meet following fundamental requirements:

1. The system must be able to meet the continually changing load demand for active and reactive power.
2. The system should support energy at minimum cost and with minimum ecological impact.
3. The "quality" of power supply must meet certain minimum standards with regard to the following factors:
   (a) Constancy of frequency.
   (b) Constancy of voltage, and
   (c) Level of reliability.

In this overall structure, these are controllers operating directly on individual system elements. For example, those pertaining to the generating unit, there are the prime mover and excitation controls. The primary purpose of the system generation control is to balance the total system generation against load demands and losses, so that the desired frequency and power interchange with neighboring systems (tie flows) is maintained. In this structure, in addition to the controllers operating directly on individual system elements such as the generators, there is usually some form of overall plant controller that coordinates the controls of closely linked elements. The plant controllers are in turn supervised by system controllers at the operating centers. The system controller actions are coordinated by pool level master controllers. The control system is thus highly distributed and relies on many different types of telemetering and control signals.

Supervisory controls and data acquisition system provides information to indicate the system status. Firstly the analysis of the load data with respect to the quality of the data and with respect to the different consumer behavior depending on seasons, week days and holidays, secondly the estimation of the load to be forecasted based on previously experienced load demands. The self organizing feature may be successfully solved the analysis task by creating classes of load patterns which are averages of several similar load patterns. Choosing the 24 hourly loads, next day peak load and 4 different day typed as inputs Basic requirements for the normal operation of a power system is that the total load must equal the total generation at any time.

The books references [14] and [15] states that reserve generation must also be scheduled in order to account for the load uncertainty and possible outages of generation plant. The reserve capacity that is spinning, synchronized and ready to take up load is generally known as spinning reserve. Some utilities include only this spinning reserve in their assessment of system adequacy, whereas others also include one or more or the following factors, interruptible loads, assistant from interconnected systems, voltage/frequency reduction. These additional factors add to the effective spinning reserve and the total entity is known as operating reserve. Historically operating reserve requirements for a power system have been done. The most frequently and method being a spinning generating reserve equal to one or more largest unites in operating. Probabilistic spinning reserve assessment is to determine the required spinning reserve capacity for the specific reliability indices.

For a power system with N components, the total number of the system states with $2^{N.}$ For example, a system with nine components will have a total of 512 states. A power system usually consist of thousands of components. There will be a great number of system states for a larger power system. The computing time required may be very long. It is also noticed from practical experiences that the probability of three and more components failing at same time is very small. It is required to practice to limit the number of states by selecting the contingencies which have larger probability of occurrence and neglecting. Those contingencies which have a probability of occurrences less than a predefined minimum value. The iteration is to cut the list of the events and reduce the calculation. System security corresponds to the ability of the power system to withstand some unforeseen but probable, disturbances, with the minimal description of service or its quality. In the area of system planning, the issue of reliability plays an important role.

System security is the counterpart of system reliability in the field of power system operation. In reliability analysis one is given the configuration of the system and the probability distribution of individual component failures. Reliability assessment translates this information into reliability measures. The planning process consists of adding components (i.e. generating units) or reconfiguring the system in order to meet accepted reliability standards. Since the analysis is done in a planning mode, these options can be implemented in due time. In an operational environment, security assessment consists of predicting the vulnerability of the system to possible evens, on a real time basis. The system being operated is different from what was planned several years earlier. Because of maintenance requirements, forced outages and changing load patterns, actual operating conditions are constantly changing, and so are the levels of system security. In order to improve an insecure condition, the operator does not have luxuries available unit, re-scheduling of generation, or calling for assistance form a neighboring system, among others.

The journal reference [22], page no. 1-6 states increasing industrials area and rapidly growing residential as well as commercial area demand more and more electric power, thereby making system very complex and complicated for controlling. In such situation power system stability is of more concern. Traditionally, power system stability is an issue related to generator angle stability only, but before power engineers have become more conscious about voltage problems in the power system. There are many factors affecting voltage stability of the power system: insufficient reactive power, automatic excitation system and its controllers connected with modern generators, voltage dependent loads, load voltage regulating transformers, static VAR compensators located in the transmission system to improve voltage etc. Normally all the generators are provided with Maximum Field Current Limiter (MXL) and the large loads in the systems are connected with Under Load Tap changers (ULTC). Under more severe contingency, like outage of major power transmitting line, the load voltage dips and the ULTC starts improving voltage levels by increasing its taps. During this time the required reactive power is supplied by nearly located generators with increase in their field currents, but if a field current reaches beyond some set limit, the MXL brings down the generator field current and generator no more applies reactive power and losses its control over its terminal voltage. So the ULTC increases its tap but no increment load voltage and still ULTC continues to step up, the load voltage decrease till it reaches at its maximum tap and the load voltage collapses because of mutual effects of MXL connected with generators and ULTC connected with loads. The device like ULTC takes action after 30 seconds or 50 seconds and then increases its taps after every 5 seconds till voltage reaches within the required limit. To study these voltage issues in the system, long line system simulations are required to perform because of slow acting ULTC dynamics and effects of MXL. To examine the voltage stability of a system all the generators are modeled with their controllers, ULTC synchronisms and voltage dependent loads are also required to model. The simulations are run for longer durations like 150 to 200 seconds.

From the journal reference [24], page no. 1-5, the problem of voltage instability has attracted the continuous interest of researchers to the last two decades due to a number of stability accidents occurred in some countries. Voltage instability is always correlated to heavily stressed power systems. Inadequate reactive power support is the main cause of voltage instability and collapse. The generator excitation limit and loads are regarded as the main mechanisms of the instability. However, how these interact during the dynamic process of voltage instability remains unclear. Thus, the study of this problem is of great importance toward an understanding of voltage collapse phenomenon. The voltage collapse scenario has been usually described as a slow decline in voltage levels, with little or no oscillation in frequency until the point in which the voltage levels plummet rapidly. Because of this time frame and lack of transient behavior, many researchers have felt comfortable with the use of power system model in which only the slow varying dynamics of synchronous machines are explicitly modeled by ignoring the excitation. Recently the effects of excitation have received a closer scrutiny. It has been reported that a spreading uncontrollable voltage collapse could be initiated when the excitation of the synchronous machines are switched from automatic to manual control (constant excitation) due to the field current limits. The major causes are uncontrolled machine flux decay dynamics that force possible cascading voltage collapse by reduction of voltage behind transient reactance. However the voltage instability mechanisms due to an interaction between the machine field flux dynamics and load have not yet been fully reported so far.

The voltage instability mechanism related high load demand is investigated when synchronous generator is under normal excitation. First, the voltage unstable phenomenon at maximum laudability limits with synchronous machine under manual and automatic excitations are explored. Secondly, the mechanism which gives rise to voltage instability due to a significant change of the flux linkage characteristic is discussed. Finally, the emphasis is given to explore performance limitation in the excitation control, caused by open loop unstable pole. To describe the voltage instability mechanism of synchronous machine under normal excitation, the simple three phase power system is used. The differential and algebraic equation of synchronous machine and nonlinear voltage dependent load are as follows:

$$\dot{\delta} = \omega r - \omega_s$$

$$2H\dot{\omega}_r = \omega_x (P_m - P_e - K_D(\omega r - \omega_s))$$

$$\tau_{dc}^r \dot{E}_q^r = E_f - E_q^r + (X_d - X_q^r) I_d$$

$$P_e = E_q^r I_q + E_d^r I_d + (X_q^r - X_d^r) I_d I_q$$

$$E_f^2 = (E_d^r - X_q^r I_q)^2 + (E_q^r + X_d^r I_d)^2$$

Nonlinear voltage dependent load;

$$P_L = P_o (V/V_0)^{n_{ps}}$$

$$Q_L = Q_o (V/V_0)^{n_{qs}}$$

The journal Reference [21], page no. 1-6 states that the management and procurement of the reactive power from the generation resource that are entitled to provide VAR as an ancillary service in the current electricity markets are very crucial in maintaining system security and reliability. Presently there are several payment schemes being used for the remuneration of the VAR service providers. Although there is no standard metrology by which the transmission operation in these markets pay. VAR resources, the cost based pricing is commonly used in most of those payment structures, where the long-term contract basis is the preferred choice of transmission operators to mitigate the potential exercise of market power that would be associated with inadequate number of regional VAR resources,. These pricing methods emphasize mostly the recovery of embedded costs, lost of opportunity costs and some other additional small amount operational costs “costs of transmission losses and operational of voltage regulators” incurred by the generation facilities for providing VAR service. While the portion of the generator embedded costs attributed to reactive power is very complicated to separate from total generator capital costs, the operational costs are very difficult to quantify and the operational costs are very difficult to quantify and the determination of opportunity costs is not straightforward is often affected by specific market arrangements. This implies that the generator VAR costs are not accurately allocated and consequently the current cost based pricing mechanisms rely to much extent on heuristics and operator's judgment to procure VAR service. Another thing is that the VAR providers should be remunerated based on their value, which reflects the relative importance of VAR sources in maintaining system security and reliability. The main factors affecting the value of an individual VAR source are its location, system configurations, operating conditions etc. They have no direct reliability with the previous embedded and variable costs. One possible way that would be used to quantify the worth of a particular VAR supplier is to assess its relative competitiveness in liberalized market of reactive power. Several researches have realized this fact and have attempted to address the procurement of VAR service in a competitive market and achieve the economical efficiency of this vital service. Although the significant role and the value of the dynamic VAR sources in mitigating voltage instability in the normal and emergency states, these research studies have barely explicitly regarded the voltage security issue in their proposals. The importance of the voltage stability consideration n VAR pricing under open access has been raised in the discussion.

The journal reference [21] focuses on the provisions of the VAR service from generators and synchronous condensers in a competitive market-based environment where the successful participants in this market will get long-term contracts with Transmission Operator (TO) to provide the required VAR whenever called upon. The reactive power procured in the VAR market is considered to be adequate in mitigating voltage security in all transition states where the voltage stability margin is explicitly treated in the proposed method. To avoid the extra VAR payment and to ensure the system security in the normal and emergency states, the objective function is adopted to minimize simultaneously the sum of the total payment of VAR service and operating costs in normal and emergency states. The total payment of VAR service includes the payment of the extra reactive capacity beyond certain amount of generators' VAR mandatory obligations and the lost of the opportunity costs. The operating costs include power loss cost in the normal state and control costs in the emergency states. The most important physical limiting factor in the ability of a generator to provide reactive power support is its generation capability limit. It represents the hard physical limitation of a generator's capability for the simultaneous production of real and reactive power. It is clear that the reactive power limits that the generator can produce depend on the active power output, where the limits of the field current, armature current and the under excitation of the generator are the boundaries that restrict the joint production of real and reactive power.

This expression is known as lot opportunity cost. The generators are obligated to provide a certain amount of reactive power without any payment of compensation from the TO. This VAR amount expressed as Q_{md1} in the lagging power factor region and Q_{md2} in the leading power factor region as shown in Figure 1, where Q_{md1} and Q_{md2} are determined based on the principle of the proportional obligations that compel the generators to provide VAR service in proportion to their active power output. Accordingly, the VAR of a generator beyond the mandatory is considered solely as an ancillary service that the generator offers and should be compensated for providing it. The provided ancillary service VAR is divided into two parts. The first part is the VAR injection or absorption that the generator provides beyond its mandatory without rescheduling its real power output and the second part is the lost of opportunity cost incurred as a result of reducing its real power output. *Region* / (Q_{md2} to $Q_{md1)}$: The reactive power produced in this region is obligatory with no payment. *Region //* (Q_{md1} to Q_1 and Q_{md2} to $Q_{2)}$: This region represents the extra reactive VAR provided by generator beyond its obligatory without rescheduling its real power output. A generator in this region is expecting a payment from the TO for its service. *Region //* (Q_{md1} to Q_1^* and Q_{md2} to Q_2^*): In this region the generator will reduce its real power output and consequently its lost revenue will be recovered by TO.

2.2. Literature Review

From the reference [7], page no. 951-961 it is vital that the reliability of a power system be maintained while holding down costs. To this end, an accurate assessment of voltage stability is indispensable. In static voltage stability assessment, the steady states corresponding to a number of parameters including the loading conditions are examined. One important concept in static assessment is that of the transfer limit surface. The transfer limit is the upper limit from the generator node and is defined as a hyper surface in load parameter space. Here the load parameter space is the multi dimensional space spanned by model loads. A steady state corresponds to a point in this load parameter space. If a loading scenario is given and the maximum loading point is calculated, a point on the transfer limit surface is obtained. Here a loading scenario is a mapping from the total load to the power of each load node. The maximum loading point is the operating point corresponding to the right hand end of the well known nose curve. In other words, the transfer limit surface is the set of maximum loading points under a range of scenarios. The transfer limit surface is the upper limit of the transfer power., hence it divides load parameter space into two regions, one in which operation is possible (hereafter the inside) and one in which operation is possible(the outside). If the operating point reaches the transfer limit through gradual increase of the load, voltages collapse may result. The transfer limit surface holds information about how the maximum loading will change when the scenario changes. For this reason, the normal vector to the transfer limit surface is useful for calculation of preventive control and stability indices as they relates to voltage stability. Representation inequality constraints in power system are the constraints on capacity of equipment and facilities. Of these, the reactive power limit of generators is known to greatly affect voltage stability. If the reactive power reaches its upper limit as the result of gradual increase in load demand, the system stability may change discontinuously. In the worst case, a stable system may suddenly become unstable. This case is referred to as a saddle limit-induced bifurcation. However cases of saddle node bifurcation have long been familiar and both direct methods and continuation methods for the computation of saddle node bifurcation points are known. The smoothness of the transfer limit surface is an important issue for applications that rely on the normal vector. When constraints are not considered the transfer limit surface is smooth but to date the transfer limit surface taking constraints into account has not been the objective of many studies.

2.2.1. Transfer Limit Surface

(a) Parameter Space:

A parameter spaces can be defined using arbitrary independent parameter. In this purpose, a parameter is defined as an dimensional space spanned by P_t. This definition is advantageous when considering constraints.

(b) Transfer limit Surface:

A maximum loading point satisfies the following power flow singularity condition

$$\frac{|\partial f|}{|\partial x|} = 0 \qquad (2.1)$$

Here $\frac{\partial f}{\partial x}$ is the Jacobian's matrix of f(.) with respect to x.

.

Note that

$$\frac{\partial f}{\partial x} = \frac{\partial f_1}{\partial x_1} \qquad (2.2)$$

The set of Σ_x of maximum loading point can be defined as follows:

$$\Sigma_x = \{\ P_t\,|0=f(x, P_t\ ),\ \frac{|\partial f|}{|\partial x|} = 0\ \} \qquad (2.3)$$

This set corresponds to a hyper surface (an m-1 –dimensional manifold) in m dimensional parameter space. This is called transfer limit surface, $\mathbf{p_t}$ cannot exist outside the transfer limit surface. Note that the above definition of the loading point and the transfer limit surface will be changed when constraints are introduced into the system

2.2.2 Break Down of the Problem

Since the transfer surface limit is m-1 dimensional manifold, it is not easy to investigate smoothness. However this problem can be broken as follows:

1. In the parameterized scenario and the subset curve, maximum loading point $R_{.l\text{-}max}$ (s) moves along subset curve as a s increases.

2. In a subset curve with possible smoothness, state of generators or state of constraints changes so that non smoothness may occur.

As a scenario, we consider a straight line passing through the origin

$$P_t = P_{ls}\ (\lambda) = P_{LS}\ \lambda \qquad (2.4)$$

where P_{LS} Є **S** and P_{LS2} Є **S** prepared.

For scenario vector to be different means that they are not parallel. The scenario vector P_{LS} **is** redefined as a function of the parameter s Є R

$$P_{LS} = P_{LS}(s) : =(1\text{-}s)P_{LS1} + P_{LS2} \qquad (2.5)$$

Varying s continuously from 0 to 1, the scenario vector can be varied continuously from P_{LS1} to P_{LS2} .

Suppose that s is a curve set. Then the set of scenarios vectors $\{ P_{t\text{-}max} | 0 \le s \le 1 \}$. $P_{LS}(s)$ ƛ is called a parameterized scenario. If the parameter s given, the scenario vector and the scenario are determined and the corresponding maximum loading point can be determined. Hence the maximum loading point corresponding to a given s can be denoted by P_{LS} **(**s).

For a given set scenario vectors P_{LS1} and $P_{LS2,}$ a subset curve, a curve on the transfer limit surface, can be defined by :

$$\{P_{t\text{-}max} | 0 \le s \le 1\} \qquad (2.6)$$

The position curve depends on P_{LS1} and P_{LS2} If the subset curve corresponds to P_{LS1}Є **S** and P_{LS2}Є **S** are all smooth, one can conclude that the transfer limit surface is smooth. On the other hand, if even one non smooth subset curve is found, the transfer limit. surface is not smooth. In this way, the problem of investigating the smoothness of a transfer limit surface can be broken down into problems of investigating the smoothness of subset curves. In the case of scenario changes, these will implicitly refer to changes in parameter. As long as there is no changes in the state of a generator, the subset curve defined by equation (2.6) , the subset curve is expected to be smooth. This is because as long as the generator state does not change, the function constituting the power flow equation does change. On the other hand, when the state of generator at maximum loading point changes with changes in s, the situation is different. The change in state of the generator is accompanied by the replacement of the power flow equations with a different one. At the point where the equation changes, there is a possibility that the smoothness of the subset curve is lost. Only the reactive power constraints for generators are considered as constraints. This can easily be modeled by introducing an upper limit to the reactive power. In the other words, when considering the constraints, the state of a generator is one of the following:

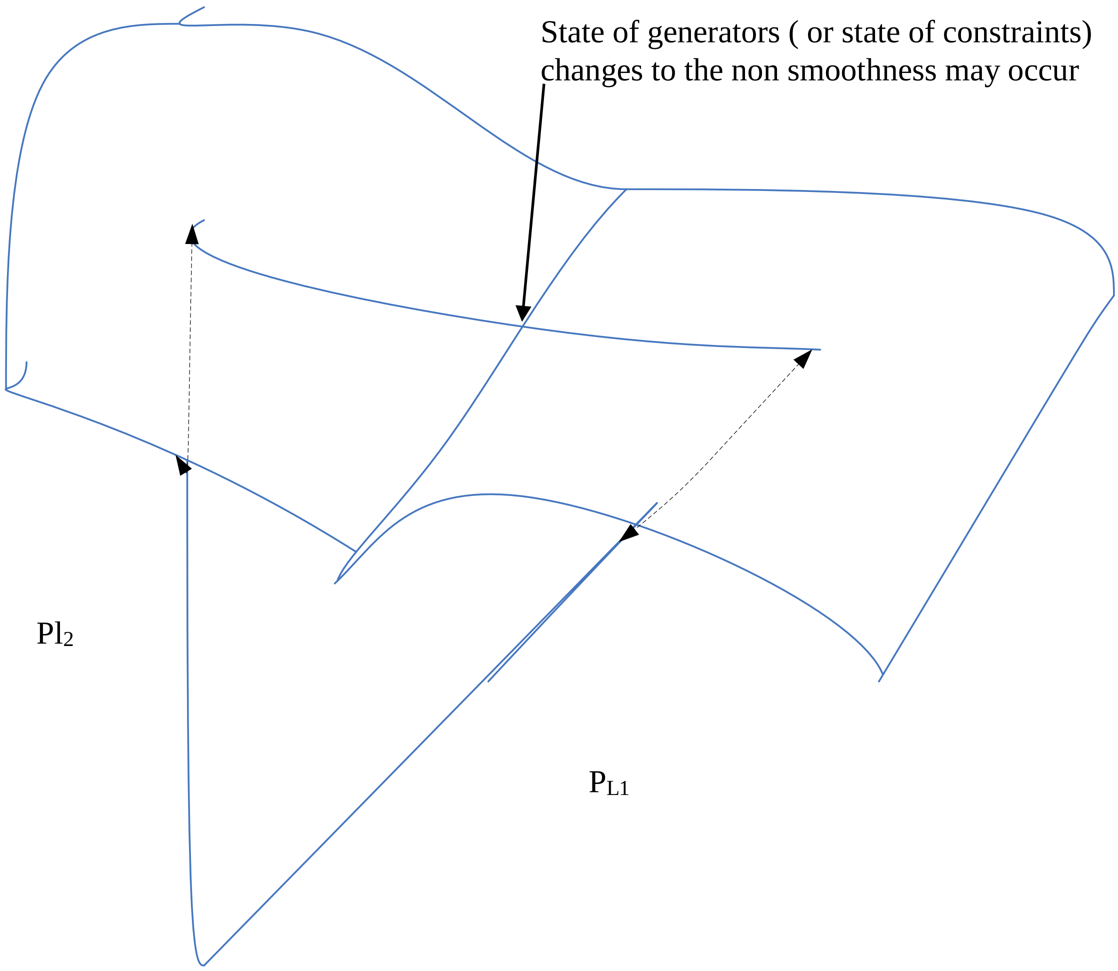


Fig: 3.1- Possible smoothness on a subset curve.

- PV node (P and V specified) with Q below an upper limit.
- PQ node (P and Q specified) with V below a reference value.

In the following distinction is referred to as the state of a generator. The reason why the term “state “ used here is that the state of a generator is determined depending upon external parameters. When there are numerous generators, a state of constraint for the entire system, reflecting the states of all the generators, can be defined. That is, if there are n generators, then the state fo constraints is 2^{nd} valued. For example, if there are two generators or two constraints, the state of constraints is (PV, PV), (PV, PQ),

(PQ, PV), or (PQ, PQ) (2.7)

A change in the state of constraints is a result of a continuous parameter change is called a constraint switching. A constraint switch point is an intersection of the component nose curve., one for which the generator in question is in the PV node (curve-V) and one for which for generator in question is the PV node (curve-V); and one for which the generator is in the PQ-node (curve-Q).

2.2.3. Definition of PQV Condition

A point at which constraint switching occurs is subject to both PV and PQ conditions. Hence such a point is obtained by specifying the value of P,Q and V for the generator. Such a condition satisfied by the switching point is called PQV condition. The following is a method for determining a point switching a PQV condition.

Suppose that a scenario is given. A constraint switching point is given by the solution to a system of simultaneous equation containing of 2 and o=c(s) with Ã as an unknown. Here c( ): $R^{n}{}_{s}\rightarrow R$ is a function representing an additional condition for the generator in question.

For example, suppose that the generator is in the PQ node in (2). Then c(), representing the additional condition, should be $c(x)\equiv V-V_T$., reflecting the condition imposed on the voltage. Here V is the voltage of the generator node in question and V_T is the reference value for this voltage. A PQV condition can be represented in the framework of the continuous method. Depending on the system conditions, the maximum loading may be reached as a result of constraint switching. That is, in this case the constraint switching point is positioned at the right hand end of the curve. This bifurcation is called a saddle limit indexed of bifurcation. If a scenario is given, a maximum loading pint can be determined. At this time, it can be clarified whether the maximum loading point is determined by the saddle-node bifurcation condition or by the saddle limit induced bifurcation condition. This is called the bifurcation type. The bifurcation is broken with consideration paid to the state of constraints. The subtype is named the bifurcation subtype. In other words, a bifurcation subtype characterizes each maximum loading point in terms of the state of constraints. Here the possible number of bifurcation subtype is counted A case in which three are n generators is considered. First case of saddle-node bifurcation are counted. S stated above. As stated above the state of constraints is 2^n- valued and saddle-node bifurcation may occur for all of these. Next saddle limit induced bifurcation for all of these. Next saddle limit induced bifurcations are counted. There are a constraints for which switching is possible, bifurcation is related to one among these. A sub-state of constraints related to the n-1 generators not related to bifurcations. Therefore the total number of possible bifurcations subtypes is 2^{n-1} (n+2).However they differ decisively in the following respects. A sate of constraints can characterize an arbitrary operating point. And in a state of constraints, , only two values, PV and PQ are considered to specify the state of each generator. On the other hand, a bifurcation subtype characterizes such maximum loading point. And in a bifurcation subtype, in addition to PV and PQ, the PQV state is also explicitly considered as determining the state of each generator. This is because of the need to handle saddle limit induced bifurcations.

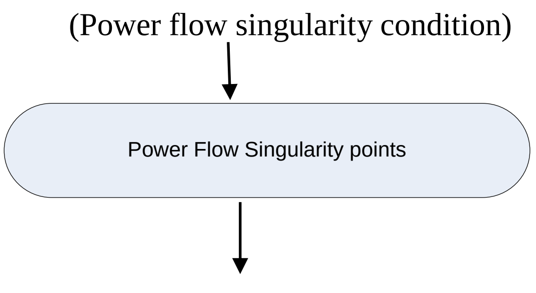
When a scenario or parameter s, the corresponding maximum loading point changes. The bifurcation sub type which characterizes the maximum loading point, may also change. A change in bifurcation subtype of a maximum loading point resulting from a continuous change in scenario is called a transition of the bifurcation subtype. When there are two or more constraints, the order in which constraint-switching occurs while moving along the nose curve toward the side of heavier loading can be considered. This order is called the switching order.

For example, when there are two constraints A and B, there are two possible switching orders, with A occurring either earlier or later. However a special case in which A and B are simultaneous should also be expected. This is called duplicate switching. The structure of the function f(,) depends on the sates of constraints. That is, if the state changes f(,) changes structurally. However ithe parameter space is behind solely in terms of $\mathbf{p}_{t.}$ That is, the structure of external parameters is independent of the structure of f(,). Hence even when there are constraints, the transfer limit surface can be defined as “the set of maximum loading pints in parameter space”. The relations between the points and surfaces defined are somewhat complex, When constraints switching occurs, the terminal voltage of the generator is subsequently falls from the reference value as the operating point moves toward heavier loads. That is, constraint switching is almost certain to worsen voltage stability. This can be represented concretely by the slope of the tangent to the nose curve. Suppose that the nose curve is parameterized monotonically by u in moving the side of higher solution through the maximum loading point toward the lower solution side. Suppose further that the slope near the constraint switching point on the curve v is $d\lambda_V/du$ and the slopes near the constraint switching point on the curve Q is $d\lambda Q/du$. Then the assumption that the constraint switching acts to worsen voltage stability is represented as follows. The slope of the nose curve in the vicinity of a straint-switching point is such that $d\lambda_V/du > d\lambda Q/du$. In other words, broadly stated, it is assumed that as the constraint-switching point the nose curve bends downward or to the left. If the constraints considered are limited to the constraint on the reactive power of the generator, this assumption is reasonable.

2.2.4 Summary of definitions of points and surfaces:

The relations between the points and surfaces defined are somewhat complex, they are summarized here:

- The parameter space is spanned by $\mathbf{P_t}$.
- Transfer limit surface is hyper surface in parameter space that corresponds to the maximum loading points.
- A maximum loading point is either a saddle-node bifurcation point or a saddle limit induced bifurcation point.
- A maximum loading point is either a saddle node bifurcation point that satisfies constraints.
- A saddle limit induced bifurcation point is a constraint switching point that satisfies the saddle limit induced bifurcation condition. $\sum_{pqv}$.
- A maximum switching point is a PQV point that satisfies constraints.
- A power flow singularity surface is a hyper surface in parameter space that corresponds to a $\sum_{s}$.
- A PQV surface is a hyper surface in parameter space that corresponds to $\sum_{pqv}$.



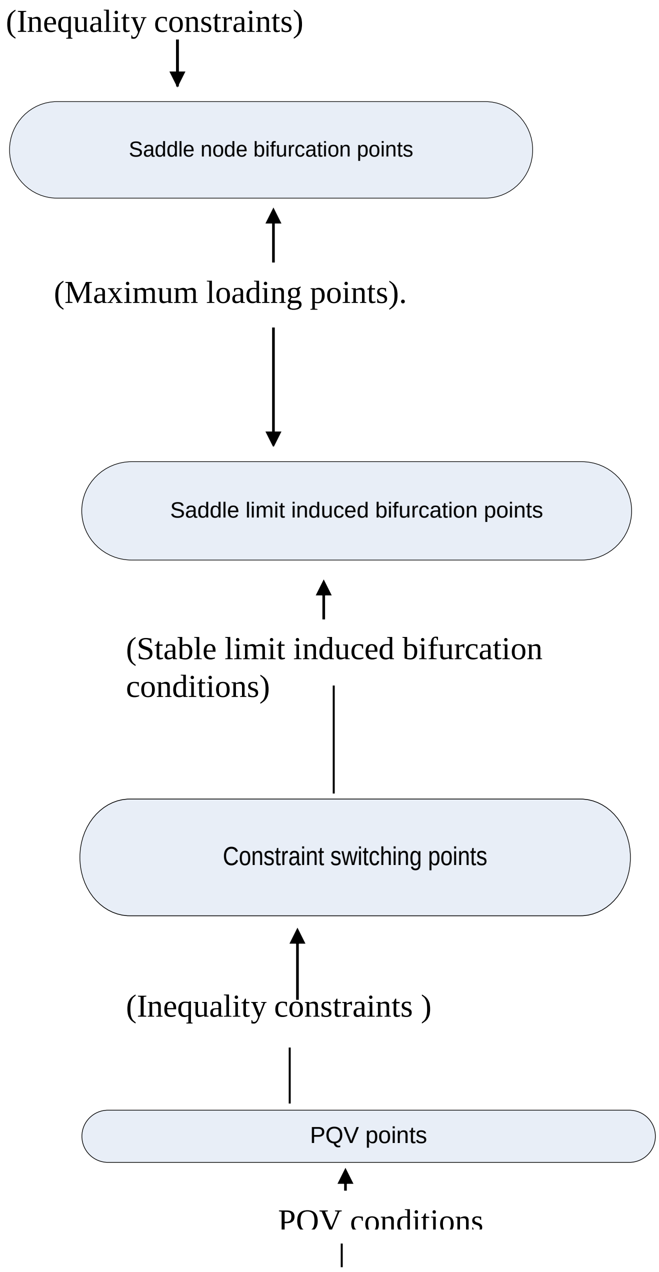


Fig3.2- Composition model of transfer limit surface.

2.2.4. PV Curve

The system model for the static analysis is described by power flow equation. Assume the differential of the sate variable equals to zero. Then the power flow equation is as follows:

$F(X, \lambda)=Q$

Fig3.2- Composition model of transfer limit surface.

where X represents the system state vector, and λ represents the load vector P_L and Q_L.

The nature of the static method of voltage stability is whether the feasible solution of the power flow equation are existed. The critical solution if the power flow can be regarded as the static voltage stability limit, that is to say, the power flow limit is the static voltage stability limit. So the static voltage stability analysis is not exactly the stability analysis in the sense of Lyapunov.

A P-V curve method which is a traditional static voltage stability analysis method is a kind of computation analysis method based on the physical conception. Setting the result of the basic system power flow, increasing the system load gradually, and calculating the system voltage corresponding to each operating point, a series of (P,V) points reflecting the relationship between the load power actually absorbed and the node voltage can be obtained and a P-V curve can be formed . The inflection point of P-V is considered as the voltage stability curve, the area above the inflection point is the voltage stability region and the area below is considered as the voltage instability region. The distance from the current system operating point to the inflection point is known as the system voltage stability region. For a definite five bus power system we can use the Gauss seidal method in multi bus system. The transfer limit surface of a power system was investigated. We specifically and explicitly defined the transfer limit surface when there are constraints. The smoothness of the transfer limit surface, taking into account the generator reactive power limits. With strict proof were not presented, the following properties were derived with at least a certain degree of logical rigor. These properties were verified through a small scale numerical example-

- The transfer limit surface of a single constraint power system is smooth.
- The transfer limit surface of a power system with two or more constraints is in general non smooth.

The degree of smoothness is not expected to be serious. Hence one can expect that applications based on a normal vector are valid even for systems with constraints. The methodology adopted and the above result can form a basis for engineering applications related to the transfer limit surface. In addition, the following formulations and techniques for numerical calculations were presented in Appendixes.

- A PQV point condition was formulated within the framework of the continuation method. The saddle limit induced bifurcation condition was formulated in a certain form.
- A solution method for the normal vectors to a PQV surface which is highly compatible with the continuous method, we described.
- It was shown that the normal vector to a power flow singularity surface and the normal vector to a PQV surface can be obtained by solving the same equation.

For a given scenario, numerous power flow-singularity points and numerous PQV points can be computed. It is considered that the set of points includes a point on the transfer limit surface, or a maximum loading point. The pints are on the transfer limit surface must violate one or more constraints. Note that, in the case of PQV points not being a saddle limit induced bifurcation is regulated as a kind of constraint violation. That is, if a points, that is free of constraint violations,. That is, if a point that is free of constraint violation is found in the set of points., it should be on the transfer limit surface. The above solution method is verified through a numerical calculation. The given solution method is unfortunately inefficient in comparison with continuation method; this is because as the number of constraints increases, the calculation requirements of this method increase exponentially calculating the load power deviation coefficient W_p and the voltage deviation coefficient W_U under three different load nodes. In the actual analysis application, it is desired definitely acceptable for the errors of system critical load power within 2% and the critical voltage within 0.05%.

Chapter 3: ANN Applications

There is an area of research called Artificial Neural Networks (ANN) with a sub field called neural-net computing. This historical perspective is mostly concerned with the latter but it cannot be said that it is entirely detached from the whole. The distinctive characteristics of neural net computing include the extent and specificity to which it advances and practices parallel distributed processing with elemental processors, and the power of several functionalities such as supervised learning and self organization. This historical perspective emphasizes the functionality of supervised learning. We come to the development of neural net computing itself. There was initial phase which combined of a leap of faith. The linear networks was not of sufficient generality but simulated much interest and the adaptive linear networks contributed to advance in signal processing and pattern recognition. In the mean time along a parallel path, in mathematics, progress had also been made on the matter of representation of continuous functions of several variables by superposition function of one variable and by sums of functions. Remarkable results were obtained but those did not have an influence on the development of neural net computing until later. In due time, a number of new results were reported on how the nonlinear multilayer feed forward net can be trained to learn multivariate functions. This brought on resurgence in the field of neural-net computing.

Subsequently a stream of mathematically oriented investigation have shown that even single hidden layer Perceptrons can be universal function approximators, and have also begun to relate perceptron like architectures to network representation of Kolmogorov's results, and to the improved forms of those results. Finally in addition to the supervised learning functionality of neural net computing, we address the matter of self organization. There the instruction is strong with psychology or more accurately with cognitive psychology. In addition to category formation through clustering is pattern space, there is the direction taken by the feature map. A potent idea improved from neural science is that of lateral excitation and inhibition. The mechanism plays a crucial role in the various modes of self organization. In this representation we have to content ourselves with merely alerting ourselves to the wonderful and interesting thing yet to come in matter of memory coding of information for storage binding of information associative recall, cross-context remembering and many others. A full fledged historical perspective would also address applications of neural-net computing to the different tasks of understanding and implementing and implementing of sight, hearing, smell and touch.

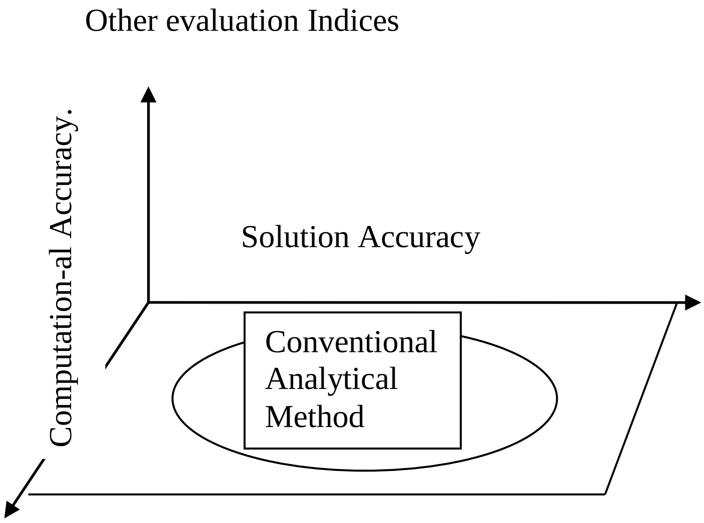


Figure 1. Expectation to ANN

Artificial neural networks (ANNs) are the distributed processing systems that have been inspired by the biological nerve system. They consists of a group of units called neurons that are analogous to the nervous system. Each neuron is connected with each other with the weights. For example the inductive learning process determines the weights on the relationships between input and output variables is identified. The methods open up new possibilities of parallel or distributed computing. It is expected that the human brain like approach provides meaningful insights into the complicated problems. As shown in Figure 1 other evaluation indices or dimensions are expected from ANN's although the conventional analytical methods discuss only the computational efficiency and the solution accuracy. It becomes more important to understand and handle complicated systems with the insights approximately. The indices may be the selef organization, adaptivity, feature extraction etc.

3.1. Variation of Multilayer Perceptions

We describe the variation of multilayer perceptrons (MlPs) applied to power system. MLP means ANN that have several neural layers. They may be divided into the following :

1. Three layered NN.
2. Four layered NN.
3. Recurrent NN (RNN).
4. Functional Link net (FLN).
5. Radial Basis Function NN (RBFNN).
6. Fuzzy NN (FNN).

Finally three layered NN means the perceptions that consists of input, hidden and output layers. Secondly four layered perceptions with two hidden layers have been used to enhance the solution accuracy. This results in over fitting due to the increase the number of parameters. From a stand point of stochastic modeling, model with many parameters do not mean good one. Since they are vulnerable to unknown data. Thirdly recurrent neural network has a context layer that captures short term and long term dynamics of input patterns. In other words, RNN corresponds to MLP with the feedback loop. The advantages of RNN is able to construct the network with a smaller neuron than MLP. The disadvantage is that the network dynamics might fail to converge a stability. Therefore it needs the learning process tailored for RNN. Furthermore a functional link net is used to consider the high nonlinearity of the problems. The relationship between the input and output variables is expressed by the quadratic equation with respect to input variable like GMDM. Expression of intermediate variables of GNDM (Group method of data handling) is applied to MLP weights. FLN is capable of handling non linear problems easily. The Radial Basis Function neural network (RBRNN) is different from MLP. The network does not use the sigmoid functions but the radial basis functions for the threshold functions. Also the weights between hidden and output layers are set unity. It is well known that the network is more flexible than the original MLP in handling nonlinear problems. Finally the fuzzy neural network is more flexible techniques that can clarify the relationships between input and out put variables. Since the conventional MLPs are inclined to express the cause and the effect of the problems to be considered, it is not easy to understand the relationship. FNN allows us to explain the problems with if then rule base.

3.2. Variations of Hopfield Nets

Variations of Hopefield nets (HNs) are applied to power systems. They are given as follows:

1. Hopefield Network.
2. Boltzman Machine
3. Gausian Machine
4. Chaos NN.

Hopefield Network (HN) has two versions- Discrete and continuous HNs. The continuous HN is preferred. Since it converges to an optimal solution in a sense of Lyapunov local stability. This network easily gets stuck in local minima. To obtain a global minima the Boltzman machine was developed to avoid the local minima. The network of a stochastic ANN is based on the idea that simulated annealing is applied. On the contrary, the Gausian machine allows us to deal with problems with continuous numbers of variables. The network make use of stochastic noise that is added to the differential equation of the continuous Hopefield net. In the same, the chaos neural net (CNN) uses nose obtained from the chaotic dynamics.

3.3. Variations of Kohnen Nets (KNNs)

KNN's have a few variables:-

1. Two dimensional grid.

    -Rectangular grid .

    -Hexagonal grid.

2. Three dimensional grid.

    (not applied to power systems).

It seems that they are not positively applied to power system although several modified or improved KNN's are developed.

3.4. Typical Application Areas

The followings are the list of the typical ANN applications in power systems.

1. Planning
2. Security assessment.
3. Fault of detection/ Diagnosis.
4. Control
5. Analysis.
6. Protection
7. Design.

Table 1 depicts the typical characteristics of load forecasting, security assessment and fault detection in power systems.

Table 1: Typical characteristics of load Forecasting, Security Assessment and Fault Detection Diagnosis

Features	Load Forecasting	Security Assessment	Fault Detection
No of input variables	Several	Many	Many.
No of output variables	One	One/Many	Many
Alternative Analytical Approach	Available	Available	Not Available
Necessity of online evaluation	**	**	**
Typical problem to be addressed	Fast learning	Topology Change	Topology changes.
Size of ANN	Small	Large	Large
Direct implementation of ANN	Acceptable	Not Easy	Not Easy.

3.5. Stumbling blocks and Future Works

ANN confronts with several problems to be solved in spite of attractive features. In ANN applications to power systems, the following problems to be solved may be found-

Optimal structure of ANN

It is necessary to determine the network size (the number of inputs and outputs neurons in MLP and the number of output network in KNN).

Online Efficient leaning Algorithms

The back propagation requires many iteration counts. It is not suitable for online learning scheme. We need a learning algorithm with good convergence characteristics. Also the BP algorithm gets stuck in local minima of weights. Efficient global optimization techniques is needed to evaluate the weights

Alleviation of "Curse of dimension"

The direct application of ANN to large scale power systems requires large scale ANN. It is quite difficult to determine the optimal weight in terms of accuracy and the computational effort. The point is how to cope with real size power system

Consideration of Network topology

We have to cope with network topologies if the system problem is related to the transmission lines. The conventional ANN applications avoid this problems.

Necessary amount of learning data

The efficient guideline for determining the necessary amount of learning data is not available in constructing ANN. The insufficient number of the data creates inappropriate models wile too much data needs a lot of computational time.

Data normalization

It is important to handle data normalization of input data so that feature extraction is obtained. It is time that choice of data normalization changes the solution accuracy.

However comprehensive research on what types of data normalization is effective on specific problems are not available.

3.6. Load Forecasting

MLP is used as one of the tools to deal with time series analysis of the load to application of ANN to load. Forecasting. Short term load forecasting is of concern. High accuracy of load forecasting improves the security and generation generation cost. But the forecasting problem is so easy because of the complicated factors such as nonlinearity and random like behavior of system loads and weather conditions. The conventional method like ARIMA, Kalman filtering and multiple regression models

3.7. Neurocomputing Hardware Requirements

Unless the notion of learning in a network, we will consider a process of forcing a network to yield a particular response to a specific input. A particular response may or may not be specified to provide external correction. Learning is necessary when the informations about inputs /outputs is unknown or incomplete a priority so that no design of a network can be performed in advance. The majority of the neural network covered requires training in a supervised or nsupervised learning mode. Some of the network however can be designed without incremental training they are designed by batch training rather than stepwise training

Back training takes place when the network weights are adjusted in a simple training step. In this mode of learning, the complete set of inputs/output learning data is needed to determine weights and feedback information produced by the network itself is not involved in developing the network. This learning technique is called recording. Learning with feed back either from the teacher or from the environmental rather than a teacher, however, is more typical for normal networks. Such learning is called incremental and is usually performed in steps.

In supervised learning , we assume that at each instant of time when the input is applied, the desired response of the system is possible by the system. In learning without supervision, the desired response is not known, thus explicit error information can not be used to improve network behavior. Unsupervised learning is some times called learning without a teacher. The terminology is not more appropriate because leaning without a teacher is not possible at all. Un-supervised learning algorithms are patterns that are typically redundant new data. The techniques of unsupervised learning is often used to perform clustering. Some information about the number of clusters or similarity versus dissimilarity of patterns can be helpful for this mode of learning (see Figure 2).

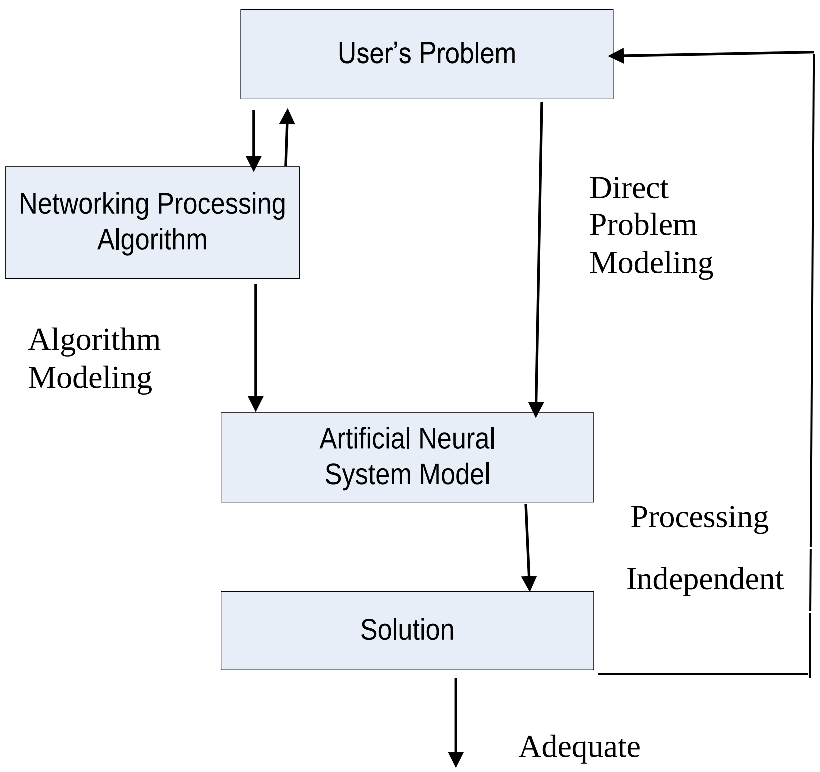


Figure 2. Problem algorithm model Flowchart.

Artificial neural system models contain both invariant and variable parameters which are called characteristics here and are essential for the system's operation. Invariant characteristics are fixed in the neuron computing model, while variable characteristics can be modeled. Invariant characteristics usually include, among others, network topology, number of bits or simply accuracy in expressing the weight value, number of bits describing the activation and output values of the neuron, and in connection density.

Variable characteristics of the model include its learning parameters, sequence of learning, recall operation as well as the presence or lack of synchronous neuron updates etc.

Simulation of most neural network model in real life applications can become computationally intensive to the degree that the processing on the conventional computers imposes constraints as the practical explanation of the large neural networks.

There are two distinct approaches currently being taken for supporting artificial neural system modeling.

1. General purpose computers, which are programmable and therefore able to simulate a variety of models.
2. Special purpose hardware, often dedicated to specific neural processing models.

Provided the training converges to an acceptable solution. Improvement of training efficiency can be achieved in a number of forms. Some of them are-

1. Dedicated hardware architectures of conventional programmable computers.
2. Parallel distributed architectures of densely inter connected computing neural nodes containing conventional multiply or multiply-add processor.
3. Reduction of the volume of the training data through the use of the generalization properties of the network.
4. Designing neuron computing integrated circuits using digital, analog or digital/ analog arrays performing simultaneous local computations within the entry array.

The degree of freedom of neural network equals to the number of interconnects and therefore proportional to the hidden neurons must be matched in some sense to the complexity of classification boundary. Currently in the absence of parametric guidance, the only proposed method of determining the best number of hidden neurons is by comparative cross validation among two or more neural networks. Moving from a small number of hidden neurons to a large number should decrease overall probability of error while maintaining error performance for the test and training data.

The saturation problem of the NN can have a disabling effect of the nonlinear function of the hidden neurons reach its upper or lower saturation limits. In this case any wide change in the input would produce no or minimal change to the output and the neurons in this case are paralyzed It is common and acceptable to have some neurons in the saturation region but too many render the NN useless.

To prevent the network saturation, the hidden neuron's must be closely monitored during its training process when impairing number of neurons reach the saturation limit and remain unmoved, the neurons must be randomly perturbed and the leaning process continued. It is imperative that this saturation check be incorporated in any NN software (Figure 3).

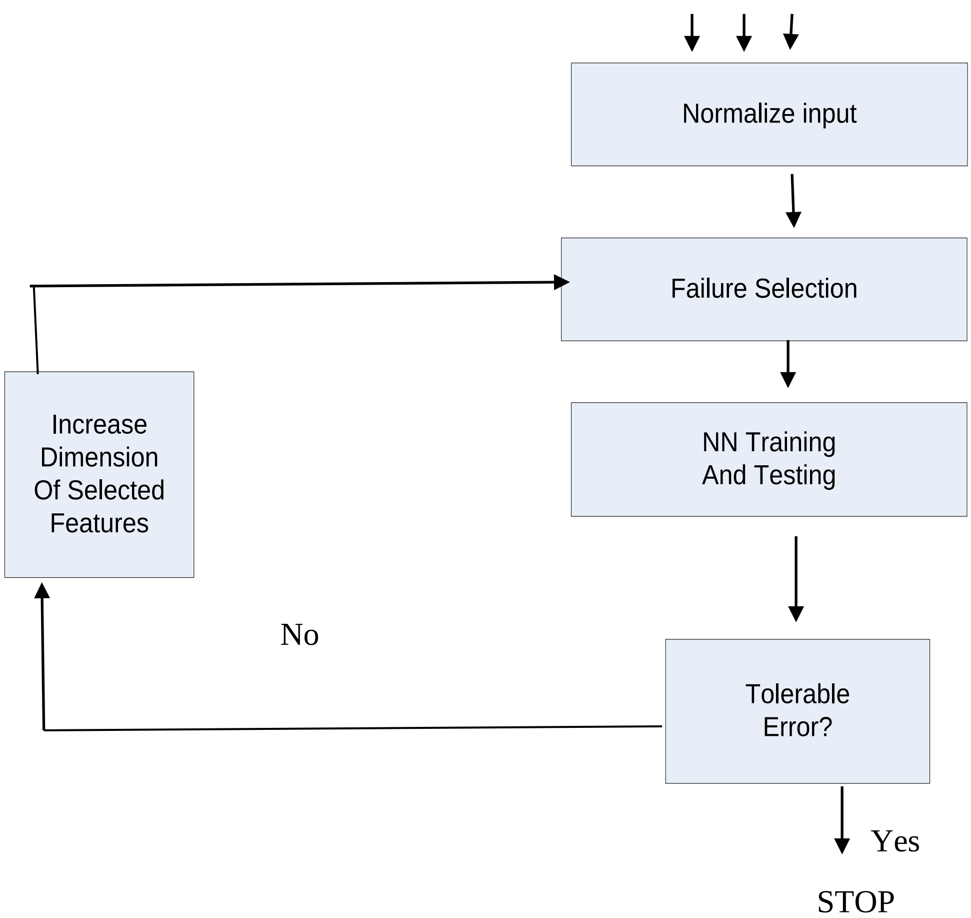


Figure 3. Block diagram of feature selection with NN training

One of the classical problems in pattern recognition is how to extract the discriminatory features from a given set of measurement. The mathematical approach to feature selection is to identify certain invariant properties of the pattern classes.

Theses properties are then used to reduce the dimensionality of the pattern vectors either through a linear transformation or through the preferential choice of a subset of attributes. Although most suggested feature selection algorithms are applicable to a large class of problems, it is important in recognize that the superiority of any one procedure is ultimately determined by the problem at hand. The combination of feature extraction in the neural network not only reduced the computational time but also increase the clarification accuracy. In classification problem, the feature should be selected to enhance the separation between classes. In many cases, the input problems and contain features with minimum value. If the correlation between the input and the NN output is weak, the NN try to force a mapping that is unlikely to result in worthwhile information. In fact, such weak correlation may stray the NN is undesirable region with high testing errors. Every neuron model consists of a processing element with a synaptic input connections and a single output. The single flow of neuron inputs x is considered to be unidirectional as indicated by arrow as is a neuron's output signal flow. A general neuron symbolic representation shoes a set of weights and the neuron's processing unit, or node. The function $f(w^t x)$ is often referred to as activation function. It's domain is the set of activation values, net of the neuron mode. We thus often use this function on f(nt). The variable net is defined as a scalar product of the weight and input vector. The neuron as a processing node perform the operation of the summation of its weight inputs or the scalar product computation to obtain net. Subsequently it performs the nonlinear operation f(nt) through its activation function.

3.8. Learning versus Normalization

There is a difference between training and normalization. A trained classifier regression machine can respond with confidence to a pattern that has not been before. The ability to properly classify data that has not seen before is referred to as synchronization memorization on the other hand guarantees that that when the NN is presented with a specific almost in the training data set, the classifier with respond in exactly in manner that it was trained to. In the case of generalization , the response to data rather than training data is not considered in the paradigm.The ability to interpolate among the training data does not necessarily imply good generalization. A properly trained classifier or regression machine should respond with the same error to the training data in to test data. If the error from the data is much higher than that from the training data , then the neural system is over determined . In other works, the degree of freedom in the classifier or regression archive is toot high. Each weight vector represents the a certain number of input vector and organizations, the input space based on he probability distribution of the input data. The training algorithm qualifies the input pattern space qualifies the input patterns space consisting input vector into at more n classes and computer the weight vector as regenerative elements of those classes.

3.9. Back Propagation

The development of powerful learning rule that can arrive at a set of connections between input, output and hidden units, in a multi-layered system, but had a large impact in this field. This learning rule is called the Back-propagation rule.

Back propagation finds the values of all of the weights that maintain the function using a method of gradient descent. That is, after each pattern has been presented, the error on that pattern is computed and each weight moved the error gradient toward its minimum value for that pattern. The error is actually is proportionality E is defined by,

$$E=\frac{1}{2}\sum_{n} (t_k-o_k)^2 \qquad (3.1)$$

where t_k is the target and o_k is the output example k.

The idea behind gradient descent is to make a change in weights proportional to the negative of the derivative of the error, as measured in the current pattern, with respect to each weights. Thus to readily compute the derivation of the error function with respect to any weight in the network, we change the weights in the following rule:

$$\Delta w_{ij} = - e \frac{\partial E}{\partial W_{ij}} \qquad (3.2)$$

where e is the constant of the error function and w_{ij} is a term in the weight matrices.

Note these weights matrices include the matrices to and from each hidden layer as well as the input and output layers.

The learning rate is an important factor for this method to work. Some take it constant or exponentially decreasing to zero with the time. An infinitesimal small rater is used in true gradient descent procedures. Larger value can give a faster convergence but values too large will result in oscillation. In Neuron method the computation of this learning rate includes the use of the heassian matrix, which is approximated to quasi Newton method.

Chapter 4: Case studies

Because of the quadratic convergence, the Newton Raphson method is mathematically superior to the Gaus Seidal method and is less prone to divergence with ill-conditioned problem. For large power systems , the Newton Raphson method is found to be more efficient and practical. The number of iteration require to obtain a solution a solution is independent of the system size, but more functional evaluations are required at each iteration. Such since in the power flow problem real power and voltage magnitude are specified for the voltage controlled buses, the power flow equation is formulated in polar form. This equation can be rewritten in terms of the bus admittance matrix, as

$$I_i = \sum_{j=11}^{n} Y_{ij} V_j \qquad (4.1)$$

In the above equation, j includes bus i. Expressing this equation in polar form, we have

$$I_i = \sum_{j-1}^{n} |Y_{ij}||V_j| \angle \theta_{ij} + \delta_j \qquad (4.2)$$

The complex power at bus i is

$$P_i - jQ_i = V_i^{*} I_i \qquad (4.3)$$

Substituting (4.2) for I_i in (4.3),

$$P_i - jQ_i = |V_i| \angle -\delta_i \sum_{j-1}^{1} |Y_{ij}|\,|V_j|\,\angle \theta_{ij} + \delta_j \qquad (4.4)$$

Separating the real and imaginary parts,

$$P_i = \sum_{j-1}^{n} |V_i|\,|V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \qquad (4.5)$$

$$Q_i = -\sum_{j-1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \qquad (4.\ 6)$$

Equations (4.5) and (4.6) constitute a set of nonlinear algebraic equations in terms of independent variables, voltage magnitude in per unit, and phase angle in radians. We have two equations for each load bus, given by (4.5) and (4.6), and one equation for each voltage controlled bus, given by (4.5). Expanding (4.5) and (4.6) in Taylor's series about the initial estimate and neglecting all higher order terms set of linear equations.

In the above equation, bus 1 is assumed to be the slack bus. The Jacobian matrix gives the linearized relationship between small changes in voltage angle $\Delta\delta_i^{(k)}$ and the voltage magnitude $\Delta|V_I^{(K)}|$ with small changes in real and reactive power $\Delta P_i^{(k)}$ and $\Delta Q_i^{(k)}$. Elements of the Jacobians matrix are the partial derivatives of (4.5) and (4.6), evaluated at and $|\Delta|v_i^{(k)}|$.

In short form, it can be written as:

$$\begin{bmatrix} \Delta P \\ \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_1 & J_2 \\ J_3 & J_4 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} \tag{4.7}$$

For voltage controlled buses, the voltage magnitudes are known. Therefore, if n buses of the system are voltage controlled, m equation involving ΔQ and ΔV, and the corresponding columns of the Jacobian matrix are eliminated. Accordingly there are n-1 real power constraints and n-1-m reactive power constraints, and the jacobian matrix is of the order (2n-2-m)$\times$(2n-2-m). **J1** is of the (n-1)$\times$(n-1), **J2** is of the (n-1-m)$\times$(n-1), **J3** is of the (n-1-m)$\times$(n-1-m) and **J2** is of the (n-1-m)$\times$(n-1-m),

The diagonal and the off diagonal elements of **J1** are

$$\frac{\partial P_i}{\partial \delta_i} = \sum_{j\neq 1} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) \tag{4.8}$$

$$\frac{\partial P_i}{\partial \delta_j} = -|V_I||V_j||Y_{ij}|\sin(\theta_{ij} - \delta_i + \delta_j) \qquad \text{j} \neq i \tag{4.9}$$

The diagonal and the off-diagonal element of **J2** are

$$\frac{\partial P_i}{\partial |v_i|} = 2|V_i||Y_{IJ}|\cos\theta_{ij} + \sum_{j\neq 1} |V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \tag{4.10}$$

$$\frac{\partial P_i}{\partial |V_j|} = |V_i||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \qquad \text{j} \neq i \tag{4.11}$$

The diagonal and off-diagonal elements of **J3** are

$$\frac{\partial Q_i}{\partial \delta_i} = \sum_{j\neq 1} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \tag{4.12}$$

$$\frac{\partial Q_i}{\partial \delta_j} = -|V_I||V_j||Y_{ij}|\cos(\theta_{ij} - \delta_i + \delta_j) \qquad \text{j} \neq i \tag{4.13}$$

The diagonal and off-diagonal elements of **J4** are

$$\frac{\partial Q_i}{\partial |v_i|} = -2|V_i||Y_{IJ}|\sin\theta_{ij} - \sum_{j\neq 1}|V_j||Y_{ij}|\sin(\theta_{ij}-\delta_i+\delta_j) \tag{4.14}$$

$$\frac{\partial Q_i}{\partial |V_j|} = |V_i||Y_{ij}|\sin(\theta_{ij}-\delta_i+\delta_j) \qquad \mathrm{j} \neq i \tag{4.15}$$

The term $\Delta P_i^{(k)}$ and $AQ_i^{(k)}$ are the difference between the scheduled and calculated values, known as the power residuals, given by

$$\Delta P_i^{(k)} = P_i^{sch} - P_i^{(k)} \tag{4.16}$$

$$\Delta Q_i^{sch} = Q_i^{sch} - Q_i^{(k)} \tag{4.17}$$

The new estimates for bus voltages are

$$\delta_i^{(k+1)} = \delta_i^{(k)} + \Delta\delta_i^{(k)} \tag{4.18}$$

$$|V_i^{(k+1)}| = |V_i^{(k)}| + \Delta|V_i^{(k)}| \tag{4.19}$$

The procedure for power flow solutions by the Newton Raphson method is as follows:

1. For load buses where p_I^{sch} and Q_i^{sch} are specified, voltage magnitudes and phase angles are set equal to the slack bus values, or 1.0 and 0.0, i.e. $|V_i^{(0)}|$=1.0 and $\delta_i^{(0)} = 0.0.$ For voltage-regulated buses,. Where $|V_i|$ and P^{sch} are specified, phase angles are set equal to the slack bus angle, or 0, i.e. $\delta_{i\delta}^{(0)} = 0.$
2. For load buses, $p_I^{(K)}$ and $Q_i^{(k)}$ are calculated from (4.5) and (4.6) and $\Delta P_i^{(k)}$ and $\Delta Q_i^{(k)}$ are calculated from (4.8) and (4.9), respectively.
3. For voltage controlled buses, $P_i^{(k)}$ and $\Delta P_i^{(k)}$ are calculated from (4.5) and (4.16), respectively.
4. The elements of the jacobian matrix (**J1**, **J2**, **J3** and **J4**) are calculated from (4.5) and (4.15), respectively.
5. The linear simultaneous equation (4.7) is solved directly by optimally ordered triangular factorization and Gaussian elimination.
6. The new voltage magnitudes and phase angles are computed from (4.18) and (4.19).
7. The process is continued until the residuals $\Delta P_i^{(k)}$ and $\Delta Q_i^{(k)}$ are less than the specified accuracy, i.e.$|\Delta P_i^{(k)}| \leq e$

Figure 4 depicts the single line diagram of the study system used in this report.

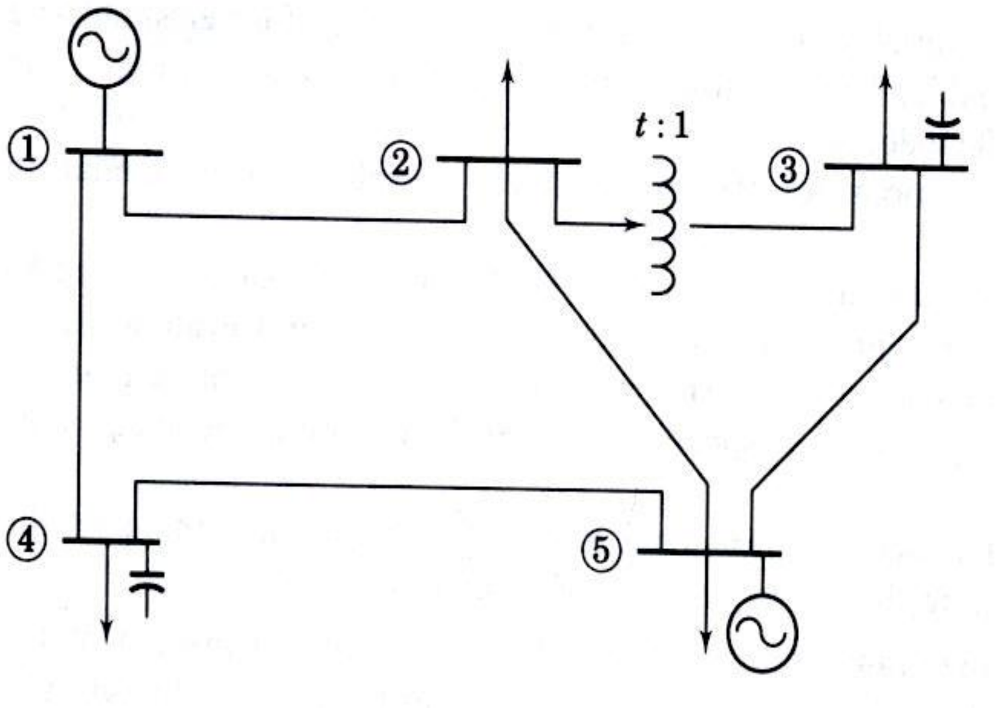


Figure 4: Five bus power system design.

(Source: The figure and the information referred from “Power system analysis”-John J. Grainger William D. Stevenson, JR.)

Table 2: Line data for the system of Figure 4

Line Bus to bus		Per Unit Series Z		Per Unit Series Y		Charging Mvar
		R	X	G	B	
1	2	0.0108	0.0649	2.5	-15	6.6
1	4	0.0235	0.0941	2.5	-10	4.0
2	5	0.0118	0.0471	5.0	-20	7.0
3	5	0.0147	0.0588	4.0	-16	8.0
4	5	0.0118	0.0529	4.0	-18	6.0

Table 3: Bus data for the system of Figure 4

Bus	Generation		Load		V	Remarks
	P(MW)	Q(Mvar)	P(MW)	Q(Mvar)	p.u.	
1					$1.01\angle 0^0$	Slack bus
2			60	35	$1.0\angle 0^0$	Load bus
3			70	42	$1.0\angle 0^0$	Load bus
4			80	50	$1.0\angle 0^0$	Load bus
5	190		65	36	$1.0\angle 0^0$	Generator bus

Table 4: Transformer data for the system of Figure 4

Transformer bus to bus	Per-unit reactance	Tap changing
2-3	0.04	0.975

Table 5: Capacitor data for the system of Figure 4

Bus	Rating Mvar
3	18
4	15

Power flow studies by using Newton Raphson program for High voltage solution

Bus No.			Votage	
From		To	Mag	Angle
1	(Slack Bus)	1	1.0195	2.0438
2	(Load bus)	2	1	2.0438
3	(Load Bus)	3	1	2.0438
4	(Load Bus)	4	2.7156	2.0438
5	(Generator Bus)	5	4.0393	2.0438

Figure 5 :Generalized power Flow studies by using Newton Raphson program for high voltage solution in per unit

Line flow tabular representation by Matlab font end design

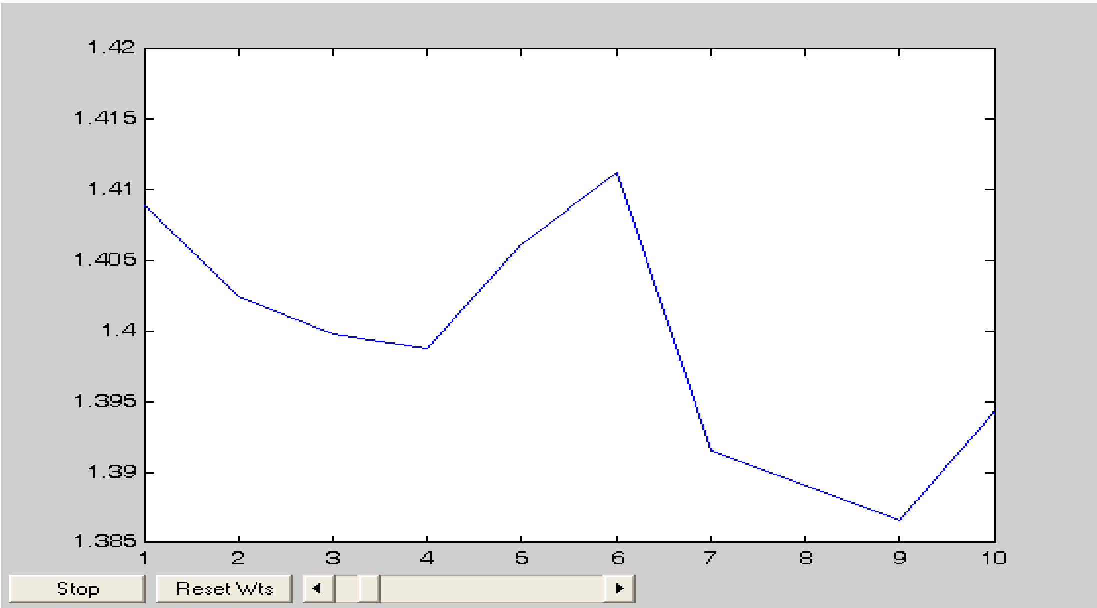
Bus no		Line Flow	Line flow
From	To	Mw	var
1	2	-3.3126	1.2579
1	4	4.7996	-18.0631
2	3	5.5923	3.2918
2	5	-50.5231	-41.9657
5	4	212.6756	154.8493
5	3	130.2075	276.223
2	1	3.443	3.443
4	5	-162.6216	69.5458
4	1	3.0978	49.6863
2	5	-50.5231	-41.9657

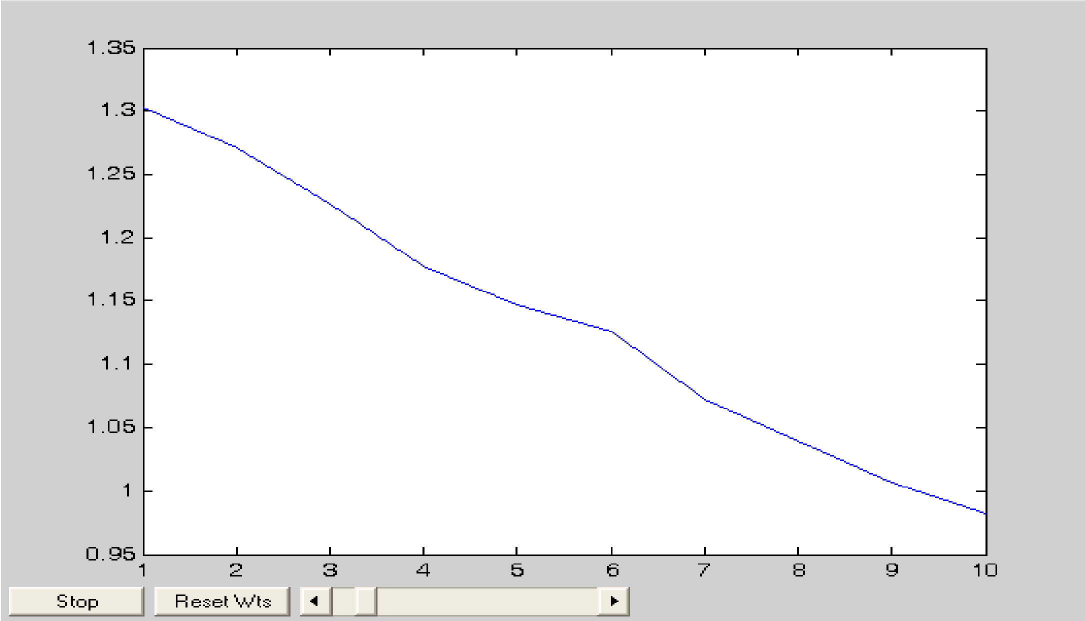
Fig 6: Generalized power flow studies by using Newton Raphson program for line flow in per unit.

Power flow studies by using Newton Raphson program for low voltage solution

Bus No. From		Bus No. To	Votage Mag	Votage Angle
1	(Reference)	1	1.02	1.6537
2	(Load bus)	2	0.062379	0.12626
3	(Load Bus)	3	1	0
4	(Load Bus)	4	0.13371	2.6413
5	(Generator Bus)	5	1.5829	1.3203

Figure 7 Generalized power flow studies by using Newton Raphson program for low voltage solution.





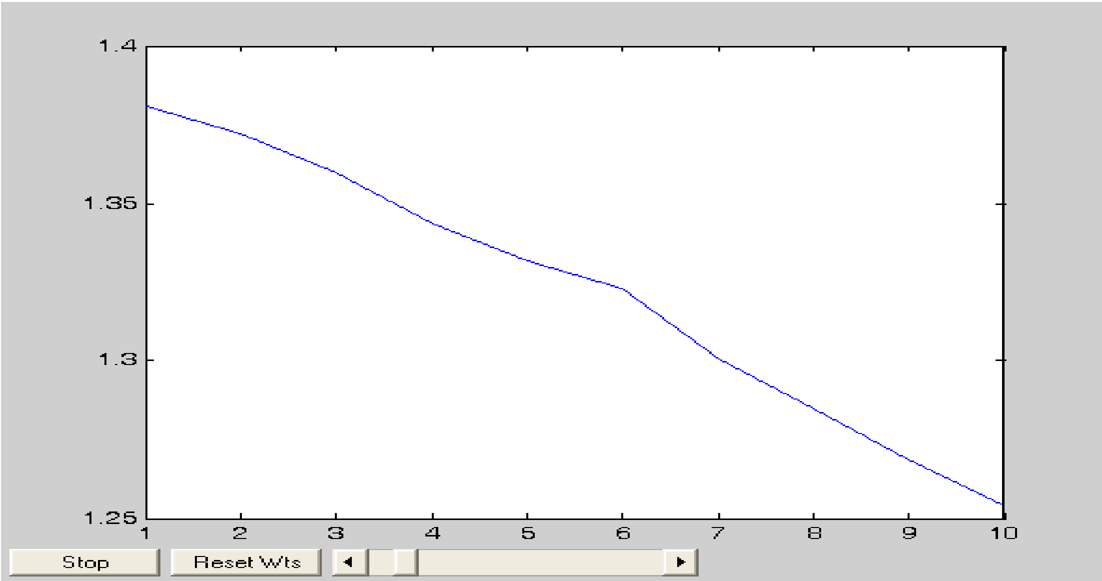


Figure 8: Small error analysis curve by using back propagation algorithm for load buses 2, 3 and 4 respectively.

Before neural network can gain the necessary recognization as useful problem solving tools in the power industry, certain fundamentals issues needed to be addressed. Some of them are associated with neural network technology, and others are problem dependent such as :

- Selection of neural network architecture and learning algorithm, such as net size, learning step, number of training patterns and iterations based on the problem dynamics.

- Determining the proper consistency of the training and testing data sets including, the range of training data, the spanning of the data in the operational space, and the statistical properties of the data.
- Formulation of features that provide high correlation between the training pattern and the desired NN response. The feature may have to be relatively insensitive to variations in topology, operation, and control characteristics of the system through the use of averaging, scaling and time gradient techniques.
- Statistical feature selection techniques to reduce the dimensionality of the input data while preserving classification accuracy. This would complement the higher level feature selection that may have already been performed through expert knowledge.
- Ability of the NN to generalize within the operational span of the system. The NN should first be able to learn the input pattern rather than memorizing them.
- The ability of the NN is to maintain its weights in a viable region without causing a large number of neurons to saturate.
- The ability of a NN to converge to an acceptable minimum within a specified range of weights.
- In neural key applications, the NN must be adaptable to slow changes in the system dynamics, and be able to update itself adaptively.
- NN inversion with Queries to enhance class boundaries and improve the data distribution in the operating space.

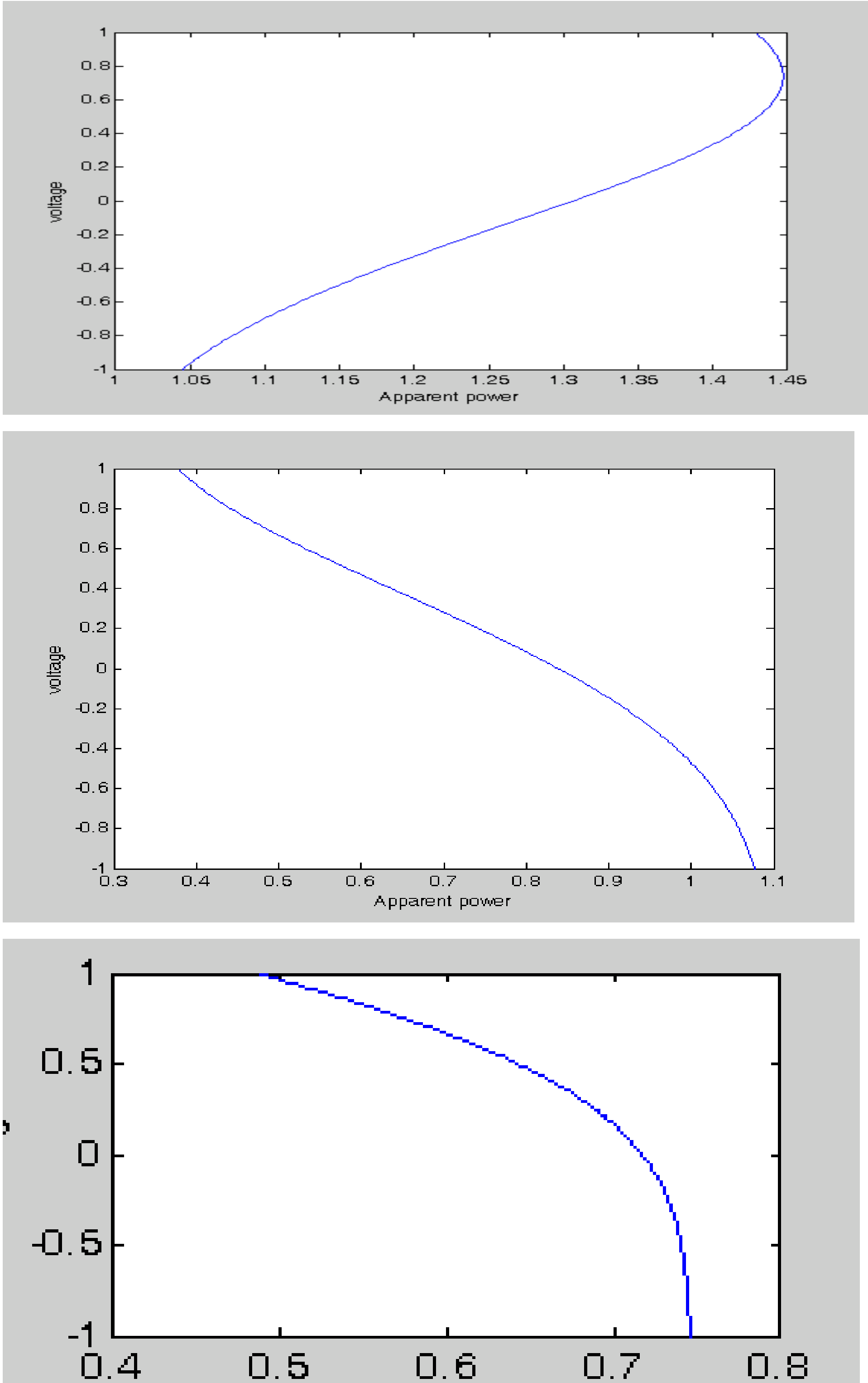
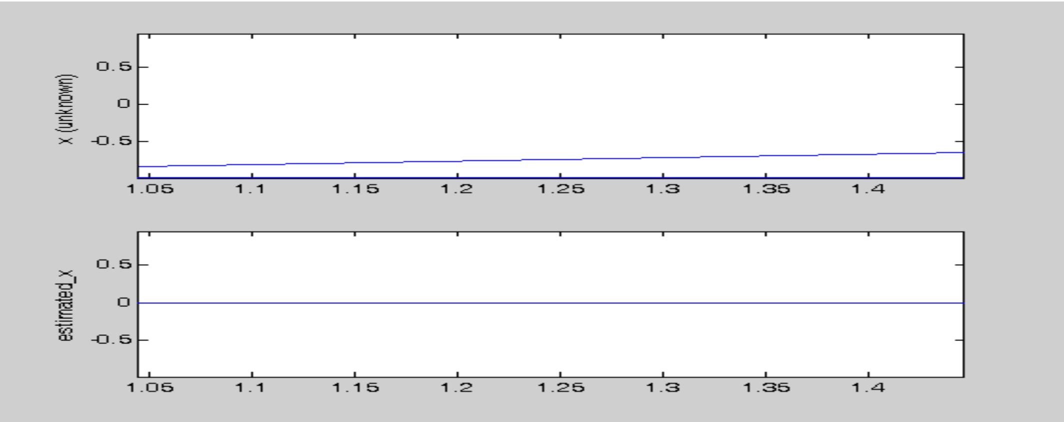
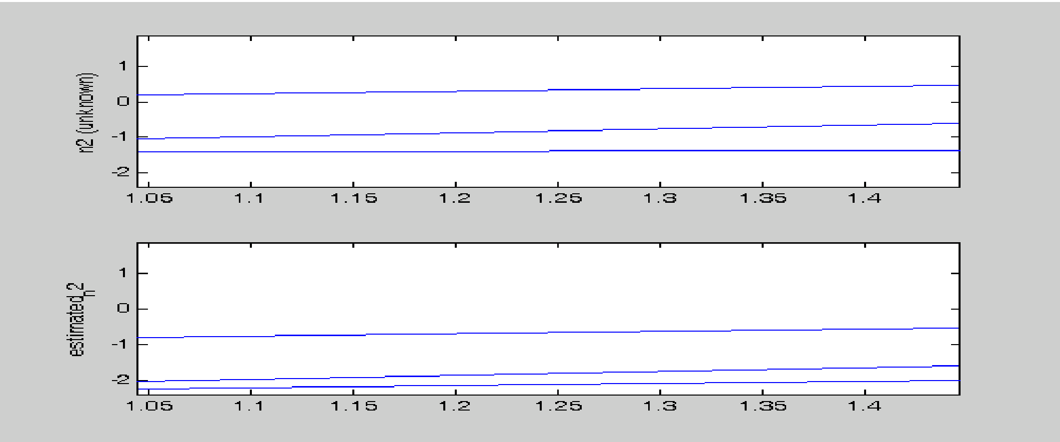


Figure 9: :PV curve for stability margin for load buses 2,3 and 4 respectively.

In small disturbance analysis, dynamic characteristics of the generators, reactors and speed governors are taking into consideration. The system operation operating point corresponding to the eigenvalu when the eigen-root locus of the system static matrix passes through the vertical or imaginary axis is the right point corresponding to the voltage collapse. Here compares the maximum load power and the critical voltage corresponding to the P-V curve's inflection point with maximum load power and the critical point of voltage collapse state matrix passes through the vertical or imaginary axis. To contrast the two power flow points, the concept of load power deviation coefficient and the voltage deviation are introduced. As a result, the error of the load power value and the critical voltage taking the inflection point of the P-V curve as the static voltage stability limit in the static voltage stability analysis. P-V curve method which is a traditional static traditional static voltage stability analysis method is a kind of computation analysis method based on the physical conception. Setting the result of the basic power flow, increasing the system load gradually, and calculating the system voltage corresponding to each operating point, a series of (P-V) points reflecting the relationship between the load power actually absorbed and a P-V curve can be formed. The reflection point of the P-V curve is considered as the voltage stability point, the area above the inflection point is the voltage stability region. The distance from the current system operating point to the inflection point is known as the system voltage stability margin.





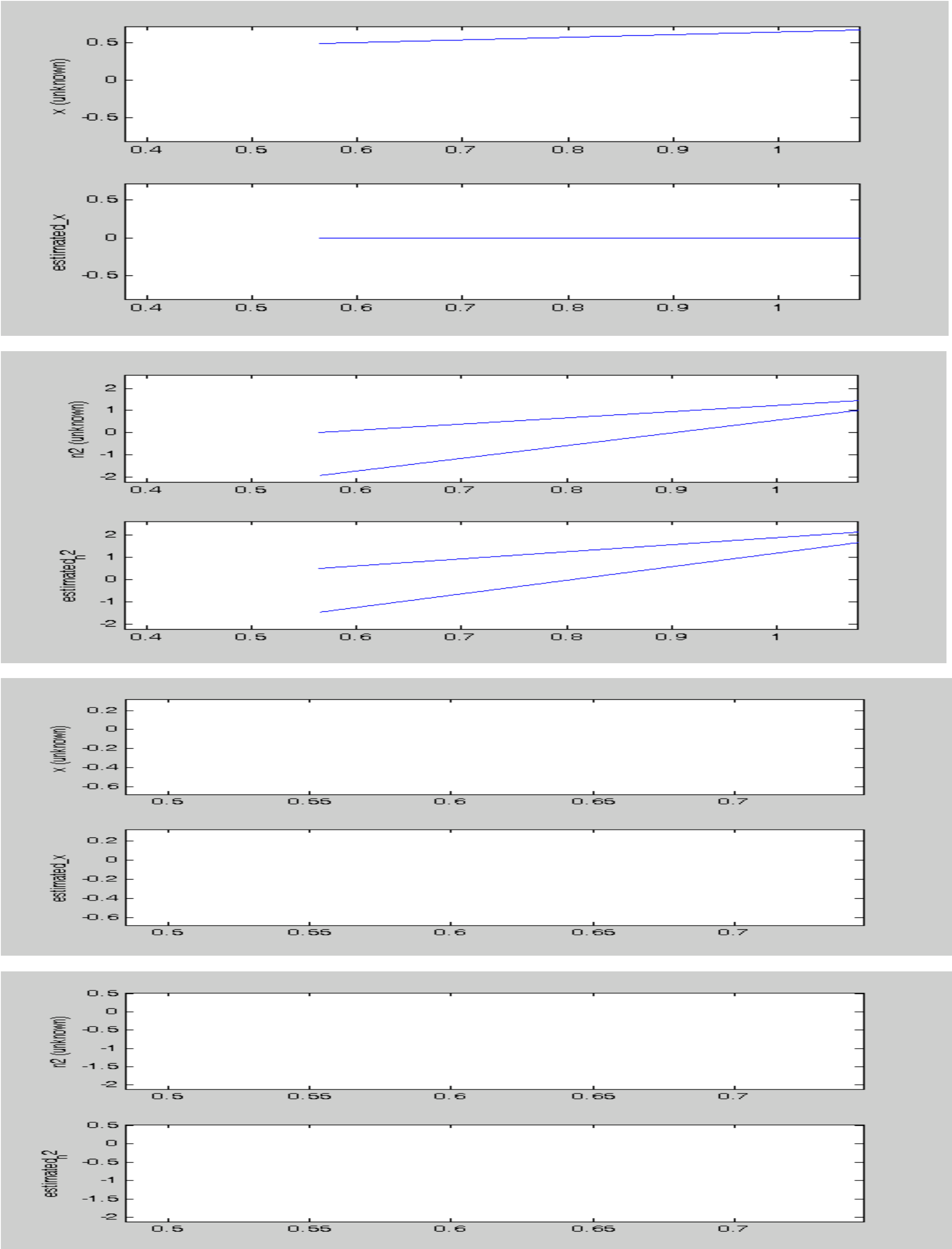


Figure 10: Noise elimination curve for both estimated_n^2 and n^2(unknown).for load buses 2,3 and 4 respectively.

When information on decisions is incomplete or the reliability is uncertain, the fuzzy logic can be a very helpful tool. The fuzzy logic theory has been applied to several areas including neural networks. Fuzzy logic is mainly used with NN to increase the dynamic range of the output neurons and reduce the effect of data noise. The supervised neural networks are trained with extracted feature and fuzzified targets. After the network is trained, the response of the network is defuzzified. The above entire system is described in the following block diagram shown in Figure 11.

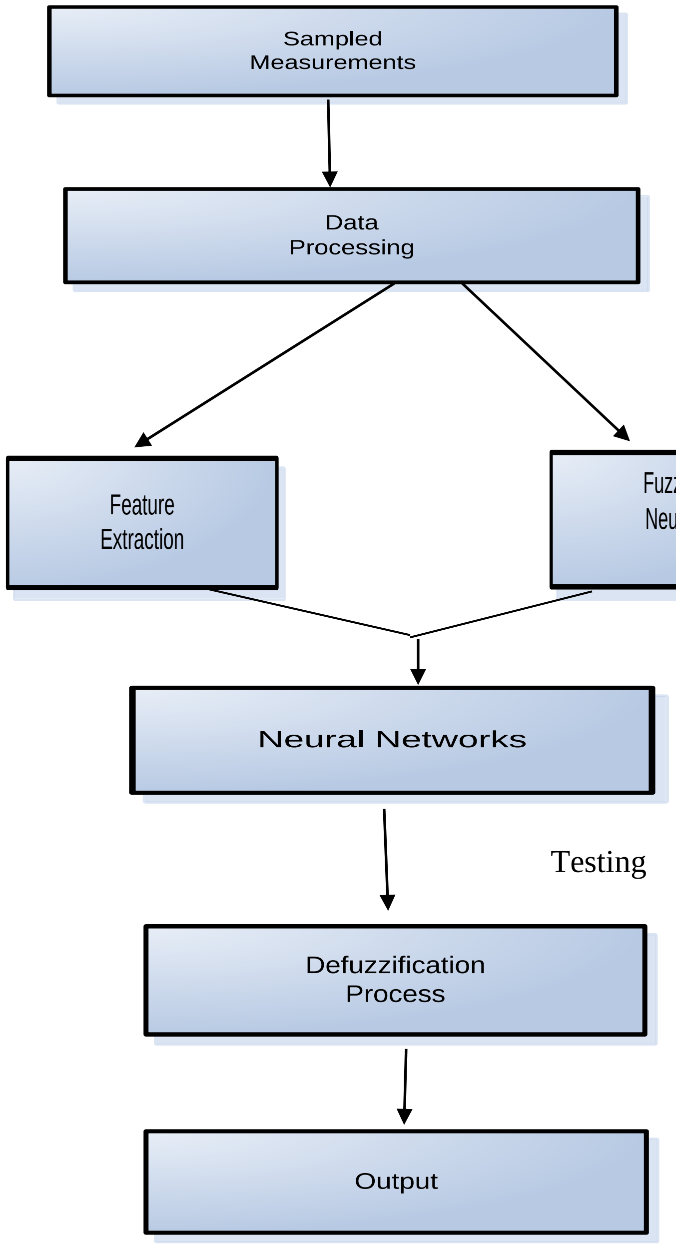


Figure 11:The fuzzified neural network process.

In the actual analysis application, it is desired definitely acceptable for the errors of system critical load power within 2% and the critical voltage within 0.05%. So it is reasonable and feasible to take the p-v inflection point as the system voltage instability point. The static voltage stability analysis method has been widely used in the analysis for the real life power system. But theoretically, static analysis method is not restrict because there is certainly some error to take the maximum power transfer point as the critical because there is certainly some error to take the maximum power transfer as the critical point of the voltage stability. It is necessary to find out how much the error is and whether it is still meaningful to use the static analysis method in the analysis of voltage stability. The above p-v curve compares the maximum load power and the critical voltage corresponding to the p-v curve's inflection point with the maximum load power and the critical point of voltage collapse corresponding to the eigen value point when the eigen locus of the static matrix passes through the vertical or imaginary axis. To compare the two power flow points, the concept of load power deviation coefficient and the voltage deviation are introduced. As a result of the error of the load power value and voltage and the critical voltage taking the inflection point of the p-v curve as the static voltage stability limit in the static voltage stability analysis can be calculated.

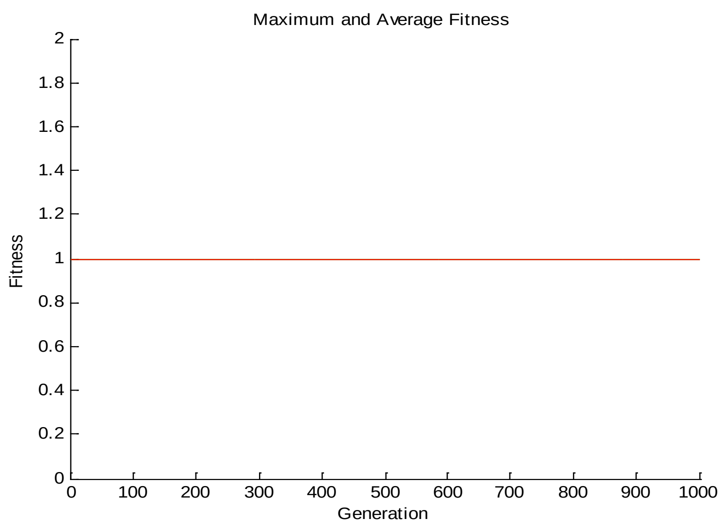


Fig 12: Average fitness of the population of solution.

Since our goal is to enhance the performance of Neural Networks, the emphasis is put on the ancillary role of genetic algorithm in the Neural Network computation. The control actions found by the generic algorithm are checked with a full Newton Raphson load flow calculation. The fitness values shown here were normalized and a value of 1 presents the theoretical case that no constraints are violated. The fitness of the best solution in the population increased considerably faster. Fig 5 presents the penalty of the constraints and the number of the controls used in the fitness of the best solution. Since the goal of the search process is first of all to find a set of control action that eliminates all constraints violations, the weight factor m_1 should be chosen sufficiently large in comparison with m_{2s}. In order to ensure that a single 0.1 p.u voltage constraint violation will cause a heavier penalty that K control action do, $m_1<10000*k*m_2$ should be chosen. In the first generation created by the GA(Genetic Algorithm), (*A.G.Bakirtzis, P. N. Biskas, C. E. Zoumas and V. Petridis, 2002)*the constraint violations will be minimized and eventually become zero, when and if a solution for the control problem is found. At this stage, the algorithm may be stopped., since the primary goal of the search process is reached. However it is possible to continue with the search process and the population of solutions will develop according to the last term of the fitness, which is the term expressing the number of controls used (K. Iba, , 1994). Unacceptable large changes of control variables are avoided by constraints in the GA. The initial population of solutions may be chosen at random, as is traditionally done. However a careful choice of the initial population can improve the efficiency in a substantial way. In view of the fact that a solution consisting of a small number of control actions is preferred, a part of the initial population is selected to present “one control action” solution. For a case of participating controls, the first i=1….k strings represent a single step increase in control i, while all other controls remain unchanged. Step size is the smallest possible, according to the coding of the variable. A similar procedure is followed for the next k strings, representing a decrease in each of the control values. In total 2k strings are selected, and the others are randomly chosen.

Chapter 6: Conclusion

Since the majority of the ANN architectures used in Security assessment (SA) and Security Enhancement (SE) are either multi layered perceptrons or kohonen classifier or Hopefield networks, we use presented the use of these three ANN architectures to solve various static and dynamic Security assessment problems. Specifically the selection of ANN architectures, the input data needed the training sets and how to evaluate the ANN performance. Since the SA and SE involves classifications, pattern recognization, prediction, estimation and fast solution, if is well suited for ANN application. However there are numerous issues which need to be considered before applying ANN to SA and SE. These include the maturity of conventional algorithmic methods in terms of both speed and accuracy and dimensionality of the operating space in which SA must be performed. For example, in SA, conventional contingency screening algorithms for predicting which contingencies will generate thermal limit violations, have achieved satisfactory results. On the other hand, there are no reliable conventional contingency screening algorithms for determining if the contingencies will generate static voltage collapse. The reasons for this is that the static voltage collapse problem is highly nonlinear complex relationships between the pre and the post contingency states and cannot be easily approximated by a simple computationally function(eg. Linearization) and therefore most suited to each nonlinear adaptive mapping as the one performed by the ANNs.

The dimensionality of the SA problems requires special solution techniques when using classical methods (eg, sparse matrix techniques). When using ANNs, the high dimensionality problem is reflected in the size of the input data(i.e. the number input neurons) and the size of training et, since one needs a sufficiently large, statistically significant training set to completely characterize the set of operating points. In daily operation, only a limited number of operating situations are planned, so the training vectors need to be selected randomly from the region of the scheduled operating points. If these operating point change significantly, some types of neural networks have to be trained again, daily if necessary (Of course, the weight vectors of trained networks can be stored off-line and used again for similar operating conditions). Moreover most ANN methods suffer from the combinatiorial explosion of the number of contingencies in the same way as classical methods. Because of ANN parallel computational approach this problems im more severe and some type of portioning sequencing and/or bounding techniques needs to be made. This is why most ANN examples reported, investigate the security of small buses up to about 20 buses. If the large systems are considered, then the ANN input should consist of features from the pre/post contingency system information (such as security indices)., rather than bus injection and network information.

Most of the ANN applications to SA and SE, reported in the literature, are of explanatory nature. They attempt to determine the feasibility of using different ANN architectures and determine which inputs and types of training produces the most accurate results. This studies can be considered to be similar to the selection of the good selection of security indices or approximate system performance (ASP) models for SA. That is finding what ASP is fast and accurate. Although the computational speed is a non issue when using ANNs training time is a crucial issue in power system security assessment.

Most artificial neural set approaches solve a more global task and then classical security assessment in which the contingency classification, ranking and evaluation are the primary problems They attempt to find a global description of the operating space (or parts of it) and its security boundaries . As statistical tools they depend heavily on good statistical representation of the operating space.

When comparing supervised and unsupervised ANNs, we note that tye have different objectives. Unsupervised approaches usually divide tye operating space into classes of operating points, thus pre-processing the data set by reducing it into a limited number of typical cases. These cases can be evaluated either with standard methods or with supervised learning. Supervised approaches attempt to approximate the security boundaries of the operating space, thus memorizing data points high dimensional function and interpolating between them.

In summary the best application of ANN to SA and SE is in improving the accuracy of the security predication by the currently available classical methods and the identification of a set of alternate SE strategies. By improving the accuracy, we mean either on-line training of off-line generated SA and SE results to take into account the measured load levels, dispatch strategy and the uncertainties in the network parameters, or the on-line integration of the various currently available ASP models and security indices to give a more accurate prediction of the system security. The application of ANNs enables one to reduce the input data dimensionality problems faced by the ANN and the selection of the training set (i.e. using off-line SA results together with the uncertainties of the load and system parameters). The ANN is used to integrate various transient instability indicators such as kinetic energies of the generators, generators accelerations, energy ratio etc. The MLPs weights are related to the performance of the various security indicators being integrated via the MLP.

Finally it should be noted that only small inroads have been made to solve the contingency problem due to line and generator outages (i.e. change in network configuration), which is one of the key problems in SA and SE. This is probably why not many ANNs are presently used in SA and SE. This problem cannot be solved by ANN technology alone, since it basically is the problem of the selecting the type of input data for the ANN.

Chapter 7: Future Research Recommendation

When the ANN is used, the investigated issues should be included:

- Problem partitioning that incorporate neural networks to expedite security calculations while preserving the advantages of conventional problem solving paradigms.
- Oracle and support software which can be extract features from the pre/post contingency power system information with respect to different power systems topologies and configurations.
- Statistical feature selection techniques to reduce the dimensionality of the input data while preserving classification accuracy. This would complement the higher level feature selection that may have already been performed expert knowledge.
- Capability of neural networks to correctly classify and generalize security among correlated and uncorrelated loading conditions. This is contrary to conforming load model that has been used in most literature to date.
- Ability of the ANN to generalize among different contingencies and operating.
- Ability of the ANN to recognize the secure region in the operational space. In other words, the ANN should be able to perform a contour tracking of the secure region.

The experience acquired from the development of the ANN based model strongly indicates that the ANN technology has matured enough to be applied successfully in many power system problems. However the success will eventually depend on the ability to remove a major obstacle ; at present there is neither a firm theory or nor even a set heuristic guidelines or procedures to assist the developer to design neural networks. In general it is viewed as an advantage of neural networks they are trained rather than programmed. However from development point of view, this feature only shifts the main effect form one task to another. The very flexibility that makes the ANN technology so amenable to data modeling also creates burden for the developers to select a ‘good’ if not the ‘best’ combination of topology, learning rules and parameters, activation functions, thresholds and input variables. At the present time, there is no complete theoretical basis to relate the above the parameters to known characteristics of the system that is being modeled. The lack of complete set of systematic design procedure constitutes the main obstacle to the practical use of neural networks. Furthermore, even a completely trained network provides little insight into the nature of the problem being solved. In the short run, since there is no clear relation of a network's own structure and the parameters to the data is attempting to model, it is very important, it is very important to choose application area that experience and knowledge has already been acquired. In the long run, substantial more work is needed to improve the theoretical underpinnings of the technology whose theoretical foundation lags far behind the practice in neural networks, as it also does in other forms of data representation compression and expression. Any further work will produce lasting results in the area if it also recognizes the fact the ANN technology can hardly provide all the modeling capabilities needed in a real life application. Consequently, any progress in ANN design should allow for integration of this technology with other modeling techniques from the statistical arema and especially with other technologies from the artificial intelligent are.

Specific area that need special attention fall into the following categories-

1. The optimal selection of the input variables that drive as ANN model is still an unresolved problem. Inclusive of all possible relevant input variables in the input set will increase the ANN complexity and the training time. It may also compromise the performance of the model. It is very important to develop a vigorous process that results in an optimal selection of the specific input variables that are important to build an acceptable model.
2. The design of the optimal ANN architecture is still an unresolved problem. Techniques that result in self building architectures, should be developed. These techniques build their networks in the course of training. Some basic work has been done but further research is required.
3. Other cost objectives should be evaluated. The simple sum of squared errors may not result in optimal result due to its sensitivity to large errors. The least median of squares or other more robust cost estimator may be more appropriate.
4. The effect of uncertainty in the input variables should be investigated. This may lead to the development of probabilities based load forecasting methods. Such algorithm should produce an expected value and a standard deviation for each forecast. This is of paramount important to the SLF users. The reliability

measures, such as confidence intervals, produced by the RBFN model is a step in that direction.

5. The optimal selection of the training set is still an unresolved problem. This can be an important problems of the distribution of data is grossly uneven. An optimal set will usually lead to better performance, lower ANN complexity and better training and generalization.

From our experience in developing the existing linear regression SLF model and the ANN based SLF models, it was found that the ANN models produce accurate load predictions under a wide variety of power system operating conditions. They are robust adaptive to changing conditions, and capable of incorporating in its forecasts the cumulative effect of such factors as recent load behavior as well as weather and random effects. The concepts used in developing the model fall into the following areas: a).selection of appropriate ANN inputs b). selection of nonlinear transformation of direct input as additional ANN input variables, c) accurate weather modeling, and d) the training process itself that has eliminated the need for on line update of the neural parameters.

The Radial Base Function Network model has the added advantage of computing reliability measures. These measures provide confidence intervals for the forecast and an extrapolation index to determine when the model is extrapolating beyond its original training data. The reliability measures and implement as additional output nodes at no additional computational cost by using available information from the fitting of the target function. These reliability measures are very useful to the operators and provide a reasonable solution to an unmet need in the industry.

Although back error propagation is the most widely used methods to train multilayer perceptrons, it is neither the only nor necessary the best approach. Indeed almost any algorithm that searches for a minimum can be used to train a layered perceptron, Back propagation is attractive because it can be performed within the neural network structure. However the technique has a number of limitations. For example, since the back-error-propagation technique is not designed to be adaptive, all data must be used every time the weights are updated. If a set of old data becomes irrelevant, the NN is retrained by using the entire new data set. Also when the new data is in conflict with the old data (data inconsistency), the effect of old data can not be removed unless the NN is retrained without the old data. The importance of some data can not be easily weighted. In addition, if the size of the NN is not adequately selected, or the convergence criterion is not realistic, thousands of iterations can be required to train a layered perceptron on even a simple problem. In addition, a training algorithm based on the steepest decent method, such as the back-error-propagation, can be very slow in the vicinity of final convergence. In the absence of data noise, additional learning takes place in a multilayered perceptrons only if new data is introduced that the neural network improperly classifies. The closer the representation comes to the concept, the smaller the chance that this happens. This is a characteristic of the least-squares and the steepest-descent techniques.

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Appendix

The list of the source code.

```
axis ij;
axis off;
axis([1,3,1,20]);
n=5;
y=zeros(n,n);
zl=.04;%The value of trainsformer reactance
a=.975;%the value of tapchanging
y(2,3)=(a-1)/zl*a;
y(1,2)=1/(.0108+.0649j);
y(1,4)=1/(.0235+0.0941j);
y(2,5)=1/(.0118+.0471j);
y(3,5)=1/(.0147+.0588j);
y(2,3)=1/(.053+.210j);
y(4,5)=1/(.0118+.0529j);
for p=1:n
   for q=1:n
      if p>q
         y(p,q)=y(q,p);
      end
   end
end
for p=1:n
   for q=1:n
      if p==q
         sum=0;
         for k=1:n
            sum=sum+y(p,k);
         end;
         y(p,q)=sum;
      end
   end
end
y
v=[1.01 1 1 1 1];
Pg=[0 0 0 0 1.90];%Assuming 100 MVA base
Qg=[0 0 0 0 0];
Pl=[0 .60 .70 .80 .65];
Ql=[0 .35 .42 .50 .36];
P=zeros(1,n);
Q=zeros(1,n);
Q12=6.6;
Q14=4.0;
Q25=7.0;
Q35=8.0;
Q45=6.0;
```

```
Q23=0;
Qc3=(Q23+Q35)/2;
Qc4=(Q14+Q45)/2;
Qc1=0
Qc2=0
Qc5=0;
Qc=[Qc1 Qc2 Qc3 Qc4 Qc5]/100;
Q=Qg-(Ql-Qc);
P=Pg-Pl;
theta=angle(y);
del=angle(v);
H=zeros(n,n);
M=zeros(n,n);
L=zeros(n,n);
N=zeros(n,n);
for t=1:n
    for k=1:n
        if (t~=k)
            H(t,k)=-abs(v(t)*v(k)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
            M(t,k)=-abs(v(t)*v(k)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            L(t,k)=+abs(v(t)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            N(t,k)=-abs(v(t)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
        end
        if (t==k)
            H(t,k)=H(t,k)-abs(v(t)*v(k)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
            M(t,k)=M(t,k)-abs(v(t)*v(k)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            L(t,k)=L(t,k)+abs(v(k)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            N(t,k)=N(t,k)-abs(v(k)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
        end
    end
end
L(t,t)=(2*abs(v(t))*abs(y(t,t)))*cos(theta(t,t)+L(t,t));
N(t,t)=(-2*abs(v(t))*abs(y(t,t)))*sin(theta(t,t)+L(t,t));
L
M
J=[H L;
    M N];
   J([1 6 7 8],:)=[];
  J(:,[1 6 7 8])=[];
       for t=1:5
       s(t)=0;
          for k=1:5
      s(t)=s(t)+v(t)*conj(y(t,k))*conj(v(k));
  end
delP(t)=P(t)-real(s(t));
delQ(t)=Q(t)-imag(s(t));
end
J
s
delP(3)=[];
```

```
delQ(:,[1 2 3])=[];
dPQ=[delP';delQ'];
dVD=inv(J)*dPQ;
dD=[dVD(1:2);0;dVD(3:4)]';
dV=[0;0;dVD(3:4)]';
dv=[0;0;0;dVD(5:6)]';
v=v+dv;
DD=del+dD;
del=del+dD;
for t=1:5
   v(t)=v(t)*(cos(del(t))+v(t)*j*sin(del(t)));
end
figure(1);
for b=3:9
   line([1,5],[2*b,2*b]);
end
for b=1:5
   line([b,b],[6,18]);
end
line([3.5,3.5],[7.15]);
line([4.5,4.5],[7.15]);
line([2.5,2.5],[7.18]);
line([2,5],[7,7]);
text(1.3,7,'Bus No. ');
text(1.8,7.5,'To');
text(1,7.5,'From');
text(2.25,6.5,'Votage');
text(2.04,7.5,'Mag');
text(2.55,7.5,'Angle');
for k=1:5
   text(1.2,8.5,'1   (Slack Bus)             1');
    text(1.2,10.5,'2       (Load bus)        2');
     text(1.2,12.5,'3      (Load Bus)        3');
      text(1.2,14.5,'4     (Load Bus)        4');
       text(1.2,16.5,'5     (Generator Bus)   5');
           text(2.15,7+2*k,num2str(abs(v(k))));
   text(2.55,7+2*k,num2str(angle(v(5))));
end
title('Power flow studies by using Newton Raphson program for High voltage
solution');
figure(2);
for kk=1:5
   for tt=1:5
       I(kk,tt)=(v(kk)-v(tt))*y(kk,tt);
   end
end
I
p12=real(v(1)*conj(I(1,2)));
q12=imag(v(1)*conj(I(1,2)));
p14=real(v(1)*conj(I(1,4)));
```

```
q14=imag(v(1)*conj(I(1,4)));
p23=real(v(2)*conj(I(2,3)));
q23=imag(v(2)*conj(I(2,3)));
p25=real(v(2)*conj(I(2,5)));
q25=real(v(2)*conj(I(2,5)));
p54=real(v(5)*conj(I(5,4)));
q54=imag(v(5)*conj(I(5,4)));
p53=real(v(5)*conj(I(5,3)));
q53=imag(v(5)*conj(I(5,3)));
p21=real(v(2)*conj(I(2,1)));
q21=real(v(2)*conj(I(2,1)));
p45=real(v(4)*conj(I(4,5)));
q45=imag(v(4)*conj(I(4,5)));
p41=real(v(4)*conj(I(4,1)));
q41=imag(v(4)*conj(I(4,1)));
p25=real(v(2)*conj(I(2,5)));
q25=imag(v(2)*conj(I(2,5)));
axis ij;
axis off;
axis([1,4,1,15]);
for b=3:17
   line([1,5],[b,b]);
end
for b=1:4
   line([b,b],[3,15]);
end
line([1.5,1.5],[4,15]);
text(1.3,3.5,'Bus no');
text(1.1,4.5,'From');
text(1.6,4.5,'To');
text(2.3,3.5,'Line Flow');
text(2.3,4.5,'Mw');
text(3.3,3.5,'Line flow');
text(3.3,4.5,'var');
text(1.2,5.5,'1            2');
text(1.2,6.5,'1            4');
text(1.2,7.5,'2            3');
text(1.2,8.5,'2            5');
text(1.2,9.5,'5            4');
text(1.2,10.5,'5            3');
text(1.2,11.5,'2            1');
text(1.2,12.5,'4            5');
text(1.2,13.5,'4            1');
text(1.2,14.5,'2            5');
text(2.4,5.5,num2str(p12));
text(3.4,5.5,num2str(q12));
text(2.4,6.5,num2str(p14));
text(3.4,6.5,num2str(q14));
text(2.4,7.5,num2str(p23));
text(3.4,7.5,num2str(q23));
```

```
text(2.4,8.5,num2str(p25));
text(3.4,8.5,num2str(q25));
text(2.4,9.5,num2str(p54));
text(3.4,9.5,num2str(q54));
text(2.4,10.5,num2str(p53));
text(3.4,10.5,num2str(q53));
text(2.4,11.5,num2str(p21));
text(3.4,11.5,num2str(q21));
text(2.4,12.5,num2str(p45));
text(3.4,12.5,num2str(q45));
text(2.4,13.5,num2str(p41));
text(3.4,13.5,num2str(q41));
text(2.4,14.5,num2str(p25));
text(3.4,14.5,num2str(q25));
title('Line flow tabular representation by Matlab font end design');
figure(3)
 axis ij;
axis off;
axis([1,3,1,20]);
vv=[1.01 .1 1 1 1];
Pg=[0 0 0 0 1.90];%Assuming 100 MVA base
Qg=[0 0 0 0 0];
Pl=[0 .60 .70 .80 .65];
Ql=[0 .35 .42 .50 .36];
n=5;
P=zeros(1,n);
Q=zeros(1,n);
Q12=6.6;
Q14=4.0;
Q25=7.0;
Q35=8.0;
Q45=6.0;
Q23=0;
Qc3=(Q23+Q35)/2;
Qc4=(Q14+Q45)/2;
Qc1=0
Qc2=0
Qc5=0;
Qc=[Qc1 Qc2 Qc3 Qc4 Qc5]/100;
Q=Qg-(Ql-Qc);
P=Pg-Pl;
theta=angle(y);
del=angle(v);
H=zeros(n,n);
M=zeros(n,n);
L=zeros(n,n);
N=zeros(n,n);
for t=1:n
    for k=1:n
        if (t~=k)
```

```
            H(t,k)=-abs(v(t)*vv(k)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
            M(t,k)=-abs(v(t)*vv(k)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            L(t,k)=+abs(v(t)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            N(t,k)=-abs(v(t)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
        end
        if (t==k)
            H(t,k)=H(t,k)-abs(v(t)*vv(k)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
            M(t,k)=M(t,k)-abs(v(t)*vv(k)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            L(t,k)=L(t,k)+abs(v(k)*y(t,k))*cos(theta(t,k)-del(t)+del(k));
            N(t,k)=N(t,k)-abs(v(k)*y(t,k))*sin(theta(t,k)-del(t)+del(k));
        end
    end
end
L(t,t)=(2*abs(v(t))*abs(y(t,t)))*cos(theta(t,t)+L(t,t));
N(t,t)=(-2*abs(v(t))*abs(y(t,t)))*sin(theta(t,t)+L(t,t));
J=[H L;
    M N];
    J([1 6 7 8],:)=[];
  J(:,[1 6 7 8])=[];
       for t=1:5
       s1(t)=0;
          for k=1:5
      s1(t)=s1(t)+vv(t)*conj(y(t,k))*conj(vv(k));
  end
delP(t)=P(t)-real(s1(t));
delQ(t)=Q(t)-imag(s1(t));
end
disp('Jackobian value and apparent power for Low voltage solution');
J
s1
delP(3)=[];
delQ(:,[1 2 3])=[];
dPQ=[delP';delQ'];
dVD=inv(J)*dPQ;
dD=[dVD(1:2);0;dVD(3:4)]';
dV=[0;0;dVD(3:4)]';
dv=[0;0;0;dVD(5:6)]';
vv=vv+dv;
DD=del+dD;
del=del+dD;
for t=1:5
    vv(t)=vv(t)*(cos(del(t))+vv(t)*j*sin(del(t)));
end
for b=3:9
    line([1,5],[2*b,2*b]);
end
for b=1:5
    line([b,b],[6,18]);
end
line([3.5,3.5],[7.15]);
```

```
line([4.5,4.5],[7.15]);
line([2.5,2.5],[7.18]);
line([2,5],[7,7]);
text(1.3,7,'Bus No. ');
text(1.8,7.5,'To');
text(1,7.5,'From');
text(2.25,6.5,'Votage');
text(2.04,7.5,'Mag');
text(2.55,7.5,'Angle');
for k=1:5
    text(1.2,8.5,'1   (Reference)             1');
     text(1.2,10.5,'2        (Load bus)         2');
      text(1.2,12.5,'3      (Load Bus)          3');
       text(1.2,14.5,'4     (Load Bus)          4');
        text(1.2,16.5,'5     (Generator Bus)     5');
            text(2.15,7+2*k,num2str(abs(vv(k))));
    text(2.55,7+2*k,num2str(angle(vv(k))));
end
title('Power flow studies by using Newton Raphson program for low voltage solution');
```

The runtime output of the generalized power flow program:

```
y =

   4.9931 -24.9963i   2.4950 -14.9931i        0             2.4981 -10.0031i        0
   2.4950 -14.9931i   8.6298 -39.4474i   1.1298 - 4.4768i        0             5.0050 -
19.9775i
        0             1.1298 - 4.4768i   5.1314 -20.4832i        0             4.0016 -16.0064i
   2.4981 -10.0031i        0                  0             6.5149 -28.0107i   4.0168 -18.0076i
        0             5.0050 -19.9775i   4.0016 -16.0064i   4.0168 -18.0076i  13.0234 -
53.9915i

Qc1 =

     0


Qc2 =

     0


L =

    5.0431    2.5200         0    2.5231         0
    2.4950    8.6298    1.1298         0    5.0050
         0    1.1298    5.1314         0    4.0016
    2.4981         0         0    6.5149    4.0168
         0    5.0050    4.0016    4.0168   71.0248
M =

   -5.0935   -2.5200         0   -2.5231         0
```

```
   -2.5200   -8.6298   -1.1298         0   -5.0050
         0   -1.1298   -5.1314         0   -4.0016
   -2.5231         0         0   -6.5149   -4.0168
         0   -5.0050   -4.0016   -4.0168  -13.0234
J =

   39.4474    4.4768         0   19.9775         0    5.0050
    4.4768   20.4832         0   16.0064         0    4.0016
         0         0   28.0107   18.0076    6.5149    4.0168
   19.9775   16.0064   18.0076   53.9915    4.0168   71.0248
         0         0   -6.5149   -4.0168   28.0107   18.0076
   -5.0050   -4.0016   -4.0168  -13.0234   18.0076  -60.4718
s =

  1.0e+002 *

   0.1014 + 0.5074i   0.1728 + 0.7904i   0.1026 + 0.4097i   0.1305 + 0.5612i   0.2605 +
1.0798i
I =

        0             0.4315 - 3.4486i        0           -16.1039 + 8.7591i        0
  -0.4315 + 3.4486i        0             3.3605 + 5.5513i        0           -42.5856 -50.0018i
        0            -3.3605 - 5.5513i        0                  0           -46.1891 -59.8507i
  16.1039 - 8.7591i        0                  0                  0           -10.1387 -64.3357i
        0            42.5856 +50.0018i  46.1891 +59.8507i  10.1387 +64.3357i        0
Qc1 =

     0
Qc2 =

     0
```

Jackobian value and apparent power for Low voltage solution

```
J =

    3.9447    1.1850         0   15.3352         0   13.7471
   -0.1075   20.4832         0  -10.8545         0   12.4257
         0         0   76.0668   15.6598   17.6922   47.5938
    8.0806  -15.0670   51.1695  218.0864  -54.1820  240.3523
         0         0  -17.6922  -47.5938   76.0668   15.6598
    1.9765   64.9185   54.1820  -52.6051   51.1695 -114.1242
s1 =
   7.8686 +37.1161i   0.9518 + 4.3542i   9.2460 +36.9372i  13.0549 +56.1215i
21.5423 +90.0033i
```

To validate the data and creating the pv cuve with dynamics:

```
  aa=[6.4849,2.0762,0.9518];
pp=aa';
bb=sort(aa);
cc=[1,.27814,.19166];
dd=[.41721,.048276,.0068744];
```

```
kk=cc';
nn=dd';
hidden_neurons = 2;
epochs = 10;
% ------- load in the data -------
% XOR data
train_inp = [kk,nn];
train_out = pp;
train_inp
train_out
% check same number of patterns in each
if size(train_inp,1) ~= size(train_out,1)
    disp('ERROR: data mismatch');
   return
end
%standardise the data to mean=0 and standard deviation=1
%inputs
mu_inp = mean(train_inp);
sigma_inp = std(train_inp);
train_inp = (train_inp(:,:) - mu_inp(:,1)) / sigma_inp(:,1);
%outputs
train_out = train_out';
mu_out = mean(train_out);
sigma_out = std(train_out);
train_out = (train_out(:,:) - mu_out(:,1)) / sigma_out(:,1);
train_out = train_out';
%read how many patterns
patterns = size(train_inp,1);
%add a bias as an input
bias = ones(patterns,1);
train_inp = [train_inp bias];
%read how many inputs
inputs = size(train_inp,2);
%---------- data loaded ------------
%--------- add some control buttons ---------
%add button for early stopping
hstop = uicontrol('Style','PushButton','String','Stop', 'Position', [5 5 70
20],'callback','earlystop = 1;');
earlystop = 0;
%add button for resetting weights
hreset = uicontrol('Style','PushButton','String','Reset Wts', 'Position',
get(hstop,'position')+[75 0 0 0],'callback','reset = 1;');
reset = 0;
%add slider to adjust the learning rate
hlr = uicontrol('Style','slider','value',.1,'Min',.01,'Max',1,'SliderStep',[0.01
0.1],'Position', get(hreset,'position')+[75 0 100 0]);
% ---------- set weights -----------------
%set initial random weights
weight_input_hidden = (randn(inputs,hidden_neurons) - 0.5)/10;
weight_hidden_output = (randn(1,hidden_neurons) - 0.5)/10;
```

```
%----------------------------------
%--- Learning Starts Here! ---------
%----------------------------------
%do a number of epochs
for iter = 1:epochs
        %get the learning rate from the slider
    alr = get(hlr,'value');
    blr = alr / 10;
        %loop through the patterns, selecting randomly
    for j = 1:patterns
      %select a random pattern
        patnum = round((rand * patterns) + 0.5);
        if patnum > patterns
            patnum = patterns;
        elseif patnum < 1
            patnum = 1;
        end
         %set the current pattern
        this_pat = train_inp(patnum,:);
        act = train_out(patnum,1);
         %calculate the current error for this pattern
        hval = (tanh(this_pat*weight_input_hidden))';
        pred = hval'*weight_hidden_output';
        error = pred - act;
        % adjust weight hidden - output
        delta_HO = error.*blr .*hval;
        weight_hidden_output = weight_hidden_output - delta_HO';
        % adjust the weights input - hidden
        delta_IH= alr.*error.*weight_hidden_output'.*(1-(hval.^2))*this_pat;
        weight_input_hidden = weight_input_hidden - delta_IH';
       end
    % -- another epoch finished

    %plot overall network error at end of each epoch
    pred = weight_hidden_output*tanh(train_inp*weight_input_hidden)';
    error = pred' - train_out;
    err(iter) =  (sum(error.^2))^0.5;
       figure(1);
    plot(err);
        %reset weights if requested
    if reset
        weight_input_hidden = (randn(inputs,hidden_neurons) - 0.5)/10;
        weight_hidden_output = (randn(1,hidden_neurons) - 0.5)/10;
        fprintf('weights reaset after %d epochs\n',iter);
        reset = 0;
    end
       %stop if requested
    if earlystop
        fprintf('stopped at epoch: %d\n',iter);
        break
```

```
    end
    %stop if error is small
    if err(iter) < 0.001
        fprintf('converged at epoch: %d\n',iter);
        break
    end
    end
   %-----FINISHED---------
   %display actual,predicted & error
   fprintf('state after %d epochs\n',iter);
   aaa = (train_out* sigma_out(:,1)) + mu_out(:,1);
   b = (pred'* sigma_out(:,1)) + mu_out(:,1);
   act_pred_err = [aaa b b-aaa]
  v=[cc dd];
s=[bb aa];
a=radbas(s);
a2 = radbas(s-1.5);
a3 = radbas(s+2);
a4 = a + a2*1 + a3*0.5;
eg = 0.2; % sum-squared error goal
sc = 1;    % spread constant
net = newrb(s,v,eg,sc);
z=-1:.01:1;
w=sim(net,z);
x=w;
y=z;
figure(2)
plot(w,z);
%set(gca,'xdir','reverse','ydir','normal');
w=x;
z=y;
hold off
xlabel('Apparent power');
ylabel('voltage')
time=s';
figure(3)
n1 = randn(size(time));
plot(time, n1)
%set(gca,'xdir','normal','ydir','reverse');
title('Noise Source n1')
xlabel('time')
ylabel('n1')
domain = linspace(min(n1), max(n1), 20);
[xx, yy] = meshgrid(domain, domain);
n1d0 = n1;                          % n1 delay 0
n1d1 = [0; n1d0(1:length(n1d0)-1)];   % n1 delay 1
n2 = 4*sin(n1d0).*n1d1./(1+n1d1.^2);  % interference
axis_limit = [min(s) max(s) min([n1;n2]) max([n1;n2])];
x = sin(40./(time+0.01));
m = x + n2;
```

```
subplot(1,1,1)
%set(gca,'xdir','reverse','ydir','normal');
plot(time, m)
set(gca,'xdir','reverse','ydir','normal');
title('Measured Signal')
xlabel('time')
ylabel('m')
delayed_n1 = [0; n1(1:length(n1)-1)];
trn_data = [delayed_n1 n1 m];
mf_n = 2;
ss = 0.2;
in_fismat=genfis1(trn_data, mf_n);
out_fismat = anfis(trn_data, in_fismat, [nan nan ss]);
estimated_n2 = evalfis(trn_data(:, 1:2), out_fismat);
estimated_x = m - estimated_n2;
axis_limit =  [min(w) max(w) min([n2; estimated_n2]) max([n2; estimated_n2])];
subplot(2,1,1)
plot(time, n2)
ylabel('n2 (unknown)'); axis(axis_limit);
subplot(2,1,2)
plot(time, estimated_n2)
ylabel('estimated_n2'); axis(axis_limit);
figure(6)
axis_limit =  [min(w) max(w) min([x; estimated_x]) max([x; estimated_x])];
subplot(2,1,1)
plot(time, x)
ylabel('x (unknown) '); axis(axis_limit);
subplot(2,1,2)
plot(time, estimated_x)
axis(axis_limit); ylabel('estimated\_x')
```