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A VOLTAGE STABILIZER FOR POWER DISTRIBUTION SYSTEMS USING NEURAL NETWORKS

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Samir JABR: A Voltage Stabilizer for Power Distribution Systems Using Neural Networks

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ABSTRACT

Voltage collapse causes many blackouts of power systems all over the world even in developed countries. SCADA systems, which were induced in most power systems, could not prevent many famous blackouts. Therefore, there is a need to find efficient solutions to remedy these problems.

This thesis attempts to design a voltage stabilizer for power distribution systems (PDS) based on artificial neural network (ANN) on-line detection of instability that works concurrently with SCADA systems as another support to help preventing voltage collapse in PDS.

The design of this voltage stabilizer has two phases. The first phase is an intelligent system which uses a back propagation learning algorithm neural network that detects instability or overload of PDS, using images of voltage outputs obtained from a MATLAB simulator for a proposed power system.

The second phase of the intelligent voltage stabilizer uses the output of the first phase which is the ANN classifier. If the intelligent system detects an overload case, the stabilizer will perform instantaneous steps to clean the deep voltage drop in PDS which may cause voltage collapse. These steps depend on raising tap-changer relays of distribution transformers then switching on capacitor banks in steps, then if it is necessary shedding part of loads with least priority. Also, if instability is detected, the stabilizer will make quick arrangement to assess stability. Loads shedding and redispatch the generators to get actions constitute the main arrangements. In every case, load shedding will be performed according to the cause of instability.

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LIST OF ABBREVIATIONS

AGC: Automatic Generation Control

ANN: Artificial Neural Network

AVC: Advanced VAR Compensators

BPA: Bonneville Power Administration

BP: Back Propagation

DVC: Dynamic VAR Compensator

ED: Economic Dispatch

EMS: Energy Management Systems

ES: Excitation System

FACTS: Flexible AC Transmission System

GDE: Governor and Diesel Engine

HTG: Hydraulic Turbine and Governor

LFC: Load Frequency Control

LP: Linear Programming

LTC: Load Tap-Changers

MLP: Multilayered Perceptron

MSE: Mean Square Error

PDS: Power Distribution System

PSS: Power System Stabilizer

RTU: Remote Terminal Units

SCADA: Supervisory Control and Data Acquisition

SCB: Switched Capacitor Banks

SVC: Static VAR Compensator

UFLS: Under Frequency Load Shedding

VS: Voltage Stabilizer

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INTRODUCTION

Voltage instability or collapse is emerging as a major concern to utility companies who aim to maintain a stable power system operation. Voltage instability has caused several major power system collapses around the world. In general these voltage stability analysis methods are classified into two categories: dynamic stability and transient stability. Dynamic stability can reproduce or predict the time response of the system voltage to a sequence of events and, therefore, help identify whether the system voltage is stable or not. The majority of transient methods are based on power flow formations to evaluate voltage stability in various terms, such as load margins and load flow feasibility.

Voltage stability analysis is concerned with the ability of assessing the power system to maintain acceptable voltages at all system buses under normal conditions and after being subjected to disturbances. A major factor contributing to voltage instability is the voltage drop that occurs when active and reactive power flow through inductive reactances of the transmission network. Voltage stability is threatened when a disturbance increases the reactive power demand beyond the sustainable capacity of the available reactive power resources. While the most common form of voltage instability is the progressive drop of bus voltages, the risk of overvoltage instability also exists and has been experienced at least on one system.

Since the voltage instability issue started to emerge, significant research efforts from the power engineering community have been devoted to studying the voltage instability mechanism and to developing analysis tools and control schemes to mitigate the instability. Meanwhile, many researchers agree that the voltage instability problem is a high order nonlinear problem as a large number of different types of devices are involved in the voltage dynamics. Also a wide variety of modeling and simulation principles and analysis and control methods of the power system voltage stability have been developed.

Artificial Neural Networks (ANN) have been used to solve many problems obtaining outstanding results in various applications such as classification, clustering, pattern recognition and forecasting among many other applications corresponding to different areas. Applications of Artificial Neural Network to the above-mentioned problem

have attained increasing importance mainly due to the efficiency of present day computers. Moreover real-time use of conventional methods in an energy management center can be difficult due to their significant large computational times. One of the main features, which can be attributed to ANN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate online response. ANN approach to voltage stability assessment and improvement has been proposed and various neural network combinations have been used. The ability of ANN to understand and properly classify such a problem of highly non-linear relationship has been established in most of them and the significant consideration is that once trained effectively ANN can classify new data much faster than it would be possible with analytical model.

Research of this thesis is motivated to contribute in solving instability problem of power distribution systems. The thesis will introduce a new voltage stabilizer for power distribution system to enhance the stability of the whole power system. The main objective of the proposed voltage stabilizer is to work concurrently with SCADA systems as another support to avoid reaching to instability problem.

The proposed voltage stabilizer has two phases, detection of on-line instability and overload of the distribution system, and quick arrangements to solve the problem. Detection of on-line instability will be performed by an intelligent system based a back propagation neural network. The neural network will be trained on patterns preprocessed from voltage images outputs in MATLAB simulator for a suggested power system facing instability and overload problems. Testing the neural network will be performed using voltage output patterns that were not exposed to the ANN. Detection of instability or overload earlier helps in arranging suitable solutions to sustain stability quickly. Instantaneous reactions of the voltage stabilizer will be performed to restore stability or clean voltage drop of the distribution system as soon as it is detected by the intelligent system.

This thesis is organized in five chapters. The first three chapters introduce background information on stability of power systems, voltage stability and artificial neural networks and their real life applications in power systems. The last two chapters focus on the developed intelligent detection system, and solutions arrangements to assess stability in the novel stabilizer.

Chapter 1 presents an introduction to power systems stability. Then various instability phenomena which are frequency instability, voltage instability, rotor instability with two sided, transient angular instability, and small-signal angular instability, are introduced.

Chapter 2 introduces voltage stability problem. First, the relation between the voltage at the receiving end and the transmitted active and reactive powers is explained, and then voltage stability is defined and classified, followed by solutions to prevent voltage instability.

Chapter 3 focuses on the artificial neural networks and the back propagation algorithm which will be used. Also it reviews real life applications of ANNs especially in power systems implementations.

Chapter 4 presents an intelligent system which will detect on-line instability or overload cases. Firstly, it presents the preprocessing of patterns that outputs from the simulation of a proposed power system. Secondly, it introduces the ANN design and topology and the results of ANN training and testing. Finally, it proceeds to discuss the efficiency of the proposed techniques.

Chapter 5 presents a new voltage stabilizer based on the decision of the intelligent system for detection of instability or overload cases. The two phases of the stabilizer, which are overload enhancement and stability assessment, are presented. Testing the voltage stabilizer on part of unacceptable cases takes place in this chapter. Finally, a discussion on the efficiency and benefits of the proposed voltage stabilizer is included.

CHAPTER ONE

STABILITY OF POWER SYSTEMS

1.1 Overview

The electric power generation-transmission-distribution grid in developed countries constitutes a large system that exhibits a range of dynamic phenomena. Stability of this system needs to be maintained even when subjected to large low-probability disturbances so that the electricity can be supplied to consumers with high reliability.

The chapter first explains the definition of power system stability and the need for power system stability studies and their types. It then proceeds to discuss on the various instability phenomena which are frequency instability, voltage instability, transient rotor angular instability, and small-signal rotor angular instability.

1.2 Definition of Power System Stability

The stability of a system is defined as the tendency and ability of the power system to develop restoring forces equal to or greater than the disturbing forces to maintain the state of equilibrium [1].

Let a system be in some equilibrium state. If upon an occurrence of a disturbance and the system is still able to achieve the equilibrium position, it is considered to be stable. The system is also considered to be stable if it converges to another equilibrium position in the proximity of initial equilibrium point. If the physical state of the system differs such that certain physical variable increases with respect to time, the system is considered to be unstable.

Therefore, the system is said to remain stable when the forces tending to hold the machines in synchronism with one another are enough to overcome the disturbances. The system stability that is of most concern is the characteristic and the behavior of the power system after a disturbance.

Another definition is given by IEEE/CIGRE Joint Task Force on Stability Terms and Definitions [2] as: "Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being

subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact".

Stability of an electric power system is thus a property of the system motion around an equilibrium set, i.e., the initial operating condition. In an equilibrium set, the various opposing forces that exist in the system are equal instantaneously (as in the case of equilibrium points) or over a cycle (as in the case of slow cyclical variations due to continuous small fluctuations in loads or periodic attractors).

At an equilibrium set, a power system may be stable for a given (large) physical disturbance, and unstable for another. A stable equilibrium set thus has a finite region of attraction; the larger the region, the more robust the system with respect to large disturbances. The region of attraction changes with the operating condition of the power system.

If following a disturbance the power system is stable, it will reach a new equilibrium state with the system integrity preserved i.e., with practically all generators and loads connected through a single contiguous transmission system. On the other hand, if the system is unstable, it will result in a run-away or run-down situation; for example, a progressive increase in angular separation of generator rotors, or a progressive decrease in bus voltages. An unstable system condition could lead to cascading outages and a shutdown of a major portion of the power system.

1.3 Why the Need of Power System Stability

The power system industry is a field where there are constant changes. Power industries are restructured to cater to more users at lower prices and better power efficiency. Power systems are becoming more complex as they become inter-connected. Load demand also increases linearly with the increase in users. Since stability phenomena limits the transfer capability of the system, there is a need to ensure stability and reliability of the power system due to economic reasons.

Power systems have originally arisen as individual self-sufficient units, where the power production matched the consumption. In a case of a severe failure, a system collapse was unavoidable and meant a total blackout and interruption of the supply for all

customers. But the restoration of the whole system and synchronization of its generators were relatively easy thanks to the small size of the system.

1.4 Stability Studies

Stability studies are generally categorized into two major areas: steady-state stability and transient stability [1]. Steady-state stability is the ability of the power system to regain synchronism after encountering slow and small disturbances. Example of slow and small disturbances is gradual power changes. The ability of the power system to regain synchronism after encountering small disturbance within a long time frame is known as dynamic stability. Transient stability studies refer to the effects of large and sudden disturbances. Examples of such faults are the sudden outrage of a transmission line or the sudden addition or removal of the large loads. Transient stability occurs when the power system is able to withstand the transient conditions following a major disturbance. Figure 1.1 introduces a classification to power stability and gives the overall picture of the power system stability problem, identifying its categories and subcategories.

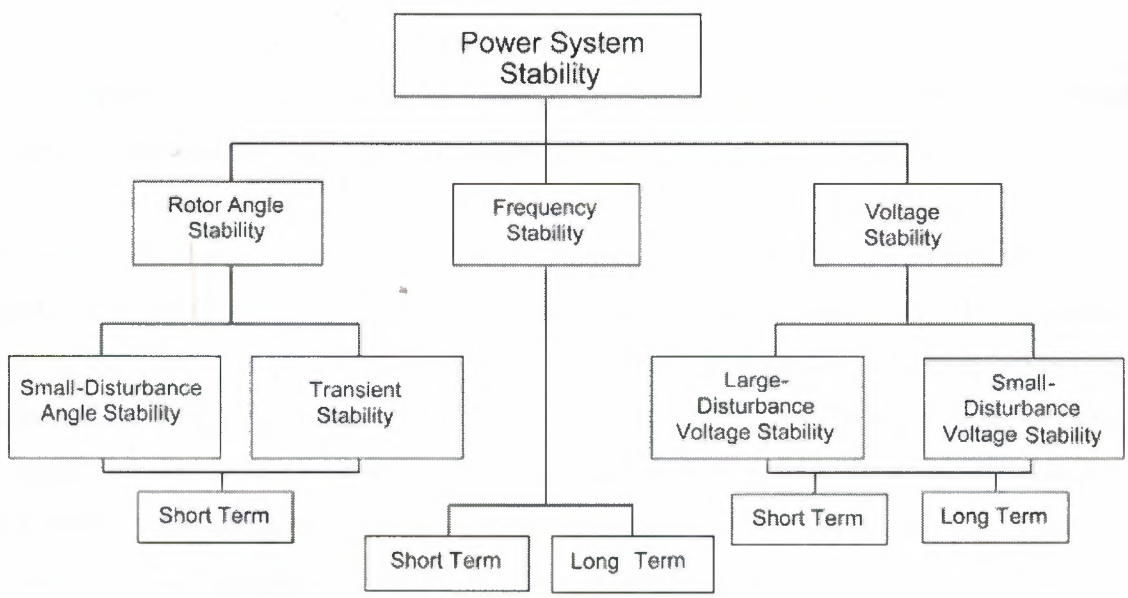

Figure 1.1 Classifications of Power System Stability [2]

1.5 Instability Phenomena

With the rising importance of the electricity for industry (and the entire society), the reliability of supply has become a serious issue. Interconnection of the separated/individual power systems have offered a number of benefits [3] , such as sharing the reserves both for a normal operation and emergency conditions, dividing of the responsibility for the frequency regulation among all generators and a possibility to generate the power in the economically most attractive areas, thus providing a good basis for the power trade.

Power systems size and complexity have grown to satisfy a larger and larger power demand. Phenomena, having a system/global nature, endangering a normal operation of power systems have appeared, explicitly: frequency instability, voltage instability, transient angular instability (also called generator's out-of-step), and local mode of small-signal angular instability (also mentioned as generator's swinging or power oscillations).

1.5.1 Frequency Instability

Frequency Instability is defined as [4]: "inability of a power system to maintain steady frequency within the operating limits. Frequency stability is defined as [2]: "the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generations and loads".

Keeping frequency within the nominal operating range (ideally at nominal constant value) is essential for a proper operation of a power system. A maximal acceptable frequency deviation (usually 2 Hz) is dictated by an optimal setting of control circuits of thermal power plants. When this boundary is reached, unit protection disconnects the power plant. This makes situation even worse – frequency further decreases and it may finally lead to the total collapse of the whole system. For the correction of small deviations, Automatic Generation Control (AGC) is used and larger deviations require so-called spinning reserves or fast start-up of generators. When more severe disturbances occur, e.g. loss of a station (all generating units), loss of a major load centre or loss of AC or DC interconnection, emergency control measures may be required to maintain frequency stability. Emergency control measures may include [4]:

- Tripping of generators
- Fast generation reduction through fast-valving or water diversion

- HVDC power transfer control
- Load shedding
- Controlled opening of interconnection to neighboring systems to prevent spreading of frequency problems
- Controlled islanding of local system into separate areas with matching generation and load.

During frequency excursions, voltage magnitudes may change significantly, especially for islanding conditions with underfrequency load shedding that unloads the system. Voltage magnitude changes, which may be higher in percentage than frequency changes, affect the load-generation imbalance. High voltage may cause undesirable generator tripping by poorly designed or coordinated loss of excitation relays or volts/Hertz relays. In an overloaded system, low voltage may cause undesirable operation of impedance relays [2].

Common practice in utilities is that most of the above actions are executed manually by a dispatcher/operator of the grid. Automatic local devices used for the load shedding are UFLS (Under Frequency Load Shedding) relays. They are usually triggered when frequency sinks to the predefined level and/or with a predefined rate of change. They are in principle same although they might be sorted in various categories [5]. Their action is disconnection of the load in several steps (5 - 20 % each) from the feeders they supervise. However, their effective use is strongly dependent on their careful tuning based on prestudies, since there is no on-line coordination between them. Another disadvantage is, that they can only react to the under frequency, increase of frequency is not covered by them at all. In some cases the impact of their operation may be negative; since they are not capable of the adaptability to the present situation (e.g. production of distributed/decentralized generation varies in time so quite often the distribution voltage level feeders feed the energy back into the network. So they don’t appear as loads and their disconnection makes situation even worse).

1.5.2 Voltage Instability

Voltage Instability is the inability of a power system to maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbance. A system enters a state of voltage instability when a disturbance, increase in load demand, or change in system conditions causes a progressive and uncontrollable drop in voltage. A system is voltage unstable if, for at least one bus in the system, the bus voltage magnitude decreases as the reactive power injection in the same bus is increased [6].

Voltage instability is basically caused by an unavailability of reactive power support in some nodes of the network, where the voltage uncontrollably falls. Lack of reactive power may essentially have two origins. Gradual increase of power demand which reactive part cannot be met in some buses or sudden change of a network topology redirecting the power flows such a way that a reactive power cannot be delivered to some buses.

The relation between the active power consumed in the monitored area and the corresponding voltages is expressed by so called PV-curves. The increased values of loading are accompanied by a decrease of voltage (except a capacitive load). When the loading is further increased, the maximum loadability point is reached, from which no additional power can be transmitted to the load under those conditions. In case of constant power loads the voltage in the node becomes uncontrollable and rapidly decreases. However, the voltage level close to this point is sometimes very low, what is not acceptable under normal operating conditions, although it is still within the stable region. But in the emergency cases, some utilities accept it for a short period.

The emergency stabilizing actions which might be taken are in principle same as in case of the frequency instability, plus:

- Change of the generator voltage set point
- Automatic shunt switching
- Control of series compensation
- Blocking of Tap Changer of transformers
- Fast redispatch of generation

The analyses of real voltage collapses have shown their wide area nature and that they can be sorted basically into two categories according to the speed of their evolution –

Transient Voltage Instability and Long-term Voltage Instability [7]. Transient Voltage Instability is in the range of seconds (usually 1 – 3 s) and the main role in the incidents played the dynamics of induction motors as a load (majority of air conditioning systems) and HVDC transmission systems. The time scale of the Long-term Voltage Instability ranges from tens of seconds up to several minutes. It involves mainly impact of a topology change or gradual load increase, i.e. fairly slow dynamics. Therefore the major part of the research activities in this area has focused on the steady state aspects of voltage stability, i.e. finding the maximum loadability point of the PV-curve.

1.5.3 Rotor Angle Instability

It deals of power system synchronism with two parts, transient angle instability, and small-signal angle instability.

1.5.3.1 Transient Angle Instability

Transient Angular Instability (also called Generator's Out-of-step) is the inability of the power system to maintain synchronism when subjected to a severe transient disturbance. The resulting system response involves large excursions of generator angles and is influenced by the nonlinear power-angle relationship [6].

In case of transient angle instability, a severe disturbance is a disturbance, which does not allow a generator to deliver its output electrical power into the network (typically a tripping of a line connecting the generator with the rest of the network in order to clear a short circuit). This power is then absorbed by the rotor of the generator, increases its kinetic energy that results in the sudden acceleration of the rotor above the acceptable revolutions and eventually damage of the generator.

Therefore the measures taken against this scenario aim mainly to either an intended dissipation of undelivered power by braking resistor (reducing the mechanical power driving the generator) or fast-valving, disconnection of the generator.

An application of traditional measure of transient angle instability – equal area criterion (expressing a balance between the accelerating and decelerating energy), on emergency control has been presented which describes the method called single machine equivalent (SIME) [8]. The angles of the generators in the system are predicted

approximately 200 ms ahead. According to it, the machines are ranked and grouped into two categories. For the generators from the critical category, one machine, infinite bus (OMIB) equivalent is modeled and extended equal area criterion is applied to assess their stability. Pre-assigned corrective action is executed if an unstable generator is identified.

1.5.3.2 Small-signal Angle Instability

Local mode of Small-signal Angular Instability is the inability of the power system to maintain synchronism under small disturbances. Such disturbances occur continually on the system because of small variations in loads and generation. The disturbances are considered sufficiently small for linearization of system equations to be permissible for purposes of analysis. Local modes or machine-system modes are associated with the swinging of units at a generating station with respect to the rest of the power system. The term local is used because the oscillations are localized at one station or small part of the power system [6].

Some power systems lack a "natural" damping of oscillations, which may occur, and they would be unstable when subjected to any minor disturbance and sometimes even under normal operation conditions if no measures increasing the damping were introduced [9]. An extension of the transmission capacity by adding a new line does not necessarily improve the damping significantly and solve the problem [10].

A traditional way of damping the oscillation is using of Power System Stabilizer (PSS), which controls/modulates the output voltage of the generator. The coordinated tuning of PSSs is a complex task, since they should be robust - work in the wide range of operation conditions and provide the best possible performance. This process is done off-line.

1.5.4 Basis for Distinction between Voltage and Rotor Angle Stability

It is important to recognize that the distinction between rotor angle stability and voltage stability is not based on weak coupling between variations in active power/angle and reactive power/voltage magnitude. In fact, coupling is strong for stressed conditions and both rotor angle stability and voltage stability are affected by pre-disturbance active power as well as reactive power flows. Instead, the distinction is based on the specific set of opposing forces that experience sustained imbalance and the principal system variable in which the consequent instability is apparent [2].

1.6 Summary

The chapter was a review for definitions of power system stability and their phenomena. It also introduced various instability phenomena which are frequency instability, voltage instability, Rotor angle instability with two subcategories transient angular instability, and small-signal angular instability.

CHAPTER TWO
VOLTAGE STABILITY AND SYSTEM SOLUTIONS

2.1 Overview

This chapter discusses the voltage stability and the related solutions. First, it explains the relation between the voltage at the receiving end and the transmitted active and reactive powers, and the sources and sinks of reactive power. Then, it discusses voltage sensitivity to loads, and the voltage stability and collapse. Finally it proposes solutions to keep voltage stability by inserting reactive power using shunt capacitor banks or/and advanced compensated VARs, or/and using synchronous machines. It, also, proposes changing the voltage at the distribution substations by transformer tap changers. The final procedure for maintaining voltage stability is load shedding. The final session introduces the control of power system.

2.2 Transfer of Active and Reactive Power

Consider the circuit in Figure 2.1. A strong source with voltage E supplies a remote load through a transmission line modeled as a series reactance. The receiving end voltage V and angle depend on the active and reactive power transmitted through the line. The active and reactive power received at the load end can be written [11]:

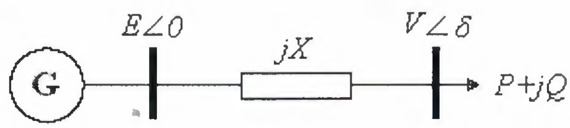

Figure 2.1 Single Line Diagram of a Simple Radial Power System

$$P = -\frac{EV}{X}\sin\delta \qquad (2.1)$$

$$Q = \frac{EV}{X}\cos\delta - \frac{V^2}{X} \qquad (2.2)$$

After eliminating using the trigonometric identity we get

$$\left(Q+\frac{V^2}{X}\right)^2+P^2=\left(\frac{EV}{X}\right)^2 \tag{2.3}$$

Solving for V^2 yields

$$V^2=\frac{E^2}{2}-QX\pm X\sqrt{\frac{E^4}{4X^2}-P^2-Q\frac{E^2}{X}} \tag{2.4}$$

Thus, the problem has real positive solutions if

$$P^2+Q\frac{E^2}{X}\leq\frac{E^4}{4X^2} \tag{2.5}$$

This inequality shows which combinations of active and reactive power that the line can supply to the load. Substituting the short-circuit power at the receiving end, $S_{SC}=E^2/X$, we get

$$P^2+QS_{SC}\leq\left(\frac{S_{SC}}{2}\right)^2 \tag{2.6}$$

Some preliminary observations that can be made from the condition (2.6) are:

- The maximum possible active power transport is $S_{SC}/2$ for Q = 0.
- The maximum possible reactive power transport is $S_{SC}/4$ for P = 0
- An injection of reactive power at the load end, i.e., Q < 0 increases the transfer limit for active power.
- The transfer limits are proportional to the line admittance and to the square of the feeding voltage E

Thus, it appears more difficult to transfer reactive than active power over the inductive line, and it seems that reactive power transfer can influence the ability of the line to carry active load. Furthermore, assume for now that the load has admittance characteristics, that is, the active and reactive power received by the load can be written

$$P+jQ=V^2G(1+j\tan(\phi)) \tag{2.7}$$

Thus, the load produces reactive power for leading power factor ($tan\ (\phi) < 0$) and absorbs reactive power for lagging power ($tan(\phi) > 0$). After normalizing equations (2.4) and (2.7) using

$$p = P / S_{SC}, \quad q = Q / S_{SC} \tag{2.8}$$

$$v = V / E, \quad g = G / (1 / X)) \tag{2.9}$$

Using normalized quantities, the positive solution to (2.4) can be written

$$v = \frac{1}{\sqrt{g^2 + (1 + g\tan(\phi))^2}} \tag{2.10}$$

Not surprisingly, there is no voltage drop over the line when the load admittance is zero and the load voltage approaches zero as the load admittance increases towards infinity.

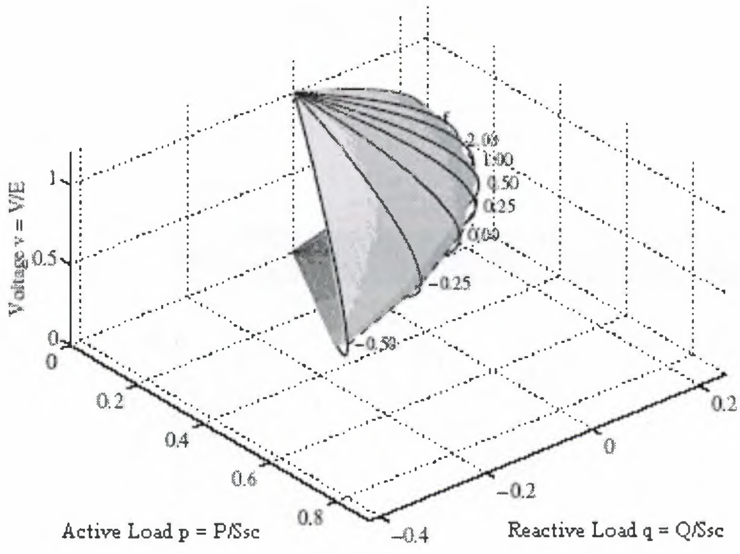

Figure 2.2 The So-Called Onion Surface as Given by Equation (2.10) Drawn Using Normalized Load Quantities [11].

Figure 2.2 shows the so-called onion surface given by (2.10) drawn in the pqv-space. It illustrates the relationship between receiving end voltage and transferred active and reactive power, and each point on the surface corresponds to a feasible operating point. The surface visualizes the set of operating points that the combined generation and transmission system can sustain. The actual operating point is determined by the apparent

load admittance, and the stability of this operating point is determined jointly by the slope of the surface and the load characteristics. The solid lines drawn on the surface correspond to operating points with varying g and constant tan (ϕ) (shown by the number beside each line). The dashed line around the "equator" of the surface corresponds to the transfer limit according to the condition (2.6).

Figure 2.3 shows so-called pv-curves [7], which are projections of the solid lines drawn on the onion surface onto the pv-plane. The rightmost point of each pv-curve marks the maximum active power transfer for a particular power factor. The corresponding voltage shown by the dashed curve is therefore often referred to as the critical voltage and the active loading as the theoretical transfer limit. The critical voltage and theoretical transfer limit increase with decreasing tan (ϕ). As will later be demonstrated, only operating points on the upper half of the pv-curve are stable when the load has constant power characteristics.

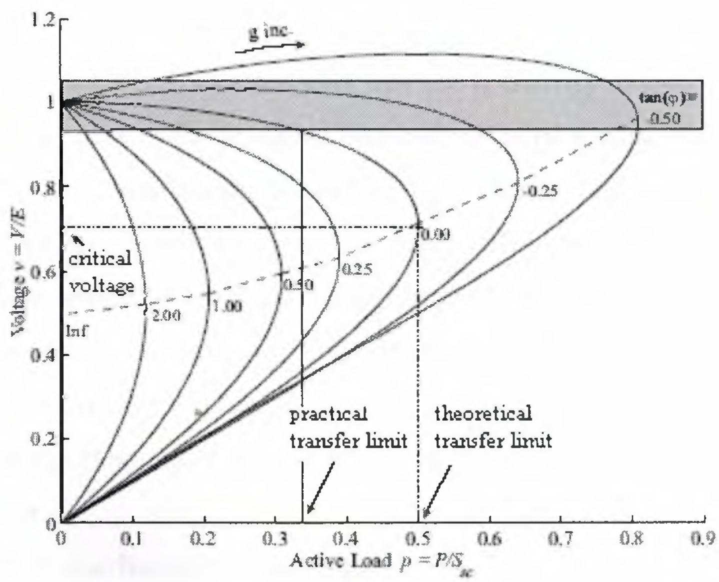

Figure 2.3 The Onion Surface Projected Onto the PV-Plane

According to the condition (2.6), the maximum power a purely active load can theoretically receive through the line is half the short-circuit power at the load bus, given that no reactive power is received at the load end. The shaded region indicates normal

operation of a line {the voltage of both ends of the line is normally kept close to the rated voltage of the line. Typical limits are $\pm 5\%$ deviation from nominal voltage or up to $\pm 5\%$ in emergency cases. The receiving end voltage at the theoretical transfer limit with a purely active load is $1/\sqrt{2} \approx 0.71$, which is normally considered unacceptable. The practical transfer limit is therefore about 35% of the short-circuit power or even lower when the load has a lagging power factor1. Capacitor banks connected at the load end are often used to increase the load end voltage and thereby the practical transfer limit. Reactive power is then being produced locally instead of transferred by the line, and the apparent power factor of the load (as seen from the transmission system) is enhanced. The operating point then shifts to another pv-curve corresponding to a lower value of *tan* (ϕ). When the operating point is on the upper part of the pv-curve, which is the case under normal operation, this corresponds to higher voltage.

The pv-curves also indicate the stiffness of system with respect to active power load variations. By overcompensating the load, such that the apparent *tan* (ϕ) becomes negative, transfer beyond half the short-circuit power with voltage close to nominal levels can theoretically be accommodated. Note however that the sensitivity to load variations, which corresponds to the steepness of the pv-curve within the shaded region, is much larger in an overcompensated system. Another important aspect is that the critical voltage is brought closer to nominal voltage. It will be shown in Section 2.5 that for constant power load characteristics, the theoretical transfer limit coincides with the voltage stability limit. Thus, the difference between the critical voltage and the voltage of the current operating point can be used as a robustness measure in terms of voltage. Similarly, the difference between the current loading and the theoretical transfer limit can be used as a robustness measure in terms of active power.

Calculation of maximum loading point

The maximum loading point can be reached through a load flow program [12, 13, 14]. The maximum loading point can be calculated by starting at the current operating point, making small increments in loading and production and re-computing load-flows at each increment until the maximum point is reached. The load-flow diverges close to maximum loading point because there are numerical problems in the solution of load-flow

equations. The load flow based method is not the most efficient, but has the following characteristics making it appropriate for voltage stability studies:

- good models for the equipment operating limits: generator capability limits, transformer tap ranges, circuit ratings and bus voltage criteria
- good models for the discrete controls: transformer tap steps and switched shunts
- capability to recognize the maximum loading point through the minimum singular value of load-flow Jacobian matrix
- familiar computer modeling, data requirements and solution algorithms
- option of using the existing computer program with miner modifications

2.3 Sources and Sinks of Reactive Power

The previous section showed that the voltage at the receiving end is highly dependent on the absorption or injection of reactive power by the load. The control of voltage is in fact closely related to the control of reactive power. An injection of reactive power at a bus that is not directly voltage regulated by a generator will in general increase the voltage of that bus and its surrounding network.

The most important sources and sinks of reactive power in power systems are:

- Overhead (AC) lines generate reactive power under light load since their production due to the line shunt capacitance exceeds the reactive losses in the line due to the line impedance. Under heavy load, lines absorb more reactive power than they produce.
- Underground (AC) cables always produce reactive power since the reactive losses never exceed the production because of their high shunt capacitance.
- Transformers always absorb reactive power because of their reactive losses. In addition, transformers with adjustable ratio can shift reactive power between their primary and secondary sides.
- Shunt capacitors generate reactive power.
- Shunt reactors absorb reactive power.
- Loads seen from the transmission system are usually inductive and therefore absorb reactive power.

- Synchronous generators, synchronous condensers and static VAR compensators can be controlled to regulate the voltage of a bus and then generate or absorb reactive power depending on the need of the surrounding network.
- Series capacitors are connected in series with highly loaded lines and thereby reduce their reactive losses.

2.4 Voltage Sensitivity of Loads

So far, it was assumed that the apparent admittance of the load is constant. However, the admittance of many loads varies with the supply voltage - either by their inherent design or by control loops connected to the load devices. Typical examples of such loads are motor drives equipped with power electronic converters and thermostatically controlled heating devices, which adjust their apparent admittance in order to consume constant power. The composite load seen from the transmission level often contains a significant amount of induction motor loads, which exhibit potentially very complex voltage behavior. However, for small voltage excursions, say less than 10 %, the active power drawn by induction motors can in the long term be approximated as constant and the reactive power as proportional to an exponential of the voltage. The dynamic response of loads to voltage changes plays a major role in the analysis and evolution of voltage instability. Simplifying matters somewhat, the load as seen from the transmission level can normally be considered as constant power in the long term since it is connected through tap changers that keep the load voltages close to their nominal values.

2.5 Voltage Stability

The voltage stability of power systems basically implies its capability of reaching and sustaining an operating point in a controllable way following a disturbance, and that the steady-state post-disturbance system voltages are acceptable. Furthermore, the term voltage instability denotes the absence of voltage stability and voltage collapse the transition phase during which a power system progresses towards an unacceptable operating point due to voltage problems, often resulting in blackouts or separation of the system into separate unsynchronized islands.

The dynamics of voltage phenomena can be divided into the two main groups: short- and long-term dynamics. Short-term phenomena act on a time scale of seconds or shorter and include, for example, the effect of generator excitation controls, induction motor recovery/stalling dynamics and FACTS devices [2]. The long-term dynamic phenomena act on a time scale of minutes and include, for example, the effect of recovery dynamics in heating load and the effect of generator over current protection systems.

As discussed in the previous section, many loads respond to a voltage drop by increasing their apparent admittance. Assume that the load supplied by the network in Figure 2.1 has such a recovery mechanism according to the normalized model

$$T\frac{dg}{dt} = p_0 - p \tag{2.11}$$

$$p = g\,v^2 \tag{2.12}$$

Thus, the load has instantaneous admittance characteristics but also an internal controller that aims to restore the power drawn to constant power p_0 with the time constant T sec. Furthermore, assuming that the load is purely active (*tan* $(\phi) = 0$) and combining (2.10) and (2.11)-(2.12), the full model can be written in the differential-algebraic form

$$T\frac{dg}{dt} = p_0 - g\,v^2 \tag{2.13}$$

$$v = \frac{1}{\sqrt{g^2+1}} \tag{2.14}$$

Substituting (2.14) in (2.13) yields

$$f(g) = \frac{dg}{dt} = \frac{1}{T}\left(p_0 - \frac{g}{1+g^2}\right) \tag{2.15}$$

Solving for stationary points yields the two solutions

$$g^* = \frac{1}{2p_0} \pm \sqrt{\frac{1}{4p_0^2} - 1} \tag{2.16}$$

Thus, it can be concluded that there are two separate equilibria if $p_0 < 0.5$ that coalesce for $p_0 = 0.5$. For $p_0 > 0.5$ it appears to be two separate equilibrium points with complex g. But g is real-valued since it has been defined as the real part of the admittance phasor in equation (2.7). Thus, we can conclude that there are no equilibria for $p_0 > 0.5$

and that a loss of equilibrium occurs when p_0 increases beyond 0.5. Since (2.16) is always positive for $p_0 > 0.5$, the admittance will increase towards infinity (or an internal limit in the load device) and the load voltage will approach zero. Small-disturbance stability analysis can be used to determine that for $p_0 < 0.5$, the low admittance solution corresponding to the upper half of the pv-curve is asymptotically stable and the high admittance solution on the lower half is unstable [15].

Assuming constant power load characteristics as above, the theoretical transfer limit marked by the dashed curve in Figures 2.2 & 2.3 therefore also becomes a steady-state voltage stability limit. However, note that the operating point may transiently move to the unstable lower part and back again to the stable equilibrium on the upper part of the pv-curve. Analogously, there is no guarantee that the system will reach a stable operating point simply because such an operating point exists. A trajectory will only approach the stable equilibrium as long at it remains within the region of attraction of the stable equilibrium. Such regions of attraction can be approximately computed using a Lyapunov-method for general dynamical systems, but the problems of finding a good Lyapunov function may make the results conservative [15].

2.6 Voltage Collapse

Voltage collapse is a system instability that involves several power system components simultaneously. It typically occurs on power systems that are heavily loaded, faulted and/or has reactive power shortages. This occurs since voltage collapse is associated with the reactive power demands of loads not being met due to limitations on the production and transmission of reactive power. The production limitations include generator and SVC reactive power limits and the reduced reactive power produced by capacitors at low voltages. The primary limitations in transmission are high reactive power losses on heavily loaded lines and line outages. Reactive power demands may also increase due to changes in the load such as, motor stalling or increased proportion of compressor load.

Voltage collapse takes place on the different timescales ranging from seconds to hours, specifically [16]:

(1) Electromechanical transient (e.g., generators, regulators, induction machines) and power electronic (e.g. SVC, HVDC) phenomena in the time range of seconds.

(2) Discrete switching devices, such as, load tap changers and excitation limiters acting at intervals of tens of seconds.

(3) Load recovery processes spanning several minutes.

There are numerous power system events known to contribute to voltage collapse.

- Increase in loading
- Generators or SVC reactive power limits
- Action of tap changing transformers
- Load recovery dynamics
- Line tripping or generator outages

Most of these changes have a large effect on reactive power production or transmission. Control actions such as switching in shunt capacitors, blocking tap changing transformers, redispatch of generation, rescheduling of generator and pilot bus voltages, secondary voltage regulation, load shedding and temporary reactive power overload of generators are countermeasures against voltage collapse. Machine angles are typically also involved in the voltage collapse. Thus, there is no sharp distinction between voltage collapse and classical transient instability. The differences between voltage collapse and classical transient instability are those of emphasis: voltage collapse focuses on loads and voltage magnitudes whereas transient instability focuses on generators and angles. Also, voltage collapse often includes longer time scale dynamics and includes the effects of continuous changes such as load increases in addition to discrete events such as line outages.

Increasing voltage levels by supplying more reactive power generally improves the margin to voltage collapse. In particular, shunt capacitors become more effective at supplying reactive power at higher voltages. Increasing voltage levels by tap changing transformer action can decrease the margin to voltage collapse by in effect increasing the reactive power demand. Still, voltage levels are a poor indicator of the margin to voltage collapse. While there are some relations between the problems of maintaining voltage levels and voltage collapse, they are best regarded as distinct problems since their analysis

is different and there is only partial overlap in the control actions used to solve both problems.

2.6.1 Voltage Collapse Indices

There are numerous indices to indicate proximity to voltage collapse that have been studied. The following is a brief introduction to these indices:

2.6.1.1 Sensitivity Factors

Sensitivity factors are indices used in several utilities throughout the world to detect voltage stability problems and to decide corrective measures [17, 18]. These indices were first used to predict voltage control problems in generator QV curves, and may be defined as

$$VSF_i = \max_i \left\{ \frac{dV_i}{dQ_i} \right\} \tag{2.17}$$

where *VSF* stands for Voltage Sensitivity Factor. As generator *i* approaches the bottom of its QV curve, the value of *VSFi* becomes large and eventually changes sign, indicating an unstable voltage control condition.

2.6.1.2 Singular Values

Singular values of a reduced matrix can be used to determine proximity to voltage collapse. Let

$$\Delta Q = J_{QV}\,\Delta V \tag{2.18}$$

with

$$\det J_{QV} = \frac{\det J}{\det J_l} \tag{2.19}$$

where J is the Jacobian in power flow equations and J_l is the real power sensitivities to angle deviations, i.e., $\frac{\partial P}{\partial \delta}$. The singular values of this reduced matrix can be used to determine proximity to voltage collapse.

2.6.1.3 Second Order Performance Indices

Indices based on first order information (linearization), such as singular values and eigen values and several other indices presented in this document, may be inadequate to predict proximity to collapse as they neglect large discontinuities in the presence of system control

limits like generator capability or transformer tap limits, as previously discussed. Conversely, it is possible to calculate a second order index that exploits additional information embedded in these indices to overcome some of these discontinuities [19].

2.6.1.4 Energy Function

Energy function, a technique based on Lyapunov stability theory, is used for both transient stability and voltage stability analysis. In this approach, power system stability is like a ball, which lies at the bottom of a valley. The stability can be understood as the ball settling to the bottom of an uneven surface when there is a disturbance. As the power system changes, the landscape of this surface and the ridges surrounding the indentations change. A voltage collapse corresponds to a ridge being sufficiently lowered so that with a small perturbation the ball can roll from the bottom of one indentation to a neighboring area. The height of the lowest ridge can be computed and used as an index to monitor the proximity to voltage collapse [20].

2.6.1.5 Loading Margin

For a particular operating point, the amount of additional load in a specific pattern of load increase that would cause a voltage collapse is called the loading margin to voltage collapse.

Loading margin is the most basic and widely accepted index of voltage collapse. If system load is chosen to be the parameter, which varies, then a system PV curve can be drawn. In this case, the loading margin to voltage collapse is the change in loading between the operating point and the nose of the curve. The advantages of the loading margin as a voltage collapse index are [21]:

- The loading margin is straightforward, well accepted and easily understood.
- The loading margin is not based on a particular system model; it only requires a static power system model and can be supplemented with dynamic system models.
- The loading margin is an accurate index that takes full account of the power system nonlinearity and limits such as reactive power control limits encountered as the loading is increased. Limits are not directly reflected as sudden changes on the loading margin.

- Once the loading margin is computed, it is easy and quick to compute its sensitivity with respect to any power system parameters or controls.

The computational costs are the most serious disadvantage of the loading margin and make it unsuitable for on-line use.

2.7 System Solutions

The potential effects of voltage instability resulting from the slow recovery of the power system voltages following a major disturbance, such as a transmission line fault. Transmission utilities have traditionally addressed voltage stability concerns by installing large static VAR compensator (SVCs) or synchronous condensers to provide the necessary dynamic reactive power support to the system following a major disturbance.

The problem of voltage stability of distribution power systems has many solutions, such as changing transformer taps, switching capacitors bank, using advanced VAR compensators, installing synchronous generators and condensers, and finally shedding loads.

2.7.1 Transformer Tap Changer Relays

A. General

Electric utilities utilize load tap-changers (LTC) to maintain customer voltage levels as the system conditions change. Typically, as load increases, the LTC will act to raise the tap position in order to maintain the voltage level. The LTC control relay will be set to operate in one of two modes - bus voltage regulation or load center voltage regulation using the line drop compensator.

Load Center voltage regulation requires a line drop compensator to regulate the voltage at the load center. Transformers at distribution substations are more likely to use load center voltage regulation than those at transmission substations. Therefore, it is important to know the mode of LTC control operation when modeling the effect of the tap-changing transformer operation during voltage collapse.

During a period of voltage collapse, the LTC control relays will detect a low voltage and begin timing to raise the tap position of the transformer.

When the voltage collapses occurs slowly, the controls will time out and begins to raise the transformer tap position. Assuming no change in the load on the transformer during this period, the LTC can often be considered a constant power load as long as the tap-changer can maintain a constant load voltage.

Since the primary voltage level drops, the current flow in the transmission system is increased to maintain the load power. This increasing current flow will further reduce the transmission system voltage, making the voltage collapse more severe.

In some cases, tap changers can also have a beneficial effect. Consider for instance, a case where a transformer is supplying predominantly motor load with power factor correction capacitors. The LTC keeps the supply voltage high and hence does not affect the real power consumption (which is relatively independent of voltage), and also maximizes the reactive support from the power factor correction capacitors. Due to this regulating effect, the LTC is an important part of the overall voltage collapse scenario.

For the more frequent case, where the real power loads have some voltage dependency, the LTC can be utilized to reduce the severity of the voltage collapse if appropriate control operation can be obtained. Blocking operation of the LTC has been widely offered as a method to reduce the negative effect on the system. Load voltage reduction can be used to reduce the loading on the system. This is similar to the peak shaving systems widely used at many utilities. Therefore the load tap-changer may be both a cause and a partial solution to the problem of voltage collapse [22].

B. LTC Blocking Schemes

The simplest method to eliminate the LTC as a contributor to voltage collapse is to block the control's automatic raise operation during any period where voltage collapse appears to be a concern. The decision to temporarily block the tap-changer can be made using locally derived information or can be made at a central location and the supervisory system can then send a blocking signal to the unit. This action may result in a period of low voltage on the affected loads.

The effect of the reduced supply voltages on power quality to customers in the whole service area must be weighed against the possible alternative of complete disconnection of some customers in a smaller area. Tap changer blocking will be more effective for voltage decays slower than the transient time frame. It will also be more

effective on loads that have a relatively high voltage dependency. In cases where the steady state value of b is high, the reduction of reactive power demand due to reduced distribution voltage will be very significant in helping keep transmission voltages up.

Local blocking schemes are implemented using voltage relays and timers to sense the voltage level on the high voltage bus at the substation.

The set point voltage is usually chosen to be a level that is less than that which occurs during maximum acceptable overload conditions. Condition exists longer than a predetermined time. The time period may vary from 1 to several seconds. The LTC is unblocked when the voltage has recovered to an acceptable level for a predetermined period of time, typically 5 seconds [22]. Since the blocking action will be removed if the voltage recovers, usually a single phase-phase voltage measurement is adequate for this scheme.

A coordinated blocking scheme can be utilized to block operation of LTC's in an area where voltage instability is imminent. The coordinated scheme can be accomplished with under voltage schemes acting independently (as described above) in a coordinated fashion at various stations within a region, or it can be a centralized scheme that recognizes a pattern of low voltages at key locations. In a centralized scheme, the LTC blocking can be implemented in substations throughout the affected region, even if the voltage at all locations is not yet below a specific threshold. The key to operation of a centralized system is the reliability of the communications system. The data needed for decision making must be collected at the central location for analysis. Control decisions must then be sent to each affected transformer location.

The effectiveness of an LTC blocking scheme at the transmission level will largely depend on whether distribution transformers are LTC-type. If the distribution transformers are LTC-type, additional measures are required to prevent their action from negating the effect of the LTC blocking scheme at the transmission level.

C. No-load Tap Changer

One method used to adjust the winding ratio of the transformer uses the no-load tap changer shown in Figure 2.4 [23]. A transformer equipped with a no-load tap changer must always be disconnected from the circuit before the ratio adjustment can be made. The

selector switch is operated under oil usually placed within the transformer itself; but it is not designed to be used as a circuit breaker. To change taps on small distribution transformers, the cover must be removed and an operating handle is used to make the tap change. For the larger type, one handle may be brought through the cover and the tap may be changed with a wheel or even a motor.

If it is necessary to change the taps when the transformer cannot be disconnected from the circuit, tap changers under-load are used. They involve the use of an autotransformer and an elaborate switching arrangement. The information regarding the switching sequence must be furnished with each transformer. Tap changers can function automatically if designed with additional control circuits: automatic tap changes are used for high-power transformers, and for voltage regulators.

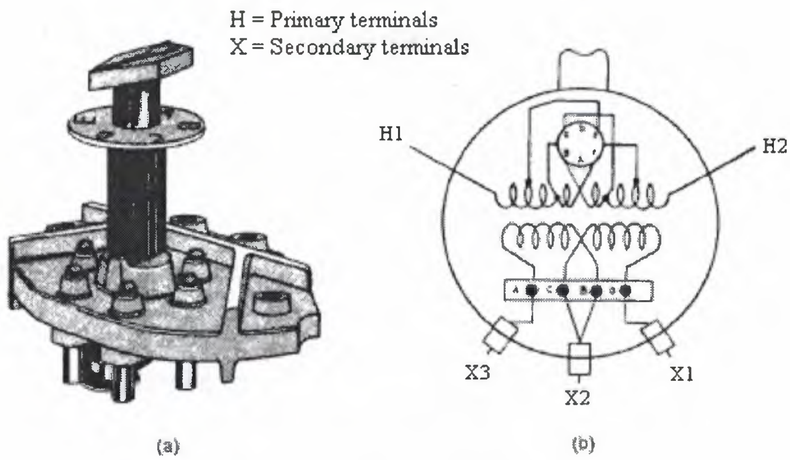

Figure 2.4: Tap Changer (a) No Load Tap Changer

(b)Typical Internal Wiring of Transformer with Tap Changer [24]

2.7.2 Switched Capacitors Bank

Many power system components in a network consume large amounts of reactive power. For example, transmission line shunt reactors, and other industrial and commercial loads need reactive power. Reactive current supports the magnetic fields in motors and transformers. Supporting both real and reactive power with the system generation requires increased generation and transmission capacity, because it increases losses in the network. Shunt-connected capacitors or synchronous condensers near the load centers are another

way to generate reactive power. Switched Capacitor Banks (SCB) have the advantage of providing reactive power close to the load centers, minimizing the distance between power generation and consumption, and do not have the maintenance problems associated with synchronous condensers. Controlling capacitance in a transmission or distribution network could be the simplest and most economical way of maintaining system voltage, minimizing system losses, and maximizing system capability. The main disadvantage of SCB is that its reactive power output is proportional to the square of the voltage and consequently when the voltage is low and the system needs them most, they are the least efficient.

Capacitor Bank Design

In order to insert reactive power to the power distribution system (PDS) the power factor (*cos* ϕ) should be increased to unity, and the angle ϕ is decreased to zero. In order to decrease the angle ϕ, reactive component of the current, $I \sin \phi$ (I_r) is to be decreased. This is achieved by introducing leading current of magnitude equal to the reactive component, in the circuit as shown by OA in Figure 2.5. This leading current I_c will lead the voltage by 90 degrees and will be in phase opposition to I_r. Therefore the leading current required to neutralize the lagging reactive component of the current to minimize the reactive power of the feeder to zero is given as:

$$\begin{aligned} I_c &= I_r = I \sin \phi \\ &= I \sqrt{1 - \cos^2 \phi} \end{aligned} \tag{2.20}$$

The value of the total capacitance required for inserting reactive power for given real power P in the circuit, at frequency f, and voltage V is determined as follows:

$$I_c = \omega C V = 2\pi f C V \tag{2.21}$$

Equating eqns. (2.20) and (2.21),

$$2\pi f C V = I \sqrt{1 - \cos^2 \phi} \tag{2.22}$$

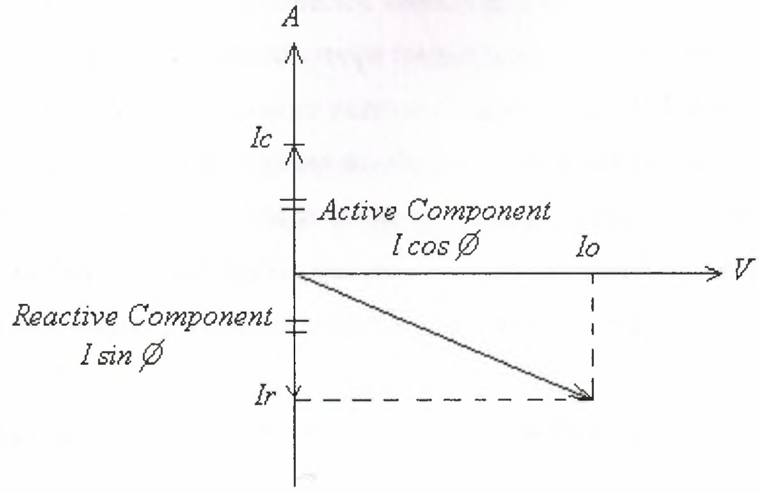

Figure 2.5 Representation of Reactive Current Component

And $$C=\frac{I}{2\pi fV}\sqrt{1-\cos^2\phi} \qquad (2.23)$$

Also $$P=IV\cos\phi \qquad (2.24)$$

From eqn. (2.24)

$$I=\frac{P}{V\cos\phi} \qquad (2.25)$$

Substituting the value of I from eqn. (2.25) into eqn. (2.23)

$$C=\frac{P}{2\pi fV^2\cos\phi}\sqrt{1-\cos^2\phi} \qquad (2.26)$$

$$C=\frac{P}{2\pi fV^2}\sqrt{\frac{1}{\cos^2\phi}-1} \qquad (2.27)$$

It is seen from the last equation that the capacitance required is inversely proportional to the square of the operating voltage, thus the total value of capacitance required per phase depends upon the nature of connection whether star or delta. In practice it is observed that the delta connection is preferable.

The protection of shunt capacitor banks requires understanding the basics of capacitor bank design and capacitor unit connections. Shunt capacitors banks are

arrangements of series/paralleled connected units. Capacitor units connected in paralleled make up a group and series connected groups form a single-phase capacitor bank.

As a general rule, the minimum number of units connected in parallel is such that isolation of one capacitor unit in a group should not cause a voltage unbalance sufficient to place more than 110% of rated voltage on the remaining capacitors of the group. Equally, the minimum number of series connected groups is that in which the complete bypass of the group does not subject the others remaining in service to a permanent over voltage of more than 110% [24].

The maximum number of capacitor units that may be placed in parallel per group is governed by a different consideration. When a capacitor bank unit fails, other capacitors in the same parallel group contain some amount of charge. This charge will drain off as a high frequency transient current that flows through the failed capacitor unit and its fuse. The fuse holder and the failed capacitor unit should withstand this discharge transient.

The discharge transient from a large number of paralleled capacitors can be severe enough to rupture the failed capacitor unit or the expulsion fuse holder, which may result in damage to adjacent units or cause a major bus fault within the bank. To minimize the probability of failure of the expulsion fuse holder, or rupture of the capacitor case, or both, the standards impose a limit to the total maximum energy stored in a paralleled connected group to 4659 kVAR [24]. In order not to violate this limit, more capacitor groups of a lower voltage rating connected in series with fewer units in parallel per group may be a suitable solution. However, this may reduce the sensitivity of the unbalance detection scheme. Splitting the bank into two sections as a double Y may be the preferred solution and may allow for better unbalance detection scheme. Another possibility is the use of current limiting fuses.

The optimum connection for a SCB depends on the best utilization of the available voltage ratings of capacitor units, fusing, and protective relaying. Virtually all substation banks are connected wye. Distribution capacitor banks, however, may be connected wye or delta. Some banks use an H configuration on each of the phases with a current transformer in the connecting branch to detect the unbalance.

Delta-connected banks are generally used only at distributions voltages and are configured with a single series group of capacitors rated at line-to-line voltage. With only

one series group of units no over voltage occurs across the remaining capacitor units from the isolation of a faulted capacitor unit. Therefore, unbalance detection is not required for protection.

Some larger banks use an H configuration in each phase with a current transformer connected between the two legs to compare the current down each leg. As long as all capacitors are normal, no current will flow through the current transformer. If a capacitor fuse operates, some current will flow through the current transformer. This bridge connection can be very sensitive. This arrangement is used on large banks with many capacitor units in parallel.

2.7.3 Advanced VAR Compensators

The emergence of new advanced VAR compensators utilizing power electronics with binary switched capacitors and inverter-based systems with or without energy storage provide utility transmission planning engineers with alternative solutions to the voltage stability problem.

Superconducting magnetic energy storage systems utilizing magnetic energy storage in the form of a superconducting coil and inverter technology have lead the way in utility applications of these new advanced VAR compensators [25]. Other commercially-available advanced VAR compensators are now increasingly being applied on utility systems for voltage stability support as well as for voltage regulation purposes.

Commercially-available advanced compensators are grouped into three categories, namely:

- Power-electronically-switched capacitors.
- Inverter-based systems without energy storage.
- Inverter-based systems with energy storage

2.7.3.1 Power-Electronically-Switched Capacitors

Compensators utilizing power-electronically-switched capacitors (e.g., (AVC) Adaptive VAR Compensator) typically consist of three or more stages of low-voltage capacitors. Capacitor stages are typically sized in binary increments, i.e., if the size of the first stage of capacitors is Q (kVAR) per phase, the size of the second and third stages would be 2Q and

4Q, respectively. Reactors are typically used in series with each stage of capacitors for detuning to eliminate harmonic resonance and large inrush currents. Capacitors are charged to peak system voltage and switched through thyristors at peak voltage to eliminate any switching transients [26].

The AVC can respond to voltage fluctuations in one cycle, or as fast as ½ cycle in specially-designed units. Single units with capacity of up to 24 MVAR at 690 V or 120 MVAR at 15 kV can be applied for dynamic voltage support. A step-up transformer would typically be used to step the output voltage up to distribution or transmission voltage level [26].

Since the AVC uses binary-switched capacitors, the reactive power output occurs in discrete steps. In a three stage unit the total output can be varied over 7 discrete steps, and in 15 steps in a four-stage unit. Since shunt-connected capacitors are utilized to provide reactive power output, the reactive power output is proportional to the square of the bus voltage.

2.7.2.2 Inverter-Based Systems without Energy Storage

These compensators (e.g., (DVC) Dynamic VAR Compensator and (DSTATCOM) Distribution Static Compensator) utilize shunt-connected voltage-source inverters to control the reactive power flow. Reactive power flow is controlled by adjusting the magnitude of the voltage output from the inverter relative to the bus voltage. Units typically have output filters and a step-up transformer to connect to the distribution bus. Typical DVC units are rated 480 V and consists of multiple 250 kVA inverter modules arranged for an output of up to ±8 MVAR continuous. Units have a one second overload capability ranging from 2.3 to 3 times the continuous rating [26]. After one second the output ramps down to its continuous rating in another second. The reactive power output of an inverter-based compensator is proportional to the bus voltage.

2.7.2.3 Inverter-Based Systems with Energy Storage

The Distributed Superconducting Magnetic Energy Storage (D-SMES) is currently the only commercially-available inverter-based system that has been applied with energy storage for voltage stability applications. The system is similar to the DVC, with an additional

superconducting magnetic energy storage module with peak output power capability of 3 MW and an average output power capability of 2.5 MW over the first 0.5 seconds of discharge [23]. The reactive power output of this compensator is also proportional to the bus voltage.

2.7.4 Synchronous Generators and Condensers

A synchronous machine is capable of generating and supplying reactive power within its capability limits to regulate system voltage. For this reason, it is an extremely valuable part of the solution to the collapse-mitigation problem. Synchronous machines considered may be generators or synchronous condensers. In terms of reactive output capability, synchronous condensers are treated similarly to static VAR sources during commissioning and maintenance in that rated output power must be demonstrated to be achieved.

2.7.4.1 Generators

Generators however are rated for specific real power output, usually at a specific power factor. During commissioning and maintenance, real power output is carefully checked to meet specified requirements. Reactive power output may be checked during commissioning, but may not be carefully checked after that. The reactive power capability may be required by the system, but is not considered to be a revenue generator.

Due to large impact on the system voltages, it may be difficult to operate large generators at their reactive capability limits (for test purposes). Therefore coordination of protection with control devices is not so frequently checked as with other reactive power sources [27]. Numerous voltages collapse or near collapse incidents have been aggravated by unexpected loss of healthy generators due to lack of coordination of protective equipment with generator capability.

The reactive power capability increases dramatically as real power output is limited. Further, the amount of reactive power available from the generator is very dependent on terminal voltage. In this respect, a generator operating at low real power output can supply significantly more reactive power at low voltages than at high voltages [22].

The increase in reactive power capability at lower real power output means that system planners and operators may choose to generate less than rated real power in order to

have more reactive power from generators at critical locations in voltage stability threatened systems. The choice of operating point (MW versus MVAR) for generators at critical locations is predetermined, and not usually subject to automatic control. It should be noted that when the generator reaches the limit of its capability, particularly in the rotor current limited region, it may not be controlling its terminal voltage. The fact that it is at its limit of capability means that it is not able to raise the terminal voltage to the reference setting of the voltage regulator. Thus the reactive power limits are to a certain extent, determined by the system conditions, and independent of the generator excitation system.

The value of a generator as a source of reactive power can be separated from its value as a source of real power, if it can be decoupled from the turbine and run as a synchronous condenser. In some plants where fuel or operating costs may make power generation uneconomic, it may be possible to convert the generator to a synchronous condenser, and use it to support voltages in an area where real power has to be imported from a remote area [27].

2.7.4.2 Motors

It is a synchronous motor working at over excitation and drawing current from the supply at leading power factor. It has an advantage that varying its excitation it can be steplessly adjusted to supply any amount of capacitive or reactive power up to its full rating. By the use of rotary amplifiers and high speed regulators, automatic stable operation is obtained even in the case of sudden change in the system conditions. It must be noted that, synchronous condenser has an inherently sinusoidal waveform and harmonics in the voltage do not exist, but the static capacitors give large harmonics in the system.

A modern synchronous capacitor is generally a six or eight pole salient pole synchronous motor. It is fitted with a robust damper winding by means of which, it is possible to start it as an induction motor at reduced voltage. The starting tapping on the starting transformer is about 25-40% of the rated voltage due to this, the starting current from the supply will be less than the rated current [28].

By jacking up the shaft by means of oil under pressure, the initial starting torque and the minimum voltage required for reliable starting are reduced. The machine runs

almost near to synchronous speed at rated voltage and is then pulled into synchronous speed.

2.7.5 Load Shedding

Load shedding is defined as [29]: "the process of deliberately removing pre-selected loads from a power system, usually done automatically by relays, in order to maintain the integrity of the system under unusual conditions".

Current practice depends on hardware control, using lines and generators. Load shedding basically means nothing more than disconnecting a radial feeder on medium voltage distribution system. Sometimes you try to avoid area with elevators. Hospitals and other very sensitive institutions are supposed to have their own backup. The most common criterion to activate load shedding is low frequency, with or without time delay, also under voltage criteria and rate of change of frequency exists, but are much less common.

Load shedding is an option that is becoming more widely used as a final means of avoiding system wide voltage collapse. This option is only considered when all other effective means of avoiding collapse are exhausted. This option may be the only effective option for various contingencies especially if the collapse is in the transient time frame, and if load characteristics result in no effective load relief by transformer load tap changer control. Load shedding results in high costs to electricity suppliers and consumers, therefore, power systems should be designed to require such actions only under very rare circumstances. Load may be shed either manually or automatically depending on the rate of voltage drop.

2.7.5.1 Manual Load Shedding

If the time frame of collapse is long-term, manual load shedding can be implemented to stabilize the voltage. This mode of operation, normally applied under inadequate generation conditions or insufficient VAR reserve, should have preplanned guidelines and procedures for the system dispatchers to implement load shedding manually.

System studies can provide load sensitivity analyses from which the critical voltage can be determined to start load shedding. Another option to assist system operators for fast action is to preprogram blocks of loads on the dispatcher control console of the SCADA system. Dispatchers can select a particular block of load in a specific area requiring load shedding

to control the voltage drop. The blocks of load can also be divided into several subgroups depending on sensitivity of the load, so that execution of the manual load shedding can be carried out in steps or in rolling sequence [22].

A major disadvantage of relying on manual load shedding is that it places a severe burden on system operators to recognize an approaching voltage stability problem and to act quickly enough to avoid a major collapse. Even with the most comprehensive preplanned guidelines, there is a danger that the particular condition that arises may not fall within the guidelines clearly enough for prompt action. However, when short term operational planning studies (time frame less than a week) show the possibility of collapse due to expected load and actual contingencies, manual shedding can be applied with good results.

2.7.5.2 Automatic Load Shedding

When the voltage instability is caused by sudden loss of critical transmission equipment or VAR generating equipment, the lead-time prior to a voltage collapse will be very short. Therefore, manual load shedding would be too slow to prevent a voltage collapse. Automatic load shedding must be used to quickly arrest a fast voltage drop and allow the voltage to recover to an acceptable level before voltage collapse can occur.

Under voltage detectors are often used to initiate automatic load shedding. For low voltage events which do not lead to collapse (such as during a normally cleared system fault), these detectors must not operate in order to prevent nuisance tripping of customer load. Security of the under voltage detectors can be increased by applying multiple phase detection, proper time coordination between fault clearing and time delay for load shedding, and use of fault detection relays to inhibit load shedding. Reliability of load shedding to prevent voltage collapse can be enhanced by use of other indicators than voltage magnitude such as voltage and power sensitivity factors or other forms of voltage stability indices.

Developing appropriate settings for the under voltage detectors and time delays are challenging problems. It might require intensive network analysis to find the desired values to provide optimum coordination between load shedding and voltage collapse. Generally, the settings are in the range of 85 to 95 percent of the operating voltages, with time delays

ranging from tens of cycles to minutes [30, 31, 32]. The sensitivity of the load to the voltage level has a great impact on the settings.

2.7.5.3 Intelligent Load Shedding

The traditional load shedding scheme, which has hardly been developed over the last 100 years, is less and less acceptable in today's society. The developments in computer and communications technology allow abandoning the stage of hardware control and relying more on intelligent control in order to maintain power system stability.

Intelligent load shedding is defined as [33]: a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable.

The objective of load shedding remains unchanged. The means to improve power stability using intelligent load shedding changes to addressing individual loads in an area, based on knowledge about the power system and these loads, in order to switch off or reduce power for a certain time.

Intelligent load shedding deals with (i) the problem of detecting situations that will go unstable if no remedial actions are taken, and (ii) to take proper action in such a way that stability is restored by minimum cost load shedding. Intelligence and communication are essential means in order to achieve this. Communication is needed in order to obtain information on where and when load shedding is needed, to obtain information on individual loads and their constraints with respect to readiness to shed, and to address individual loads in order to reduce load or switch them off. Intelligence is needed in order to find optimal scenarios for the amount of load to shed and the location of these loads.

2.7.5.4 Requirements and Scenarios for Intelligent Load Shedding

The main requirement on "intelligent load shedding" is that it should be regarded as a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable. The work with intelligent load shedding can be divided in a number of stages [34]:

- To improve present load shedding schemes (where a circuit breaker on the 10/20 kV level is opened), to a scheme where individual load objects in the area are addressed and switched off, or ordered to reduce power, for a certain time.
- To keep track on the load available to be shed in every instant.
- To find an "optimal" amount of load to shed, with respect to a certain disturbance.
- To find the "optimal" location of the load to be shed, with respect to a certain disturbance.
- To specify/find relevant disturbances to prepare load shedding for, and to "interpolate" between these to find suitable actions for real disturbances.
- To initiate "intelligent load shedding" - when approaching voltage instability, angular instability, frequency instability or cascaded outages.

A main consideration in intelligent load shedding will be the cost criterion. Strategies may be based on dynamic prices and on electric market.

2.8 Voltage Stability Related Works

There are many researches contribute in solving voltage stability. Part of these researches use artificial neural networks and others use different algorithms. In [35] an artificial neural network application to power system voltage stability improvement is introduced, and in [36] a novel algorithm for on-line voltage stability assessment based on feed forward neural network is introduced, while [37] introduces a development of an improved on-line voltage stability index using synchronized phasor measurement

2.8.1 Artificial Neural Network Application to Power System Voltage Stability Improvement

This work deals with development of ANN architecture, which provide solutions for monitoring, and control of voltage stability in the day-to-day operation of power systems. It focuses on evaluating the performance of ANN for control and improvement of Power System Voltage Stability problem [35].

A minimization algorithm for improving voltage stability margin based on L-Index and employing non-linear least squares optimization technique is presented. The control

variables considered are switchable VAR compensators, OLTC transformers and generators excitation. The model used for the power system includes limits for reactive power generation at generators, load characteristics and generation control characteristics. Generally in reactive power dispatch the objective is either to minimize real power losses or to minimize the deviations of voltages from desired values. The objective in the proposed algorithm is to minimize the sum of squares of L-indices at all or a subset of critical nodes (decided from voltage stability point of view) in the system. Results obtained from the proposed algorithm are compared with Minimum singular value (MSV) of the modified power flow Jacobean matrix. The increase of load margin to voltage collapse is demonstrated.

A conclusion of the work is: A prototype of an ANN for monitoring and control of power system voltage stability margin improvement has been developed. The proposed ANN tries to improve the voltage stability margin using SVCs, Generator excitation and OLTC transformers as controllers for different loading conditions for a practical EHV Indian power system and encouraging results have been obtained.

2.8.2 Novel Algorithm for Online Voltage Stability Assessment Based on Feed Forward Neural Network

This work presents an online voltage stability assessment method using the feed forward neural network. In this method feed forward neural network is trained for the L indices values, which is a scalar measure of the voltage stability for all the power system buses during normal and contingent situations [36].

Main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained Artificial Neural Network at every time instant unlike the other techniques. The easiness in calculating the stability indices using Index L is exploited for learning the voltage profile of any complex system by ANN.

Thus the stability margin and voltage profile locally for individual buses as well as the global stability margin and improvement measures of the power system can be assessed at the same time with the proposed technique. Another feature of the proposed method is its ability in developing L indices of all the system buses during both normal and contingent

situations using the trained ANNs. This aspect has not been considered as a single problem so far in the earlier research works.

The trained ANN is then tested on the practical 367 bus system to prove its practical use using MATLAB neural network toolbox. The approach was found to be extremely useful to use as energy management software for online establishment of voltage stability margins and to find out the associated limits at each bus.

The proposed network architecture is a three layer feed forward structure including input, output and hidden layer using a back propagation algorithm. Following algorithmic steps describes in detail the approach used for investigating the different parameters and functions in the MATLAB toolbox.

Step 1: A conventional voltage stability algorithm is run with the test system for simulated loading conditions. Using this first the base case and the maximum loading conditions of the test system are determined using the conventional software. Then the load conditions are varied from base case till full load and training samples are generated.

Step 2: Create a database for the input vector in the following form $\left[P_g^T\, Q_g^T\, V_g^T\, P_l^T\, Q_l^T\, V_l^T\right]^T$ where, P_g, Q_g, P_l and Q_l are the real and reactive power in generator as well as load buses respectively and V_g and V_l are bus voltage at generator and load buses. Further, create target vector in the form of L-indices for the corresponding input vectors.

Step 3: Find the minimum and maximum values of the input vector, remove redundancies and normalize to suit to train the selected feed forward neural network.

Step 4: Select the set of training parameters such as number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

Step 5: Train the network based on a set of transfer functions and number of neurons. The number of neurons in each layer is varied initially and optimum combination is found out depending on the training period and performance error.

Step 6: Find the most suitable combination of the activation function. Behavioral accuracy depends on the uniformity in values of L-indices at all the buses. It can happen that the

network gives output, which is accurate for some buses but may be unacceptable on some others.

Step 7: Change the training function keeping same transfer functions and optimum number of neurons in each layer.

Step 8: Find the most suitable network based on the simplicity least possible Mean Square Error and computational speed. Further use various test functions to confirm the effectiveness of the proposed neural network. At this state the functions and all the parameters are finalized for a particular combination.

A conclusion of the work is: An artificial neural network technique for on line assessment of power system voltage stability using a developed training algorithm for all system buses has been presented with detail steps involved with MATLAB neural network toolbox. Unlike other reported techniques, the main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained artificial neural network at every monitoring period. The stability margin and voltage profile for individual buses, the global stability margin, as well as possible improvement measures of the power system can be assessed at the same time during both normal and contingent situations using the trained ANN. Training and testing results form all cases, including contingencies on a practical power systems network shows that the proposed ANN algorithm is capable to learn and perform as a tool for online voltage stability analysis by measuring the L-indices for all the vulnerable buses.

2.8.3 Development of an Improved On-Line Voltage Stability Index Using Synchronized Phasor Measurement

Most techniques are computationally demanding and cannot be used in an on-line application. A voltage stability index (VSI) can be designed to estimate the distance of the current operating point to the voltage marginally stable point during the system operation. This research work developed a new VSI that not only can detect the system voltage marginally stable point but also is computationally efficient for on-line applications. Starting with deriving a method to predict three types of maximum transferable power of a single source power system, the new VSI is based on the three calculated load margins [37]. In order to apply the VSI to large power systems, a method has been developed to

simplify the large network behind a load bus into a single source and a single transmission line given the synchronized phasor measurements of the power system variables and network parameters. The simplified system model, to which the developed VSI can be applied, preserves the power flow and the voltage of the particular load bus. The proposed voltage stability assessment method, therefore, provides a VSI of each individual load bus and can identify the load bus that is the most vulnerable to voltage collapse.

The developed VSI is a reliable assessment of the voltage stability margin of an individual load and is suitable for on-line implementation for detecting the emerging short-term and long-term voltage instability. The sub-tasks of developing this improved voltage stability index are the following:

- Development of a new computationally efficient load margin assessment method based on synchronized phasor measurements and the power system network topology and parameters.
- Derivation of VSI of individual load buses and the power system based upon the calculated load margin.
- Implementation and testing of the new VSI on various power systems.

The new VSI was tested on three power systems which are BPA 10-bus test system, IEEE 30-bus test case and CIGRE 32-bus test system. Results from these three test cases provided validation of the applicability and accuracy of the proposed VSI.

A conclusion of the work is: Test results of applying the proposed voltage stability assessment method on three power systems have demonstrated that it has the following salient features:

- The proposed method can identify the system voltage marginally stable point with satisfactory accuracy.
- The proposed method provides system voltage security in the format of a load margin that is readable and informative.
- The proposed method can identify the load bus that is the most susceptible to voltage collapse.
- The proposed method is computationally efficient, and can be easily implemented to predict the voltage stability of large power systems in almost real time.

The main contribution of this dissertation is the development of a practical synchronized phasor measurement based voltage stability index that can accurately predict the power system voltage stability with affordable computational demands for on-line applications. The proposed voltage stability assessment method could be incorporated into wide area protection and control systems to monitor the power system voltage stability security. Also, the newly proposed network reduction method enables users to analyze the voltage stability of each load bus and design of distributed control schemes to prevent voltage collapse.

2.9 Power System Control

Given the complexity of the power system and its dynamic phenomena, one would expect that various controls have been developed over time to control various phenomena. These developments have followed the availability of enabling hardware technologies (e.g. electronics, communications, and microprocessors) as well as the evolution of control methodologies.

When a fault (short circuit) occurs, the faulted equipment has to be isolated. A short circuit is characterized by very low voltages and very high currents, which can be detected and the faulted equipment identified. If the fault is on a shunt element, like a generator or a distribution feeder, the relay will isolate it by opening the connecting circuit breakers. If the fault is on a series element, like a transmission line or transformer, the breakers on both sides have to be opened to isolate it. The main characteristic of the protection system is that it operates quickly, often in tens of milliseconds, so as to protect the equipment from damage.

2.9.1 Voltage Control

As is mentioned before, one way to control node voltages is by varying the excitation of the rotating generators. This is done by a feedback control loop that changes the excitation current in the generator to maintain a particular node voltage. This control is very fast.

Another way to control node voltage is to change the tap setting of a transformer connected to the node. Other ways are to switch shunt capacitors or reactors at the nodes.

NEAR EAST UNIVERSITY

GRADUATE SCHOOL OF APPLIED AND SOCIAL SCIENCES

A VOLTAGE STABILIZER FOR POWER DISTRIBUTION SYSTEMS USING NEURAL NETWORKS

Samir JABR

Master Thesis

Department of Electrical and Electronic Engineering

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Approval of Director of Graduate School of Applied and Social Sciences

Prof. Dr. Fahreddin M. SADIKOĞLU

We certify this thesis is satisfactory for the award of the degree of Master of Science in Electrical and Electronic Engineering

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ABSTRACT

Voltage collapse causes many blackouts of power systems all over the world even in developed countries. SCADA systems, which were induced in most power systems, could not prevent many famous blackouts. Therefore, there is a need to find efficient solutions to remedy these problems.

This thesis attempts to design a voltage stabilizer for power distribution systems (PDS) based on artificial neural network (ANN) on-line detection of instability that works concurrently with SCADA systems as another support to help preventing voltage collapse in PDS.

The design of this voltage stabilizer has two phases. The first phase is an intelligent system which uses a back propagation learning algorithm neural network that detects instability or overload of PDS, using images of voltage outputs obtained from a MATLAB simulator for a proposed power system.

The second phase of the intelligent voltage stabilizer uses the output of the first phase which is the ANN classifier. If the intelligent system detects an overload case, the stabilizer will perform instantaneous steps to clean the deep voltage drop in PDS which may cause voltage collapse. These steps depend on raising tap-changer relays of distribution transformers then switching on capacitor banks in steps, then if it is necessary shedding part of loads with least priority. Also, if instability is detected, the stabilizer will make quick arrangement to assess stability. Loads shedding and redispatch the generators to get actions constitute the main arrangements. In every case, load shedding will be performed according to the cause of instability.

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LIST OF ABBREVIATIONS

AGC: Automatic Generation Control

ANN: Artificial Neural Network

AVC: Advanced VAR Compensators

BPA: Bonneville Power Administration

BP: Back Propagation

DVC: Dynamic VAR Compensator

ED: Economic Dispatch

EMS: Energy Management Systems

ES: Excitation System

FACTS: Flexible AC Transmission System

GDE: Governor and Diesel Engine

HTG: Hydraulic Turbine and Governor

LFC: Load Frequency Control

LP: Linear Programming

LTC: Load Tap-Changers

MLP: Multilayered Perceptron

MSE: Mean Square Error

PDS: Power Distribution System

PSS: Power System Stabilizer

RTU: Remote Terminal Units

SCADA: Supervisory Control and Data Acquisition

SCB: Switched Capacitor Banks

SVC: Static VAR Compensator

UFLS: Under Frequency Load Shedding

VS: Voltage Stabilizer

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INTRODUCTION

Voltage instability or collapse is emerging as a major concern to utility companies who aim to maintain a stable power system operation. Voltage instability has caused several major power system collapses around the world. In general these voltage stability analysis methods are classified into two categories: dynamic stability and transient stability. Dynamic stability can reproduce or predict the time response of the system voltage to a sequence of events and, therefore, help identify whether the system voltage is stable or not. The majority of transient methods are based on power flow formations to evaluate voltage stability in various terms, such as load margins and load flow feasibility.

Voltage stability analysis is concerned with the ability of assessing the power system to maintain acceptable voltages at all system buses under normal conditions and after being subjected to disturbances. A major factor contributing to voltage instability is the voltage drop that occurs when active and reactive power flow through inductive reactances of the transmission network. Voltage stability is threatened when a disturbance increases the reactive power demand beyond the sustainable capacity of the available reactive power resources. While the most common form of voltage instability is the progressive drop of bus voltages, the risk of overvoltage instability also exists and has been experienced at least on one system.

Since the voltage instability issue started to emerge, significant research efforts from the power engineering community have been devoted to studying the voltage instability mechanism and to developing analysis tools and control schemes to mitigate the instability. Meanwhile, many researchers agree that the voltage instability problem is a high order nonlinear problem as a large number of different types of devices are involved in the voltage dynamics. Also a wide variety of modeling and simulation principles and analysis and control methods of the power system voltage stability have been developed.

Artificial Neural Networks (ANN) have been used to solve many problems obtaining outstanding results in various applications such as classification, clustering, pattern recognition and forecasting among many other applications corresponding to different areas. Applications of Artificial Neural Network to the above-mentioned problem

have attained increasing importance mainly due to the efficiency of present day computers. Moreover real-time use of conventional methods in an energy management center can be difficult due to their significant large computational times. One of the main features, which can be attributed to ANN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate online response. ANN approach to voltage stability assessment and improvement has been proposed and various neural network combinations have been used. The ability of ANN to understand and properly classify such a problem of highly non-linear relationship has been established in most of them and the significant consideration is that once trained effectively ANN can classify new data much faster than it would be possible with analytical model.

Research of this thesis is motivated to contribute in solving instability problem of power distribution systems. The thesis will introduce a new voltage stabilizer for power distribution system to enhance the stability of the whole power system. The main objective of the proposed voltage stabilizer is to work concurrently with SCADA systems as another support to avoid reaching to instability problem.

The proposed voltage stabilizer has two phases, detection of on-line instability and overload of the distribution system, and quick arrangements to solve the problem. Detection of on-line instability will be performed by an intelligent system based a back propagation neural network. The neural network will be trained on patterns preprocessed from voltage images outputs in MATLAB simulator for a suggested power system facing instability and overload problems. Testing the neural network will be performed using voltage output patterns that were not exposed to the ANN. Detection of instability or overload earlier helps in arranging suitable solutions to sustain stability quickly. Instantaneous reactions of the voltage stabilizer will be performed to restore stability or clean voltage drop of the distribution system as soon as it is detected by the intelligent system.

This thesis is organized in five chapters. The first three chapters introduce background information on stability of power systems, voltage stability and artificial neural networks and their real life applications in power systems. The last two chapters focus on the developed intelligent detection system, and solutions arrangements to assess stability in the novel stabilizer.

Chapter 1 presents an introduction to power systems stability. Then various instability phenomena which are frequency instability, voltage instability, rotor instability with two sided, transient angular instability, and small-signal angular instability, are introduced.

Chapter 2 introduces voltage stability problem. First, the relation between the voltage at the receiving end and the transmitted active and reactive powers is explained, and then voltage stability is defined and classified, followed by solutions to prevent voltage instability.

Chapter 3 focuses on the artificial neural networks and the back propagation algorithm which will be used. Also it reviews real life applications of ANNs especially in power systems implementations.

Chapter 4 presents an intelligent system which will detect on-line instability or overload cases. Firstly, it presents the preprocessing of patterns that outputs from the simulation of a proposed power system. Secondly, it introduces the ANN design and topology and the results of ANN training and testing. Finally, it proceeds to discuss the efficiency of the proposed techniques.

Chapter 5 presents a new voltage stabilizer based on the decision of the intelligent system for detection of instability or overload cases. The two phases of the stabilizer, which are overload enhancement and stability assessment, are presented. Testing the voltage stabilizer on part of unacceptable cases takes place in this chapter. Finally, a discussion on the efficiency and benefits of the proposed voltage stabilizer is included.

CHAPTER ONE
STABILITY OF POWER SYSTEMS

1.1 Overview

The electric power generation-transmission-distribution grid in developed countries constitutes a large system that exhibits a range of dynamic phenomena. Stability of this system needs to be maintained even when subjected to large low-probability disturbances so that the electricity can be supplied to consumers with high reliability.

The chapter first explains the definition of power system stability and the need for power system stability studies and their types. It then proceeds to discuss on the various instability phenomena which are frequency instability, voltage instability, transient rotor angular instability, and small-signal rotor angular instability.

1.2 Definition of Power System Stability

The stability of a system is defined as the tendency and ability of the power system to develop restoring forces equal to or greater than the disturbing forces to maintain the state of equilibrium [1].

Let a system be in some equilibrium state. If upon an occurrence of a disturbance and the system is still able to achieve the equilibrium position, it is considered to be stable. The system is also considered to be stable if it converges to another equilibrium position in the proximity of initial equilibrium point. If the physical state of the system differs such that certain physical variable increases with respect to time, the system is considered to be unstable.

Therefore, the system is said to remain stable when the forces tending to hold the machines in synchronism with one another are enough to overcome the disturbances. The system stability that is of most concern is the characteristic and the behavior of the power system after a disturbance.

Another definition is given by IEEE/CIGRE Joint Task Force on Stability Terms and Definitions [2] as: "Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being

subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact".

Stability of an electric power system is thus a property of the system motion around an equilibrium set, i.e., the initial operating condition. In an equilibrium set, the various opposing forces that exist in the system are equal instantaneously (as in the case of equilibrium points) or over a cycle (as in the case of slow cyclical variations due to continuous small fluctuations in loads or periodic attractors).

At an equilibrium set, a power system may be stable for a given (large) physical disturbance, and unstable for another. A stable equilibrium set thus has a finite region of attraction; the larger the region, the more robust the system with respect to large disturbances. The region of attraction changes with the operating condition of the power system.

If following a disturbance the power system is stable, it will reach a new equilibrium state with the system integrity preserved i.e., with practically all generators and loads connected through a single contiguous transmission system. On the other hand, if the system is unstable, it will result in a run-away or run-down situation; for example, a progressive increase in angular separation of generator rotors, or a progressive decrease in bus voltages. An unstable system condition could lead to cascading outages and a shutdown of a major portion of the power system.

1.3 Why the Need of Power System Stability

The power system industry is a field where there are constant changes. Power industries are restructured to cater to more users at lower prices and better power efficiency. Power systems are becoming more complex as they become inter-connected. Load demand also increases linearly with the increase in users. Since stability phenomena limits the transfer capability of the system, there is a need to ensure stability and reliability of the power system due to economic reasons.

Power systems have originally arisen as individual self-sufficient units, where the power production matched the consumption. In a case of a severe failure, a system collapse was unavoidable and meant a total blackout and interruption of the supply for all

customers. But the restoration of the whole system and synchronization of its generators were relatively easy thanks to the small size of the system.

1.4 Stability Studies

Stability studies are generally categorized into two major areas: steady-state stability and transient stability [1]. Steady-state stability is the ability of the power system to regain synchronism after encountering slow and small disturbances. Example of slow and small disturbances is gradual power changes. The ability of the power system to regain synchronism after encountering small disturbance within a long time frame is known as dynamic stability. Transient stability studies refer to the effects of large and sudden disturbances. Examples of such faults are the sudden outrage of a transmission line or the sudden addition or removal of the large loads. Transient stability occurs when the power system is able to withstand the transient conditions following a major disturbance. Figure 1.1 introduces a classification to power stability and gives the overall picture of the power system stability problem, identifying its categories and subcategories.

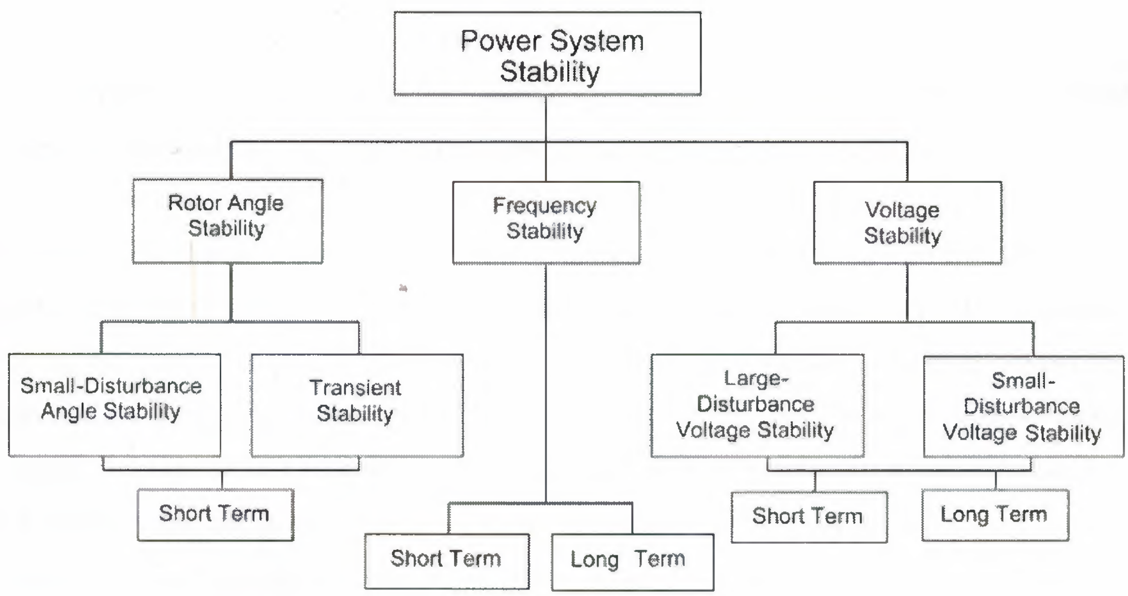


Figure 1.1 Classifications of Power System Stability [2]

1.5 Instability Phenomena

With the rising importance of the electricity for industry (and the entire society), the reliability of supply has become a serious issue. Interconnection of the separated/individual power systems have offered a number of benefits [3] , such as sharing the reserves both for a normal operation and emergency conditions, dividing of the responsibility for the frequency regulation among all generators and a possibility to generate the power in the economically most attractive areas, thus providing a good basis for the power trade.

Power systems size and complexity have grown to satisfy a larger and larger power demand. Phenomena, having a system/global nature, endangering a normal operation of power systems have appeared, explicitly: frequency instability, voltage instability, transient angular instability (also called generator's out-of-step), and local mode of small-signal angular instability (also mentioned as generator's swinging or power oscillations).

1.5.1 Frequency Instability

Frequency Instability is defined as [4]: "inability of a power system to maintain steady frequency within the operating limits. Frequency stability is defined as [2]: "the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generations and loads".

Keeping frequency within the nominal operating range (ideally at nominal constant value) is essential for a proper operation of a power system. A maximal acceptable frequency deviation (usually 2 Hz) is dictated by an optimal setting of control circuits of thermal power plants. When this boundary is reached, unit protection disconnects the power plant. This makes situation even worse – frequency further decreases and it may finally lead to the total collapse of the whole system. For the correction of small deviations, Automatic Generation Control (AGC) is used and larger deviations require so-called spinning reserves or fast start-up of generators. When more severe disturbances occur, e.g. loss of a station (all generating units), loss of a major load centre or loss of AC or DC interconnection, emergency control measures may be required to maintain frequency stability. Emergency control measures may include [4]:

- Tripping of generators
- Fast generation reduction through fast-valving or water diversion

- HVDC power transfer control
- Load shedding
- Controlled opening of interconnection to neighboring systems to prevent spreading of frequency problems
- Controlled islanding of local system into separate areas with matching generation and load.

During frequency excursions, voltage magnitudes may change significantly, especially for islanding conditions with underfrequency load shedding that unloads the system. Voltage magnitude changes, which may be higher in percentage than frequency changes, affect the load-generation imbalance. High voltage may cause undesirable generator tripping by poorly designed or coordinated loss of excitation relays or volts/Hertz relays. In an overloaded system, low voltage may cause undesirable operation of impedance relays [2].

Common practice in utilities is that most of the above actions are executed manually by a dispatcher/operator of the grid. Automatic local devices used for the load shedding are UFLS (Under Frequency Load Shedding) relays. They are usually triggered when frequency sinks to the predefined level and/or with a predefined rate of change. They are in principle same although they might be sorted in various categories [5]. Their action is disconnection of the load in several steps (5 - 20 % each) from the feeders they supervise. However, their effective use is strongly dependent on their careful tuning based on prestudies, since there is no on-line coordination between them. Another disadvantage is, that they can only react to the under frequency, increase of frequency is not covered by them at all. In some cases the impact of their operation may be negative; since they are not capable of the adaptability to the present situation (e.g. production of distributed/decentralized generation varies in time so quite often the distribution voltage level feeders feed the energy back into the network. So they don't appear as loads and their disconnection makes situation even worse).

1.5.2 Voltage Instability

Voltage Instability is the inability of a power system to maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbance. A system enters a state of voltage instability when a disturbance, increase in load demand, or change in system conditions causes a progressive and uncontrollable drop in voltage. A system is voltage unstable if, for at least one bus in the system, the bus voltage magnitude decreases as the reactive power injection in the same bus is increased [6].

Voltage instability is basically caused by an unavailability of reactive power support in some nodes of the network, where the voltage uncontrollably falls. Lack of reactive power may essentially have two origins. Gradual increase of power demand which reactive part cannot be met in some buses or sudden change of a network topology redirecting the power flows such a way that a reactive power cannot be delivered to some buses.

The relation between the active power consumed in the monitored area and the corresponding voltages is expressed by so called PV-curves. The increased values of loading are accompanied by a decrease of voltage (except a capacitive load). When the loading is further increased, the maximum loadability point is reached, from which no additional power can be transmitted to the load under those conditions. In case of constant power loads the voltage in the node becomes uncontrollable and rapidly decreases. However, the voltage level close to this point is sometimes very low, what is not acceptable under normal operating conditions, although it is still within the stable region. But in the emergency cases, some utilities accept it for a short period.

The emergency stabilizing actions which might be taken are in principle same as in case of the frequency instability, plus:

- Change of the generator voltage set point
- Automatic shunt switching
- Control of series compensation
- Blocking of Tap Changer of transformers
- Fast redispatch of generation

The analyses of real voltage collapses have shown their wide area nature and that they can be sorted basically into two categories according to the speed of their evolution –

Transient Voltage Instability and Long-term Voltage Instability [7]. Transient Voltage Instability is in the range of seconds (usually 1 – 3 s) and the main role in the incidents played the dynamics of induction motors as a load (majority of air conditioning systems) and HVDC transmission systems. The time scale of the Long-term Voltage Instability ranges from tens of seconds up to several minutes. It involves mainly impact of a topology change or gradual load increase, i.e. fairly slow dynamics. Therefore the major part of the research activities in this area has focused on the steady state aspects of voltage stability, i.e. finding the maximum loadability point of the PV-curve.

1.5.3 Rotor Angle Instability

It deals of power system synchronism with two parts, transient angle instability, and small-signal angle instability.

1.5.3.1 Transient Angle Instability

Transient Angular Instability (also called Generator's Out-of-step) is the inability of the power system to maintain synchronism when subjected to a severe transient disturbance. The resulting system response involves large excursions of generator angles and is influenced by the nonlinear power-angle relationship [6].

In case of transient angle instability, a severe disturbance is a disturbance, which does not allow a generator to deliver its output electrical power into the network (typically a tripping of a line connecting the generator with the rest of the network in order to clear a short circuit). This power is then absorbed by the rotor of the generator, increases its kinetic energy that results in the sudden acceleration of the rotor above the acceptable revolutions and eventually damage of the generator.

Therefore the measures taken against this scenario aim mainly to either an intended dissipation of undelivered power by braking resistor (reducing the mechanical power driving the generator) or fast-valving, disconnection of the generator.

An application of traditional measure of transient angle instability – equal area criterion (expressing a balance between the accelerating and decelerating energy), on emergency control has been presented which describes the method called single machine equivalent (SIME) [8]. The angles of the generators in the system are predicted

approximately 200 ms ahead. According to it, the machines are ranked and grouped into two categories. For the generators from the critical category, one machine, infinite bus (OMIB) equivalent is modeled and extended equal area criterion is applied to assess their stability. Pre-assigned corrective action is executed if an unstable generator is identified.

1.5.3.2 Small-signal Angle Instability

Local mode of Small-signal Angular Instability is the inability of the power system to maintain synchronism under small disturbances. Such disturbances occur continually on the system because of small variations in loads and generation. The disturbances are considered sufficiently small for linearization of system equations to be permissible for purposes of analysis. Local modes or machine-system modes are associated with the swinging of units at a generating station with respect to the rest of the power system. The term local is used because the oscillations are localized at one station or small part of the power system [6].

Some power systems lack a "natural" damping of oscillations, which may occur, and they would be unstable when subjected to any minor disturbance and sometimes even under normal operation conditions if no measures increasing the damping were introduced [9]. An extension of the transmission capacity by adding a new line does not necessarily improve the damping significantly and solve the problem [10].

A traditional way of damping the oscillation is using of Power System Stabilizer (PSS), which controls/modulates the output voltage of the generator. The coordinated tuning of PSSs is a complex task, since they should be robust - work in the wide range of operation conditions and provide the best possible performance. This process is done off-line.

1.5.4 Basis for Distinction between Voltage and Rotor Angle Stability

It is important to recognize that the distinction between rotor angle stability and voltage stability is not based on weak coupling between variations in active power/angle and reactive power/voltage magnitude. In fact, coupling is strong for stressed conditions and both rotor angle stability and voltage stability are affected by pre-disturbance active power as well as reactive power flows. Instead, the distinction is based on the specific set of opposing forces that experience sustained imbalance and the principal system variable in which the consequent instability is apparent [2].

1.6 Summary

The chapter was a review for definitions of power system stability and their phenomena. It also introduced various instability phenomena which are frequency instability, voltage instability, Rotor angle instability with two subcategories transient angular instability, and small-signal angular instability.

CHAPTER TWO

VOLTAGE STABILITY AND SYSTEM SOLUTIONS

2.1 Overview

This chapter discusses the voltage stability and the related solutions. First, it explains the relation between the voltage at the receiving end and the transmitted active and reactive powers, and the sources and sinks of reactive power. Then, it discusses voltage sensitivity to loads, and the voltage stability and collapse. Finally it proposes solutions to keep voltage stability by inserting reactive power using shunt capacitor banks or/and advanced compensated VARs, or/and using synchronous machines. It, also, proposes changing the voltage at the distribution substations by transformer tap changers. The final procedure for maintaining voltage stability is load shedding. The final session introduces the control of power system.

2.2 Transfer of Active and Reactive Power

Consider the circuit in Figure 2.1. A strong source with voltage E supplies a remote load through a transmission line modeled as a series reactance. The receiving end voltage V and angle depend on the active and reactive power transmitted through the line. The active and reactive power received at the load end can be written [11]:

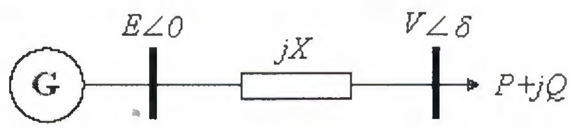


Figure 2.1 Single Line Diagram of a Simple Radial Power System

$$P = -\frac{EV}{X}\sin\delta \qquad (2.1)$$

$$Q = \frac{EV}{X}\cos\delta - \frac{V^2}{X} \qquad (2.2)$$

After eliminating using the trigonometric identity we get

$$\left(Q+\frac{V^2}{X}\right)^2+P^2=\left(\frac{EV}{X}\right)^2 \tag{2.3}$$

Solving for V^2 yields

$$V^2=\frac{E^2}{2}-QX\pm X\sqrt{\frac{E^4}{4X^2}-P^2-Q\frac{E^2}{X}} \tag{2.4}$$

Thus, the problem has real positive solutions if

$$P^2+Q\frac{E^2}{X}\leq\frac{E^4}{4X^2} \tag{2.5}$$

This inequality shows which combinations of active and reactive power that the line can supply to the load. Substituting the short-circuit power at the receiving end, $S_{SC}=E^2/X$, we get

$$P^2+QS_{SC}\leq\left(\frac{S_{SC}}{2}\right)^2 \tag{2.6}$$

Some preliminary observations that can be made from the condition (2.6) are:

- The maximum possible active power transport is $S_{SC}/2$ for Q = 0.
- The maximum possible reactive power transport is $S_{SC}/4$ for P = 0
- An injection of reactive power at the load end, i.e., Q < 0 increases the transfer limit for active power.
- The transfer limits are proportional to the line admittance and to the square of the feeding voltage E

Thus, it appears more difficult to transfer reactive than active power over the inductive line, and it seems that reactive power transfer can influence the ability of the line to carry active load. Furthermore, assume for now that the load has admittance characteristics, that is, the active and reactive power received by the load can be written

$$P+jQ=V^2G(1+j\tan(\phi)) \tag{2.7}$$

Thus, the load produces reactive power for leading power factor (*tan* $(\phi) < 0$) and absorbs reactive power for lagging power ($tan(\phi) > 0$). After normalizing equations (2.4) and (2.7) using

$$p = P / S_{SC}, \quad q = Q / S_{SC} \tag{2.8}$$

$$v = V / E, \quad g = G / (1 / X)) \tag{2.9}$$

Using normalized quantities, the positive solution to (2.4) can be written

$$v = \frac{1}{\sqrt{g^2 + (1 + g\tan(\phi))^2}} \tag{2.10}$$

Not surprisingly, there is no voltage drop over the line when the load admittance is zero and the load voltage approaches zero as the load admittance increases towards infinity.

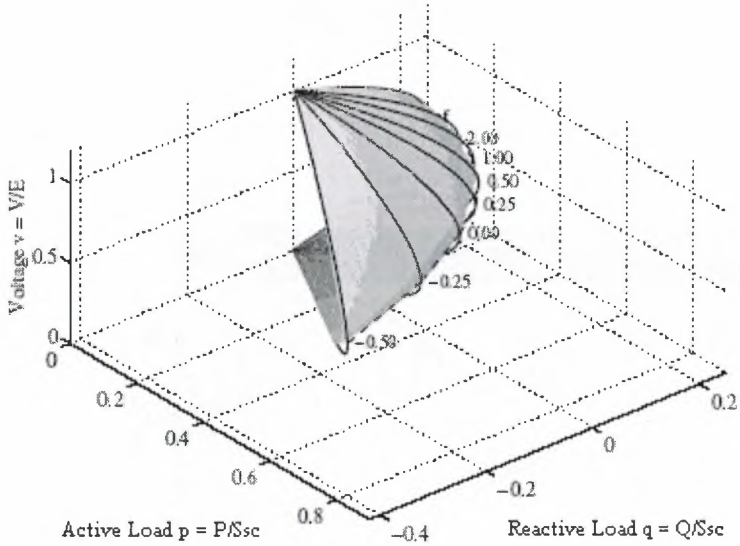


Figure 2.2 The So-Called Onion Surface as Given by Equation (2.10) Drawn Using Normalized Load Quantities [11].

Figure 2.2 shows the so-called onion surface given by (2.10) drawn in the pqv-space. It illustrates the relationship between receiving end voltage and transferred active and reactive power, and each point on the surface corresponds to a feasible operating point. The surface visualizes the set of operating points that the combined generation and transmission system can sustain. The actual operating point is determined by the apparent

load admittance, and the stability of this operating point is determined jointly by the slope of the surface and the load characteristics. The solid lines drawn on the surface correspond to operating points with varying g and constant tan (ϕ) (shown by the number beside each line). The dashed line around the "equator" of the surface corresponds to the transfer limit according to the condition (2.6).

Figure 2.3 shows so-called pv-curves [7], which are projections of the solid lines drawn on the onion surface onto the pv-plane. The rightmost point of each pv-curve marks the maximum active power transfer for a particular power factor. The corresponding voltage shown by the dashed curve is therefore often referred to as the critical voltage and the active loading as the theoretical transfer limit. The critical voltage and theoretical transfer limit increase with decreasing tan (ϕ). As will later be demonstrated, only operating points on the upper half of the pv-curve are stable when the load has constant power characteristics.

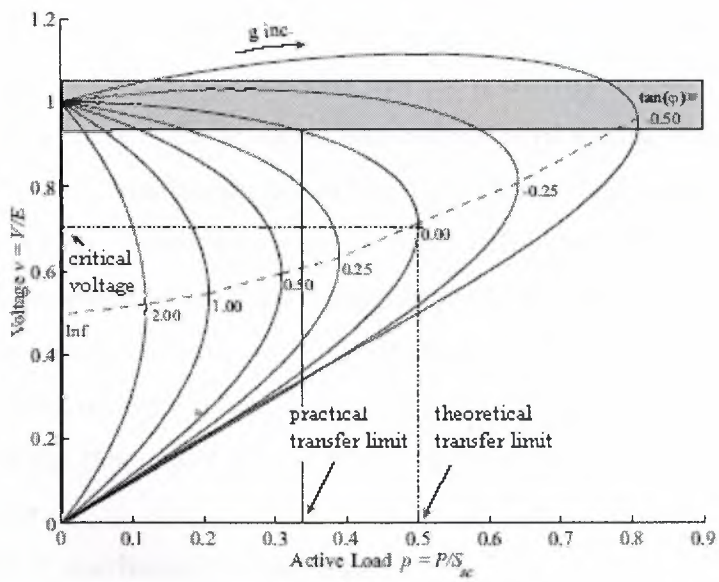


Figure 2.3 The Onion Surface Projected Onto the PV-Plane

According to the condition (2.6), the maximum power a purely active load can theoretically receive through the line is half the short-circuit power at the load bus, given that no reactive power is received at the load end. The shaded region indicates normal

operation of a line {the voltage of both ends of the line is normally kept close to the rated voltage of the line. Typical limits are $\pm 5\%$ deviation from nominal voltage or up to $\pm 5\%$ in emergency cases. The receiving end voltage at the theoretical transfer limit with a purely active load is $1/\sqrt{2} \approx 0.71$, which is normally considered unacceptable. The practical transfer limit is therefore about 35% of the short-circuit power or even lower when the load has a lagging power factor1. Capacitor banks connected at the load end are often used to increase the load end voltage and thereby the practical transfer limit. Reactive power is then being produced locally instead of transferred by the line, and the apparent power factor of the load (as seen from the transmission system) is enhanced. The operating point then shifts to another pv-curve corresponding to a lower value of *tan* (ϕ). When the operating point is on the upper part of the pv-curve, which is the case under normal operation, this corresponds to higher voltage.

The pv-curves also indicate the stiffness of system with respect to active power load variations. By overcompensating the load, such that the apparent *tan* (ϕ) becomes negative, transfer beyond half the short-circuit power with voltage close to nominal levels can theoretically be accommodated. Note however that the sensitivity to load variations, which corresponds to the steepness of the pv-curve within the shaded region, is much larger in an overcompensated system. Another important aspect is that the critical voltage is brought closer to nominal voltage. It will be shown in Section 2.5 that for constant power load characteristics, the theoretical transfer limit coincides with the voltage stability limit. Thus, the difference between the critical voltage and the voltage of the current operating point can be used as a robustness measure in terms of voltage. Similarly, the difference between the current loading and the theoretical transfer limit can be used as a robustness measure in terms of active power.

Calculation of maximum loading point

The maximum loading point can be reached through a load flow program [12, 13, 14]. The maximum loading point can be calculated by starting at the current operating point, making small increments in loading and production and re-computing load-flows at each increment until the maximum point is reached. The load-flow diverges close to maximum loading point because there are numerical problems in the solution of load-flow

equations. The load flow based method is not the most efficient, but has the following characteristics making it appropriate for voltage stability studies:

- good models for the equipment operating limits: generator capability limits, transformer tap ranges, circuit ratings and bus voltage criteria
- good models for the discrete controls: transformer tap steps and switched shunts
- capability to recognize the maximum loading point through the minimum singular value of load-flow Jacobian matrix
- familiar computer modeling, data requirements and solution algorithms
- option of using the existing computer program with miner modifications

2.3 Sources and Sinks of Reactive Power

The previous section showed that the voltage at the receiving end is highly dependent on the absorption or injection of reactive power by the load. The control of voltage is in fact closely related to the control of reactive power. An injection of reactive power at a bus that is not directly voltage regulated by a generator will in general increase the voltage of that bus and its surrounding network.

The most important sources and sinks of reactive power in power systems are:

- Overhead (AC) lines generate reactive power under light load since their production due to the line shunt capacitance exceeds the reactive losses in the line due to the line impedance. Under heavy load, lines absorb more reactive power than they produce.
- Underground (AC) cables always produce reactive power since the reactive losses never exceed the production because of their high shunt capacitance.
- Transformers always absorb reactive power because of their reactive losses. In addition, transformers with adjustable ratio can shift reactive power between their primary and secondary sides.
- Shunt capacitors generate reactive power.
- Shunt reactors absorb reactive power.
- Loads seen from the transmission system are usually inductive and therefore absorb reactive power.

- Synchronous generators, synchronous condensers and static VAR compensators can be controlled to regulate the voltage of a bus and then generate or absorb reactive power depending on the need of the surrounding network.
- Series capacitors are connected in series with highly loaded lines and thereby reduce their reactive losses.

2.4 Voltage Sensitivity of Loads

So far, it was assumed that the apparent admittance of the load is constant. However, the admittance of many loads varies with the supply voltage - either by their inherent design or by control loops connected to the load devices. Typical examples of such loads are motor drives equipped with power electronic converters and thermostatically controlled heating devices, which adjust their apparent admittance in order to consume constant power. The composite load seen from the transmission level often contains a significant amount of induction motor loads, which exhibit potentially very complex voltage behavior. However, for small voltage excursions, say less than 10 %, the active power drawn by induction motors can in the long term be approximated as constant and the reactive power as proportional to an exponential of the voltage. The dynamic response of loads to voltage changes plays a major role in the analysis and evolution of voltage instability. Simplifying matters somewhat, the load as seen from the transmission level can normally be considered as constant power in the long term since it is connected through tap changers that keep the load voltages close to their nominal values.

2.5 Voltage Stability

The voltage stability of power systems basically implies its capability of reaching and sustaining an operating point in a controllable way following a disturbance, and that the steady-state post-disturbance system voltages are acceptable. Furthermore, the term voltage instability denotes the absence of voltage stability and voltage collapse the transition phase during which a power system progresses towards an unacceptable operating point due to voltage problems, often resulting in blackouts or separation of the system into separate unsynchronized islands.

The dynamics of voltage phenomena can be divided into the two main groups: short- and long-term dynamics. Short-term phenomena act on a time scale of seconds or shorter and include, for example, the effect of generator excitation controls, induction motor recovery/stalling dynamics and FACTS devices [2]. The long-term dynamic phenomena act on a time scale of minutes and include, for example, the effect of recovery dynamics in heating load and the effect of generator over current protection systems.

As discussed in the previous section, many loads respond to a voltage drop by increasing their apparent admittance. Assume that the load supplied by the network in Figure 2.1 has such a recovery mechanism according to the normalized model

$$T\frac{dg}{dt} = p_0 - p \tag{2.11}$$

$$p = g\,v^2 \tag{2.12}$$

Thus, the load has instantaneous admittance characteristics but also an internal controller that aims to restore the power drawn to constant power p_0 with the time constant T sec. Furthermore, assuming that the load is purely active (*tan* $(\phi) = 0$) and combining (2.10) and (2.11)-(2.12), the full model can be written in the differential-algebraic form

$$T\frac{dg}{dt} = p_0 - g\,v^2 \tag{2.13}$$

$$v = \frac{1}{\sqrt{g^2+1}} \tag{2.14}$$

Substituting (2.14) in (2.13) yields

$$f(g) = \frac{dg}{dt} = \frac{1}{T}\left(p_0 - \frac{g}{1+g^2}\right) \tag{2.15}$$

Solving for stationary points yields the two solutions

$$g^* = \frac{1}{2p_0} \pm \sqrt{\frac{1}{4p_0^2} - 1} \tag{2.16}$$

Thus, it can be concluded that there are two separate equilibria if $p_0 < 0.5$ that coalesce for $p_0 = 0.5$. For $p_0 > 0.5$ it appears to be two separate equilibrium points with complex g. But g is real-valued since it has been defined as the real part of the admittance phasor in equation (2.7). Thus, we can conclude that there are no equilibria for $p_0 > 0.5$

and that a loss of equilibrium occurs when p_0 increases beyond 0.5. Since (2.16) is always positive for $p_0 > 0.5$, the admittance will increase towards infinity (or an internal limit in the load device) and the load voltage will approach zero. Small-disturbance stability analysis can be used to determine that for $p_0 < 0.5$, the low admittance solution corresponding to the upper half of the pv-curve is asymptotically stable and the high admittance solution on the lower half is unstable [15].

Assuming constant power load characteristics as above, the theoretical transfer limit marked by the dashed curve in Figures 2.2 & 2.3 therefore also becomes a steady-state voltage stability limit. However, note that the operating point may transiently move to the unstable lower part and back again to the stable equilibrium on the upper part of the pv-curve. Analogously, there is no guarantee that the system will reach a stable operating point simply because such an operating point exists. A trajectory will only approach the stable equilibrium as long at it remains within the region of attraction of the stable equilibrium. Such regions of attraction can be approximately computed using a Lyapunov-method for general dynamical systems, but the problems of finding a good Lyapunov function may make the results conservative [15].

2.6 Voltage Collapse

Voltage collapse is a system instability that involves several power system components simultaneously. It typically occurs on power systems that are heavily loaded, faulted and/or has reactive power shortages. This occurs since voltage collapse is associated with the reactive power demands of loads not being met due to limitations on the production and transmission of reactive power. The production limitations include generator and SVC reactive power limits and the reduced reactive power produced by capacitors at low voltages. The primary limitations in transmission are high reactive power losses on heavily loaded lines and line outages. Reactive power demands may also increase due to changes in the load such as, motor stalling or increased proportion of compressor load.

Voltage collapse takes place on the different timescales ranging from seconds to hours, specifically [16]:

(1) Electromechanical transient (e.g., generators, regulators, induction machines) and power electronic (e.g. SVC, HVDC) phenomena in the time range of seconds.

(2) Discrete switching devices, such as, load tap changers and excitation limiters acting at intervals of tens of seconds.

(3) Load recovery processes spanning several minutes.

There are numerous power system events known to contribute to voltage collapse.

- Increase in loading
- Generators or SVC reactive power limits
- Action of tap changing transformers
- Load recovery dynamics
- Line tripping or generator outages

Most of these changes have a large effect on reactive power production or transmission. Control actions such as switching in shunt capacitors, blocking tap changing transformers, redispatch of generation, rescheduling of generator and pilot bus voltages, secondary voltage regulation, load shedding and temporary reactive power overload of generators are countermeasures against voltage collapse. Machine angles are typically also involved in the voltage collapse. Thus, there is no sharp distinction between voltage collapse and classical transient instability. The differences between voltage collapse and classical transient instability are those of emphasis: voltage collapse focuses on loads and voltage magnitudes whereas transient instability focuses on generators and angles. Also, voltage collapse often includes longer time scale dynamics and includes the effects of continuous changes such as load increases in addition to discrete events such as line outages.

Increasing voltage levels by supplying more reactive power generally improves the margin to voltage collapse. In particular, shunt capacitors become more effective at supplying reactive power at higher voltages. Increasing voltage levels by tap changing transformer action can decrease the margin to voltage collapse by in effect increasing the reactive power demand. Still, voltage levels are a poor indicator of the margin to voltage collapse. While there are some relations between the problems of maintaining voltage levels and voltage collapse, they are best regarded as distinct problems since their analysis

is different and there is only partial overlap in the control actions used to solve both problems.

2.6.1 Voltage Collapse Indices

There are numerous indices to indicate proximity to voltage collapse that have been studied. The following is a brief introduction to these indices:

2.6.1.1 Sensitivity Factors

Sensitivity factors are indices used in several utilities throughout the world to detect voltage stability problems and to decide corrective measures [17, 18]. These indices were first used to predict voltage control problems in generator QV curves, and may be defined as

$$VSF_i = \max_i \left\{ \frac{dV_i}{dQ_i} \right\} \tag{2.17}$$

where *VSF* stands for Voltage Sensitivity Factor. As generator *i* approaches the bottom of its QV curve, the value of *VSFi* becomes large and eventually changes sign, indicating an unstable voltage control condition.

2.6.1.2 Singular Values

Singular values of a reduced matrix can be used to determine proximity to voltage collapse. Let

$$\Delta Q = J_{QV}\, \Delta V \tag{2.18}$$

with

$$\det J_{QV} = \frac{\det J}{\det J_I} \tag{2.19}$$

where J is the Jacobian in power flow equations and J_I is the real power sensitivities to angle deviations, i.e., $\frac{\partial P}{\partial \delta}$. The singular values of this reduced matrix can be used to determine proximity to voltage collapse.

2.6.1.3 Second Order Performance Indices

Indices based on first order information (linearization), such as singular values and eigen values and several other indices presented in this document, may be inadequate to predict proximity to collapse as they neglect large discontinuities in the presence of system control

limits like generator capability or transformer tap limits, as previously discussed. Conversely, it is possible to calculate a second order index that exploits additional information embedded in these indices to overcome some of these discontinuities [19].

2.6.1.4 Energy Function

Energy function, a technique based on Lyapunov stability theory, is used for both transient stability and voltage stability analysis. In this approach, power system stability is like a ball, which lies at the bottom of a valley. The stability can be understood as the ball settling to the bottom of an uneven surface when there is a disturbance. As the power system changes, the landscape of this surface and the ridges surrounding the indentations change. A voltage collapse corresponds to a ridge being sufficiently lowered so that with a small perturbation the ball can roll from the bottom of one indentation to a neighboring area. The height of the lowest ridge can be computed and used as an index to monitor the proximity to voltage collapse [20].

2.6.1.5 Loading Margin

For a particular operating point, the amount of additional load in a specific pattern of load increase that would cause a voltage collapse is called the loading margin to voltage collapse.

Loading margin is the most basic and widely accepted index of voltage collapse. If system load is chosen to be the parameter, which varies, then a system PV curve can be drawn. In this case, the loading margin to voltage collapse is the change in loading between the operating point and the nose of the curve. The advantages of the loading margin as a voltage collapse index are [21]:

- The loading margin is straightforward, well accepted and easily understood.
- The loading margin is not based on a particular system model; it only requires a static power system model and can be supplemented with dynamic system models.
- The loading margin is an accurate index that takes full account of the power system nonlinearity and limits such as reactive power control limits encountered as the loading is increased. Limits are not directly reflected as sudden changes on the loading margin.

- Once the loading margin is computed, it is easy and quick to compute its sensitivity with respect to any power system parameters or controls.

The computational costs are the most serious disadvantage of the loading margin and make it unsuitable for on-line use.

2.7 System Solutions

The potential effects of voltage instability resulting from the slow recovery of the power system voltages following a major disturbance, such as a transmission line fault. Transmission utilities have traditionally addressed voltage stability concerns by installing large static VAR compensator (SVCs) or synchronous condensers to provide the necessary dynamic reactive power support to the system following a major disturbance.

The problem of voltage stability of distribution power systems has many solutions, such as changing transformer taps, switching capacitors bank, using advanced VAR compensators, installing synchronous generators and condensers, and finally shedding loads.

2.7.1 Transformer Tap Changer Relays

A. General

Electric utilities utilize load tap-changers (LTC) to maintain customer voltage levels as the system conditions change. Typically, as load increases, the LTC will act to raise the tap position in order to maintain the voltage level. The LTC control relay will be set to operate in one of two modes - bus voltage regulation or load center voltage regulation using the line drop compensator.

Load Center voltage regulation requires a line drop compensator to regulate the voltage at the load center. Transformers at distribution substations are more likely to use load center voltage regulation than those at transmission substations. Therefore, it is important to know the mode of LTC control operation when modeling the effect of the tap-changing transformer operation during voltage collapse.

During a period of voltage collapse, the LTC control relays will detect a low voltage and begin timing to raise the tap position of the transformer.

When the voltage collapses occurs slowly, the controls will time out and begins to raise the transformer tap position. Assuming no change in the load on the transformer during this period, the LTC can often be considered a constant power load as long as the tap-changer can maintain a constant load voltage.

Since the primary voltage level drops, the current flow in the transmission system is increased to maintain the load power. This increasing current flow will further reduce the transmission system voltage, making the voltage collapse more severe.

In some cases, tap changers can also have a beneficial effect. Consider for instance, a case where a transformer is supplying predominantly motor load with power factor correction capacitors. The LTC keeps the supply voltage high and hence does not affect the real power consumption (which is relatively independent of voltage), and also maximizes the reactive support from the power factor correction capacitors. Due to this regulating effect, the LTC is an important part of the overall voltage collapse scenario.

For the more frequent case, where the real power loads have some voltage dependency, the LTC can be utilized to reduce the severity of the voltage collapse if appropriate control operation can be obtained. Blocking operation of the LTC has been widely offered as a method to reduce the negative effect on the system. Load voltage reduction can be used to reduce the loading on the system. This is similar to the peak shaving systems widely used at many utilities. Therefore the load tap-changer may be both a cause and a partial solution to the problem of voltage collapse [22].

B. LTC Blocking Schemes

The simplest method to eliminate the LTC as a contributor to voltage collapse is to block the control's automatic raise operation during any period where voltage collapse appears to be a concern. The decision to temporarily block the tap-changer can be made using locally derived information or can be made at a central location and the supervisory system can then send a blocking signal to the unit. This action may result in a period of low voltage on the affected loads.

The effect of the reduced supply voltages on power quality to customers in the whole service area must be weighed against the possible alternative of complete disconnection of some customers in a smaller area. Tap changer blocking will be more effective for voltage decays slower than the transient time frame. It will also be more

effective on loads that have a relatively high voltage dependency. In cases where the steady state value of b is high, the reduction of reactive power demand due to reduced distribution voltage will be very significant in helping keep transmission voltages up.

Local blocking schemes are implemented using voltage relays and timers to sense the voltage level on the high voltage bus at the substation.

The set point voltage is usually chosen to be a level that is less than that which occurs during maximum acceptable overload conditions. Condition exists longer than a predetermined time. The time period may vary from 1 to several seconds. The LTC is unblocked when the voltage has recovered to an acceptable level for a predetermined period of time, typically 5 seconds [22]. Since the blocking action will be removed if the voltage recovers, usually a single phase-phase voltage measurement is adequate for this scheme.

A coordinated blocking scheme can be utilized to block operation of LTC's in an area where voltage instability is imminent. The coordinated scheme can be accomplished with under voltage schemes acting independently (as described above) in a coordinated fashion at various stations within a region, or it can be a centralized scheme that recognizes a pattern of low voltages at key locations. In a centralized scheme, the LTC blocking can be implemented in substations throughout the affected region, even if the voltage at all locations is not yet below a specific threshold. The key to operation of a centralized system is the reliability of the communications system. The data needed for decision making must be collected at the central location for analysis. Control decisions must then be sent to each affected transformer location.

The effectiveness of an LTC blocking scheme at the transmission level will largely depend on whether distribution transformers are LTC-type. If the distribution transformers are LTC-type, additional measures are required to prevent their action from negating the effect of the LTC blocking scheme at the transmission level.

C. No-load Tap Changer

One method used to adjust the winding ratio of the transformer uses the no-load tap changer shown in Figure 2.4 [23]. A transformer equipped with a no-load tap changer must always be disconnected from the circuit before the ratio adjustment can be made. The

selector switch is operated under oil usually placed within the transformer itself; but it is not designed to be used as a circuit breaker. To change taps on small distribution transformers, the cover must be removed and an operating handle is used to make the tap change. For the larger type, one handle may be brought through the cover and the tap may be changed with a wheel or even a motor.

If it is necessary to change the taps when the transformer cannot be disconnected from the circuit, tap changers under-load are used. They involve the use of an autotransformer and an elaborate switching arrangement. The information regarding the switching sequence must be furnished with each transformer. Tap changers can function automatically if designed with additional control circuits: automatic tap changes are used for high-power transformers, and for voltage regulators.

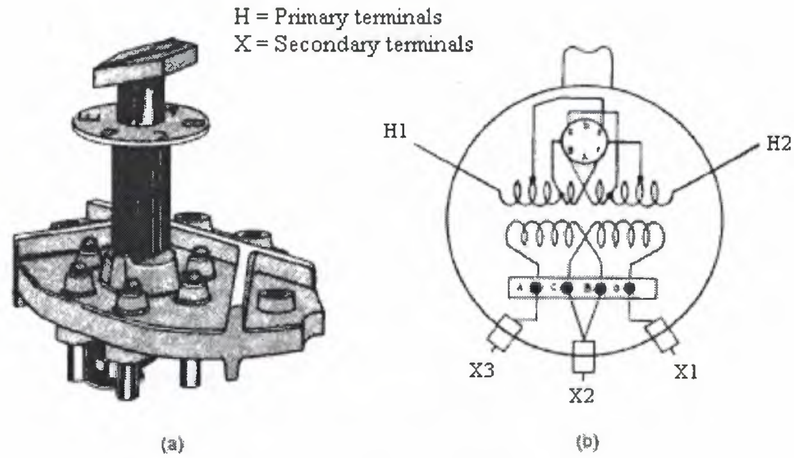


Figure 2.4: Tap Changer (a) No Load Tap Changer
(b)Typical Internal Wiring of Transformer with Tap Changer [24]

2.7.2 Switched Capacitors Bank

Many power system components in a network consume large amounts of reactive power. For example, transmission line shunt reactors, and other industrial and commercial loads need reactive power. Reactive current supports the magnetic fields in motors and transformers. Supporting both real and reactive power with the system generation requires increased generation and transmission capacity, because it increases losses in the network. Shunt-connected capacitors or synchronous condensers near the load centers are another

way to generate reactive power. Switched Capacitor Banks (SCB) have the advantage of providing reactive power close to the load centers, minimizing the distance between power generation and consumption, and do not have the maintenance problems associated with synchronous condensers. Controlling capacitance in a transmission or distribution network could be the simplest and most economical way of maintaining system voltage, minimizing system losses, and maximizing system capability. The main disadvantage of SCB is that its reactive power output is proportional to the square of the voltage and consequently when the voltage is low and the system needs them most, they are the least efficient.

Capacitor Bank Design

In order to insert reactive power to the power distribution system (PDS) the power factor (*cos* ϕ) should be increased to unity, and the angle ϕ is decreased to zero. In order to decrease the angle ϕ, reactive component of the current, $I \sin \phi$ (I_r) is to be decreased. This is achieved by introducing leading current of magnitude equal to the reactive component, in the circuit as shown by OA in Figure 2.5. This leading current I_c will lead the voltage by 90 degrees and will be in phase opposition to I_r. Therefore the leading current required to neutralize the lagging reactive component of the current to minimize the reactive power of the feeder to zero is given as:

$$\begin{aligned} I_c &= I_r = I \sin \phi \\ &= I \sqrt{1-\cos^2 \phi} \end{aligned} \tag{2.20}$$

The value of the total capacitance required for inserting reactive power for given real power P in the circuit, at frequency f, and voltage V is determined as follows:

$$I_c = \omega C V = 2\pi f C V \tag{2.21}$$

Equating eqns. (2.20) and (2.21),

$$2\pi f C V = I \sqrt{1-\cos^2 \phi} \tag{2.22}$$

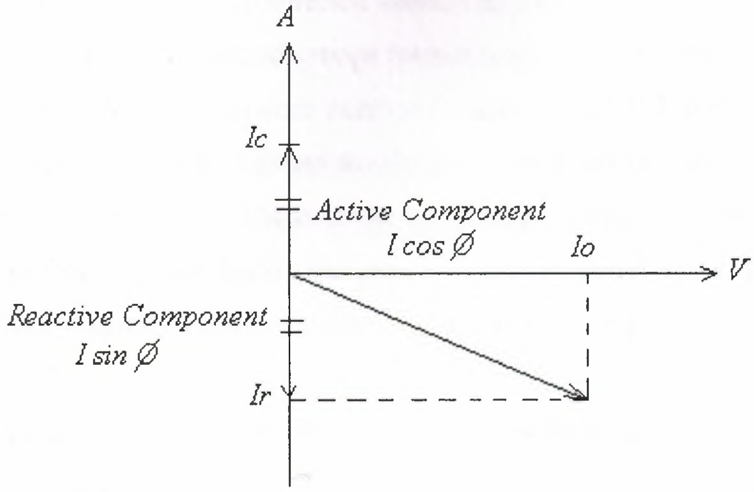


Figure 2.5 Representation of Reactive Current Component

And $$C = \frac{I}{2\pi f V}\sqrt{1-\cos^2\phi} \tag{2.23}$$

Also $$P = IV\cos\phi \tag{2.24}$$

From eqn. (2.24)

$$I = \frac{P}{V\cos\phi} \tag{2.25}$$

Substituting the value of I from eqn. (2.25) into eqn. (2.23)

$$C = \frac{P}{2\pi f V^2 \cos\phi}\sqrt{1-\cos^2\phi} \tag{2.26}$$

$$C = \frac{P}{2\pi f V^2}\sqrt{\frac{1}{\cos^2\phi}-1} \tag{2.27}$$

It is seen from the last equation that the capacitance required is inversely proportional to the square of the operating voltage, thus the total value of capacitance required per phase depends upon the nature of connection whether star or delta. In practice it is observed that the delta connection is preferable.

The protection of shunt capacitor banks requires understanding the basics of capacitor bank design and capacitor unit connections. Shunt capacitors banks are

arrangements of series/paralleled connected units. Capacitor units connected in paralleled make up a group and series connected groups form a single-phase capacitor bank.

As a general rule, the minimum number of units connected in parallel is such that isolation of one capacitor unit in a group should not cause a voltage unbalance sufficient to place more than 110% of rated voltage on the remaining capacitors of the group. Equally, the minimum number of series connected groups is that in which the complete bypass of the group does not subject the others remaining in service to a permanent over voltage of more than 110% [24].

The maximum number of capacitor units that may be placed in parallel per group is governed by a different consideration. When a capacitor bank unit fails, other capacitors in the same parallel group contain some amount of charge. This charge will drain off as a high frequency transient current that flows through the failed capacitor unit and its fuse. The fuse holder and the failed capacitor unit should withstand this discharge transient.

The discharge transient from a large number of paralleled capacitors can be severe enough to rupture the failed capacitor unit or the expulsion fuse holder, which may result in damage to adjacent units or cause a major bus fault within the bank. To minimize the probability of failure of the expulsion fuse holder, or rupture of the capacitor case, or both, the standards impose a limit to the total maximum energy stored in a paralleled connected group to 4659 kVAR [24]. In order not to violate this limit, more capacitor groups of a lower voltage rating connected in series with fewer units in parallel per group may be a suitable solution. However, this may reduce the sensitivity of the unbalance detection scheme. Splitting the bank into two sections as a double Y may be the preferred solution and may allow for better unbalance detection scheme. Another possibility is the use of current limiting fuses.

The optimum connection for a SCB depends on the best utilization of the available voltage ratings of capacitor units, fusing, and protective relaying. Virtually all substation banks are connected wye. Distribution capacitor banks, however, may be connected wye or delta. Some banks use an H configuration on each of the phases with a current transformer in the connecting branch to detect the unbalance.

Delta-connected banks are generally used only at distributions voltages and are configured with a single series group of capacitors rated at line-to-line voltage. With only

one series group of units no over voltage occurs across the remaining capacitor units from the isolation of a faulted capacitor unit. Therefore, unbalance detection is not required for protection.

Some larger banks use an H configuration in each phase with a current transformer connected between the two legs to compare the current down each leg. As long as all capacitors are normal, no current will flow through the current transformer. If a capacitor fuse operates, some current will flow through the current transformer. This bridge connection can be very sensitive. This arrangement is used on large banks with many capacitor units in parallel.

2.7.3 Advanced VAR Compensators

The emergence of new advanced VAR compensators utilizing power electronics with binary switched capacitors and inverter-based systems with or without energy storage provide utility transmission planning engineers with alternative solutions to the voltage stability problem.

Superconducting magnetic energy storage systems utilizing magnetic energy storage in the form of a superconducting coil and inverter technology have lead the way in utility applications of these new advanced VAR compensators [25]. Other commercially-available advanced VAR compensators are now increasingly being applied on utility systems for voltage stability support as well as for voltage regulation purposes.

Commercially-available advanced compensators are grouped into three categories, namely:

- Power-electronically-switched capacitors.
- Inverter-based systems without energy storage.
- Inverter-based systems with energy storage

2.7.3.1 Power-Electronically-Switched Capacitors

Compensators utilizing power-electronically-switched capacitors (e.g., (AVC) Adaptive VAR Compensator) typically consist of three or more stages of low-voltage capacitors. Capacitor stages are typically sized in binary increments, i.e., if the size of the first stage of capacitors is Q (kVAR) per phase, the size of the second and third stages would be 2Q and

4Q, respectively. Reactors are typically used in series with each stage of capacitors for detuning to eliminate harmonic resonance and large inrush currents. Capacitors are charged to peak system voltage and switched through thyristors at peak voltage to eliminate any switching transients [26].

The AVC can respond to voltage fluctuations in one cycle, or as fast as ½ cycle in specially-designed units. Single units with capacity of up to 24 MVAR at 690 V or 120 MVAR at 15 kV can be applied for dynamic voltage support. A step-up transformer would typically be used to step the output voltage up to distribution or transmission voltage level [26].

Since the AVC uses binary-switched capacitors, the reactive power output occurs in discrete steps. In a three stage unit the total output can be varied over 7 discrete steps, and in 15 steps in a four-stage unit. Since shunt-connected capacitors are utilized to provide reactive power output, the reactive power output is proportional to the square of the bus voltage.

2.7.2.2 Inverter-Based Systems without Energy Storage

These compensators (e.g., (DVC) Dynamic VAR Compensator and (DSTATCOM) Distribution Static Compensator) utilize shunt-connected voltage-source inverters to control the reactive power flow. Reactive power flow is controlled by adjusting the magnitude of the voltage output from the inverter relative to the bus voltage. Units typically have output filters and a step-up transformer to connect to the distribution bus. Typical DVC units are rated 480 V and consists of multiple 250 kVA inverter modules arranged for an output of up to ±8 MVAR continuous. Units have a one second overload capability ranging from 2.3 to 3 times the continuous rating [26]. After one second the output ramps down to its continuous rating in another second. The reactive power output of an inverter-based compensator is proportional to the bus voltage.

2.7.2.3 Inverter-Based Systems with Energy Storage

The Distributed Superconducting Magnetic Energy Storage (D-SMES) is currently the only commercially-available inverter-based system that has been applied with energy storage for voltage stability applications. The system is similar to the DVC, with an additional

superconducting magnetic energy storage module with peak output power capability of 3 MW and an average output power capability of 2.5 MW over the first 0.5 seconds of discharge [23]. The reactive power output of this compensator is also proportional to the bus voltage.

2.7.4 Synchronous Generators and Condensers

A synchronous machine is capable of generating and supplying reactive power within its capability limits to regulate system voltage. For this reason, it is an extremely valuable part of the solution to the collapse-mitigation problem. Synchronous machines considered may be generators or synchronous condensers. In terms of reactive output capability, synchronous condensers are treated similarly to static VAR sources during commissioning and maintenance in that rated output power must be demonstrated to be achieved.

2.7.4.1 Generators

Generators however are rated for specific real power output, usually at a specific power factor. During commissioning and maintenance, real power output is carefully checked to meet specified requirements. Reactive power output may be checked during commissioning, but may not be carefully checked after that. The reactive power capability may be required by the system, but is not considered to be a revenue generator.

Due to large impact on the system voltages, it may be difficult to operate large generators at their reactive capability limits (for test purposes). Therefore coordination of protection with control devices is not so frequently checked as with other reactive power sources [27]. Numerous voltages collapse or near collapse incidents have been aggravated by unexpected loss of healthy generators due to lack of coordination of protective equipment with generator capability.

The reactive power capability increases dramatically as real power output is limited. Further, the amount of reactive power available from the generator is very dependent on terminal voltage. In this respect, a generator operating at low real power output can supply significantly more reactive power at low voltages than at high voltages [22].

The increase in reactive power capability at lower real power output means that system planners and operators may choose to generate less than rated real power in order to

have more reactive power from generators at critical locations in voltage stability threatened systems. The choice of operating point (MW versus MVAR) for generators at critical locations is predetermined, and not usually subject to automatic control. It should be noted that when the generator reaches the limit of its capability, particularly in the rotor current limited region, it may not be controlling its terminal voltage. The fact that it is at its limit of capability means that it is not able to raise the terminal voltage to the reference setting of the voltage regulator. Thus the reactive power limits are to a certain extent, determined by the system conditions, and independent of the generator excitation system.

The value of a generator as a source of reactive power can be separated from its value as a source of real power, if it can be decoupled from the turbine and run as a synchronous condenser. In some plants where fuel or operating costs may make power generation uneconomic, it may be possible to convert the generator to a synchronous condenser, and use it to support voltages in an area where real power has to be imported from a remote area [27].

2.7.4.2 Motors

It is a synchronous motor working at over excitation and drawing current from the supply at leading power factor. It has an advantage that varying its excitation it can be steplessly adjusted to supply any amount of capacitive or reactive power up to its full rating. By the use of rotary amplifiers and high speed regulators, automatic stable operation is obtained even in the case of sudden change in the system conditions. It must be noted that, synchronous condenser has an inherently sinusoidal waveform and harmonics in the voltage do not exist, but the static capacitors give large harmonics in the system.

A modern synchronous capacitor is generally a six or eight pole salient pole synchronous motor. It is fitted with a robust damper winding by means of which, it is possible to start it as an induction motor at reduced voltage. The starting tapping on the starting transformer is about 25-40% of the rated voltage due to this, the starting current from the supply will be less than the rated current [28].

By jacking up the shaft by means of oil under pressure, the initial starting torque and the minimum voltage required for reliable starting are reduced. The machine runs

almost near to synchronous speed at rated voltage and is then pulled into synchronous speed.

2.7.5 Load Shedding

Load shedding is defined as [29]: "the process of deliberately removing pre-selected loads from a power system, usually done automatically by relays, in order to maintain the integrity of the system under unusual conditions".

Current practice depends on hardware control, using lines and generators. Load shedding basically means nothing more than disconnecting a radial feeder on medium voltage distribution system. Sometimes you try to avoid area with elevators. Hospitals and other very sensitive institutions are supposed to have their own backup. The most common criterion to activate load shedding is low frequency, with or without time delay, also under voltage criteria and rate of change of frequency exists, but are much less common.

Load shedding is an option that is becoming more widely used as a final means of avoiding system wide voltage collapse. This option is only considered when all other effective means of avoiding collapse are exhausted. This option may be the only effective option for various contingencies especially if the collapse is in the transient time frame, and if load characteristics result in no effective load relief by transformer load tap changer control. Load shedding results in high costs to electricity suppliers and consumers, therefore, power systems should be designed to require such actions only under very rare circumstances. Load may be shed either manually or automatically depending on the rate of voltage drop.

2.7.5.1 Manual Load Shedding

If the time frame of collapse is long-term, manual load shedding can be implemented to stabilize the voltage. This mode of operation, normally applied under inadequate generation conditions or insufficient VAR reserve, should have preplanned guidelines and procedures for the system dispatchers to implement load shedding manually.

System studies can provide load sensitivity analyses from which the critical voltage can be determined to start load shedding. Another option to assist system operators for fast action is to preprogram blocks of loads on the dispatcher control console of the SCADA system. Dispatchers can select a particular block of load in a specific area requiring load shedding

to control the voltage drop. The blocks of load can also be divided into several subgroups depending on sensitivity of the load, so that execution of the manual load shedding can be carried out in steps or in rolling sequence [22].

A major disadvantage of relying on manual load shedding is that it places a severe burden on system operators to recognize an approaching voltage stability problem and to act quickly enough to avoid a major collapse. Even with the most comprehensive preplanned guidelines, there is a danger that the particular condition that arises may not fall within the guidelines clearly enough for prompt action. However, when short term operational planning studies (time frame less than a week) show the possibility of collapse due to expected load and actual contingencies, manual shedding can be applied with good results.

2.7.5.2 Automatic Load Shedding

When the voltage instability is caused by sudden loss of critical transmission equipment or VAR generating equipment, the lead-time prior to a voltage collapse will be very short. Therefore, manual load shedding would be too slow to prevent a voltage collapse. Automatic load shedding must be used to quickly arrest a fast voltage drop and allow the voltage to recover to an acceptable level before voltage collapse can occur.

Under voltage detectors are often used to initiate automatic load shedding. For low voltage events which do not lead to collapse (such as during a normally cleared system fault), these detectors must not operate in order to prevent nuisance tripping of customer load. Security of the under voltage detectors can be increased by applying multiple phase detection, proper time coordination between fault clearing and time delay for load shedding, and use of fault detection relays to inhibit load shedding. Reliability of load shedding to prevent voltage collapse can be enhanced by use of other indicators than voltage magnitude such as voltage and power sensitivity factors or other forms of voltage stability indices.

Developing appropriate settings for the under voltage detectors and time delays are challenging problems. It might require intensive network analysis to find the desired values to provide optimum coordination between load shedding and voltage collapse. Generally, the settings are in the range of 85 to 95 percent of the operating voltages, with time delays

ranging from tens of cycles to minutes [30, 31, 32]. The sensitivity of the load to the voltage level has a great impact on the settings.

2.7.5.3 Intelligent Load Shedding

The traditional load shedding scheme, which has hardly been developed over the last 100 years, is less and less acceptable in today's society. The developments in computer and communications technology allow abandoning the stage of hardware control and relying more on intelligent control in order to maintain power system stability.

Intelligent load shedding is defined as [33]: a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable.

The objective of load shedding remains unchanged. The means to improve power stability using intelligent load shedding changes to addressing individual loads in an area, based on knowledge about the power system and these loads, in order to switch off or reduce power for a certain time.

Intelligent load shedding deals with (i) the problem of detecting situations that will go unstable if no remedial actions are taken, and (ii) to take proper action in such a way that stability is restored by minimum cost load shedding. Intelligence and communication are essential means in order to achieve this. Communication is needed in order to obtain information on where and when load shedding is needed, to obtain information on individual loads and their constraints with respect to readiness to shed, and to address individual loads in order to reduce load or switch them off. Intelligence is needed in order to find optimal scenarios for the amount of load to shed and the location of these loads.

2.7.5.4 Requirements and Scenarios for Intelligent Load Shedding

The main requirement on "intelligent load shedding" is that it should be regarded as a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable. The work with intelligent load shedding can be divided in a number of stages [34]:

- To improve present load shedding schemes (where a circuit breaker on the 10/20 kV level is opened), to a scheme where individual load objects in the area are addressed and switched off, or ordered to reduce power, for a certain time.
- To keep track on the load available to be shed in every instant.
- To find an "optimal" amount of load to shed, with respect to a certain disturbance.
- To find the "optimal" location of the load to be shed, with respect to a certain disturbance.
- To specify/find relevant disturbances to prepare load shedding for, and to "interpolate" between these to find suitable actions for real disturbances.
- To initiate "intelligent load shedding" - when approaching voltage instability, angular instability, frequency instability or cascaded outages.

A main consideration in intelligent load shedding will be the cost criterion. Strategies may be based on dynamic prices and on electric market.

2.8 Voltage Stability Related Works

There are many researches contribute in solving voltage stability. Part of these researches use artificial neural networks and others use different algorithms. In [35] an artificial neural network application to power system voltage stability improvement is introduced, and in [36] a novel algorithm for on-line voltage stability assessment based on feed forward neural network is introduced, while [37] introduces a development of an improved on-line voltage stability index using synchronized phasor measurement

2.8.1 Artificial Neural Network Application to Power System Voltage Stability Improvement

This work deals with development of ANN architecture, which provide solutions for monitoring, and control of voltage stability in the day-to-day operation of power systems. It focuses on evaluating the performance of ANN for control and improvement of Power System Voltage Stability problem [35].

A minimization algorithm for improving voltage stability margin based on L-Index and employing non-linear least squares optimization technique is presented. The control

variables considered are switchable VAR compensators, OLTC transformers and generators excitation. The model used for the power system includes limits for reactive power generation at generators, load characteristics and generation control characteristics. Generally in reactive power dispatch the objective is either to minimize real power losses or to minimize the deviations of voltages from desired values. The objective in the proposed algorithm is to minimize the sum of squares of L-indices at all or a subset of critical nodes (decided from voltage stability point of view) in the system. Results obtained from the proposed algorithm are compared with Minimum singular value (MSV) of the modified power flow Jacobean matrix. The increase of load margin to voltage collapse is demonstrated.

A conclusion of the work is: A prototype of an ANN for monitoring and control of power system voltage stability margin improvement has been developed. The proposed ANN tries to improve the voltage stability margin using SVCs, Generator excitation and OLTC transformers as controllers for different loading conditions for a practical EHV Indian power system and encouraging results have been obtained.

2.8.2 Novel Algorithm for Online Voltage Stability Assessment Based on Feed Forward Neural Network

This work presents an online voltage stability assessment method using the feed forward neural network. In this method feed forward neural network is trained for the L indices values, which is a scalar measure of the voltage stability for all the power system buses during normal and contingent situations [36].

Main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained Artificial Neural Network at every time instant unlike the other techniques. The easiness in calculating the stability indices using Index L is exploited for learning the voltage profile of any complex system by ANN.

Thus the stability margin and voltage profile locally for individual buses as well as the global stability margin and improvement measures of the power system can be assessed at the same time with the proposed technique. Another feature of the proposed method is its ability in developing L indices of all the system buses during both normal and contingent

situations using the trained ANNs. This aspect has not been considered as a single problem so far in the earlier research works.

The trained ANN is then tested on the practical 367 bus system to prove its practical use using MATLAB neural network toolbox. The approach was found to be extremely useful to use as energy management software for online establishment of voltage stability margins and to find out the associated limits at each bus.

The proposed network architecture is a three layer feed forward structure including input, output and hidden layer using a back propagation algorithm. Following algorithmic steps describes in detail the approach used for investigating the different parameters and functions in the MATLAB toolbox.

Step 1: A conventional voltage stability algorithm is run with the test system for simulated loading conditions. Using this first the base case and the maximum loading conditions of the test system are determined using the conventional software. Then the load conditions are varied from base case till full load and training samples are generated.

Step 2: Create a database for the input vector in the following form $\left[P_g^T\, Q_g^T\, V_g^T\, P_l^T\, Q_l^T\, V_l^T\right]^T$ where, P_g, Q_g, P_l *and* Q_l are the real and reactive power in generator as well as load buses respectively and V_g *and* V_l are bus voltage at generator and load buses. Further, create target vector in the form of L-indices for the corresponding input vectors.

Step 3: Find the minimum and maximum values of the input vector, remove redundancies and normalize to suit to train the selected feed forward neural network.

Step 4: Select the set of training parameters such as number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

Step 5: Train the network based on a set of transfer functions and number of neurons. The number of neurons in each layer is varied initially and optimum combination is found out depending on the training period and performance error.

Step 6: Find the most suitable combination of the activation function. Behavioral accuracy depends on the uniformity in values of L-indices at all the buses. It can happen that the

network gives output, which is accurate for some buses but may be unacceptable on some others.

Step 7: Change the training function keeping same transfer functions and optimum number of neurons in each layer.

Step 8: Find the most suitable network based on the simplicity least possible Mean Square Error and computational speed. Further use various test functions to confirm the effectiveness of the proposed neural network. At this state the functions and all the parameters are finalized for a particular combination.

A conclusion of the work is: An artificial neural network technique for on line assessment of power system voltage stability using a developed training algorithm for all system buses has been presented with detail steps involved with MATLAB neural network toolbox. Unlike other reported techniques, the main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained artificial neural network at every monitoring period. The stability margin and voltage profile for individual buses, the global stability margin, as well as possible improvement measures of the power system can be assessed at the same time during both normal and contingent situations using the trained ANN. Training and testing results form all cases, including contingencies on a practical power systems network shows that the proposed ANN algorithm is capable to learn and perform as a tool for online voltage stability analysis by measuring the L-indices for all the vulnerable buses.

2.8.3 Development of an Improved On-Line Voltage Stability Index Using Synchronized Phasor Measurement

Most techniques are computationally demanding and cannot be used in an on-line application. A voltage stability index (VSI) can be designed to estimate the distance of the current operating point to the voltage marginally stable point during the system operation. This research work developed a new VSI that not only can detect the system voltage marginally stable point but also is computationally efficient for on-line applications. Starting with deriving a method to predict three types of maximum transferable power of a single source power system, the new VSI is based on the three calculated load margins [37]. In order to apply the VSI to large power systems, a method has been developed to

simplify the large network behind a load bus into a single source and a single transmission line given the synchronized phasor measurements of the power system variables and network parameters. The simplified system model, to which the developed VSI can be applied, preserves the power flow and the voltage of the particular load bus. The proposed voltage stability assessment method, therefore, provides a VSI of each individual load bus and can identify the load bus that is the most vulnerable to voltage collapse.

The developed VSI is a reliable assessment of the voltage stability margin of an individual load and is suitable for on-line implementation for detecting the emerging short-term and long-term voltage instability. The sub-tasks of developing this improved voltage stability index are the following:

- Development of a new computationally efficient load margin assessment method based on synchronized phasor measurements and the power system network topology and parameters.
- Derivation of VSI of individual load buses and the power system based upon the calculated load margin.
- Implementation and testing of the new VSI on various power systems.

The new VSI was tested on three power systems which are BPA 10-bus test system, IEEE 30-bus test case and CIGRE 32-bus test system. Results from these three test cases provided validation of the applicability and accuracy of the proposed VSI.

A conclusion of the work is: Test results of applying the proposed voltage stability assessment method on three power systems have demonstrated that it has the following salient features:

- The proposed method can identify the system voltage marginally stable point with satisfactory accuracy.
- The proposed method provides system voltage security in the format of a load margin that is readable and informative.
- The proposed method can identify the load bus that is the most susceptible to voltage collapse.
- The proposed method is computationally efficient, and can be easily implemented to predict the voltage stability of large power systems in almost real time.

The main contribution of this dissertation is the development of a practical synchronized phasor measurement based voltage stability index that can accurately predict the power system voltage stability with affordable computational demands for on-line applications. The proposed voltage stability assessment method could be incorporated into wide area protection and control systems to monitor the power system voltage stability security. Also, the newly proposed network reduction method enables users to analyze the voltage stability of each load bus and design of distributed control schemes to prevent voltage collapse.

2.9 Power System Control

Given the complexity of the power system and its dynamic phenomena, one would expect that various controls have been developed over time to control various phenomena. These developments have followed the availability of enabling hardware technologies (e.g. electronics, communications, and microprocessors) as well as the evolution of control methodologies.

When a fault (short circuit) occurs, the faulted equipment has to be isolated. A short circuit is characterized by very low voltages and very high currents, which can be detected and the faulted equipment identified. If the fault is on a shunt element, like a generator or a distribution feeder, the relay will isolate it by opening the connecting circuit breakers. If the fault is on a series element, like a transmission line or transformer, the breakers on both sides have to be opened to isolate it. The main characteristic of the protection system is that it operates quickly, often in tens of milliseconds, so as to protect the equipment from damage.

2.9.1 Voltage Control

As is mentioned before, one way to control node voltages is by varying the excitation of the rotating generators. This is done by a feedback control loop that changes the excitation current in the generator to maintain a particular node voltage. This control is very fast.

Another way to control node voltage is to change the tap setting of a transformer connected to the node. Other ways are to switch shunt capacitors or reactors at the nodes.

These changes can be made manually by the operator or automatically by implementing a feedback control that senses the node voltage and activates the control. Unlike the generator excitation control, transformer taps and shunt reactances can only be changed in discrete quantities. Often this type of control schemes has time delays built into them to avoid excessive control actions [38].

More recently power electronic control devices have been introduced in the shunt reactance voltage control schemes. This makes the control much more continuous and often is done it a much faster time frame than the usual shunt switching. These static VAR compensators (SVC) are becoming more common.

As is obvious, voltage control is always a local control. However, controlling the voltage at one node affects the neighboring nodes.

2.9.2 Transmission Power Flow Control

Most power systems have free flowing transmission lines. This means that although power injections and node voltages are controlled quite closely, the power flow on each transmission line is usually not controlled. However, such control is feasible.

A phase shifting transformer can control the power flow across it by changing the phase using taps. This has been used, especially on the Eastern interconnection in North America. The control is local, discrete and slow. A power electronic version of this is now under experimentation.

The major advantage of the AC transmission grid is its free flowing lines with relatively less control and so the wholesale control of every transmission line is not desirable and is not contemplated. However, controls on some lines have always been necessary and some new advantages may be realized in the more deregulated power system when monitoring transactions between buyers and sellers have to be better controlled [39].

2.9.3 Frequency Control

Frequency is controlled by balancing the load with generation. The governors on every generator senses any change in the rotational speed and adjusts the mechanical input power. This governor control is the primary control for maintaining frequency. A secondary control to set the governor set-points is used to ensure that the steady state always returns to

nominal. The governor control is local at the generator and fast. The secondary control is done over the whole system. This secondary control is done by the central controller and is slow. This control is also known as Automatic Generation Control (AGC) or Load Frequency Control (LFC) [38].

As the deviation of frequency from nominal is a symptom of the imbalance between generation and load, the frequency control performance requirement depends on how well one wants to control the power supply commitments made between seller and buyer.

2.9.4 Control Center

As mentioned in the above sections most of the controls are local. The only area wide control is the secondary frequency control or AGC. This is implemented as a feedback control loop in which the generator outputs and tie-line flows are measured and brought back to the control center and the governor control set-points are calculated and sent out to the generators from the control center. The data rate – both input and output – is between 2 and 4 seconds.

The control center performs many other functions although AGC is the only automatic feedback control function. The main function is real time data acquisition from all over the grid so that the operator can monitor its operation. Another is the manual operation of controls like opening or closing circuit breakers, changing transformer taps, etc. These functions are jointly known as the Supervisory Control and Data Acquisition (SCADA) and the control center is often referred to as SCADA.

A control center energy management system (EMS) generally consists of four major elements as shown in figure 2.6 [39]:

- The supervisory control and data acquisition (SCADA) system
- The automatic generation control (AGC) system
- The energy management applications and database
- The user interface (UI) system.

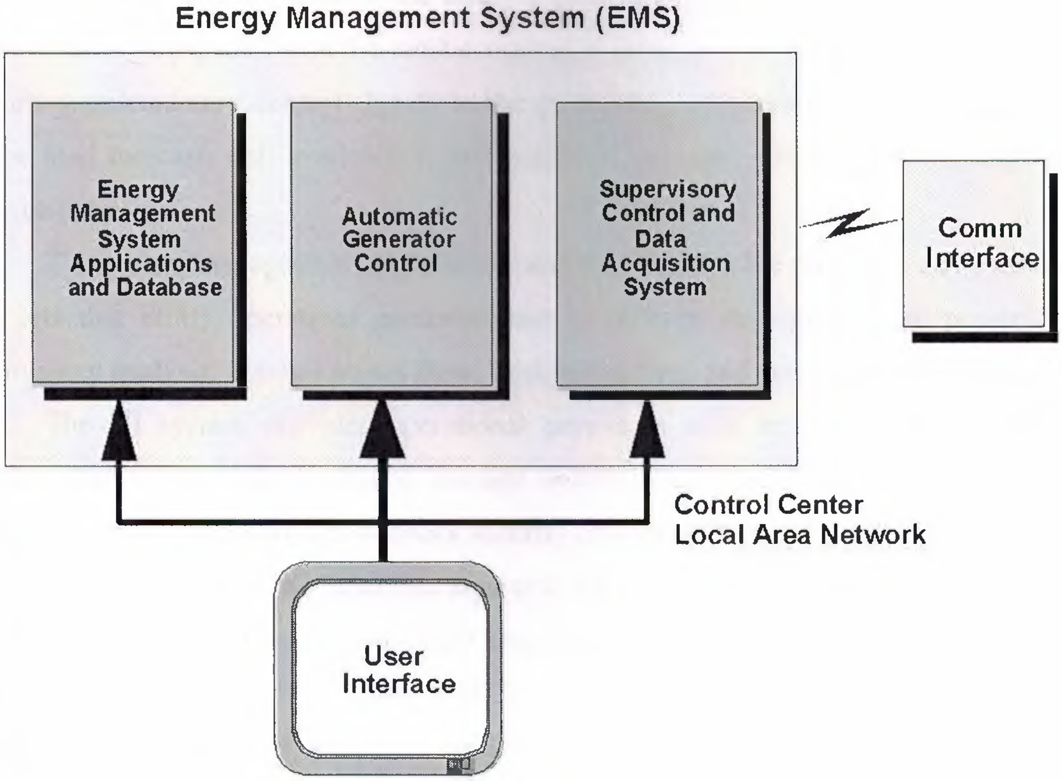


Figure 2.6 Elements of the Control Center Energy Management System

The SCADA system manages the RTU communications, collects the electric system data from the field through a series of front-end processors, initiates alarms to the operations personnel, and issues control commands to the field as directed by the applications in the control center system. The SCADA system typically consists of a host or master computer, one or more field data-gathering and control units (RTUs), and a collection of standard and/or custom software used to monitor and control remote field data elements. SCADA systems may have 30,000 to 50,000 data collection points and may transmit analog information (e.g., generator megawatts) as well as digital or status information (e.g., breaker open/close state). SCADA systems can also send a control signal (e.g., start a pump) as well as receive a status input as feedback to the control operation (e.g., the pump is started). Current computing power allows SCADA systems to perform complex sequencing operations and provides for frequent collection (e.g., every 2 seconds) of power system data.

The AGC system controls the utility's generating units to ensure that the optimal system load is being met, with the most economical generation available. The AGC system submits supplementary control signals to the generating units to adjust their output based on the load forecast, unit availability, unit response rate, and scheduled interchange with other utilities.

The energy management applications and database are the programs and associated data sets that utility operations personnel use to manage state estimation, power flow, contingency analysis, optimal power flow, load forecasting, and generation unit allocation.

The UI system provides operational personnel with an interactive interface to monitor electric system performance, manage system alarm conditions, and study potential system conditions to ensure that network security criteria are met.

These SCADA-AGC functions at central control centers evolved in the earlier part of the last century but in the 60s their implementation was accomplished with digital computers. Remote terminal units (RTU) were positioned in every substation and generating station to gather local data and this data was then transmitted from the RTUs to the control center over communication lines, usually microwave channels but sometimes telephone lines. This scheme is shown in Figure 2.7. The data normally includes the switching statuses (on/off) of all the circuit breakers as well as the current values and voltages of complex power. Although these control centers are quite separate from other computer systems, it does accumulate a large set of historical data that can be utilized for various engineering study and analysis. Thus it is quite common to have a network connection to third party (usually engineering) computers [38].

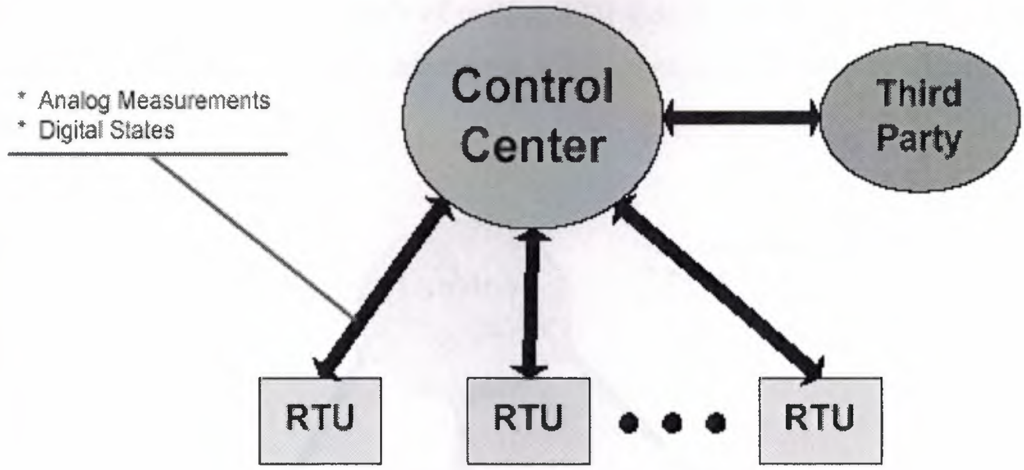


Figure 2.7 The Control Center has Direct Communication Channels to The RTUs at each Substation and Generating Station

As the computational power of the control centers grew, more functions have been added to the control centers. The main one has been the state estimator which calculates the real time steady state model of the network. This real time model can then be used for two kinds of calculations.

One, known as security analysis, can study the effects of disturbances (contingencies) and can alert the operator if the post-contingency conditions violate limits. The other, usually using a family of analysis known as optimal power flow, can suggest better operational conditions. All these analytical tools provide better operational guidance to the operator than the old SCADA systems could and are now known as Energy Management Systems (EMS).

Another recent trend has been the increasing use of microprocessors and faster communication within the substations to gather more real time data. This data gathered at the few milliseconds rate is stored at the substations but is too voluminous as yet to be broadcast. Instead certain sequences of this data – say, after an emergency or disturbance – are then imported, increasingly, over some sort of network and then used for study purposes. This is shown in Figure 2.8 What this means is that data is now being measured and gathered at the substations at a much faster rate than can be communicated to the

control center which is only capable of polling RTU data at the rate of a few seconds. The excess data can be recorded at the substations and for now is gathered only after the fact for studies [38].

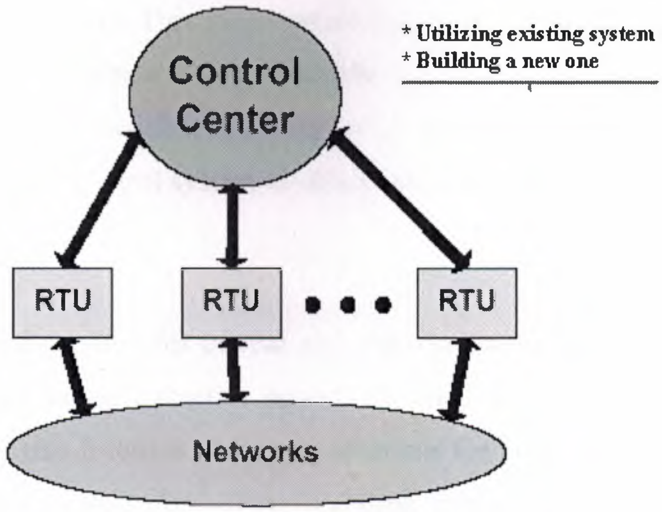


Figure 2.8 The RTUs has Direct Communication Channels with The Control Center and with Networks

Power system control can then be summarized as follows [39]:

- Most automatic controls are local.
- At the generator there is the governor control of generator output, the exciter control of generator terminal voltage and sometimes, power system stabilizer (PSS) control. These are continuous fast feedback control.
- Node voltages can also be controlled by transformer taps and shunt reactances. These are slow discrete controls but new continuous fast static VAR compensators (SVC) are becoming available for use.
- Where DC transmission is used, fast continuous control of line flow is available and new tools to do so on AC lines are becoming available. Slow controls using phase shifting transformers are still being used in a few places.

- Protective relays that isolate faulted equipment operate locally but are very fast. With communication from other parts of the network, they have great potential for fast control.
- The secondary frequency control of generator governor set-points is the only area wide control used today. This slow control implemented through the central control center is discrete at the rate of a few seconds.
- Much more data at very fast rates are being gathered at the substations but the communication and control system to utilize this data for faster controls is lacking.

2.10 Summary

This chapter introduced the transfer of real and reactive power through the transmission system and sources and sinks of reactive power, and then discussed voltage stability and voltage collapse. After that it introduced many solutions for voltage instability or collapse and some related research work for voltage stability. Finally it explained the control of power system. Part of these solutions will be used to enhance the voltage drop of PDS and to restore voltage stability in the intelligent voltage stabilizer in the last chapter.

CHAPTER THREE

ARTIFICIAL NEURAL NETWORKS

3.1 Overview

Neural networks emerged about 50 years ago. Their early abilities were exaggerated, casting doubts on the field as a whole. There is a recent renewed interest in the field, however, because of new techniques and a better theoretical understanding of their capabilities.

The basic concepts of artificial neural networks (ANN) will be explained in this chapter in addition to back propagation algorithm which will be used in our work for instability detection. Also, this chapter will describe real life applications of prediction ANN and uses of ANN in Electrical Power Systems.

3.2 Introduction to ANN

Neural networks have seen an explosion of interest over the last few years, and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology and physics. Indeed, anywhere that there are problems of prediction, classification or control, neural networks are being introduced. This sweeping success can be attributed to a few key factors:

- **Power.** Neural networks are very sophisticated modeling techniques capable of modeling extremely complex functions. In particular, neural networks are nonlinear. For many years linear modeling has been the commonly used technique in most modeling domains since linear models have well-known optimization strategies. Where the linear approximation was not valid the models suffered accordingly. Neural networks also keep in check the curse of dimensionality problem that bedevils attempts to model nonlinear functions with large numbers of variables.
- **Ease of use.** Neural networks learn by example. The neural network user gathers representative data, and then invokes training algorithms to automatically learn the structure of the data. Although the user does need to have some heuristic knowledge of how to select and prepare data, how to select an appropriate neural network, and how to interpret

the results, the level of user knowledge needed to successfully apply neural networks is much lower than would be the case using some more traditional nonlinear statistical methods.

Neural networks can be divided into three architectures, namely single layer, multilayer network and competitive layer. The number of layers in a net is defined based on the number of interconnected weight in the neuron. Single layer network consists only one layer of connection weights. Whereas, multilayer networks consists of more than one layer of connection weights. The network also consists of additional layer called hidden layer. Multilayer networks can be used to solve more complicated problems compared to single layer network. Both of the network are also called feed-forward network where the signal flows from the input units to the output units in a forward direction. The competitive layer network, for example the Recurrent Networks is a feedback network where there are closed-loop signal from a unit back to itself.

3.3 Learning in Neural Networks

Assume there are n input units, $X_1,\ldots, X_n$ with input signals $x_1,\ldots, x_n$. When the network receives the signals (x_i) from input units (X_i), the net input to output (Y_j) is calculated by summing the weighted input signals. The matrix multiplication method for calculating the net input is shown in the equation below.

$$u_j = \sum_{i=1}^{n} W_i X_i$$

where, w_{ij} is the connection weights of input unit x_i and output unit y_j.

The network output (y_i) is calculated using the activation function $f(x)$. In which $y_i = f(x)$, where x is u_j. The computed weight from the training is stored and will become the information or knowledge for the future application.

Neural networks learning algorithms can be divided into two main groups that are supervised (or associative learning) and unsupervised (self-organization) learning. Many supervised and unsupervised learning ANN have been invented.

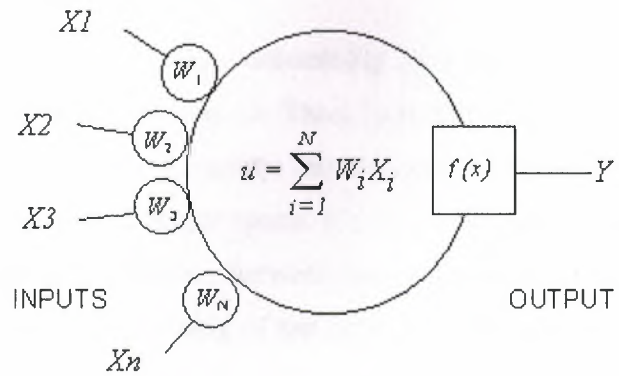


Figure 3.1 Weight of Perceptron

3.3.1 Supervised Learning

Supervised learning is based on the target value or the desired outputs. During training the network tries to match the outputs with the desired target values. This method has two sub varieties called auto-associative and hetero-associative. In auto-associative learning, the target values are the same as the inputs, whereas in hetero-associative learning, the targets are generally different from the inputs.

One of the most commonly used supervised ANN model is back propagation network that uses back propagation learning algorithm. Back propagation of errors or generalized delta rule is a decent method to minimize the total squared error of the output computed by the net.

3.3.2 Unsupervised Learning

Unsupervised learning method is not given any target value. A desired output of the network is unknown. During training the network performs some kind of data compression such as dimensionality reduction or clustering. The network learns the distribution of patterns and makes a classification of that pattern where, similar patterns are assigned to the same output cluster. Kohonen network is the best example of unsupervised learning network. Kohonen network refers to three types of networks that are Vector Quantization, Self-Organizing Map and Learning Vector Quantization.

3.3.3 Training the Network

Training the network could be time consuming. It usually learns after several epochs, depending on how large the network is. Thus, large network required more training time compared to the smaller one. Basically, the network is trained for several epochs and stopped after reaching the maximum epoch. For the same reason minimum error tolerance is used provided that the difference between network output and known outcome is less than the specified value. The training of the network could also stop after meeting certain stopping criteria [40].

3.4 Back Propagation Algorithm

3.4.1 Back Propagation Neural Networks

Back Propagation (BP), a euphemism for the generalized delta rule including momentum, is a supervised learning algorithm that applies to non-linear, multilayer; feed forward structure of nodes (networks). It works on minimizing the Mean Square Error (MSE) of the network.

The architecture of a BP network refers to the way it decodes information, that is the direction of information during recall. In a BP neural network the nodes are organized in input, hidden, and output layers, as in Figure 3.2.

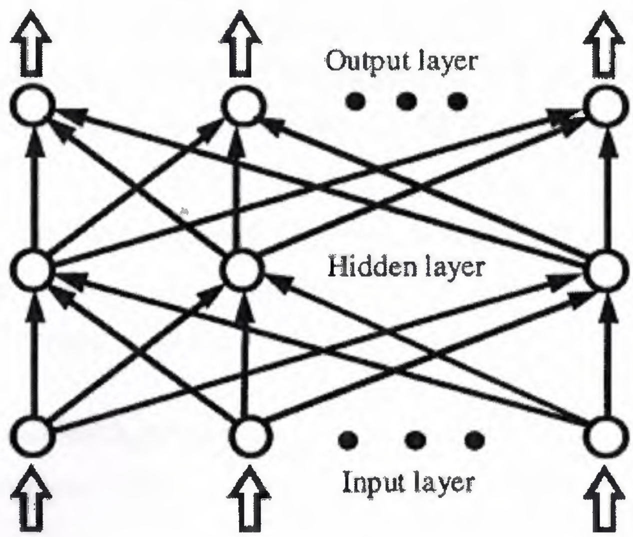


Figure 3.2 Back Propagation Neural Network [41]

3.5.2 Training BP Networks

Training of a BP neural network is achieved by presenting inputs to the network with the desired outputs. The network processes the inputs into its own simulated outputs. Input layer neurons receive the data to be processed by the network and the output layer holds the global computation results. One or more hidden layers may be present depending on problem complexity but quite often one layer suffices. All neurons within the input layer are connected to all neurons of the first hidden layer. These are subsequently connected to all neurons of the second hidden layer, if one is present, or to the neurons of the output layer. A weighting factor is associated with each connection. The same process is repeated with all adjacent hidden layers until the input layer is reached. At that moment all synaptic weights are updated. As neural networks are trained on sample data, these should be of high quality and representative of the domain [42].

The weight change rule is a development of the perceptron learning rule. Weights are changed by an amount proportional to the error at that unit times the output of the unit feeding into the weight. Running the network consists of:

- Forward pass:

  The outputs are calculated and the error at the output units calculated.

- Backward pass:

  The output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

For each data pair to be learned a forward pass and backwards pass is performed. This is repeated over and over again until the error is at a low enough level or the process reach the maximum number of epochs.

3.5.3 Mathematical Approach

Step 0: Initialize weights: to small random values (-1.0 → +1.0);

Step 1: Apply a sample: apply to the input a sample vector u_k having desired output vector y_k ;

Step 2: Forward Phase:

Starting from the first hidden layer and propagating towards the output layer:

2.1. Calculate the activation values for the units at layer L as:

2.1.1. If L-1 is the input layer

$$a_{h_L}^{k} = \sum_{j=0}^{N} W_{jh_L} u_j^k$$

2.1.2. If L-1 is a hidden layer

$$a_{h_L}^{k} = \sum_{j_{L-1}=0}^{N} W_{j_{(L-1)}h_L} x_{j_{(L-1)}h_L}^{k}$$

2.2. Calculate the output values for the units at layer L as:

$$x_{h_L}^{k} = f\,(a_{h_L}^{k})$$

in which use i_o instead of h_L if it is an output layer

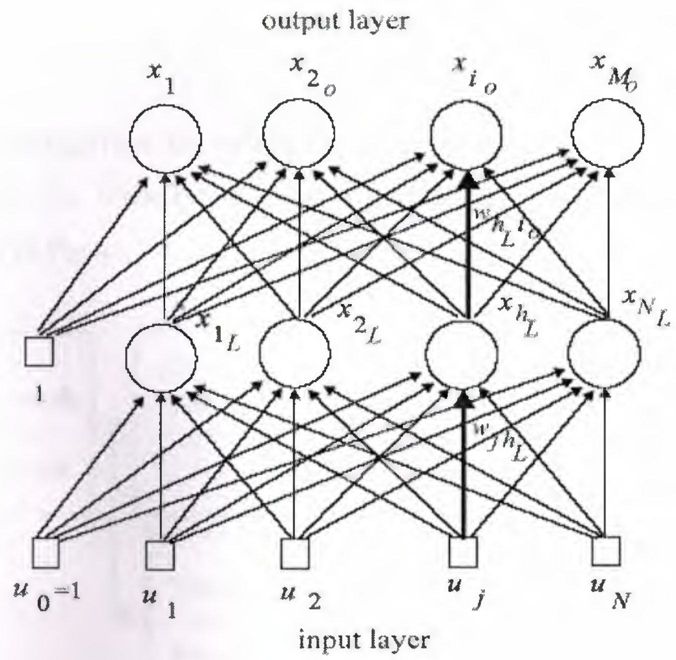


Figure 3.3 Multilayer BP Network [43]

Step 3: Output errors: Calculate the error terms at the output layer as:

$$\delta_{i_o}^k = (y_{i_o}^k - x_{i_o}^k) f_o^{'}(a_{i_o}^k)$$

Step 4: Backward Phase Propagate error backward to the input layer through each layer L using the error term

$$\delta_{h_L}^k = f_L^{'}(a_{h_L}^k) \sum_{i_{L+1}=1}^{N_{L+1}} \delta_{i_{(L+1)}}^k w_{h_L i_{(L+1)}}^k$$

in which, use i_o instead of $i_{(L+1)}$ if $(L+1)$ is an output layer;

Step 5: Weight update: Update weights according to the formula

$$w_{j_{(L-1)} h_L}(t+1) = w_{j_{(L-1)} h_L}(t) + \eta \delta_{h_L}^k x_{j_{(L-1)}}^k$$

Step 6: Repeat steps 1-6 until the stop criterion is satisfied, which may be chosen as the mean of the total error

$$< e^k > = < \tfrac{1}{2} \sum_{i_o=1}^{M} (y_{i_o}^k - x_{i_o}^k)^2 >$$

is sufficiently small [43].

3.5.4 Back Propagation Algorithm Block Diagram

The block diagram of the Back Propagation Algorithm consists from several processing blocks as it is shown in Figure 3.4.

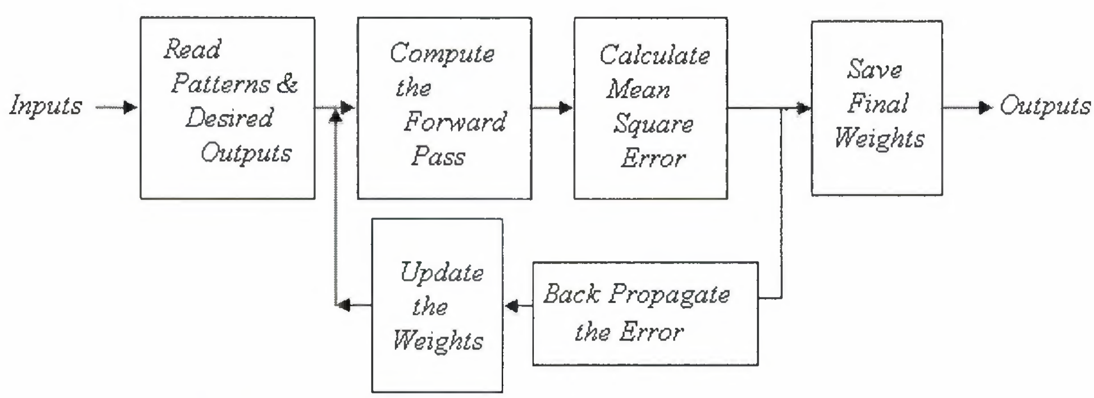


Figure 3.4 Back Propagation Algorithm Block Diagram

3.5 Applications of ANNs

The main applications of ANNs are for signal processing and pattern recognition. The algorithmic treatment represents a combination of mathematical theory and heuristic justification for neural models. The ultimate objective is the implementation of digital neuro-computers, embracing technologies of VLSI, adaptive, digital and parallel processing.

From an application driven perspective, one can see that the strength of neural networks are nonlinear, adaptive and parallel processing. Neural networks have found many successful applications in computer vision, signal/image processing, speech/character recognition, expert systems, medical image analysis, remote sensing, robotic processing, industrial inspection, and scientific exploration. The application domains of neural nets can be roughly divided into the following categories: association, clustering, classifications, pattern completion, regression and generalization, and optimization [44].

Table 3.1 summarizes the different types of ANNs and their potential applications.

Table 3.1 ANNs Selector and Their Applications [45]

Analytical Technique	Tools	Applications	
Associations, sequential patterns	statistics	Marketing:	market basket analysis
Pattern recognition	statistics, neural networks, machine induction	Security:	number plates, fingerprints
		Computing & telecomms.:	speech, vision and handwriting
		Finance:	signature and bank note verification
		Engineering:	product inspection, maintenance inspections
Clustering	neural networks, statistics	Marketing:	market segmentation
		Energy:	mineral exploration
		Engineering:	design reuse
Classification	machine induction, neural networks	Marketing:	target marketing
		Defense:	radar images
		Food & Ag.:	fruit, catch and livestock grading
		Medicine:	ultrasound and ECG images, lab. diagnosis, psychiatric care, illness severity
		Comp. & telecoms:	OCR, computer virus detection
		Finance:	risk assessment, bond rating, fraud detection
		Engineering:	quality control
Modeling	regression (curve fitting), neural networks	Marketing:	ranking/scoring customers, pricing models
		Security:	fingerprint matching
		Finance:	bankruptcy prediction, property valuation
		Engineering:	process control
Forecasting	statistics, neural networks	Marketing:	sales, business demand, holiday preferences
		Meteorology:	weather prediction
		Food & Ag.	crop yields
		Finance:	forex rate prediction, stock market changes
		Engineering:	inventory control, power demand prediction
Constraint satisfaction	linear programming, neural networks, genetic algorithms, AI planning, CLP	Engineering:	Job shop and stock route scheduling

3.6 Using ANNs in Power Systems

A prototype network is used to control operations of a power system that was so successful at optimizing large synchronous generators and load flow. Also, neural networks can organize the distribution of supplied electrical power between many power stations connected in grid. The rating capacity of each station and the main demand consumers are inputs of the net. As the demand changes during a day the output of the network is the amount of electrical power that each station should supply as percentage of its rating [43].

3.6.1 A Review of Applications of ANNs in Power Systems

This part is an overview of application of ANNs in power system operation and control. The comparison of the number of published papers in IEEE proceedings and conference papers in this field during 1990-1996 with them during 2000-2005 has showed that the following fields has attracted the most attention in the past five years [46]:

1- load forecasting

2- fault diagnosis/fault location

3- economic dispatch

4- security assessment

5- transient stability

Table 3.2 summarizes the number of published papers about application of ANNs in power system operation and control topics in two time intervals [46]. The first time interval is from 1990 to 1996, while the second one is from 2000 to 2005. These papers are published in IEEE proceedings and conferences. It seems that the comparison of two columns can be used as a proof of successful or unsuccessful operation of NN in related power system operation field. Figure 3.8 shows the percentage of the number of published papers during 2000-2005 in a circle form [46]. This figure shows that some fields such as load forecasting fault diagnosis/fault location, economic dispatch, security assessment and transient stability.

Table 3.2 ANNs in Power Systems – Survey of Papers 1990-1996 and 2000-April 2005

Power System Subject	No. of Published Papers from 1990 to 1996 using ANN	No. of Published Papers from 2000 to April 2005 using ANN
Planning		
- Expansion		
Generation	-	1
Transmission	-	1
Distribution	-	-
- Structural : Reactive power	1	-
- Reliability	-	1
Operation		
1. Plant		
- Generation Scheduling	-	4
- Economic Dispatch ODF	1	14
- Unit Commitment	-	-
- Reactive Power Dispatch	1	1
- Voltage Control	4	3
- Security Assessment		
Static	7	3
Dynamic	6	9
- Maintenance Scheduling	3	1
- Contract Management	-	-
- Equipment Monitoring	4	3
2. System		
- Load Forecasting	12	23
- Load Management	-	-
- Alarm Processing/Fault Diagnoses	13	20
- Service Restoration	-	2
- Network Switching	-	-
- Contingency Analysis	1	2
- Facts	-	-
- State Estimation	4	2
Analysis & Modeling		
- Power Flow	4	4
- Harmonics	-	3
- Transient Stability	5	9
- Dynamic Stability/Control Design	13	7
- Simulation/Operations	-	1
- Protection	7	4

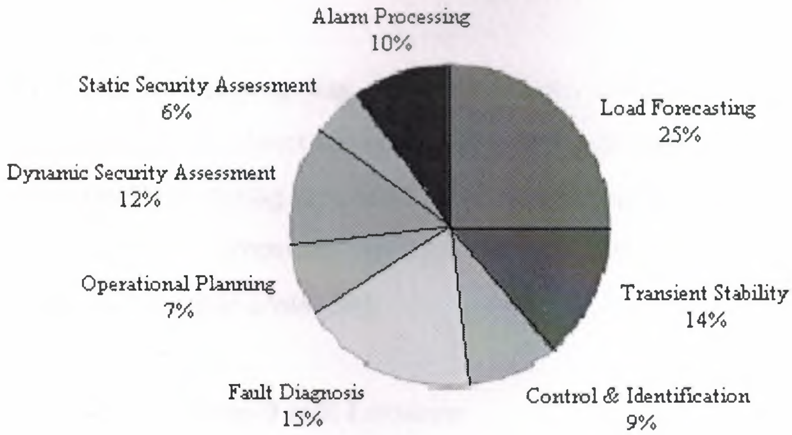


Figure 3.5 Neural Network Applications in Power Systems; 2000 – April 2005

3.6.2 Various ANNs Applications in Power System Subjects

Applications of ANNs in electrical power system are wide. The purpose of this section is to explore how the ANNs techniques are utilized in power systems especially in load forecasting, fault diagnosis or location, economic dispatch and security assessment.

3.6.2.1 Load Forecasting

Commonly and popular problem that has an important role in economic, financial, development, expansion and planning is load forecasting of power systems. Generally most of the papers and projects in this area are categorized into three groups:

• Short-term load forecasting over an interval ranging from an hour to a week is important for various applications such as unit commitment, economic dispatch, energy transfer scheduling and real time control. A lot of studies have been done for using of short-term load forecasting with different methods [47-52]. Some of these methods have main limitations such as neglecting of some forecasting attribute condition, difficulty to find functional relationship between all attribute variable and instantaneous load demand, difficulty to upgrade the set of rules that govern at expert system and disability to adjust themselves with rapid nonlinear system-load changes.

The ANNs can be used to solve these problems. Most of the projects using ANNs have considered many factors such as weather condition, holidays, weekends and special

sport matches days in forecasting model, successfully. This is because of learning ability of ANNs with many input factors.

• Mid-term load forecasting that range from one month to five years, used to purchase enough fuel for power plants after electricity tariffs are calculated [53].

• Long-term load forecasting covering from 5 to 20 years or more, used by planning engineers and economists to determine the type and the size of generating plants that minimize both fixed and variable costs [54].

3.6.2.2 Fault Diagnosis/Fault Location

Progress in the areas of communication and digital technology has increased the amount of information available at supervisory control and data acquisition (SCADA) systems [55, 56]. Although information is very useful, during events that cause outages, the operator may be overwhelmed by the excessive number of simultaneously operating alarms, which increases the time required for identifying the main outage cause and to start the restoration process. Besides, factors such as stress and inexperience can affect the operator's performance; thus, the availability of a tool to support the real-time decision-making process is welcome. The protection devices are responsible for detecting the occurrence of a fault, and when necessary, they send trip signals to circuit breakers (CBs) in order to isolate the defective part of the system. However, when relays or CBs do not work properly, larger parts of the system may be disconnected. After such events, in order to avoid damages to energy distribution utilities and consumers, it is essential to restore the system as soon as possible [57].

Nevertheless, before starting the restoration, it is necessary to identify the event that caused the sequence of alarms such as protection system failure, defects in communication channels, corrupted data acquisition [58].

The heuristic nature of the reasoning involved in the operator's analysis and the absence of an analytical formulation, leads to the use of artificial intelligence techniques. Expert systems, neural networks, fuzzy logic, genetic algorithms (GAs), and Petri nets constitute the principal techniques applied to the fault diagnosis problem [59].

From Table 3.2, it is seen that the major effort to detect and rectify power system faults in 90's, concentrate on expert system methods. Its main defect is the incapacity of

generalization and the difficulty of validating and maintaining large rule-bases. Recently, using model-based systems including temporal characteristics of protection schemes based on expert systems and ANNs developed.

The main advantage of neural network is its flexibility with noisy data and its main drawback is long time required for training feed forward network with back propagation training algorithm, especially when dimension of the power network is high. To short the training time using these substitute methods proposed: the general regression neural network (GRNN) in feed forward topology, the probabilistic neural network (PNN), adaptive neuro-fuzzy methods and the selective back propagation algorithm [60].

3.6.2.3 Economic Dispatch

Main goal of economic dispatch (ED) consists of minimizing the operating costs depending on demand and subject to certain constraints, i.e. how to allocate the required load demand between the available generation units [61, 62]. In practice, the whole of the unit operating range is not always available for load allocation due to physical operation limitations.

Several methods have been used in past for solving economic dispatch problems including Lagrangian relaxation method, linear programming (LP) techniques specially dynamic programming (DP), Beale's quadratic programming, Newton-Raphson's economic method, Lagrangian augmented function, and recently Genetic algorithms and ANNs. Because of, economic dispatch problem becomes a non-convex optimization problem, the Lagrangian multiplier method, which is commonly used in ED problems; can not to be directly applied any longer. Dynamic programming approach is one of the widely employed methods but for a practical-sized system, the fine step size and the large units number often cause the 'curse of dimensionality'.

Main drawbacks of genetic algorithm and tabu search for ED are difficulty to define the fitness function, find the several sub-optimum solutions without guaranty that this solution isn't locally and longer search time [46].

Neural networks and specially the Hopfield model, have a well-demonstrated capability of solving combinational optimization problem. This model has been employed to solve the conventional ED problems for units with continuous or piecewise quadratic fuel cost functions. Because of this network's capability to consider all constrained

limitation such as transmission line loss and transmission capability limitations, penalty factor when we have special units, control the unit's pollutions and etc., caused increasing the paper proposed recently [46].

3.6.2.4 Security Assessment

The principle task of an electric power system is to deliver the power requested by the customers, without exceeding acceptable voltage and frequency limits. This task has to be solved in real time and in safe, reliable and economical manner.

Generally there are two types of security assessments: static security assessment and dynamic security assessment [63 - 67]. In both types different operational states are defined as follows:

- Normal or secure state: In the normal state, all customer demands are met and operating limit is within presented limits.
- Alert or critical state: In this state the system variables are still within limits and constrain are satisfied, but little disturbance can lead to variable toward instability.
- Emergency or insecure state: the power system enters the emergency mode of operation upon violation of security related inequality constraints.

In practical power systems the dimension of the operating system is very high. To overcome this "curse of high dimensionality", three main approaches can be followed:

- Restrict the number of contingences and characterization of the security boundaries. This is for example done with supervised ANNs like MLP.
- Reduce the dimension of the operating vector; this is for example done with unsupervised ANNs like Oja-Sanger networks.
- Quantify of the operating point into a reduced number of classes, this is done with clustering algorithms for instance the nearest neighbor or the k-means clustering algorithms.

Commonly ANN that satisfies these conditions is multilayered Perceptron (MLP) with back propagation learning algorithm. The reason for this is on-line learning capability.

There are two problems with using MLP, selecting of input data and overtraining. A good method for first problem is using some of the security indicators presently calculated by the energy management system (EMS) as inputs to the ANN [68].

3.7 Summary

This chapter introduced the main concepts of artificial neural networks, and then introduced the concepts of the back propagation learning algorithm that will be implemented in our intelligent system. Much of concern in this chapter was directed to the applications of ANNs in electrical power systems. As a summary, it is convenient to apply ANN for instability and overload detection as part of an intelligent system next chapter.

CHAPTER FOUR
INTELLIGENT DETECTION OF INSTABILITY OF POWER DISTRIBUTION SYSTEMS

4.1 Overview

Voltage stability problems have been one of the major concerns for electric utilities as a result of system heavy loading. This chapter reports on an investigation into the application of artificial neural network (ANN) in on-line voltage instability detection. A discussion over the efficiency of the proposed techniques is also included.

4.2 Problem Analysis and Solution

Power systems may face some events like blackouts as a result of faults on some parts of the system or like getting overloaded which makes some loads switch off as a result of extreme voltage drop. These events mostly force the system to go to instability. As mentioned before our concern is on the stability of distribution substations which is one of the main parts of stability of the whole power system. Remote terminal units (RTU) which is part of SCADA can record RMS of voltages and the currents of the three phases with respect to time as curves all the time including unusual events.

The hypothesis which is presented within this thesis suggests that these graphs of unusual events during a year can be taken and sampled to a fixed number of samples. Voltage samples are normalized and then vectorized to be used as inputs to the neural network to train it for detecting events that may happen in future.

The neural network will have three outputs: stable case, unstable case or overload case. The next procedure is to arrange solutions to the system for the unstable and overload cases which will be discussed in the next chapter.

The neural network is used in this work to substitute the human monitor in the control center of the power system. It also works as another support for decision to help preventing voltage instability in case of late reaction from control center after a disturbance

risk. It uses the images of the three phase voltages as human monitor watching curves of three phase voltages and currents on monitor screen.

4.2.1 Data Acquisition

In our work as lack of recorded data, a power system is proposed which is the BPA test case study with some modification as seen in Figure 4.1. This proposed power system is simulated in computer using ready blocks in powerlib in MATLAB. Our concern is on the transient stability of one distribution power station which in our case is substation number 7 in the system. The the voltages of load 7 are taken as outputs of the circuit after simulation of 20 seconds.

Ordinary faults are induced on the generation station or on transmission grid of the system for a short time (2-3 seconds) then recovered and their effect is recorded on load 7 in order to simulate unstable cases. Also, one of the generators is switched off during simulation in different times and their effect is recorded on load 7. In another way, large additional loads are added to load 7 in different times to force the substation 7 to be overloaded and the terminal voltage is lowered to less than 95% of nominal voltage which outputs overload case. In the same manner, small additional loads are added or subtracted from load 7 in different times to simulate normally loaded system which makes the terminal voltage is higher than 95% of nominal voltage, and also the effect is recorded to register stable case.

These outputs are graphs of the sinusoidal waves of voltage during the twenty seconds of simulation. For every second on the graph there are 50 full waves, which make them concentrated and appear like a block. With visual inspection of these graphs, the upper level of these waves will be considered as the output with respect to time as from RTU in SCADA devices.

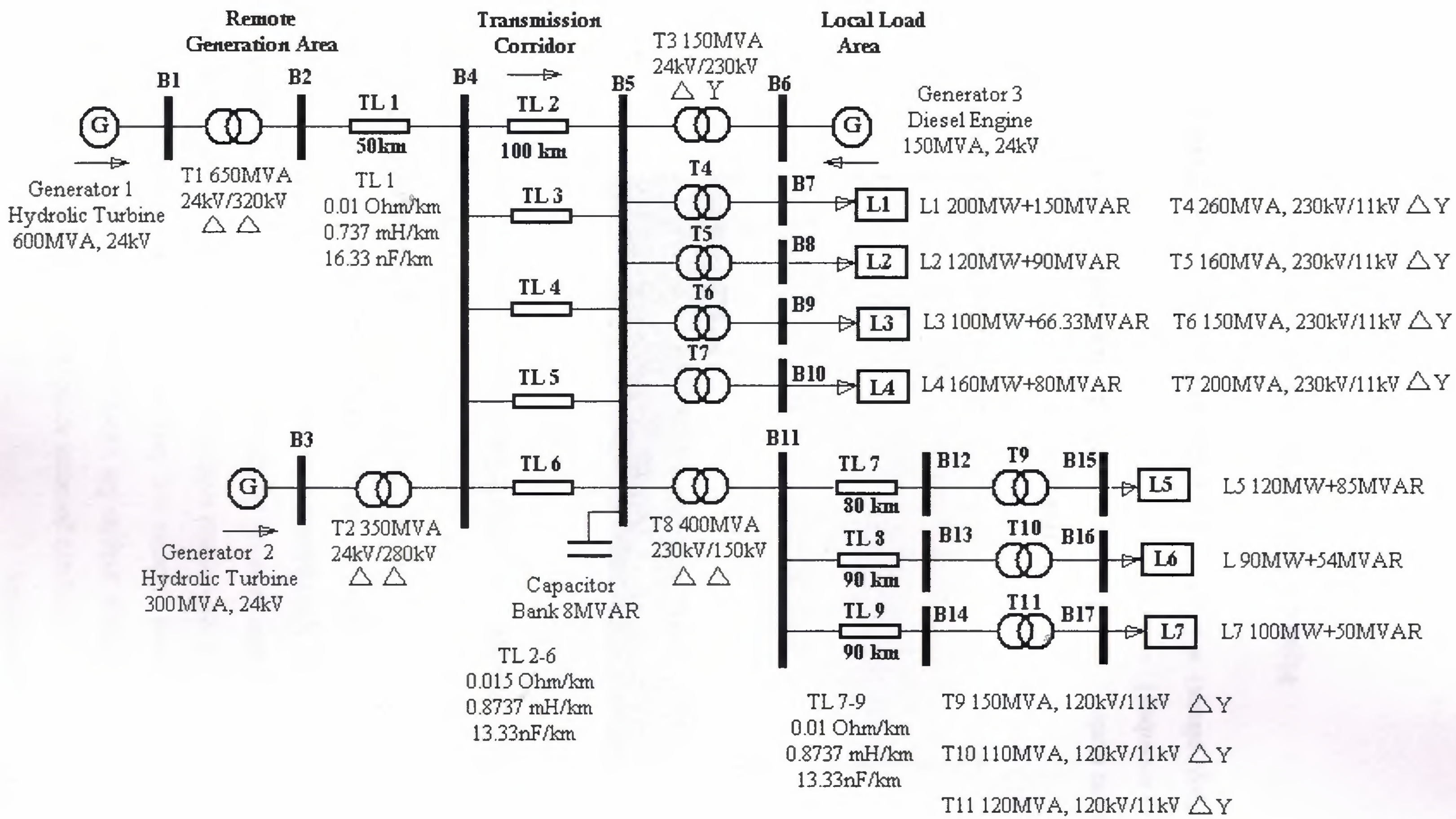


Figure 4.1 One Line Diagram of Test Case System

4.2.2 Patterns Preparation

The following steps are executed to prepare patterns to be inputs to the neural network.

First Step: The output voltage graphs for every case from simulation are extracted and saved as digital images. These images are denoted with three subscribes. The first subscribe (i) represents the case of the system with (i = 1-3), where 1 represents stable state of the system, 2 represents unstable state of the system and 3 represents overload state of the system. The second subscribe (j) represents the number of the case which with (j = 1-18). The third subscribe (k) represent the phase voltage with (k = 1-3), where 1 is for voltage on phase A, 2 is for voltage of phase B and 3 is for voltage on phase C. The size of every image is 500 x 840 pixels. Figure 4.2 shows an example of denoting one voltage graph, whereas figure 4.3 illustrates one example for the three images for every case.

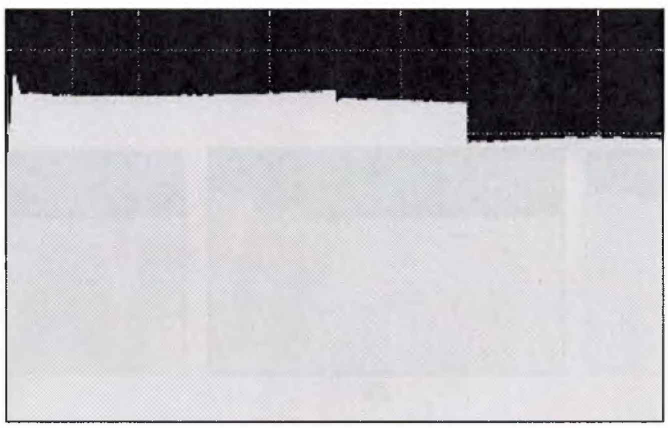


image i_j_k

i (system state) = 1,2,3 1 = stable, 2 = unstable, 3 = overload

j (case number) = 1 - 18

k (voltage phase) = 1,2,3 1 = phase a, 2 = phase b, 3 = phase c

Figure 4.2 Image Data Base Denotion

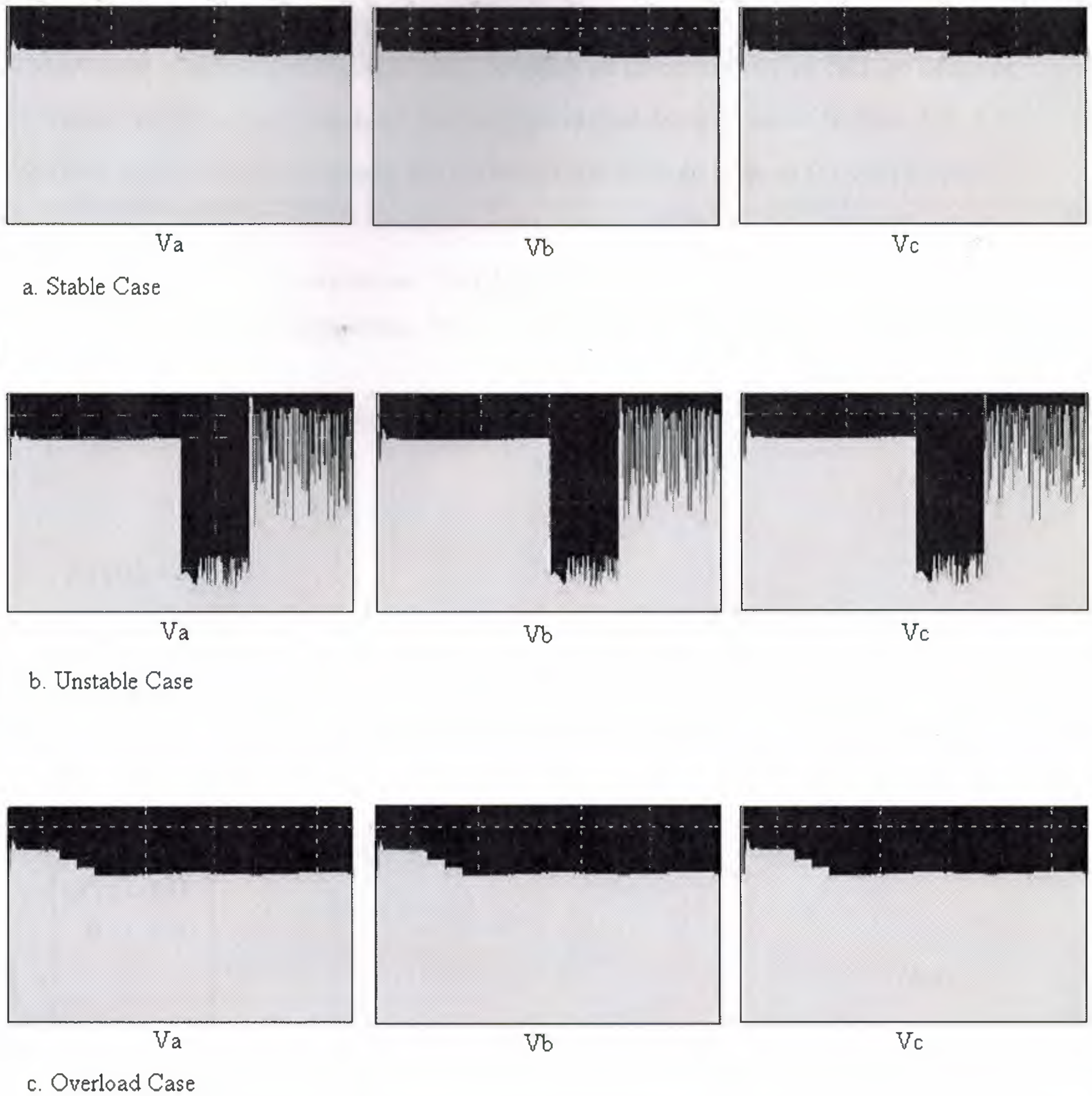


Figure 4.3 Examples of Training Cases

Second Step: Every image is converted to gray then resized to 400x202 pixels.

Third Step: In every image and for every column starting from column 2 to column 201 and from last row going up the value of the pixel, where the first discontinuity or change is found, the number of this row is saved in a vector. This saved value represents the highest value of the voltage of that column in that image. As a result 200 values are saved for every image. Equation 4.1 shows the general form of the vector and equations

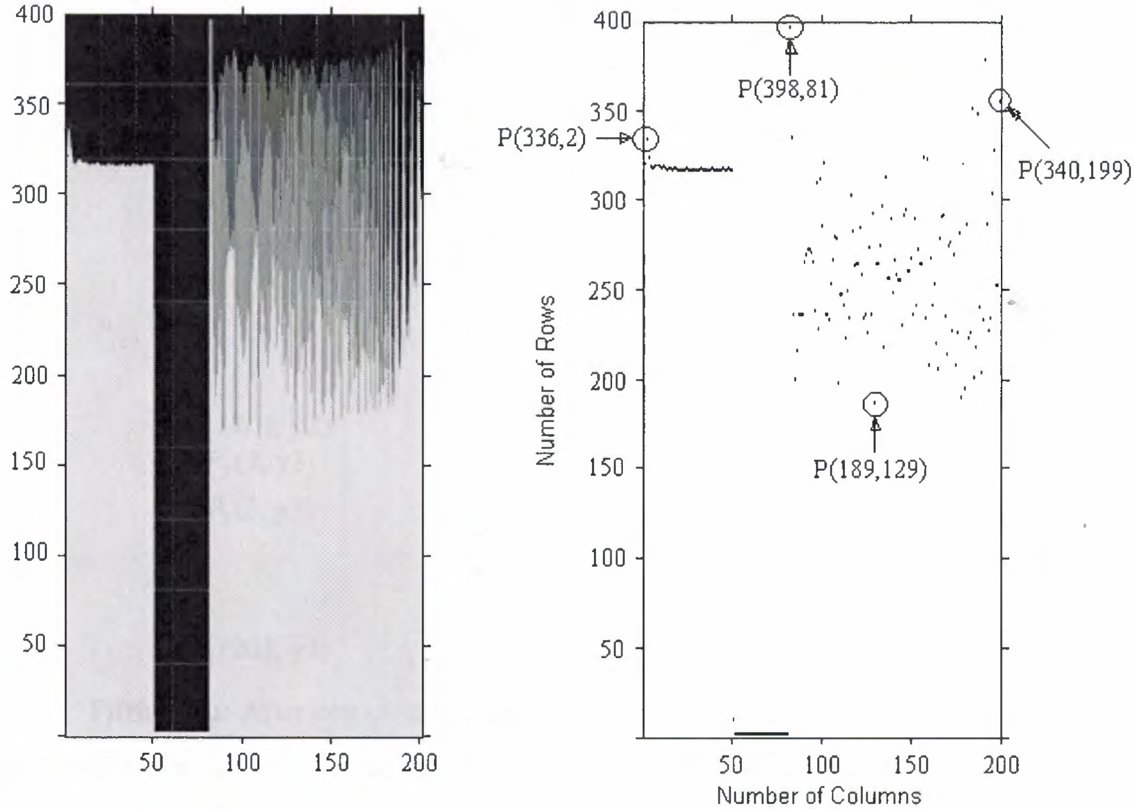
4.2, 4.3, and 4.4 show the form of the vector for image voltage a, b, and c respectively. Figure 4.4 shows one example of finding pixel position of discontinuity or change of color or in other words the maximum value of the voltage in that image, while figures 4.5, 4.6, and 4.7 introduce examples on extracting the curves of the voltage images for every case.

$$P_k = [P_k(x, y)] \qquad \begin{Bmatrix} x \text{ is any value from } 2 \rightarrow 201 \\ y \text{ is any value from } 1 \rightarrow 400 \end{Bmatrix} \tag{4.1}$$

$$P_1 = \begin{bmatrix} P_1(2, y1) \\ P_1(3, y1) \\ .. \\ .. \\ P_1(201, y1) \end{bmatrix} \tag{4.2}$$

$$P_2 = \begin{bmatrix} P_2(2, y2) \\ P_2(3, y2) \\ .. \\ .. \\ P_2(201, y2) \end{bmatrix} \tag{4.3}$$

$$P_3 = \begin{bmatrix} P_3(2, y3) \\ P_3(3, y3) \\ .. \\ .. \\ P_3(201, y3) \end{bmatrix} \tag{4.4}$$



a. Resized Gray Image b. Pixel Position of Color Change

Figure 4.4 Finding Pixel Position of Discontinuity or Color Change

Fourth Step: For every case which consists of 3 images, 600 values are saved as a vector which represents one pattern as in equation 4.5.

$$P_{123} = \begin{bmatrix} P_1(2, y1) \\ P_1(3, y1) \\ .. \\ .. \\ P_1(201, y1) \\ P_2(2, y2) \\ P_2(3, y2) \\ .. \\ .. \\ P_2(201, y2) \\ P_3(2, y3) \\ P_3(3, y3) \\ .. \\ .. \\ P_3(201, y3) \end{bmatrix} \quad (4.5)$$

Fifth Step: After completing steps (1 - 4) for every case, the number of the patterns (*NP*) will be the same as the number of the cases. From image denotion i, j & k:

$$NP = i * j \quad (4.6)$$

$$NP = 3 * 18 = 54 \quad (4.7)$$

Sixth Step: These pattern values are normalized to values between 0 and 1 by division on 400 (the highest number of rows) as given in equation 4.8.

$$Nor.P = P_{123} / 400 \quad (4.8)$$

Seventh Step: These normalized patterns are then fed as inputs to the neural network classifier for training and later for testing.

Figure 4.7 shows the block diagram of the patterns preparation phase, as part of the intelligent system.

NEAR EAST UNIVERSITY

GRADUATE SCHOOL OF APPLIED AND SOCIAL SCIENCES

A VOLTAGE STABILIZER FOR POWER DISTRIBUTION SYSTEMS USING NEURAL NETWORKS

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Master Thesis

Department of Electrical and Electronic Engineering

Nicosia - 2007

Samir JABR: A Voltage Stabilizer for Power Distribution Systems Using Neural Networks

Approval of Director of Graduate School of Applied and Social Sciences

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We certify this thesis is satisfactory for the award of the degree of Master of Science in Electrical and Electronic Engineering

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ABSTRACT

Voltage collapse causes many blackouts of power systems all over the world even in developed countries. SCADA systems, which were induced in most power systems, could not prevent many famous blackouts. Therefore, there is a need to find efficient solutions to remedy these problems.

This thesis attempts to design a voltage stabilizer for power distribution systems (PDS) based on artificial neural network (ANN) on-line detection of instability that works concurrently with SCADA systems as another support to help preventing voltage collapse in PDS.

The design of this voltage stabilizer has two phases. The first phase is an intelligent system which uses a back propagation learning algorithm neural network that detects instability or overload of PDS, using images of voltage outputs obtained from a MATLAB simulator for a proposed power system.

The second phase of the intelligent voltage stabilizer uses the output of the first phase which is the ANN classifier. If the intelligent system detects an overload case, the stabilizer will perform instantaneous steps to clean the deep voltage drop in PDS which may cause voltage collapse. These steps depend on raising tap-changer relays of distribution transformers then switching on capacitor banks in steps, then if it is necessary shedding part of loads with least priority. Also, if instability is detected, the stabilizer will make quick arrangement to assess stability. Loads shedding and redispatch the generators to get actions constitute the main arrangements. In every case, load shedding will be performed according to the cause of instability.

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LIST OF ABBREVIATIONS

AGC: Automatic Generation Control

ANN: Artificial Neural Network

AVC: Advanced VAR Compensators

BPA: Bonneville Power Administration

BP: Back Propagation

DVC: Dynamic VAR Compensator

ED: Economic Dispatch

EMS: Energy Management Systems

ES: Excitation System

FACTS: Flexible AC Transmission System

GDE: Governor and Diesel Engine

HTG: Hydraulic Turbine and Governor

LFC: Load Frequency Control

LP: Linear Programming

LTC: Load Tap-Changers

MLP: Multilayered Perceptron

MSE: Mean Square Error

PDS: Power Distribution System

PSS: Power System Stabilizer

RTU: Remote Terminal Units

SCADA: Supervisory Control and Data Acquisition

SCB: Switched Capacitor Banks

SVC: Static VAR Compensator

UFLS: Under Frequency Load Shedding

VS: Voltage Stabilizer

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INTRODUCTION

Voltage instability or collapse is emerging as a major concern to utility companies who aim to maintain a stable power system operation. Voltage instability has caused several major power system collapses around the world. In general these voltage stability analysis methods are classified into two categories: dynamic stability and transient stability. Dynamic stability can reproduce or predict the time response of the system voltage to a sequence of events and, therefore, help identify whether the system voltage is stable or not. The majority of transient methods are based on power flow formations to evaluate voltage stability in various terms, such as load margins and load flow feasibility.

Voltage stability analysis is concerned with the ability of assessing the power system to maintain acceptable voltages at all system buses under normal conditions and after being subjected to disturbances. A major factor contributing to voltage instability is the voltage drop that occurs when active and reactive power flow through inductive reactances of the transmission network. Voltage stability is threatened when a disturbance increases the reactive power demand beyond the sustainable capacity of the available reactive power resources. While the most common form of voltage instability is the progressive drop of bus voltages, the risk of overvoltage instability also exists and has been experienced at least on one system.

Since the voltage instability issue started to emerge, significant research efforts from the power engineering community have been devoted to studying the voltage instability mechanism and to developing analysis tools and control schemes to mitigate the instability. Meanwhile, many researchers agree that the voltage instability problem is a high order nonlinear problem as a large number of different types of devices are involved in the voltage dynamics. Also a wide variety of modeling and simulation principles and analysis and control methods of the power system voltage stability have been developed.

Artificial Neural Networks (ANN) have been used to solve many problems obtaining outstanding results in various applications such as classification, clustering, pattern recognition and forecasting among many other applications corresponding to different areas. Applications of Artificial Neural Network to the above-mentioned problem

have attained increasing importance mainly due to the efficiency of present day computers. Moreover real-time use of conventional methods in an energy management center can be difficult due to their significant large computational times. One of the main features, which can be attributed to ANN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate online response. ANN approach to voltage stability assessment and improvement has been proposed and various neural network combinations have been used. The ability of ANN to understand and properly classify such a problem of highly non-linear relationship has been established in most of them and the significant consideration is that once trained effectively ANN can classify new data much faster than it would be possible with analytical model.

Research of this thesis is motivated to contribute in solving instability problem of power distribution systems. The thesis will introduce a new voltage stabilizer for power distribution system to enhance the stability of the whole power system. The main objective of the proposed voltage stabilizer is to work concurrently with SCADA systems as another support to avoid reaching to instability problem.

The proposed voltage stabilizer has two phases, detection of on-line instability and overload of the distribution system, and quick arrangements to solve the problem. Detection of on-line instability will be performed by an intelligent system based a back propagation neural network. The neural network will be trained on patterns preprocessed from voltage images outputs in MATLAB simulator for a suggested power system facing instability and overload problems. Testing the neural network will be performed using voltage output patterns that were not exposed to the ANN. Detection of instability or overload earlier helps in arranging suitable solutions to sustain stability quickly. Instantaneous reactions of the voltage stabilizer will be performed to restore stability or clean voltage drop of the distribution system as soon as it is detected by the intelligent system.

This thesis is organized in five chapters. The first three chapters introduce background information on stability of power systems, voltage stability and artificial neural networks and their real life applications in power systems. The last two chapters focus on the developed intelligent detection system, and solutions arrangements to assess stability in the novel stabilizer.

Chapter 1 presents an introduction to power systems stability. Then various instability phenomena which are frequency instability, voltage instability, rotor instability with two sided, transient angular instability, and small-signal angular instability, are introduced.

Chapter 2 introduces voltage stability problem. First, the relation between the voltage at the receiving end and the transmitted active and reactive powers is explained, and then voltage stability is defined and classified, followed by solutions to prevent voltage instability.

Chapter 3 focuses on the artificial neural networks and the back propagation algorithm which will be used. Also it reviews real life applications of ANNs especially in power systems implementations.

Chapter 4 presents an intelligent system which will detect on-line instability or overload cases. Firstly, it presents the preprocessing of patterns that outputs from the simulation of a proposed power system. Secondly, it introduces the ANN design and topology and the results of ANN training and testing. Finally, it proceeds to discuss the efficiency of the proposed techniques.

Chapter 5 presents a new voltage stabilizer based on the decision of the intelligent system for detection of instability or overload cases. The two phases of the stabilizer, which are overload enhancement and stability assessment, are presented. Testing the voltage stabilizer on part of unacceptable cases takes place in this chapter. Finally, a discussion on the efficiency and benefits of the proposed voltage stabilizer is included.

CHAPTER ONE
STABILITY OF POWER SYSTEMS

1.1 Overview

The electric power generation-transmission-distribution grid in developed countries constitutes a large system that exhibits a range of dynamic phenomena. Stability of this system needs to be maintained even when subjected to large low-probability disturbances so that the electricity can be supplied to consumers with high reliability.

The chapter first explains the definition of power system stability and the need for power system stability studies and their types. It then proceeds to discuss on the various instability phenomena which are frequency instability, voltage instability, transient rotor angular instability, and small-signal rotor angular instability.

1.2 Definition of Power System Stability

The stability of a system is defined as the tendency and ability of the power system to develop restoring forces equal to or greater than the disturbing forces to maintain the state of equilibrium [1].

Let a system be in some equilibrium state. If upon an occurrence of a disturbance and the system is still able to achieve the equilibrium position, it is considered to be stable. The system is also considered to be stable if it converges to another equilibrium position in the proximity of initial equilibrium point. If the physical state of the system differs such that certain physical variable increases with respect to time, the system is considered to be unstable.

Therefore, the system is said to remain stable when the forces tending to hold the machines in synchronism with one another are enough to overcome the disturbances. The system stability that is of most concern is the characteristic and the behavior of the power system after a disturbance.

Another definition is given by IEEE/CIGRE Joint Task Force on Stability Terms and Definitions [2] as: "Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being

subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact".

Stability of an electric power system is thus a property of the system motion around an equilibrium set, i.e., the initial operating condition. In an equilibrium set, the various opposing forces that exist in the system are equal instantaneously (as in the case of equilibrium points) or over a cycle (as in the case of slow cyclical variations due to continuous small fluctuations in loads or periodic attractors).

At an equilibrium set, a power system may be stable for a given (large) physical disturbance, and unstable for another. A stable equilibrium set thus has a finite region of attraction; the larger the region, the more robust the system with respect to large disturbances. The region of attraction changes with the operating condition of the power system.

If following a disturbance the power system is stable, it will reach a new equilibrium state with the system integrity preserved i.e., with practically all generators and loads connected through a single contiguous transmission system. On the other hand, if the system is unstable, it will result in a run-away or run-down situation; for example, a progressive increase in angular separation of generator rotors, or a progressive decrease in bus voltages. An unstable system condition could lead to cascading outages and a shutdown of a major portion of the power system.

1.3 Why the Need of Power System Stability

The power system industry is a field where there are constant changes. Power industries are restructured to cater to more users at lower prices and better power efficiency. Power systems are becoming more complex as they become inter-connected. Load demand also increases linearly with the increase in users. Since stability phenomena limits the transfer capability of the system, there is a need to ensure stability and reliability of the power system due to economic reasons.

Power systems have originally arisen as individual self-sufficient units, where the power production matched the consumption. In a case of a severe failure, a system collapse was unavoidable and meant a total blackout and interruption of the supply for all

customers. But the restoration of the whole system and synchronization of its generators were relatively easy thanks to the small size of the system.

1.4 Stability Studies

Stability studies are generally categorized into two major areas: steady-state stability and transient stability [1]. Steady-state stability is the ability of the power system to regain synchronism after encountering slow and small disturbances. Example of slow and small disturbances is gradual power changes. The ability of the power system to regain synchronism after encountering small disturbance within a long time frame is known as dynamic stability. Transient stability studies refer to the effects of large and sudden disturbances. Examples of such faults are the sudden outrage of a transmission line or the sudden addition or removal of the large loads. Transient stability occurs when the power system is able to withstand the transient conditions following a major disturbance. Figure 1.1 introduces a classification to power stability and gives the overall picture of the power system stability problem, identifying its categories and subcategories.

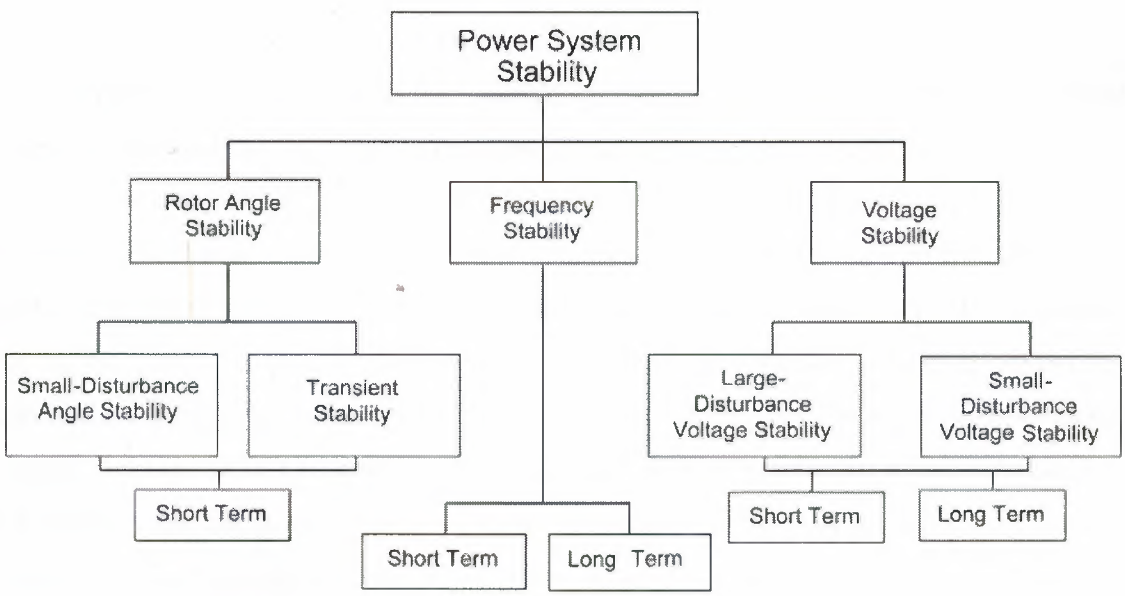


Figure 1.1 Classifications of Power System Stability [2]

1.5 Instability Phenomena

With the rising importance of the electricity for industry (and the entire society), the reliability of supply has become a serious issue. Interconnection of the separated/individual power systems have offered a number of benefits [3] , such as sharing the reserves both for a normal operation and emergency conditions, dividing of the responsibility for the frequency regulation among all generators and a possibility to generate the power in the economically most attractive areas, thus providing a good basis for the power trade.

Power systems size and complexity have grown to satisfy a larger and larger power demand. Phenomena, having a system/global nature, endangering a normal operation of power systems have appeared, explicitly: frequency instability, voltage instability, transient angular instability (also called generator's out-of-step), and local mode of small-signal angular instability (also mentioned as generator's swinging or power oscillations).

1.5.1 Frequency Instability

Frequency Instability is defined as [4]: "inability of a power system to maintain steady frequency within the operating limits. Frequency stability is defined as [2]: "the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generations and loads".

Keeping frequency within the nominal operating range (ideally at nominal constant value) is essential for a proper operation of a power system. A maximal acceptable frequency deviation (usually 2 Hz) is dictated by an optimal setting of control circuits of thermal power plants. When this boundary is reached, unit protection disconnects the power plant. This makes situation even worse – frequency further decreases and it may finally lead to the total collapse of the whole system. For the correction of small deviations, Automatic Generation Control (AGC) is used and larger deviations require so-called spinning reserves or fast start-up of generators. When more severe disturbances occur, e.g. loss of a station (all generating units), loss of a major load centre or loss of AC or DC interconnection, emergency control measures may be required to maintain frequency stability. Emergency control measures may include [4]:

- Tripping of generators
- Fast generation reduction through fast-valving or water diversion

- HVDC power transfer control
- Load shedding
- Controlled opening of interconnection to neighboring systems to prevent spreading of frequency problems
- Controlled islanding of local system into separate areas with matching generation and load.

During frequency excursions, voltage magnitudes may change significantly, especially for islanding conditions with underfrequency load shedding that unloads the system. Voltage magnitude changes, which may be higher in percentage than frequency changes, affect the load-generation imbalance. High voltage may cause undesirable generator tripping by poorly designed or coordinated loss of excitation relays or volts/Hertz relays. In an overloaded system, low voltage may cause undesirable operation of impedance relays [2].

Common practice in utilities is that most of the above actions are executed manually by a dispatcher/operator of the grid. Automatic local devices used for the load shedding are UFLS (Under Frequency Load Shedding) relays. They are usually triggered when frequency sinks to the predefined level and/or with a predefined rate of change. They are in principle same although they might be sorted in various categories [5]. Their action is disconnection of the load in several steps (5 - 20 % each) from the feeders they supervise. However, their effective use is strongly dependent on their careful tuning based on prestudies, since there is no on-line coordination between them. Another disadvantage is, that they can only react to the under frequency, increase of frequency is not covered by them at all. In some cases the impact of their operation may be negative; since they are not capable of the adaptability to the present situation (e.g. production of distributed/decentralized generation varies in time so quite often the distribution voltage level feeders feed the energy back into the network. So they don't appear as loads and their disconnection makes situation even worse).

1.5.2 Voltage Instability

Voltage Instability is the inability of a power system to maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbance. A system enters a state of voltage instability when a disturbance, increase in load demand, or change in system conditions causes a progressive and uncontrollable drop in voltage. A system is voltage unstable if, for at least one bus in the system, the bus voltage magnitude decreases as the reactive power injection in the same bus is increased [6].

Voltage instability is basically caused by an unavailability of reactive power support in some nodes of the network, where the voltage uncontrollably falls. Lack of reactive power may essentially have two origins. Gradual increase of power demand which reactive part cannot be met in some buses or sudden change of a network topology redirecting the power flows such a way that a reactive power cannot be delivered to some buses.

The relation between the active power consumed in the monitored area and the corresponding voltages is expressed by so called PV-curves. The increased values of loading are accompanied by a decrease of voltage (except a capacitive load). When the loading is further increased, the maximum loadability point is reached, from which no additional power can be transmitted to the load under those conditions. In case of constant power loads the voltage in the node becomes uncontrollable and rapidly decreases. However, the voltage level close to this point is sometimes very low, what is not acceptable under normal operating conditions, although it is still within the stable region. But in the emergency cases, some utilities accept it for a short period.

The emergency stabilizing actions which might be taken are in principle same as in case of the frequency instability, plus:

- Change of the generator voltage set point
- Automatic shunt switching
- Control of series compensation
- Blocking of Tap Changer of transformers
- Fast redispatch of generation

The analyses of real voltage collapses have shown their wide area nature and that they can be sorted basically into two categories according to the speed of their evolution –

Transient Voltage Instability and Long-term Voltage Instability [7]. Transient Voltage Instability is in the range of seconds (usually 1 – 3 s) and the main role in the incidents played the dynamics of induction motors as a load (majority of air conditioning systems) and HVDC transmission systems. The time scale of the Long-term Voltage Instability ranges from tens of seconds up to several minutes. It involves mainly impact of a topology change or gradual load increase, i.e. fairly slow dynamics. Therefore the major part of the research activities in this area has focused on the steady state aspects of voltage stability, i.e. finding the maximum loadability point of the PV-curve.

1.5.3 Rotor Angle Instability

It deals of power system synchronism with two parts, transient angle instability, and small-signal angle instability.

1.5.3.1 Transient Angle Instability

Transient Angular Instability (also called Generator's Out-of-step) is the inability of the power system to maintain synchronism when subjected to a severe transient disturbance. The resulting system response involves large excursions of generator angles and is influenced by the nonlinear power-angle relationship [6].

In case of transient angle instability, a severe disturbance is a disturbance, which does not allow a generator to deliver its output electrical power into the network (typically a tripping of a line connecting the generator with the rest of the network in order to clear a short circuit). This power is then absorbed by the rotor of the generator, increases its kinetic energy that results in the sudden acceleration of the rotor above the acceptable revolutions and eventually damage of the generator.

Therefore the measures taken against this scenario aim mainly to either an intended dissipation of undelivered power by braking resistor (reducing the mechanical power driving the generator) or fast-valving, disconnection of the generator.

An application of traditional measure of transient angle instability – equal area criterion (expressing a balance between the accelerating and decelerating energy), on emergency control has been presented which describes the method called single machine equivalent (SIME) [8]. The angles of the generators in the system are predicted

approximately 200 ms ahead. According to it, the machines are ranked and grouped into two categories. For the generators from the critical category, one machine, infinite bus (OMIB) equivalent is modeled and extended equal area criterion is applied to assess their stability. Pre-assigned corrective action is executed if an unstable generator is identified.

1.5.3.2 Small-signal Angle Instability

Local mode of Small-signal Angular Instability is the inability of the power system to maintain synchronism under small disturbances. Such disturbances occur continually on the system because of small variations in loads and generation. The disturbances are considered sufficiently small for linearization of system equations to be permissible for purposes of analysis. Local modes or machine-system modes are associated with the swinging of units at a generating station with respect to the rest of the power system. The term local is used because the oscillations are localized at one station or small part of the power system [6].

Some power systems lack a "natural" damping of oscillations, which may occur, and they would be unstable when subjected to any minor disturbance and sometimes even under normal operation conditions if no measures increasing the damping were introduced [9]. An extension of the transmission capacity by adding a new line does not necessarily improve the damping significantly and solve the problem [10].

A traditional way of damping the oscillation is using of Power System Stabilizer (PSS), which controls/modulates the output voltage of the generator. The coordinated tuning of PSSs is a complex task, since they should be robust - work in the wide range of operation conditions and provide the best possible performance. This process is done off-line.

1.5.4 Basis for Distinction between Voltage and Rotor Angle Stability

It is important to recognize that the distinction between rotor angle stability and voltage stability is not based on weak coupling between variations in active power/angle and reactive power/voltage magnitude. In fact, coupling is strong for stressed conditions and both rotor angle stability and voltage stability are affected by pre-disturbance active power as well as reactive power flows. Instead, the distinction is based on the specific set of opposing forces that experience sustained imbalance and the principal system variable in which the consequent instability is apparent [2].

1.6 Summary

The chapter was a review for definitions of power system stability and their phenomena. It also introduced various instability phenomena which are frequency instability, voltage instability, Rotor angle instability with two subcategories transient angular instability, and small-signal angular instability.

CHAPTER TWO

VOLTAGE STABILITY AND SYSTEM SOLUTIONS

2.1 Overview

This chapter discusses the voltage stability and the related solutions. First, it explains the relation between the voltage at the receiving end and the transmitted active and reactive powers, and the sources and sinks of reactive power. Then, it discusses voltage sensitivity to loads, and the voltage stability and collapse. Finally it proposes solutions to keep voltage stability by inserting reactive power using shunt capacitor banks or/and advanced compensated VARs, or/and using synchronous machines. It, also, proposes changing the voltage at the distribution substations by transformer tap changers. The final procedure for maintaining voltage stability is load shedding. The final session introduces the control of power system.

2.2 Transfer of Active and Reactive Power

Consider the circuit in Figure 2.1. A strong source with voltage E supplies a remote load through a transmission line modeled as a series reactance. The receiving end voltage V and angle depend on the active and reactive power transmitted through the line. The active and reactive power received at the load end can be written [11]:

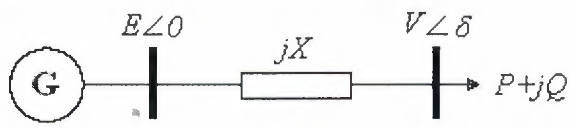


Figure 2.1 Single Line Diagram of a Simple Radial Power System

$$P = -\frac{EV}{X}\sin\delta \qquad (2.1)$$

$$Q = \frac{EV}{X}\cos\delta - \frac{V^2}{X} \qquad (2.2)$$

After eliminating using the trigonometric identity we get

$$\left(Q+\frac{V^2}{X}\right)^2+P^2=\left(\frac{EV}{X}\right)^2 \tag{2.3}$$

Solving for V^2 yields

$$V^2=\frac{E^2}{2}-QX\pm X\sqrt{\frac{E^4}{4X^2}-P^2-Q\frac{E^2}{X}} \tag{2.4}$$

Thus, the problem has real positive solutions if

$$P^2+Q\frac{E^2}{X}\leq\frac{E^4}{4X^2} \tag{2.5}$$

This inequality shows which combinations of active and reactive power that the line can supply to the load. Substituting the short-circuit power at the receiving end, $S_{SC}={E^2}/{X}$, we get

$$P^2+QS_{SC}\leq\left(\frac{S_{SC}}{2}\right)^2 \tag{2.6}$$

Some preliminary observations that can be made from the condition (2.6) are:

- The maximum possible active power transport is $S_{SC}/2$ for Q = 0.
- The maximum possible reactive power transport is $S_{SC}/4$ for P = 0
- An injection of reactive power at the load end, i.e., Q < 0 increases the transfer limit for active power.
- The transfer limits are proportional to the line admittance and to the square of the feeding voltage E

Thus, it appears more difficult to transfer reactive than active power over the inductive line, and it seems that reactive power transfer can influence the ability of the line to carry active load. Furthermore, assume for now that the load has admittance characteristics, that is, the active and reactive power received by the load can be written

$$P+jQ=V^2G(1+j\tan(\phi)) \tag{2.7}$$

Thus, the load produces reactive power for leading power factor *($\tan(\phi) < 0$)* and absorbs reactive power for lagging power *($\tan(\phi) > 0$)*. After normalizing equations (2.4) and (2.7) using

$$p = P/S_{SC}, \quad q = Q/S_{SC} \tag{2.8}$$

$$v = V/E, \quad g = G/(1/X)) \tag{2.9}$$

Using normalized quantities, the positive solution to (2.4) can be written

$$v = \frac{1}{\sqrt{g^2 + (1 + g\tan(\phi))^2}} \tag{2.10}$$

Not surprisingly, there is no voltage drop over the line when the load admittance is zero and the load voltage approaches zero as the load admittance increases towards infinity.

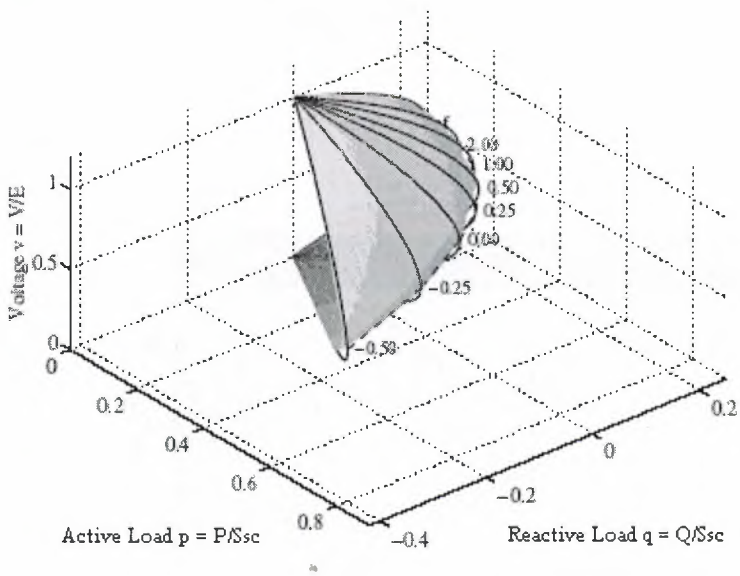


Figure 2.2 The So-Called Onion Surface as Given by Equation (2.10) Drawn Using Normalized Load Quantities [11].

Figure 2.2 shows the so-called onion surface given by (2.10) drawn in the pqv-space. It illustrates the relationship between receiving end voltage and transferred active and reactive power, and each point on the surface corresponds to a feasible operating point. The surface visualizes the set of operating points that the combined generation and transmission system can sustain. The actual operating point is determined by the apparent

load admittance, and the stability of this operating point is determined jointly by the slope of the surface and the load characteristics. The solid lines drawn on the surface correspond to operating points with varying g and constant tan (ϕ) (shown by the number beside each line). The dashed line around the "equator" of the surface corresponds to the transfer limit according to the condition (2.6).

Figure 2.3 shows so-called pv-curves [7], which are projections of the solid lines drawn on the onion surface onto the pv-plane. The rightmost point of each pv-curve marks the maximum active power transfer for a particular power factor. The corresponding voltage shown by the dashed curve is therefore often referred to as the critical voltage and the active loading as the theoretical transfer limit. The critical voltage and theoretical transfer limit increase with decreasing tan (ϕ). As will later be demonstrated, only operating points on the upper half of the pv-curve are stable when the load has constant power characteristics.

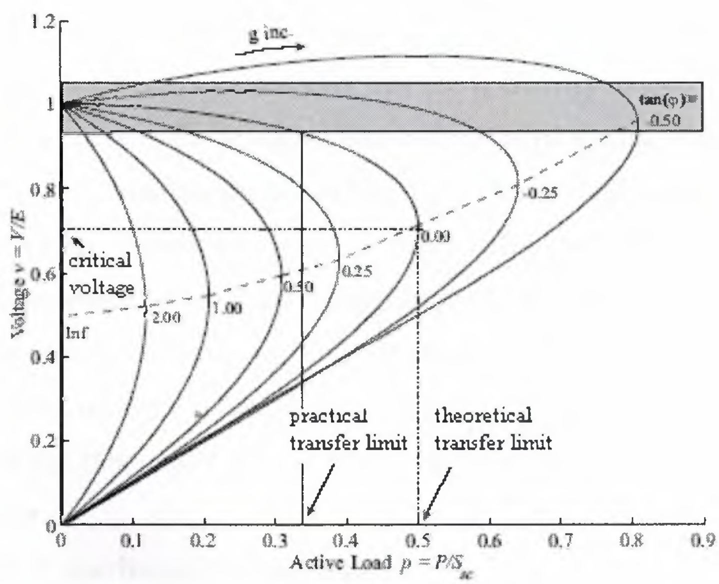


Figure 2.3 The Onion Surface Projected Onto the PV-Plane

According to the condition (2.6), the maximum power a purely active load can theoretically receive through the line is half the short-circuit power at the load bus, given that no reactive power is received at the load end. The shaded region indicates normal

operation of a line {the voltage of both ends of the line is normally kept close to the rated voltage of the line. Typical limits are $\pm 5\%$ deviation from nominal voltage or up to $\pm 5\%$ in emergency cases. The receiving end voltage at the theoretical transfer limit with a purely active load is $1/\sqrt{2} \approx 0.71$, which is normally considered unacceptable. The practical transfer limit is therefore about 35% of the short-circuit power or even lower when the load has a lagging power factor1. Capacitor banks connected at the load end are often used to increase the load end voltage and thereby the practical transfer limit. Reactive power is then being produced locally instead of transferred by the line, and the apparent power factor of the load (as seen from the transmission system) is enhanced. The operating point then shifts to another pv-curve corresponding to a lower value of *tan* (ϕ). When the operating point is on the upper part of the pv-curve, which is the case under normal operation, this corresponds to higher voltage.

The pv-curves also indicate the stiffness of system with respect to active power load variations. By overcompensating the load, such that the apparent *tan* (ϕ) becomes negative, transfer beyond half the short-circuit power with voltage close to nominal levels can theoretically be accommodated. Note however that the sensitivity to load variations, which corresponds to the steepness of the pv-curve within the shaded region, is much larger in an overcompensated system. Another important aspect is that the critical voltage is brought closer to nominal voltage. It will be shown in Section 2.5 that for constant power load characteristics, the theoretical transfer limit coincides with the voltage stability limit. Thus, the difference between the critical voltage and the voltage of the current operating point can be used as a robustness measure in terms of voltage. Similarly, the difference between the current loading and the theoretical transfer limit can be used as a robustness measure in terms of active power.

Calculation of maximum loading point

The maximum loading point can be reached through a load flow program [12, 13, 14]. The maximum loading point can be calculated by starting at the current operating point, making small increments in loading and production and re-computing load-flows at each increment until the maximum point is reached. The load-flow diverges close to maximum loading point because there are numerical problems in the solution of load-flow

equations. The load flow based method is not the most efficient, but has the following characteristics making it appropriate for voltage stability studies:

- good models for the equipment operating limits: generator capability limits, transformer tap ranges, circuit ratings and bus voltage criteria
- good models for the discrete controls: transformer tap steps and switched shunts
- capability to recognize the maximum loading point through the minimum singular value of load-flow Jacobian matrix
- familiar computer modeling, data requirements and solution algorithms
- option of using the existing computer program with miner modifications

2.3 Sources and Sinks of Reactive Power

The previous section showed that the voltage at the receiving end is highly dependent on the absorption or injection of reactive power by the load. The control of voltage is in fact closely related to the control of reactive power. An injection of reactive power at a bus that is not directly voltage regulated by a generator will in general increase the voltage of that bus and its surrounding network.

The most important sources and sinks of reactive power in power systems are:

- Overhead (AC) lines generate reactive power under light load since their production due to the line shunt capacitance exceeds the reactive losses in the line due to the line impedance. Under heavy load, lines absorb more reactive power than they produce.
- Underground (AC) cables always produce reactive power since the reactive losses never exceed the production because of their high shunt capacitance.
- Transformers always absorb reactive power because of their reactive losses. In addition, transformers with adjustable ratio can shift reactive power between their primary and secondary sides.
- Shunt capacitors generate reactive power.
- Shunt reactors absorb reactive power.
- Loads seen from the transmission system are usually inductive and therefore absorb reactive power.

- Synchronous generators, synchronous condensers and static VAR compensators can be controlled to regulate the voltage of a bus and then generate or absorb reactive power depending on the need of the surrounding network.
- Series capacitors are connected in series with highly loaded lines and thereby reduce their reactive losses.

2.4 Voltage Sensitivity of Loads

So far, it was assumed that the apparent admittance of the load is constant. However, the admittance of many loads varies with the supply voltage - either by their inherent design or by control loops connected to the load devices. Typical examples of such loads are motor drives equipped with power electronic converters and thermostatically controlled heating devices, which adjust their apparent admittance in order to consume constant power. The composite load seen from the transmission level often contains a significant amount of induction motor loads, which exhibit potentially very complex voltage behavior. However, for small voltage excursions, say less than 10 %, the active power drawn by induction motors can in the long term be approximated as constant and the reactive power as proportional to an exponential of the voltage. The dynamic response of loads to voltage changes plays a major role in the analysis and evolution of voltage instability. Simplifying matters somewhat, the load as seen from the transmission level can normally be considered as constant power in the long term since it is connected through tap changers that keep the load voltages close to their nominal values.

2.5 Voltage Stability

The voltage stability of power systems basically implies its capability of reaching and sustaining an operating point in a controllable way following a disturbance, and that the steady-state post-disturbance system voltages are acceptable. Furthermore, the term voltage instability denotes the absence of voltage stability and voltage collapse the transition phase during which a power system progresses towards an unacceptable operating point due to voltage problems, often resulting in blackouts or separation of the system into separate unsynchronized islands.

The dynamics of voltage phenomena can be divided into the two main groups: short- and long-term dynamics. Short-term phenomena act on a time scale of seconds or shorter and include, for example, the effect of generator excitation controls, induction motor recovery/stalling dynamics and FACTS devices [2]. The long-term dynamic phenomena act on a time scale of minutes and include, for example, the effect of recovery dynamics in heating load and the effect of generator over current protection systems.

As discussed in the previous section, many loads respond to a voltage drop by increasing their apparent admittance. Assume that the load supplied by the network in Figure 2.1 has such a recovery mechanism according to the normalized model

$$T\frac{dg}{dt} = p_0 - p \tag{2.11}$$

$$p = g\,v^2 \tag{2.12}$$

Thus, the load has instantaneous admittance characteristics but also an internal controller that aims to restore the power drawn to constant power p_0 with the time constant T sec. Furthermore, assuming that the load is purely active (*tan* $(\phi) = 0$) and combining (2.10) and (2.11)-(2.12), the full model can be written in the differential-algebraic form

$$T\frac{dg}{dt} = p_0 - g\,v^2 \tag{2.13}$$

$$v = \frac{1}{\sqrt{g^2+1}} \tag{2.14}$$

Substituting (2.14) in (2.13) yields

$$f(g) = \frac{dg}{dt} = \frac{1}{T}\left(p_0 - \frac{g}{1+g^2}\right) \tag{2.15}$$

Solving for stationary points yields the two solutions

$$g^* = \frac{1}{2p_0} \pm \sqrt{\frac{1}{4p_0^2} - 1} \tag{2.16}$$

Thus, it can be concluded that there are two separate equilibria if $p_0 < 0.5$ that coalesce for $p_0 = 0.5$. For $p_0 > 0.5$ it appears to be two separate equilibrium points with complex g. But g is real-valued since it has been defined as the real part of the admittance phasor in equation (2.7). Thus, we can conclude that there are no equilibria for $p_0 > 0.5$

and that a loss of equilibrium occurs when p_0 increases beyond 0.5. Since (2.16) is always positive for $p_0 > 0.5$, the admittance will increase towards infinity (or an internal limit in the load device) and the load voltage will approach zero. Small-disturbance stability analysis can be used to determine that for $p_0 < 0.5$, the low admittance solution corresponding to the upper half of the pv-curve is asymptotically stable and the high admittance solution on the lower half is unstable [15].

Assuming constant power load characteristics as above, the theoretical transfer limit marked by the dashed curve in Figures 2.2 & 2.3 therefore also becomes a steady-state voltage stability limit. However, note that the operating point may transiently move to the unstable lower part and back again to the stable equilibrium on the upper part of the pv-curve. Analogously, there is no guarantee that the system will reach a stable operating point simply because such an operating point exists. A trajectory will only approach the stable equilibrium as long at it remains within the region of attraction of the stable equilibrium. Such regions of attraction can be approximately computed using a Lyapunov-method for general dynamical systems, but the problems of finding a good Lyapunov function may make the results conservative [15].

2.6 Voltage Collapse

Voltage collapse is a system instability that involves several power system components simultaneously. It typically occurs on power systems that are heavily loaded, faulted and/or has reactive power shortages. This occurs since voltage collapse is associated with the reactive power demands of loads not being met due to limitations on the production and transmission of reactive power. The production limitations include generator and SVC reactive power limits and the reduced reactive power produced by capacitors at low voltages. The primary limitations in transmission are high reactive power losses on heavily loaded lines and line outages. Reactive power demands may also increase due to changes in the load such as, motor stalling or increased proportion of compressor load.

Voltage collapse takes place on the different timescales ranging from seconds to hours, specifically [16]:

(1) Electromechanical transient (e.g., generators, regulators, induction machines) and power electronic (e.g. SVC, HVDC) phenomena in the time range of seconds.

(2) Discrete switching devices, such as, load tap changers and excitation limiters acting at intervals of tens of seconds.

(3) Load recovery processes spanning several minutes.

There are numerous power system events known to contribute to voltage collapse.

- Increase in loading
- Generators or SVC reactive power limits
- Action of tap changing transformers
- Load recovery dynamics
- Line tripping or generator outages

Most of these changes have a large effect on reactive power production or transmission. Control actions such as switching in shunt capacitors, blocking tap changing transformers, redispatch of generation, rescheduling of generator and pilot bus voltages, secondary voltage regulation, load shedding and temporary reactive power overload of generators are countermeasures against voltage collapse. Machine angles are typically also involved in the voltage collapse. Thus, there is no sharp distinction between voltage collapse and classical transient instability. The differences between voltage collapse and classical transient instability are those of emphasis: voltage collapse focuses on loads and voltage magnitudes whereas transient instability focuses on generators and angles. Also, voltage collapse often includes longer time scale dynamics and includes the effects of continuous changes such as load increases in addition to discrete events such as line outages.

Increasing voltage levels by supplying more reactive power generally improves the margin to voltage collapse. In particular, shunt capacitors become more effective at supplying reactive power at higher voltages. Increasing voltage levels by tap changing transformer action can decrease the margin to voltage collapse by in effect increasing the reactive power demand. Still, voltage levels are a poor indicator of the margin to voltage collapse. While there are some relations between the problems of maintaining voltage levels and voltage collapse, they are best regarded as distinct problems since their analysis

is different and there is only partial overlap in the control actions used to solve both problems.

2.6.1 Voltage Collapse Indices

There are numerous indices to indicate proximity to voltage collapse that have been studied. The following is a brief introduction to these indices:

2.6.1.1 Sensitivity Factors

Sensitivity factors are indices used in several utilities throughout the world to detect voltage stability problems and to decide corrective measures [17, 18]. These indices were first used to predict voltage control problems in generator QV curves, and may be defined as

$$VSF_i = \max_i \left\{ \frac{dV_i}{dQ_i} \right\} \tag{2.17}$$

where *VSF* stands for Voltage Sensitivity Factor. As generator *i* approaches the bottom of its QV curve, the value of *VSFi* becomes large and eventually changes sign, indicating an unstable voltage control condition.

2.6.1.2 Singular Values

Singular values of a reduced matrix can be used to determine proximity to voltage collapse. Let

$$\Delta Q = J_{QV}\, \Delta V \tag{2.18}$$

with

$$\det J_{QV} = \frac{\det J}{\det J_l} \tag{2.19}$$

where J is the Jacobian in power flow equations and J_l is the real power sensitivities to angle deviations, i.e., $\frac{\partial P}{\partial \delta}$. The singular values of this reduced matrix can be used to determine proximity to voltage collapse.

2.6.1.3 Second Order Performance Indices

Indices based on first order information (linearization), such as singular values and eigen values and several other indices presented in this document, may be inadequate to predict proximity to collapse as they neglect large discontinuities in the presence of system control

limits like generator capability or transformer tap limits, as previously discussed. Conversely, it is possible to calculate a second order index that exploits additional information embedded in these indices to overcome some of these discontinuities [19].

2.6.1.4 Energy Function

Energy function, a technique based on Lyapunov stability theory, is used for both transient stability and voltage stability analysis. In this approach, power system stability is like a ball, which lies at the bottom of a valley. The stability can be understood as the ball settling to the bottom of an uneven surface when there is a disturbance. As the power system changes, the landscape of this surface and the ridges surrounding the indentations change. A voltage collapse corresponds to a ridge being sufficiently lowered so that with a small perturbation the ball can roll from the bottom of one indentation to a neighboring area. The height of the lowest ridge can be computed and used as an index to monitor the proximity to voltage collapse [20].

2.6.1.5 Loading Margin

For a particular operating point, the amount of additional load in a specific pattern of load increase that would cause a voltage collapse is called the loading margin to voltage collapse.

Loading margin is the most basic and widely accepted index of voltage collapse. If system load is chosen to be the parameter, which varies, then a system PV curve can be drawn. In this case, the loading margin to voltage collapse is the change in loading between the operating point and the nose of the curve. The advantages of the loading margin as a voltage collapse index are [21]:

- The loading margin is straightforward, well accepted and easily understood.
- The loading margin is not based on a particular system model; it only requires a static power system model and can be supplemented with dynamic system models.
- The loading margin is an accurate index that takes full account of the power system nonlinearity and limits such as reactive power control limits encountered as the loading is increased. Limits are not directly reflected as sudden changes on the loading margin.

- Once the loading margin is computed, it is easy and quick to compute its sensitivity with respect to any power system parameters or controls.

The computational costs are the most serious disadvantage of the loading margin and make it unsuitable for on-line use.

2.7 System Solutions

The potential effects of voltage instability resulting from the slow recovery of the power system voltages following a major disturbance, such as a transmission line fault. Transmission utilities have traditionally addressed voltage stability concerns by installing large static VAR compensator (SVCs) or synchronous condensers to provide the necessary dynamic reactive power support to the system following a major disturbance.

The problem of voltage stability of distribution power systems has many solutions, such as changing transformer taps, switching capacitors bank, using advanced VAR compensators, installing synchronous generators and condensers, and finally shedding loads.

2.7.1 Transformer Tap Changer Relays

A. General

Electric utilities utilize load tap-changers (LTC) to maintain customer voltage levels as the system conditions change. Typically, as load increases, the LTC will act to raise the tap position in order to maintain the voltage level. The LTC control relay will be set to operate in one of two modes - bus voltage regulation or load center voltage regulation using the line drop compensator.

Load Center voltage regulation requires a line drop compensator to regulate the voltage at the load center. Transformers at distribution substations are more likely to use load center voltage regulation than those at transmission substations. Therefore, it is important to know the mode of LTC control operation when modeling the effect of the tap-changing transformer operation during voltage collapse.

During a period of voltage collapse, the LTC control relays will detect a low voltage and begin timing to raise the tap position of the transformer.

When the voltage collapses occurs slowly, the controls will time out and begins to raise the transformer tap position. Assuming no change in the load on the transformer during this period, the LTC can often be considered a constant power load as long as the tap-changer can maintain a constant load voltage.

Since the primary voltage level drops, the current flow in the transmission system is increased to maintain the load power. This increasing current flow will further reduce the transmission system voltage, making the voltage collapse more severe.

In some cases, tap changers can also have a beneficial effect. Consider for instance, a case where a transformer is supplying predominantly motor load with power factor correction capacitors. The LTC keeps the supply voltage high and hence does not affect the real power consumption (which is relatively independent of voltage), and also maximizes the reactive support from the power factor correction capacitors. Due to this regulating effect, the LTC is an important part of the overall voltage collapse scenario.

For the more frequent case, where the real power loads have some voltage dependency, the LTC can be utilized to reduce the severity of the voltage collapse if appropriate control operation can be obtained. Blocking operation of the LTC has been widely offered as a method to reduce the negative effect on the system. Load voltage reduction can be used to reduce the loading on the system. This is similar to the peak shaving systems widely used at many utilities. Therefore the load tap-changer may be both a cause and a partial solution to the problem of voltage collapse [22].

B. LTC Blocking Schemes

The simplest method to eliminate the LTC as a contributor to voltage collapse is to block the control's automatic raise operation during any period where voltage collapse appears to be a concern. The decision to temporarily block the tap-changer can be made using locally derived information or can be made at a central location and the supervisory system can then send a blocking signal to the unit. This action may result in a period of low voltage on the affected loads.

The effect of the reduced supply voltages on power quality to customers in the whole service area must be weighed against the possible alternative of complete disconnection of some customers in a smaller area. Tap changer blocking will be more effective for voltage decays slower than the transient time frame. It will also be more

effective on loads that have a relatively high voltage dependency. In cases where the steady state value of b is high, the reduction of reactive power demand due to reduced distribution voltage will be very significant in helping keep transmission voltages up.

Local blocking schemes are implemented using voltage relays and timers to sense the voltage level on the high voltage bus at the substation.

The set point voltage is usually chosen to be a level that is less than that which occurs during maximum acceptable overload conditions. Condition exists longer than a predetermined time. The time period may vary from 1 to several seconds. The LTC is unblocked when the voltage has recovered to an acceptable level for a predetermined period of time, typically 5 seconds [22]. Since the blocking action will be removed if the voltage recovers, usually a single phase-phase voltage measurement is adequate for this scheme.

A coordinated blocking scheme can be utilized to block operation of LTC's in an area where voltage instability is imminent. The coordinated scheme can be accomplished with under voltage schemes acting independently (as described above) in a coordinated fashion at various stations within a region, or it can be a centralized scheme that recognizes a pattern of low voltages at key locations. In a centralized scheme, the LTC blocking can be implemented in substations throughout the affected region, even if the voltage at all locations is not yet below a specific threshold. The key to operation of a centralized system is the reliability of the communications system. The data needed for decision making must be collected at the central location for analysis. Control decisions must then be sent to each affected transformer location.

The effectiveness of an LTC blocking scheme at the transmission level will largely depend on whether distribution transformers are LTC-type. If the distribution transformers are LTC-type, additional measures are required to prevent their action from negating the effect of the LTC blocking scheme at the transmission level.

C. No-load Tap Changer

One method used to adjust the winding ratio of the transformer uses the no-load tap changer shown in Figure 2.4 [23]. A transformer equipped with a no-load tap changer must always be disconnected from the circuit before the ratio adjustment can be made. The

selector switch is operated under oil usually placed within the transformer itself; but it is not designed to be used as a circuit breaker. To change taps on small distribution transformers, the cover must be removed and an operating handle is used to make the tap change. For the larger type, one handle may be brought through the cover and the tap may be changed with a wheel or even a motor.

If it is necessary to change the taps when the transformer cannot be disconnected from the circuit, tap changers under-load are used. They involve the use of an autotransformer and an elaborate switching arrangement. The information regarding the switching sequence must be furnished with each transformer. Tap changers can function automatically if designed with additional control circuits: automatic tap changes are used for high-power transformers, and for voltage regulators.

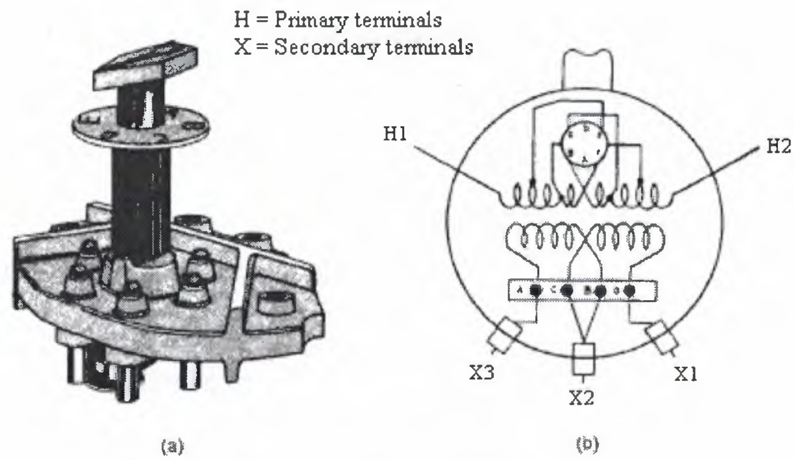


Figure 2.4: Tap Changer (a) No Load Tap Changer

(b)Typical Internal Wiring of Transformer with Tap Changer [24]

2.7.2 Switched Capacitors Bank

Many power system components in a network consume large amounts of reactive power. For example, transmission line shunt reactors, and other industrial and commercial loads need reactive power. Reactive current supports the magnetic fields in motors and transformers. Supporting both real and reactive power with the system generation requires increased generation and transmission capacity, because it increases losses in the network. Shunt-connected capacitors or synchronous condensers near the load centers are another

way to generate reactive power. Switched Capacitor Banks (SCB) have the advantage of providing reactive power close to the load centers, minimizing the distance between power generation and consumption, and do not have the maintenance problems associated with synchronous condensers. Controlling capacitance in a transmission or distribution network could be the simplest and most economical way of maintaining system voltage, minimizing system losses, and maximizing system capability. The main disadvantage of SCB is that its reactive power output is proportional to the square of the voltage and consequently when the voltage is low and the system needs them most, they are the least efficient.

Capacitor Bank Design

In order to insert reactive power to the power distribution system (PDS) the power factor (*cos* ϕ) should be increased to unity, and the angle ϕ is decreased to zero. In order to decrease the angle ϕ, reactive component of the current, $I \sin \phi$ (I_r) is to be decreased. This is achieved by introducing leading current of magnitude equal to the reactive component, in the circuit as shown by OA in Figure 2.5. This leading current I_c will lead the voltage by 90 degrees and will be in phase opposition to I_r. Therefore the leading current required to neutralize the lagging reactive component of the current to minimize the reactive power of the feeder to zero is given as:

$$\begin{aligned} I_c &= I_r = I \sin \phi \\ &= I \sqrt{1-\cos^2 \phi} \end{aligned} \tag{2.20}$$

The value of the total capacitance required for inserting reactive power for given real power P in the circuit, at frequency f, and voltage V is determined as follows:

$$I_c = \omega CV = 2\pi fCV \tag{2.21}$$

Equating eqns. (2.20) and (2.21),

$$2\pi fCV = I\sqrt{1-\cos^2 \phi} \tag{2.22}$$

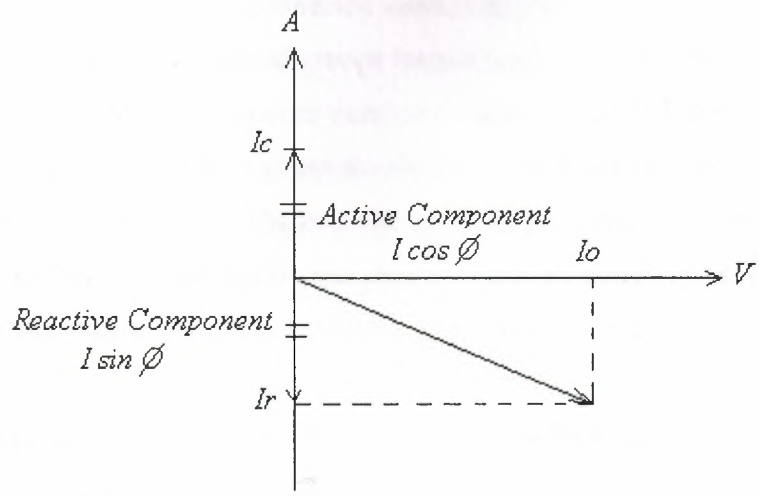


Figure 2.5 Representation of Reactive Current Component

And $$C = \frac{I}{2\pi f V}\sqrt{1-\cos^2\phi} \tag{2.23}$$

Also $$P = IV\cos\phi \tag{2.24}$$

From eqn. (2.24)

$$I = \frac{P}{V\cos\phi} \tag{2.25}$$

Substituting the value of I from eqn. (2.25) into eqn. (2.23)

$$C = \frac{P}{2\pi f V^2 \cos\phi}\sqrt{1-\cos^2\phi} \tag{2.26}$$

$$C = \frac{P}{2\pi f V^2}\sqrt{\frac{1}{\cos^2\phi}-1} \tag{2.27}$$

It is seen from the last equation that the capacitance required is inversely proportional to the square of the operating voltage, thus the total value of capacitance required per phase depends upon the nature of connection whether star or delta. In practice it is observed that the delta connection is preferable.

The protection of shunt capacitor banks requires understanding the basics of capacitor bank design and capacitor unit connections. Shunt capacitors banks are

arrangements of series/paralleled connected units. Capacitor units connected in paralleled make up a group and series connected groups form a single-phase capacitor bank.

As a general rule, the minimum number of units connected in parallel is such that isolation of one capacitor unit in a group should not cause a voltage unbalance sufficient to place more than 110% of rated voltage on the remaining capacitors of the group. Equally, the minimum number of series connected groups is that in which the complete bypass of the group does not subject the others remaining in service to a permanent over voltage of more than 110% [24].

The maximum number of capacitor units that may be placed in parallel per group is governed by a different consideration. When a capacitor bank unit fails, other capacitors in the same parallel group contain some amount of charge. This charge will drain off as a high frequency transient current that flows through the failed capacitor unit and its fuse. The fuse holder and the failed capacitor unit should withstand this discharge transient.

The discharge transient from a large number of paralleled capacitors can be severe enough to rupture the failed capacitor unit or the expulsion fuse holder, which may result in damage to adjacent units or cause a major bus fault within the bank. To minimize the probability of failure of the expulsion fuse holder, or rupture of the capacitor case, or both, the standards impose a limit to the total maximum energy stored in a paralleled connected group to 4659 kVAR [24]. In order not to violate this limit, more capacitor groups of a lower voltage rating connected in series with fewer units in parallel per group may be a suitable solution. However, this may reduce the sensitivity of the unbalance detection scheme. Splitting the bank into two sections as a double Y may be the preferred solution and may allow for better unbalance detection scheme. Another possibility is the use of current limiting fuses.

The optimum connection for a SCB depends on the best utilization of the available voltage ratings of capacitor units, fusing, and protective relaying. Virtually all substation banks are connected wye. Distribution capacitor banks, however, may be connected wye or delta. Some banks use an H configuration on each of the phases with a current transformer in the connecting branch to detect the unbalance.

Delta-connected banks are generally used only at distributions voltages and are configured with a single series group of capacitors rated at line-to-line voltage. With only

one series group of units no over voltage occurs across the remaining capacitor units from the isolation of a faulted capacitor unit. Therefore, unbalance detection is not required for protection.

Some larger banks use an H configuration in each phase with a current transformer connected between the two legs to compare the current down each leg. As long as all capacitors are normal, no current will flow through the current transformer. If a capacitor fuse operates, some current will flow through the current transformer. This bridge connection can be very sensitive. This arrangement is used on large banks with many capacitor units in parallel.

2.7.3 Advanced VAR Compensators

The emergence of new advanced VAR compensators utilizing power electronics with binary switched capacitors and inverter-based systems with or without energy storage provide utility transmission planning engineers with alternative solutions to the voltage stability problem.

Superconducting magnetic energy storage systems utilizing magnetic energy storage in the form of a superconducting coil and inverter technology have lead the way in utility applications of these new advanced VAR compensators [25]. Other commercially-available advanced VAR compensators are now increasingly being applied on utility systems for voltage stability support as well as for voltage regulation purposes.
Commercially-available advanced compensators are grouped into three categories, namely:

- Power-electronically-switched capacitors.
- Inverter-based systems without energy storage.
- Inverter-based systems with energy storage

2.7.3.1 Power-Electronically-Switched Capacitors

Compensators utilizing power-electronically-switched capacitors (e.g., (AVC) Adaptive VAR Compensator) typically consist of three or more stages of low-voltage capacitors. Capacitor stages are typically sized in binary increments, i.e., if the size of the first stage of capacitors is Q (kVAR) per phase, the size of the second and third stages would be 2Q and

4Q, respectively. Reactors are typically used in series with each stage of capacitors for detuning to eliminate harmonic resonance and large inrush currents. Capacitors are charged to peak system voltage and switched through thyristors at peak voltage to eliminate any switching transients [26].

The AVC can respond to voltage fluctuations in one cycle, or as fast as ½ cycle in specially-designed units. Single units with capacity of up to 24 MVAR at 690 V or 120 MVAR at 15 kV can be applied for dynamic voltage support. A step-up transformer would typically be used to step the output voltage up to distribution or transmission voltage level [26].

Since the AVC uses binary-switched capacitors, the reactive power output occurs in discrete steps. In a three stage unit the total output can be varied over 7 discrete steps, and in 15 steps in a four-stage unit. Since shunt-connected capacitors are utilized to provide reactive power output, the reactive power output is proportional to the square of the bus voltage.

2.7.2.2 Inverter-Based Systems without Energy Storage

These compensators (e.g., (DVC) Dynamic VAR Compensator and (DSTATCOM) Distribution Static Compensator) utilize shunt-connected voltage-source inverters to control the reactive power flow. Reactive power flow is controlled by adjusting the magnitude of the voltage output from the inverter relative to the bus voltage. Units typically have output filters and a step-up transformer to connect to the distribution bus. Typical DVC units are rated 480 V and consists of multiple 250 kVA inverter modules arranged for an output of up to ±8 MVAR continuous. Units have a one second overload capability ranging from 2.3 to 3 times the continuous rating [26]. After one second the output ramps down to its continuous rating in another second. The reactive power output of an inverter-based compensator is proportional to the bus voltage.

2.7.2.3 Inverter-Based Systems with Energy Storage

The Distributed Superconducting Magnetic Energy Storage (D-SMES) is currently the only commercially-available inverter-based system that has been applied with energy storage for voltage stability applications. The system is similar to the DVC, with an additional

superconducting magnetic energy storage module with peak output power capability of 3 MW and an average output power capability of 2.5 MW over the first 0.5 seconds of discharge [23]. The reactive power output of this compensator is also proportional to the bus voltage.

2.7.4 Synchronous Generators and Condensers

A synchronous machine is capable of generating and supplying reactive power within its capability limits to regulate system voltage. For this reason, it is an extremely valuable part of the solution to the collapse-mitigation problem. Synchronous machines considered may be generators or synchronous condensers. In terms of reactive output capability, synchronous condensers are treated similarly to static VAR sources during commissioning and maintenance in that rated output power must be demonstrated to be achieved.

2.7.4.1 Generators

Generators however are rated for specific real power output, usually at a specific power factor. During commissioning and maintenance, real power output is carefully checked to meet specified requirements. Reactive power output may be checked during commissioning, but may not be carefully checked after that. The reactive power capability may be required by the system, but is not considered to be a revenue generator.

Due to large impact on the system voltages, it may be difficult to operate large generators at their reactive capability limits (for test purposes). Therefore coordination of protection with control devices is not so frequently checked as with other reactive power sources [27]. Numerous voltages collapse or near collapse incidents have been aggravated by unexpected loss of healthy generators due to lack of coordination of protective equipment with generator capability.

The reactive power capability increases dramatically as real power output is limited. Further, the amount of reactive power available from the generator is very dependent on terminal voltage. In this respect, a generator operating at low real power output can supply significantly more reactive power at low voltages than at high voltages [22].

The increase in reactive power capability at lower real power output means that system planners and operators may choose to generate less than rated real power in order to

have more reactive power from generators at critical locations in voltage stability threatened systems. The choice of operating point (MW versus MVAR) for generators at critical locations is predetermined, and not usually subject to automatic control. It should be noted that when the generator reaches the limit of its capability, particularly in the rotor current limited region, it may not be controlling its terminal voltage. The fact that it is at its limit of capability means that it is not able to raise the terminal voltage to the reference setting of the voltage regulator. Thus the reactive power limits are to a certain extent, determined by the system conditions, and independent of the generator excitation system.

The value of a generator as a source of reactive power can be separated from its value as a source of real power, if it can be decoupled from the turbine and run as a synchronous condenser. In some plants where fuel or operating costs may make power generation uneconomic, it may be possible to convert the generator to a synchronous condenser, and use it to support voltages in an area where real power has to be imported from a remote area [27].

2.7.4.2 Motors

It is a synchronous motor working at over excitation and drawing current from the supply at leading power factor. It has an advantage that varying its excitation it can be steplessly adjusted to supply any amount of capacitive or reactive power up to its full rating. By the use of rotary amplifiers and high speed regulators, automatic stable operation is obtained even in the case of sudden change in the system conditions. It must be noted that, synchronous condenser has an inherently sinusoidal waveform and harmonics in the voltage do not exist, but the static capacitors give large harmonics in the system.

A modern synchronous capacitor is generally a six or eight pole salient pole synchronous motor. It is fitted with a robust damper winding by means of which, it is possible to start it as an induction motor at reduced voltage. The starting tapping on the starting transformer is about 25-40% of the rated voltage due to this, the starting current from the supply will be less than the rated current [28].

By jacking up the shaft by means of oil under pressure, the initial starting torque and the minimum voltage required for reliable starting are reduced. The machine runs

almost near to synchronous speed at rated voltage and is then pulled into synchronous speed.

2.7.5 Load Shedding

Load shedding is defined as [29]: "the process of deliberately removing pre-selected loads from a power system, usually done automatically by relays, in order to maintain the integrity of the system under unusual conditions".

Current practice depends on hardware control, using lines and generators. Load shedding basically means nothing more than disconnecting a radial feeder on medium voltage distribution system. Sometimes you try to avoid area with elevators. Hospitals and other very sensitive institutions are supposed to have their own backup. The most common criterion to activate load shedding is low frequency, with or without time delay, also under voltage criteria and rate of change of frequency exists, but are much less common.

Load shedding is an option that is becoming more widely used as a final means of avoiding system wide voltage collapse. This option is only considered when all other effective means of avoiding collapse are exhausted. This option may be the only effective option for various contingencies especially if the collapse is in the transient time frame, and if load characteristics result in no effective load relief by transformer load tap changer control. Load shedding results in high costs to electricity suppliers and consumers, therefore, power systems should be designed to require such actions only under very rare circumstances. Load may be shed either manually or automatically depending on the rate of voltage drop.

2.7.5.1 Manual Load Shedding

If the time frame of collapse is long-term, manual load shedding can be implemented to stabilize the voltage. This mode of operation, normally applied under inadequate generation conditions or insufficient VAR reserve, should have preplanned guidelines and procedures for the system dispatchers to implement load shedding manually.

System studies can provide load sensitivity analyses from which the critical voltage can be determined to start load shedding. Another option to assist system operators for fast action is to preprogram blocks of loads on the dispatcher control console of the SCADA system. Dispatchers can select a particular block of load in a specific area requiring load shedding

to control the voltage drop. The blocks of load can also be divided into several subgroups depending on sensitivity of the load, so that execution of the manual load shedding can be carried out in steps or in rolling sequence [22].

A major disadvantage of relying on manual load shedding is that it places a severe burden on system operators to recognize an approaching voltage stability problem and to act quickly enough to avoid a major collapse. Even with the most comprehensive preplanned guidelines, there is a danger that the particular condition that arises may not fall within the guidelines clearly enough for prompt action. However, when short term operational planning studies (time frame less than a week) show the possibility of collapse due to expected load and actual contingencies, manual shedding can be applied with good results.

2.7.5.2 Automatic Load Shedding

When the voltage instability is caused by sudden loss of critical transmission equipment or VAR generating equipment, the lead-time prior to a voltage collapse will be very short. Therefore, manual load shedding would be too slow to prevent a voltage collapse. Automatic load shedding must be used to quickly arrest a fast voltage drop and allow the voltage to recover to an acceptable level before voltage collapse can occur.

Under voltage detectors are often used to initiate automatic load shedding. For low voltage events which do not lead to collapse (such as during a normally cleared system fault), these detectors must not operate in order to prevent nuisance tripping of customer load. Security of the under voltage detectors can be increased by applying multiple phase detection, proper time coordination between fault clearing and time delay for load shedding, and use of fault detection relays to inhibit load shedding. Reliability of load shedding to prevent voltage collapse can be enhanced by use of other indicators than voltage magnitude such as voltage and power sensitivity factors or other forms of voltage stability indices.

Developing appropriate settings for the under voltage detectors and time delays are challenging problems. It might require intensive network analysis to find the desired values to provide optimum coordination between load shedding and voltage collapse. Generally, the settings are in the range of 85 to 95 percent of the operating voltages, with time delays

ranging from tens of cycles to minutes [30, 31, 32]. The sensitivity of the load to the voltage level has a great impact on the settings.

2.7.5.3 Intelligent Load Shedding

The traditional load shedding scheme, which has hardly been developed over the last 100 years, is less and less acceptable in today's society. The developments in computer and communications technology allow abandoning the stage of hardware control and relying more on intelligent control in order to maintain power system stability.

Intelligent load shedding is defined as [33]: a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable.

The objective of load shedding remains unchanged. The means to improve power stability using intelligent load shedding changes to addressing individual loads in an area, based on knowledge about the power system and these loads, in order to switch off or reduce power for a certain time.

Intelligent load shedding deals with (i) the problem of detecting situations that will go unstable if no remedial actions are taken, and (ii) to take proper action in such a way that stability is restored by minimum cost load shedding. Intelligence and communication are essential means in order to achieve this. Communication is needed in order to obtain information on where and when load shedding is needed, to obtain information on individual loads and their constraints with respect to readiness to shed, and to address individual loads in order to reduce load or switch them off. Intelligence is needed in order to find optimal scenarios for the amount of load to shed and the location of these loads.

2.7.5.4 Requirements and Scenarios for Intelligent Load Shedding

The main requirement on "intelligent load shedding" is that it should be regarded as a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable. The work with intelligent load shedding can be divided in a number of stages [34]:

- To improve present load shedding schemes (where a circuit breaker on the 10/20 kV level is opened), to a scheme where individual load objects in the area are addressed and switched off, or ordered to reduce power, for a certain time.
- To keep track on the load available to be shed in every instant.
- To find an "optimal" amount of load to shed, with respect to a certain disturbance.
- To find the "optimal" location of the load to be shed, with respect to a certain disturbance.
- To specify/find relevant disturbances to prepare load shedding for, and to "interpolate" between these to find suitable actions for real disturbances.
- To initiate "intelligent load shedding" - when approaching voltage instability, angular instability, frequency instability or cascaded outages.

A main consideration in intelligent load shedding will be the cost criterion. Strategies may be based on dynamic prices and on electric market.

2.8 Voltage Stability Related Works

There are many researches contribute in solving voltage stability. Part of these researches use artificial neural networks and others use different algorithms. In [35] an artificial neural network application to power system voltage stability improvement is introduced, and in [36] a novel algorithm for on-line voltage stability assessment based on feed forward neural network is introduced, while [37] introduces a development of an improved on-line voltage stability index using synchronized phasor measurement

2.8.1 Artificial Neural Network Application to Power System Voltage Stability Improvement

This work deals with development of ANN architecture, which provide solutions for monitoring, and control of voltage stability in the day-to-day operation of power systems. It focuses on evaluating the performance of ANN for control and improvement of Power System Voltage Stability problem [35].

A minimization algorithm for improving voltage stability margin based on L-Index and employing non-linear least squares optimization technique is presented. The control

variables considered are switchable VAR compensators, OLTC transformers and generators excitation. The model used for the power system includes limits for reactive power generation at generators, load characteristics and generation control characteristics. Generally in reactive power dispatch the objective is either to minimize real power losses or to minimize the deviations of voltages from desired values. The objective in the proposed algorithm is to minimize the sum of squares of L-indices at all or a subset of critical nodes (decided from voltage stability point of view) in the system. Results obtained from the proposed algorithm are compared with Minimum singular value (MSV) of the modified power flow Jacobean matrix. The increase of load margin to voltage collapse is demonstrated.

A conclusion of the work is: A prototype of an ANN for monitoring and control of power system voltage stability margin improvement has been developed. The proposed ANN tries to improve the voltage stability margin using SVCs, Generator excitation and OLTC transformers as controllers for different loading conditions for a practical EHV Indian power system and encouraging results have been obtained.

2.8.2 Novel Algorithm for Online Voltage Stability Assessment Based on Feed Forward Neural Network

This work presents an online voltage stability assessment method using the feed forward neural network. In this method feed forward neural network is trained for the L indices values, which is a scalar measure of the voltage stability for all the power system buses during normal and contingent situations [36].

Main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained Artificial Neural Network at every time instant unlike the other techniques. The easiness in calculating the stability indices using Index L is exploited for learning the voltage profile of any complex system by ANN.

Thus the stability margin and voltage profile locally for individual buses as well as the global stability margin and improvement measures of the power system can be assessed at the same time with the proposed technique. Another feature of the proposed method is its ability in developing L indices of all the system buses during both normal and contingent

situations using the trained ANNs. This aspect has not been considered as a single problem so far in the earlier research works.

The trained ANN is then tested on the practical 367 bus system to prove its practical use using MATLAB neural network toolbox. The approach was found to be extremely useful to use as energy management software for online establishment of voltage stability margins and to find out the associated limits at each bus.

The proposed network architecture is a three layer feed forward structure including input, output and hidden layer using a back propagation algorithm. Following algorithmic steps describes in detail the approach used for investigating the different parameters and functions in the MATLAB toolbox.

Step 1: A conventional voltage stability algorithm is run with the test system for simulated loading conditions. Using this first the base case and the maximum loading conditions of the test system are determined using the conventional software. Then the load conditions are varied from base case till full load and training samples are generated.

Step 2: Create a database for the input vector in the following form $\left[P_g^T\, Q_g^T\, V_g^T\, P_l^T\, Q_l^T\, V_l^T\right]^T$ where, P_g, Q_g, P_l and Q_l are the real and reactive power in generator as well as load buses respectively and V_g and V_l are bus voltage at generator and load buses. Further, create target vector in the form of L-indices for the corresponding input vectors.

Step 3: Find the minimum and maximum values of the input vector, remove redundancies and normalize to suit to train the selected feed forward neural network.

Step 4: Select the set of training parameters such as number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

Step 5: Train the network based on a set of transfer functions and number of neurons. The number of neurons in each layer is varied initially and optimum combination is found out depending on the training period and performance error.

Step 6: Find the most suitable combination of the activation function. Behavioral accuracy depends on the uniformity in values of L-indices at all the buses. It can happen that the

network gives output, which is accurate for some buses but may be unacceptable on some others.

Step 7: Change the training function keeping same transfer functions and optimum number of neurons in each layer.

Step 8: Find the most suitable network based on the simplicity least possible Mean Square Error and computational speed. Further use various test functions to confirm the effectiveness of the proposed neural network. At this state the functions and all the parameters are finalized for a particular combination.

A conclusion of the work is: An artificial neural network technique for on line assessment of power system voltage stability using a developed training algorithm for all system buses has been presented with detail steps involved with MATLAB neural network toolbox. Unlike other reported techniques, the main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained artificial neural network at every monitoring period. The stability margin and voltage profile for individual buses, the global stability margin, as well as possible improvement measures of the power system can be assessed at the same time during both normal and contingent situations using the trained ANN. Training and testing results form all cases, including contingencies on a practical power systems network shows that the proposed ANN algorithm is capable to learn and perform as a tool for online voltage stability analysis by measuring the L-indices for all the vulnerable buses.

2.8.3 Development of an Improved On-Line Voltage Stability Index Using Synchronized Phasor Measurement

Most techniques are computationally demanding and cannot be used in an on-line application. A voltage stability index (VSI) can be designed to estimate the distance of the current operating point to the voltage marginally stable point during the system operation. This research work developed a new VSI that not only can detect the system voltage marginally stable point but also is computationally efficient for on-line applications. Starting with deriving a method to predict three types of maximum transferable power of a single source power system, the new VSI is based on the three calculated load margins [37]. In order to apply the VSI to large power systems, a method has been developed to

simplify the large network behind a load bus into a single source and a single transmission line given the synchronized phasor measurements of the power system variables and network parameters. The simplified system model, to which the developed VSI can be applied, preserves the power flow and the voltage of the particular load bus. The proposed voltage stability assessment method, therefore, provides a VSI of each individual load bus and can identify the load bus that is the most vulnerable to voltage collapse.

The developed VSI is a reliable assessment of the voltage stability margin of an individual load and is suitable for on-line implementation for detecting the emerging short-term and long-term voltage instability. The sub-tasks of developing this improved voltage stability index are the following:

- Development of a new computationally efficient load margin assessment method based on synchronized phasor measurements and the power system network topology and parameters.
- Derivation of VSI of individual load buses and the power system based upon the calculated load margin.
- Implementation and testing of the new VSI on various power systems.

The new VSI was tested on three power systems which are BPA 10-bus test system, IEEE 30-bus test case and CIGRE 32-bus test system. Results from these three test cases provided validation of the applicability and accuracy of the proposed VSI.

A conclusion of the work is: Test results of applying the proposed voltage stability assessment method on three power systems have demonstrated that it has the following salient features:

- The proposed method can identify the system voltage marginally stable point with satisfactory accuracy.
- The proposed method provides system voltage security in the format of a load margin that is readable and informative.
- The proposed method can identify the load bus that is the most susceptible to voltage collapse.
- The proposed method is computationally efficient, and can be easily implemented to predict the voltage stability of large power systems in almost real time.

The main contribution of this dissertation is the development of a practical synchronized phasor measurement based voltage stability index that can accurately predict the power system voltage stability with affordable computational demands for on-line applications. The proposed voltage stability assessment method could be incorporated into wide area protection and control systems to monitor the power system voltage stability security. Also, the newly proposed network reduction method enables users to analyze the voltage stability of each load bus and design of distributed control schemes to prevent voltage collapse.

2.9 Power System Control

Given the complexity of the power system and its dynamic phenomena, one would expect that various controls have been developed over time to control various phenomena. These developments have followed the availability of enabling hardware technologies (e.g. electronics, communications, and microprocessors) as well as the evolution of control methodologies.

When a fault (short circuit) occurs, the faulted equipment has to be isolated. A short circuit is characterized by very low voltages and very high currents, which can be detected and the faulted equipment identified. If the fault is on a shunt element, like a generator or a distribution feeder, the relay will isolate it by opening the connecting circuit breakers. If the fault is on a series element, like a transmission line or transformer, the breakers on both sides have to be opened to isolate it. The main characteristic of the protection system is that it operates quickly, often in tens of milliseconds, so as to protect the equipment from damage.

2.9.1 Voltage Control

As is mentioned before, one way to control node voltages is by varying the excitation of the rotating generators. This is done by a feedback control loop that changes the excitation current in the generator to maintain a particular node voltage. This control is very fast.

Another way to control node voltage is to change the tap setting of a transformer connected to the node. Other ways are to switch shunt capacitors or reactors at the nodes.

These changes can be made manually by the operator or automatically by implementing a feedback control that senses the node voltage and activates the control. Unlike the generator excitation control, transformer taps and shunt reactances can only be changed in discrete quantities. Often this type of control schemes has time delays built into them to avoid excessive control actions [38].

More recently power electronic control devices have been introduced in the shunt reactance voltage control schemes. This makes the control much more continuous and often is done it a much faster time frame than the usual shunt switching. These static VAR compensators (SVC) are becoming more common.

As is obvious, voltage control is always a local control. However, controlling the voltage at one node affects the neighboring nodes.

2.9.2 Transmission Power Flow Control

Most power systems have free flowing transmission lines. This means that although power injections and node voltages are controlled quite closely, the power flow on each transmission line is usually not controlled. However, such control is feasible.

A phase shifting transformer can control the power flow across it by changing the phase using taps. This has been used, especially on the Eastern interconnection in North America. The control is local, discrete and slow. A power electronic version of this is now under experimentation.

The major advantage of the AC transmission grid is its free flowing lines with relatively less control and so the wholesale control of every transmission line is not desirable and is not contemplated. However, controls on some lines have always been necessary and some new advantages may be realized in the more deregulated power system when monitoring transactions between buyers and sellers have to be better controlled [39].

2.9.3 Frequency Control

Frequency is controlled by balancing the load with generation. The governors on every generator senses any change in the rotational speed and adjusts the mechanical input power. This governor control is the primary control for maintaining frequency. A secondary control to set the governor set-points is used to ensure that the steady state always returns to

nominal. The governor control is local at the generator and fast. The secondary control is done over the whole system. This secondary control is done by the central controller and is slow. This control is also known as Automatic Generation Control (AGC) or Load Frequency Control (LFC) [38].

As the deviation of frequency from nominal is a symptom of the imbalance between generation and load, the frequency control performance requirement depends on how well one wants to control the power supply commitments made between seller and buyer.

2.9.4 Control Center

As mentioned in the above sections most of the controls are local. The only area wide control is the secondary frequency control or AGC. This is implemented as a feedback control loop in which the generator outputs and tie-line flows are measured and brought back to the control center and the governor control set-points are calculated and sent out to the generators from the control center. The data rate – both input and output – is between 2 and 4 seconds.

The control center performs many other functions although AGC is the only automatic feedback control function. The main function is real time data acquisition from all over the grid so that the operator can monitor its operation. Another is the manual operation of controls like opening or closing circuit breakers, changing transformer taps, etc. These functions are jointly known as the Supervisory Control and Data Acquisition (SCADA) and the control center is often referred to as SCADA.

A control center energy management system (EMS) generally consists of four major elements as shown in figure 2.6 [39]:

- The supervisory control and data acquisition (SCADA) system
- The automatic generation control (AGC) system
- The energy management applications and database
- The user interface (UI) system.

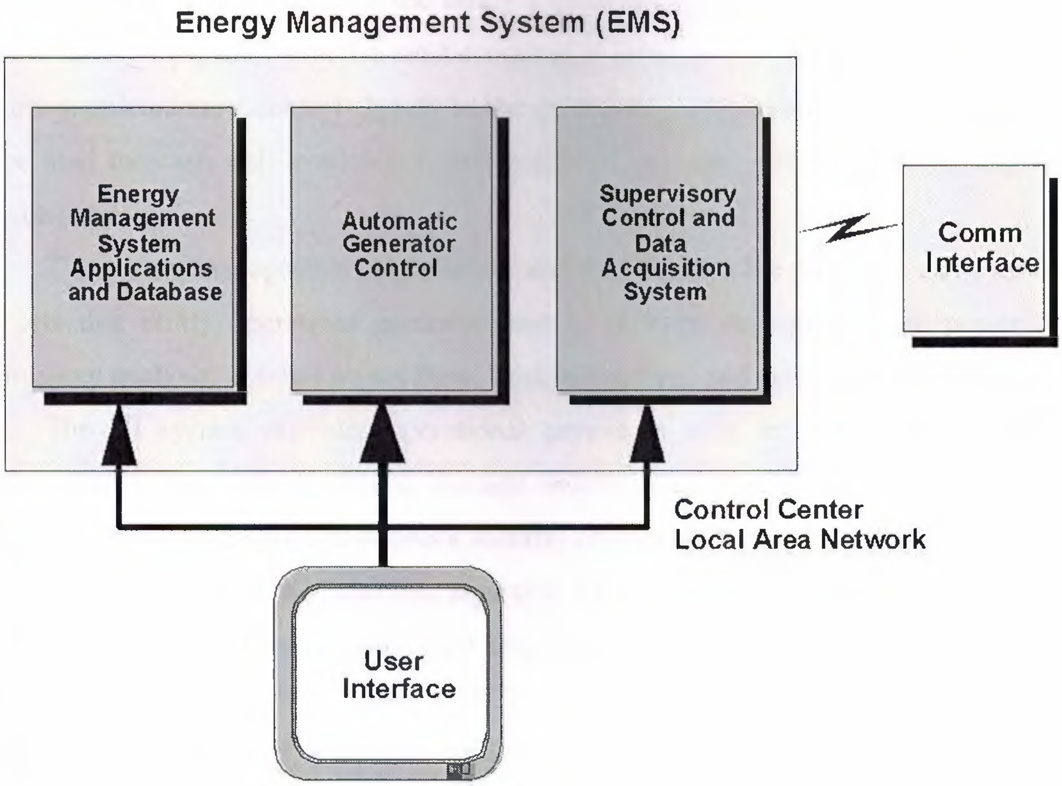


Figure 2.6 Elements of the Control Center Energy Management System

The SCADA system manages the RTU communications, collects the electric system data from the field through a series of front-end processors, initiates alarms to the operations personnel, and issues control commands to the field as directed by the applications in the control center system. The SCADA system typically consists of a host or master computer, one or more field data-gathering and control units (RTUs), and a collection of standard and/or custom software used to monitor and control remote field data elements. SCADA systems may have 30,000 to 50,000 data collection points and may transmit analog information (e.g., generator megawatts) as well as digital or status information (e.g., breaker open/close state). SCADA systems can also send a control signal (e.g., start a pump) as well as receive a status input as feedback to the control operation (e.g., the pump is started). Current computing power allows SCADA systems to perform complex sequencing operations and provides for frequent collection (e.g., every 2 seconds) of power system data.

The AGC system controls the utility's generating units to ensure that the optimal system load is being met, with the most economical generation available. The AGC system submits supplementary control signals to the generating units to adjust their output based on the load forecast, unit availability, unit response rate, and scheduled interchange with other utilities.

The energy management applications and database are the programs and associated data sets that utility operations personnel use to manage state estimation, power flow, contingency analysis, optimal power flow, load forecasting, and generation unit allocation.

The UI system provides operational personnel with an interactive interface to monitor electric system performance, manage system alarm conditions, and study potential system conditions to ensure that network security criteria are met.

These SCADA-AGC functions at central control centers evolved in the earlier part of the last century but in the 60s their implementation was accomplished with digital computers. Remote terminal units (RTU) were positioned in every substation and generating station to gather local data and this data was then transmitted from the RTUs to the control center over communication lines, usually microwave channels but sometimes telephone lines. This scheme is shown in Figure 2.7. The data normally includes the switching statuses (on/off) of all the circuit breakers as well as the current values and voltages of complex power. Although these control centers are quite separate from other computer systems, it does accumulate a large set of historical data that can be utilized for various engineering study and analysis. Thus it is quite common to have a network connection to third party (usually engineering) computers [38].

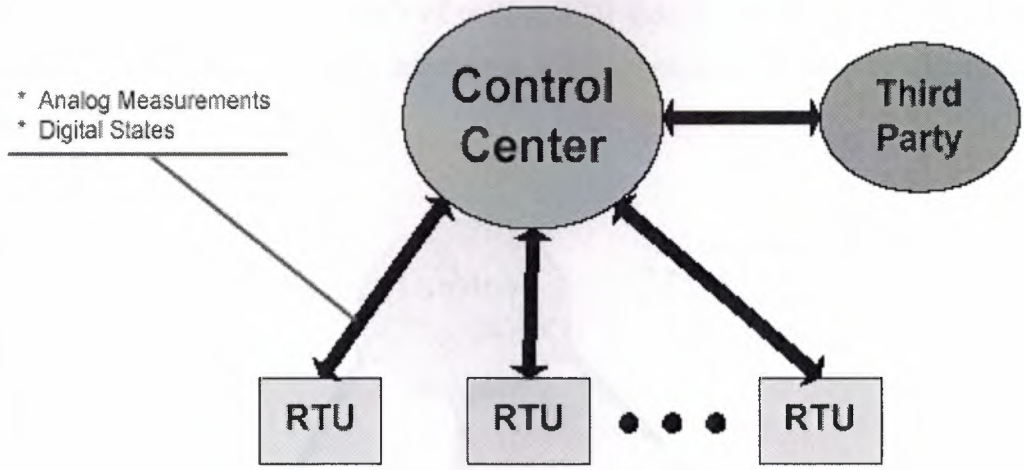


Figure 2.7 The Control Center has Direct Communication Channels to The RTUs at each Substation and Generating Station

As the computational power of the control centers grew, more functions have been added to the control centers. The main one has been the state estimator which calculates the real time steady state model of the network. This real time model can then be used for two kinds of calculations.

One, known as security analysis, can study the effects of disturbances (contingencies) and can alert the operator if the post-contingency conditions violate limits. The other, usually using a family of analysis known as optimal power flow, can suggest better operational conditions. All these analytical tools provide better operational guidance to the operator than the old SCADA systems could and are now known as Energy Management Systems (EMS).

Another recent trend has been the increasing use of microprocessors and faster communication within the substations to gather more real time data. This data gathered at the few milliseconds rate is stored at the substations but is too voluminous as yet to be broadcast. Instead certain sequences of this data – say, after an emergency or disturbance – are then imported, increasingly, over some sort of network and then used for study purposes. This is shown in Figure 2.8 What this means is that data is now being measured and gathered at the substations at a much faster rate than can be communicated to the

control center which is only capable of polling RTU data at the rate of a few seconds. The excess data can be recorded at the substations and for now is gathered only after the fact for studies [38].

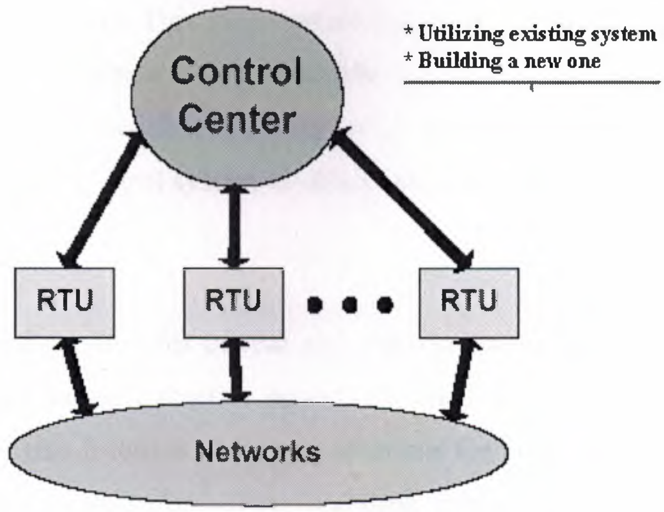


Figure 2.8 The RTUs has Direct Communication Channels with The Control Center and with Networks

Power system control can then be summarized as follows [39]:

- Most automatic controls are local.
- At the generator there is the governor control of generator output, the exciter control of generator terminal voltage and sometimes, power system stabilizer (PSS) control. These are continuous fast feedback control.
- Node voltages can also be controlled by transformer taps and shunt reactances. These are slow discrete controls but new continuous fast static VAR compensators (SVC) are becoming available for use.
- Where DC transmission is used, fast continuous control of line flow is available and new tools to do so on AC lines are becoming available. Slow controls using phase shifting transformers are still being used in a few places.

- Protective relays that isolate faulted equipment operate locally but are very fast. With communication from other parts of the network, they have great potential for fast control.
- The secondary frequency control of generator governor set-points is the only area wide control used today. This slow control implemented through the central control center is discrete at the rate of a few seconds.
- Much more data at very fast rates are being gathered at the substations but the communication and control system to utilize this data for faster controls is lacking.

2.10 Summary

This chapter introduced the transfer of real and reactive power through the transmission system and sources and sinks of reactive power, and then discussed voltage stability and voltage collapse. After that it introduced many solutions for voltage instability or collapse and some related research work for voltage stability. Finally it explained the control of power system. Part of these solutions will be used to enhance the voltage drop of PDS and to restore voltage stability in the intelligent voltage stabilizer in the last chapter.

CHAPTER THREE
ARTIFICIAL NEURAL NETWORKS

3.1 Overview

Neural networks emerged about 50 years ago. Their early abilities were exaggerated, casting doubts on the field as a whole. There is a recent renewed interest in the field, however, because of new techniques and a better theoretical understanding of their capabilities.

The basic concepts of artificial neural networks (ANN) will be explained in this chapter in addition to back propagation algorithm which will be used in our work for instability detection. Also, this chapter will describe real life applications of prediction ANN and uses of ANN in Electrical Power Systems.

3.2 Introduction to ANN

Neural networks have seen an explosion of interest over the last few years, and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology and physics. Indeed, anywhere that there are problems of prediction, classification or control, neural networks are being introduced. This sweeping success can be attributed to a few key factors:

- **Power.** Neural networks are very sophisticated modeling techniques capable of modeling extremely complex functions. In particular, neural networks are nonlinear. For many years linear modeling has been the commonly used technique in most modeling domains since linear models have well-known optimization strategies. Where the linear approximation was not valid the models suffered accordingly. Neural networks also keep in check the curse of dimensionality problem that bedevils attempts to model nonlinear functions with large numbers of variables.
- **Ease of use.** Neural networks learn by example. The neural network user gathers representative data, and then invokes training algorithms to automatically learn the structure of the data. Although the user does need to have some heuristic knowledge of how to select and prepare data, how to select an appropriate neural network, and how to interpret

the results, the level of user knowledge needed to successfully apply neural networks is much lower than would be the case using some more traditional nonlinear statistical methods.

Neural networks can be divided into three architectures, namely single layer, multilayer network and competitive layer. The number of layers in a net is defined based on the number of interconnected weight in the neuron. Single layer network consists only one layer of connection weights. Whereas, multilayer networks consists of more than one layer of connection weights. The network also consists of additional layer called hidden layer. Multilayer networks can be used to solve more complicated problems compared to single layer network. Both of the network are also called feed-forward network where the signal flows from the input units to the output units in a forward direction. The competitive layer network, for example the Recurrent Networks is a feedback network where there are closed-loop signal from a unit back to itself.

3.3 Learning in Neural Networks

Assume there are n input units, $X_1,\ldots,\ X_n$ with input signals $x_1,\ldots,x_n$. When the network receives the signals (x_i) from input units (X_i), the net input to output (Y_j) is calculated by summing the weighted input signals. The matrix multiplication method for calculating the net input is shown in the equation below.

$$u_j = \sum_{i=1}^{n} W_i X_i$$

where, w_{ij} is the connection weights of input unit x_i and output unit y_j.

The network output (y_i) is calculated using the activation function $f(x)$. In which y_i $= f(x)$, where x is u_j. The computed weight from the training is stored and will become the information or knowledge for the future application.

Neural networks learning algorithms can be divided into two main groups that are supervised (or associative learning) and unsupervised (self-organization) learning. Many supervised and unsupervised learning ANN have been invented.

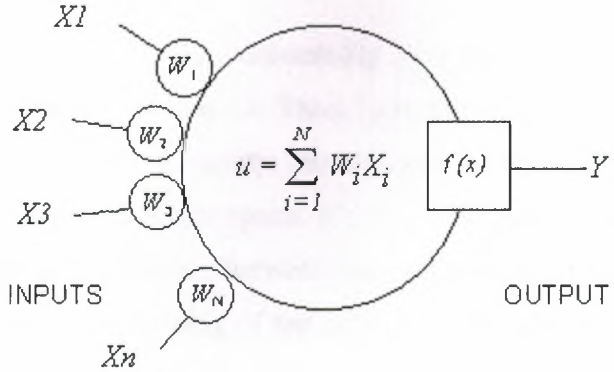


Figure 3.1 Weight of Perceptron

3.3.1 Supervised Learning

Supervised learning is based on the target value or the desired outputs. During training the network tries to match the outputs with the desired target values. This method has two sub varieties called auto-associative and hetero-associative. In auto-associative learning, the target values are the same as the inputs, whereas in hetero-associative learning, the targets are generally different from the inputs.

One of the most commonly used supervised ANN model is back propagation network that uses back propagation learning algorithm. Back propagation of errors or generalized delta rule is a decent method to minimize the total squared error of the output computed by the net.

3.3.2 Unsupervised Learning

Unsupervised learning method is not given any target value. A desired output of the network is unknown. During training the network performs some kind of data compression such as dimensionality reduction or clustering. The network learns the distribution of patterns and makes a classification of that pattern where, similar patterns are assigned to the same output cluster. Kohonen network is the best example of unsupervised learning network. Kohonen network refers to three types of networks that are Vector Quantization, Self-Organizing Map and Learning Vector Quantization.

3.3.3 Training the Network

Training the network could be time consuming. It usually learns after several epochs, depending on how large the network is. Thus, large network required more training time compared to the smaller one. Basically, the network is trained for several epochs and stopped after reaching the maximum epoch. For the same reason minimum error tolerance is used provided that the difference between network output and known outcome is less than the specified value. The training of the network could also stop after meeting certain stopping criteria [40].

3.4 Back Propagation Algorithm

3.4.1 Back Propagation Neural Networks

Back Propagation (BP), a euphemism for the generalized delta rule including momentum, is a supervised learning algorithm that applies to non-linear, multilayer; feed forward structure of nodes (networks). It works on minimizing the Mean Square Error (MSE) of the network.

The architecture of a BP network refers to the way it decodes information, that is the direction of information during recall. In a BP neural network the nodes are organized in input, hidden, and output layers, as in Figure 3.2.

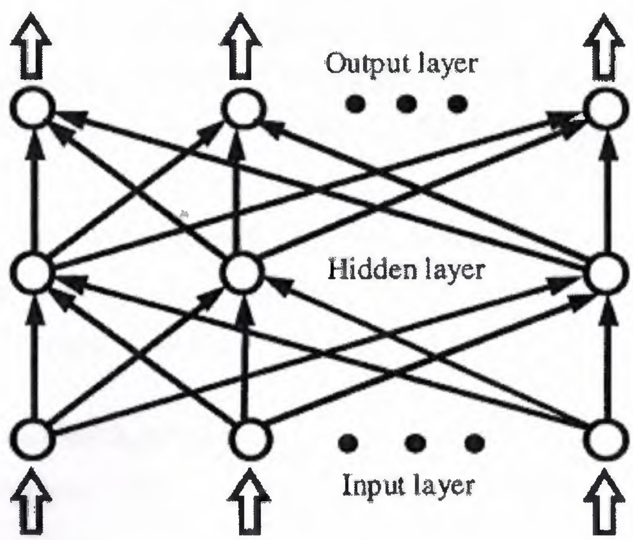


Figure 3.2 Back Propagation Neural Network [41]

3.5.2 Training BP Networks

Training of a BP neural network is achieved by presenting inputs to the network with the desired outputs. The network processes the inputs into its own simulated outputs. Input layer neurons receive the data to be processed by the network and the output layer holds the global computation results. One or more hidden layers may be present depending on problem complexity but quite often one layer suffices. All neurons within the input layer are connected to all neurons of the first hidden layer. These are subsequently connected to all neurons of the second hidden layer, if one is present, or to the neurons of the output layer. A weighting factor is associated with each connection. The same process is repeated with all adjacent hidden layers until the input layer is reached. At that moment all synaptic weights are updated. As neural networks are trained on sample data, these should be of high quality and representative of the domain [42].

The weight change rule is a development of the perceptron learning rule. Weights are changed by an amount proportional to the error at that unit times the output of the unit feeding into the weight. Running the network consists of:

- Forward pass:

  The outputs are calculated and the error at the output units calculated.

- Backward pass:

  The output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

For each data pair to be learned a forward pass and backwards pass is performed. This is repeated over and over again until the error is at a low enough level or the process reach the maximum number of epochs.

3.5.3 Mathematical Approach

Step 0: Initialize weights: to small random values (-1.0 → +1.0);

Step 1: Apply a sample: apply to the input a sample vector u_k having desired output vector y_k ;

Step 2: Forward Phase:

Starting from the first hidden layer and propagating towards the output layer:

2.1. Calculate the activation values for the units at layer L as:

2.1.1. If L-1 is the input layer

$$a_{h_L}^k = \sum_{j=0}^{N} W_{jh_L} u_j^k$$

2.1.2. If L-1 is a hidden layer

$$a_{h_L}^k = \sum_{j_{L-1}=0}^{N} W_{j_{(L-1)}h_L} x_{j_{(L-1)}h_L}^k$$

2.2. Calculate the output values for the units at layer L as:

$$x_{h_L}^k = f\,(a_{h_L}^k)$$

in which use i_o instead of h_L if it is an output layer

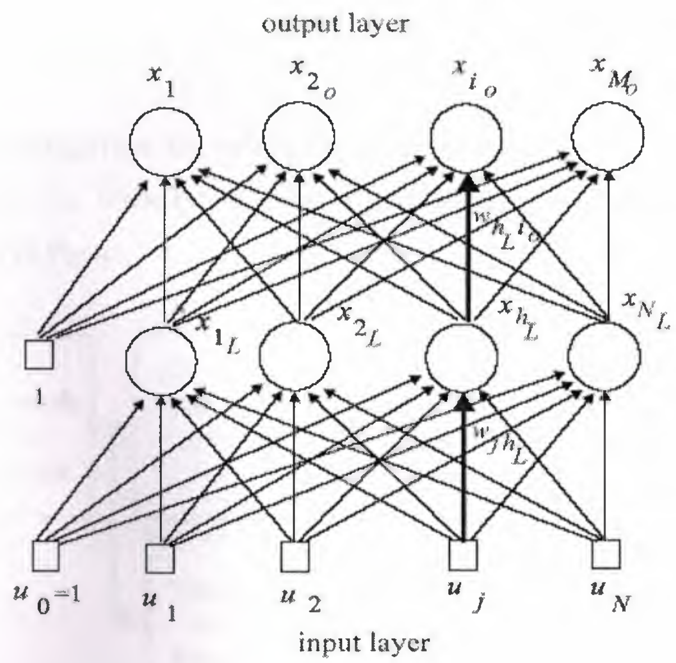


Figure 3.3 Multilayer BP Network [43]

Step 3: Output errors: Calculate the error terms at the output layer as:

$$\delta_{i_o}^k = (y_{i_o}^k - x_{i_o}^k) f_o^{'}(a_{i_o}^k)$$

Step 4: Backward Phase Propagate error backward to the input layer through each layer *L* using the error term

$$\delta_{h_L}^k = f_L^{'}(a_{h_L}^k) \sum_{i_{L+1}=1}^{N_{L+1}} \delta_{i_{(L+1)}}^k w_{h_L i_{(L+1)}}^k$$

in which, use i_o instead of $i_{(L+1)}$ if (*L*+1) is an output layer;

Step 5: Weight update: Update weights according to the formula

$$w_{j_{(L-1)} h_L}(t+1) = w_{j_{(L-1)} h_L}(t) + \eta \delta_{h_L}^k x_{j_{(L-1)}}^k$$

Step 6: Repeat steps 1-6 until the stop criterion is satisfied, which may be chosen as the mean of the total error

$$< e^k > = < \tfrac{1}{2} \sum_{i_o=1}^{M} (y_{i_o}^k - x_{i_o}^k)^2 >$$

is sufficiently small [43].

3.5.4 Back Propagation Algorithm Block Diagram

The block diagram of the Back Propagation Algorithm consists from several processing blocks as it is shown in Figure 3.4.

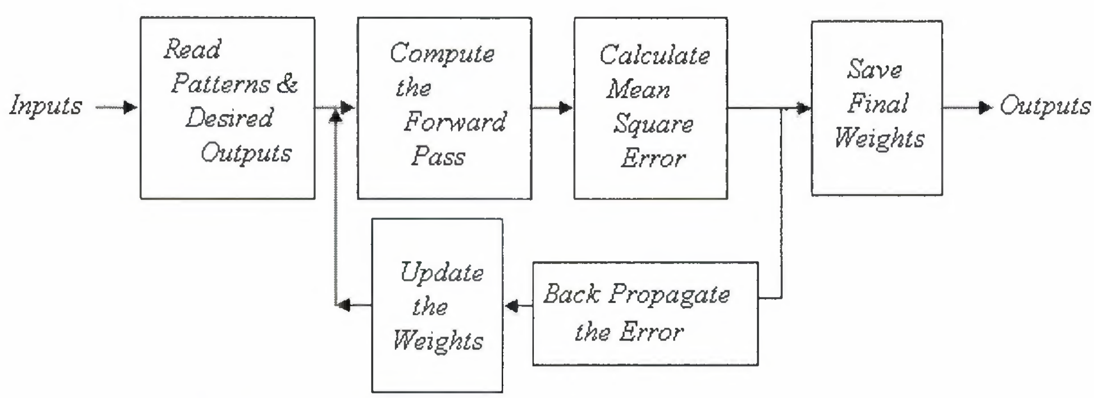


Figure 3.4 Back Propagation Algorithm Block Diagram

3.5 Applications of ANNs

The main applications of ANNs are for signal processing and pattern recognition. The algorithmic treatment represents a combination of mathematical theory and heuristic justification for neural models. The ultimate objective is the implementation of digital neuro-computers, embracing technologies of VLSI, adaptive, digital and parallel processing.

From an application driven perspective, one can see that the strength of neural networks are nonlinear, adaptive and parallel processing. Neural networks have found many successful applications in computer vision, signal/image processing, speech/character recognition, expert systems, medical image analysis, remote sensing, robotic processing, industrial inspection, and scientific exploration. The application domains of neural nets can be roughly divided into the following categories: association, clustering, classifications, pattern completion, regression and generalization, and optimization [44].

Table 3.1 summarizes the different types of ANNs and their potential applications.

Table 3.1 ANNs Selector and Their Applications [45]

Analytical Technique	Tools	Applications	
Associations, sequential patterns	statistics	Marketing:	market basket analysis
Pattern recognition	statistics, neural networks, machine induction	Security:	number plates, fingerprints
		Computing & telecomms.:	speech, vision and handwriting
		Finance:	signature and bank note verification
		Engineering:	product inspection, maintenance inspections
Clustering	neural networks, statistics	Marketing:	market segmentation
		Energy:	mineral exploration
		Engineering:	design reuse
Classification	machine induction, neural networks	Marketing:	target marketing
		Defense:	radar images
		Food & Ag.:	fruit, catch and livestock grading
		Medicine:	ultrasound and ECG images, lab. diagnosis, psychiatric care, illness severity
		Comp. & telecoms:	OCR, computer virus detection
		Finance:	risk assessment, bond rating, fraud detection
		Engineering:	quality control
Modeling	regression (curve fitting), neural networks	Marketing:	ranking/scoring customers, pricing models
		Security:	fingerprint matching
		Finance:	bankruptcy prediction, property valuation
		Engineering:	process control
Forecasting	statistics, neural networks	Marketing:	sales, business demand, holiday preferences
		Meteorology:	weather prediction
		Food & Ag.	crop yields
		Finance:	forex rate prediction, stock market changes
		Engineering:	inventory control, power demand prediction
Constraint satisfaction	linear programming, neural networks, genetic algorithms, AI planning, CLP	Engineering:	Job shop and stock route scheduling

3.6 Using ANNs in Power Systems

A prototype network is used to control operations of a power system that was so successful at optimizing large synchronous generators and load flow. Also, neural networks can organize the distribution of supplied electrical power between many power stations connected in grid. The rating capacity of each station and the main demand consumers are inputs of the net. As the demand changes during a day the output of the network is the amount of electrical power that each station should supply as percentage of its rating [43].

3.6.1 A Review of Applications of ANNs in Power Systems

This part is an overview of application of ANNs in power system operation and control. The comparison of the number of published papers in IEEE proceedings and conference papers in this field during 1990-1996 with them during 2000-2005 has showed that the following fields has attracted the most attention in the past five years [46]:

1- load forecasting

2- fault diagnosis/fault location

3- economic dispatch

4- security assessment

5- transient stability

Table 3.2 summarizes the number of published papers about application of ANNs in power system operation and control topics in two time intervals [46]. The first time interval is from 1990 to 1996, while the second one is from 2000 to 2005. These papers are published in IEEE proceedings and conferences. It seems that the comparison of two columns can be used as a proof of successful or unsuccessful operation of NN in related power system operation field. Figure 3.8 shows the percentage of the number of published papers during 2000-2005 in a circle form [46]. This figure shows that some fields such as load forecasting fault diagnosis/fault location, economic dispatch, security assessment and transient stability.

Table 3.2 ANNs in Power Systems – Survey of Papers 1990-1996 and 2000-April 2005

Power System Subject	No. of Published Papers from 1990 to 1996 using ANN	No. of Published Papers from 2000 to April 2005 using ANN
Planning		
- Expansion		
Generation	-	1
Transmission	-	1
Distribution	-	-
- Structural : Reactive power	1	-
- Reliability	-	1
Operation		
1. Plant		
- Generation Scheduling	-	4
- Economic Dispatch ODF	1	14
- Unit Commitment	-	-
- Reactive Power Dispatch	1	1
- Voltage Control	4	3
- Security Assessment		
Static	7	3
Dynamic	6	9
- Maintenance Scheduling	3	1
- Contract Management	-	-
- Equipment Monitoring	4	3
2. System		
- Load Forecasting	12	23
- Load Management	-	-
- Alarm Processing/Fault Diagnoses	13	20
- Service Restoration	-	2
- Network Switching	-	-
- Contingency Analysis	1	2
- Facts	-	-
- State Estimation	4	2
Analysis & Modeling		
- Power Flow	4	4
- Harmonics	-	3
- Transient Stability	5	9
- Dynamic Stability/Control Design	13	7
- Simulation/Operations	-	1
- Protection	7	4

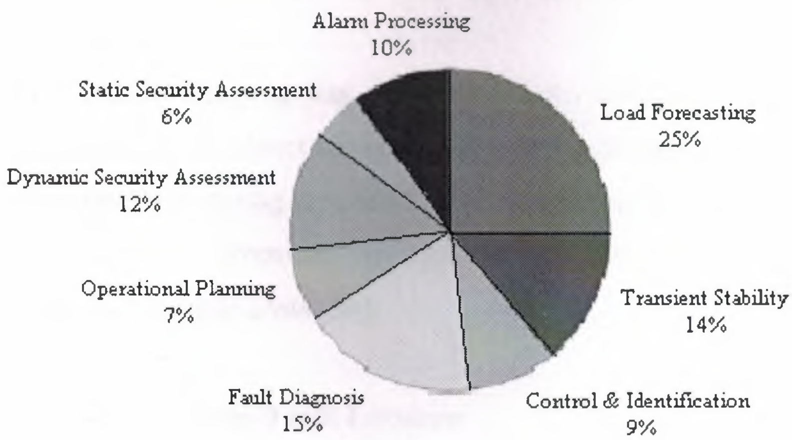


Figure 3.5 Neural Network Applications in Power Systems; 2000 – April 2005

3.6.2 Various ANNs Applications in Power System Subjects

Applications of ANNs in electrical power system are wide. The purpose of this section is to explore how the ANNs techniques are utilized in power systems especially in load forecasting, fault diagnosis or location, economic dispatch and security assessment.

3.6.2.1 Load Forecasting

Commonly and popular problem that has an important role in economic, financial, development, expansion and planning is load forecasting of power systems. Generally most of the papers and projects in this area are categorized into three groups:

• Short-term load forecasting over an interval ranging from an hour to a week is important for various applications such as unit commitment, economic dispatch, energy transfer scheduling and real time control. A lot of studies have been done for using of short-term load forecasting with different methods [47-52]. Some of these methods have main limitations such as neglecting of some forecasting attribute condition, difficulty to find functional relationship between all attribute variable and instantaneous load demand, difficulty to upgrade the set of rules that govern at expert system and disability to adjust themselves with rapid nonlinear system-load changes.

The ANNs can be used to solve these problems. Most of the projects using ANNs have considered many factors such as weather condition, holidays, weekends and special

sport matches days in forecasting model, successfully. This is because of learning ability of ANNs with many input factors.

• Mid-term load forecasting that range from one month to five years, used to purchase enough fuel for power plants after electricity tariffs are calculated [53].

• Long-term load forecasting covering from 5 to 20 years or more, used by planning engineers and economists to determine the type and the size of generating plants that minimize both fixed and variable costs [54].

3.6.2.2 Fault Diagnosis/Fault Location

Progress in the areas of communication and digital technology has increased the amount of information available at supervisory control and data acquisition (SCADA) systems [55, 56]. Although information is very useful, during events that cause outages, the operator may be overwhelmed by the excessive number of simultaneously operating alarms, which increases the time required for identifying the main outage cause and to start the restoration process. Besides, factors such as stress and inexperience can affect the operator's performance; thus, the availability of a tool to support the real-time decision-making process is welcome. The protection devices are responsible for detecting the occurrence of a fault, and when necessary, they send trip signals to circuit breakers (CBs) in order to isolate the defective part of the system. However, when relays or CBs do not work properly, larger parts of the system may be disconnected. After such events, in order to avoid damages to energy distribution utilities and consumers, it is essential to restore the system as soon as possible [57].

Nevertheless, before starting the restoration, it is necessary to identify the event that caused the sequence of alarms such as protection system failure, defects in communication channels, corrupted data acquisition [58].

The heuristic nature of the reasoning involved in the operator's analysis and the absence of an analytical formulation, leads to the use of artificial intelligence techniques. Expert systems, neural networks, fuzzy logic, genetic algorithms (GAs), and Petri nets constitute the principal techniques applied to the fault diagnosis problem [59].

From Table 3.2, it is seen that the major effort to detect and rectify power system faults in 90's, concentrate on expert system methods. Its main defect is the incapacity of

generalization and the difficulty of validating and maintaining large rule-bases. Recently, using model-based systems including temporal characteristics of protection schemes based on expert systems and ANNs developed.

The main advantage of neural network is its flexibility with noisy data and its main drawback is long time required for training feed forward network with back propagation training algorithm, especially when dimension of the power network is high. To short the training time using these substitute methods proposed: the general regression neural network (GRNN) in feed forward topology, the probabilistic neural network (PNN), adaptive neuro-fuzzy methods and the selective back propagation algorithm [60].

3.6.2.3 Economic Dispatch

Main goal of economic dispatch (ED) consists of minimizing the operating costs depending on demand and subject to certain constraints, i.e. how to allocate the required load demand between the available generation units [61, 62]. In practice, the whole of the unit operating range is not always available for load allocation due to physical operation limitations.

Several methods have been used in past for solving economic dispatch problems including Lagrangian relaxation method, linear programming (LP) techniques specially dynamic programming (DP), Beale's quadratic programming, Newton-Raphson's economic method, Lagrangian augmented function, and recently Genetic algorithms and ANNs. Because of, economic dispatch problem becomes a non-convex optimization problem, the Lagrangian multiplier method, which is commonly used in ED problems; can not to be directly applied any longer. Dynamic programming approach is one of the widely employed methods but for a practical-sized system, the fine step size and the large units number often cause the 'curse of dimensionality'.

Main drawbacks of genetic algorithm and tabu search for ED are difficulty to define the fitness function, find the several sub-optimum solutions without guaranty that this solution isn't locally and longer search time [46].

Neural networks and specially the Hopfield model, have a well-demonstrated capability of solving combinational optimization problem. This model has been employed to solve the conventional ED problems for units with continuous or piecewise quadratic fuel cost functions. Because of this network's capability to consider all constrained

limitation such as transmission line loss and transmission capability limitations, penalty factor when we have special units, control the unit's pollutions and etc., caused increasing the paper proposed recently [46].

3.6.2.4 Security Assessment

The principle task of an electric power system is to deliver the power requested by the customers, without exceeding acceptable voltage and frequency limits. This task has to be solved in real time and in safe, reliable and economical manner.

Generally there are two types of security assessments: static security assessment and dynamic security assessment [63 - 67]. In both types different operational states are defined as follows:

• Normal or secure state: In the normal state, all customer demands are met and operating limit is within presented limits.

• Alert or critical state: In this state the system variables are still within limits and constrain are satisfied, but little disturbance can lead to variable toward instability.

• Emergency or insecure state: the power system enters the emergency mode of operation upon violation of security related inequality constraints.

In practical power systems the dimension of the operating system is very high. To overcome this "curse of high dimensionality", three main approaches can be followed:

• Restrict the number of contingences and characterization of the security boundaries. This is for example done with supervised ANNs like MLP.

• Reduce the dimension of the operating vector; this is for example done with unsupervised ANNs like Oja-Sanger networks.

• Quantify of the operating point into a reduced number of classes, this is done with clustering algorithms for instance the nearest neighbor or the k-means clustering algorithms.

Commonly ANN that satisfies these conditions is multilayered Perceptron (MLP) with back propagation learning algorithm. The reason for this is on-line learning capability.

There are two problems with using MLP, selecting of input data and overtraining. A good method for first problem is using some of the security indicators presently calculated by the energy management system (EMS) as inputs to the ANN [68].

3.7 Summary

This chapter introduced the main concepts of artificial neural networks, and then introduced the concepts of the back propagation learning algorithm that will be implemented in our intelligent system. Much of concern in this chapter was directed to the applications of ANNs in electrical power systems. As a summary, it is convenient to apply ANN for instability and overload detection as part of an intelligent system next chapter.

CHAPTER FOUR
INTELLIGENT DETECTION OF INSTABILITY OF POWER DISTRIBUTION SYSTEMS

4.1 Overview

Voltage stability problems have been one of the major concerns for electric utilities as a result of system heavy loading. This chapter reports on an investigation into the application of artificial neural network (ANN) in on-line voltage instability detection. A discussion over the efficiency of the proposed techniques is also included.

4.2 Problem Analysis and Solution

Power systems may face some events like blackouts as a result of faults on some parts of the system or like getting overloaded which makes some loads switch off as a result of extreme voltage drop. These events mostly force the system to go to instability. As mentioned before our concern is on the stability of distribution substations which is one of the main parts of stability of the whole power system. Remote terminal units (RTU) which is part of SCADA can record RMS of voltages and the currents of the three phases with respect to time as curves all the time including unusual events.

The hypothesis which is presented within this thesis suggests that these graphs of unusual events during a year can be taken and sampled to a fixed number of samples. Voltage samples are normalized and then vectorized to be used as inputs to the neural network to train it for detecting events that may happen in future.

The neural network will have three outputs: stable case, unstable case or overload case. The next procedure is to arrange solutions to the system for the unstable and overload cases which will be discussed in the next chapter.

The neural network is used in this work to substitute the human monitor in the control center of the power system. It also works as another support for decision to help preventing voltage instability in case of late reaction from control center after a disturbance

risk. It uses the images of the three phase voltages as human monitor watching curves of three phase voltages and currents on monitor screen.

4.2.1 Data Acquisition

In our work as lack of recorded data, a power system is proposed which is the BPA test case study with some modification as seen in Figure 4.1. This proposed power system is simulated in computer using ready blocks in powerlib in MATLAB. Our concern is on the transient stability of one distribution power station which in our case is substation number 7 in the system. The the voltages of load 7 are taken as outputs of the circuit after simulation of 20 seconds.

Ordinary faults are induced on the generation station or on transmission grid of the system for a short time (2-3 seconds) then recovered and their effect is recorded on load 7 in order to simulate unstable cases. Also, one of the generators is switched off during simulation in different times and their effect is recorded on load 7. In another way, large additional loads are added to load 7 in different times to force the substation 7 to be overloaded and the terminal voltage is lowered to less than 95% of nominal voltage which outputs overload case. In the same manner, small additional loads are added or subtracted from load 7 in different times to simulate normally loaded system which makes the terminal voltage is higher than 95% of nominal voltage, and also the effect is recorded to register stable case.

These outputs are graphs of the sinusoidal waves of voltage during the twenty seconds of simulation. For every second on the graph there are 50 full waves, which make them concentrated and appear like a block. With visual inspection of these graphs, the upper level of these waves will be considered as the output with respect to time as from RTU in SCADA devices.

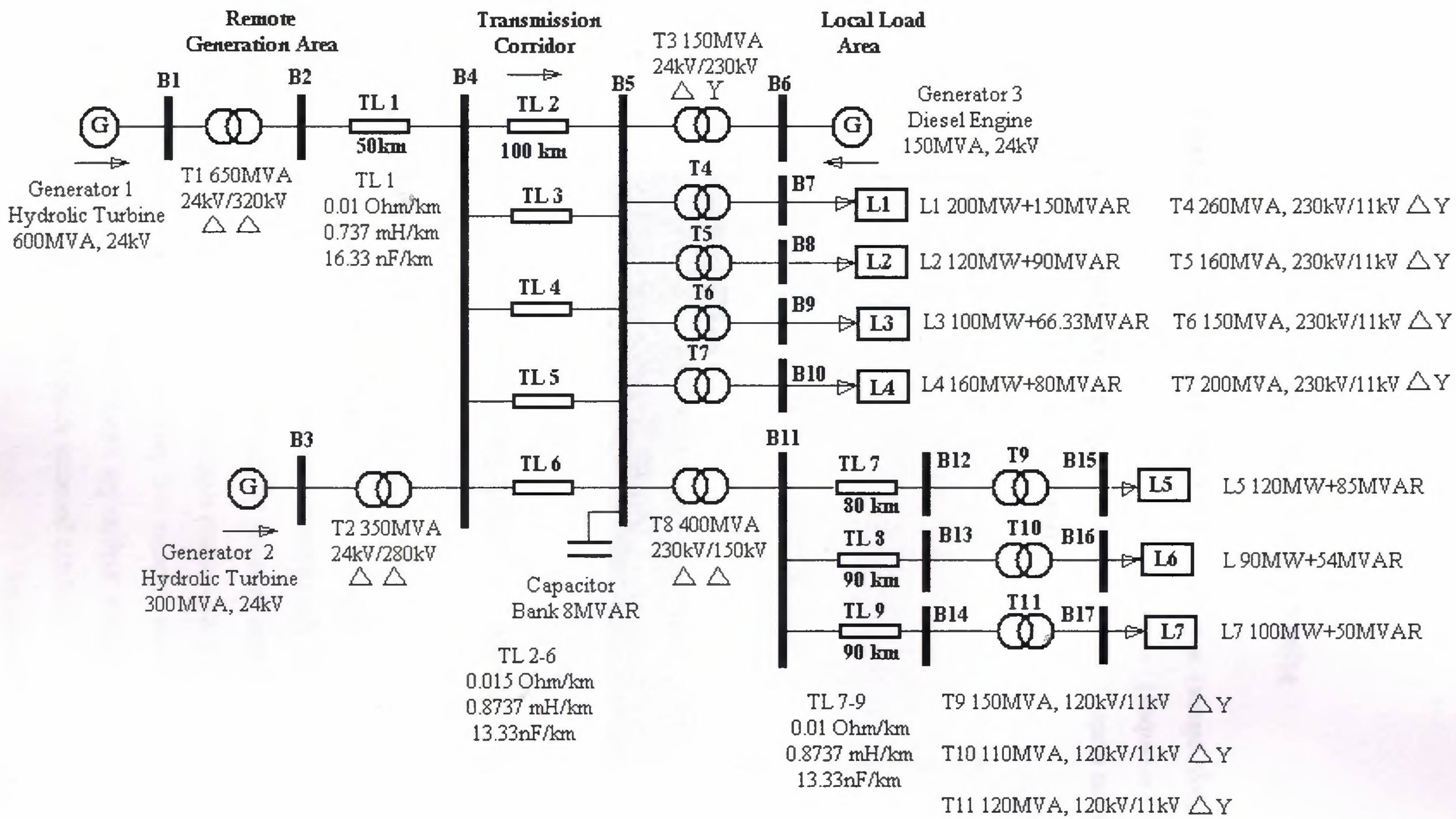


Figure 4.1 One Line Diagram of Test Case System

4.2.2 Patterns Preparation

The following steps are executed to prepare patterns to be inputs to the neural network.

First Step: The output voltage graphs for every case from simulation are extracted and saved as digital images. These images are denoted with three subscribes. The first subscribe (i) represents the case of the system with (i = 1-3), where 1 represents stable state of the system, 2 represents unstable state of the system and 3 represents overload state of the system. The second subscribe (j) represents the number of the case which with (j = 1-18). The third subscribe (k) represent the phase voltage with (k = 1-3), where 1 is for voltage on phase A, 2 is for voltage of phase B and 3 is for voltage on phase C. The size of every image is 500 x 840 pixels. Figure 4.2 shows an example of denoting one voltage graph, whereas figure 4.3 illustrates one example for the three images for every case.

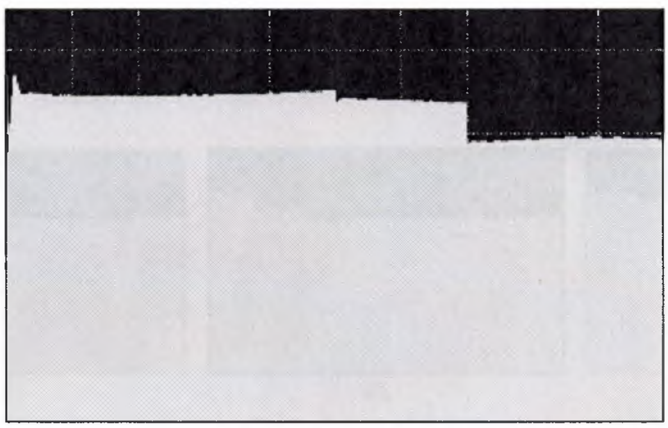


image i_j_k

i (system state) = 1,2,3 1 = stable, 2 = unstable, 3 = overload

j (case number) = 1 - 18

k (voltage phase) = 1,2,3 1 = phase a, 2 = phase b, 3 = phase c

Figure 4.2 Image Data Base Denotion

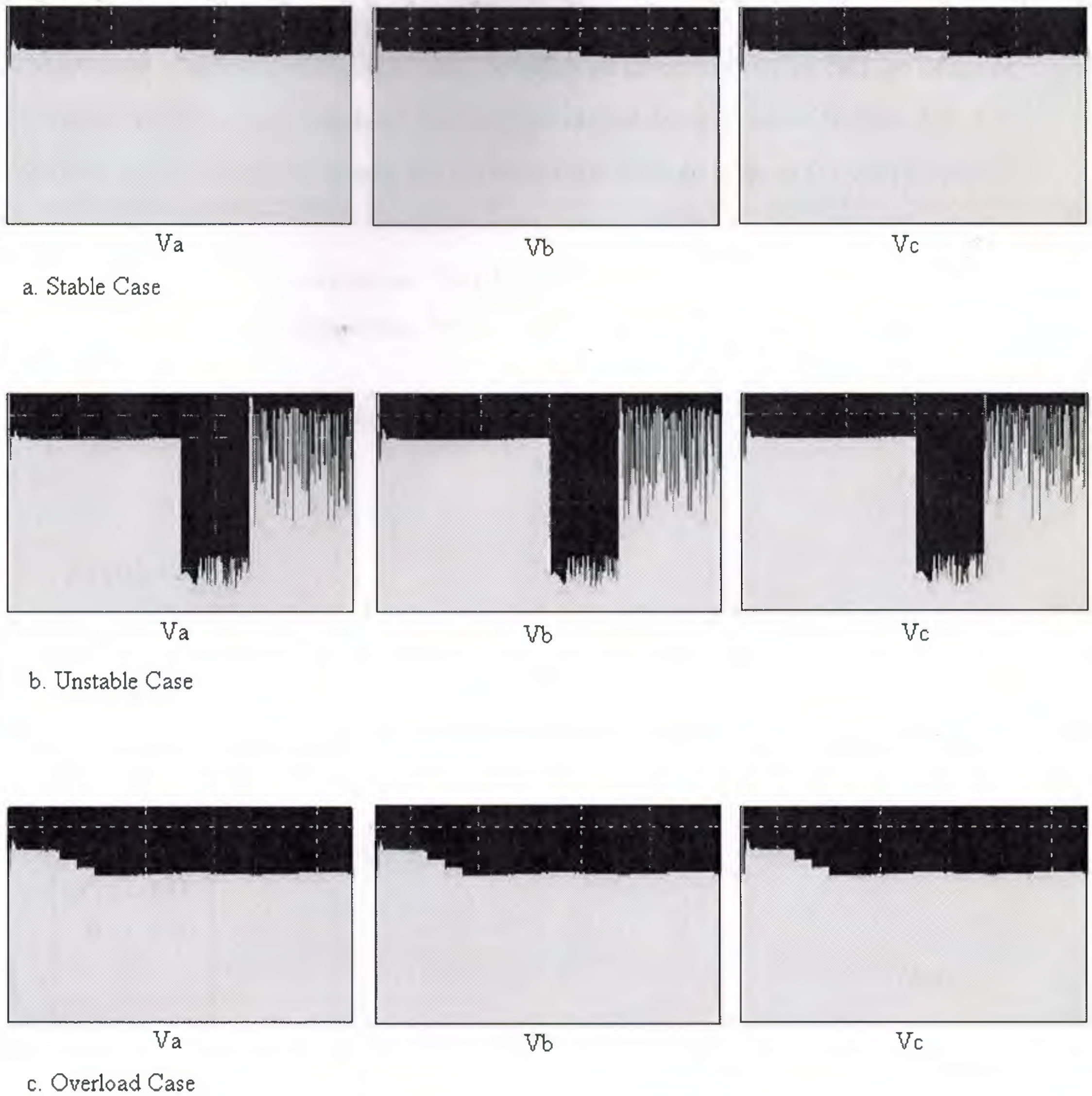


Figure 4.3 Examples of Training Cases

Second Step: Every image is converted to gray then resized to 400x202 pixels.

Third Step: In every image and for every column starting from column 2 to column 201 and from last row going up the value of the pixel, where the first discontinuity or change is found, the number of this row is saved in a vector. This saved value represents the highest value of the voltage of that column in that image. As a result 200 values are saved for every image. Equation 4.1 shows the general form of the vector and equations

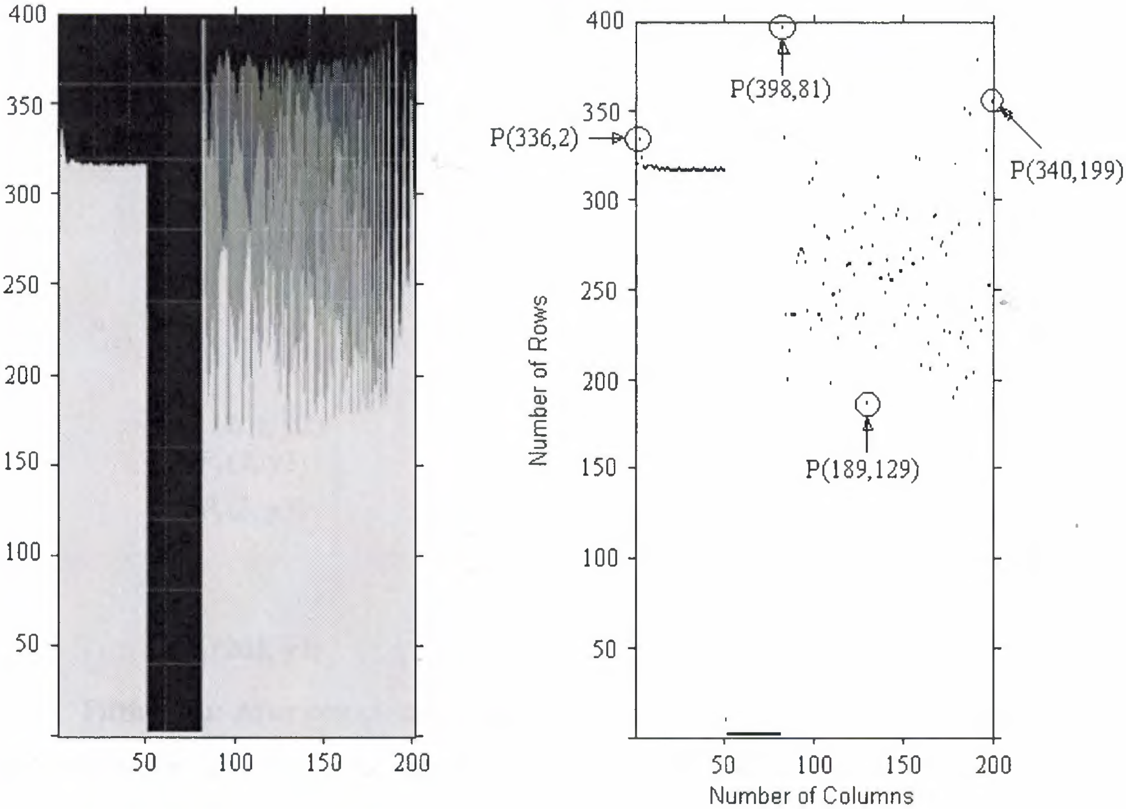
4.2, 4.3, and 4.4 show the form of the vector for image voltage a, b, and c respectively. Figure 4.4 shows one example of finding pixel position of discontinuity or change of color or in other words the maximum value of the voltage in that image, while figures 4.5, 4.6, and 4.7 introduce examples on extracting the curves of the voltage images for every case.

$$P_k = [P_k(x, y)] \qquad \begin{Bmatrix} x \text{ is any value from } 2 \rightarrow 201 \\ y \text{ is any value from } 1 \rightarrow 400 \end{Bmatrix} \tag{4.1}$$

$$P_1 = \begin{bmatrix} P_1(2, y1) \\ P_1(3, y1) \\ .. \\ .. \\ P_1(201, y1) \end{bmatrix} \tag{4.2}$$

$$P_2 = \begin{bmatrix} P_2(2, y2) \\ P_2(3, y2) \\ .. \\ .. \\ P_2(201, y2) \end{bmatrix} \tag{4.3}$$

$$P_3 = \begin{bmatrix} P_3(2, y3) \\ P_3(3, y3) \\ .. \\ .. \\ P_3(201, y3) \end{bmatrix} \tag{4.4}$$



a. Resized Gray Image

b. Pixel Position of Color Change

Figure 4.4 Finding Pixel Position of Discontinuity or Color Change

Fourth Step: For every case which consists of 3 images, 600 values are saved as a vector which represents one pattern as in equation 4.5.

$$P_{123} = \begin{bmatrix} P_1(2, y1) \\ P_1(3, y1) \\ .. \\ .. \\ P_1(201, y1) \\ P_2(2, y2) \\ P_2(3, y2) \\ .. \\ .. \\ P_2(201, y2) \\ P_3(2, y3) \\ P_3(3, y3) \\ .. \\ .. \\ P_3(201, y3) \end{bmatrix} \tag{4.5}$$

Fifth Step: After completing steps (1 - 4) for every case, the number of the patterns (*NP*) will be the same as the number of the cases. From image denotion i, j & k:

$$NP = i * j \tag{4.6}$$

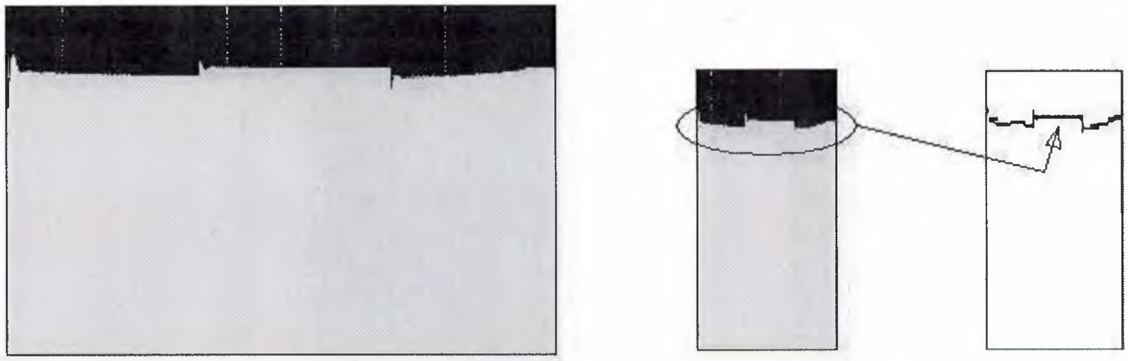
$$NP = 3 * 18 = 54 \tag{4.7}$$

Sixth Step: These pattern values are normalized to values between 0 and 1 by division on 400 (the highest number of rows) as given in equation 4.8.

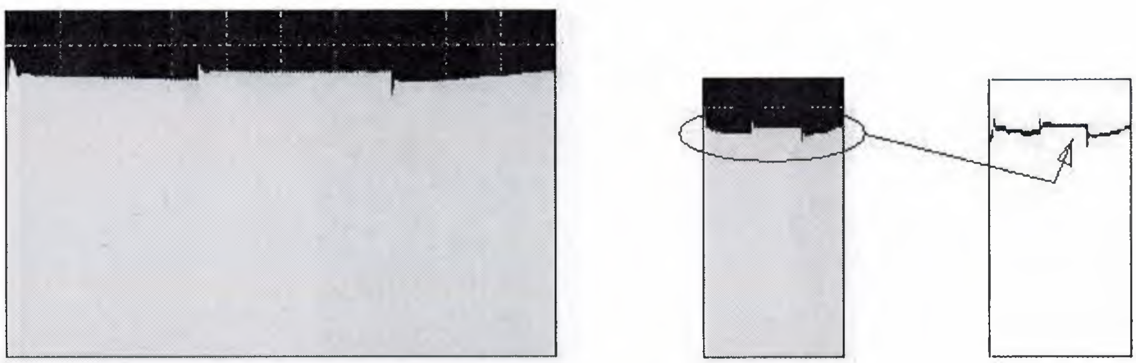
$$Nor.P = P_{123} / 400 \tag{4.8}$$

Seventh Step: These normalized patterns are then fed as inputs to the neural network classifier for training and later for testing.

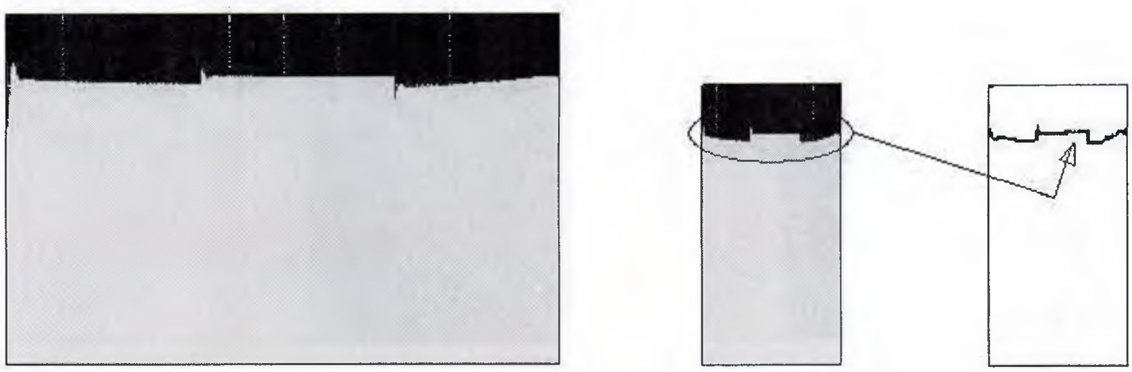
Figure 4.7 shows the block diagram of the patterns preparation phase, as part of the intelligent system.



Va

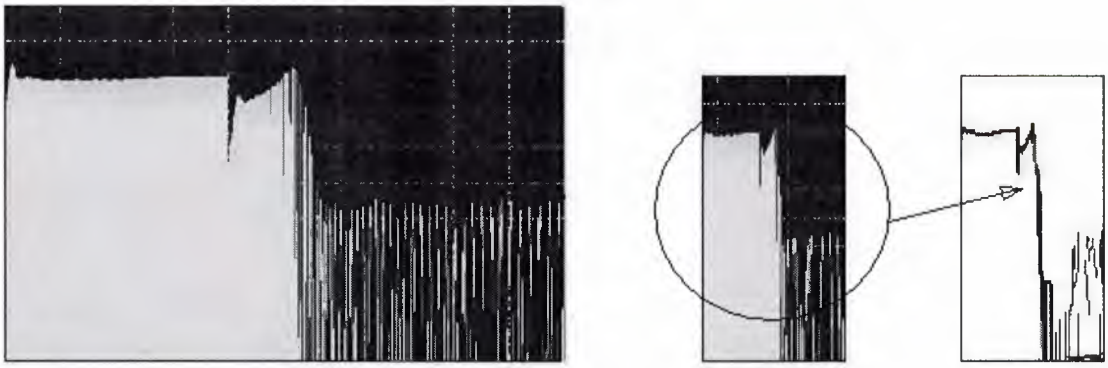


Vb

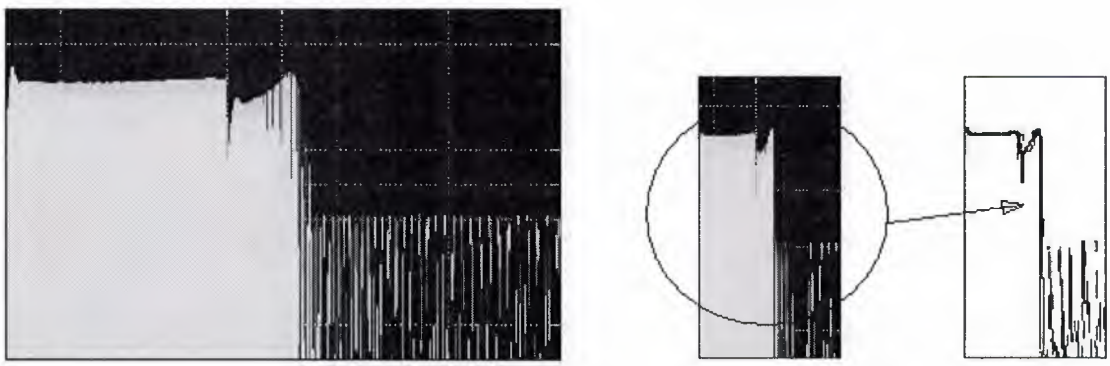


Vc

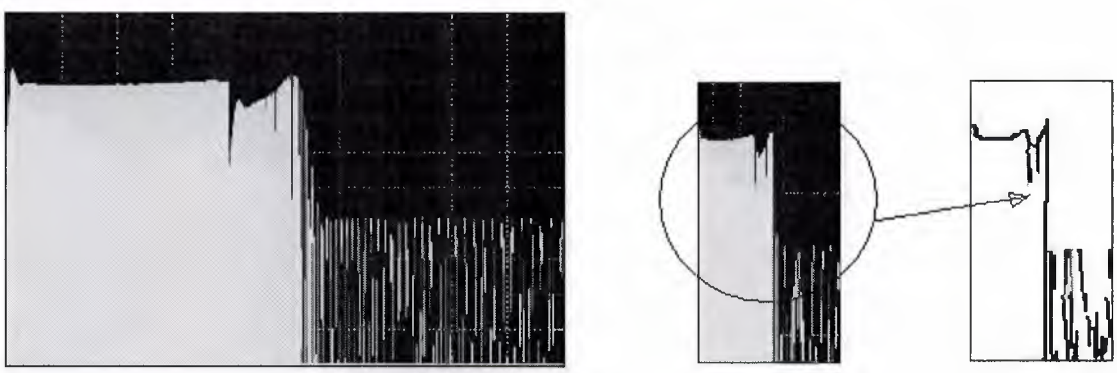
Figure 4.5 Extracting Curve for Stable Case



Va

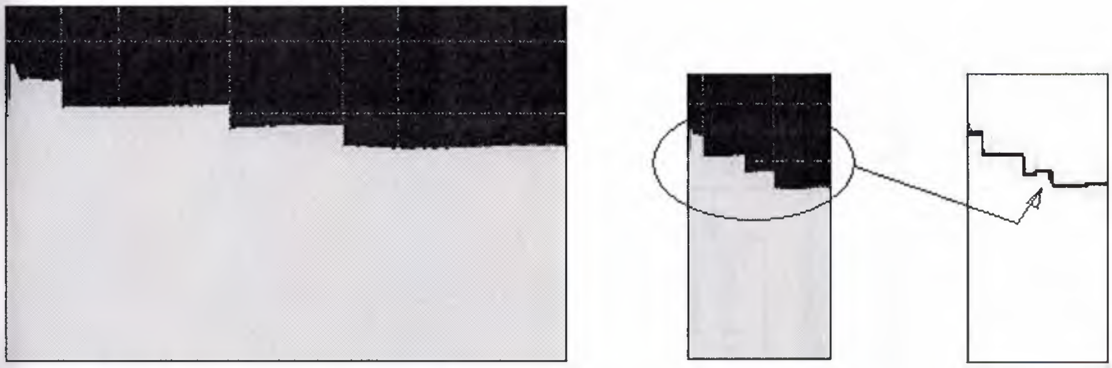


Vb

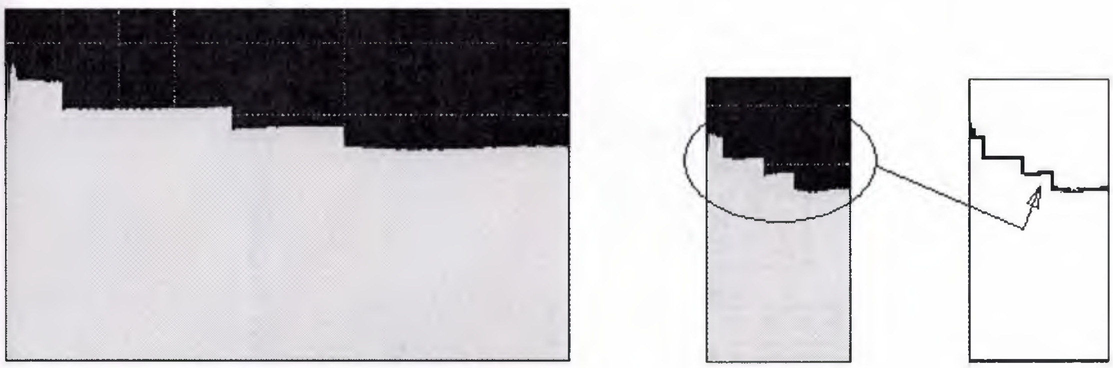


Vc

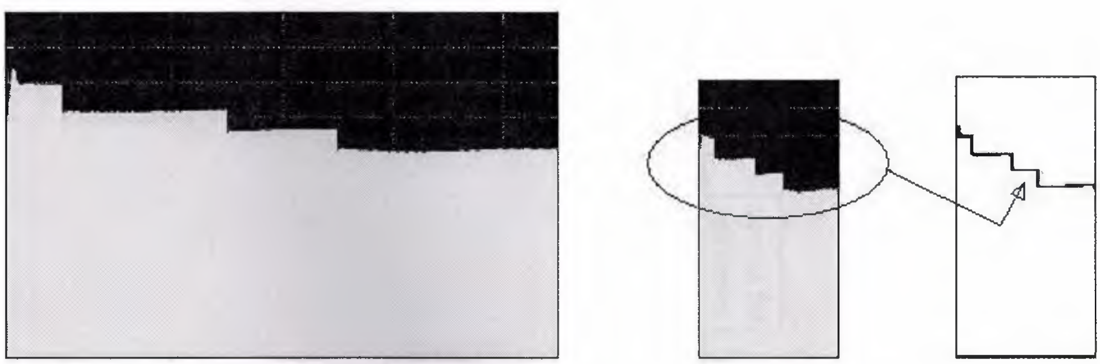
Figure 4.6 Extracting Curve for Unstable Case



Va



Vb



Vc

Figure 4.7 Extracting Curve for Overload Case

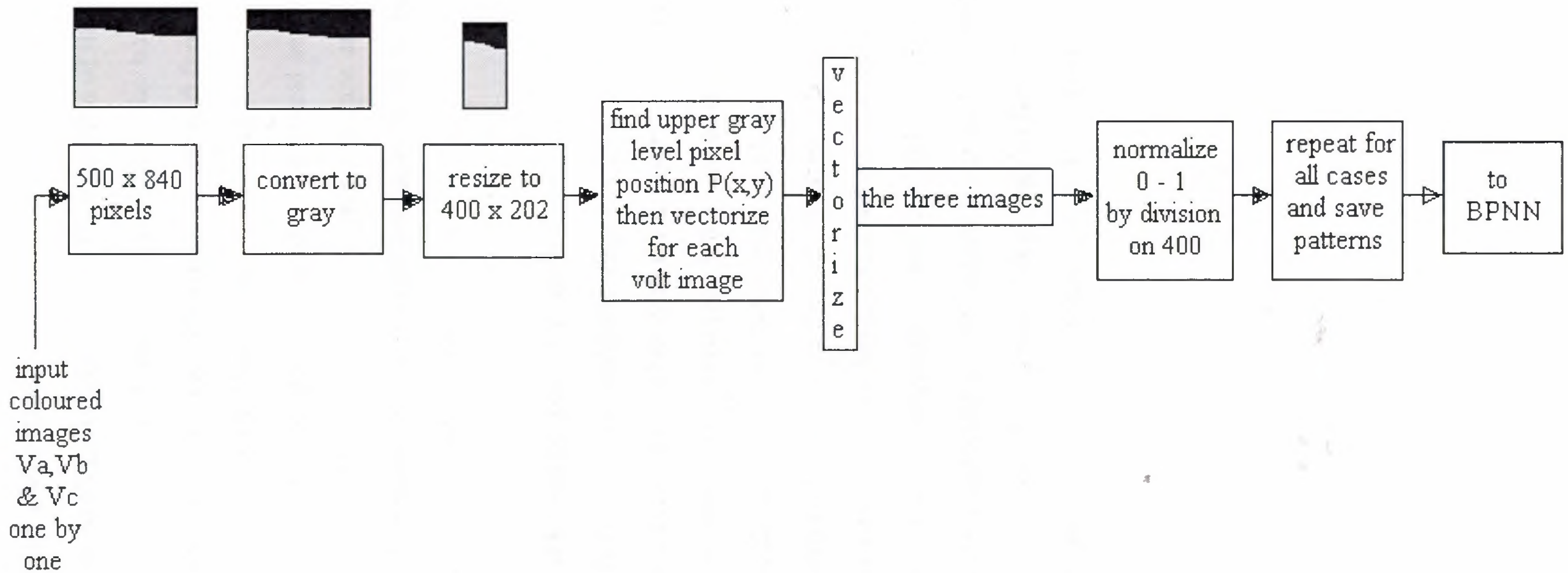


Figure 4.8 Block Diagram of Patterns Preparation

4.3 Intelligent Instability Detection

Neural Network simulator in MATLAB will be used for detection of instability or overload as unusual states of power systems. The neural network uses the back propagation (PB) learning algorithm due to its simplicity and efficiency. A sigmoid function will be used in the PB for the transfer function as it enables a finite number of nodes in the single hidden layer to uniformly approximate any continuous function. The neural network will be trained on three types of cases which are the stable case, the unstable case and the overload case. After that several cases will be tested by the trained neural network to be classified as one of the previous cases (stable, or unstable, or overload).

4.3.1 Neural Network Design and Structure

The neural network, which is used for implementing our proposed intelligent system, is based on back propagation learning algorithm with three layers. The input layer consists of 600 neurons as the size of the input layer must match the size of the patterns after reshaping the position of pixel where the discontinuity from gray to black and vectorizing the three images of voltage. The number of neurons in the output layer is three which is the number of the three cases stable, unstable, and overload. The number of neurons in the hidden layer is 28 neurons and it is chosen by experiments to get the higher recognition and accuracy rates. The input layer is fully connected to the hidden layer and the hidden layer is fully connected to the output layer. Figure 4.9 shows the topology of the back propagation neural network and the image pre-processing phase, while figure 4.10 shows the flowchart of the neural network training.

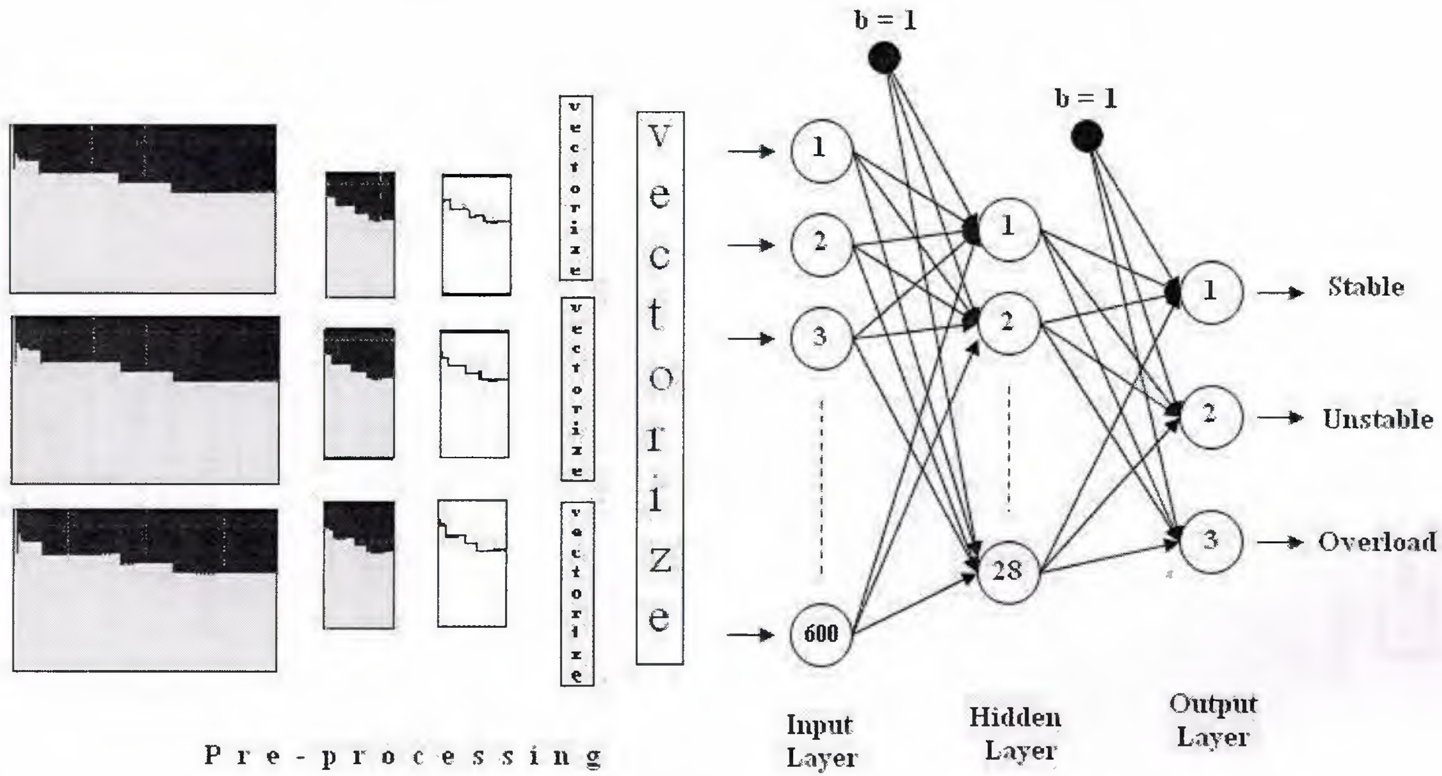


Figure 4.9 Back Propagation Neural Network Topology

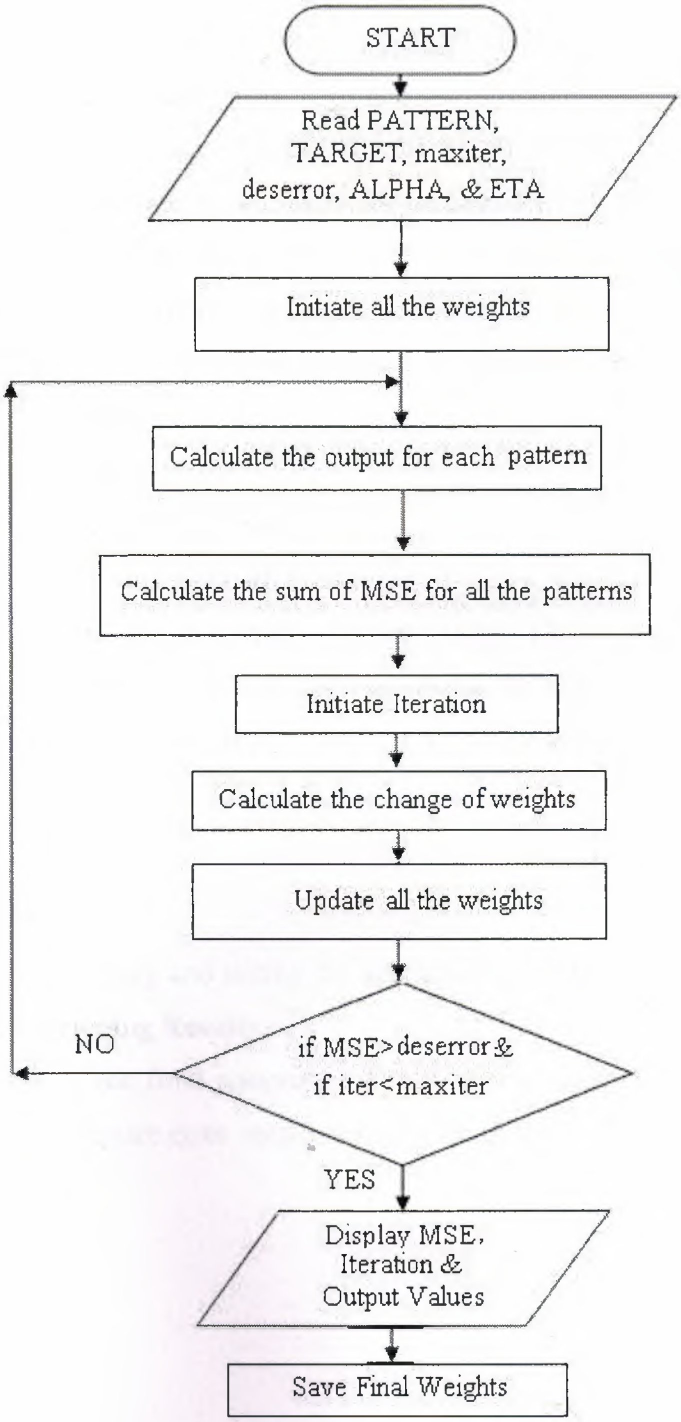


Figure 4.10 Neural Network Training Flowchart

4.3.2 Training and Testing the Network

The implementation of the proposed intelligent system uses fifty four simulated cases, where eighteen are stable cases, eighteen are unstable cases, and eighteen are overload cases. Every case has three images for the three voltage phases. Every set of cases are divided into ten for training and eight for testing. This means that the neural network will be tested with cases that have not been exposed to it during training.

There are 30 training patterns: 10 from stable cases, 10 from unstable cases and 10 from over load cases. The desired outputs for each case of training are:

T1 = [1 0 0] for stable case

T2 = [0 1 0] for unstable case

T3 = [0 0 1] for the overload case

After the neural network converges or learns, the final weights are saved and used for testing the trained network with new cases. The remaining twenty four cases are preprocessed to prepare the test patterns (using the same steps as in section 4.2.2) to be delivered to the neural network. It will use the saved weights to calculate the output of test patterns and launch the results.

4.4 Results

After finishing training and testing the neural network, the results are launched.

4.4.1 Training Results

Table 4.1 shows the final parameters of the neural network for training and Figure 4.10 shows the mean square error versus iteration for training.

Table 4.1 Final Parameters of Trained Neural Network

Number of Input Neurons	**600**
Number of Hidden Neurons	**28**
Number of Output Neurons	**3**
Learning Rate (Eta)	**0.001**
Momentum Factor (Alpha)	**0.33**
Minimum Error	**0.002**
Initial Random Weights Ranges	**-0.31 to 0.31**
Number of Iterations	**12165**
Training Time (seconds)	**963.4219***
Run Time of one forward pass (seconds)	**0.0214***
Tolerance	**0.8**

* The results were obtained using a 1.7 GHz Intel PC with 256MB RAM, Windows XP and MATLAB 7.

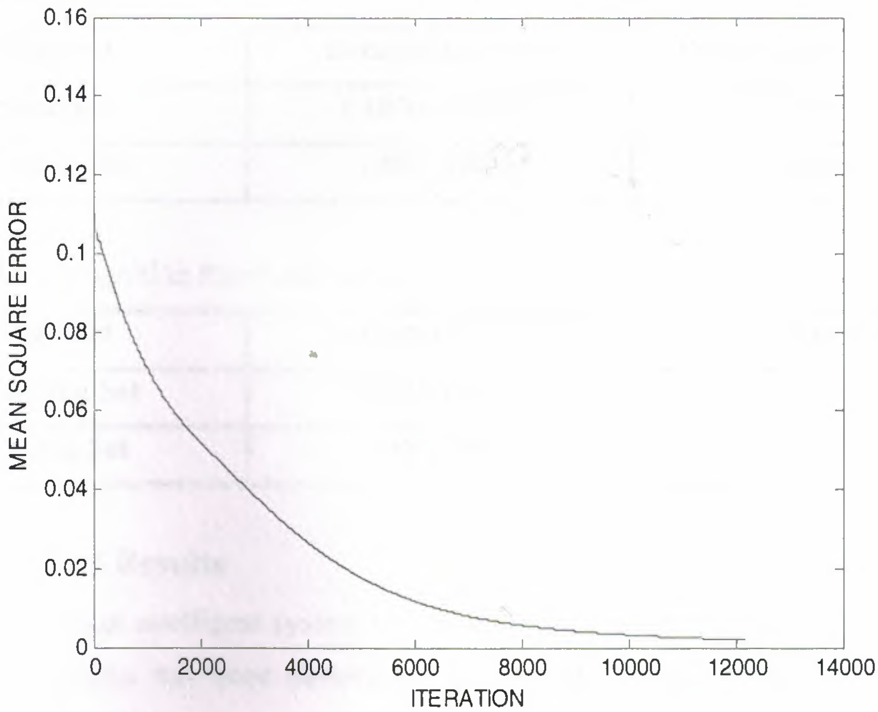


Figure 4.11 Mean Square Error vs. Iterations Curve

4.4.3 Testing Results

The following tables will show the recognition rate and accuracy rate for all cases then for every case separately to illustrate the efficiency of the proposed intelligent system.

Table 4.2 Recognition Rates and Accuracy of Training and Testing for All Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(30/30) 100%**	**93.15%**
Testing Set	**(23/24) 95.83%**	**93.62%**

Table 4.3 Recognition Rates and Accuracy of Training and Testing for Stable Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(10/10) 100%**	**94.10%**
Testing Set	**(7/8) 87.5%**	**87.47%**

Table 4.4 Recognition Rates and Accuracy of Training and Testing for Unstable Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(10/10) 100%**	**96.29%**
Testing Set	**(8/8) 100%**	**96.44%**

Table 4.5 Recognition Rates and Accuracy of Training and Testing for Overload Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(10/10) 100%**	**89.41%**
Testing Set	**(8/8) 100%**	**90.69%**

4.5 Analysis of Results

A fast and efficient intelligent system for detection instability or overload states of power distribution systems has been developed. The neural network learnt the preprocessed voltage images which results from the simulated power system after 12165 iterations within 963.4 seconds. The neural network was trained on 30 system cases; which comprised 10 stable cases, 10 unstable cases and 10 overload cases. The running time for the generalized neural network after training to run one forward pass was 0.0214 seconds. The reduction of training and testing time was due to reducing the input patterns of our intelligent detection system which comes via reprocessing voltage simulated images and finding the pixel position where the first discontinuity or change in color is found. Our intelligent instability detection system recognized correctly all the thirty input patterns in the training set as it is expected or in other word the recognition rate for the training set was 100%. The recognition accuracy of the training set was 93.15% which is higher than the output classification tolerance that was set to 80% for both training and testing the neural network.

Our intelligent instability detection system was tested with 24 power system cases that were not exposed to the neural network before; these comprised 8 stable cases, 8 unstable cases and 8 overload cases. From all the twenty four tested cases, twenty three cases were correctly classified, thus yielding 95.83% correct detection. The recognition accuracy of all the testing set was 93.62%. Table 4.2 summarizes the recognition rate and accuracy rate of all the training and testing set.

The success and efficiency of our novel intelligent system is in its capability to detect instability cases with high recognition and accuracy rates. From table 4.3 the recognition rate for the unstable cases was (8/8) or 100% with 96.44% accuracy rate. Also, the recognition rate of overload cases was (8/8) or 100% with 90.69% accuracy rate as seen in table 4.4. The least recognition rate was for the stable case, which was (7/8) or 87.5% with 87.47% recognition accuracy as listed in table 4.5.

The last one of the stable cases was incorrectly classified as overload case with 0.7255 recognition value. However, this single incorrect detection is not considered dangerous for two reasons. First, it will be a problem if the intelligent system classifies an unstable case or an overload case as a stable case. On the contrary, it identified all the unstable and overload cases correctly with high accuracy rate. Second, the treatment system which will be introduced in the next chapter will solve this incorrect detection.

4.6 Summary

This chapter presented an investigation of the use of an ANN in detecting transient instability of power distribution systems. A test case system was simulated in MATLAB and the output graphs were saved then prepared to be induced as patterns to the ANN. The ANN showed excellent performance in classifying or in other words detecting instability or overload cases. As soon as the ANN detects unstable or overload case, a solution will arise to solve the problem as will be discussed in the next chapter.

CHAPTER FIVE
PROPOSED VOLTAGE STABILIZER

5.1 Overview

A new voltage stabilizer based on the decision of the intelligent system for detection of instability or overload cases will be introduced in this chapter. Also, results of simulation for some cases will be performed and discussed. At the end, the efficiency and benefits of this proposed voltage stabilizer will be discussed.

5.2 Introduction to Voltage Stabilizer

The transient stability analysis is one of the main studies carried out in Electric Power Systems. This analysis can be carried out, e.g., by simulation (numerical solution of nonlinear differential equations that describe the system dynamic). An alternative procedure consists of obtaining the analysis without solving such differential equations.

As mentioned before our concern in this work is to solve the transient stability of power distribution systems (PDS). Because the lack of previous data from a real power system for instability detection of PDS, a proposed power system is designed based on the BPA test case study and it is simulated using MATLAB. The output results are preprocessed and induced to the ANN to decide if the PDS is unstable or overloaded or stable (see chapter four). If the decision is one of the two last cases, then a voltage stabilizer (VS) must exist to restore stability and return the system to normal voltage and frequency. The proposed stabilizer has two branches, one to solve the instantaneous voltage drop which result from the overload state, and the other to solve transient instability of the system. After a while and when the system returns to stability the stabilizer should make reverse procedures to return the control devices to its normal conditions.

Before proceeding in details of the voltage stabilizer, specifications of the proposed power system will be introduced

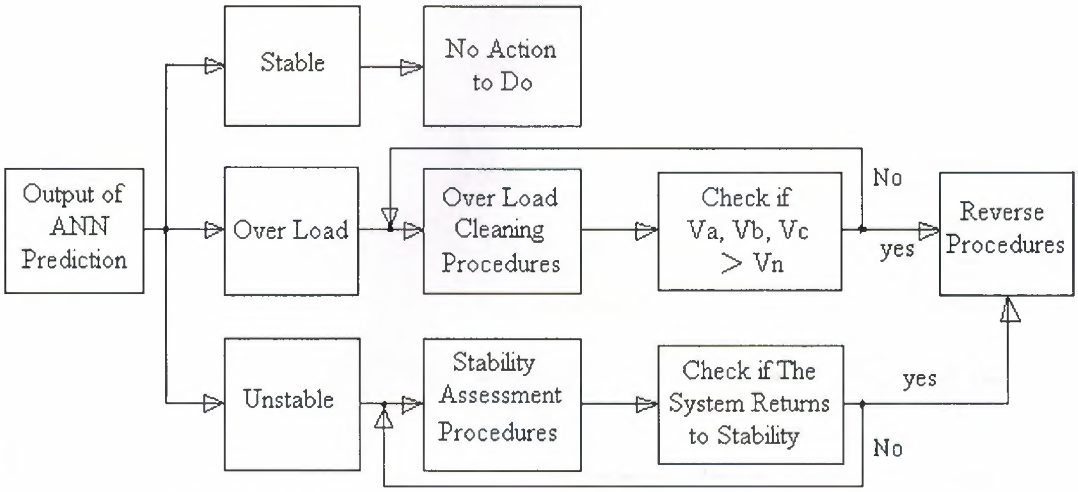


Figure 5.1 General Block Diagram of the Proposed Voltage Stabilizer

5.3 Modeling and Simulation of Proposed Power System

Recalling the one line diagram of the proposed power system which based on Bonneville Power Administration (BPA) and introduced in the previous chapter and extending load 7 to low voltage distribution will be seen in figure 5.2. There are three generators in our proposed power system. Generators 1 and 2 are Synchronous Machine associated with Hydraulic Turbine and Governor (HTG) and Excitation System (ES), while generator 3 is Synchronous Machine associated with Governor and Diesel Engine (GDE) and Excitation System. Generators 1 and 2 are in the remote area feeding the system with most of needed power, while generator 3 is in the local load area feeding the system with power in case of disturbances and regulating the loads bus. All the following specifications are taken from MATLAB7.1 Toolbox.

5.3.1 Modeling of Generator 1 and Generator 2 and their Hydraulic Governor and Exciter

Generator 1 is fed with the mechanical power through hydraulic turbine and governor (HTG1) and is fed with excitation field current from the excitation system (ES1) as shown in figure 5.3. Generator 2 is fed with the mechanical power through hydraulic turbine and governor (HTG2) and is fed with excitation field current from the excitation system (ES2) as shown in figure 5.4.

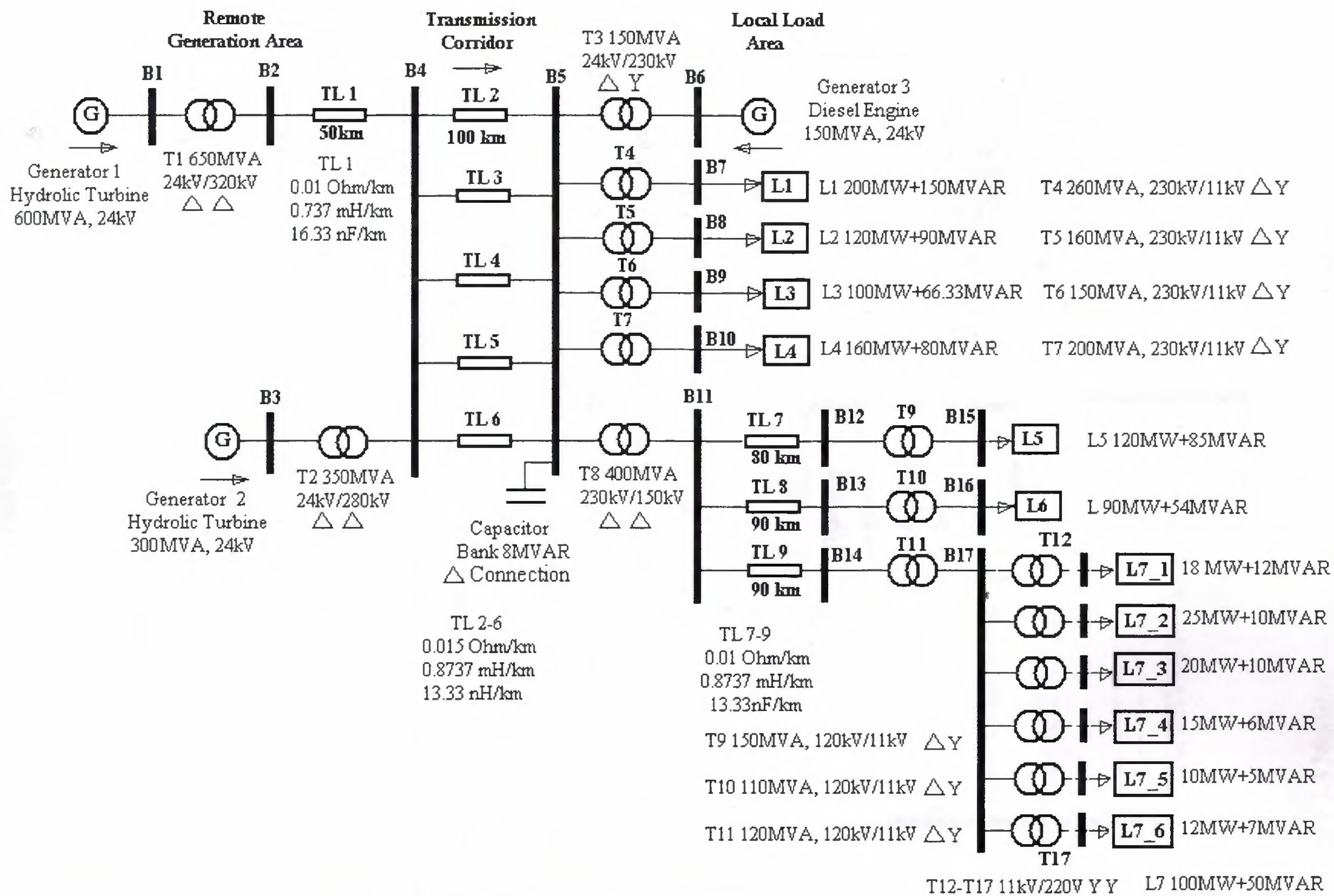


Figure 5.2 One Line Diagram of Extended Test Case System

5.3.1.1 Specifications of G1 and G2

Rotor type: Specify rotor type: Salient-pole or Round (cylindrical). It is chosen Salient-pole for the three generators.

Nominal power, voltage, frequency, and field current: The total three-phase apparent power Pn (VA), RMS line-to-line voltage Vn (V), and frequency fn (Hz). They are set for G1 as [600e6, 24000, 50] and for G2 as [300e6, 24000, 50].

Stator: The resistance Rs (pu), leakage inductance X1 (pu), and d-axis and q-axis magnetizing inductances Xd (pu) and Xq (pu). They are set for G1 and G2 as [2.8544e-3, 0.18, 1.305, 0.474].

Inertia, friction factor, and pole pairs: The inertia coefficient H (s), friction factor F (pu), and number of pole pairs p. They are set for G1 and G2 as [3.7, 0, 32].

Initial conditions: The initial speed deviation (% of nominal speed), electrical angle of the rotor e (degrees), line current magnitudes ia, ib, ic (pu) and phase angles pha, phb, phc (degrees), and the initial field voltage Vf (pu). They are set for G1 as [0, -16.6861, 0.950218, 0.950218, 0.950218, 48.1093, -71.8907, 168.109, 1.44424] and for G2 as [0, -16.6861, 0.950218, 0.950218, 0.950218, 48.1093, -71.8907, 168.109, 1.4].

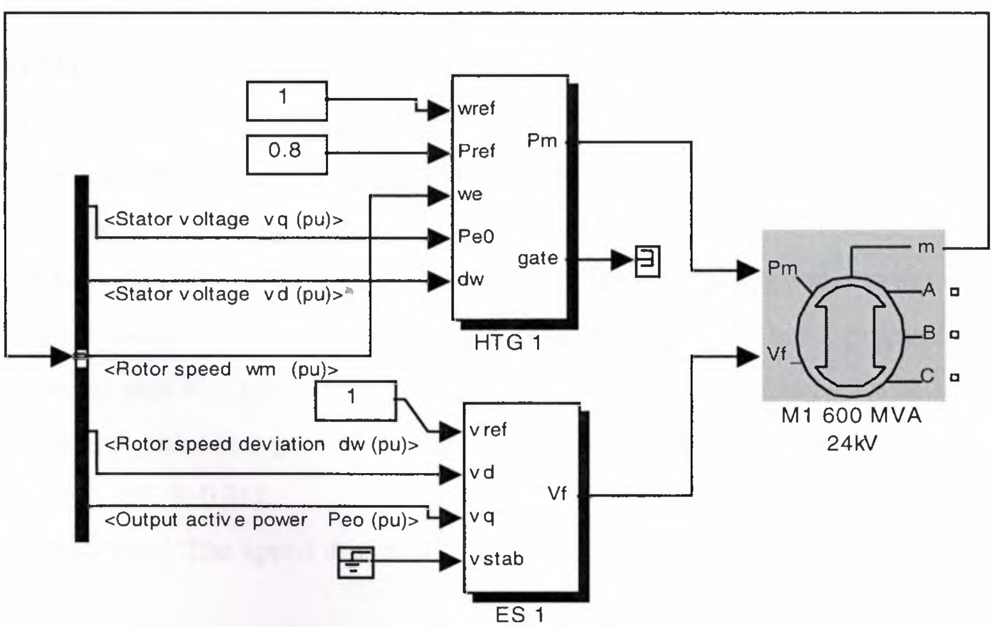


Figure 5.3 Modeling of Generator 1 and its Hydraulic Governor and Exciter

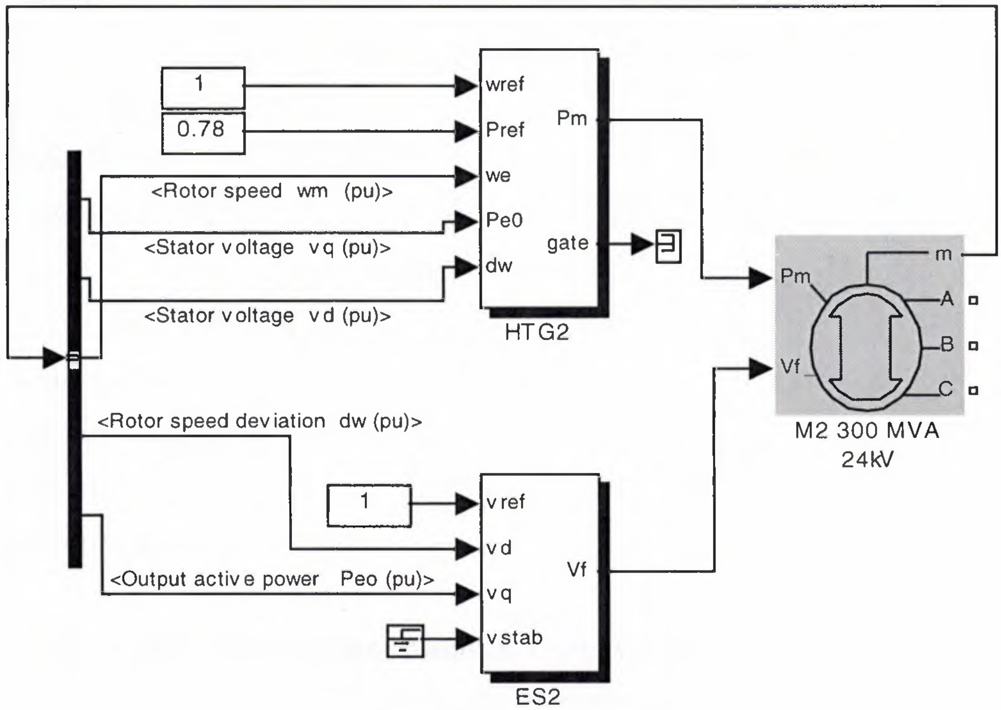


Figure 5.4 Modeling of Generator 2 and its Hydraulic Governor and Exciter

5.3.1.2 Specifications of HTG1 and HTG2

Servo-motor: The gain Ka and time constant Ta, in seconds (s), of the first-order system representing the servomotor are [5/3 0.07].

Gate opening limits: The limits gmin and gmax (p.u.) imposed on the gate opening, and vgmin and vgmax (p.u./s) imposed on gate speed are [0.01, 0.97518, -0.1, 0.1].

Permanent droop and regulator: The static gain of the governor is equal to the inverse of the permanent droop Rp in the feedback loop. The PID regulator has a proportional gain Kp, an integral gain Ki, and a derivative gain Kd. The high-frequency gain of the PID is limited by a first-order low-pass filter with time constant Td (s). The numerical values are [0.05, 1.163, 0.105, 0, 0.01].

Hydraulic turbine: The speed deviation damping coefficient and water starting time Tw (s) are [0, 2.67].

Droop reference: Specifies the input of the feedback loop: gate position (set to 1) or electrical power deviation (set to 0). It is set to zero.

Initial mechanical power: The initial mechanical power Pm0 (p.u.) at the machine's shaft is 1.00579 for HTG1 and 1 for HTG2. This value is automatically updated by the load flow utility of the Powergui block.

HTG1 and HTG2 Inputs and Outputs:

ωref: Reference speed, in p.u.

Pref: Reference mechanical power in p.u.

ωe: Machine actual speed, in p.u.

Pe0: Machine actual electrical power in p.u.

dw: Speed deviation, in p.u.

Pm: Mechanical power Pm for the Synchronous Machine block, in p.u.

gate: Gate opening, in p.u.

5.3.2 Modeling of Generator 3 and Its Governor and Exciter

Generator 3 is fed with the mechanical power through governor and diesel engine (GDE) and is fed with excitation field current from the excitation system (ES3) as shown in figure 5.5.

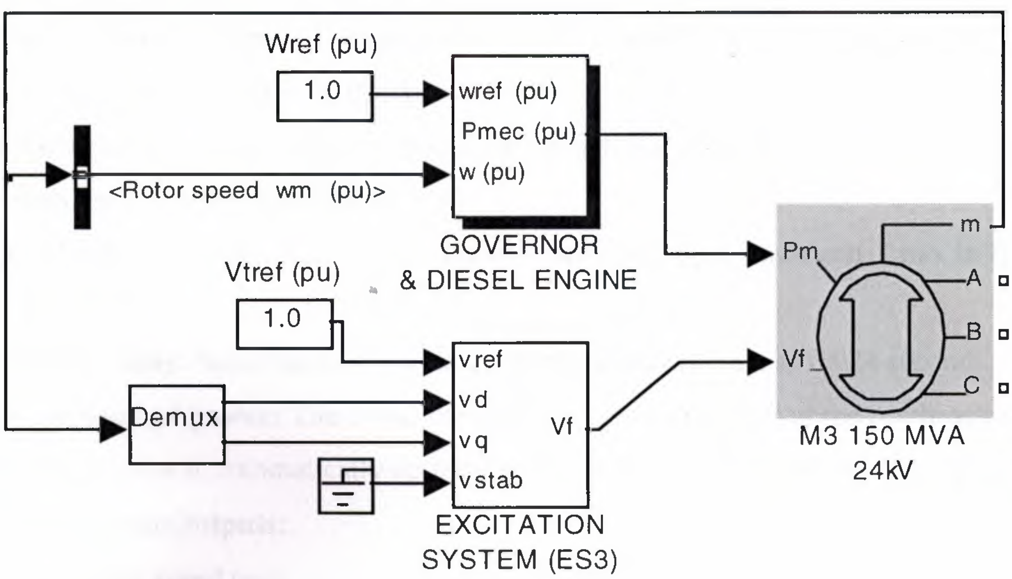


Figure 5.5 Modeling of Generator 3 and its Governor and Diesel Engine and Excitation System

5.3.2.1 Specifications of G3

Rotor type: Specify rotor type: Salient-pole or Round (cylindrical). It is chosen Salient-pole for the three generators.

Nominal power, voltage, frequency: The total three-phase apparent power Pn (VA), RMS line-to-line voltage Vn (V), and frequency fn (Hz). They are set for G3 as [150e6, 24000, 50].

Stator: The resistance Rs (pu), leakage inductance X1 (pu), and d-axis and q-axis magnetizing inductances Xd (pu) and Xq (pu). They are set for G3 as [2.8544e-3, 0.13, 1.05, 0.414]

Inertia, friction factor, and pole pairs: The inertia coefficient H (s), friction factor F (pu), and number of pole pairs p. They are set for G3 as [3.7, 0, 32].

Initial conditions: The initial speed deviation (% of nominal speed), electrical angle of the rotor e (degrees), line current magnitudes ia, ib, ic (pu) and phase angles pha, phb, phc (degrees), and the initial field voltage Vf (pu). They are set for G3 as [0, -16.6861, 0.950218, 0.950218, 0.950218, 48.1093, -71.8907, 168.109, 1]

5.3.2.2 Specifications of GDE

Regulation gain K: K is the gain of the controller transfer function and set as 40.

Regulation time constants: The parameters of the controller transfer function T1, T2 and T3 in seconds are set as [0.01, 0.02, 0.2]

Actuator time constants: The parameters of the actuator transfer function T4, T5 and T6 in seconds are set as [0.25, 0.009, 0.0384]

Torque limits: The minimum and maximum values of torque Tmin and Tmax in (pu) are set as [0, 1.1]

Engine time delay: Specifies the time delay of motor Td (s) is set as 0.024 seconds.

Initial mechanical power: The initial mechanical power Pm0 (pu) at the machine's shaft is set as 1. This value is automatically updated by the load flow utility of the Powergui block.

GDE Inputs and Outputs:

ωref: Reference speed (pu)

ωm: Rotor speed ωm (pu)

Pmec: Mechanical power Pm for the Synchronous Machine block (pu)

5.3.2.3 Specifications of the Excitation Systems ES1, ES2 and ES3

Low-pass filter time constant: The time constant Tr, in seconds (s), of the first-order system that represents the stator terminal voltage transducer and is set for the three systems as 20e-3 seconds.

Regulator gain and time constant: The gain Ka and time constant Ta, in seconds (s), of the first-order system represent the main regulator. They are set for ES1 and ES2 as [300, 0.001] and for ES3 [200, 0.02]

Exciter: The gain Ke and time constant Te, in seconds (s), of the first-order system representing the exciter. It is for the three systems as [1, 0].

Transient gain reduction: The time constants Tb, in seconds (s), and Tc, in seconds (s), of the first-order system representing a lead-lag compensator. They are for the three systems as [0, 0].

Damping filter gain and time constant: The gain Kf and time constant Tf, in seconds (s), of the first-order system representing a derivative feedback. They are for the three systems as [0.001, 0.1].

Regulator output limits and gain: Limits Efmin and Efmax are imposed on the output of the voltage regulator. The upper limit can be constant and equal to Efmax, or variable and equal to the rectified stator terminal voltage Vtf times a proportional gain Kp. If Kp is set to 0, the former applies. If Kp is set to a positive value, the latter applies. They are set for ES1 and ES2 as [-11.5, 11.5, 0], and for ES3 as [0, 6, 0].

Initial values of terminal voltage and field voltage: The initial values of terminal voltage Vt0 (pu) and field voltage Vf0 (pu). Both Vt0 and Vf0 values are automatically updated by the load flow utility of the Powergui block. They are set for ES1 as [1, 2.61202], for ES2 [1, 2.39592] and for ES3 as [1, 1.72942].

Inputs and Outputs

vref: The desired value, in p.u., of the stator terminal voltage.

vd: vd component, in p.u., of the terminal voltage.

vq: vq component, in p.u., of the terminal voltage.

vstab: Connect this input to a power system stabilizer to provide additional stabilization of power system oscillations.

Vf: The field voltage, in p.u., for the Synchronous Machine block.

5.4 Voltage Stabilizer for Overload Cases

As soon as the ANN predicts over load case, the VS will begin its work. The design of the VS depends on the solutions that had been discussed in section 2.7. Figure 5.1 shows the general block diagram of the proposed VS.

The first move is from the tap changer relay of the step-down transformer to raise the terminal voltage (Vt) 5% from nominal voltage (Vn). After waiting two seconds check if Vt is still less than 0.95 Vn. If yes go to the second move and if no (i.e. the voltage becomes greater than 0.95) stop VS procedures. The maximum raise of tap relay changer of the transformer is set based on IEEE standards [69]. The value of allowed minimum voltage drop is chosen 0.95 Vn according to IEEE standard (Std 141-1993) where the recommended voltage drop of distribution systems is (0.9-0.95) Vn and the recommended voltage raise is (1.05-1.10) Vn [69]. Also according to other standards, in NEC 210-19 FPN No. 4, the recommended voltage drop of distribution systems is (0.95-0.97) Vn, and in 1C.2.1—Voltage Level and Range ENGINEERING Standards and Technical Support Department, and ANSI C84.1–1989, the recommended voltage drop of distribution systems is (0.95) Vn.

If the terminal load voltage is V_L and terminal transformer voltage V_t , then

$$V_L = V_t \tag{5.1}$$

and after the tap relay of the transformer raise its output by 5%, the new terminal load voltage will be:

$$V_{Ln} = 1.05 V_t \tag{5.2}$$

The second move is switching on the capacitor bank step by step. Every step is 20% from the capacitance switched on parallel to the load. After every step wait two seconds then check if *Vt* is still less than 0.95 *Vn*. If yes switch on another 20% from capacitor bank, and if no stop VS procedures. If 100% of the capacitor bank is switched on and *Vt* is still less than 0.95 *Vn* go to the third move. The proceeding discussion is to show the influence of adding capacitor bank to the system. Figure 5.6 shows the power triangle for the substation in PDS before and after switching on capacitor bank parallel to the loads.

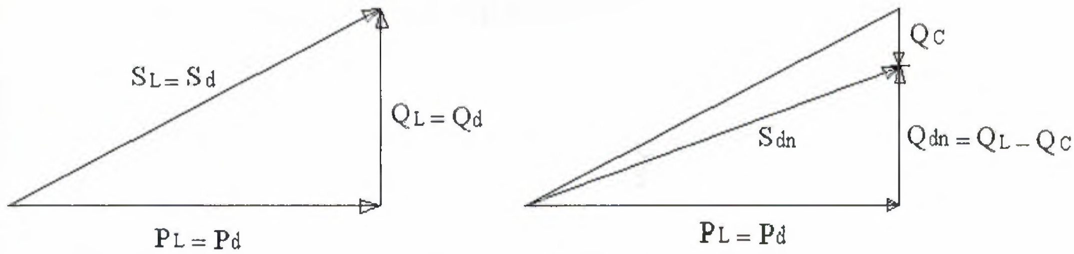


Figure 5.6 Power Triangle for PDS (a) before Capacitor Switching, (b) after Capacitor Switching

Let's assume that the apparent power of the load is S_L, the active power is P_L , the inductive reactive power is Q_L and the apparent power delivered to the load is S_d, the active power is P_d, the inductive reactive power is Q_d and the capacitive reactive power from the capacitor is Q_C ,then

$$|S_L| = \sqrt{(Q_L^2 + P_L^2)} \tag{5.3}$$

$$|S_d| = \sqrt{(Q_d^2 + P_d^2)} \tag{5.4}$$

$$S_L = S_d \tag{5.5}$$

Let's assume the L-L load current is I_L and the L-L terminal load voltage is V_L, then

$$|I_L| = \frac{|S_L|}{|V_L|.\sqrt{3}} \tag{5.6}$$

The new delivered inductive reactive power (Q_{dn}) is given by:

$$Q_{dn} = Q_d - Q_C \tag{5.7}$$

and the new delivered apparent power (S_{dn}) is given by:

$$|S_{dn}| = \sqrt{((Q_d - Q_C)^2 + P_d^2)} \tag{5.8}$$

and the new load current (I_{Ln}) will be reduced and is given by:

$$|I_{Ln}| = \frac{|S_{dn}|}{|V_L|.\sqrt{3}} \tag{5.9}$$

so the load voltage difference will be:

$$\Delta V_L = \Delta I_L . Z_{TL} \tag{5.10}$$

and the L-L terminal load voltage will be increased by ΔV_L and become:

$$V_{Ln} = \Delta V_L + V_L \tag{5.11}$$

The third move is low voltage load shedding. As known the output of power distribution substation consists from many medium to low voltage step down transformers connected to the low voltage loads. Shedding loads is chosen to be intelligent and automatic. Intelligence is needed in order to find optimal scenarios for the amount of load to shed and the location of these loads. A main consideration in intelligent load shedding will be the cost criterion. Strategies may be based on dynamic prices and on electric market. Figure 5.7 shows the triangles of power before and after load shedding.

Returning to the P-V graphs in CH2, and if the load is working on a curve, then after load shedding it will work on the same curve but with a position earlier to the first position making the terminal voltage in the allowed margin, assuming the power factor does not changed, as illustrated in figure 5.8.

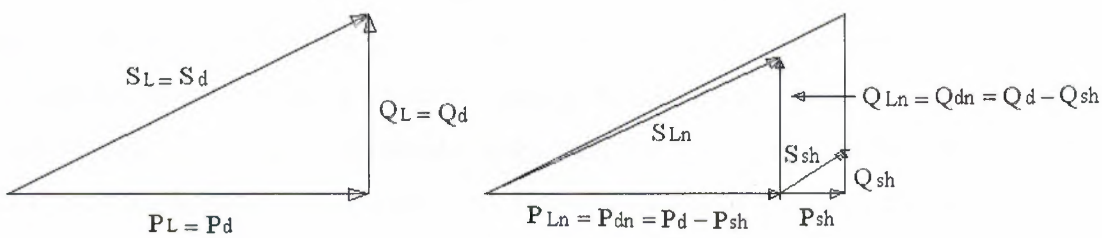


Figure 5.7 Power Triangle for PDS (a) before Load Shedding, (b) after Load Shedding

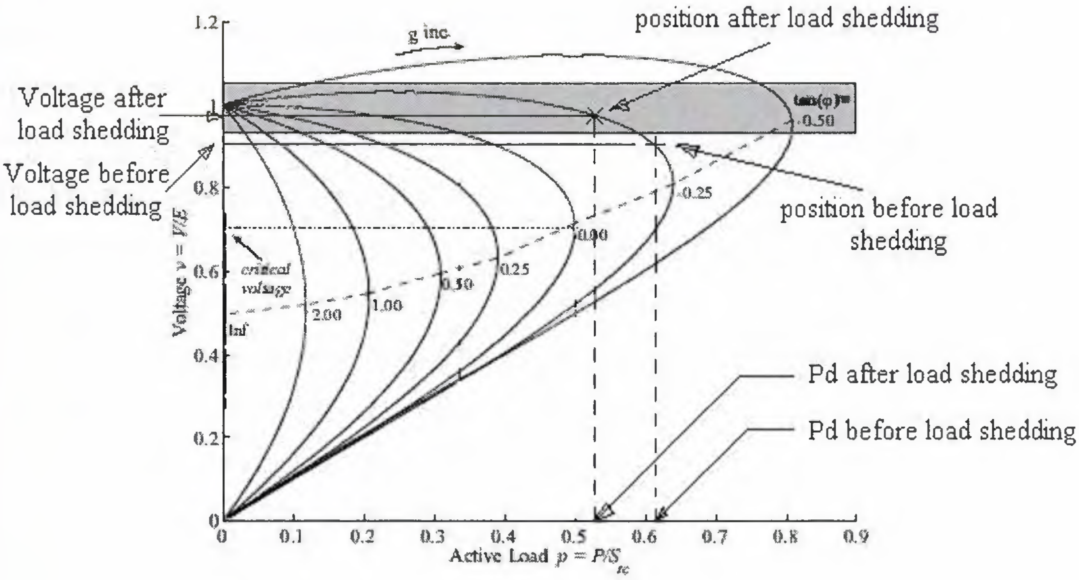


Figure 5.8 Power Voltage Curve before and after Load Shedding

For this proposed power system lLoad shedding will take place in three steps in the proposed VS. The first step is shedding the least priority medium and low voltage loads that used in general activities like general motor water pumps, or water treatment pumps. As it is known that companies of electrical energy market make contracts with some duty or tourism areas to sell them electrical energy with low prices, and on the other hand it can shed their loads in case of disturbances. The second step is shedding the lowest electrical energy price. The third step is shedding the loads that have the second low price. Figure 5.9 shows the block diagram of voltage stabilizer for overload cases as it is explained previously while figure 5.10 shows the flowchart of it.

The algorithm for overload enhancement is summarized as follows:

Step 1: Raise tap changer relay of distribution transformer by 5%.

Step 2: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 3: If no stop and if yes switch on 20% from the capacitor bank.

Step 4: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 5: If no stop and if yes switch on another 20% from the capacitor bank.

Step 6: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 7: If no stop and if yes switch on another 20% from the capacitor bank.

Step 8: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 9: If no stop and if yes switch on another 20% from the capacitor bank.

Step 10: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 11: If no stop and if yes switch on another 20% from the capacitor bank.

Step 12: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 13: If no stop and if yes shed low voltage load L7_1.

Step 14: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 15: If no stop and if yes shed low voltage load L7_2.

Step 16: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 17: If no stop and if yes shed low voltage load L7_3.

Step 18: Stop actions.

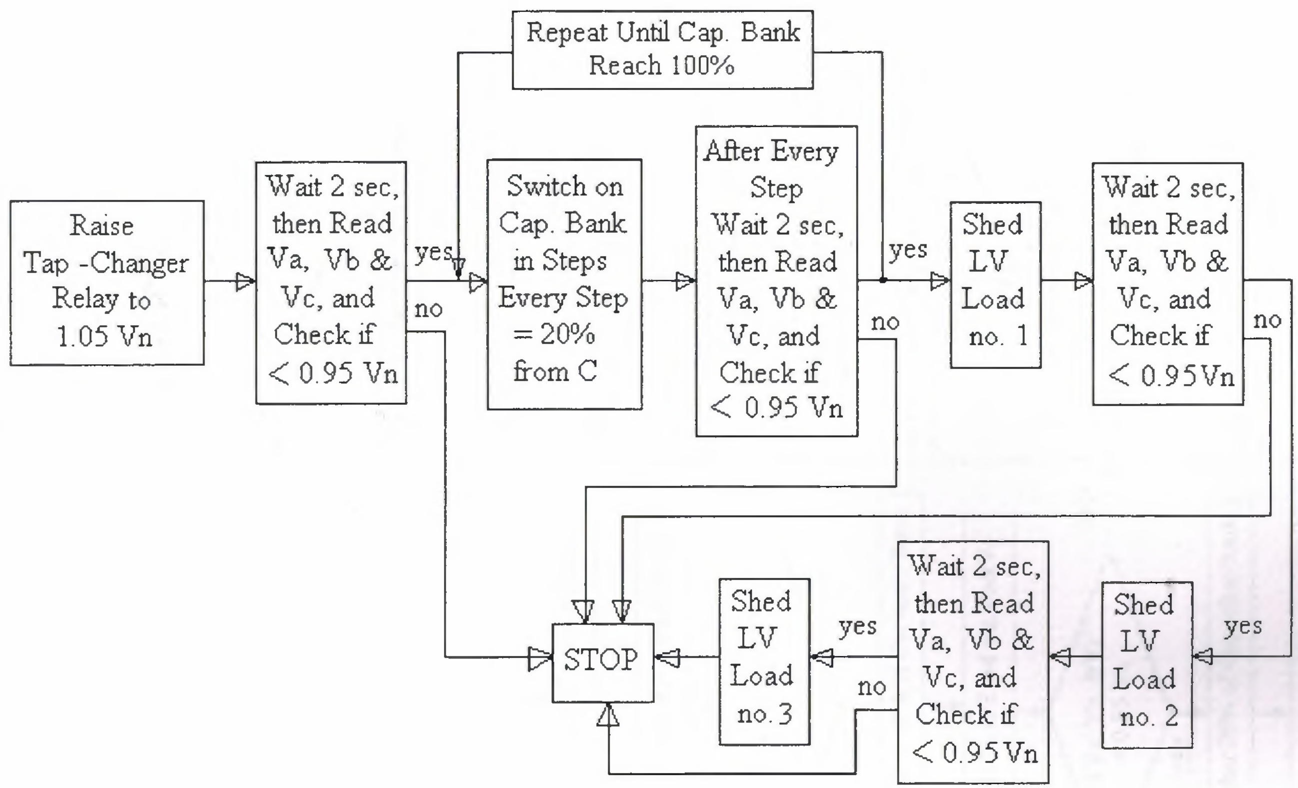


Figure 5.9 Block Diagram of the Proposed Voltage Stabilizer for Overload Cases

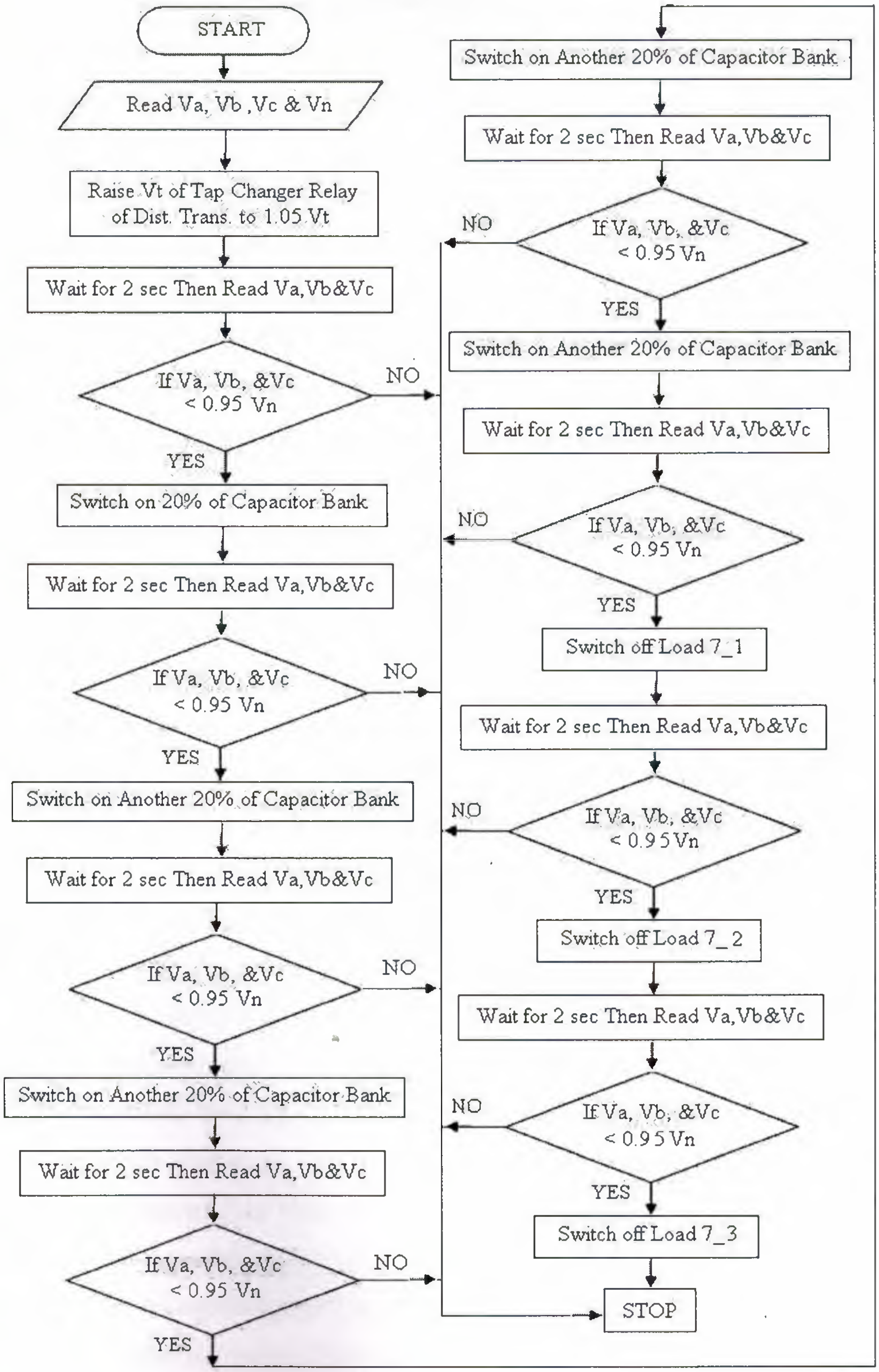


Figure 5.10 Flowchart of the Proposed Voltage Stabilizer for Overload Cases

5.5 Voltage Stabilizer for Unstable Cases

As it is illustrated in chapter 1, voltage instability is basically caused by an unavailability of reactive power support in some nodes of the network, where the voltage uncontrollably falls. Lack of reactive power may essentially have two origins. Gradual increase of power demand which reactive part cannot be met in some buses or sudden change of a network topology redirecting the power flows such a way that a reactive power cannot be delivered to some buses. Voltage instability of a substation in PDS is part of instability of the whole power system. It is caused due to faults or disturbances in its environment or due to instability of the whole power system. Procedures to restore stability of the PDS substation will be effective if the disturbances are in its environment, otherwise procedures from all PDS substations with coordination of the whole system must arise to restore stability. Local voltage stabilizer can't distinguish the cause of instability, as a results its actions to restore stability may not be effective unless it comes in comprehensive of all PDS substations and other parts of the system.

In our performance of unstable cases during simulation faults are induced in different parts in the main transmission corridor or switching off part of generators during work or starting simulation with some parts of generator are not connected to the system. Also, some faults, like line to line faults or three phases to ground faults or disconnection of one transmission line are induced in the environment of the studied substation. As a result, the cases of instability achieved are with different performance on the studied substation.

In this stabilizer the first action is shedding part of low voltage loads and fast redispatch of generation. In some instability situations switching capacitor bank may not achieve the hoped performance because the impact of their operation may be negative.

The algorithm for stability restoration is as follows:

Step 1: Redispatch generators and shed one forth of loads approximately.

Step 2: Wait 0.1 second then shed another forth of loads approximately.

Step 3: Wait 0.1 second then shed another forth of loads approximately.

Step 4: Wait 0.5 second then read Va, Vb, Vc and the frequency F.

Step 5: Wait another 0.5 second then read Va, Vb, Vc and F again.

Step 6: Check if F is decreasing or increasing, and check if Va, Vb and Vc are decreasing or increasing.

Step 7: If F is decreasing and Va, Vb and Vc are decreasing, wait few (3-5) seconds then read them again. Check if F is increasing and Va, Vb and Vc are decreasing or stay in the same level. If the answer is yes it means that stability is achieved. Wait few (3-5) seconds then switch on the last shed loads. But, if the answer is F is still decreasing, redispatch generators and stop actions.

Step 8: If the answer of step 6 is F is decreasing and the voltages are increasing, or if F is increasing and the voltages are increasing or some of them is decreasing and the others are increasing just redispatch generators and stop actions (because in case of increasing F shedding loads will not achieve stability and the excitation system of the generators must decrease excitation current).

Figure 5.11 shows the general block diagram of the proposed voltage stabilizer for unstable cases, while figure 5.12 shows the flowchart of it.

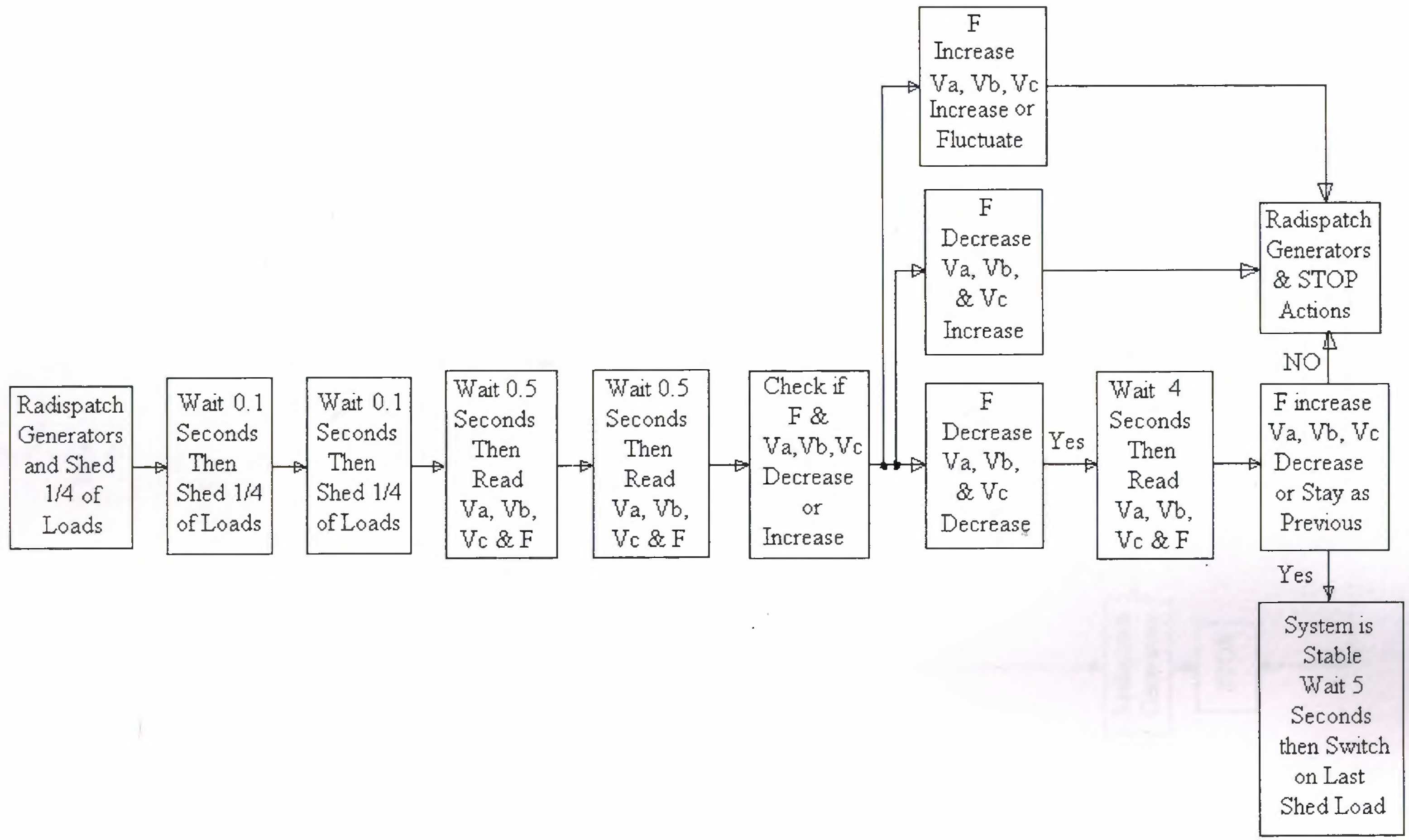


Figure 5.11 Block Diagram of Proposed Voltage Stabilizes for Unstable Cases

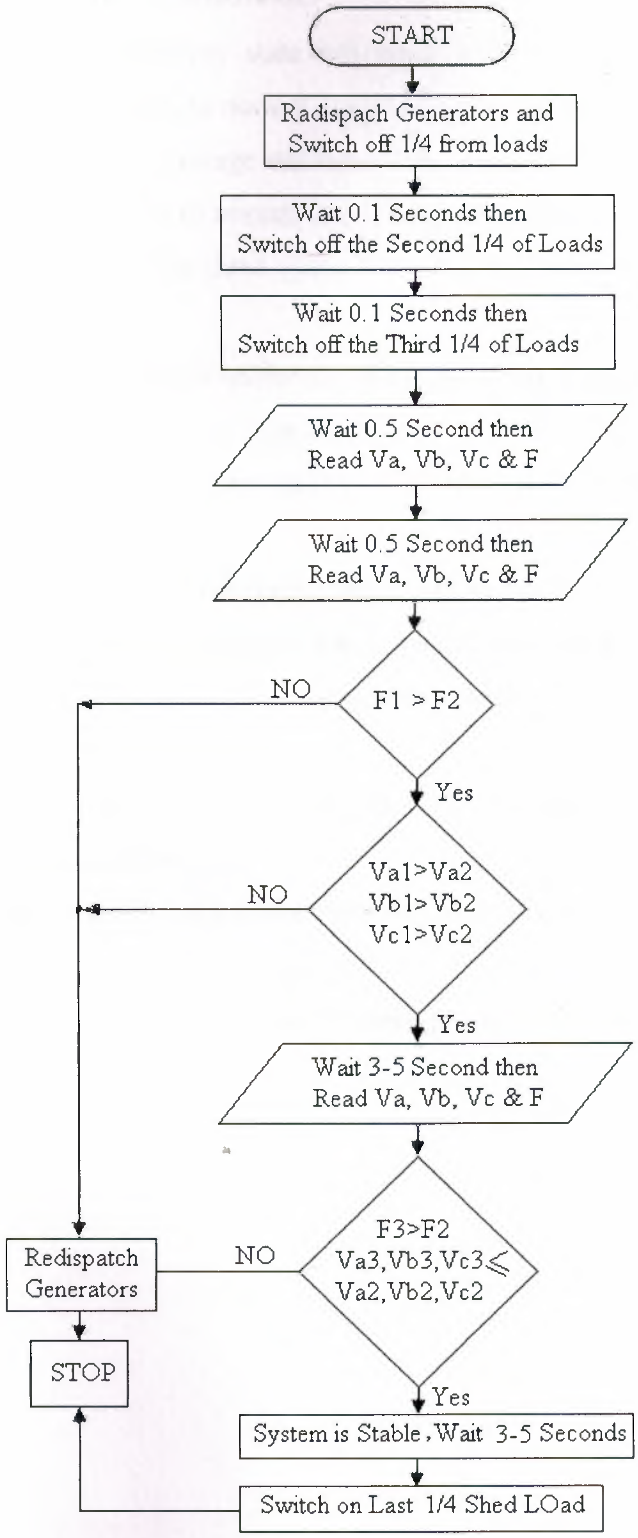


Figure 5.12 Flowchart of the Proposed Voltage Stabilizer for Unstable Cases

5.6 Recovering Normal Conditions

After overload state or instability state has been cleared and the voltages rises, then arrangements to return the PDS to normal conditions must be performed in condition these arrangement do not affect the voltage stability or force the PDS to overload. The proposed procedures to return the system to normal conditions are summarized as follows:

Step 1: Read the voltage of the three phases and check if they are equal or greater than 110% of nominal voltage.

Step 2: If the answer is yes switch on the last shed load, then wait 1 minute.

Step 3: If the answer of step 1 is no, wait 1 minute and repeat steps 1 and 2.

Step 4: Read the voltage of the three phases and check if they are equal or greater than 110% of nominal voltage.

Step 5: If the answer of step 4 is yes repeat step 2 and 4 until all loads are switched on.

Step 6: If the answer of step 4 is no, then wait 1 minute and repeat step 4.

Step 7: After waiting 1 minute read the voltages and check if they equal or exceed 110% of nominal voltage.

Step 8: If the answer is yes switch off 20% of capacitor bank and wait 1 minute.

Step 9: If the answer is no repeat step 7.

Step 10: Repeat steps 7 and 8 until all the capacitor bank switched off.

Figure 5.13 shows the flowchart of all the recovery procedures.

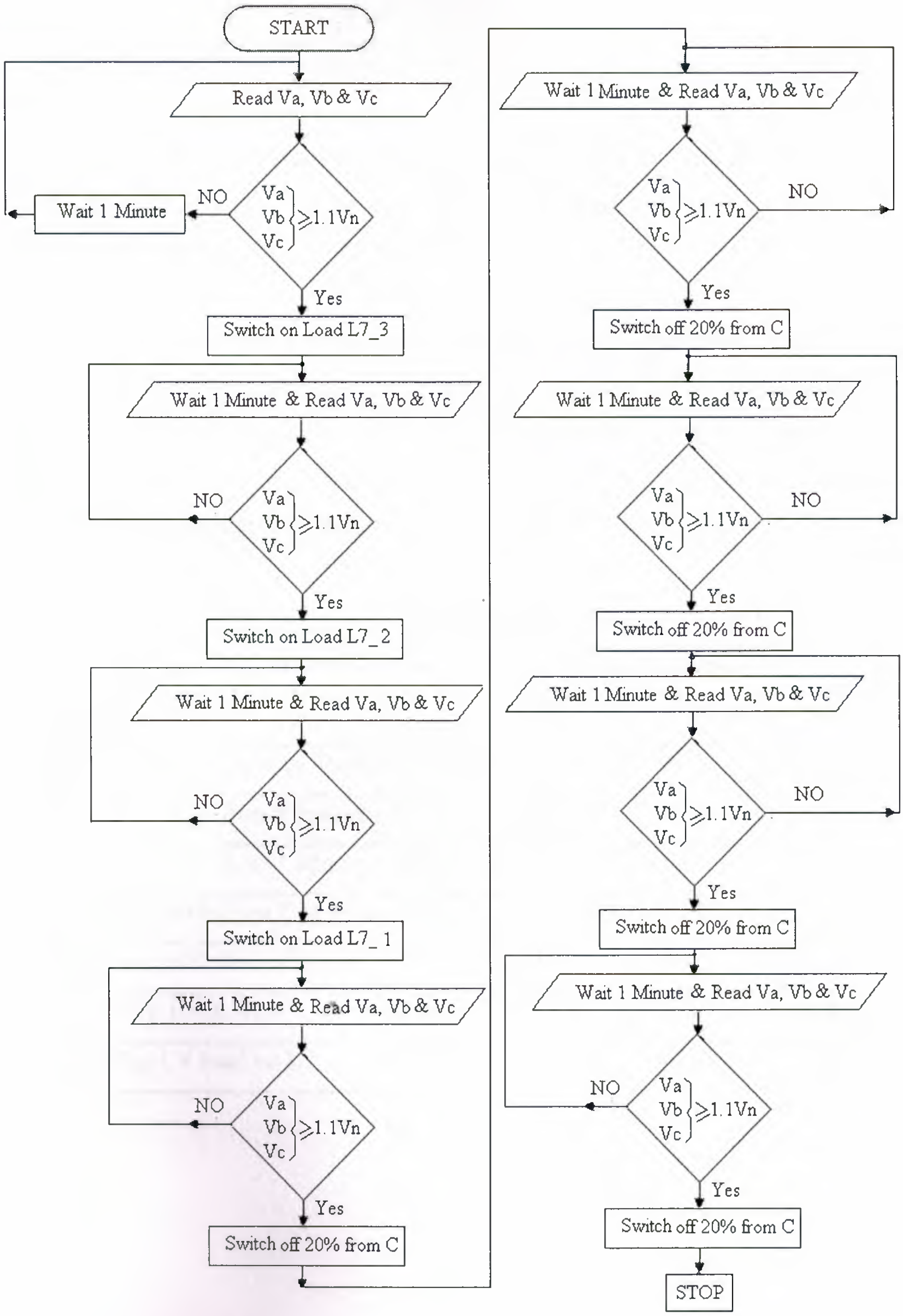


Figure 5.13 Flowchart of all the Recovery Procedures

5.7 Results

After the two branches of the stabilizer are designed, it is tested and simulated for some detected cases.

5.7.1 Simulation Results of the Voltage Stabilizer for Overload Cases

In order to prove the efficiency of the proposed voltage stabilizer (VS), it is tested by three detected cases from the neural network as overload case.

First Case is case no. 3.7 which consists from image3_7_1, image3_7_2 and image3_7_3 (see appendix B for data base). The final voltage after 20 seconds simulation, which detected by ANN as overload case, was 8.45 kV. Steps 1-13 of the voltage stabilizer for overload enhancement algorithm are performed to raise the terminal voltage of the load to 10.85 kV. The outputs of every step are listed in table 5.1 below. Also, figure 5.14 illustrates the simulated output of the proposed voltage stabilizer for overload cases.

Table 5.1: Numerical Outputs of Actions from VS for Overload Case 1

Type of Stabilizer Action	V_L after Action (kV)
Before Start	8.45
Raising Tap Changer of Transformer 5%	8.49
Switching 20% from Capacitor Bank	8.56
Switching 40% from Capacitor Bank	8.69
Switching 60% from Capacitor Bank	8.88
Switching 80% from Capacitor Bank	9.17
Switching 100% from Capacitor Bank	9.43
Shedding LV load no L7_1	10.85

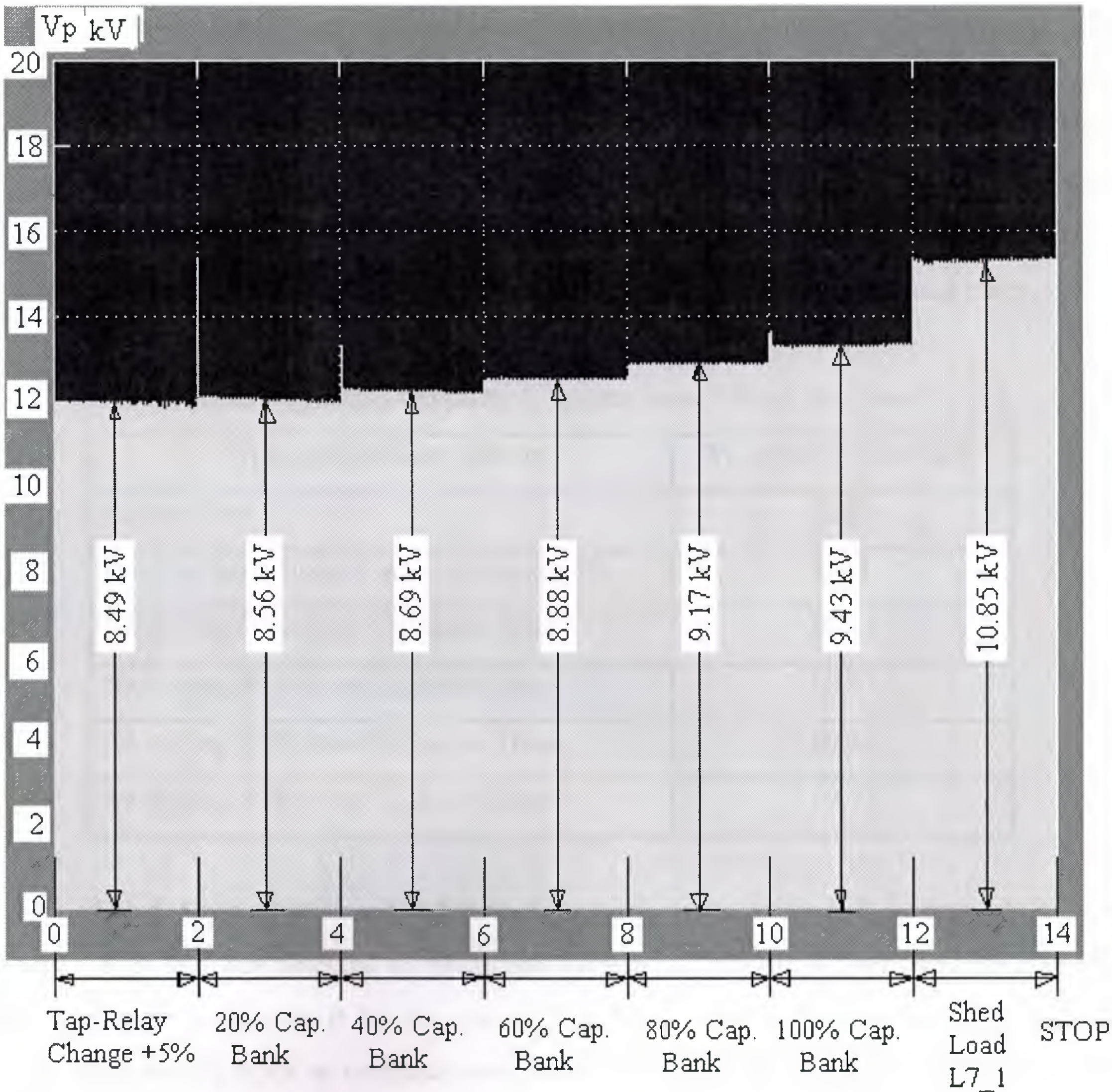


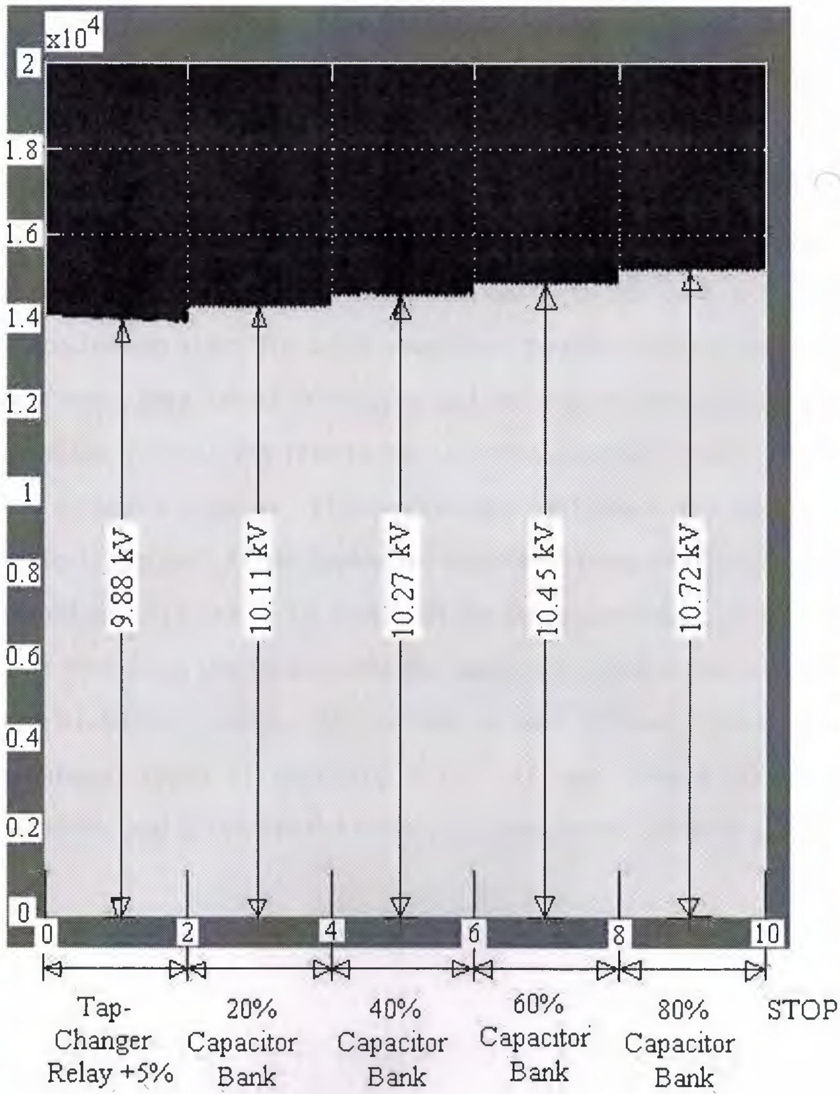
Figure 5.14 Results of Voltage Stabilizer for Overload Case 1

Second Case is case no. 3.2 which consists from image3_2_1, image3_2_2 and image3_2_3 (see appendix B for data base). The final voltage after 20 seconds simulation, which detected by ANN as overload case, was 9.83 kV. Steps 1-9 of the voltage stabilizer for overload enhancement algorithm are performed to raise the terminal voltage of the load to 10.72 kV. The outputs of every step are listed in table 5.2 below. Also, figure 5.15 illustrates the simulated output of the proposed voltage stabilizer for overload cases.

Table 5.2: Numerical Outputs of Actions from VS for Overload Case 2

Type of Stabilizer Action	**V_L after Action (kV)**
Before Start	9.83
Raising Tap Changer of Transformer 5%	9.88
Switching 20% from Capacitor Bank	10.11
Switching 40% from Capacitor Bank	10.27
Switching 60% from Capacitor Bank	10.45
Switching 80% from Capacitor Bank	10.72

Third Case is case no. 1.8 which consists from image1_8_1, image1_8_2 and image1_8_3 and was detected by intelligent system incorrectly as overload case instead of stable case (see appendix B for data base). The final voltage after 20 seconds simulation, which detected by ANN as overload case, was 10.80 kV. Only the first step of the voltage stabilizer for overload enhancement algorithm, which was raising tap changer relay of distribution transformer 5%, is performed raising the terminal voltage of the load to 11.03 kV. This value (100.3% Vn) is still in the allowed voltage range. Figure 5.16 illustrates the simulated output of the proposed voltage stabilizer for overload cases for this incorrectly detected case.



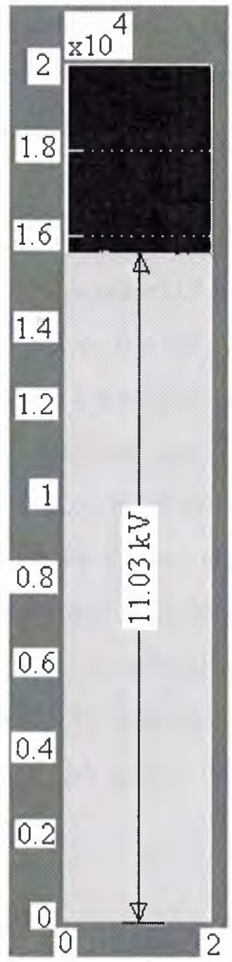


Figure 5.15 Results of Voltage Stabilizer for Overload Case 2

Figure 5.16 Results of Voltage Stabilizer for Overload Case 3

5.7.2 Simulation Results of the Voltage Stabilizer for Unstable Cases

In order to prove the efficiency of the proposed voltage stabilizer (VS) for unstable cases, it is tested by one detected cases from the neural network as unstable case in which the frequency is decreasing.

The Case is case no. 2.3 which consists from image2_3_1, image2_3_2 and image2_3_3 (see appendix B for data base). In this case, generator 1 is switched of after 8 seconds from start. The other generators couldn't deliver the needed power for the system as a result they forced to collapse and the system goes to blackout. Steps 1-8 of the voltage stabilizer for stability restoration algorithm are performed to recover the fault and sustain the system's stability. These steps are performed for all medium voltage distribution system. Figure 5.17 illustrates the simulated output of the situation of the system without stabilizer and figure 5.18 shows all the steps and output of stabilizer for this unstable case. It is seen from the figures that the stabilizer could restore stability of the system although the excitation systems of machine 2 and 3 were limited. Figure 5.19 illustrates the simulated speed of generator 2 for this case, where (a) illustrates the speed without stabilizer and (b) shows the speed after the actions from the stabilizer.

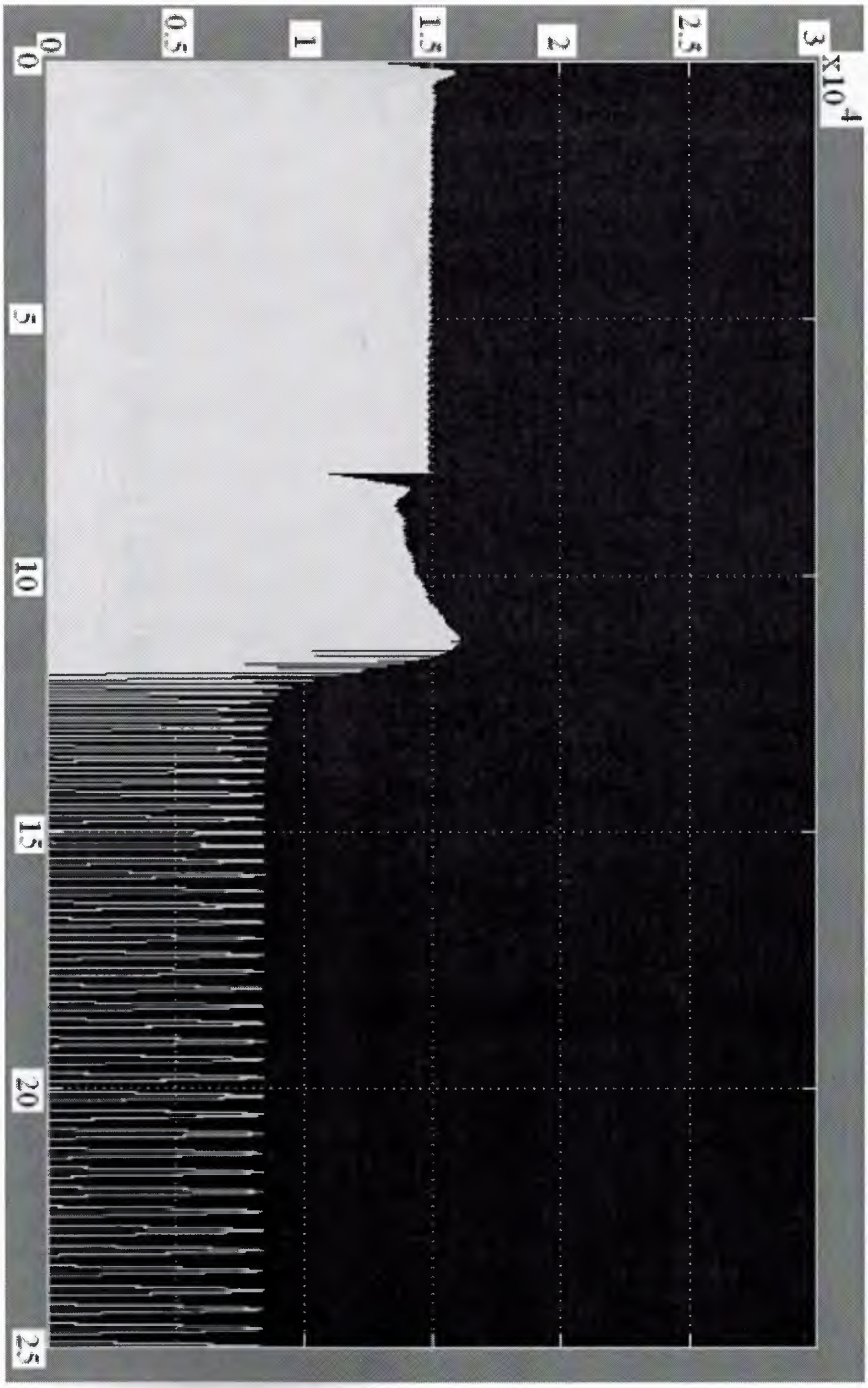


Figure 5.17 Original Unstable Case Without VS

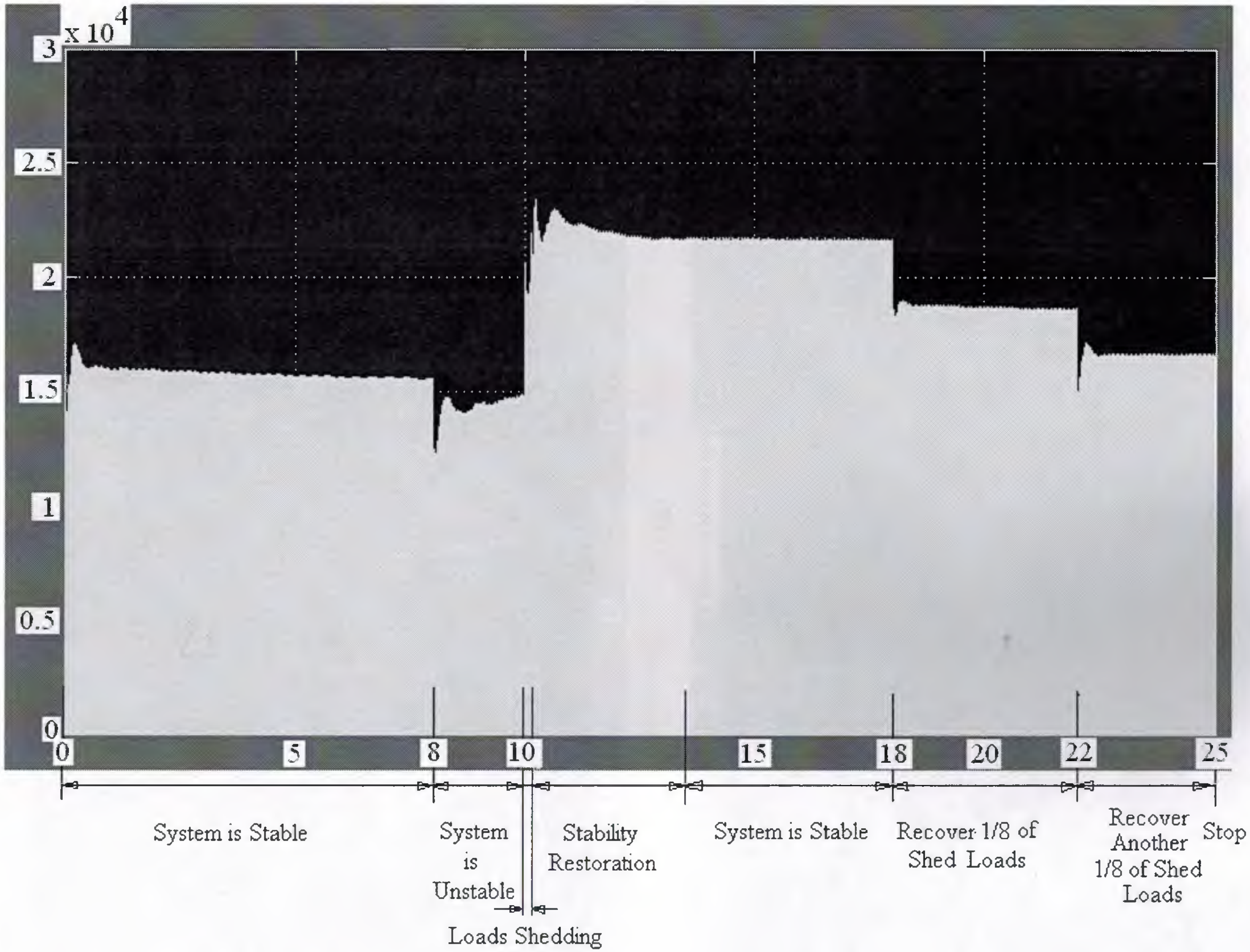
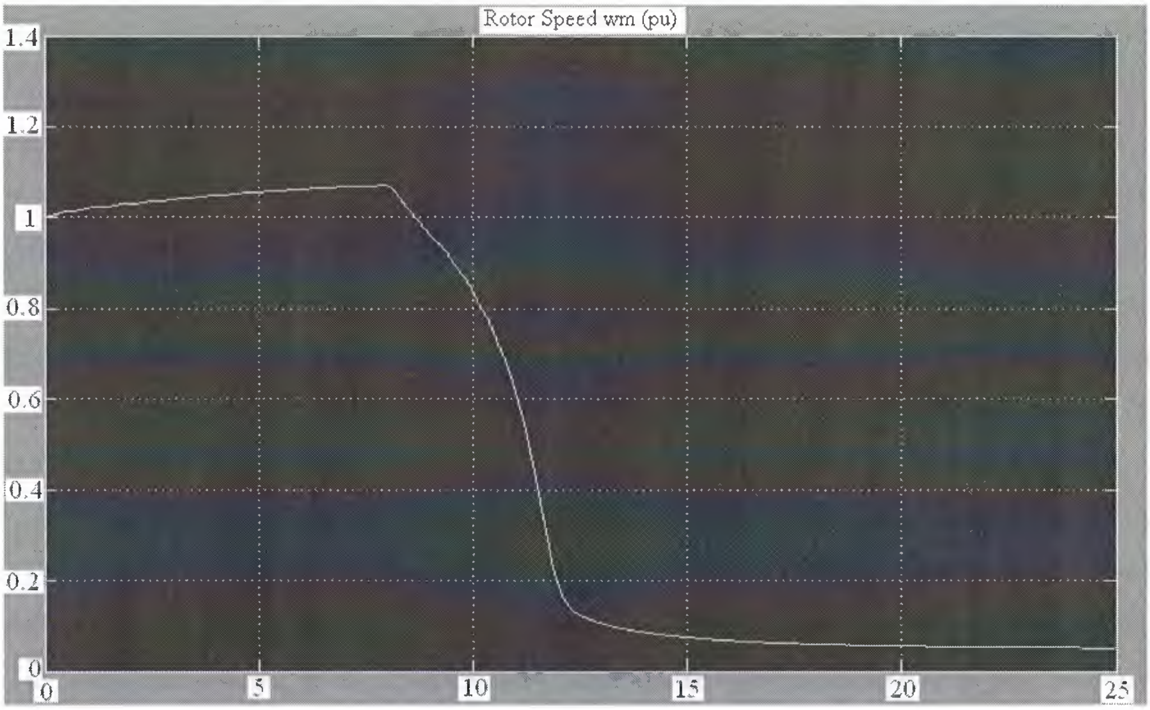
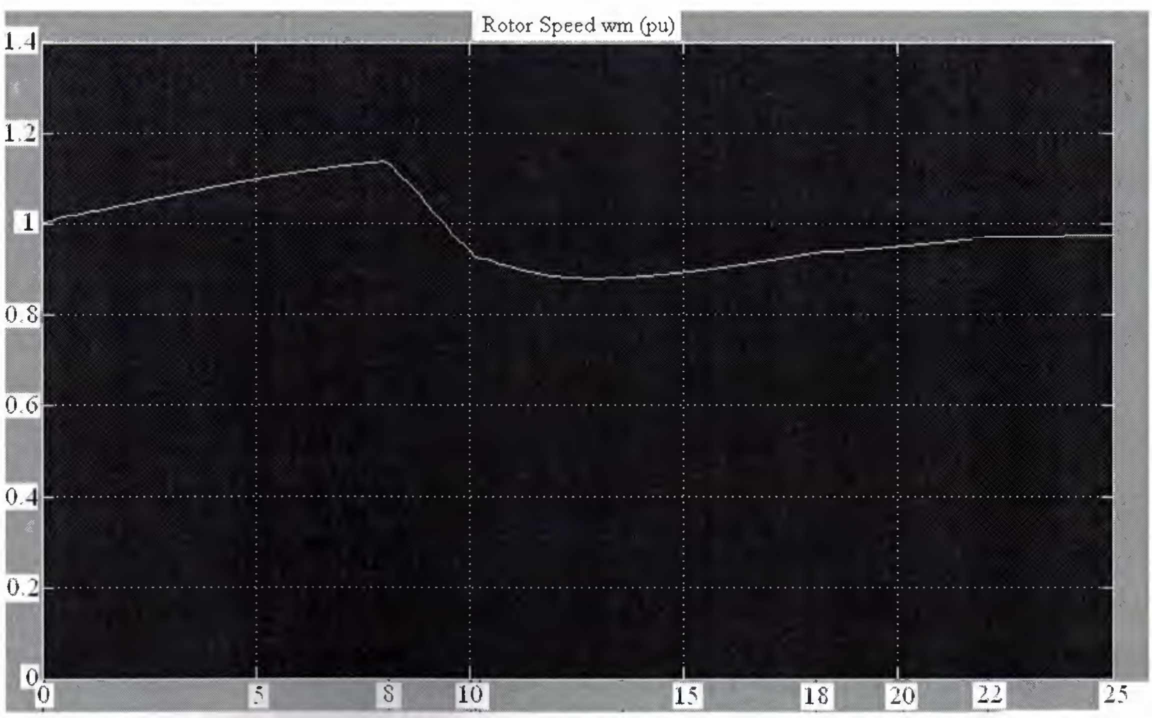


Figure 5.18 Results of VS for Unstable Case



(a)



(b)

Figure 5.19 Speed of Generator 2 (a) without VS, (b) after VS

5.8 Analysis of Results

A new voltage stabilizer (VS) for power distribution systems is designed and tested. The voltage stabilizer starts its actions according to the decision of the intelligent detection system. In case of detection an overload system the proposed voltage stabilizer performs instantaneous actions to clean the extreme voltage drop which result from the overload. After the system returns to normal loads and the overload state is cleaned, the VS starts reverse actions to recover the normal condition of the system. Also, in case of detection an unstable system the VS perform quick procedures to restore stability of the system. After assessment of the stability the VS perform inverse actions to return the system to normal conditions.

The proposed VS is tested for the two states, the overload and the unstable states by MATLAB Power Systems Simulator. Testing the VS for overload state was for three different cases. In the first case the VS is tested in an extreme voltage drop of the system. The terminal voltage of the load of substation of the distribution system was 8.45 kV (76.82% Vn), and after the instantaneous actions from the VS the terminal voltage raised to 10.85 kV (98.64% Vn). The time consumed to achieve this voltage raise (21.82% Vn) was 14 seconds. Although the least priority loads are shed, the other loads still working in normal voltages and the system is far from voltage collapse.

In the second tested case the load terminal voltage was 9.83 kV (89.36% Vn) and was raised to 10.72 kV (97.45% Vn). This voltage raise took place in 10 seconds. In this case the voltage was raised by inducing positive reactive power from the capacitor bank. Just 80% from the capacitor bank is switched on to raise the voltage 8.09% Vn and returns the system to work in normal voltage and far from voltage collapse.

The third tested case of the VS was the incorrect detection from the intelligent detection system when it is detected as overload case. The VS need one step which was raising the tap changer relay by 5% Vn to keep the system stable.

The proposed VS is also tested on one unstable case, in which the frequency was falling down quickly and the machines to collapse after machine 1 was turned off. After shedding 75% from loads the other machines increase their speed and return the system stable preventing from system collapse. The VS made orders to switch on the last ¼ shed load keeping the operating loads to work on nominal voltage. Although half loads still shed the system restore stability preventing the machines to reach to complete blackouts.

According to the above results, the proposed voltage stabilizer for power distribution system is efficient in cleaning overload and restoring stability. This VS can be implemented in PDS to work concurrent with SCADA devices to prevent voltage collapse and blackouts of the power systems, or to work alone as temporal substitute of SCADA devices.

Intelligent system on-line detection was not performed in this scheme because the simulation in MATLAB was performed on ready boxes and it is not allowed to change them. In a real power system, intelligent system on-line detection could be performed by inducing samples of voltages of the three phases instantaneously to the neural network to detect instability or overload cases.

5.9 Summary

This chapter introduced a new voltage stabilizer for power distribution system working due to the decision of the intelligent detection system. The VS was tested on 4 cases, 3 overload detection cases and 1 unstable detection case. From the above results it is proved that the proposed voltage stabilizer is efficient in keeping the system stable and not overload.

CONCLUSION

The ability to maintain system stability in a deregulated power system environment is a major challenge. Power system voltage instabilities are dynamic phenomena, in which numerous nonlinear devices are involved, can cause significant damage economically. In order to assess voltage stability and to prevent voltage collapse, research work has been carried out and is presented within this thesis. The thesis introduces an intelligent voltage stabilizer that work concurrently with SCADA system to perform quick steps to restore the stability of power distribution systems.

Design of this intelligent voltage stabilizer is based on an intelligent system on-line detection of instability or overload. As soon as the intelligent system detects unstable case or overload case, instantaneous steps are performed to sustain the power distribution system to restore its stability.

The intelligent detection system is based on an artificial neural network which uses back propagation learning algorithm. The ANN is trained on earlier events for instability or voltage collapse, to detect on-line instability or overload of power distribution system. An assumed power system was designed and simulated in MATLAB. Part of output voltage images were preprocessed to form patterns to be induced to the ANN for training and the rest for testing. Results of testing show the efficiency of the ANN in detecting instability and overload with high recognition rates and accuracy.

The voltage stabilizer which uses the decision of the intelligent system reacts in quick steps to restore the voltage stability of the distribution system or to clean the extreme voltage drop which caused by the overload state of the system. The organized steps to overcome the overload state are summarized in raising tap changer relays of distribution transformers, switching capacitor banks in steps and then if necessary shedding part of low voltage loads. If the voltage stabilizer is sensed for instability it goes directly to shed part of loads in the low voltage level to help in preventing the machines from switching off.

The stabilizer was tested with three overload cases and one instability case in which the main generator failed to feed the system with power forcing the other machines to sharply slow their speed. In the three cases of overload the stabilizer succeeded to raise the load voltage to allowed level in short time. Also, it succeeded to restore the stability of the system and to prevent the system to go to blackout.

The successful implementation of the intelligent detection system in detecting instability and overload of the PDS with high recognition rates and accuracy suggests that it could be efficiently used as a first phase of the intelligent voltage stabilizer to detect on-line instability and overload, which makes stability restoration quicker and more efficient. Also, the accurate performance of the second phase, which is the voltage stabilizer, in cleaning the voltage drop in the PDS and restoring the stability of a power system that was at the edge of instability danger preventing from blackout to the whole system, recommends using such a voltage stabilizer to work concurrently with SCADA system in keeping the PDS more stable.

The implementation of this work used an assumed power system with the following considerations:

- The power system parameters (generators, transmission lines, distribution transformers and buses variables) are not included in the design of the voltage stabilizer, thus the results of it were evaluated accordingly.
- The outputs of this program are not compared with any program available and the efficiency of the system was evaluated accordingly.
- The fault clearing duration for real power systems is 0.05 seconds but in simulation process it is set to 2 to 3 seconds.
- Single phase to ground faults contribute 80% of faults but in simulation of faults to achieve unstable cases, equal cases of three phases, two phases and single phase faults are performed.

Future work and future development of the proposed system include redesigning the voltage stabilizer to be fully intelligent by increasing the dependence on the intelligent system to find the direct optimal solution to clean the deep voltage drop or to find the optimal quantity of loads to be shed in order to restore stability quickly.

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APPENDIX A

MATLAB Programs

A.1 Neural Network Training and Testing Program

```
clear all
close all
clc
image_number = 3;
image_expression1 = 10;
image_expression2 = 3;
PATTERNS1 = [];
PATTERNS2 = [];
t = cputime;
cd( 'C:\Documents and Settings\Administrator\Desktop\new Voltage Outputs Train')
for k = 1:image_number
  for l = 1:image_expression1
    for m = 1:image_expression2
      IM = strcat(['image' int2str(k),'_' int2str(l),'_' int2str(m),'.jpg']);
      OI = imread(IM);
      GI = rgb2gray(OI);
      SI = imresize(GI,[400 202],'bicubic');
      for c = 2:201
        for d = 1:400
        n=401-d;
        if SI(n,c)<= 150
        vector_image = reshape(d,[],1);
        PATTERNS1 = [PATTERNS1 vector_image];
        break
        end
        end
      end
    end
  end
end
vector_image2 = reshape(PATTERNS1,[],(image_number*image_expression1));
PATTERNS2 = [PATTERNS2 vector_image2]/400;
Pre_Processing_Time = cputime - t;
disp(sprintf('PRE-PROCESSING TIME IS %8.4f',Pre_Processing_Time));% Display the
processing time
%%%%***** Neural Network *****%%%%
deserror = 0.002;                    % Desired Error
ETA = 0.001;                         % Learning Rate
ALP = 0.33;                          % Momentum Factor
```

```
maxiter=30000;                          % Maximum iteration
%%%% Training Patterns %%%%
PATTERNS2;
%%%% Desired Output %%%%
T1 = [1;0;0];
T2 = [0;1;0];
T3 = [0;0;1];
PATT = 30;                          % no of patterns
a = -0.31; b = 0.31;
for j= 1 : PATT
j;
hidw = a + (b-a) * rand(28,600);         % Selection the weights values between -0.31 and
0.31
outw = a + (b-a) * rand(3,28);
dhidw=0;                            % Initiate the change of hidden weight as zero
doutw=0;                            % Initiate the change of output weight as zero
hidb = a + (b-a) * rand(28,1);           % Selection the weights values 0f Bias Neurons
between 0.31 and -0.31
outb = a + (b-a) * rand(3,1);
dhidb=0;                            % Initiate the change of hidden weight as zero
doutb=0;                            % Initiate the change of output weight as zero

TARGET = [T1 T1 T1 T1 T1 T1 T1 T1 T1 T1 T2 T2 T2 T2 T2 T2 T2 T2 T2 T2 T3 T3 T3
T3 T3 T3 T3 T3 T3 T3];
out1(:,j) = PATTERNS2(:,j);              % Forward pass, compute outputs out1
neth = (hidw * out1(:,j));
out2(:,j) = logsig( neth );             % Forward pass, compute outputs out2
neto = (outw*out2(:,j));
out3(:,j) = logsig( neto );             % Forward pass, compute outputs out3
out3(:,j);
end
e =TARGET - out3;                     % Calculate the error
error = 1/2*(mean(diag(e).*diag(e)));
iter=1;                             % Initiate the iteration
t = cputime;                          % Begin processing time calculation
while  error >= deserror & iter<maxiter    % Compare the error with goal error
   for j=1:PATTERN
dfout2 = dlogsig( neth , out2(:,j) ;
dfout3 = dlogsig( neto , out3(:,j) ;       % Calculate the signal error
dout = -2*diag(dfout3) * e(:,j);          % Adjustments at output layer
dhid = diag(dfout2) * outw'* dout;         % Adjustments at hidden layer
oldoutw = outw;
oldhidw = hidw;
oldoutb = outb;
oldhidb = hidb;
```

```
outw = outw - (1-ALP)*(ETA*dout*out2(:,j)' + ALP*doutw;  % Update Weight of output
layer
hidw = hidw - (1-ALP)*(ETA*dhid*out1(:,j)' + ALP*dhidw;  % Update Weight of hidden
layer
outb = outb - (1-ALP)*(ETA*dout) + ALP*doutb ;  % Update bias Weight of output layer
hidb = hidb - (1-ALP)*(ETA*dhid) + ALP*dhidb;  % Update bias Weight of hidden layer
dhidw = hidw-oldhidw;                 % Calculate the change of hidden weight
doutw = outw - oldoutw;               % Calculate the change of output weight
dhidb = hidb - oldhidb;               % Calculate the change of hidden weight from Bias
Neuron
doutb = outb - oldoutb;               % Calculate the change of output weight from Bias
Neuron
out1(:,j) = PATTERNS2(:,j);               % Calculate the outputs again
neth = (hidw * out1(:,j))+hidb;
neto = (outw*out2(:,j))+outb;
out3(:,j) = logsig( neto );
   end
out3;
e = TARGET - out3;
error = 1/2*(mean(diag(e).*diag(e)));      % Calculate the mean sguare value of the error
disp(sprintf('ITER No.%6d       Mean Square Error =%10.5f%',iter,error));% Display the
error and the iteration
mse(iter)=error;
iter=iter+1;
end
Training_Time = cputime - t;                        % End processing time calculation
disp(sprintf('TRAINING TIME IS %8.4f',Training_Time));% Display the processing time
plot(mse,'k');
xlabel('ITERATION');
ylabel('MEAN SQUARE ERROR');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Test the patterns and default the output after training
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for i=1:PATT
PATTERNS2;
Train_out1 = PATTERNS2(:,i);
neth = (hidw * Train_out1)+hidb;
Train_out2 = logsig( neth );
neto = (outw * Train_out2)+outb;
Train_out3 = logsig( neto );
TRAIN_RESULTS = Train_out3
end
One_Forward_Run_Time = cputime - t;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%% This Part of Program is for Test
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
disp(sprintf('If You Want To Continue To Test Press Enter'));
pause
image_number = 3;
image_expression11 = 8;
image_expression12 = 3;
PATTERNS3 = [];
PATTERNS4 = [];
Tolirance = 0.8;
cd( 'C:\Documents and Settings\Administrator\Desktop\new Voltage Outputs Test')
for k = 1:image_number
  for l = 1:image_expression11
    for m = 1:image_expression12
      IM = strcat(['image' int2str(k),'_' int2str(l),'_' int2str(m),'.jpg']);
      OI = imread(IM);
      GI = rgb2gray(OI);
      SI = imresize(GI,[400 202],'bicubic');
      for c = 2:201
        for d = 1:400
          n=401-d;
          if SI(n,c)<= 150
          vector_image3 = (reshape(d,[],1))/400;
          PATTERNS3 = [PATTERNS3 vector_image3];
          break
          end
        end
      end
    end
  end
end
PATTEST = image_number*image_expression11;
vector_image4 = (reshape(PATTERNS3,[],(PATTEST)));
PATTERNS4 = [PATTERNS4 vector_image4];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for i=1:image_expression11
PATTERNS4;
Test_out1 = PATTERNS4(:,i);
neth = (hidw * Test_out1)+hidb;
Test_out2 = logsig( neth );
neto = (outw * Test_out2)+outb;
Test_out3 = logsig( neto );
TEST_RESULTS = Test_out3;
  if  Test_out3(1,:)>=Tolirance
  disp(sprintf('Stable Case     Recognition Percentage = %4.2f',Test_out3(1,:)*100));
  end
  if  Test_out3(1,:)<Tolirance
    max(Test_out3(j,:));
```

```
        if j==1
        disp(sprintf('Stable Case      Recognition Percentage = %4.2f',Test_out3(1,:)*100));
        elseif j==2
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
        elseif j==3
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
        end
    end
end
for i=(image_expression11+1):(image_expression11*2)
PATTERNS4;
Test_out1 = PATTERNS4(:,i);
neth = (hidw * Test_out1)+hidb;
Test_out2 = logsig( neth );
neto = (outw * Test_out2)+outb;
Test_out3 = logsig( neto );
TEST_RESULTS = Test_out3;

    if  Test_out3(2,:)>=Tolirance
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
    end
    if  Test_out3(2,:)<Tolirance
        max(Test_out3(j,:));
        if j==1
        disp(sprintf('Stable Case      Recognition Percentage = %4.2f',Test_out3(1,:)*100));
        elseif j==2
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
        elseif j==3
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
        end
    end
end
for i=(image_expression11*2 +1):(image_expression11*3)
PATTERNS4;
Test_out1 = PATTERNS4(:,i);
neth = (hidw * Test_out1)+hidb;
Test_out2 = logsig( neth );
neto = (outw * Test_out2)+outb;
Test_out3 = logsig( neto );
TEST_RESULTS = Test_out3;
    if  Test_out3(3,:)>=Tolirance
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
    if  Test_out3(3,:)<Tolirance
        max(Test_out3(j,:));
        if j==1
        disp(sprintf('Stable Case      Recognition Percentage = %4.2f',Test_out3(1,:)*100));
```

```
        elseif j==2
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
        elseif j==3
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
        end
    end
end
```

NEAR EAST UNIVERSITY

GRADUATE SCHOOL OF APPLIED AND SOCIAL SCIENCES

A VOLTAGE STABILIZER FOR POWER DISTRIBUTION SYSTEMS USING NEURAL NETWORKS

Samir JABR

Master Thesis

Department of Electrical and Electronic Engineering

Nicosia - 2007

Samir JABR: A Voltage Stabilizer for Power Distribution Systems Using Neural Networks

Approval of Director of Graduate School of Applied and Social Sciences

Prof. Dr. Fahreddin M. SADIKOĞLU

We certify this thesis is satisfactory for the award of the degree of Master of Science in Electrical and Electronic Engineering

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ABSTRACT

Voltage collapse causes many blackouts of power systems all over the world even in developed countries. SCADA systems, which were induced in most power systems, could not prevent many famous blackouts. Therefore, there is a need to find efficient solutions to remedy these problems.

This thesis attempts to design a voltage stabilizer for power distribution systems (PDS) based on artificial neural network (ANN) on-line detection of instability that works concurrently with SCADA systems as another support to help preventing voltage collapse in PDS.

The design of this voltage stabilizer has two phases. The first phase is an intelligent system which uses a back propagation learning algorithm neural network that detects instability or overload of PDS, using images of voltage outputs obtained from a MATLAB simulator for a proposed power system.

The second phase of the intelligent voltage stabilizer uses the output of the first phase which is the ANN classifier. If the intelligent system detects an overload case, the stabilizer will perform instantaneous steps to clean the deep voltage drop in PDS which may cause voltage collapse. These steps depend on raising tap-changer relays of distribution transformers then switching on capacitor banks in steps, then if it is necessary shedding part of loads with least priority. Also, if instability is detected, the stabilizer will make quick arrangement to assess stability. Loads shedding and redispatch the generators to get actions constitute the main arrangements. In every case, load shedding will be performed according to the cause of instability.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

AGC: Automatic Generation Control

ANN: Artificial Neural Network

AVC: Advanced VAR Compensators

BPA: Bonneville Power Administration

BP: Back Propagation

DVC: Dynamic VAR Compensator

ED: Economic Dispatch

EMS: Energy Management Systems

ES: Excitation System

FACTS: Flexible AC Transmission System

GDE: Governor and Diesel Engine

HTG: Hydraulic Turbine and Governor

LFC: Load Frequency Control

LP: Linear Programming

LTC: Load Tap-Changers

MLP: Multilayered Perceptron

MSE: Mean Square Error

PDS: Power Distribution System

PSS: Power System Stabilizer

RTU: Remote Terminal Units

SCADA: Supervisory Control and Data Acquisition

SCB: Switched Capacitor Banks

SVC: Static VAR Compensator

UFLS: Under Frequency Load Shedding

VS: Voltage Stabilizer

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INTRODUCTION

Voltage instability or collapse is emerging as a major concern to utility companies who aim to maintain a stable power system operation. Voltage instability has caused several major power system collapses around the world. In general these voltage stability analysis methods are classified into two categories: dynamic stability and transient stability. Dynamic stability can reproduce or predict the time response of the system voltage to a sequence of events and, therefore, help identify whether the system voltage is stable or not. The majority of transient methods are based on power flow formations to evaluate voltage stability in various terms, such as load margins and load flow feasibility.

Voltage stability analysis is concerned with the ability of assessing the power system to maintain acceptable voltages at all system buses under normal conditions and after being subjected to disturbances. A major factor contributing to voltage instability is the voltage drop that occurs when active and reactive power flow through inductive reactances of the transmission network. Voltage stability is threatened when a disturbance increases the reactive power demand beyond the sustainable capacity of the available reactive power resources. While the most common form of voltage instability is the progressive drop of bus voltages, the risk of overvoltage instability also exists and has been experienced at least on one system.

Since the voltage instability issue started to emerge, significant research efforts from the power engineering community have been devoted to studying the voltage instability mechanism and to developing analysis tools and control schemes to mitigate the instability. Meanwhile, many researchers agree that the voltage instability problem is a high order nonlinear problem as a large number of different types of devices are involved in the voltage dynamics. Also a wide variety of modeling and simulation principles and analysis and control methods of the power system voltage stability have been developed.

Artificial Neural Networks (ANN) have been used to solve many problems obtaining outstanding results in various applications such as classification, clustering, pattern recognition and forecasting among many other applications corresponding to different areas. Applications of Artificial Neural Network to the above-mentioned problem

have attained increasing importance mainly due to the efficiency of present day computers. Moreover real-time use of conventional methods in an energy management center can be difficult due to their significant large computational times. One of the main features, which can be attributed to ANN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate online response. ANN approach to voltage stability assessment and improvement has been proposed and various neural network combinations have been used. The ability of ANN to understand and properly classify such a problem of highly non-linear relationship has been established in most of them and the significant consideration is that once trained effectively ANN can classify new data much faster than it would be possible with analytical model.

Research of this thesis is motivated to contribute in solving instability problem of power distribution systems. The thesis will introduce a new voltage stabilizer for power distribution system to enhance the stability of the whole power system. The main objective of the proposed voltage stabilizer is to work concurrently with SCADA systems as another support to avoid reaching to instability problem.

The proposed voltage stabilizer has two phases, detection of on-line instability and overload of the distribution system, and quick arrangements to solve the problem. Detection of on-line instability will be performed by an intelligent system based a back propagation neural network. The neural network will be trained on patterns preprocessed from voltage images outputs in MATLAB simulator for a suggested power system facing instability and overload problems. Testing the neural network will be performed using voltage output patterns that were not exposed to the ANN. Detection of instability or overload earlier helps in arranging suitable solutions to sustain stability quickly. Instantaneous reactions of the voltage stabilizer will be performed to restore stability or clean voltage drop of the distribution system as soon as it is detected by the intelligent system.

This thesis is organized in five chapters. The first three chapters introduce background information on stability of power systems, voltage stability and artificial neural networks and their real life applications in power systems. The last two chapters focus on the developed intelligent detection system, and solutions arrangements to assess stability in the novel stabilizer.

Chapter 1 presents an introduction to power systems stability. Then various instability phenomena which are frequency instability, voltage instability, rotor instability with two sided, transient angular instability, and small-signal angular instability, are introduced.

Chapter 2 introduces voltage stability problem. First, the relation between the voltage at the receiving end and the transmitted active and reactive powers is explained, and then voltage stability is defined and classified, followed by solutions to prevent voltage instability.

Chapter 3 focuses on the artificial neural networks and the back propagation algorithm which will be used. Also it reviews real life applications of ANNs especially in power systems implementations.

Chapter 4 presents an intelligent system which will detect on-line instability or overload cases. Firstly, it presents the preprocessing of patterns that outputs from the simulation of a proposed power system. Secondly, it introduces the ANN design and topology and the results of ANN training and testing. Finally, it proceeds to discuss the efficiency of the proposed techniques.

Chapter 5 presents a new voltage stabilizer based on the decision of the intelligent system for detection of instability or overload cases. The two phases of the stabilizer, which are overload enhancement and stability assessment, are presented. Testing the voltage stabilizer on part of unacceptable cases takes place in this chapter. Finally, a discussion on the efficiency and benefits of the proposed voltage stabilizer is included.

CHAPTER ONE
STABILITY OF POWER SYSTEMS

1.1 Overview

The electric power generation-transmission-distribution grid in developed countries constitutes a large system that exhibits a range of dynamic phenomena. Stability of this system needs to be maintained even when subjected to large low-probability disturbances so that the electricity can be supplied to consumers with high reliability.

The chapter first explains the definition of power system stability and the need for power system stability studies and their types. It then proceeds to discuss on the various instability phenomena which are frequency instability, voltage instability, transient rotor angular instability, and small-signal rotor angular instability.

1.2 Definition of Power System Stability

The stability of a system is defined as the tendency and ability of the power system to develop restoring forces equal to or greater than the disturbing forces to maintain the state of equilibrium [1].

Let a system be in some equilibrium state. If upon an occurrence of a disturbance and the system is still able to achieve the equilibrium position, it is considered to be stable. The system is also considered to be stable if it converges to another equilibrium position in the proximity of initial equilibrium point. If the physical state of the system differs such that certain physical variable increases with respect to time, the system is considered to be unstable.

Therefore, the system is said to remain stable when the forces tending to hold the machines in synchronism with one another are enough to overcome the disturbances. The system stability that is of most concern is the characteristic and the behavior of the power system after a disturbance.

Another definition is given by IEEE/CIGRE Joint Task Force on Stability Terms and Definitions [2] as: "Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being

subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact".

Stability of an electric power system is thus a property of the system motion around an equilibrium set, i.e., the initial operating condition. In an equilibrium set, the various opposing forces that exist in the system are equal instantaneously (as in the case of equilibrium points) or over a cycle (as in the case of slow cyclical variations due to continuous small fluctuations in loads or periodic attractors).

At an equilibrium set, a power system may be stable for a given (large) physical disturbance, and unstable for another. A stable equilibrium set thus has a finite region of attraction; the larger the region, the more robust the system with respect to large disturbances. The region of attraction changes with the operating condition of the power system.

If following a disturbance the power system is stable, it will reach a new equilibrium state with the system integrity preserved i.e., with practically all generators and loads connected through a single contiguous transmission system. On the other hand, if the system is unstable, it will result in a run-away or run-down situation; for example, a progressive increase in angular separation of generator rotors, or a progressive decrease in bus voltages. An unstable system condition could lead to cascading outages and a shutdown of a major portion of the power system.

1.3 Why the Need of Power System Stability

The power system industry is a field where there are constant changes. Power industries are restructured to cater to more users at lower prices and better power efficiency. Power systems are becoming more complex as they become inter-connected. Load demand also increases linearly with the increase in users. Since stability phenomena limits the transfer capability of the system, there is a need to ensure stability and reliability of the power system due to economic reasons.

Power systems have originally arisen as individual self-sufficient units, where the power production matched the consumption. In a case of a severe failure, a system collapse was unavoidable and meant a total blackout and interruption of the supply for all

customers. But the restoration of the whole system and synchronization of its generators were relatively easy thanks to the small size of the system.

1.4 Stability Studies

Stability studies are generally categorized into two major areas: steady-state stability and transient stability [1]. Steady-state stability is the ability of the power system to regain synchronism after encountering slow and small disturbances. Example of slow and small disturbances is gradual power changes. The ability of the power system to regain synchronism after encountering small disturbance within a long time frame is known as dynamic stability. Transient stability studies refer to the effects of large and sudden disturbances. Examples of such faults are the sudden outrage of a transmission line or the sudden addition or removal of the large loads. Transient stability occurs when the power system is able to withstand the transient conditions following a major disturbance. Figure 1.1 introduces a classification to power stability and gives the overall picture of the power system stability problem, identifying its categories and subcategories.

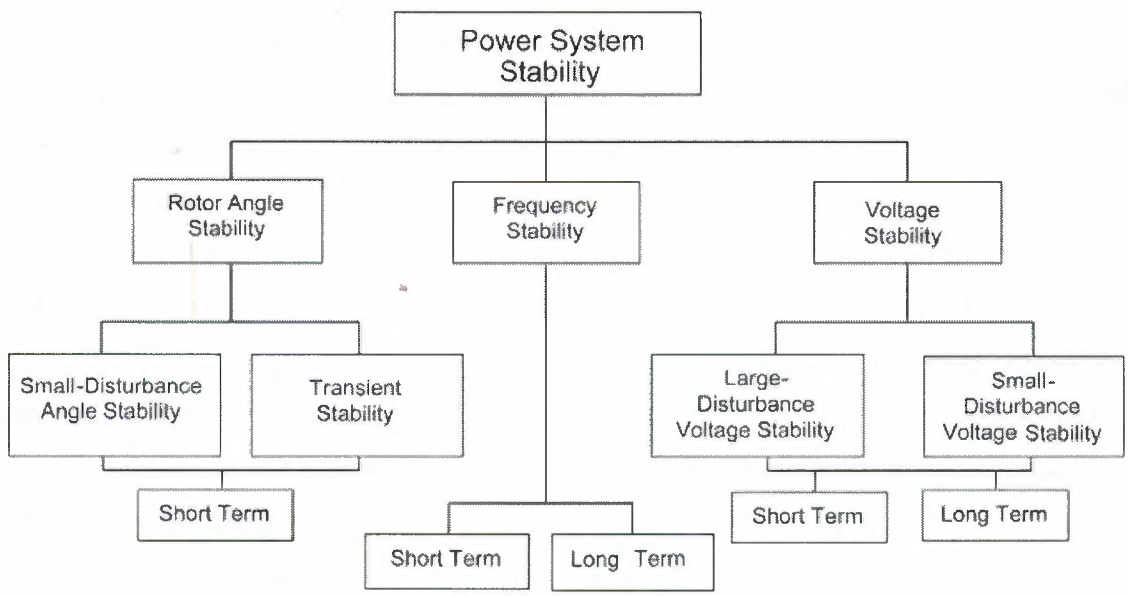


Figure 1.1 Classifications of Power System Stability [2]

1.5 Instability Phenomena

With the rising importance of the electricity for industry (and the entire society), the reliability of supply has become a serious issue. Interconnection of the separated/individual power systems have offered a number of benefits [3] , such as sharing the reserves both for a normal operation and emergency conditions, dividing of the responsibility for the frequency regulation among all generators and a possibility to generate the power in the economically most attractive areas, thus providing a good basis for the power trade.

Power systems size and complexity have grown to satisfy a larger and larger power demand. Phenomena, having a system/global nature, endangering a normal operation of power systems have appeared, explicitly: frequency instability, voltage instability, transient angular instability (also called generator's out-of-step), and local mode of small-signal angular instability (also mentioned as generator's swinging or power oscillations).

1.5.1 Frequency Instability

Frequency Instability is defined as [4]: "inability of a power system to maintain steady frequency within the operating limits. Frequency stability is defined as [2]: "the ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generations and loads".

Keeping frequency within the nominal operating range (ideally at nominal constant value) is essential for a proper operation of a power system. A maximal acceptable frequency deviation (usually 2 Hz) is dictated by an optimal setting of control circuits of thermal power plants. When this boundary is reached, unit protection disconnects the power plant. This makes situation even worse – frequency further decreases and it may finally lead to the total collapse of the whole system. For the correction of small deviations, Automatic Generation Control (AGC) is used and larger deviations require so-called spinning reserves or fast start-up of generators. When more severe disturbances occur, e.g. loss of a station (all generating units), loss of a major load centre or loss of AC or DC interconnection, emergency control measures may be required to maintain frequency stability. Emergency control measures may include [4]:

- Tripping of generators
- Fast generation reduction through fast-valving or water diversion

- HVDC power transfer control
- Load shedding
- Controlled opening of interconnection to neighboring systems to prevent spreading of frequency problems
- Controlled islanding of local system into separate areas with matching generation and load.

During frequency excursions, voltage magnitudes may change significantly, especially for islanding conditions with underfrequency load shedding that unloads the system. Voltage magnitude changes, which may be higher in percentage than frequency changes, affect the load-generation imbalance. High voltage may cause undesirable generator tripping by poorly designed or coordinated loss of excitation relays or volts/Hertz relays. In an overloaded system, low voltage may cause undesirable operation of impedance relays [2].

Common practice in utilities is that most of the above actions are executed manually by a dispatcher/operator of the grid. Automatic local devices used for the load shedding are UFLS (Under Frequency Load Shedding) relays. They are usually triggered when frequency sinks to the predefined level and/or with a predefined rate of change. They are in principle same although they might be sorted in various categories [5]. Their action is disconnection of the load in several steps (5 - 20 % each) from the feeders they supervise. However, their effective use is strongly dependent on their careful tuning based on prestudies, since there is no on-line coordination between them. Another disadvantage is, that they can only react to the under frequency, increase of frequency is not covered by them at all. In some cases the impact of their operation may be negative; since they are not capable of the adaptability to the present situation (e.g. production of distributed/decentralized generation varies in time so quite often the distribution voltage level feeders feed the energy back into the network. So they don't appear as loads and their disconnection makes situation even worse).

1.5.2 Voltage Instability

Voltage Instability is the inability of a power system to maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbance. A system enters a state of voltage instability when a disturbance, increase in load demand, or change in system conditions causes a progressive and uncontrollable drop in voltage. A system is voltage unstable if, for at least one bus in the system, the bus voltage magnitude decreases as the reactive power injection in the same bus is increased [6].

Voltage instability is basically caused by an unavailability of reactive power support in some nodes of the network, where the voltage uncontrollably falls. Lack of reactive power may essentially have two origins. Gradual increase of power demand which reactive part cannot be met in some buses or sudden change of a network topology redirecting the power flows such a way that a reactive power cannot be delivered to some buses.

The relation between the active power consumed in the monitored area and the corresponding voltages is expressed by so called PV-curves. The increased values of loading are accompanied by a decrease of voltage (except a capacitive load). When the loading is further increased, the maximum loadability point is reached, from which no additional power can be transmitted to the load under those conditions. In case of constant power loads the voltage in the node becomes uncontrollable and rapidly decreases. However, the voltage level close to this point is sometimes very low, what is not acceptable under normal operating conditions, although it is still within the stable region. But in the emergency cases, some utilities accept it for a short period.

The emergency stabilizing actions which might be taken are in principle same as in case of the frequency instability, plus:

- Change of the generator voltage set point
- Automatic shunt switching
- Control of series compensation
- Blocking of Tap Changer of transformers
- Fast redispatch of generation

The analyses of real voltage collapses have shown their wide area nature and that they can be sorted basically into two categories according to the speed of their evolution –

Transient Voltage Instability and Long-term Voltage Instability [7]. Transient Voltage Instability is in the range of seconds (usually 1 – 3 s) and the main role in the incidents played the dynamics of induction motors as a load (majority of air conditioning systems) and HVDC transmission systems. The time scale of the Long-term Voltage Instability ranges from tens of seconds up to several minutes. It involves mainly impact of a topology change or gradual load increase, i.e. fairly slow dynamics. Therefore the major part of the research activities in this area has focused on the steady state aspects of voltage stability, i.e. finding the maximum loadability point of the PV-curve.

1.5.3 Rotor Angle Instability

It deals of power system synchronism with two parts, transient angle instability, and small-signal angle instability.

1.5.3.1 Transient Angle Instability

Transient Angular Instability (also called Generator's Out-of-step) is the inability of the power system to maintain synchronism when subjected to a severe transient disturbance. The resulting system response involves large excursions of generator angles and is influenced by the nonlinear power-angle relationship [6].

In case of transient angle instability, a severe disturbance is a disturbance, which does not allow a generator to deliver its output electrical power into the network (typically a tripping of a line connecting the generator with the rest of the network in order to clear a short circuit). This power is then absorbed by the rotor of the generator, increases its kinetic energy that results in the sudden acceleration of the rotor above the acceptable revolutions and eventually damage of the generator.

Therefore the measures taken against this scenario aim mainly to either an intended dissipation of undelivered power by braking resistor (reducing the mechanical power driving the generator) or fast-valving, disconnection of the generator.

An application of traditional measure of transient angle instability – equal area criterion (expressing a balance between the accelerating and decelerating energy), on emergency control has been presented which describes the method called single machine equivalent (SIME) [8]. The angles of the generators in the system are predicted

approximately 200 ms ahead. According to it, the machines are ranked and grouped into two categories. For the generators from the critical category, one machine, infinite bus (OMIB) equivalent is modeled and extended equal area criterion is applied to assess their stability. Pre-assigned corrective action is executed if an unstable generator is identified.

1.5.3.2 Small-signal Angle Instability

Local mode of Small-signal Angular Instability is the inability of the power system to maintain synchronism under small disturbances. Such disturbances occur continually on the system because of small variations in loads and generation. The disturbances are considered sufficiently small for linearization of system equations to be permissible for purposes of analysis. Local modes or machine-system modes are associated with the swinging of units at a generating station with respect to the rest of the power system. The term local is used because the oscillations are localized at one station or small part of the power system [6].

Some power systems lack a "natural" damping of oscillations, which may occur, and they would be unstable when subjected to any minor disturbance and sometimes even under normal operation conditions if no measures increasing the damping were introduced [9]. An extension of the transmission capacity by adding a new line does not necessarily improve the damping significantly and solve the problem [10].

A traditional way of damping the oscillation is using of Power System Stabilizer (PSS), which controls/modulates the output voltage of the generator. The coordinated tuning of PSSs is a complex task, since they should be robust - work in the wide range of operation conditions and provide the best possible performance. This process is done off-line.

1.5.4 Basis for Distinction between Voltage and Rotor Angle Stability

It is important to recognize that the distinction between rotor angle stability and voltage stability is not based on weak coupling between variations in active power/angle and reactive power/voltage magnitude. In fact, coupling is strong for stressed conditions and both rotor angle stability and voltage stability are affected by pre-disturbance active power as well as reactive power flows. Instead, the distinction is based on the specific set of opposing forces that experience sustained imbalance and the principal system variable in which the consequent instability is apparent [2].

1.6 Summary

The chapter was a review for definitions of power system stability and their phenomena. It also introduced various instability phenomena which are frequency instability, voltage instability, Rotor angle instability with two subcategories transient angular instability, and small-signal angular instability.

CHAPTER TWO

VOLTAGE STABILITY AND SYSTEM SOLUTIONS

2.1 Overview

This chapter discusses the voltage stability and the related solutions. First, it explains the relation between the voltage at the receiving end and the transmitted active and reactive powers, and the sources and sinks of reactive power. Then, it discusses voltage sensitivity to loads, and the voltage stability and collapse. Finally it proposes solutions to keep voltage stability by inserting reactive power using shunt capacitor banks or/and advanced compensated VARs, or/and using synchronous machines. It, also, proposes changing the voltage at the distribution substations by transformer tap changers. The final procedure for maintaining voltage stability is load shedding. The final session introduces the control of power system.

2.2 Transfer of Active and Reactive Power

Consider the circuit in Figure 2.1. A strong source with voltage E supplies a remote load through a transmission line modeled as a series reactance. The receiving end voltage V and angle depend on the active and reactive power transmitted through the line. The active and reactive power received at the load end can be written [11]:

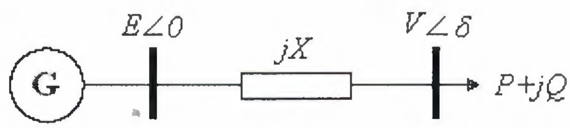


Figure 2.1 Single Line Diagram of a Simple Radial Power System

$$P = -\frac{EV}{X}\sin\delta \tag{2.1}$$

$$Q = \frac{EV}{X}\cos\delta - \frac{V^2}{X} \tag{2.2}$$

After eliminating using the trigonometric identity we get

$$\left(Q+\frac{V^2}{X}\right)^2+P^2=\left(\frac{EV}{X}\right)^2 \qquad (2.3)$$

Solving for V^2 yields

$$V^2=\frac{E^2}{2}-QX\pm X\sqrt{\frac{E^4}{4X^2}-P^2-Q\frac{E^2}{X}} \qquad (2.4)$$

Thus, the problem has real positive solutions if

$$P^2+Q\frac{E^2}{X}\leq\frac{E^4}{4X^2} \qquad (2.5)$$

This inequality shows which combinations of active and reactive power that the line can supply to the load. Substituting the short-circuit power at the receiving end, $S_{SC}={E^2}/{X}$, we get

$$P^2+QS_{SC}\leq\left(\frac{S_{SC}}{2}\right)^2 \qquad (2.6)$$

Some preliminary observations that can be made from the condition (2.6) are:

- The maximum possible active power transport is $S_{SC}/2$ for Q = 0.
- The maximum possible reactive power transport is $S_{SC}/4$ for P = 0
- An injection of reactive power at the load end, i.e., Q < 0 increases the transfer limit for active power.
- The transfer limits are proportional to the line admittance and to the square of the feeding voltage E

Thus, it appears more difficult to transfer reactive than active power over the inductive line, and it seems that reactive power transfer can influence the ability of the line to carry active load. Furthermore, assume for now that the load has admittance characteristics, that is, the active and reactive power received by the load can be written

$$P+jQ=V^2G(1+j\tan(\phi)) \qquad (2.7)$$

Thus, the load produces reactive power for leading power factor *($tan(\phi) < 0$)* and absorbs reactive power for lagging power *($tan(\phi) > 0$)*. After normalizing equations (2.4) and (2.7) using

$$p = P / S_{SC}, \quad q = Q / S_{SC} \tag{2.8}$$

$$v = V / E, \quad g = G / (1 / X)) \tag{2.9}$$

Using normalized quantities, the positive solution to (2.4) can be written

$$v = \frac{1}{\sqrt{g^2 + (1 + g\tan(\phi))^2}} \tag{2.10}$$

Not surprisingly, there is no voltage drop over the line when the load admittance is zero and the load voltage approaches zero as the load admittance increases towards infinity.

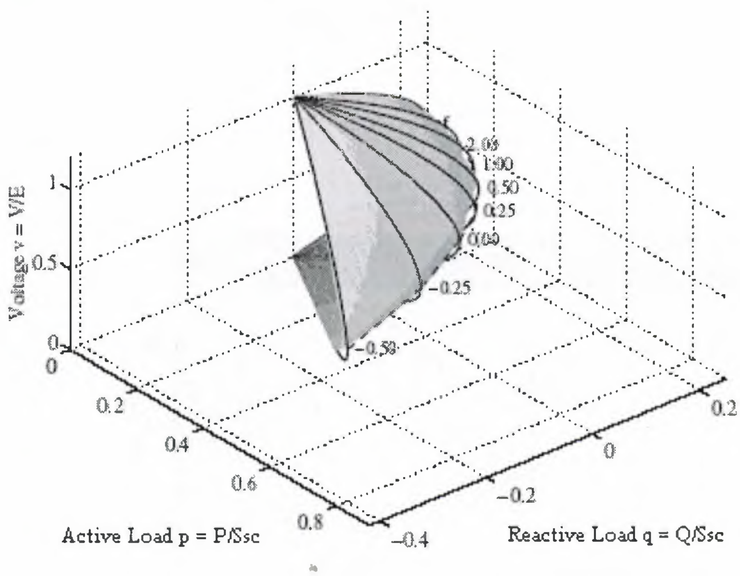


Figure 2.2 The So-Called Onion Surface as Given by Equation (2.10) Drawn Using Normalized Load Quantities [11].

Figure 2.2 shows the so-called onion surface given by (2.10) drawn in the pqv-space. It illustrates the relationship between receiving end voltage and transferred active and reactive power, and each point on the surface corresponds to a feasible operating point. The surface visualizes the set of operating points that the combined generation and transmission system can sustain. The actual operating point is determined by the apparent

load admittance, and the stability of this operating point is determined jointly by the slope of the surface and the load characteristics. The solid lines drawn on the surface correspond to operating points with varying g and constant tan (ϕ) (shown by the number beside each line). The dashed line around the "equator" of the surface corresponds to the transfer limit according to the condition (2.6).

Figure 2.3 shows so-called pv-curves [7], which are projections of the solid lines drawn on the onion surface onto the pv-plane. The rightmost point of each pv-curve marks the maximum active power transfer for a particular power factor. The corresponding voltage shown by the dashed curve is therefore often referred to as the critical voltage and the active loading as the theoretical transfer limit. The critical voltage and theoretical transfer limit increase with decreasing tan (ϕ). As will later be demonstrated, only operating points on the upper half of the pv-curve are stable when the load has constant power characteristics.

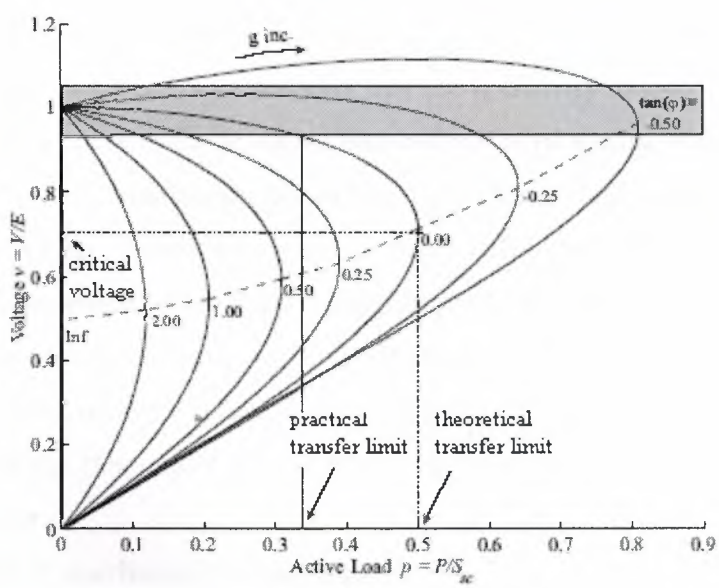


Figure 2.3 The Onion Surface Projected Onto the PV-Plane

According to the condition (2.6), the maximum power a purely active load can theoretically receive through the line is half the short-circuit power at the load bus, given that no reactive power is received at the load end. The shaded region indicates normal

operation of a line {the voltage of both ends of the line is normally kept close to the rated voltage of the line. Typical limits are $\pm 5\%$ deviation from nominal voltage or up to $\pm 5\%$ in emergency cases. The receiving end voltage at the theoretical transfer limit with a purely active load is $1/\sqrt{2} \approx 0.71$, which is normally considered unacceptable. The practical transfer limit is therefore about 35% of the short-circuit power or even lower when the load has a lagging power factor1. Capacitor banks connected at the load end are often used to increase the load end voltage and thereby the practical transfer limit. Reactive power is then being produced locally instead of transferred by the line, and the apparent power factor of the load (as seen from the transmission system) is enhanced. The operating point then shifts to another pv-curve corresponding to a lower value of *tan* (ϕ). When the operating point is on the upper part of the pv-curve, which is the case under normal operation, this corresponds to higher voltage.

The pv-curves also indicate the stiffness of system with respect to active power load variations. By overcompensating the load, such that the apparent *tan* (ϕ) becomes negative, transfer beyond half the short-circuit power with voltage close to nominal levels can theoretically be accommodated. Note however that the sensitivity to load variations, which corresponds to the steepness of the pv-curve within the shaded region, is much larger in an overcompensated system. Another important aspect is that the critical voltage is brought closer to nominal voltage. It will be shown in Section 2.5 that for constant power load characteristics, the theoretical transfer limit coincides with the voltage stability limit. Thus, the difference between the critical voltage and the voltage of the current operating point can be used as a robustness measure in terms of voltage. Similarly, the difference between the current loading and the theoretical transfer limit can be used as a robustness measure in terms of active power.

Calculation of maximum loading point

The maximum loading point can be reached through a load flow program [12, 13, 14]. The maximum loading point can be calculated by starting at the current operating point, making small increments in loading and production and re-computing load-flows at each increment until the maximum point is reached. The load-flow diverges close to maximum loading point because there are numerical problems in the solution of load-flow

equations. The load flow based method is not the most efficient, but has the following characteristics making it appropriate for voltage stability studies:

- good models for the equipment operating limits: generator capability limits, transformer tap ranges, circuit ratings and bus voltage criteria
- good models for the discrete controls: transformer tap steps and switched shunts
- capability to recognize the maximum loading point through the minimum singular value of load-flow Jacobian matrix
- familiar computer modeling, data requirements and solution algorithms
- option of using the existing computer program with miner modifications

2.3 Sources and Sinks of Reactive Power

The previous section showed that the voltage at the receiving end is highly dependent on the absorption or injection of reactive power by the load. The control of voltage is in fact closely related to the control of reactive power. An injection of reactive power at a bus that is not directly voltage regulated by a generator will in general increase the voltage of that bus and its surrounding network.

The most important sources and sinks of reactive power in power systems are:

- Overhead (AC) lines generate reactive power under light load since their production due to the line shunt capacitance exceeds the reactive losses in the line due to the line impedance. Under heavy load, lines absorb more reactive power than they produce.
- Underground (AC) cables always produce reactive power since the reactive losses never exceed the production because of their high shunt capacitance.
- Transformers always absorb reactive power because of their reactive losses. In addition, transformers with adjustable ratio can shift reactive power between their primary and secondary sides.
- Shunt capacitors generate reactive power.
- Shunt reactors absorb reactive power.
- Loads seen from the transmission system are usually inductive and therefore absorb reactive power.

- Synchronous generators, synchronous condensers and static VAR compensators can be controlled to regulate the voltage of a bus and then generate or absorb reactive power depending on the need of the surrounding network.
- Series capacitors are connected in series with highly loaded lines and thereby reduce their reactive losses.

2.4 Voltage Sensitivity of Loads

So far, it was assumed that the apparent admittance of the load is constant. However, the admittance of many loads varies with the supply voltage - either by their inherent design or by control loops connected to the load devices. Typical examples of such loads are motor drives equipped with power electronic converters and thermostatically controlled heating devices, which adjust their apparent admittance in order to consume constant power. The composite load seen from the transmission level often contains a significant amount of induction motor loads, which exhibit potentially very complex voltage behavior. However, for small voltage excursions, say less than 10 %, the active power drawn by induction motors can in the long term be approximated as constant and the reactive power as proportional to an exponential of the voltage. The dynamic response of loads to voltage changes plays a major role in the analysis and evolution of voltage instability. Simplifying matters somewhat, the load as seen from the transmission level can normally be considered as constant power in the long term since it is connected through tap changers that keep the load voltages close to their nominal values.

2.5 Voltage Stability

The voltage stability of power systems basically implies its capability of reaching and sustaining an operating point in a controllable way following a disturbance, and that the steady-state post-disturbance system voltages are acceptable. Furthermore, the term voltage instability denotes the absence of voltage stability and voltage collapse the transition phase during which a power system progresses towards an unacceptable operating point due to voltage problems, often resulting in blackouts or separation of the system into separate unsynchronized islands.

The dynamics of voltage phenomena can be divided into the two main groups: short- and long-term dynamics. Short-term phenomena act on a time scale of seconds or shorter and include, for example, the effect of generator excitation controls, induction motor recovery/stalling dynamics and FACTS devices [2]. The long-term dynamic phenomena act on a time scale of minutes and include, for example, the effect of recovery dynamics in heating load and the effect of generator over current protection systems.

As discussed in the previous section, many loads respond to a voltage drop by increasing their apparent admittance. Assume that the load supplied by the network in Figure 2.1 has such a recovery mechanism according to the normalized model

$$T\frac{dg}{dt}=p_0-p \tag{2.11}$$

$$p = g\,v^2 \tag{2.12}$$

Thus, the load has instantaneous admittance characteristics but also an internal controller that aims to restore the power drawn to constant power p_0 with the time constant T sec. Furthermore, assuming that the load is purely active (*tan* $(\phi) = 0$) and combining (2.10) and (2.11)-(2.12), the full model can be written in the differential-algebraic form

$$T\frac{dg}{dt}=p_0-g\,v^2 \tag{2.13}$$

$$v = \frac{1}{\sqrt{g^2+1}} \tag{2.14}$$

Substituting (2.14) in (2.13) yields

$$f(g)=\frac{dg}{dt}=\frac{1}{T}(p_0-\frac{g}{1+g^2}) \tag{2.15}$$

Solving for stationary points yields the two solutions

$$g^*=\frac{1}{2p_0}\pm\sqrt{\frac{1}{4p_0^2}-1} \tag{2.16}$$

Thus, it can be concluded that there are two separate equilibria if $p_0 < 0.5$ that coalesce for $p_0 = 0.5$. For $p_0 > 0.5$ it appears to be two separate equilibrium points with complex g. But g is real-valued since it has been defined as the real part of the admittance phasor in equation (2.7). Thus, we can conclude that there are no equilibria for $p_0 > 0.5$

and that a loss of equilibrium occurs when p_0 increases beyond 0.5. Since (2.16) is always positive for $p_0 > 0.5$, the admittance will increase towards infinity (or an internal limit in the load device) and the load voltage will approach zero. Small-disturbance stability analysis can be used to determine that for $p_0 < 0.5$, the low admittance solution corresponding to the upper half of the pv-curve is asymptotically stable and the high admittance solution on the lower half is unstable [15].

Assuming constant power load characteristics as above, the theoretical transfer limit marked by the dashed curve in Figures 2.2 & 2.3 therefore also becomes a steady-state voltage stability limit. However, note that the operating point may transiently move to the unstable lower part and back again to the stable equilibrium on the upper part of the pv-curve. Analogously, there is no guarantee that the system will reach a stable operating point simply because such an operating point exists. A trajectory will only approach the stable equilibrium as long at it remains within the region of attraction of the stable equilibrium. Such regions of attraction can be approximately computed using a Lyapunov-method for general dynamical systems, but the problems of finding a good Lyapunov function may make the results conservative [15].

2.6 Voltage Collapse

Voltage collapse is a system instability that involves several power system components simultaneously. It typically occurs on power systems that are heavily loaded, faulted and/or has reactive power shortages. This occurs since voltage collapse is associated with the reactive power demands of loads not being met due to limitations on the production and transmission of reactive power. The production limitations include generator and SVC reactive power limits and the reduced reactive power produced by capacitors at low voltages. The primary limitations in transmission are high reactive power losses on heavily loaded lines and line outages. Reactive power demands may also increase due to changes in the load such as, motor stalling or increased proportion of compressor load.

Voltage collapse takes place on the different timescales ranging from seconds to hours, specifically [16]:

(1) Electromechanical transient (e.g., generators, regulators, induction machines) and power electronic (e.g. SVC, HVDC) phenomena in the time range of seconds.

(2) Discrete switching devices, such as, load tap changers and excitation limiters acting at intervals of tens of seconds.

(3) Load recovery processes spanning several minutes.

There are numerous power system events known to contribute to voltage collapse.

- Increase in loading
- Generators or SVC reactive power limits
- Action of tap changing transformers
- Load recovery dynamics
- Line tripping or generator outages

Most of these changes have a large effect on reactive power production or transmission. Control actions such as switching in shunt capacitors, blocking tap changing transformers, redispatch of generation, rescheduling of generator and pilot bus voltages, secondary voltage regulation, load shedding and temporary reactive power overload of generators are countermeasures against voltage collapse. Machine angles are typically also involved in the voltage collapse. Thus, there is no sharp distinction between voltage collapse and classical transient instability. The differences between voltage collapse and classical transient instability are those of emphasis: voltage collapse focuses on loads and voltage magnitudes whereas transient instability focuses on generators and angles. Also, voltage collapse often includes longer time scale dynamics and includes the effects of continuous changes such as load increases in addition to discrete events such as line outages.

Increasing voltage levels by supplying more reactive power generally improves the margin to voltage collapse. In particular, shunt capacitors become more effective at supplying reactive power at higher voltages. Increasing voltage levels by tap changing transformer action can decrease the margin to voltage collapse by in effect increasing the reactive power demand. Still, voltage levels are a poor indicator of the margin to voltage collapse. While there are some relations between the problems of maintaining voltage levels and voltage collapse, they are best regarded as distinct problems since their analysis

is different and there is only partial overlap in the control actions used to solve both problems.

2.6.1 Voltage Collapse Indices

There are numerous indices to indicate proximity to voltage collapse that have been studied. The following is a brief introduction to these indices:

2.6.1.1 Sensitivity Factors

Sensitivity factors are indices used in several utilities throughout the world to detect voltage stability problems and to decide corrective measures [17, 18]. These indices were first used to predict voltage control problems in generator QV curves, and may be defined as

$$VSF_i = \max_i \left\{ \frac{dV_i}{dQ_i} \right\} \tag{2.17}$$

where *VSF* stands for Voltage Sensitivity Factor. As generator *i* approaches the bottom of its QV curve, the value of *VSFi* becomes large and eventually changes sign, indicating an unstable voltage control condition.

2.6.1.2 Singular Values

Singular values of a reduced matrix can be used to determine proximity to voltage collapse. Let

$$\Delta Q = J_{QV}\, \Delta V \tag{2.18}$$

with

$$\det J_{QV} = \frac{\det J}{\det J_l} \tag{2.19}$$

where J is the Jacobian in power flow equations and J_l is the real power sensitivities to angle deviations, i.e., $\frac{\partial P}{\partial \delta}$. The singular values of this reduced matrix can be used to determine proximity to voltage collapse.

2.6.1.3 Second Order Performance Indices

Indices based on first order information (linearization), such as singular values and eigen values and several other indices presented in this document, may be inadequate to predict proximity to collapse as they neglect large discontinuities in the presence of system control

limits like generator capability or transformer tap limits, as previously discussed. Conversely, it is possible to calculate a second order index that exploits additional information embedded in these indices to overcome some of these discontinuities [19].

2.6.1.4 Energy Function

Energy function, a technique based on Lyapunov stability theory, is used for both transient stability and voltage stability analysis. In this approach, power system stability is like a ball, which lies at the bottom of a valley. The stability can be understood as the ball settling to the bottom of an uneven surface when there is a disturbance. As the power system changes, the landscape of this surface and the ridges surrounding the indentations change. A voltage collapse corresponds to a ridge being sufficiently lowered so that with a small perturbation the ball can roll from the bottom of one indentation to a neighboring area. The height of the lowest ridge can be computed and used as an index to monitor the proximity to voltage collapse [20].

2.6.1.5 Loading Margin

For a particular operating point, the amount of additional load in a specific pattern of load increase that would cause a voltage collapse is called the loading margin to voltage collapse.

Loading margin is the most basic and widely accepted index of voltage collapse. If system load is chosen to be the parameter, which varies, then a system PV curve can be drawn. In this case, the loading margin to voltage collapse is the change in loading between the operating point and the nose of the curve. The advantages of the loading margin as a voltage collapse index are [21]:

- The loading margin is straightforward, well accepted and easily understood.
- The loading margin is not based on a particular system model; it only requires a static power system model and can be supplemented with dynamic system models.
- The loading margin is an accurate index that takes full account of the power system nonlinearity and limits such as reactive power control limits encountered as the loading is increased. Limits are not directly reflected as sudden changes on the loading margin.

- Once the loading margin is computed, it is easy and quick to compute its sensitivity with respect to any power system parameters or controls.

The computational costs are the most serious disadvantage of the loading margin and make it unsuitable for on-line use.

2.7 System Solutions

The potential effects of voltage instability resulting from the slow recovery of the power system voltages following a major disturbance, such as a transmission line fault. Transmission utilities have traditionally addressed voltage stability concerns by installing large static VAR compensator (SVCs) or synchronous condensers to provide the necessary dynamic reactive power support to the system following a major disturbance.

The problem of voltage stability of distribution power systems has many solutions, such as changing transformer taps, switching capacitors bank, using advanced VAR compensators, installing synchronous generators and condensers, and finally shedding loads.

2.7.1 Transformer Tap Changer Relays

A. General

Electric utilities utilize load tap-changers (LTC) to maintain customer voltage levels as the system conditions change. Typically, as load increases, the LTC will act to raise the tap position in order to maintain the voltage level. The LTC control relay will be set to operate in one of two modes - bus voltage regulation or load center voltage regulation using the line drop compensator.

Load Center voltage regulation requires a line drop compensator to regulate the voltage at the load center. Transformers at distribution substations are more likely to use load center voltage regulation than those at transmission substations. Therefore, it is important to know the mode of LTC control operation when modeling the effect of the tap-changing transformer operation during voltage collapse.

During a period of voltage collapse, the LTC control relays will detect a low voltage and begin timing to raise the tap position of the transformer.

When the voltage collapses occurs slowly, the controls will time out and begins to raise the transformer tap position. Assuming no change in the load on the transformer during this period, the LTC can often be considered a constant power load as long as the tap-changer can maintain a constant load voltage.

Since the primary voltage level drops, the current flow in the transmission system is increased to maintain the load power. This increasing current flow will further reduce the transmission system voltage, making the voltage collapse more severe.

In some cases, tap changers can also have a beneficial effect. Consider for instance, a case where a transformer is supplying predominantly motor load with power factor correction capacitors. The LTC keeps the supply voltage high and hence does not affect the real power consumption (which is relatively independent of voltage), and also maximizes the reactive support from the power factor correction capacitors. Due to this regulating effect, the LTC is an important part of the overall voltage collapse scenario.

For the more frequent case, where the real power loads have some voltage dependency, the LTC can be utilized to reduce the severity of the voltage collapse if appropriate control operation can be obtained. Blocking operation of the LTC has been widely offered as a method to reduce the negative effect on the system. Load voltage reduction can be used to reduce the loading on the system. This is similar to the peak shaving systems widely used at many utilities. Therefore the load tap-changer may be both a cause and a partial solution to the problem of voltage collapse [22].

B. LTC Blocking Schemes

The simplest method to eliminate the LTC as a contributor to voltage collapse is to block the control's automatic raise operation during any period where voltage collapse appears to be a concern. The decision to temporarily block the tap-changer can be made using locally derived information or can be made at a central location and the supervisory system can then send a blocking signal to the unit. This action may result in a period of low voltage on the affected loads.

The effect of the reduced supply voltages on power quality to customers in the whole service area must be weighed against the possible alternative of complete disconnection of some customers in a smaller area. Tap changer blocking will be more effective for voltage decays slower than the transient time frame. It will also be more

effective on loads that have a relatively high voltage dependency. In cases where the steady state value of b is high, the reduction of reactive power demand due to reduced distribution voltage will be very significant in helping keep transmission voltages up.

Local blocking schemes are implemented using voltage relays and timers to sense the voltage level on the high voltage bus at the substation.

The set point voltage is usually chosen to be a level that is less than that which occurs during maximum acceptable overload conditions. Condition exists longer than a predetermined time. The time period may vary from 1 to several seconds. The LTC is unblocked when the voltage has recovered to an acceptable level for a predetermined period of time, typically 5 seconds [22]. Since the blocking action will be removed if the voltage recovers, usually a single phase-phase voltage measurement is adequate for this scheme.

A coordinated blocking scheme can be utilized to block operation of LTC's in an area where voltage instability is imminent. The coordinated scheme can be accomplished with under voltage schemes acting independently (as described above) in a coordinated fashion at various stations within a region, or it can be a centralized scheme that recognizes a pattern of low voltages at key locations. In a centralized scheme, the LTC blocking can be implemented in substations throughout the affected region, even if the voltage at all locations is not yet below a specific threshold. The key to operation of a centralized system is the reliability of the communications system. The data needed for decision making must be collected at the central location for analysis. Control decisions must then be sent to each affected transformer location.

The effectiveness of an LTC blocking scheme at the transmission level will largely depend on whether distribution transformers are LTC-type. If the distribution transformers are LTC-type, additional measures are required to prevent their action from negating the effect of the LTC blocking scheme at the transmission level.

C. No-load Tap Changer

One method used to adjust the winding ratio of the transformer uses the no-load tap changer shown in Figure 2.4 [23]. A transformer equipped with a no-load tap changer must always be disconnected from the circuit before the ratio adjustment can be made. The

selector switch is operated under oil usually placed within the transformer itself; but it is not designed to be used as a circuit breaker. To change taps on small distribution transformers, the cover must be removed and an operating handle is used to make the tap change. For the larger type, one handle may be brought through the cover and the tap may be changed with a wheel or even a motor.

If it is necessary to change the taps when the transformer cannot be disconnected from the circuit, tap changers under-load are used. They involve the use of an autotransformer and an elaborate switching arrangement. The information regarding the switching sequence must be furnished with each transformer. Tap changers can function automatically if designed with additional control circuits: automatic tap changes are used for high-power transformers, and for voltage regulators.

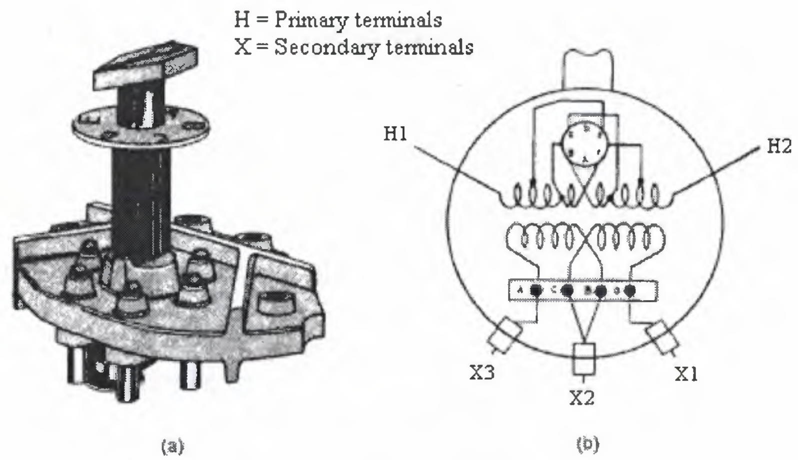


Figure 2.4: Tap Changer (a) No Load Tap Changer

(b)Typical Internal Wiring of Transformer with Tap Changer [24]

2.7.2 Switched Capacitors Bank

Many power system components in a network consume large amounts of reactive power. For example, transmission line shunt reactors, and other industrial and commercial loads need reactive power. Reactive current supports the magnetic fields in motors and transformers. Supporting both real and reactive power with the system generation requires increased generation and transmission capacity, because it increases losses in the network. Shunt-connected capacitors or synchronous condensers near the load centers are another

way to generate reactive power. Switched Capacitor Banks (SCB) have the advantage of providing reactive power close to the load centers, minimizing the distance between power generation and consumption, and do not have the maintenance problems associated with synchronous condensers. Controlling capacitance in a transmission or distribution network could be the simplest and most economical way of maintaining system voltage, minimizing system losses, and maximizing system capability. The main disadvantage of SCB is that its reactive power output is proportional to the square of the voltage and consequently when the voltage is low and the system needs them most, they are the least efficient.

Capacitor Bank Design

In order to insert reactive power to the power distribution system (PDS) the power factor (*cos* ϕ) should be increased to unity, and the angle ϕ is decreased to zero. In order to decrease the angle ϕ, reactive component of the current, $I \sin \phi$ (I_r) is to be decreased. This is achieved by introducing leading current of magnitude equal to the reactive component, in the circuit as shown by OA in Figure 2.5. This leading current I_c will lead the voltage by 90 degrees and will be in phase opposition to I_r. Therefore the leading current required to neutralize the lagging reactive component of the current to minimize the reactive power of the feeder to zero is given as:

$$\begin{aligned} I_c &= I_r = I \sin \phi \\ &= I \sqrt{1-\cos^2 \phi} \end{aligned} \tag{2.20}$$

The value of the total capacitance required for inserting reactive power for given real power P in the circuit, at frequency f, and voltage V is determined as follows:

$$I_c = \omega C V = 2\pi f C V \tag{2.21}$$

Equating eqns. (2.20) and (2.21),

$$2\pi f C V = I \sqrt{1-\cos^2 \phi} \tag{2.22}$$

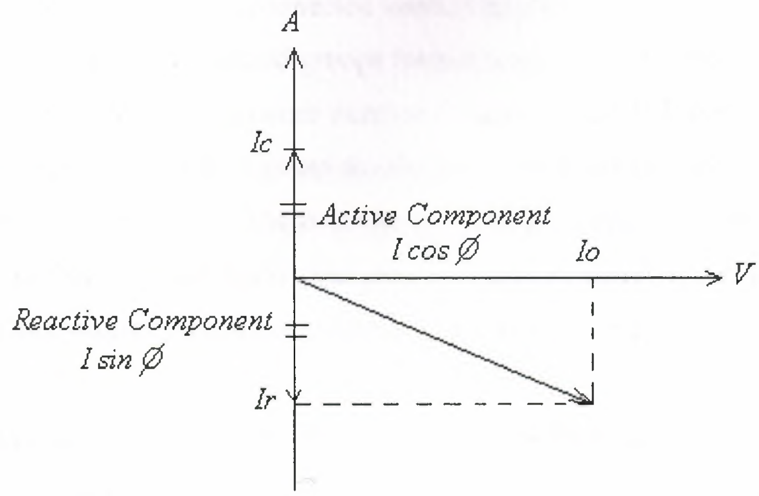


Figure 2.5 Representation of Reactive Current Component

And $$C = \frac{I}{2\pi fV}\sqrt{1-\cos^2\phi} \tag{2.23}$$

Also $$P = IV\cos\phi \tag{2.24}$$

From eqn. (2.24)

$$I = \frac{P}{V\cos\phi} \tag{2.25}$$

Substituting the value of I from eqn. (2.25) into eqn. (2.23)

$$C = \frac{P}{2\pi fV^2\cos\phi}\sqrt{1-\cos^2\phi} \tag{2.26}$$

$$C = \frac{P}{2\pi fV^2}\sqrt{\frac{1}{\cos^2\phi}-1} \tag{2.27}$$

It is seen from the last equation that the capacitance required is inversely proportional to the square of the operating voltage, thus the total value of capacitance required per phase depends upon the nature of connection whether star or delta. In practice it is observed that the delta connection is preferable.

The protection of shunt capacitor banks requires understanding the basics of capacitor bank design and capacitor unit connections. Shunt capacitors banks are

arrangements of series/paralleled connected units. Capacitor units connected in paralleled make up a group and series connected groups form a single-phase capacitor bank.

As a general rule, the minimum number of units connected in parallel is such that isolation of one capacitor unit in a group should not cause a voltage unbalance sufficient to place more than 110% of rated voltage on the remaining capacitors of the group. Equally, the minimum number of series connected groups is that in which the complete bypass of the group does not subject the others remaining in service to a permanent over voltage of more than 110% [24].

The maximum number of capacitor units that may be placed in parallel per group is governed by a different consideration. When a capacitor bank unit fails, other capacitors in the same parallel group contain some amount of charge. This charge will drain off as a high frequency transient current that flows through the failed capacitor unit and its fuse. The fuse holder and the failed capacitor unit should withstand this discharge transient.

The discharge transient from a large number of paralleled capacitors can be severe enough to rupture the failed capacitor unit or the expulsion fuse holder, which may result in damage to adjacent units or cause a major bus fault within the bank. To minimize the probability of failure of the expulsion fuse holder, or rupture of the capacitor case, or both, the standards impose a limit to the total maximum energy stored in a paralleled connected group to 4659 kVAR [24]. In order not to violate this limit, more capacitor groups of a lower voltage rating connected in series with fewer units in parallel per group may be a suitable solution. However, this may reduce the sensitivity of the unbalance detection scheme. Splitting the bank into two sections as a double Y may be the preferred solution and may allow for better unbalance detection scheme. Another possibility is the use of current limiting fuses.

The optimum connection for a SCB depends on the best utilization of the available voltage ratings of capacitor units, fusing, and protective relaying. Virtually all substation banks are connected wye. Distribution capacitor banks, however, may be connected wye or delta. Some banks use an H configuration on each of the phases with a current transformer in the connecting branch to detect the unbalance.

Delta-connected banks are generally used only at distributions voltages and are configured with a single series group of capacitors rated at line-to-line voltage. With only

one series group of units no over voltage occurs across the remaining capacitor units from the isolation of a faulted capacitor unit. Therefore, unbalance detection is not required for protection.

Some larger banks use an H configuration in each phase with a current transformer connected between the two legs to compare the current down each leg. As long as all capacitors are normal, no current will flow through the current transformer. If a capacitor fuse operates, some current will flow through the current transformer. This bridge connection can be very sensitive. This arrangement is used on large banks with many capacitor units in parallel.

2.7.3 Advanced VAR Compensators

The emergence of new advanced VAR compensators utilizing power electronics with binary switched capacitors and inverter-based systems with or without energy storage provide utility transmission planning engineers with alternative solutions to the voltage stability problem.

Superconducting magnetic energy storage systems utilizing magnetic energy storage in the form of a superconducting coil and inverter technology have lead the way in utility applications of these new advanced VAR compensators [25]. Other commercially-available advanced VAR compensators are now increasingly being applied on utility systems for voltage stability support as well as for voltage regulation purposes.

Commercially-available advanced compensators are grouped into three categories, namely:

- Power-electronically-switched capacitors.
- Inverter-based systems without energy storage.
- Inverter-based systems with energy storage

2.7.3.1 Power-Electronically-Switched Capacitors

Compensators utilizing power-electronically-switched capacitors (e.g., (AVC) Adaptive VAR Compensator) typically consist of three or more stages of low-voltage capacitors. Capacitor stages are typically sized in binary increments, i.e., if the size of the first stage of capacitors is Q (kVAR) per phase, the size of the second and third stages would be 2Q and

4Q, respectively. Reactors are typically used in series with each stage of capacitors for detuning to eliminate harmonic resonance and large inrush currents. Capacitors are charged to peak system voltage and switched through thyristors at peak voltage to eliminate any switching transients [26].

The AVC can respond to voltage fluctuations in one cycle, or as fast as ½ cycle in specially-designed units. Single units with capacity of up to 24 MVAR at 690 V or 120 MVAR at 15 kV can be applied for dynamic voltage support. A step-up transformer would typically be used to step the output voltage up to distribution or transmission voltage level [26].

Since the AVC uses binary-switched capacitors, the reactive power output occurs in discrete steps. In a three stage unit the total output can be varied over 7 discrete steps, and in 15 steps in a four-stage unit. Since shunt-connected capacitors are utilized to provide reactive power output, the reactive power output is proportional to the square of the bus voltage.

2.7.2.2 Inverter-Based Systems without Energy Storage

These compensators (e.g., (DVC) Dynamic VAR Compensator and (DSTATCOM) Distribution Static Compensator) utilize shunt-connected voltage-source inverters to control the reactive power flow. Reactive power flow is controlled by adjusting the magnitude of the voltage output from the inverter relative to the bus voltage. Units typically have output filters and a step-up transformer to connect to the distribution bus. Typical DVC units are rated 480 V and consists of multiple 250 kVA inverter modules arranged for an output of up to ±8 MVAR continuous. Units have a one second overload capability ranging from 2.3 to 3 times the continuous rating [26]. After one second the output ramps down to its continuous rating in another second. The reactive power output of an inverter-based compensator is proportional to the bus voltage.

2.7.2.3 Inverter-Based Systems with Energy Storage

The Distributed Superconducting Magnetic Energy Storage (D-SMES) is currently the only commercially-available inverter-based system that has been applied with energy storage for voltage stability applications. The system is similar to the DVC, with an additional

superconducting magnetic energy storage module with peak output power capability of 3 MW and an average output power capability of 2.5 MW over the first 0.5 seconds of discharge [23]. The reactive power output of this compensator is also proportional to the bus voltage.

2.7.4 Synchronous Generators and Condensers

A synchronous machine is capable of generating and supplying reactive power within its capability limits to regulate system voltage. For this reason, it is an extremely valuable part of the solution to the collapse-mitigation problem. Synchronous machines considered may be generators or synchronous condensers. In terms of reactive output capability, synchronous condensers are treated similarly to static VAR sources during commissioning and maintenance in that rated output power must be demonstrated to be achieved.

2.7.4.1 Generators

Generators however are rated for specific real power output, usually at a specific power factor. During commissioning and maintenance, real power output is carefully checked to meet specified requirements. Reactive power output may be checked during commissioning, but may not be carefully checked after that. The reactive power capability may be required by the system, but is not considered to be a revenue generator.

Due to large impact on the system voltages, it may be difficult to operate large generators at their reactive capability limits (for test purposes). Therefore coordination of protection with control devices is not so frequently checked as with other reactive power sources [27]. Numerous voltages collapse or near collapse incidents have been aggravated by unexpected loss of healthy generators due to lack of coordination of protective equipment with generator capability.

The reactive power capability increases dramatically as real power output is limited. Further, the amount of reactive power available from the generator is very dependent on terminal voltage. In this respect, a generator operating at low real power output can supply significantly more reactive power at low voltages than at high voltages [22].

The increase in reactive power capability at lower real power output means that system planners and operators may choose to generate less than rated real power in order to

have more reactive power from generators at critical locations in voltage stability threatened systems. The choice of operating point (MW versus MVAR) for generators at critical locations is predetermined, and not usually subject to automatic control. It should be noted that when the generator reaches the limit of its capability, particularly in the rotor current limited region, it may not be controlling its terminal voltage. The fact that it is at its limit of capability means that it is not able to raise the terminal voltage to the reference setting of the voltage regulator. Thus the reactive power limits are to a certain extent, determined by the system conditions, and independent of the generator excitation system.

The value of a generator as a source of reactive power can be separated from its value as a source of real power, if it can be decoupled from the turbine and run as a synchronous condenser. In some plants where fuel or operating costs may make power generation uneconomic, it may be possible to convert the generator to a synchronous condenser, and use it to support voltages in an area where real power has to be imported from a remote area [27].

2.7.4.2 Motors

It is a synchronous motor working at over excitation and drawing current from the supply at leading power factor. It has an advantage that varying its excitation it can be steplessly adjusted to supply any amount of capacitive or reactive power up to its full rating. By the use of rotary amplifiers and high speed regulators, automatic stable operation is obtained even in the case of sudden change in the system conditions. It must be noted that, synchronous condenser has an inherently sinusoidal waveform and harmonics in the voltage do not exist, but the static capacitors give large harmonics in the system.

A modern synchronous capacitor is generally a six or eight pole salient pole synchronous motor. It is fitted with a robust damper winding by means of which, it is possible to start it as an induction motor at reduced voltage. The starting tapping on the starting transformer is about 25-40% of the rated voltage due to this, the starting current from the supply will be less than the rated current [28].

By jacking up the shaft by means of oil under pressure, the initial starting torque and the minimum voltage required for reliable starting are reduced. The machine runs

almost near to synchronous speed at rated voltage and is then pulled into synchronous speed.

2.7.5 Load Shedding

Load shedding is defined as [29]: "the process of deliberately removing pre-selected loads from a power system, usually done automatically by relays, in order to maintain the integrity of the system under unusual conditions".

Current practice depends on hardware control, using lines and generators. Load shedding basically means nothing more than disconnecting a radial feeder on medium voltage distribution system. Sometimes you try to avoid area with elevators. Hospitals and other very sensitive institutions are supposed to have their own backup. The most common criterion to activate load shedding is low frequency, with or without time delay, also under voltage criteria and rate of change of frequency exists, but are much less common.

Load shedding is an option that is becoming more widely used as a final means of avoiding system wide voltage collapse. This option is only considered when all other effective means of avoiding collapse are exhausted. This option may be the only effective option for various contingencies especially if the collapse is in the transient time frame, and if load characteristics result in no effective load relief by transformer load tap changer control. Load shedding results in high costs to electricity suppliers and consumers, therefore, power systems should be designed to require such actions only under very rare circumstances. Load may be shed either manually or automatically depending on the rate of voltage drop.

2.7.5.1 Manual Load Shedding

If the time frame of collapse is long-term, manual load shedding can be implemented to stabilize the voltage. This mode of operation, normally applied under inadequate generation conditions or insufficient VAR reserve, should have preplanned guidelines and procedures for the system dispatchers to implement load shedding manually.

System studies can provide load sensitivity analyses from which the critical voltage can be determined to start load shedding. Another option to assist system operators for fast action is to preprogram blocks of loads on the dispatcher control console of the SCADA system. Dispatchers can select a particular block of load in a specific area requiring load shedding

to control the voltage drop. The blocks of load can also be divided into several subgroups depending on sensitivity of the load, so that execution of the manual load shedding can be carried out in steps or in rolling sequence [22].

A major disadvantage of relying on manual load shedding is that it places a severe burden on system operators to recognize an approaching voltage stability problem and to act quickly enough to avoid a major collapse. Even with the most comprehensive preplanned guidelines, there is a danger that the particular condition that arises may not fall within the guidelines clearly enough for prompt action. However, when short term operational planning studies (time frame less than a week) show the possibility of collapse due to expected load and actual contingencies, manual shedding can be applied with good results.

2.7.5.2 Automatic Load Shedding

When the voltage instability is caused by sudden loss of critical transmission equipment or VAR generating equipment, the lead-time prior to a voltage collapse will be very short. Therefore, manual load shedding would be too slow to prevent a voltage collapse. Automatic load shedding must be used to quickly arrest a fast voltage drop and allow the voltage to recover to an acceptable level before voltage collapse can occur.

Under voltage detectors are often used to initiate automatic load shedding. For low voltage events which do not lead to collapse (such as during a normally cleared system fault), these detectors must not operate in order to prevent nuisance tripping of customer load. Security of the under voltage detectors can be increased by applying multiple phase detection, proper time coordination between fault clearing and time delay for load shedding, and use of fault detection relays to inhibit load shedding. Reliability of load shedding to prevent voltage collapse can be enhanced by use of other indicators than voltage magnitude such as voltage and power sensitivity factors or other forms of voltage stability indices.

Developing appropriate settings for the under voltage detectors and time delays are challenging problems. It might require intensive network analysis to find the desired values to provide optimum coordination between load shedding and voltage collapse. Generally, the settings are in the range of 85 to 95 percent of the operating voltages, with time delays

ranging from tens of cycles to minutes [30, 31, 32]. The sensitivity of the load to the voltage level has a great impact on the settings.

2.7.5.3 Intelligent Load Shedding

The traditional load shedding scheme, which has hardly been developed over the last 100 years, is less and less acceptable in today's society. The developments in computer and communications technology allow abandoning the stage of hardware control and relying more on intelligent control in order to maintain power system stability.

Intelligent load shedding is defined as [33]: a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable.

The objective of load shedding remains unchanged. The means to improve power stability using intelligent load shedding changes to addressing individual loads in an area, based on knowledge about the power system and these loads, in order to switch off or reduce power for a certain time.

Intelligent load shedding deals with (i) the problem of detecting situations that will go unstable if no remedial actions are taken, and (ii) to take proper action in such a way that stability is restored by minimum cost load shedding. Intelligence and communication are essential means in order to achieve this. Communication is needed in order to obtain information on where and when load shedding is needed, to obtain information on individual loads and their constraints with respect to readiness to shed, and to address individual loads in order to reduce load or switch them off. Intelligence is needed in order to find optimal scenarios for the amount of load to shed and the location of these loads.

2.7.5.4 Requirements and Scenarios for Intelligent Load Shedding

The main requirement on "intelligent load shedding" is that it should be regarded as a means to improve power system stability, by providing smooth load relief, in situations where the power system otherwise would go unstable. The work with intelligent load shedding can be divided in a number of stages [34]:

- To improve present load shedding schemes (where a circuit breaker on the 10/20 kV level is opened), to a scheme where individual load objects in the area are addressed and switched off, or ordered to reduce power, for a certain time.
- To keep track on the load available to be shed in every instant.
- To find an "optimal" amount of load to shed, with respect to a certain disturbance.
- To find the "optimal" location of the load to be shed, with respect to a certain disturbance.
- To specify/find relevant disturbances to prepare load shedding for, and to "interpolate" between these to find suitable actions for real disturbances.
- To initiate "intelligent load shedding" - when approaching voltage instability, angular instability, frequency instability or cascaded outages.

A main consideration in intelligent load shedding will be the cost criterion. Strategies may be based on dynamic prices and on electric market.

2.8 Voltage Stability Related Works

There are many researches contribute in solving voltage stability. Part of these researches use artificial neural networks and others use different algorithms. In [35] an artificial neural network application to power system voltage stability improvement is introduced, and in [36] a novel algorithm for on-line voltage stability assessment based on feed forward neural network is introduced, while [37] introduces a development of an improved on-line voltage stability index using synchronized phasor measurement

2.8.1 Artificial Neural Network Application to Power System Voltage Stability Improvement

This work deals with development of ANN architecture, which provide solutions for monitoring, and control of voltage stability in the day-to-day operation of power systems. It focuses on evaluating the performance of ANN for control and improvement of Power System Voltage Stability problem [35].

A minimization algorithm for improving voltage stability margin based on L-Index and employing non-linear least squares optimization technique is presented. The control

variables considered are switchable VAR compensators, OLTC transformers and generators excitation. The model used for the power system includes limits for reactive power generation at generators, load characteristics and generation control characteristics. Generally in reactive power dispatch the objective is either to minimize real power losses or to minimize the deviations of voltages from desired values. The objective in the proposed algorithm is to minimize the sum of squares of L-indices at all or a subset of critical nodes (decided from voltage stability point of view) in the system. Results obtained from the proposed algorithm are compared with Minimum singular value (MSV) of the modified power flow Jacobean matrix. The increase of load margin to voltage collapse is demonstrated.

A conclusion of the work is: A prototype of an ANN for monitoring and control of power system voltage stability margin improvement has been developed. The proposed ANN tries to improve the voltage stability margin using SVCs, Generator excitation and OLTC transformers as controllers for different loading conditions for a practical EHV Indian power system and encouraging results have been obtained.

2.8.2 Novel Algorithm for Online Voltage Stability Assessment Based on Feed Forward Neural Network

This work presents an online voltage stability assessment method using the feed forward neural network. In this method feed forward neural network is trained for the L indices values, which is a scalar measure of the voltage stability for all the power system buses during normal and contingent situations [36].

Main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained Artificial Neural Network at every time instant unlike the other techniques. The easiness in calculating the stability indices using Index L is exploited for learning the voltage profile of any complex system by ANN.

Thus the stability margin and voltage profile locally for individual buses as well as the global stability margin and improvement measures of the power system can be assessed at the same time with the proposed technique. Another feature of the proposed method is its ability in developing L indices of all the system buses during both normal and contingent

situations using the trained ANNs. This aspect has not been considered as a single problem so far in the earlier research works.

The trained ANN is then tested on the practical 367 bus system to prove its practical use using MATLAB neural network toolbox. The approach was found to be extremely useful to use as energy management software for online establishment of voltage stability margins and to find out the associated limits at each bus.

The proposed network architecture is a three layer feed forward structure including input, output and hidden layer using a back propagation algorithm. Following algorithmic steps describes in detail the approach used for investigating the different parameters and functions in the MATLAB toolbox.

Step 1: A conventional voltage stability algorithm is run with the test system for simulated loading conditions. Using this first the base case and the maximum loading conditions of the test system are determined using the conventional software. Then the load conditions are varied from base case till full load and training samples are generated.

Step 2: Create a database for the input vector in the following form $\left[P_g^T\, Q_g^T\, V_g^T\, P_l^T\, Q_l^T\, V_l^T\right]^T$ where, P_g, Q_g, P_l *and* Q_l are the real and reactive power in generator as well as load buses respectively and V_g *and* V_l are bus voltage at generator and load buses. Further, create target vector in the form of L-indices for the corresponding input vectors.

Step 3: Find the minimum and maximum values of the input vector, remove redundancies and normalize to suit to train the selected feed forward neural network.

Step 4: Select the set of training parameters such as number of epochs, learning increment and rate, performance goal with Mean Squared Error (MSE) and minimum and maximum gradient.

Step 5: Train the network based on a set of transfer functions and number of neurons. The number of neurons in each layer is varied initially and optimum combination is found out depending on the training period and performance error.

Step 6: Find the most suitable combination of the activation function. Behavioral accuracy depends on the uniformity in values of L-indices at all the buses. It can happen that the

network gives output, which is accurate for some buses but may be unacceptable on some others.

Step 7: Change the training function keeping same transfer functions and optimum number of neurons in each layer.

Step 8: Find the most suitable network based on the simplicity least possible Mean Square Error and computational speed. Further use various test functions to confirm the effectiveness of the proposed neural network. At this state the functions and all the parameters are finalized for a particular combination.

A conclusion of the work is: An artificial neural network technique for on line assessment of power system voltage stability using a developed training algorithm for all system buses has been presented with detail steps involved with MATLAB neural network toolbox. Unlike other reported techniques, the main advantage of the proposed method is that the voltage stability indices for all the buses in the power system can be calculated using the trained artificial neural network at every monitoring period. The stability margin and voltage profile for individual buses, the global stability margin, as well as possible improvement measures of the power system can be assessed at the same time during both normal and contingent situations using the trained ANN. Training and testing results form all cases, including contingencies on a practical power systems network shows that the proposed ANN algorithm is capable to learn and perform as a tool for online voltage stability analysis by measuring the L-indices for all the vulnerable buses.

2.8.3 Development of an Improved On-Line Voltage Stability Index Using Synchronized Phasor Measurement

Most techniques are computationally demanding and cannot be used in an on-line application. A voltage stability index (VSI) can be designed to estimate the distance of the current operating point to the voltage marginally stable point during the system operation. This research work developed a new VSI that not only can detect the system voltage marginally stable point but also is computationally efficient for on-line applications. Starting with deriving a method to predict three types of maximum transferable power of a single source power system, the new VSI is based on the three calculated load margins [37]. In order to apply the VSI to large power systems, a method has been developed to

simplify the large network behind a load bus into a single source and a single transmission line given the synchronized phasor measurements of the power system variables and network parameters. The simplified system model, to which the developed VSI can be applied, preserves the power flow and the voltage of the particular load bus. The proposed voltage stability assessment method, therefore, provides a VSI of each individual load bus and can identify the load bus that is the most vulnerable to voltage collapse.

The developed VSI is a reliable assessment of the voltage stability margin of an individual load and is suitable for on-line implementation for detecting the emerging short-term and long-term voltage instability. The sub-tasks of developing this improved voltage stability index are the following:

- Development of a new computationally efficient load margin assessment method based on synchronized phasor measurements and the power system network topology and parameters.
- Derivation of VSI of individual load buses and the power system based upon the calculated load margin.
- Implementation and testing of the new VSI on various power systems.

The new VSI was tested on three power systems which are BPA 10-bus test system, IEEE 30-bus test case and CIGRE 32-bus test system. Results from these three test cases provided validation of the applicability and accuracy of the proposed VSI.

A conclusion of the work is: Test results of applying the proposed voltage stability assessment method on three power systems have demonstrated that it has the following salient features:

- The proposed method can identify the system voltage marginally stable point with satisfactory accuracy.
- The proposed method provides system voltage security in the format of a load margin that is readable and informative.
- The proposed method can identify the load bus that is the most susceptible to voltage collapse.
- The proposed method is computationally efficient, and can be easily implemented to predict the voltage stability of large power systems in almost real time.

The main contribution of this dissertation is the development of a practical synchronized phasor measurement based voltage stability index that can accurately predict the power system voltage stability with affordable computational demands for on-line applications. The proposed voltage stability assessment method could be incorporated into wide area protection and control systems to monitor the power system voltage stability security. Also, the newly proposed network reduction method enables users to analyze the voltage stability of each load bus and design of distributed control schemes to prevent voltage collapse.

2.9 Power System Control

Given the complexity of the power system and its dynamic phenomena, one would expect that various controls have been developed over time to control various phenomena. These developments have followed the availability of enabling hardware technologies (e.g. electronics, communications, and microprocessors) as well as the evolution of control methodologies.

When a fault (short circuit) occurs, the faulted equipment has to be isolated. A short circuit is characterized by very low voltages and very high currents, which can be detected and the faulted equipment identified. If the fault is on a shunt element, like a generator or a distribution feeder, the relay will isolate it by opening the connecting circuit breakers. If the fault is on a series element, like a transmission line or transformer, the breakers on both sides have to be opened to isolate it. The main characteristic of the protection system is that it operates quickly, often in tens of milliseconds, so as to protect the equipment from damage.

2.9.1 Voltage Control

As is mentioned before, one way to control node voltages is by varying the excitation of the rotating generators. This is done by a feedback control loop that changes the excitation current in the generator to maintain a particular node voltage. This control is very fast.

Another way to control node voltage is to change the tap setting of a transformer connected to the node. Other ways are to switch shunt capacitors or reactors at the nodes.

These changes can be made manually by the operator or automatically by implementing a feedback control that senses the node voltage and activates the control. Unlike the generator excitation control, transformer taps and shunt reactances can only be changed in discrete quantities. Often this type of control schemes has time delays built into them to avoid excessive control actions [38].

More recently power electronic control devices have been introduced in the shunt reactance voltage control schemes. This makes the control much more continuous and often is done it a much faster time frame than the usual shunt switching. These static VAR compensators (SVC) are becoming more common.

As is obvious, voltage control is always a local control. However, controlling the voltage at one node affects the neighboring nodes.

2.9.2 Transmission Power Flow Control

Most power systems have free flowing transmission lines. This means that although power injections and node voltages are controlled quite closely, the power flow on each transmission line is usually not controlled. However, such control is feasible.

A phase shifting transformer can control the power flow across it by changing the phase using taps. This has been used, especially on the Eastern interconnection in North America. The control is local, discrete and slow. A power electronic version of this is now under experimentation.

The major advantage of the AC transmission grid is its free flowing lines with relatively less control and so the wholesale control of every transmission line is not desirable and is not contemplated. However, controls on some lines have always been necessary and some new advantages may be realized in the more deregulated power system when monitoring transactions between buyers and sellers have to be better controlled [39].

2.9.3 Frequency Control

Frequency is controlled by balancing the load with generation. The governors on every generator senses any change in the rotational speed and adjusts the mechanical input power. This governor control is the primary control for maintaining frequency. A secondary control to set the governor set-points is used to ensure that the steady state always returns to

nominal. The governor control is local at the generator and fast. The secondary control is done over the whole system. This secondary control is done by the central controller and is slow. This control is also known as Automatic Generation Control (AGC) or Load Frequency Control (LFC) [38].

As the deviation of frequency from nominal is a symptom of the imbalance between generation and load, the frequency control performance requirement depends on how well one wants to control the power supply commitments made between seller and buyer.

2.9.4 Control Center

As mentioned in the above sections most of the controls are local. The only area wide control is the secondary frequency control or AGC. This is implemented as a feedback control loop in which the generator outputs and tie-line flows are measured and brought back to the control center and the governor control set-points are calculated and sent out to the generators from the control center. The data rate – both input and output – is between 2 and 4 seconds.

The control center performs many other functions although AGC is the only automatic feedback control function. The main function is real time data acquisition from all over the grid so that the operator can monitor its operation. Another is the manual operation of controls like opening or closing circuit breakers, changing transformer taps, etc. These functions are jointly known as the Supervisory Control and Data Acquisition (SCADA) and the control center is often referred to as SCADA.

A control center energy management system (EMS) generally consists of four major elements as shown in figure 2.6 [39]:

- The supervisory control and data acquisition (SCADA) system
- The automatic generation control (AGC) system
- The energy management applications and database
- The user interface (UI) system.

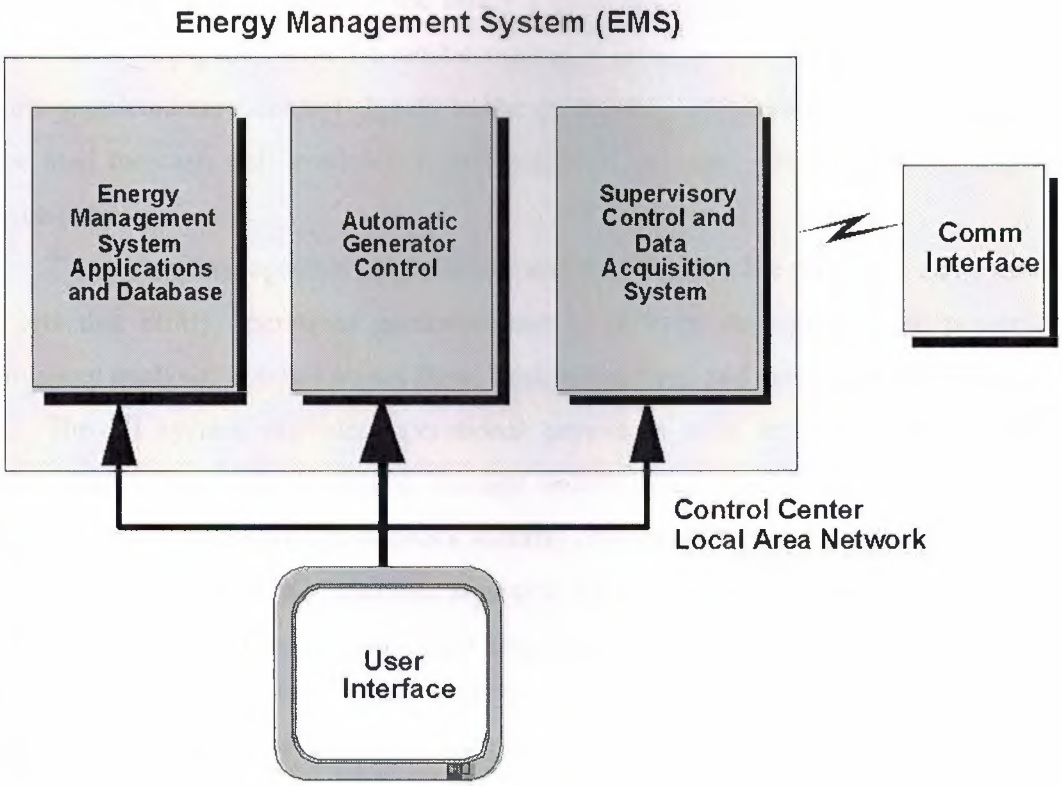


Figure 2.6 Elements of the Control Center Energy Management System

The SCADA system manages the RTU communications, collects the electric system data from the field through a series of front-end processors, initiates alarms to the operations personnel, and issues control commands to the field as directed by the applications in the control center system. The SCADA system typically consists of a host or master computer, one or more field data-gathering and control units (RTUs), and a collection of standard and/or custom software used to monitor and control remote field data elements. SCADA systems may have 30,000 to 50,000 data collection points and may transmit analog information (e.g., generator megawatts) as well as digital or status information (e.g., breaker open/close state). SCADA systems can also send a control signal (e.g., start a pump) as well as receive a status input as feedback to the control operation (e.g., the pump is started). Current computing power allows SCADA systems to perform complex sequencing operations and provides for frequent collection (e.g., every 2 seconds) of power system data.

The AGC system controls the utility's generating units to ensure that the optimal system load is being met, with the most economical generation available. The AGC system submits supplementary control signals to the generating units to adjust their output based on the load forecast, unit availability, unit response rate, and scheduled interchange with other utilities.

The energy management applications and database are the programs and associated data sets that utility operations personnel use to manage state estimation, power flow, contingency analysis, optimal power flow, load forecasting, and generation unit allocation.

The UI system provides operational personnel with an interactive interface to monitor electric system performance, manage system alarm conditions, and study potential system conditions to ensure that network security criteria are met.

These SCADA-AGC functions at central control centers evolved in the earlier part of the last century but in the 60s their implementation was accomplished with digital computers. Remote terminal units (RTU) were positioned in every substation and generating station to gather local data and this data was then transmitted from the RTUs to the control center over communication lines, usually microwave channels but sometimes telephone lines. This scheme is shown in Figure 2.7. The data normally includes the switching statuses (on/off) of all the circuit breakers as well as the current values and voltages of complex power. Although these control centers are quite separate from other computer systems, it does accumulate a large set of historical data that can be utilized for various engineering study and analysis. Thus it is quite common to have a network connection to third party (usually engineering) computers [38].

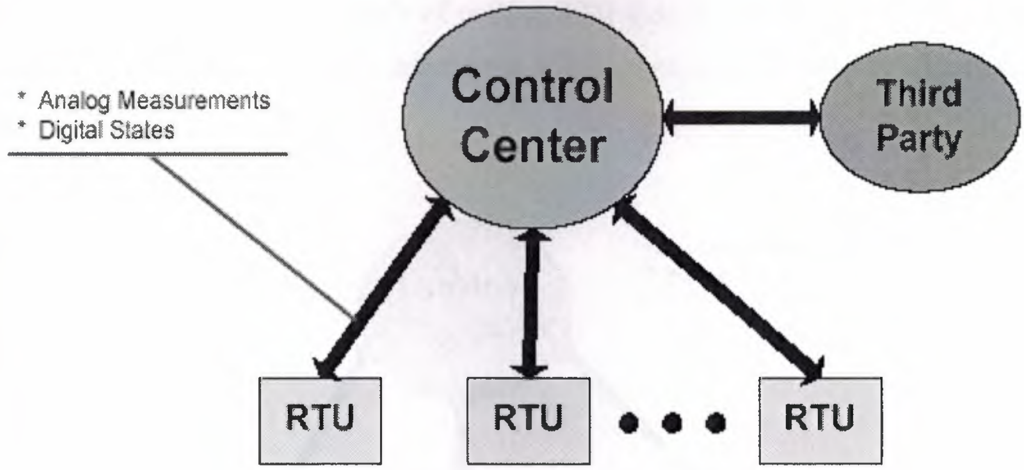


Figure 2.7 The Control Center has Direct Communication Channels to The RTUs at each Substation and Generating Station

As the computational power of the control centers grew, more functions have been added to the control centers. The main one has been the state estimator which calculates the real time steady state model of the network. This real time model can then be used for two kinds of calculations.

One, known as security analysis, can study the effects of disturbances (contingencies) and can alert the operator if the post-contingency conditions violate limits. The other, usually using a family of analysis known as optimal power flow, can suggest better operational conditions. All these analytical tools provide better operational guidance to the operator than the old SCADA systems could and are now known as Energy Management Systems (EMS).

Another recent trend has been the increasing use of microprocessors and faster communication within the substations to gather more real time data. This data gathered at the few milliseconds rate is stored at the substations but is too voluminous as yet to be broadcast. Instead certain sequences of this data – say, after an emergency or disturbance – are then imported, increasingly, over some sort of network and then used for study purposes. This is shown in Figure 2.8 What this means is that data is now being measured and gathered at the substations at a much faster rate than can be communicated to the

control center which is only capable of polling RTU data at the rate of a few seconds. The excess data can be recorded at the substations and for now is gathered only after the fact for studies [38].

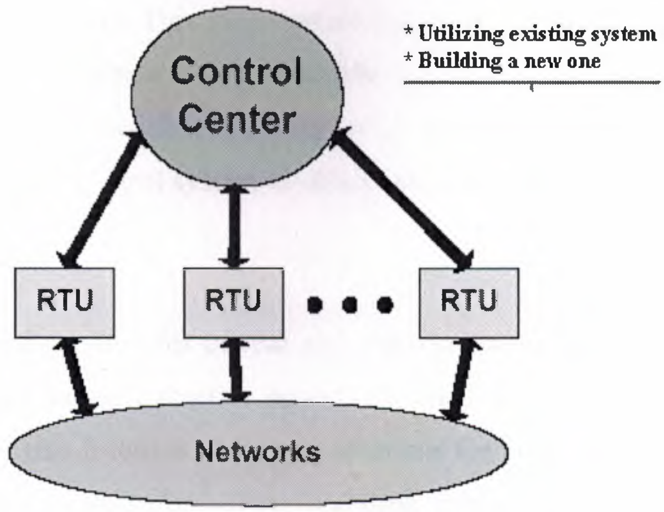


Figure 2.8 The RTUs has Direct Communication Channels with The Control Center and with Networks

Power system control can then be summarized as follows [39]:

- Most automatic controls are local.
- At the generator there is the governor control of generator output, the exciter control of generator terminal voltage and sometimes, power system stabilizer (PSS) control. These are continuous fast feedback control.
- Node voltages can also be controlled by transformer taps and shunt reactances. These are slow discrete controls but new continuous fast static VAR compensators (SVC) are becoming available for use.
- Where DC transmission is used, fast continuous control of line flow is available and new tools to do so on AC lines are becoming available. Slow controls using phase shifting transformers are still being used in a few places.

- Protective relays that isolate faulted equipment operate locally but are very fast. With communication from other parts of the network, they have great potential for fast control.
- The secondary frequency control of generator governor set-points is the only area wide control used today. This slow control implemented through the central control center is discrete at the rate of a few seconds.
- Much more data at very fast rates are being gathered at the substations but the communication and control system to utilize this data for faster controls is lacking.

2.10 Summary

This chapter introduced the transfer of real and reactive power through the transmission system and sources and sinks of reactive power, and then discussed voltage stability and voltage collapse. After that it introduced many solutions for voltage instability or collapse and some related research work for voltage stability. Finally it explained the control of power system. Part of these solutions will be used to enhance the voltage drop of PDS and to restore voltage stability in the intelligent voltage stabilizer in the last chapter.

CHAPTER THREE
ARTIFICIAL NEURAL NETWORKS

3.1 Overview

Neural networks emerged about 50 years ago. Their early abilities were exaggerated, casting doubts on the field as a whole. There is a recent renewed interest in the field, however, because of new techniques and a better theoretical understanding of their capabilities.

The basic concepts of artificial neural networks (ANN) will be explained in this chapter in addition to back propagation algorithm which will be used in our work for instability detection. Also, this chapter will describe real life applications of prediction ANN and uses of ANN in Electrical Power Systems.

3.2 Introduction to ANN

Neural networks have seen an explosion of interest over the last few years, and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology and physics. Indeed, anywhere that there are problems of prediction, classification or control, neural networks are being introduced. This sweeping success can be attributed to a few key factors:

- **Power.** Neural networks are very sophisticated modeling techniques capable of modeling extremely complex functions. In particular, neural networks are nonlinear. For many years linear modeling has been the commonly used technique in most modeling domains since linear models have well-known optimization strategies. Where the linear approximation was not valid the models suffered accordingly. Neural networks also keep in check the curse of dimensionality problem that bedevils attempts to model nonlinear functions with large numbers of variables.
- **Ease of use.** Neural networks learn by example. The neural network user gathers representative data, and then invokes training algorithms to automatically learn the structure of the data. Although the user does need to have some heuristic knowledge of how to select and prepare data, how to select an appropriate neural network, and how to interpret

the results, the level of user knowledge needed to successfully apply neural networks is much lower than would be the case using some more traditional nonlinear statistical methods.

Neural networks can be divided into three architectures, namely single layer, multilayer network and competitive layer. The number of layers in a net is defined based on the number of interconnected weight in the neuron. Single layer network consists only one layer of connection weights. Whereas, multilayer networks consists of more than one layer of connection weights. The network also consists of additional layer called hidden layer. Multilayer networks can be used to solve more complicated problems compared to single layer network. Both of the network are also called feed-forward network where the signal flows from the input units to the output units in a forward direction. The competitive layer network, for example the Recurrent Networks is a feedback network where there are closed-loop signal from a unit back to itself.

3.3 Learning in Neural Networks

Assume there are n input units, $X_1,\ldots,\ X_n$ with input signals $x_1,\ldots,x_n$. When the network receives the signals (x_i) from input units (X_i), the net input to output (Y_j) is calculated by summing the weighted input signals. The matrix multiplication method for calculating the net input is shown in the equation below.

$$u_j = \sum_{i=1}^{n} W_i X_i$$

where, w_{ij} is the connection weights of input unit x_i and output unit y_j.

The network output (y_i) is calculated using the activation function $f(x)$. In which $y_i = f(x)$, where x is u_j. The computed weight from the training is stored and will become the information or knowledge for the future application.

Neural networks learning algorithms can be divided into two main groups that are supervised (or associative learning) and unsupervised (self-organization) learning. Many supervised and unsupervised learning ANN have been invented.

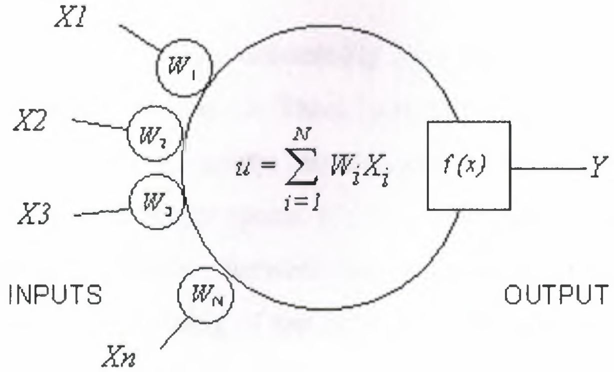


Figure 3.1 Weight of Perceptron

3.3.1 Supervised Learning

Supervised learning is based on the target value or the desired outputs. During training the network tries to match the outputs with the desired target values. This method has two sub varieties called auto-associative and hetero-associative. In auto-associative learning, the target values are the same as the inputs, whereas in hetero-associative learning, the targets are generally different from the inputs.

One of the most commonly used supervised ANN model is back propagation network that uses back propagation learning algorithm. Back propagation of errors or generalized delta rule is a decent method to minimize the total squared error of the output computed by the net.

3.3.2 Unsupervised Learning

Unsupervised learning method is not given any target value. A desired output of the network is unknown. During training the network performs some kind of data compression such as dimensionality reduction or clustering. The network learns the distribution of patterns and makes a classification of that pattern where, similar patterns are assigned to the same output cluster. Kohonen network is the best example of unsupervised learning network. Kohonen network refers to three types of networks that are Vector Quantization, Self-Organizing Map and Learning Vector Quantization.

3.3.3 Training the Network

Training the network could be time consuming. It usually learns after several epochs, depending on how large the network is. Thus, large network required more training time compared to the smaller one. Basically, the network is trained for several epochs and stopped after reaching the maximum epoch. For the same reason minimum error tolerance is used provided that the difference between network output and known outcome is less than the specified value. The training of the network could also stop after meeting certain stopping criteria [40].

3.4 Back Propagation Algorithm

3.4.1 Back Propagation Neural Networks

Back Propagation (BP), a euphemism for the generalized delta rule including momentum, is a supervised learning algorithm that applies to non-linear, multilayer; feed forward structure of nodes (networks). It works on minimizing the Mean Square Error (MSE) of the network.

The architecture of a BP network refers to the way it decodes information, that is the direction of information during recall. In a BP neural network the nodes are organized in input, hidden, and output layers, as in Figure 3.2.

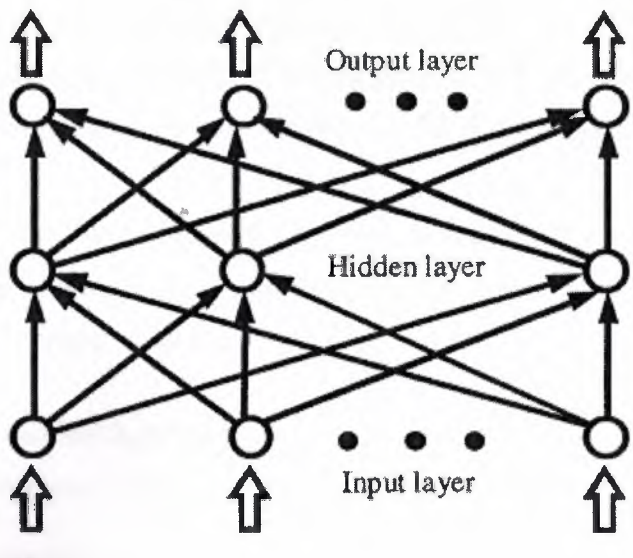


Figure 3.2 Back Propagation Neural Network [41]

3.5.2 Training BP Networks

Training of a BP neural network is achieved by presenting inputs to the network with the desired outputs. The network processes the inputs into its own simulated outputs. Input layer neurons receive the data to be processed by the network and the output layer holds the global computation results. One or more hidden layers may be present depending on problem complexity but quite often one layer suffices. All neurons within the input layer are connected to all neurons of the first hidden layer. These are subsequently connected to all neurons of the second hidden layer, if one is present, or to the neurons of the output layer. A weighting factor is associated with each connection. The same process is repeated with all adjacent hidden layers until the input layer is reached. At that moment all synaptic weights are updated. As neural networks are trained on sample data, these should be of high quality and representative of the domain [42].

The weight change rule is a development of the perceptron learning rule. Weights are changed by an amount proportional to the error at that unit times the output of the unit feeding into the weight. Running the network consists of:

- Forward pass:

  The outputs are calculated and the error at the output units calculated.

- Backward pass:

  The output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

For each data pair to be learned a forward pass and backwards pass is performed. This is repeated over and over again until the error is at a low enough level or the process reach the maximum number of epochs.

3.5.3 Mathematical Approach

Step 0: Initialize weights: to small random values (-1.0 → +1.0);

Step 1: Apply a sample: apply to the input a sample vector u_k having desired output vector y_k ;

Step 2: Forward Phase:

Starting from the first hidden layer and propagating towards the output layer:

2.1. Calculate the activation values for the units at layer L as:

2.1.1. If L-1 is the input layer

$$a_{h_L}^k = \sum_{j=0}^{N} W_{jh_L} u_j^k$$

2.1.2. If L-1 is a hidden layer

$$a_{h_L}^k = \sum_{j_{L-1}=0}^{N} W_{j_{(L-1)}h_L} x_{j_{(L-1)}h_L}^k$$

2.2. Calculate the output values for the units at layer L as:

$$x_{h_L}^k = f\,(a_{h_L}^k)$$

in which use i_o instead of h_L if it is an output layer

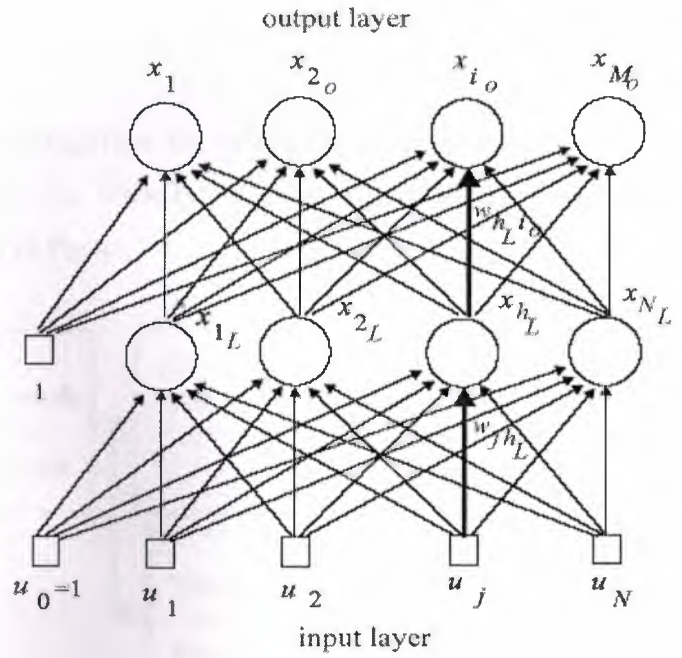


Figure 3.3 Multilayer BP Network [43]

Step 3: Output errors: Calculate the error terms at the output layer as:

$$\delta_{i_o}^k = (y_{i_o}^k - x_{i_o}^k) f_o^{'}(a_{i_o}^k)$$

Step 4: Backward Phase Propagate error backward to the input layer through each layer L using the error term

$$\delta_{h_L}^k = f_L^{'}(a_{h_L}^k) \sum_{i_{L+1}=1}^{N_{L+1}} \delta_{i_{(L+1)}}^k w_{h_L i_{(L+1)}}^k$$

in which, use i_o instead of $i_{(L+1)}$ if $(L+1)$ is an output layer;

Step 5: Weight update: Update weights according to the formula

$$w_{j_{(L-1)} h_L}(t+1) = w_{j_{(L-1)} h_L}(t) + \eta \delta_{h_L}^k x_{j_{(L-1)}}^k$$

Step 6: Repeat steps 1-6 until the stop criterion is satisfied, which may be chosen as the mean of the total error

$$< e^k > = < \tfrac{1}{2} \sum_{i_o=1}^{M} (y_{i_o}^k - x_{i_o}^k)^2 >$$

is sufficiently small [43].

3.5.4 Back Propagation Algorithm Block Diagram

The block diagram of the Back Propagation Algorithm consists from several processing blocks as it is shown in Figure 3.4.

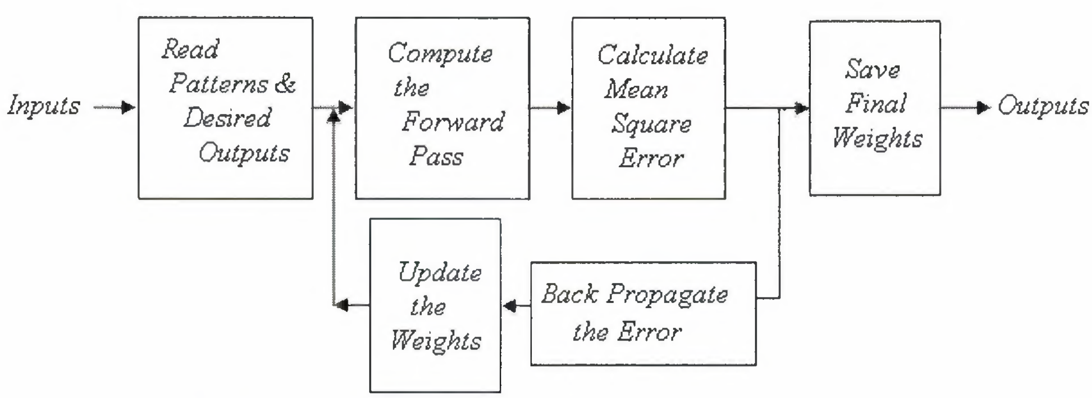


Figure 3.4 Back Propagation Algorithm Block Diagram

3.5 Applications of ANNs

The main applications of ANNs are for signal processing and pattern recognition. The algorithmic treatment represents a combination of mathematical theory and heuristic justification for neural models. The ultimate objective is the implementation of digital neuro-computers, embracing technologies of VLSI, adaptive, digital and parallel processing.

From an application driven perspective, one can see that the strength of neural networks are nonlinear, adaptive and parallel processing. Neural networks have found many successful applications in computer vision, signal/image processing, speech/character recognition, expert systems, medical image analysis, remote sensing, robotic processing, industrial inspection, and scientific exploration. The application domains of neural nets can be roughly divided into the following categories: association, clustering, classifications, pattern completion, regression and generalization, and optimization [44].

Table 3.1 summarizes the different types of ANNs and their potential applications.

Table 3.1 ANNs Selector and Their Applications [45]

Analytical Technique	Tools	Applications	
Associations, sequential patterns	statistics	Marketing:	market basket analysis
Pattern recognition	statistics, neural networks, machine induction	Security:	number plates, fingerprints
		Computing & telecomms.:	speech, vision and handwriting
		Finance:	signature and bank note verification
		Engineering:	product inspection, maintenance inspections
Clustering	neural networks, statistics	Marketing:	market segmentation
		Energy:	mineral exploration
		Engineering:	design reuse
Classification	machine induction, neural networks	Marketing:	target marketing
		Defense:	radar images
		Food & Ag.:	fruit, catch and livestock grading
		Medicine:	ultrasound and ECG images, lab. diagnosis, psychiatric care, illness severity
		Comp. & telecoms:	OCR, computer virus detection
		Finance:	risk assessment, bond rating, fraud detection
		Engineering:	quality control
Modeling	regression (curve fitting), neural networks	Marketing:	ranking/scoring customers, pricing models
		Security:	fingerprint matching
		Finance:	bankruptcy prediction, property valuation
		Engineering:	process control
Forecasting	statistics, neural networks	Marketing:	sales, business demand, holiday preferences
		Meteorology:	weather prediction
		Food & Ag.	crop yields
		Finance:	forex rate prediction, stock market changes
		Engineering:	inventory control, power demand prediction
Constraint satisfaction	linear programming, neural networks, genetic algorithms, AI planning, CLP	Engineering:	Job shop and stock route scheduling

3.6 Using ANNs in Power Systems

A prototype network is used to control operations of a power system that was so successful at optimizing large synchronous generators and load flow. Also, neural networks can organize the distribution of supplied electrical power between many power stations connected in grid. The rating capacity of each station and the main demand consumers are inputs of the net. As the demand changes during a day the output of the network is the amount of electrical power that each station should supply as percentage of its rating [43].

3.6.1 A Review of Applications of ANNs in Power Systems

This part is an overview of application of ANNs in power system operation and control. The comparison of the number of published papers in IEEE proceedings and conference papers in this field during 1990-1996 with them during 2000-2005 has showed that the following fields has attracted the most attention in the past five years [46]:

1- load forecasting

2- fault diagnosis/fault location

3- economic dispatch

4- security assessment

5- transient stability

Table 3.2 summarizes the number of published papers about application of ANNs in power system operation and control topics in two time intervals [46]. The first time interval is from 1990 to 1996, while the second one is from 2000 to 2005. These papers are published in IEEE proceedings and conferences. It seems that the comparison of two columns can be used as a proof of successful or unsuccessful operation of NN in related power system operation field. Figure 3.8 shows the percentage of the number of published papers during 2000-2005 in a circle form [46]. This figure shows that some fields such as load forecasting fault diagnosis/fault location, economic dispatch, security assessment and transient stability.

Table 3.2 ANNs in Power Systems – Survey of Papers 1990-1996 and 2000-April 2005

Power System Subject	No. of Published Papers from 1990 to 1996 using ANN	No. of Published Papers from 2000 to April 2005 using ANN
Planning		
- Expansion		
Generation	-	1
Transmission	-	1
Distribution	-	-
- Structural : Reactive power	1	-
- Reliability	-	1
Operation		
1. Plant		
- Generation Scheduling	-	4
- Economic Dispatch ODF	1	14
- Unit Commitment	-	-
- Reactive Power Dispatch	1	1
- Voltage Control	4	3
- Security Assessment		
Static	7	3
Dynamic	6	9
- Maintenance Scheduling	3	1
- Contract Management	-	-
- Equipment Monitoring	4	3
2. System		
- Load Forecasting	12	23
- Load Management	-	-
- Alarm Processing/Fault Diagnoses	13	20
- Service Restoration	-	2
- Network Switching	-	-
- Contingency Analysis	1	2
- Facts	-	-
- State Estimation	4	2
Analysis & Modeling		
- Power Flow	4	4
- Harmonics	-	3
- Transient Stability	5	9
- Dynamic Stability/Control Design	13	7
- Simulation/Operations	-	1
- Protection	7	4

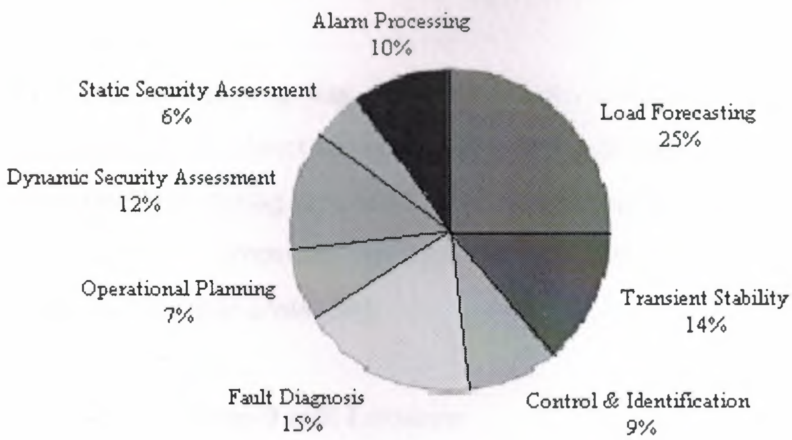


Figure 3.5 Neural Network Applications in Power Systems; 2000 – April 2005

3.6.2 Various ANNs Applications in Power System Subjects

Applications of ANNs in electrical power system are wide. The purpose of this section is to explore how the ANNs techniques are utilized in power systems especially in load forecasting, fault diagnosis or location, economic dispatch and security assessment.

3.6.2.1 Load Forecasting

Commonly and popular problem that has an important role in economic, financial, development, expansion and planning is load forecasting of power systems. Generally most of the papers and projects in this area are categorized into three groups:

• Short-term load forecasting over an interval ranging from an hour to a week is important for various applications such as unit commitment, economic dispatch, energy transfer scheduling and real time control. A lot of studies have been done for using of short-term load forecasting with different methods [47-52]. Some of these methods have main limitations such as neglecting of some forecasting attribute condition, difficulty to find functional relationship between all attribute variable and instantaneous load demand, difficulty to upgrade the set of rules that govern at expert system and disability to adjust themselves with rapid nonlinear system-load changes.

The ANNs can be used to solve these problems. Most of the projects using ANNs have considered many factors such as weather condition, holidays, weekends and special

sport matches days in forecasting model, successfully. This is because of learning ability of ANNs with many input factors.

• Mid-term load forecasting that range from one month to five years, used to purchase enough fuel for power plants after electricity tariffs are calculated [53].

• Long-term load forecasting covering from 5 to 20 years or more, used by planning engineers and economists to determine the type and the size of generating plants that minimize both fixed and variable costs [54].

3.6.2.2 Fault Diagnosis/Fault Location

Progress in the areas of communication and digital technology has increased the amount of information available at supervisory control and data acquisition (SCADA) systems [55, 56]. Although information is very useful, during events that cause outages, the operator may be overwhelmed by the excessive number of simultaneously operating alarms, which increases the time required for identifying the main outage cause and to start the restoration process. Besides, factors such as stress and inexperience can affect the operator's performance; thus, the availability of a tool to support the real-time decision-making process is welcome. The protection devices are responsible for detecting the occurrence of a fault, and when necessary, they send trip signals to circuit breakers (CBs) in order to isolate the defective part of the system. However, when relays or CBs do not work properly, larger parts of the system may be disconnected. After such events, in order to avoid damages to energy distribution utilities and consumers, it is essential to restore the system as soon as possible [57].

Nevertheless, before starting the restoration, it is necessary to identify the event that caused the sequence of alarms such as protection system failure, defects in communication channels, corrupted data acquisition [58].

The heuristic nature of the reasoning involved in the operator's analysis and the absence of an analytical formulation, leads to the use of artificial intelligence techniques. Expert systems, neural networks, fuzzy logic, genetic algorithms (GAs), and Petri nets constitute the principal techniques applied to the fault diagnosis problem [59].

From Table 3.2, it is seen that the major effort to detect and rectify power system faults in 90's, concentrate on expert system methods. Its main defect is the incapacity of

generalization and the difficulty of validating and maintaining large rule-bases. Recently, using model-based systems including temporal characteristics of protection schemes based on expert systems and ANNs developed.

The main advantage of neural network is its flexibility with noisy data and its main drawback is long time required for training feed forward network with back propagation training algorithm, especially when dimension of the power network is high. To short the training time using these substitute methods proposed: the general regression neural network (GRNN) in feed forward topology, the probabilistic neural network (PNN), adaptive neuro-fuzzy methods and the selective back propagation algorithm [60].

3.6.2.3 Economic Dispatch

Main goal of economic dispatch (ED) consists of minimizing the operating costs depending on demand and subject to certain constraints, i.e. how to allocate the required load demand between the available generation units [61, 62]. In practice, the whole of the unit operating range is not always available for load allocation due to physical operation limitations.

Several methods have been used in past for solving economic dispatch problems including Lagrangian relaxation method, linear programming (LP) techniques specially dynamic programming (DP), Beale's quadratic programming, Newton-Raphson's economic method, Lagrangian augmented function, and recently Genetic algorithms and ANNs. Because of, economic dispatch problem becomes a non-convex optimization problem, the Lagrangian multiplier method, which is commonly used in ED problems; can not to be directly applied any longer. Dynamic programming approach is one of the widely employed methods but for a practical-sized system, the fine step size and the large units number often cause the 'curse of dimensionality'.

Main drawbacks of genetic algorithm and tabu search for ED are difficulty to define the fitness function, find the several sub-optimum solutions without guaranty that this solution isn't locally and longer search time [46].

Neural networks and specially the Hopfield model, have a well-demonstrated capability of solving combinational optimization problem. This model has been employed to solve the conventional ED problems for units with continuous or piecewise quadratic fuel cost functions. Because of this network's capability to consider all constrained

limitation such as transmission line loss and transmission capability limitations, penalty factor when we have special units, control the unit's pollutions and etc., caused increasing the paper proposed recently [46].

3.6.2.4 Security Assessment

The principle task of an electric power system is to deliver the power requested by the customers, without exceeding acceptable voltage and frequency limits. This task has to be solved in real time and in safe, reliable and economical manner.

Generally there are two types of security assessments: static security assessment and dynamic security assessment [63 - 67]. In both types different operational states are defined as follows:

• Normal or secure state: In the normal state, all customer demands are met and operating limit is within presented limits.

• Alert or critical state: In this state the system variables are still within limits and constrain are satisfied, but little disturbance can lead to variable toward instability.

• Emergency or insecure state: the power system enters the emergency mode of operation upon violation of security related inequality constraints.

In practical power systems the dimension of the operating system is very high. To overcome this "curse of high dimensionality", three main approaches can be followed:

• Restrict the number of contingences and characterization of the security boundaries. This is for example done with supervised ANNs like MLP.

• Reduce the dimension of the operating vector; this is for example done with unsupervised ANNs like Oja-Sanger networks.

• Quantify of the operating point into a reduced number of classes, this is done with clustering algorithms for instance the nearest neighbor or the k-means clustering algorithms.

Commonly ANN that satisfies these conditions is multilayered Perceptron (MLP) with back propagation learning algorithm. The reason for this is on-line learning capability.

There are two problems with using MLP, selecting of input data and overtraining. A good method for first problem is using some of the security indicators presently calculated by the energy management system (EMS) as inputs to the ANN [68].

3.7 Summary

This chapter introduced the main concepts of artificial neural networks, and then introduced the concepts of the back propagation learning algorithm that will be implemented in our intelligent system. Much of concern in this chapter was directed to the applications of ANNs in electrical power systems. As a summary, it is convenient to apply ANN for instability and overload detection as part of an intelligent system next chapter.

CHAPTER FOUR
INTELLIGENT DETECTION OF INSTABILITY OF POWER DISTRIBUTION SYSTEMS

4.1 Overview

Voltage stability problems have been one of the major concerns for electric utilities as a result of system heavy loading. This chapter reports on an investigation into the application of artificial neural network (ANN) in on-line voltage instability detection. A discussion over the efficiency of the proposed techniques is also included.

4.2 Problem Analysis and Solution

Power systems may face some events like blackouts as a result of faults on some parts of the system or like getting overloaded which makes some loads switch off as a result of extreme voltage drop. These events mostly force the system to go to instability. As mentioned before our concern is on the stability of distribution substations which is one of the main parts of stability of the whole power system. Remote terminal units (RTU) which is part of SCADA can record RMS of voltages and the currents of the three phases with respect to time as curves all the time including unusual events.

The hypothesis which is presented within this thesis suggests that these graphs of unusual events during a year can be taken and sampled to a fixed number of samples. Voltage samples are normalized and then vectorized to be used as inputs to the neural network to train it for detecting events that may happen in future.

The neural network will have three outputs: stable case, unstable case or overload case. The next procedure is to arrange solutions to the system for the unstable and overload cases which will be discussed in the next chapter.

The neural network is used in this work to substitute the human monitor in the control center of the power system. It also works as another support for decision to help preventing voltage instability in case of late reaction from control center after a disturbance

risk. It uses the images of the three phase voltages as human monitor watching curves of three phase voltages and currents on monitor screen.

4.2.1 Data Acquisition

In our work as lack of recorded data, a power system is proposed which is the BPA test case study with some modification as seen in Figure 4.1. This proposed power system is simulated in computer using ready blocks in powerlib in MATLAB. Our concern is on the transient stability of one distribution power station which in our case is substation number 7 in the system. The the voltages of load 7 are taken as outputs of the circuit after simulation of 20 seconds.

Ordinary faults are induced on the generation station or on transmission grid of the system for a short time (2-3 seconds) then recovered and their effect is recorded on load 7 in order to simulate unstable cases. Also, one of the generators is switched off during simulation in different times and their effect is recorded on load 7. In another way, large additional loads are added to load 7 in different times to force the substation 7 to be overloaded and the terminal voltage is lowered to less than 95% of nominal voltage which outputs overload case. In the same manner, small additional loads are added or subtracted from load 7 in different times to simulate normally loaded system which makes the terminal voltage is higher than 95% of nominal voltage, and also the effect is recorded to register stable case.

These outputs are graphs of the sinusoidal waves of voltage during the twenty seconds of simulation. For every second on the graph there are 50 full waves, which make them concentrated and appear like a block. With visual inspection of these graphs, the upper level of these waves will be considered as the output with respect to time as from RTU in SCADA devices.

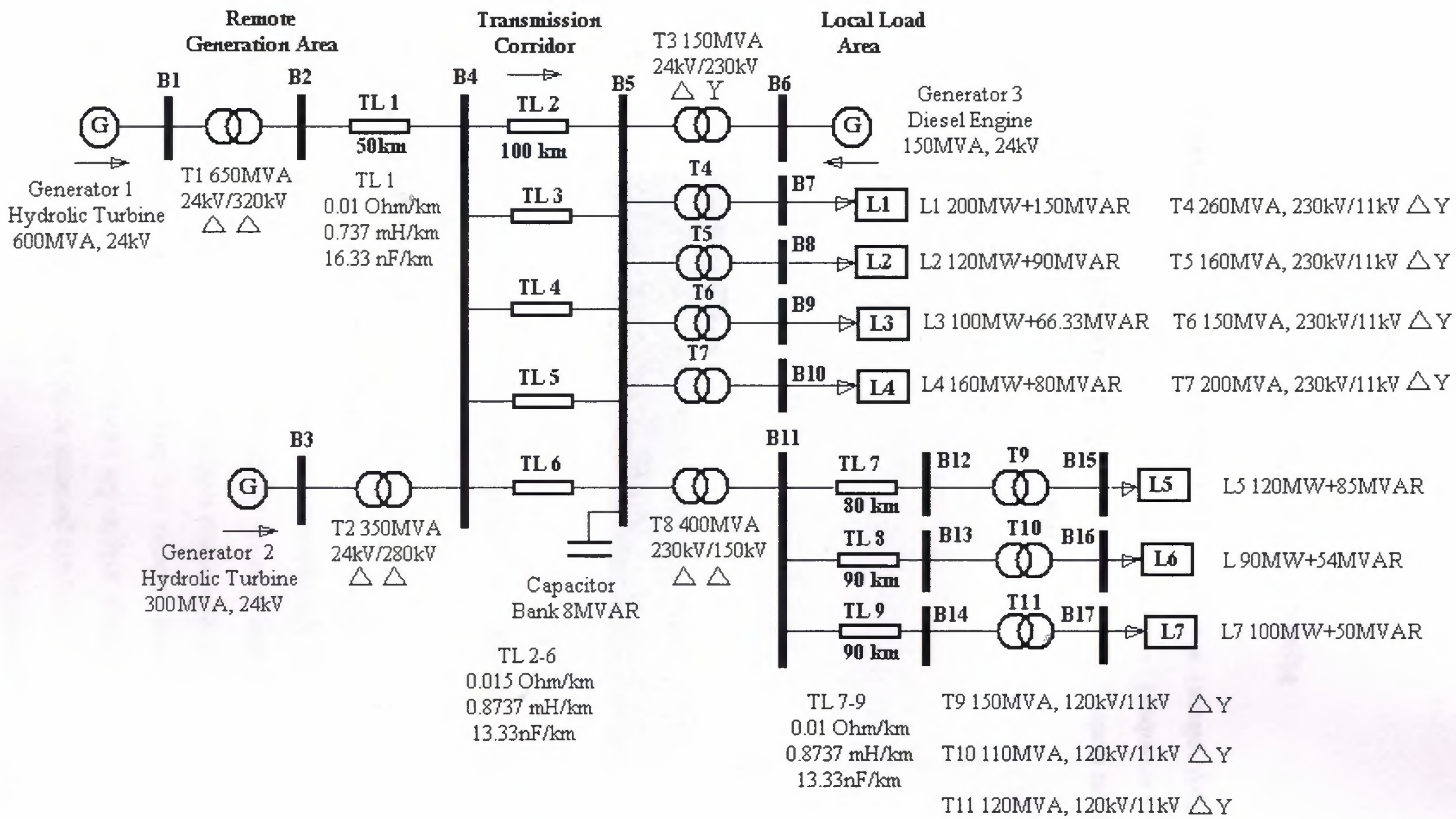


Figure 4.1 One Line Diagram of Test Case System

4.2.2 Patterns Preparation

The following steps are executed to prepare patterns to be inputs to the neural network.

First Step: The output voltage graphs for every case from simulation are extracted and saved as digital images. These images are denoted with three subscribes. The first subscribe (i) represents the case of the system with (i = 1-3), where 1 represents stable state of the system, 2 represents unstable state of the system and 3 represents overload state of the system. The second subscribe (j) represents the number of the case which with (j = 1-18). The third subscribe (k) represent the phase voltage with (k = 1-3), where 1 is for voltage on phase A, 2 is for voltage of phase B and 3 is for voltage on phase C. The size of every image is 500 x 840 pixels. Figure 4.2 shows an example of denoting one voltage graph, whereas figure 4.3 illustrates one example for the three images for every case.

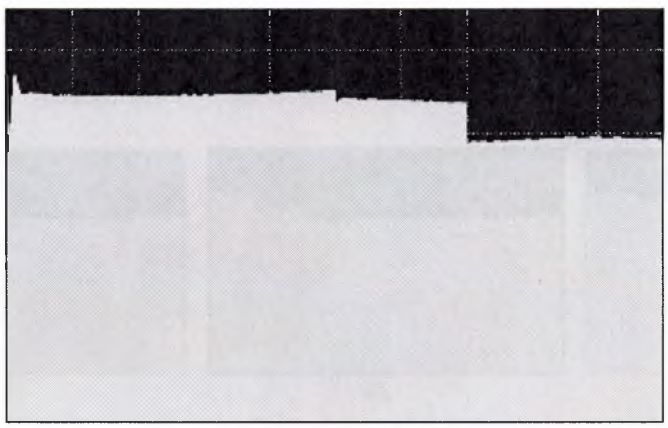


image i_j_k

i (system state)	**= 1,2,3**	**1 = stable, 2 = unstable, 3 = overload**
j (case number)	**= 1 - 18**	
k (voltage phase)	**= 1,2,3**	**1 = phase a, 2 = phase b, 3 = phase c**

Figure 4.2 Image Data Base Denotion

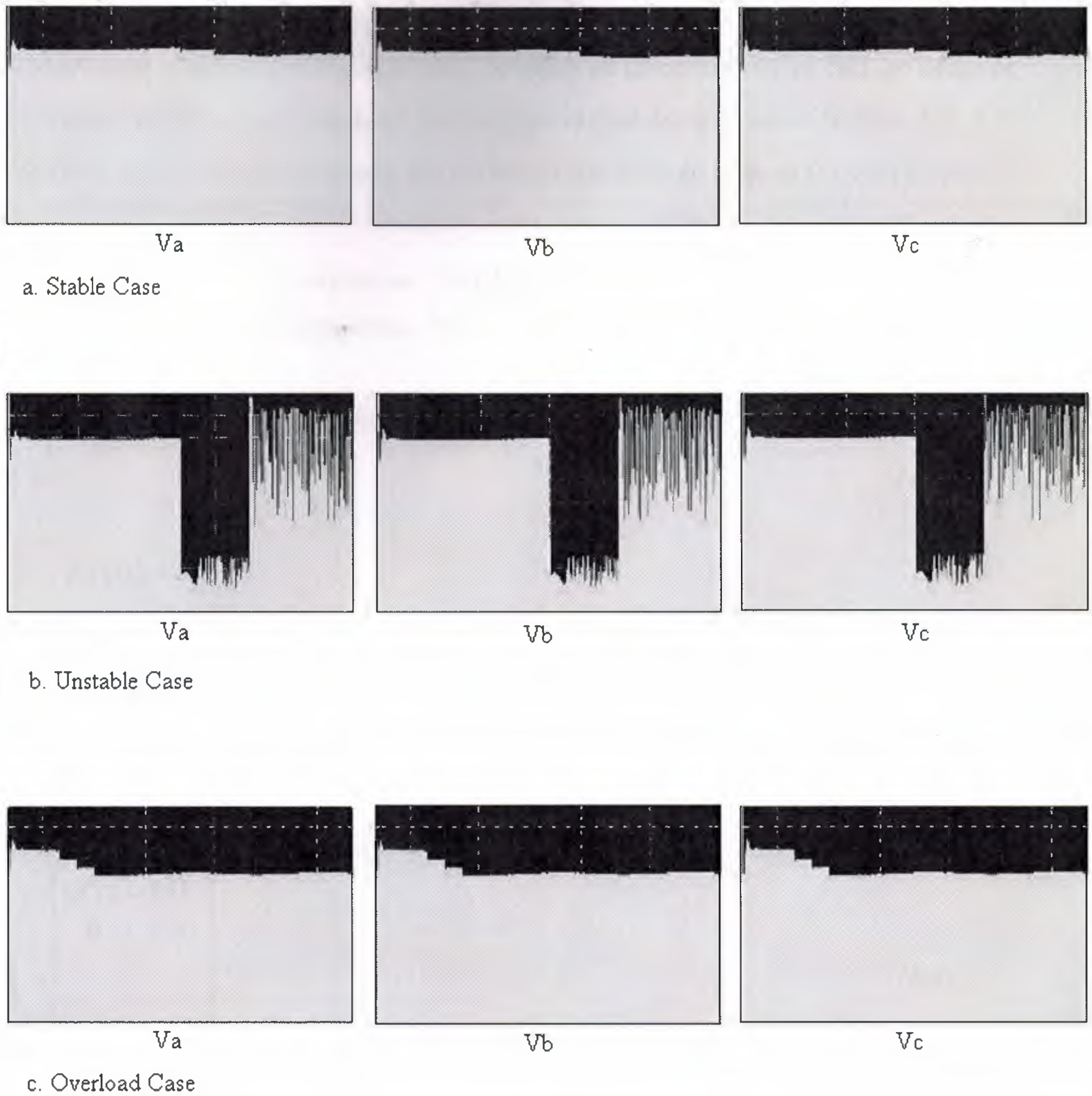


Figure 4.3 Examples of Training Cases

Second Step: Every image is converted to gray then resized to 400x202 pixels.

Third Step: In every image and for every column starting from column 2 to column 201 and from last row going up the value of the pixel, where the first discontinuity or change is found, the number of this row is saved in a vector. This saved value represents the highest value of the voltage of that column in that image. As a result 200 values are saved for every image. Equation 4.1 shows the general form of the vector and equations

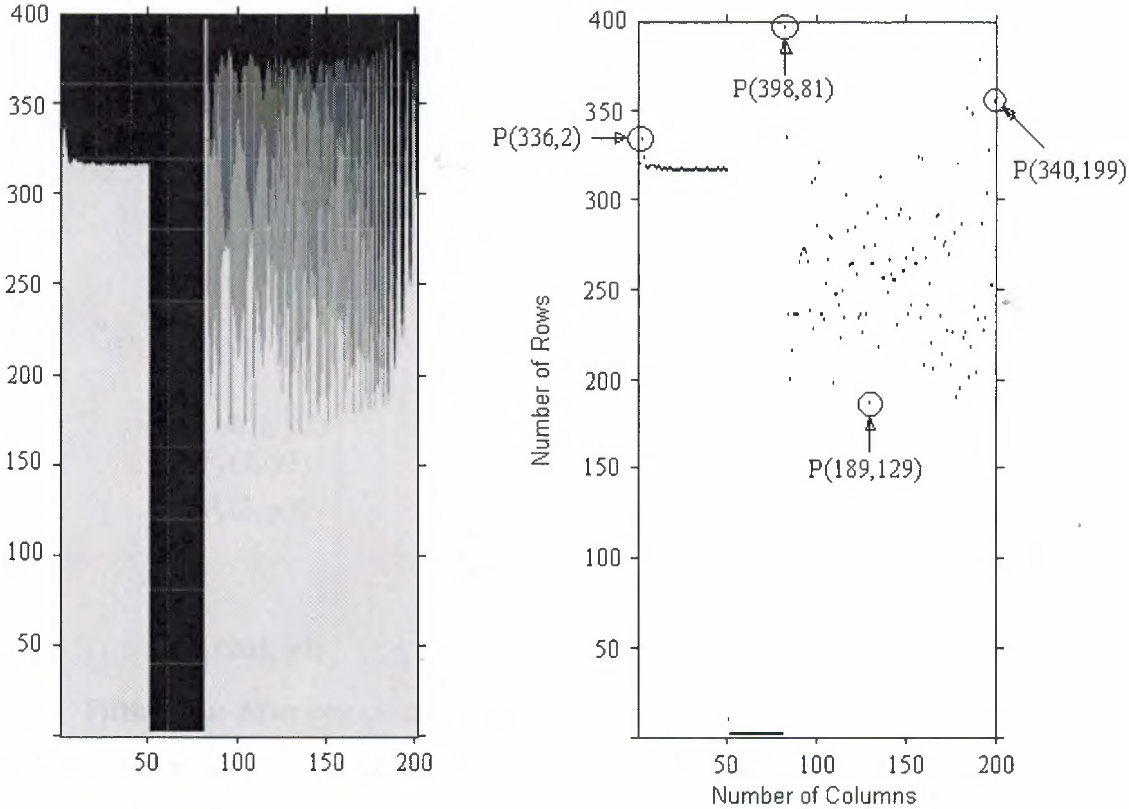
4.2, 4.3, and 4.4 show the form of the vector for image voltage a, b, and c respectively. Figure 4.4 shows one example of finding pixel position of discontinuity or change of color or in other words the maximum value of the voltage in that image, while figures 4.5, 4.6, and 4.7 introduce examples on extracting the curves of the voltage images for every case.

$$P_k = [P_k(x, y)] \qquad \begin{Bmatrix} x \text{ is any value from } 2 \rightarrow 201 \\ y \text{ is any value from } 1 \rightarrow 400 \end{Bmatrix} \tag{4.1}$$

$$P_1 = \begin{bmatrix} P_1(2, y1) \\ P_1(3, y1) \\ .. \\ .. \\ P_1(201, y1) \end{bmatrix} \tag{4.2}$$

$$P_2 = \begin{bmatrix} P_2(2, y2) \\ P_2(3, y2) \\ .. \\ .. \\ P_2(201, y2) \end{bmatrix} \tag{4.3}$$

$$P_3 = \begin{bmatrix} P_3(2, y3) \\ P_3(3, y3) \\ .. \\ .. \\ P_3(201, y3) \end{bmatrix} \tag{4.4}$$



a. Resized Gray Image b. Pixel Position of Color Change

Figure 4.4 Finding Pixel Position of Discontinuity or Color Change

Fourth Step: For every case which consists of 3 images, 600 values are saved as a vector which represents one pattern as in equation 4.5.

$$P_{123} = \begin{bmatrix} P_1(2, y1) \\ P_1(3, y1) \\ .. \\ .. \\ P_1(201, y1) \\ P_2(2, y2) \\ P_2(3, y2) \\ .. \\ .. \\ P_2(201, y2) \\ P_3(2, y3) \\ P_3(3, y3) \\ .. \\ .. \\ P_3(201, y3) \end{bmatrix} \quad (4.5)$$

Fifth Step: After completing steps (1 - 4) for every case, the number of the patterns (*NP*) will be the same as the number of the cases. From image denotion i, j & k:

$$NP = i * j \quad (4.6)$$

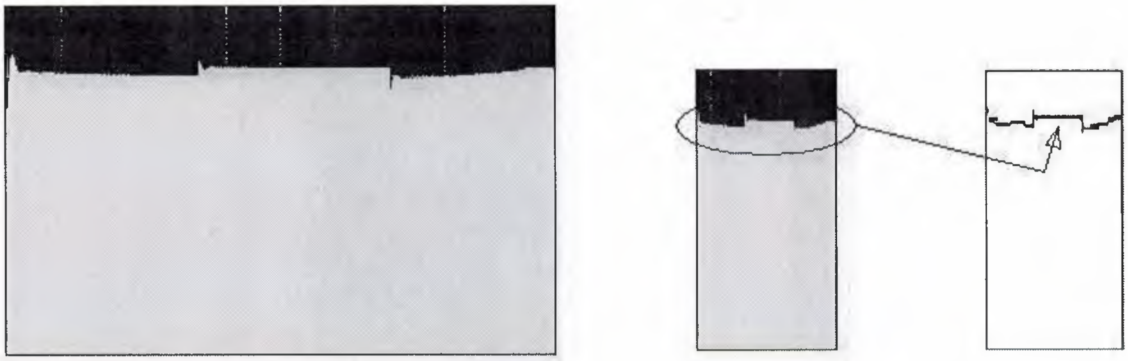
$$NP = 3 * 18 = 54 \quad (4.7)$$

Sixth Step: These pattern values are normalized to values between 0 and 1 by division on 400 (the highest number of rows) as given in equation 4.8.

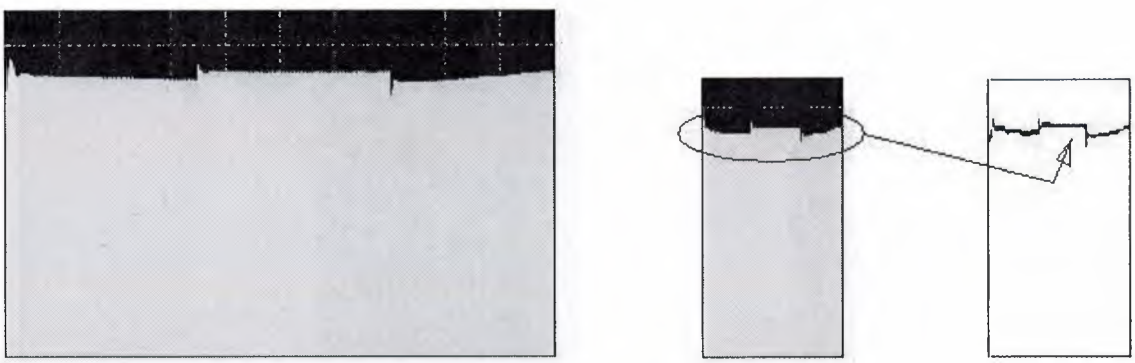
$$Nor.P = P_{123} / 400 \quad (4.8)$$

Seventh Step: These normalized patterns are then fed as inputs to the neural network classifier for training and later for testing.

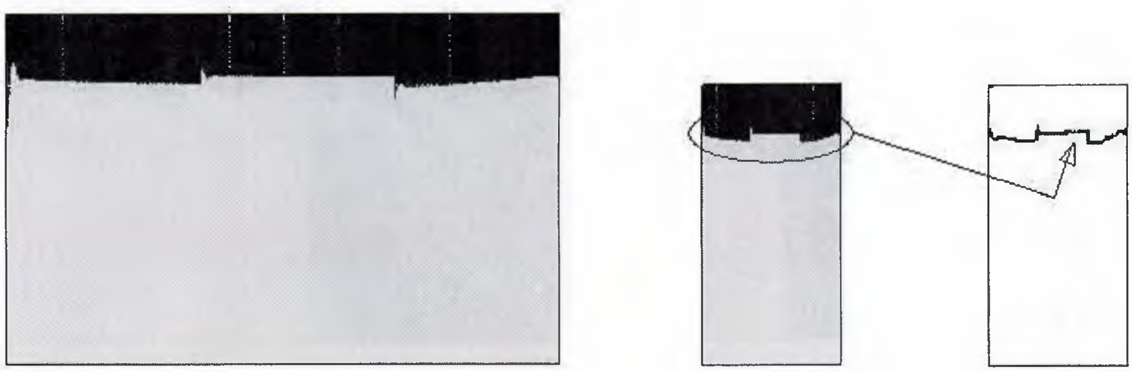
Figure 4.7 shows the block diagram of the patterns preparation phase, as part of the intelligent system.



Va

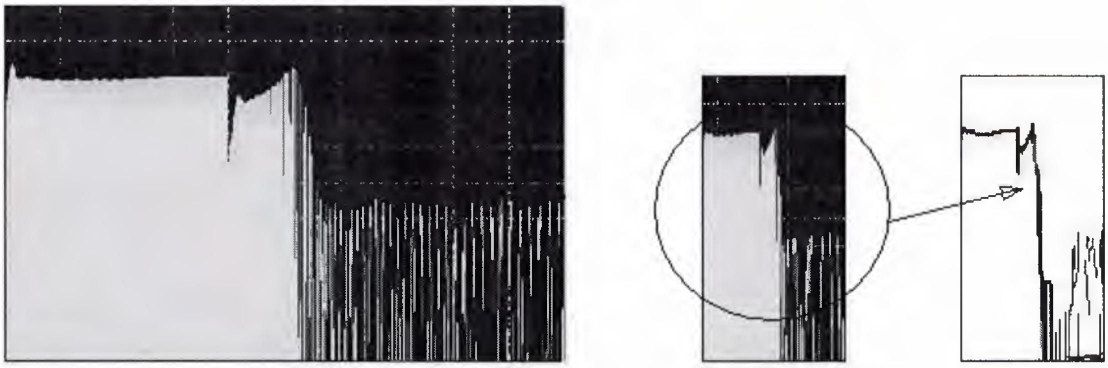


Vb

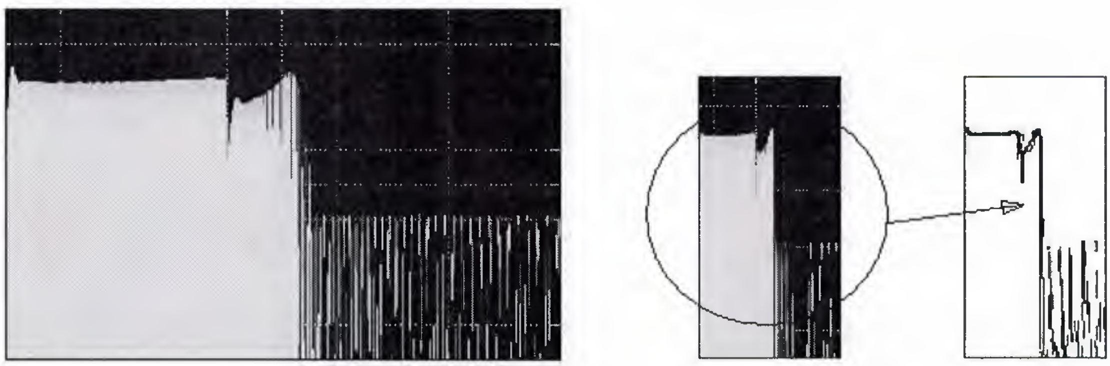


Vc

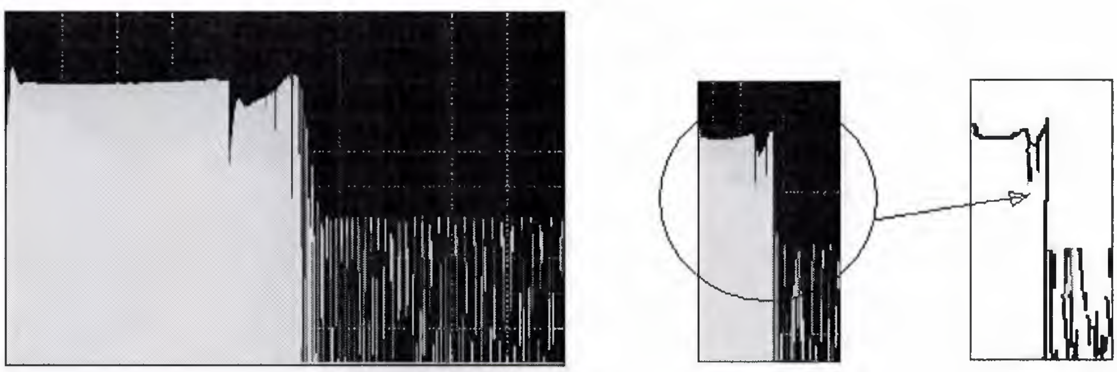
Figure 4.5 Extracting Curve for Stable Case



Va

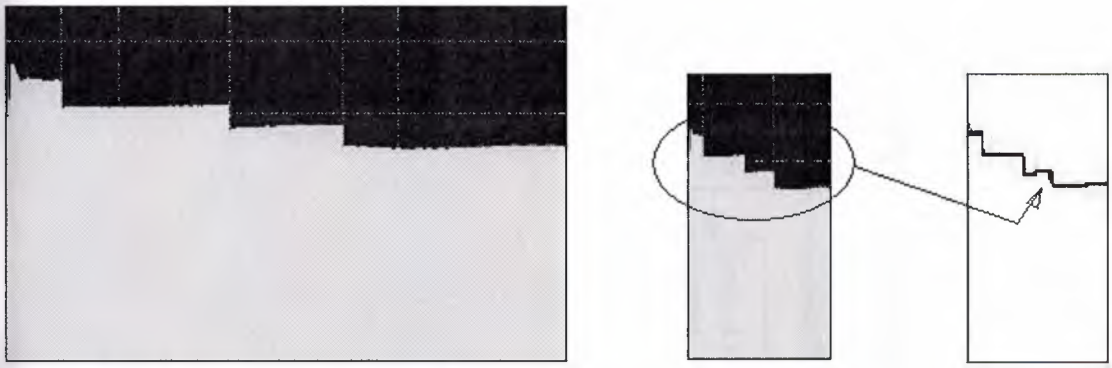


Vb

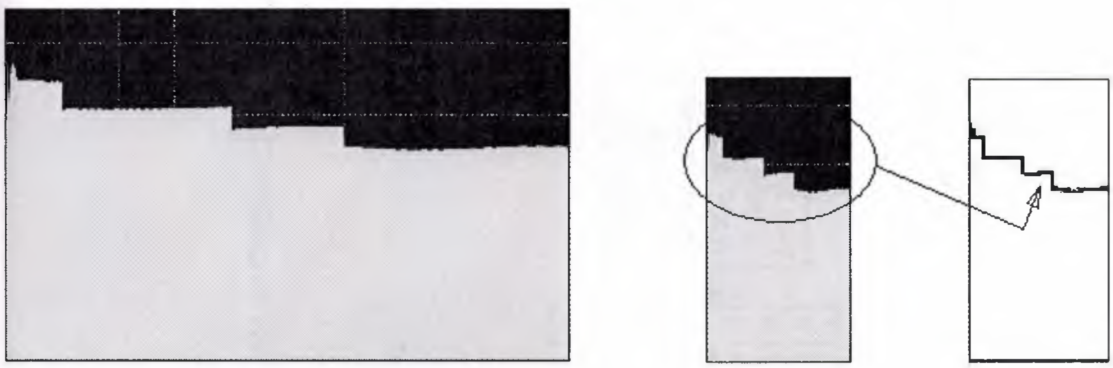


Vc

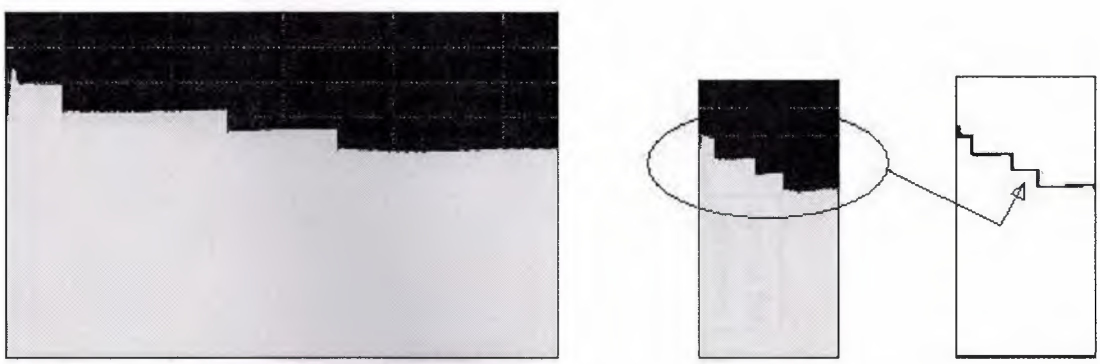
Figure 4.6 Extracting Curve for Unstable Case



Va



Vb



Vc

Figure 4.7 Extracting Curve for Overload Case

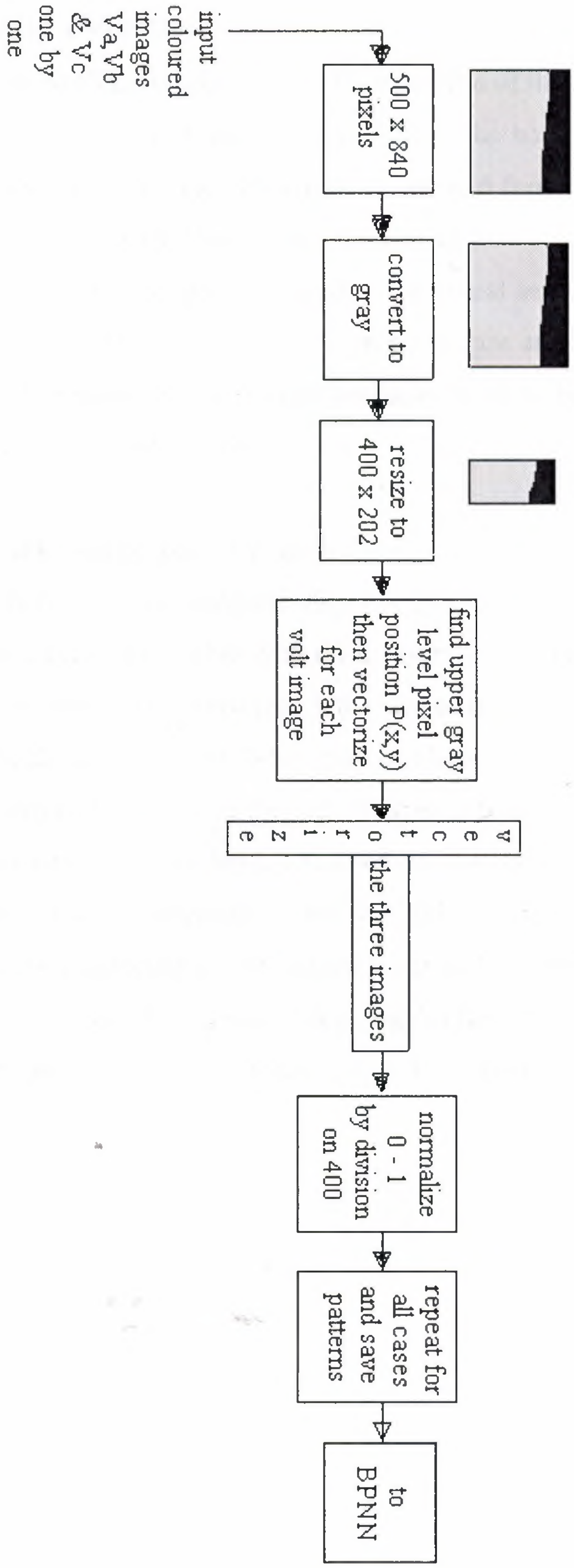


Figure 4.8 Block Diagram of Patterns Preparation

4.3 Intelligent Instability Detection

Neural Network simulator in MATLAB will be used for detection of instability or overload as unusual states of power systems. The neural network uses the back propagation (PB) learning algorithm due to its simplicity and efficiency. A sigmoid function will be used in the PB for the transfer function as it enables a finite number of nodes in the single hidden layer to uniformly approximate any continuous function. The neural network will be trained on three types of cases which are the stable case, the unstable case and the overload case. After that several cases will be tested by the trained neural network to be classified as one of the previous cases (stable, or unstable, or overload).

4.3.1 Neural Network Design and Structure

The neural network, which is used for implementing our proposed intelligent system, is based on back propagation learning algorithm with three layers. The input layer consists of 600 neurons as the size of the input layer must match the size of the patterns after reshaping the position of pixel where the discontinuity from gray to black and vectorizing the three images of voltage. The number of neurons in the output layer is three which is the number of the three cases stable, unstable, and overload. The number of neurons in the hidden layer is 28 neurons and it is chosen by experiments to get the higher recognition and accuracy rates. The input layer is fully connected to the hidden layer and the hidden layer is fully connected to the output layer. Figure 4.9 shows the topology of the back propagation neural network and the image pre-processing phase, while figure 4.10 shows the flowchart of the neural network training.

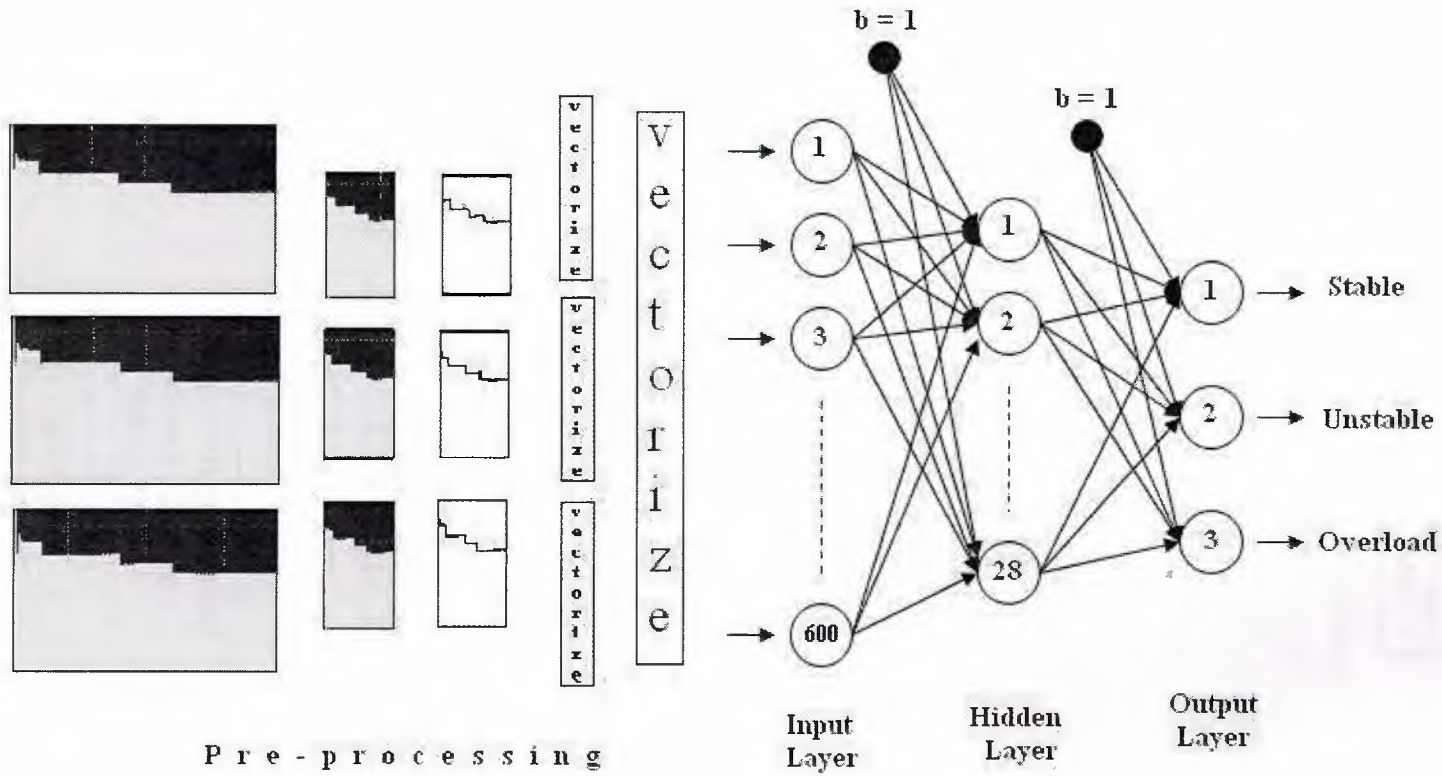


Figure 4.9 Back Propagation Neural Network Topology

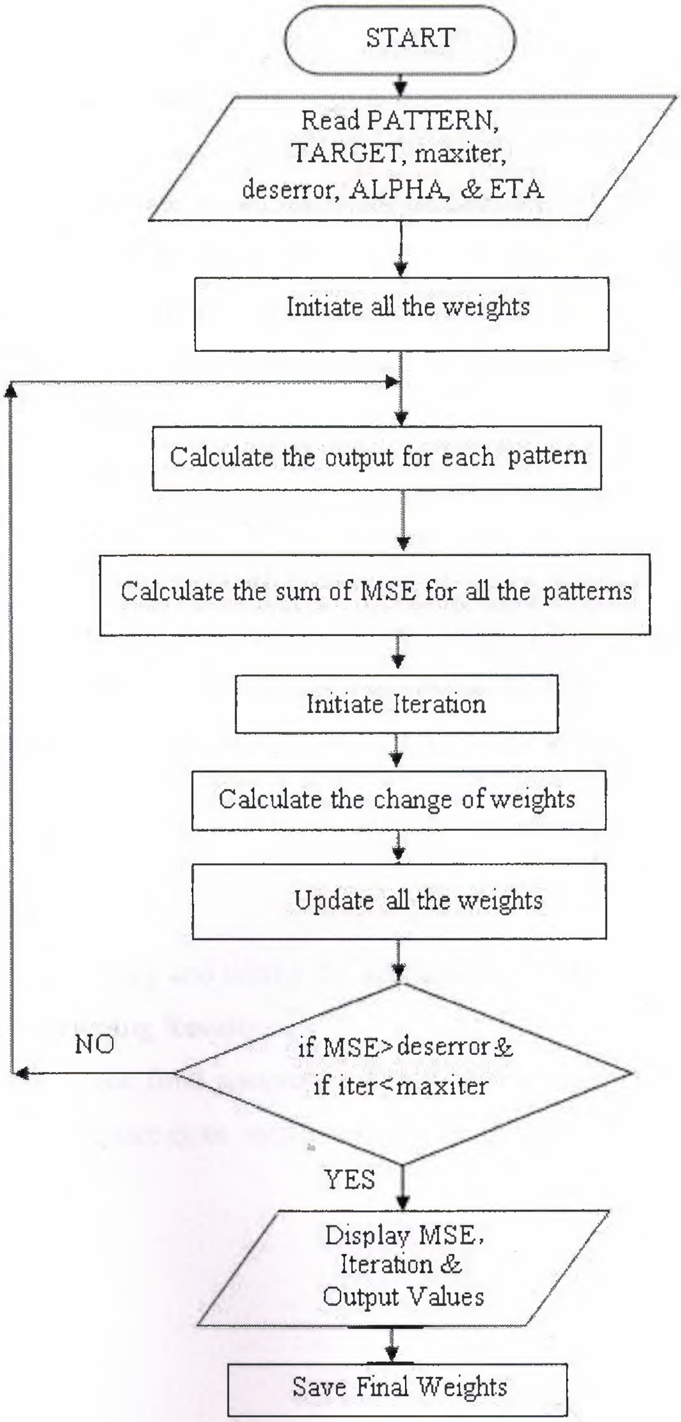


Figure 4.10 Neural Network Training Flowchart

4.3.2 Training and Testing the Network

The implementation of the proposed intelligent system uses fifty four simulated cases, where eighteen are stable cases, eighteen are unstable cases, and eighteen are overload cases. Every case has three images for the three voltage phases. Every set of cases are divided into ten for training and eight for testing. This means that the neural network will be tested with cases that have not been exposed to it during training.

There are 30 training patterns: 10 from stable cases, 10 from unstable cases and 10 from over load cases. The desired outputs for each case of training are:

T1 = [1 0 0] for stable case

T2 = [0 1 0] for unstable case

T3 = [0 0 1] for the overload case

After the neural network converges or learns, the final weights are saved and used for testing the trained network with new cases. The remaining twenty four cases are preprocessed to prepare the test patterns (using the same steps as in section 4.2.2) to be delivered to the neural network. It will use the saved weights to calculate the output of test patterns and launch the results.

4.4 Results

After finishing training and testing the neural network, the results are launched.

4.4.1 Training Results

Table 4.1 shows the final parameters of the neural network for training and Figure 4.10 shows the mean square error versus iteration for training.

Table 4.1 Final Parameters of Trained Neural Network

Number of Input Neurons	**600**
Number of Hidden Neurons	**28**
Number of Output Neurons	**3**
Learning Rate (Eta)	**0.001**
Momentum Factor (Alpha)	**0.33**
Minimum Error	**0.002**
Initial Random Weights Ranges	**-0.31 to 0.31**
Number of Iterations	**12165**
Training Time (seconds)	**963.4219***
Run Time of one forward pass (seconds)	**0.0214***
Tolerance	**0.8**

* The results were obtained using a 1.7 GHz Intel PC with 256MB RAM, Windows XP and MATLAB 7.

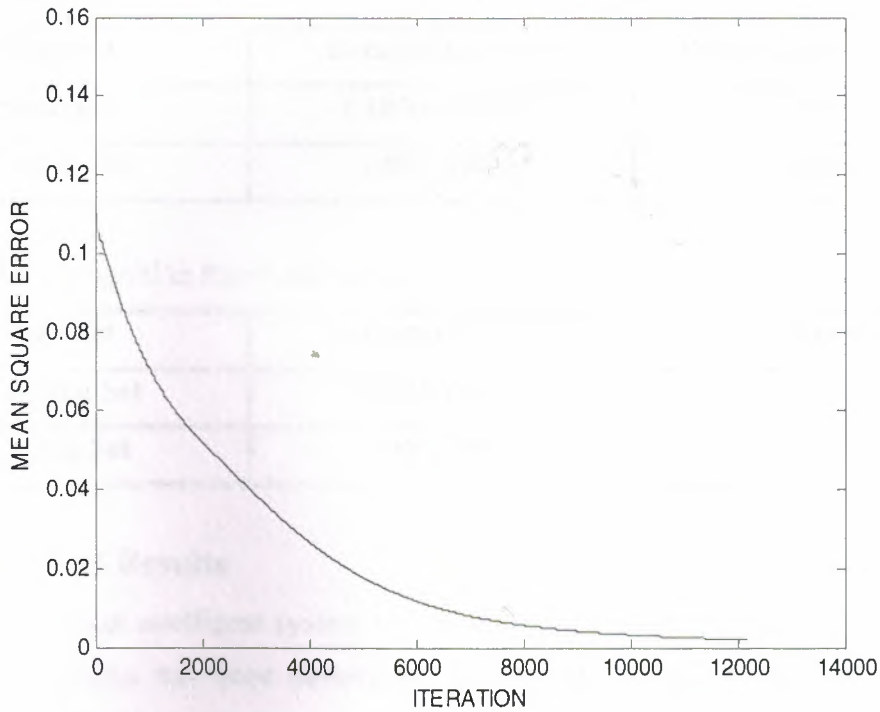


Figure 4.11 Mean Square Error vs. Iterations Curve

4.4.3 Testing Results

The following tables will show the recognition rate and accuracy rate for all cases then for every case separately to illustrate the efficiency of the proposed intelligent system.

Table 4.2 Recognition Rates and Accuracy of Training and Testing for All Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(30/30) 100%**	**93.15%**
Testing Set	**(23/24) 95.83%**	**93.62%**

Table 4.3 Recognition Rates and Accuracy of Training and Testing for Stable Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(10/10) 100%**	**94.10%**
Testing Set	**(7/8) 87.5%**	**87.47%**

Table 4.4 Recognition Rates and Accuracy of Training and Testing for Unstable Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(10/10) 100%**	**96.29%**
Testing Set	**(8/8) 100%**	**96.44%**

Table 4.5 Recognition Rates and Accuracy of Training and Testing for Overload Cases

Case Set	Recognition Rate	Recognition Accuracy
Training Set	**(10/10) 100%**	**89.41%**
Testing Set	**(8/8) 100%**	**90.69%**

4.5 Analysis of Results

A fast and efficient intelligent system for detection instability or overload states of power distribution systems has been developed. The neural network learnt the preprocessed voltage images which results from the simulated power system after 12165 iterations within 963.4 seconds. The neural network was trained on 30 system cases; which comprised 10 stable cases, 10 unstable cases and 10 overload cases. The running time for the generalized neural network after training to run one forward pass was 0.0214 seconds. The reduction of training and testing time was due to reducing the input patterns of our intelligent detection system which comes via reprocessing voltage simulated images and finding the pixel position where the first discontinuity or change in color is found. Our intelligent instability detection system recognized correctly all the thirty input patterns in the training set as it is expected or in other word the recognition rate for the training set was 100%. The recognition accuracy of the training set was 93.15% which is higher than the output classification tolerance that was set to 80% for both training and testing the neural network.

Our intelligent instability detection system was tested with 24 power system cases that were not exposed to the neural network before; these comprised 8 stable cases, 8 unstable cases and 8 overload cases. From all the twenty four tested cases, twenty three cases were correctly classified, thus yielding 95.83% correct detection. The recognition accuracy of all the testing set was 93.62%. Table 4.2 summarizes the recognition rate and accuracy rate of all the training and testing set.

The success and efficiency of our novel intelligent system is in its capability to detect instability cases with high recognition and accuracy rates. From table 4.3 the recognition rate for the unstable cases was (8/8) or 100% with 96.44% accuracy rate. Also, the recognition rate of overload cases was (8/8) or 100% with 90.69% accuracy rate as seen in table 4.4. The least recognition rate was for the stable case, which was (7/8) or 87.5% with 87.47% recognition accuracy as listed in table 4.5.

The last one of the stable cases was incorrectly classified as overload case with 0.7255 recognition value. However, this single incorrect detection is not considered dangerous for two reasons. First, it will be a problem if the intelligent system classifies an unstable case or an overload case as a stable case. On the contrary, it identified all the unstable and overload cases correctly with high accuracy rate. Second, the treatment system which will be introduced in the next chapter will solve this incorrect detection.

4.6 Summary

This chapter presented an investigation of the use of an ANN in detecting transient instability of power distribution systems. A test case system was simulated in MATLAB and the output graphs were saved then prepared to be induced as patterns to the ANN. The ANN showed excellent performance in classifying or in other words detecting instability or overload cases. As soon as the ANN detects unstable or overload case, a solution will arise to solve the problem as will be discussed in the next chapter.

CHAPTER FIVE
PROPOSED VOLTAGE STABILIZER

5.1 Overview

A new voltage stabilizer based on the decision of the intelligent system for detection of instability or overload cases will be introduced in this chapter. Also, results of simulation for some cases will be performed and discussed. At the end, the efficiency and benefits of this proposed voltage stabilizer will be discussed.

5.2 Introduction to Voltage Stabilizer

The transient stability analysis is one of the main studies carried out in Electric Power Systems. This analysis can be carried out, e.g., by simulation (numerical solution of nonlinear differential equations that describe the system dynamic). An alternative procedure consists of obtaining the analysis without solving such differential equations.

As mentioned before our concern in this work is to solve the transient stability of power distribution systems (PDS). Because the lack of previous data from a real power system for instability detection of PDS, a proposed power system is designed based on the BPA test case study and it is simulated using MATLAB. The output results are preprocessed and induced to the ANN to decide if the PDS is unstable or overloaded or stable (see chapter four). If the decision is one of the two last cases, then a voltage stabilizer (VS) must exist to restore stability and return the system to normal voltage and frequency. The proposed stabilizer has two branches, one to solve the instantaneous voltage drop which result from the overload state, and the other to solve transient instability of the system. After a while and when the system returns to stability the stabilizer should make reverse procedures to return the control devices to its normal conditions.

Before proceeding in details of the voltage stabilizer, specifications of the proposed power system will be introduced

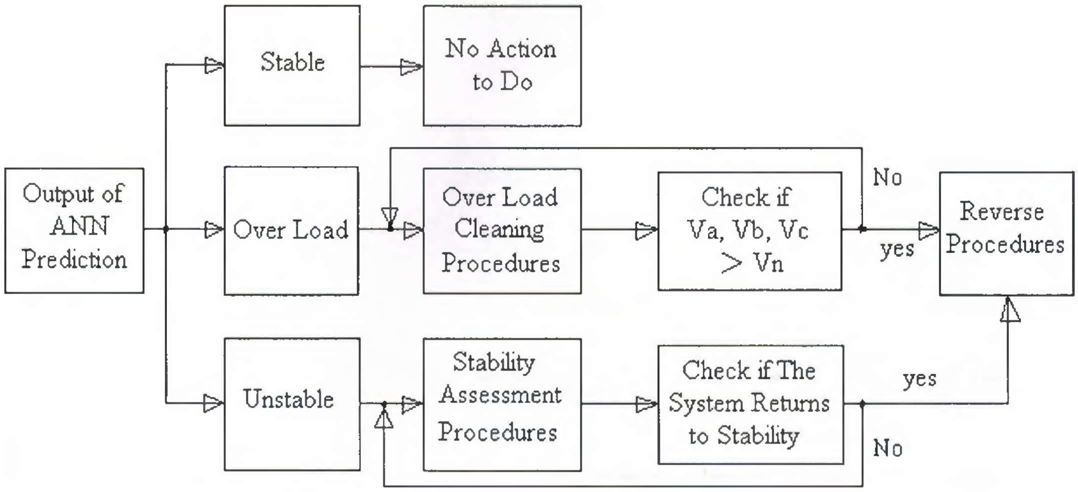


Figure 5.1 General Block Diagram of the Proposed Voltage Stabilizer

5.3 Modeling and Simulation of Proposed Power System

Recalling the one line diagram of the proposed power system which based on Bonneville Power Administration (BPA) and introduced in the previous chapter and extending load 7 to low voltage distribution will be seen in figure 5.2. There are three generators in our proposed power system. Generators 1 and 2 are Synchronous Machine associated with Hydraulic Turbine and Governor (HTG) and Excitation System (ES), while generator 3 is Synchronous Machine associated with Governor and Diesel Engine (GDE) and Excitation System. Generators 1 and 2 are in the remote area feeding the system with most of needed power, while generator 3 is in the local load area feeding the system with power in case of disturbances and regulating the loads bus. All the following specifications are taken from MATLAB7.1 Toolbox.

5.3.1 Modeling of Generator 1 and Generator 2 and their Hydraulic Governor and Exciter

Generator 1 is fed with the mechanical power through hydraulic turbine and governor (HTG1) and is fed with excitation field current from the excitation system (ES1) as shown in figure 5.3. Generator 2 is fed with the mechanical power through hydraulic turbine and governor (HTG2) and is fed with excitation field current from the excitation system (ES2) as shown in figure 5.4.

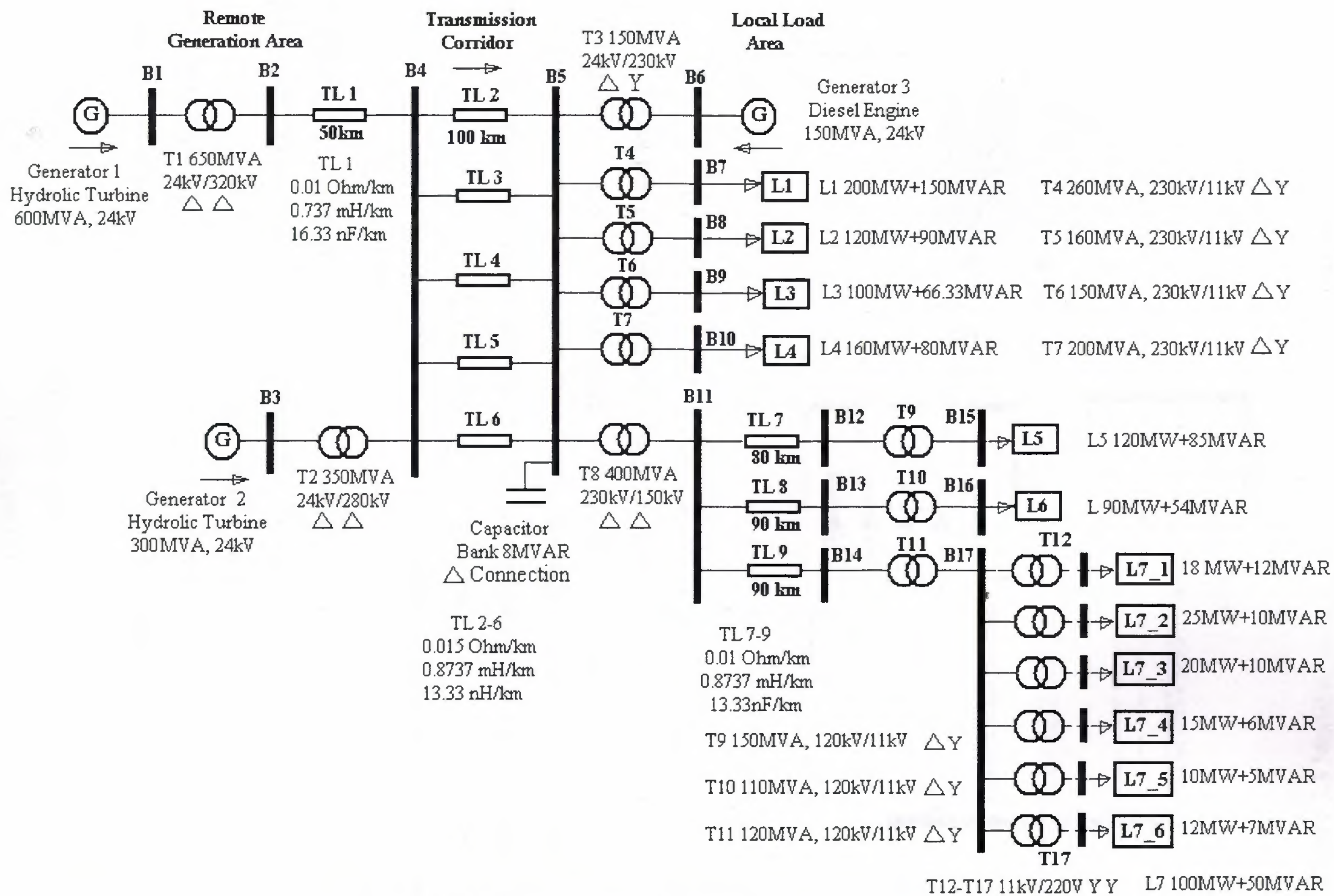


Figure 5.2 One Line Diagram of Extended Test Case System

5.3.1.1 Specifications of G1 and G2

Rotor type: Specify rotor type: Salient-pole or Round (cylindrical). It is chosen Salient-pole for the three generators.

Nominal power, voltage, frequency, and field current: The total three-phase apparent power Pn (VA), RMS line-to-line voltage Vn (V), and frequency fn (Hz). They are set for G1 as [600e6, 24000, 50] and for G2 as [300e6, 24000, 50].

Stator: The resistance Rs (pu), leakage inductance X1 (pu), and d-axis and q-axis magnetizing inductances Xd (pu) and Xq (pu). They are set for G1 and G2 as [2.8544e-3, 0.18, 1.305, 0.474].

Inertia, friction factor, and pole pairs: The inertia coefficient H (s), friction factor F (pu), and number of pole pairs p. They are set for G1 and G2 as [3.7, 0, 32].

Initial conditions: The initial speed deviation (% of nominal speed), electrical angle of the rotor e (degrees), line current magnitudes ia, ib, ic (pu) and phase angles pha, phb, phc (degrees), and the initial field voltage Vf (pu). They are set for G1 as [0, -16.6861, 0.950218, 0.950218, 0.950218, 48.1093, -71.8907, 168.109, 1.44424] and for G2 as [0, -16.6861, 0.950218, 0.950218, 0.950218, 48.1093, -71.8907, 168.109, 1.4].

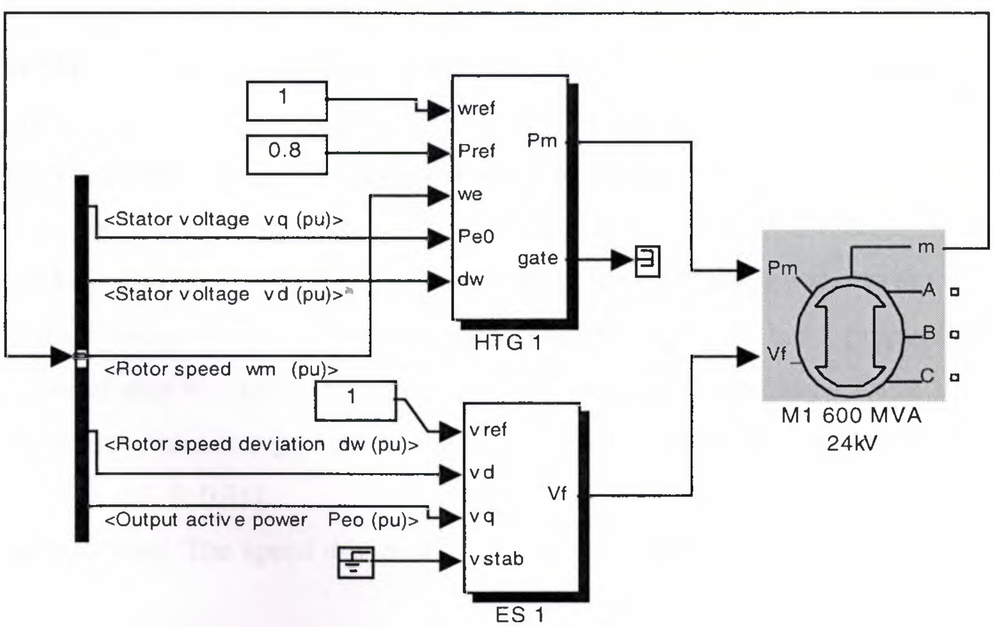


Figure 5.3 Modeling of Generator 1 and its Hydraulic Governor and Exciter

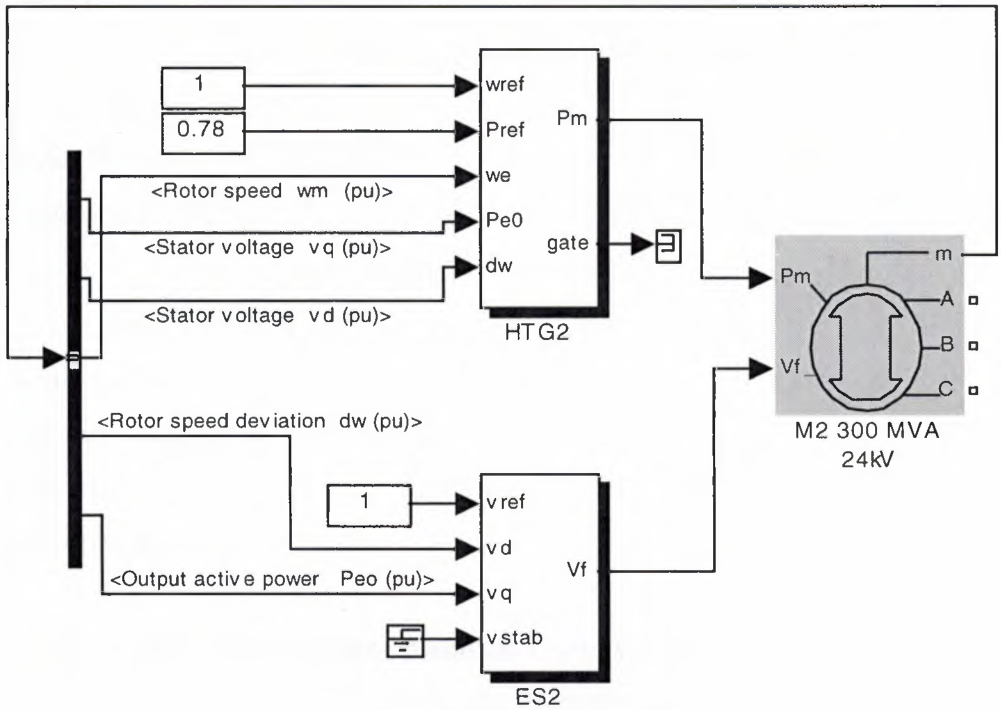


Figure 5.4 Modeling of Generator 2 and its Hydraulic Governor and Exciter

5.3.1.2 Specifications of HTG1 and HTG2

Servo-motor: The gain Ka and time constant Ta, in seconds (s), of the first-order system representing the servomotor are [5/3 0.07].

Gate opening limits: The limits gmin and gmax (p.u.) imposed on the gate opening, and vgmin and vgmax (p.u./s) imposed on gate speed are [0.01, 0.97518, -0.1, 0.1].

Permanent droop and regulator: The static gain of the governor is equal to the inverse of the permanent droop Rp in the feedback loop. The PID regulator has a proportional gain Kp, an integral gain Ki, and a derivative gain Kd. The high-frequency gain of the PID is limited by a first-order low-pass filter with time constant Td (s). The numerical values are [0.05, 1.163, 0.105, 0, 0.01].

Hydraulic turbine: The speed deviation damping coefficient and water starting time Tw (s) are [0, 2.67].

Droop reference: Specifies the input of the feedback loop: gate position (set to 1) or electrical power deviation (set to 0). It is set to zero.

Initial mechanical power: The initial mechanical power Pm0 (p.u.) at the machine's shaft is 1.00579 for HTG1 and 1 for HTG2. This value is automatically updated by the load flow utility of the Powergui block.

HTG1 and HTG2 Inputs and Outputs:

ωref: Reference speed, in p.u.

Pref: Reference mechanical power in p.u.

ωe: Machine actual speed, in p.u.

Pe0: Machine actual electrical power in p.u.

dw: Speed deviation, in p.u.

Pm: Mechanical power Pm for the Synchronous Machine block, in p.u.

gate: Gate opening, in p.u.

5.3.2 Modeling of Generator 3 and Its Governor and Exciter

Generator 3 is fed with the mechanical power through governor and diesel engine (GDE) and is fed with excitation field current from the excitation system (ES3) as shown in figure 5.5.

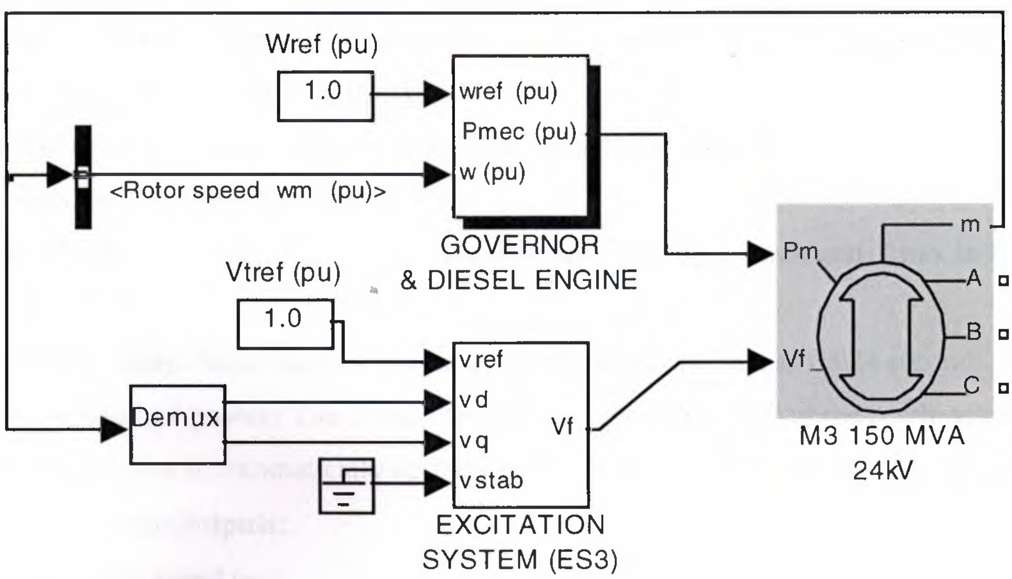


Figure 5.5 Modeling of Generator 3 and its Governor and Diesel Engine and Excitation System

5.3.2.1 Specifications of G3

Rotor type: Specify rotor type: Salient-pole or Round (cylindrical). It is chosen Salient-pole for the three generators.

Nominal power, voltage, frequency: The total three-phase apparent power Pn (VA), RMS line-to-line voltage Vn (V), and frequency fn (Hz). They are set for G3 as [150e6, 24000, 50].

Stator: The resistance Rs (pu), leakage inductance X1 (pu), and d-axis and q-axis magnetizing inductances Xd (pu) and Xq (pu). They are set for G3 as [2.8544e-3, 0.13, 1.05, 0.414]

Inertia, friction factor, and pole pairs: The inertia coefficient H (s), friction factor F (pu), and number of pole pairs p. They are set for G3 as [3.7, 0, 32].

Initial conditions: The initial speed deviation (% of nominal speed), electrical angle of the rotor e (degrees), line current magnitudes ia, ib, ic (pu) and phase angles pha, phb, phc (degrees), and the initial field voltage Vf (pu). They are set for G3 as [0, -16.6861, 0.950218, 0.950218, 0.950218, 48.1093, -71.8907, 168.109, 1]

5.3.2.2 Specifications of GDE

Regulation gain K: K is the gain of the controller transfer function and set as 40.

Regulation time constants: The parameters of the controller transfer function T1, T2 and T3 in seconds are set as [0.01, 0.02, 0.2]

Actuator time constants: The parameters of the actuator transfer function T4, T5 and T6 in seconds are set as [0.25, 0.009, 0.0384]

Torque limits: The minimum and maximum values of torque Tmin and Tmax in (pu) are set as [0, 1.1]

Engine time delay: Specifies the time delay of motor Td (s) is set as 0.024 seconds.

Initial mechanical power: The initial mechanical power Pm0 (pu) at the machine's shaft is set as 1. This value is automatically updated by the load flow utility of the Powergui block.

GDE Inputs and Outputs:

ωref: Reference speed (pu)

ωm: Rotor speed ωm (pu)

Pmec: Mechanical power Pm for the Synchronous Machine block (pu)

5.3.2.3 Specifications of the Excitation Systems ES1, ES2 and ES3

Low-pass filter time constant: The time constant Tr, in seconds (s), of the first-order system that represents the stator terminal voltage transducer and is set for the three systems as 20e-3 seconds.

Regulator gain and time constant: The gain Ka and time constant Ta, in seconds (s), of the first-order system represent the main regulator. They are set for ES1 and ES2 as [300, 0.001] and for ES3 [200, 0.02]

Exciter: The gain Ke and time constant Te, in seconds (s), of the first-order system representing the exciter. It is for the three systems as [1, 0].

Transient gain reduction: The time constants Tb, in seconds (s), and Tc, in seconds (s), of the first-order system representing a lead-lag compensator. They are for the three systems as [0, 0].

Damping filter gain and time constant: The gain Kf and time constant Tf, in seconds (s), of the first-order system representing a derivative feedback. They are for the three systems as [0.001, 0.1].

Regulator output limits and gain: Limits Efmin and Efmax are imposed on the output of the voltage regulator. The upper limit can be constant and equal to Efmax, or variable and equal to the rectified stator terminal voltage Vtf times a proportional gain Kp. If Kp is set to 0, the former applies. If Kp is set to a positive value, the latter applies. They are set for ES1 and ES2 as [-11.5, 11.5, 0], and for ES3 as [0, 6, 0].

Initial values of terminal voltage and field voltage: The initial values of terminal voltage Vt0 (pu) and field voltage Vf0 (pu). Both Vt0 and Vf0 values are automatically updated by the load flow utility of the Powergui block. They are set for ES1 as [1, 2.61202], for ES2 [1, 2.39592] and for ES3 as [1, 1.72942].

Inputs and Outputs

vref: The desired value, in p.u., of the stator terminal voltage.

vd: vd component, in p.u., of the terminal voltage.

vq: vq component, in p.u., of the terminal voltage.

vstab: Connect this input to a power system stabilizer to provide additional stabilization of power system oscillations.

Vf: The field voltage, in p.u., for the Synchronous Machine block.

5.4 Voltage Stabilizer for Overload Cases

As soon as the ANN predicts over load case, the VS will begin its work. The design of the VS depends on the solutions that had been discussed in section 2.7. Figure 5.1 shows the general block diagram of the proposed VS.

The first move is from the tap changer relay of the step-down transformer to raise the terminal voltage (Vt) 5% from nominal voltage (Vn). After waiting two seconds check if Vt is still less than 0.95 Vn. If yes go to the second move and if no (i.e. the voltage becomes greater than 0.95) stop VS procedures. The maximum raise of tap relay changer of the transformer is set based on IEEE standards [69]. The value of allowed minimum voltage drop is chosen 0.95 Vn according to IEEE standard (Std 141-1993) where the recommended voltage drop of distribution systems is (0.9-0.95) Vn and the recommended voltage raise is (1.05-1.10) Vn [69]. Also according to other standards, in NEC 210-19 FPN No. 4, the recommended voltage drop of distribution systems is (0.95-0.97) Vn, and in 1C.2.1—Voltage Level and Range ENGINEERING Standards and Technical Support Department, and ANSI C84.1–1989, the recommended voltage drop of distribution systems is (0.95) Vn.

If the terminal load voltage is V_L and terminal transformer voltage V_t , then

$$V_L = V_t \tag{5.1}$$

and after the tap relay of the transformer raise its output by 5%, the new terminal load voltage will be:

$$V_{Ln} = 1.05 V_t \tag{5.2}$$

The second move is switching on the capacitor bank step by step. Every step is 20% from the capacitance switched on parallel to the load. After every step wait two seconds then check if *Vt* is still less than 0.95 *Vn*. If yes switch on another 20% from capacitor bank, and if no stop VS procedures. If 100% of the capacitor bank is switched on and *Vt* is still less than 0.95 *Vn* go to the third move. The proceeding discussion is to show the influence of adding capacitor bank to the system. Figure 5.6 shows the power triangle for the substation in PDS before and after switching on capacitor bank parallel to the loads.

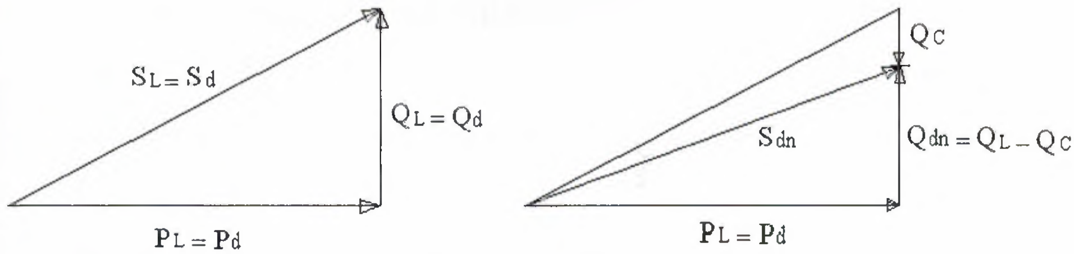


Figure 5.6 Power Triangle for PDS (a) before Capacitor Switching, (b) after Capacitor Switching

Let's assume that the apparent power of the load is S_L, the active power is P_L , the inductive reactive power is Q_L and the apparent power delivered to the load is S_d, the active power is P_d, the inductive reactive power is Q_d and the capacitive reactive power from the capacitor is Q_C ,then

$$|S_L| = \sqrt{(Q_L^2 + P_L^2)} \tag{5.3}$$

$$|S_d| = \sqrt{(Q_d^2 + P_d^2)} \tag{5.4}$$

$$S_L = S_d \tag{5.5}$$

Let's assume the L-L load current is I_L and the L-L terminal load voltage is V_L, then

$$|I_L| = \frac{|S_L|}{|V_L|.\sqrt{3}} \tag{5.6}$$

The new delivered inductive reactive power (Q_{dn}) is given by:

$$Q_{dn} = Q_d - Q_C \tag{5.7}$$

and the new delivered apparent power (S_{dn}) is given by:

$$|S_{dn}| = \sqrt{((Q_d - Q_C)^2 + P_d^2)} \tag{5.8}$$

and the new load current (I_{Ln}) will be reduced and is given by:

$$|I_{Ln}| = \frac{|S_{dn}|}{|V_L|.\sqrt{3}} \tag{5.9}$$

so the load voltage difference will be:

$$\Delta V_L = \Delta I_L . Z_{TL} \tag{5.10}$$

and the L-L terminal load voltage will be increased by ΔV_L and become:

$$V_{Ln} = \Delta V_L + V_L \tag{5.11}$$

The third move is low voltage load shedding. As known the output of power distribution substation consists from many medium to low voltage step down transformers connected to the low voltage loads. Shedding loads is chosen to be intelligent and automatic. Intelligence is needed in order to find optimal scenarios for the amount of load to shed and the location of these loads. A main consideration in intelligent load shedding will be the cost criterion. Strategies may be based on dynamic prices and on electric market. Figure 5.7 shows the triangles of power before and after load shedding.

Returning to the P-V graphs in CH2, and if the load is working on a curve, then after load shedding it will work on the same curve but with a position earlier to the first position making the terminal voltage in the allowed margin, assuming the power factor does not changed, as illustrated in figure 5.8.

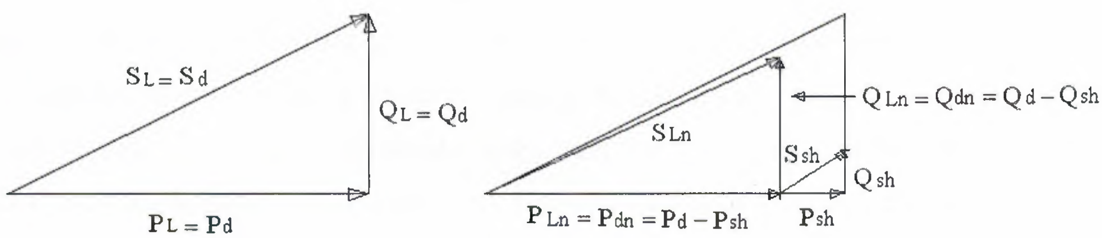


Figure 5.7 Power Triangle for PDS (a) before Load Shedding, (b) after Load Shedding

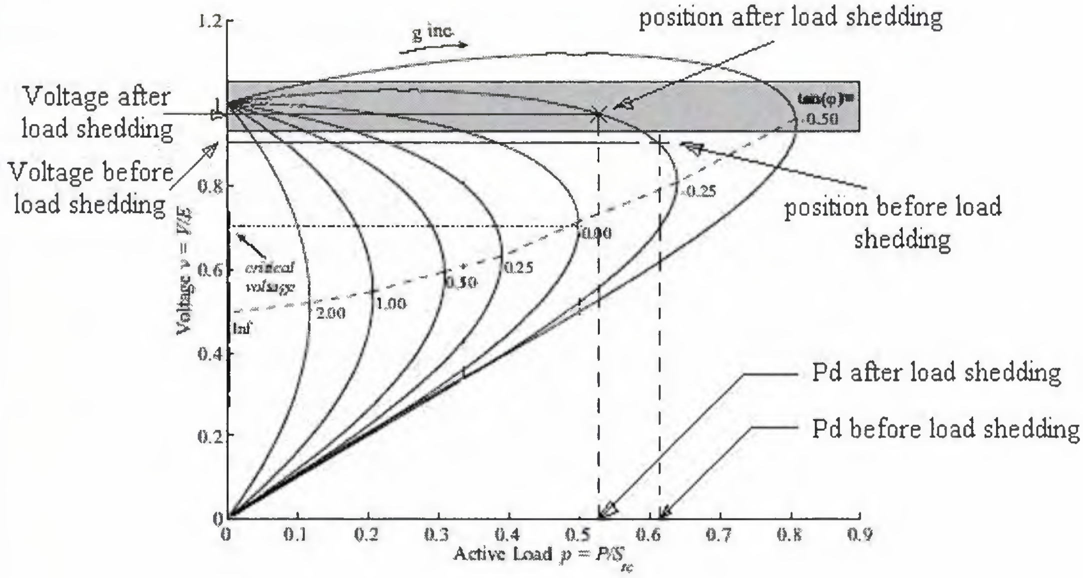


Figure 5.8 Power Voltage Curve before and after Load Shedding

For this proposed power system lLoad shedding will take place in three steps in the proposed VS. The first step is shedding the least priority medium and low voltage loads that used in general activities like general motor water pumps, or water treatment pumps. As it is known that companies of electrical energy market make contracts with some duty or tourism areas to sell them electrical energy with low prices, and on the other hand it can shed their loads in case of disturbances. The second step is shedding the lowest electrical energy price. The third step is shedding the loads that have the second low price. Figure 5.9 shows the block diagram of voltage stabilizer for overload cases as it is explained previously while figure 5.10 shows the flowchart of it.

The algorithm for overload enhancement is summarized as follows:

Step 1: Raise tap changer relay of distribution transformer by 5%.

Step 2: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 3: If no stop and if yes switch on 20% from the capacitor bank.

Step 4: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 5: If no stop and if yes switch on another 20% from the capacitor bank.

Step 6: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 7: If no stop and if yes switch on another 20% from the capacitor bank.

Step 8: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 9: If no stop and if yes switch on another 20% from the capacitor bank.

Step 10: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 11: If no stop and if yes switch on another 20% from the capacitor bank.

Step 12: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 13: If no stop and if yes shed low voltage load L7_1.

Step 14: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 15: If no stop and if yes shed low voltage load L7_2.

Step 16: Wait 2 second then check if Va, Vb, Vc are still less than 0.95 Vn.

Step 17: If no stop and if yes shed low voltage load L7_3.

Step 18: Stop actions.

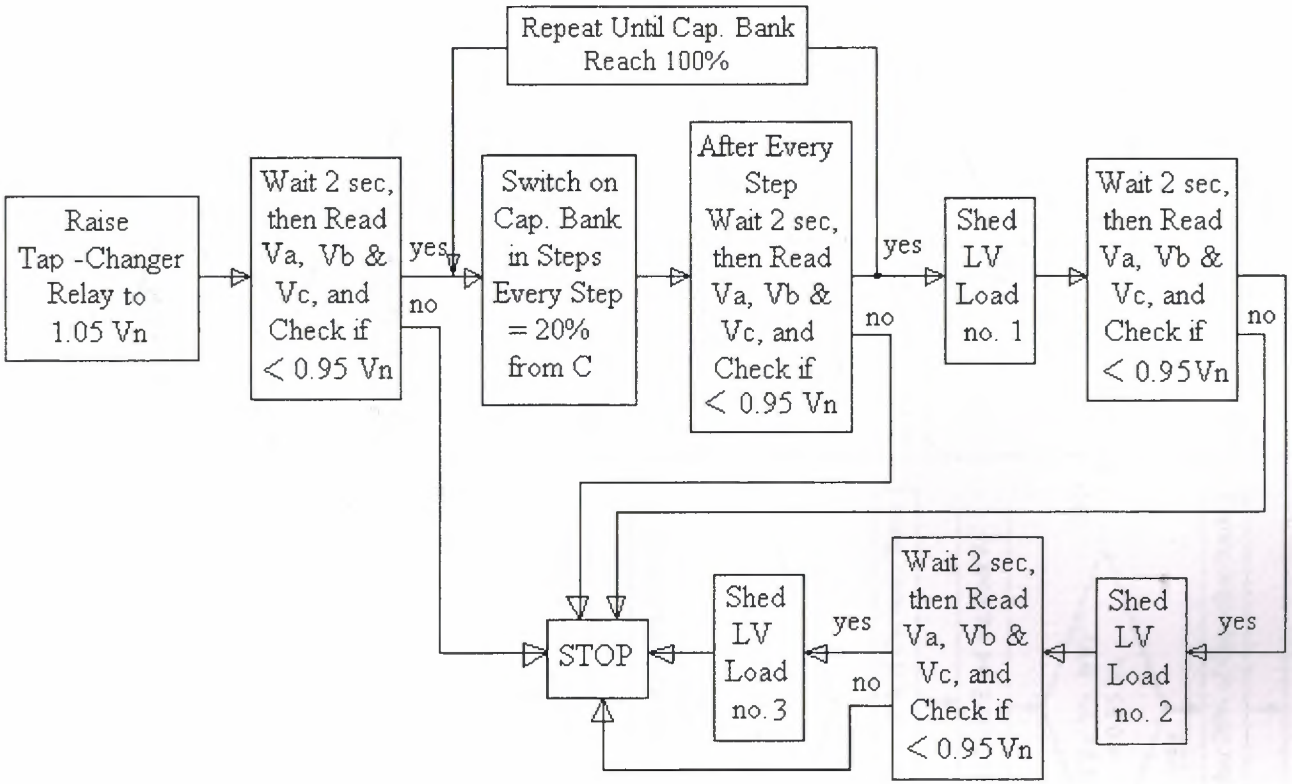


Figure 5.9 Block Diagram of the Proposed Voltage Stabilizer for Overload Cases

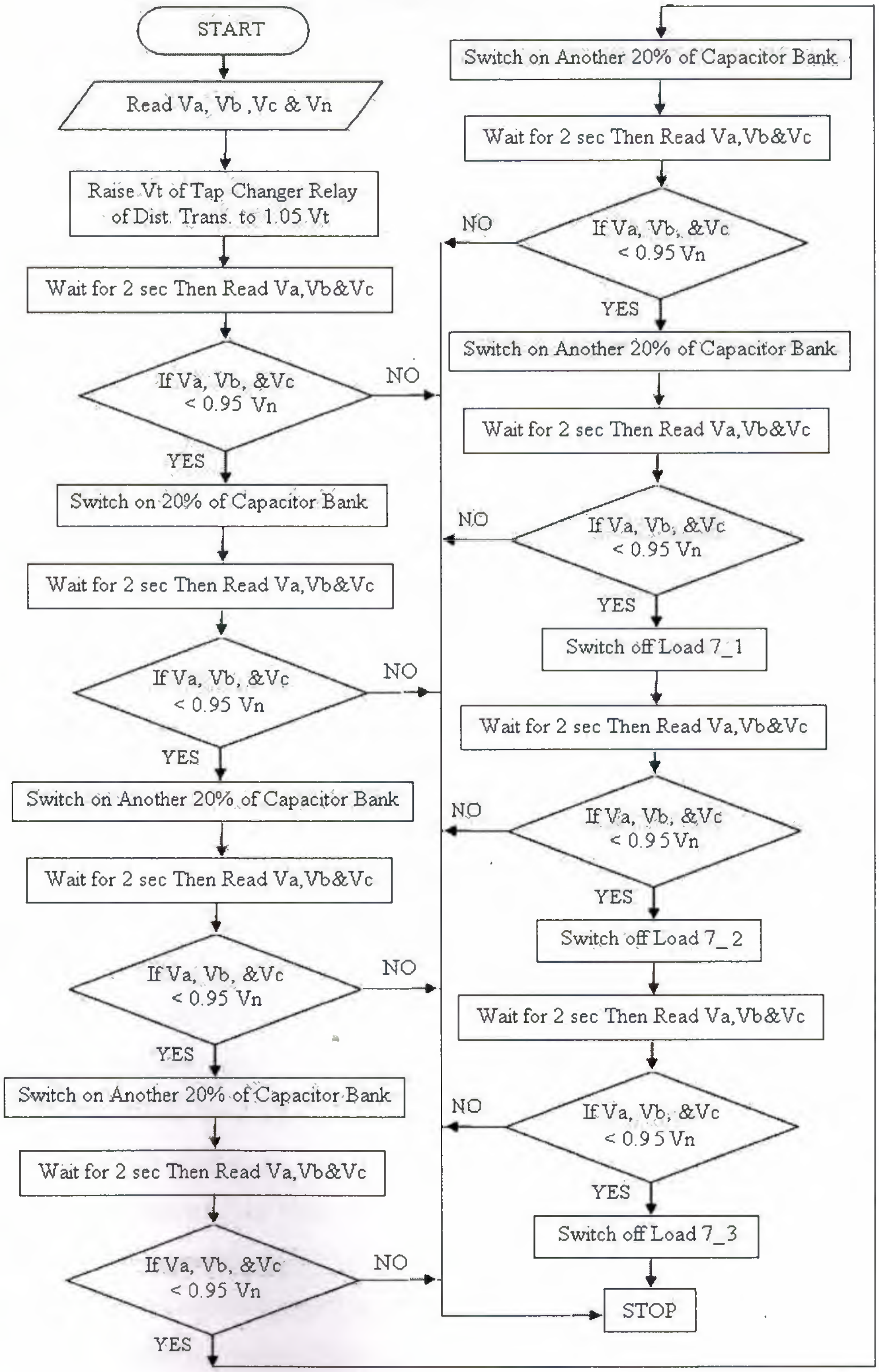


Figure 5.10 Flowchart of the Proposed Voltage Stabilizer for Overload Cases

5.5 Voltage Stabilizer for Unstable Cases

As it is illustrated in chapter 1, voltage instability is basically caused by an unavailability of reactive power support in some nodes of the network, where the voltage uncontrollably falls. Lack of reactive power may essentially have two origins. Gradual increase of power demand which reactive part cannot be met in some buses or sudden change of a network topology redirecting the power flows such a way that a reactive power cannot be delivered to some buses. Voltage instability of a substation in PDS is part of instability of the whole power system. It is caused due to faults or disturbances in its environment or due to instability of the whole power system. Procedures to restore stability of the PDS substation will be effective if the disturbances are in its environment, otherwise procedures from all PDS substations with coordination of the whole system must arise to restore stability. Local voltage stabilizer can't distinguish the cause of instability, as a results its actions to restore stability may not be effective unless it comes in comprehensive of all PDS substations and other parts of the system.

In our performance of unstable cases during simulation faults are induced in different parts in the main transmission corridor or switching off part of generators during work or starting simulation with some parts of generator are not connected to the system. Also, some faults, like line to line faults or three phases to ground faults or disconnection of one transmission line are induced in the environment of the studied substation. As a result, the cases of instability achieved are with different performance on the studied substation.

In this stabilizer the first action is shedding part of low voltage loads and fast redispatch of generation. In some instability situations switching capacitor bank may not achieve the hoped performance because the impact of their operation may be negative.

The algorithm for stability restoration is as follows:

Step 1: Redispatch generators and shed one forth of loads approximately.

Step 2: Wait 0.1 second then shed another forth of loads approximately.

Step 3: Wait 0.1 second then shed another forth of loads approximately.

Step 4: Wait 0.5 second then read Va, Vb, Vc and the frequency F.

Step 5: Wait another 0.5 second then read Va, Vb, Vc and F again.

Step 6: Check if F is decreasing or increasing, and check if Va, Vb and Vc are decreasing or increasing.

Step 7: If F is decreasing and Va, Vb and Vc are decreasing, wait few (3-5) seconds then read them again. Check if F is increasing and Va, Vb and Vc are decreasing or stay in the same level. If the answer is yes it means that stability is achieved. Wait few (3-5) seconds then switch on the last shed loads. But, if the answer is F is still decreasing, redispatch generators and stop actions.

Step 8: If the answer of step 6 is F is decreasing and the voltages are increasing, or if F is increasing and the voltages are increasing or some of them is decreasing and the others are increasing just redispatch generators and stop actions (because in case of increasing F shedding loads will not achieve stability and the excitation system of the generators must decrease excitation current).

Figure 5.11 shows the general block diagram of the proposed voltage stabilizer for unstable cases, while figure 5.12 shows the flowchart of it.

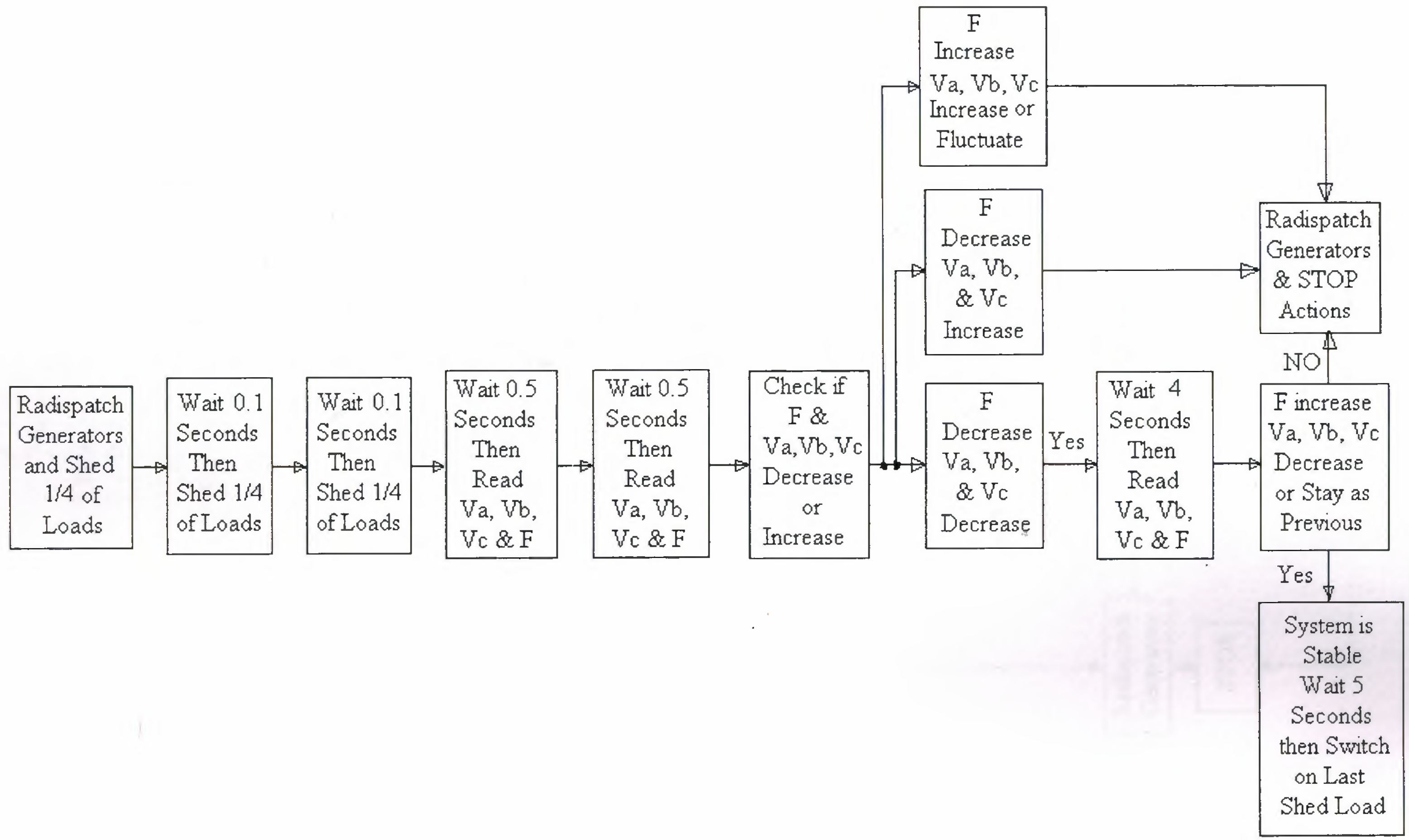


Figure 5.11 Block Diagram of Proposed Voltage Stabilizes for Unstable Cases

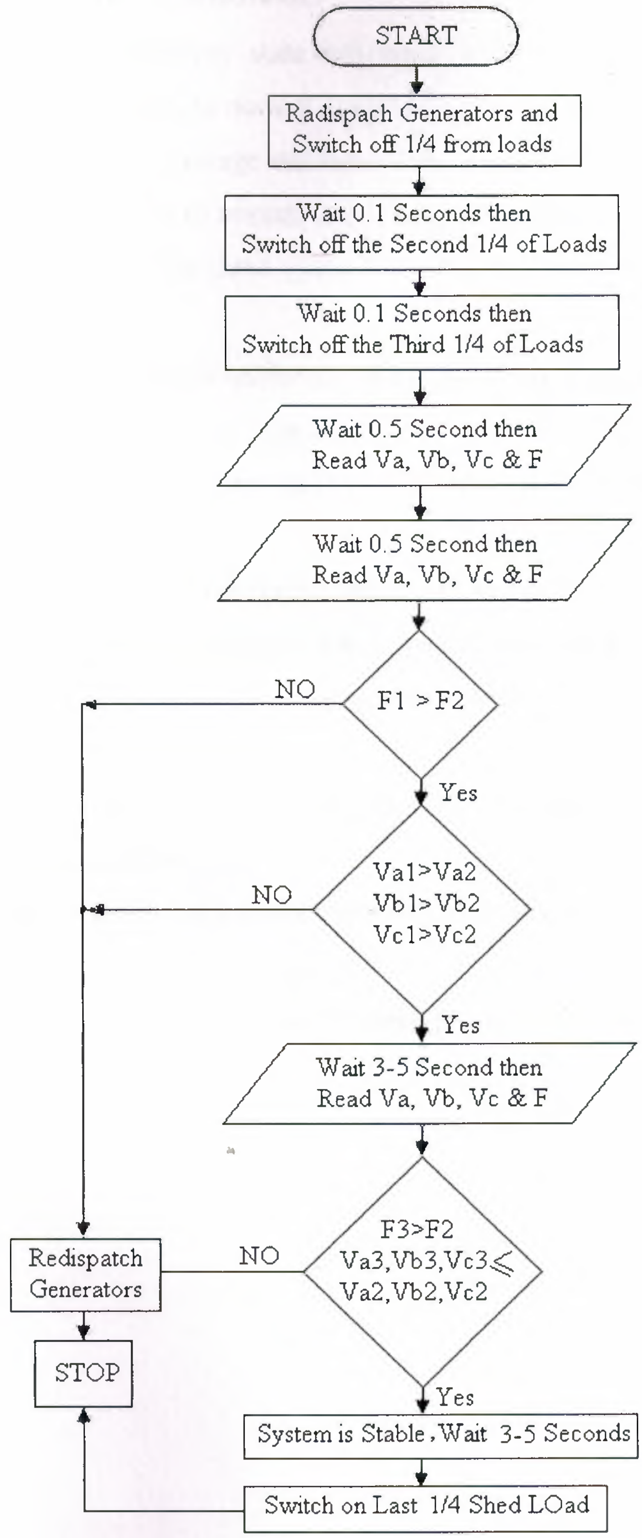


Figure 5.12 Flowchart of the Proposed Voltage Stabilizer for Unstable Cases

5.6 Recovering Normal Conditions

After overload state or instability state has been cleared and the voltages rises, then arrangements to return the PDS to normal conditions must be performed in condition these arrangement do not affect the voltage stability or force the PDS to overload. The proposed procedures to return the system to normal conditions are summarized as follows:

Step 1: Read the voltage of the three phases and check if they are equal or greater than 110% of nominal voltage.

Step 2: If the answer is yes switch on the last shed load, then wait 1 minute.

Step 3: If the answer of step 1 is no, wait 1 minute and repeat steps 1 and 2.

Step 4: Read the voltage of the three phases and check if they are equal or greater than 110% of nominal voltage.

Step 5: If the answer of step 4 is yes repeat step 2 and 4 until all loads are switched on.

Step 6: If the answer of step 4 is no, then wait 1 minute and repeat step 4.

Step 7: After waiting 1 minute read the voltages and check if they equal or exceed 110% of nominal voltage.

Step 8: If the answer is yes switch off 20% of capacitor bank and wait 1 minute.

Step 9: If the answer is no repeat step 7.

Step 10: Repeat steps 7 and 8 until all the capacitor bank switched off.

Figure 5.13 shows the flowchart of all the recovery procedures.

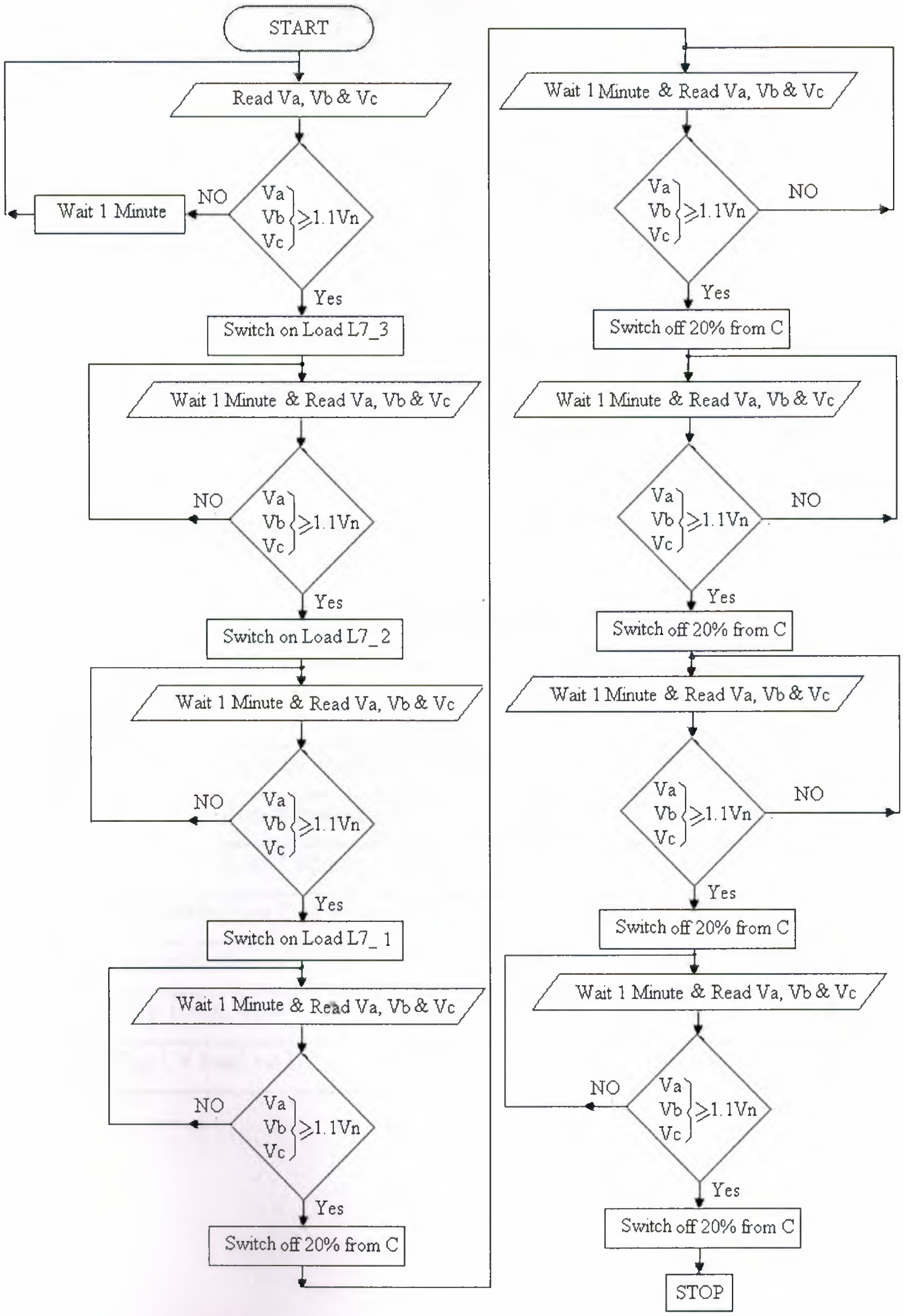


Figure 5.13 Flowchart of all the Recovery Procedures

5.7 Results

After the two branches of the stabilizer are designed, it is tested and simulated for some detected cases.

5.7.1 Simulation Results of the Voltage Stabilizer for Overload Cases

In order to prove the efficiency of the proposed voltage stabilizer (VS), it is tested by three detected cases from the neural network as overload case.

First Case is case no. 3.7 which consists from image3_7_1, image3_7_2 and image3_7_3 (see appendix B for data base). The final voltage after 20 seconds simulation, which detected by ANN as overload case, was 8.45 kV. Steps 1-13 of the voltage stabilizer for overload enhancement algorithm are performed to raise the terminal voltage of the load to 10.85 kV. The outputs of every step are listed in table 5.1 below. Also, figure 5.14 illustrates the simulated output of the proposed voltage stabilizer for overload cases.

Table 5.1: Numerical Outputs of Actions from VS for Overload Case 1

Type of Stabilizer Action	V_L after Action (kV)
Before Start	8.45
Raising Tap Changer of Transformer 5%	8.49
Switching 20% from Capacitor Bank	8.56
Switching 40% from Capacitor Bank	8.69
Switching 60% from Capacitor Bank	8.88
Switching 80% from Capacitor Bank	9.17
Switching 100% from Capacitor Bank	9.43
Shedding LV load no L7_1	10.85

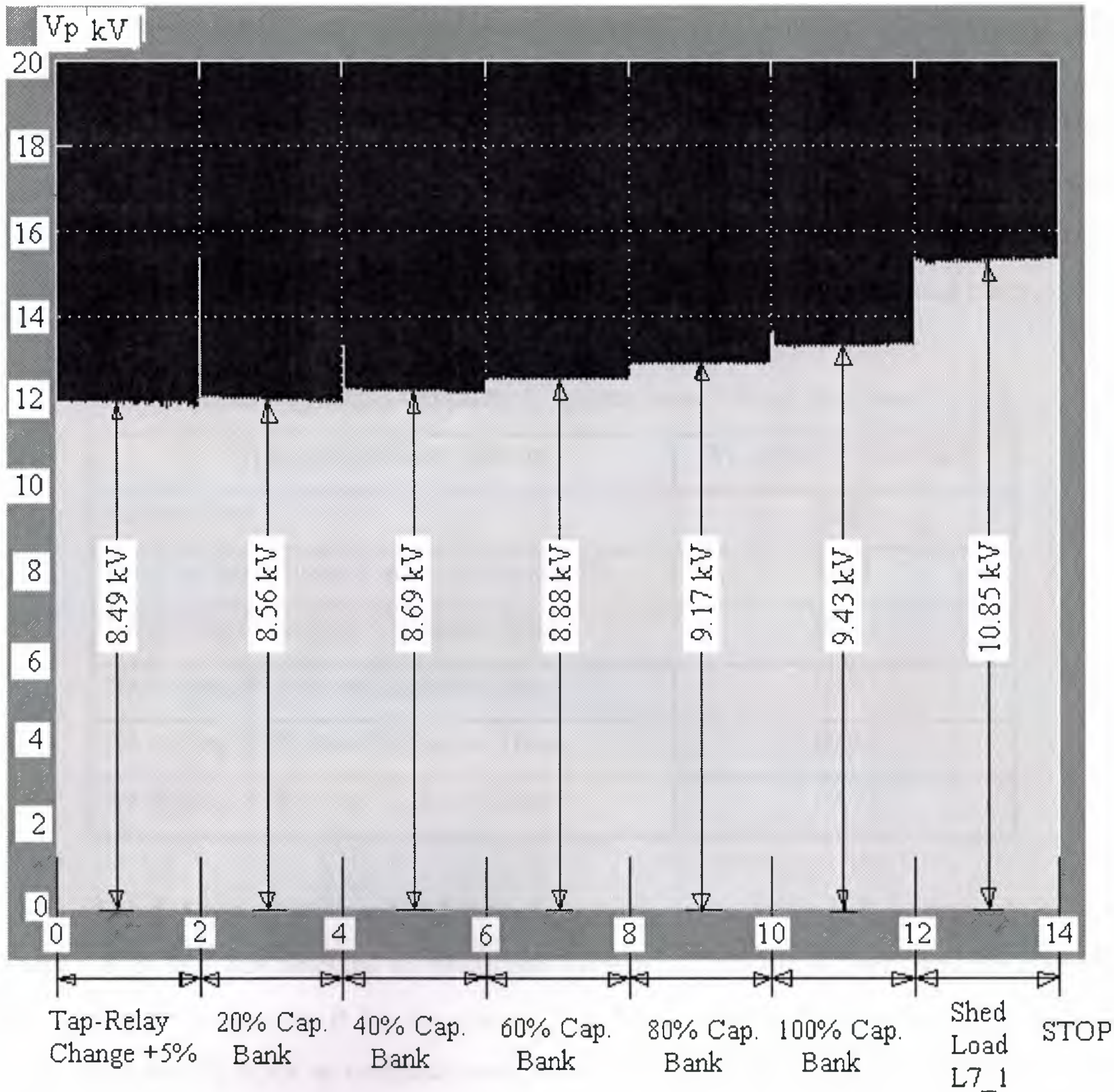


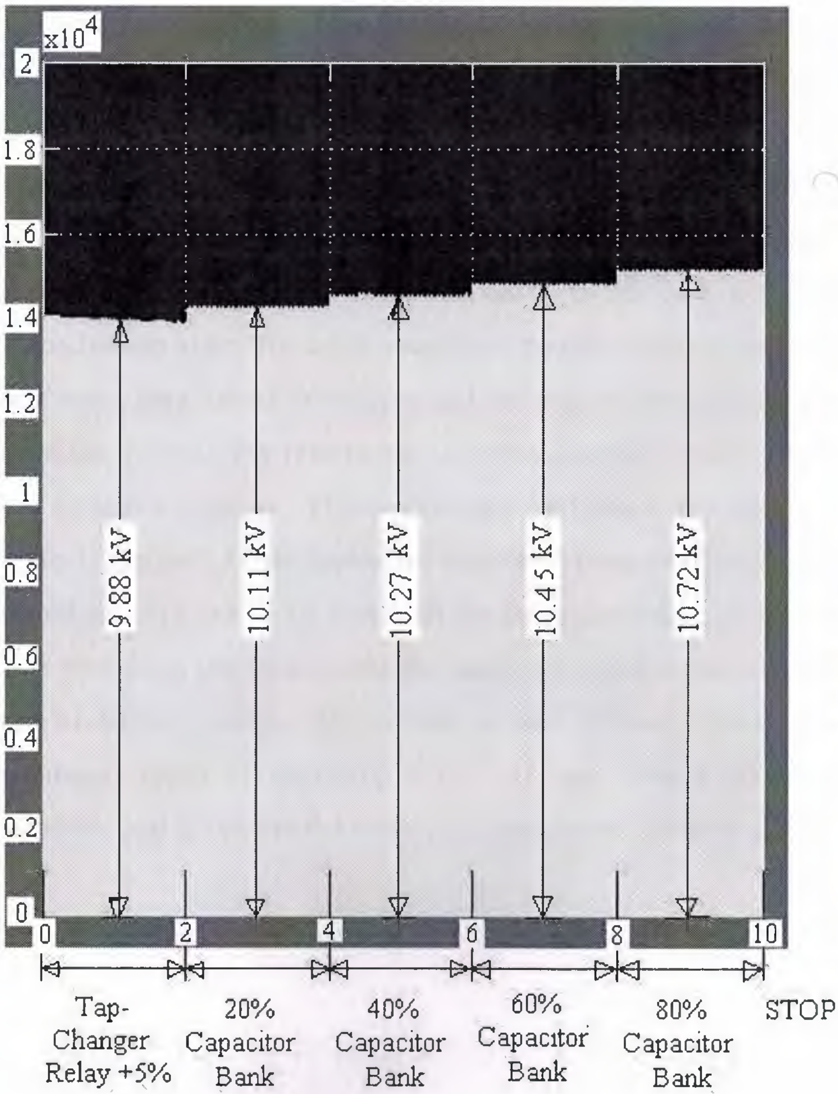
Figure 5.14 Results of Voltage Stabilizer for Overload Case 1

Second Case is case no. 3.2 which consists from image3_2_1, image3_2_2 and image3_2_3 (see appendix B for data base). The final voltage after 20 seconds simulation, which detected by ANN as overload case, was 9.83 kV. Steps 1-9 of the voltage stabilizer for overload enhancement algorithm are performed to raise the terminal voltage of the load to 10.72 kV. The outputs of every step are listed in table 5.2 below. Also, figure 5.15 illustrates the simulated output of the proposed voltage stabilizer for overload cases.

Table 5.2: Numerical Outputs of Actions from VS for Overload Case 2

Type of Stabilizer Action	**V_L after Action (kV)**
Before Start	9.83
Raising Tap Changer of Transformer 5%	9.88
Switching 20% from Capacitor Bank	10.11
Switching 40% from Capacitor Bank	10.27
Switching 60% from Capacitor Bank	10.45
Switching 80% from Capacitor Bank	10.72

Third Case is case no. 1.8 which consists from image1_8_1, image1_8_2 and image1_8_3 and was detected by intelligent system incorrectly as overload case instead of stable case (see appendix B for data base). The final voltage after 20 seconds simulation, which detected by ANN as overload case, was 10.80 kV. Only the first step of the voltage stabilizer for overload enhancement algorithm, which was raising tap changer relay of distribution transformer 5%, is performed raising the terminal voltage of the load to 11.03 kV. This value (100.3% Vn) is still in the allowed voltage range. Figure 5.16 illustrates the simulated output of the proposed voltage stabilizer for overload cases for this incorrectly detected case.



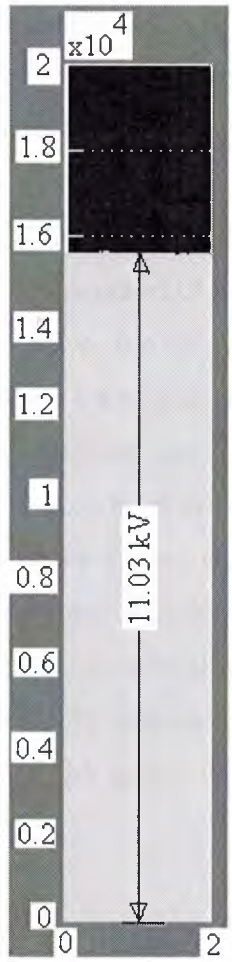


Figure 5.15 Results of Voltage Stabilizer for Overload Case 2

Figure 5.16 Results of Voltage Stabilizer for Overload Case 3

5.7.2 Simulation Results of the Voltage Stabilizer for Unstable Cases

In order to prove the efficiency of the proposed voltage stabilizer (VS) for unstable cases, it is tested by one detected cases from the neural network as unstable case in which the frequency is decreasing.

The Case is case no. 2.3 which consists from image2_3_1, image2_3_2 and image2_3_3 (see appendix B for data base). In this case, generator 1 is switched of after 8 seconds from start. The other generators couldn't deliver the needed power for the system as a result they forced to collapse and the system goes to blackout. Steps 1-8 of the voltage stabilizer for stability restoration algorithm are performed to recover the fault and sustain the system's stability. These steps are performed for all medium voltage distribution system. Figure 5.17 illustrates the simulated output of the situation of the system without stabilizer and figure 5.18 shows all the steps and output of stabilizer for this unstable case. It is seen from the figures that the stabilizer could restore stability of the system although the excitation systems of machine 2 and 3 were limited. Figure 5.19 illustrates the simulated speed of generator 2 for this case, where (a) illustrates the speed without stabilizer and (b) shows the speed after the actions from the stabilizer.

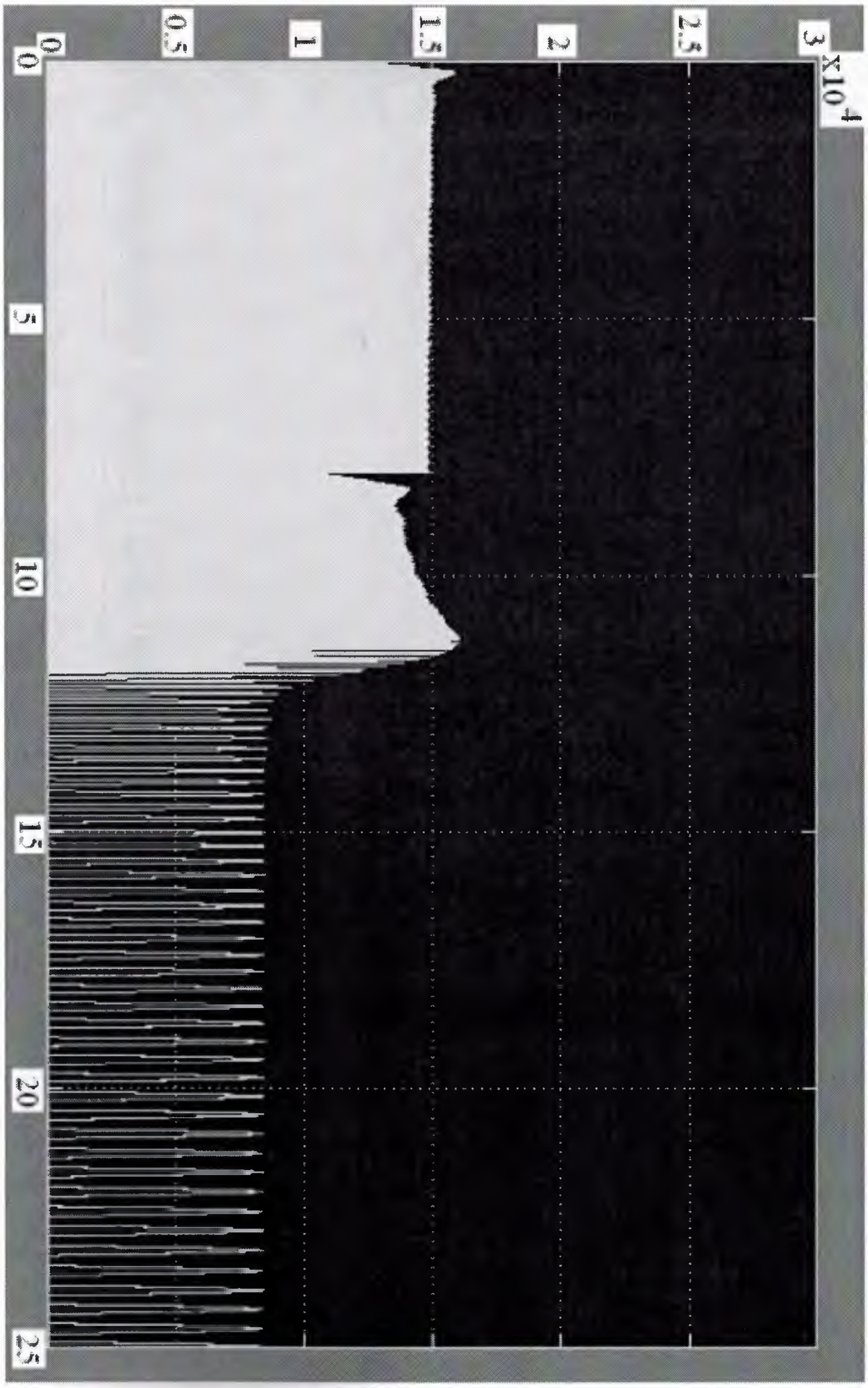


Figure 5.17 Original Unstable Case Without VS

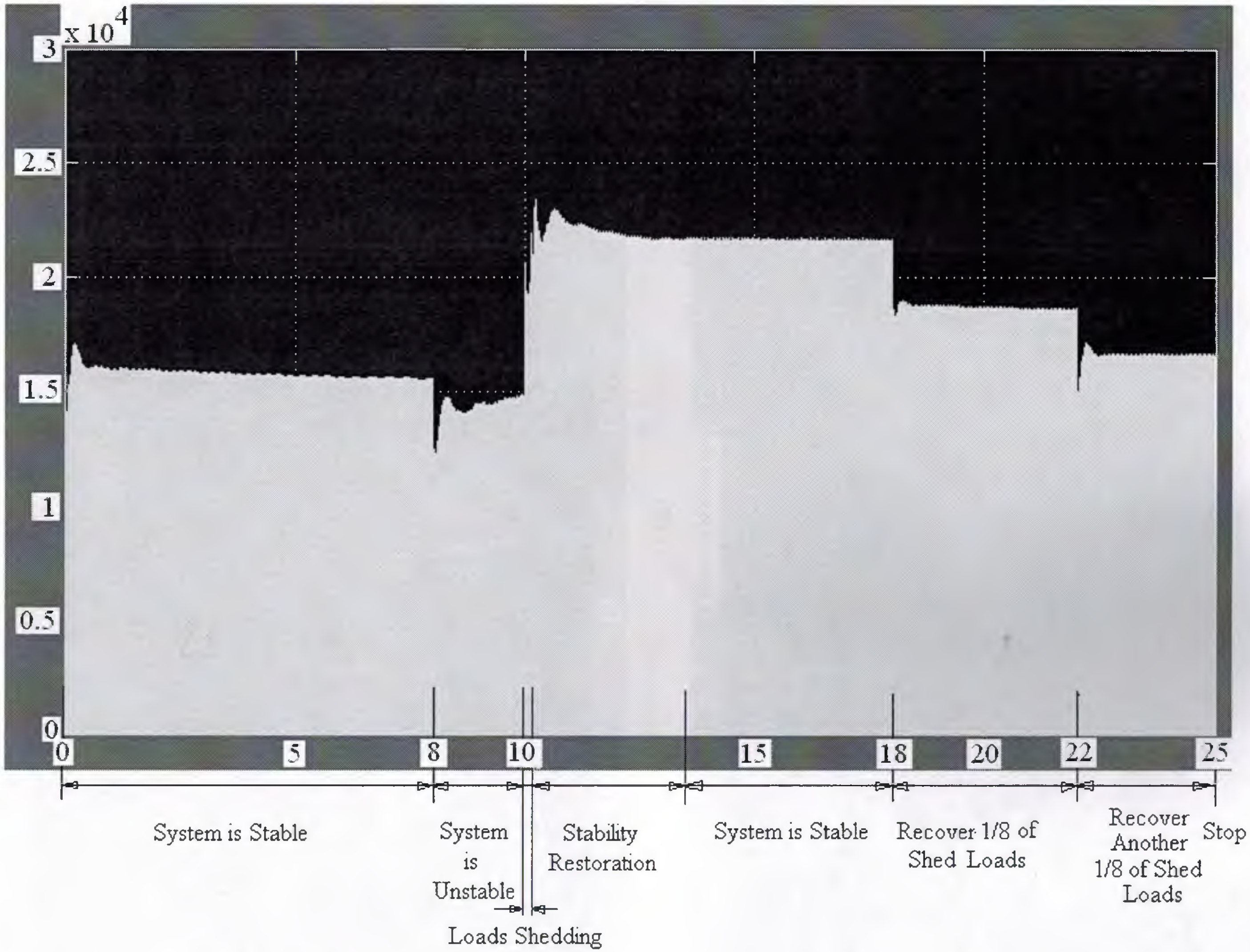
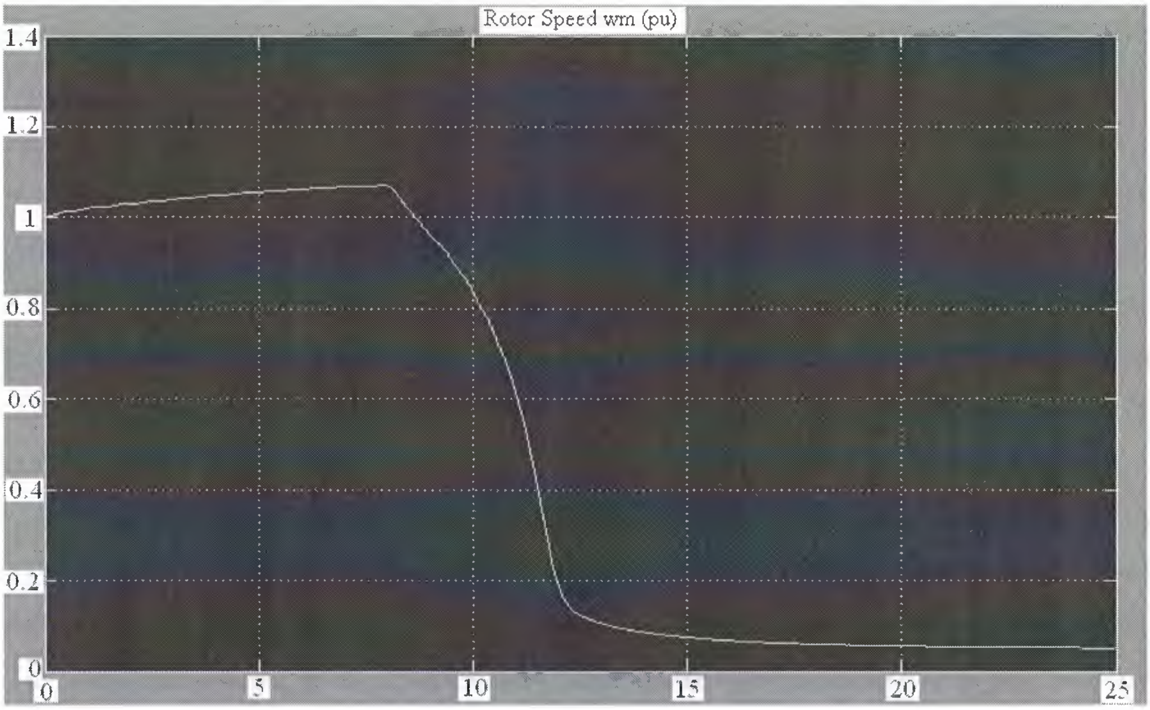
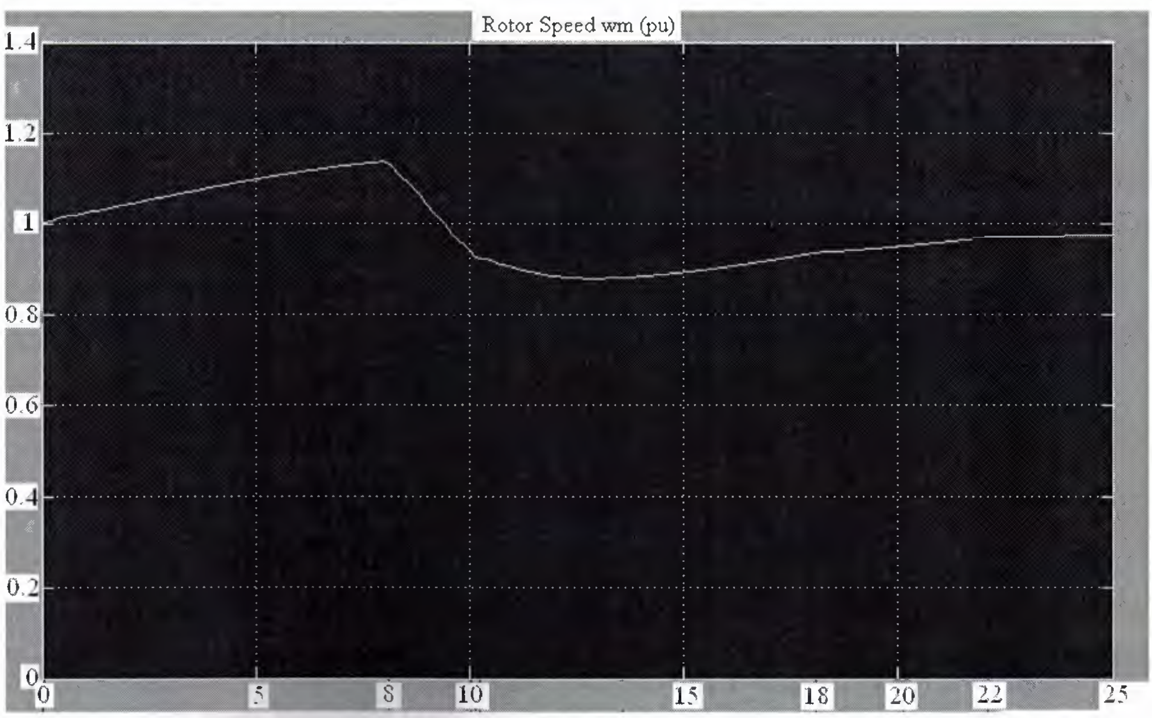


Figure 5.18 Results of VS for Unstable Case



(a)



(b)

Figure 5.19 Speed of Generator 2 (a) without VS, (b) after VS

5.8 Analysis of Results

A new voltage stabilizer (VS) for power distribution systems is designed and tested. The voltage stabilizer starts its actions according to the decision of the intelligent detection system. In case of detection an overload system the proposed voltage stabilizer performs instantaneous actions to clean the extreme voltage drop which result from the overload. After the system returns to normal loads and the overload state is cleaned, the VS starts reverse actions to recover the normal condition of the system. Also, in case of detection an unstable system the VS perform quick procedures to restore stability of the system. After assessment of the stability the VS perform inverse actions to return the system to normal conditions.

The proposed VS is tested for the two states, the overload and the unstable states by MATLAB Power Systems Simulator. Testing the VS for overload state was for three different cases. In the first case the VS is tested in an extreme voltage drop of the system. The terminal voltage of the load of substation of the distribution system was 8.45 kV (76.82% Vn), and after the instantaneous actions from the VS the terminal voltage raised to 10.85 kV (98.64% Vn). The time consumed to achieve this voltage raise (21.82% Vn) was 14 seconds. Although the least priority loads are shed, the other loads still working in normal voltages and the system is far from voltage collapse.

In the second tested case the load terminal voltage was 9.83 kV (89.36% Vn) and was raised to 10.72 kV (97.45% Vn). This voltage raise took place in 10 seconds. In this case the voltage was raised by inducing positive reactive power from the capacitor bank. Just 80% from the capacitor bank is switched on to raise the voltage 8.09% Vn and returns the system to work in normal voltage and far from voltage collapse.

The third tested case of the VS was the incorrect detection from the intelligent detection system when it is detected as overload case. The VS need one step which was raising the tap changer relay by 5% Vn to keep the system stable.

The proposed VS is also tested on one unstable case, in which the frequency was falling down quickly and the machines to collapse after machine 1 was turned off. After shedding 75% from loads the other machines increase their speed and return the system stable preventing from system collapse. The VS made orders to switch on the last ¼ shed load keeping the operating loads to work on nominal voltage. Although half loads still shed the system restore stability preventing the machines to reach to complete blackouts.

According to the above results, the proposed voltage stabilizer for power distribution system is efficient in cleaning overload and restoring stability. This VS can be implemented in PDS to work concurrent with SCADA devices to prevent voltage collapse and blackouts of the power systems, or to work alone as temporal substitute of SCADA devices.

Intelligent system on-line detection was not performed in this scheme because the simulation in MATLAB was performed on ready boxes and it is not allowed to change them. In a real power system, intelligent system on-line detection could be performed by inducing samples of voltages of the three phases instantaneously to the neural network to detect instability or overload cases.

5.9 Summary

This chapter introduced a new voltage stabilizer for power distribution system working due to the decision of the intelligent detection system. The VS was tested on 4 cases, 3 overload detection cases and 1 unstable detection case. From the above results it is proved that the proposed voltage stabilizer is efficient in keeping the system stable and not overload.

CONCLUSION

The ability to maintain system stability in a deregulated power system environment is a major challenge. Power system voltage instabilities are dynamic phenomena, in which numerous nonlinear devices are involved, can cause significant damage economically. In order to assess voltage stability and to prevent voltage collapse, research work has been carried out and is presented within this thesis. The thesis introduces an intelligent voltage stabilizer that work concurrently with SCADA system to perform quick steps to restore the stability of power distribution systems.

Design of this intelligent voltage stabilizer is based on an intelligent system on-line detection of instability or overload. As soon as the intelligent system detects unstable case or overload case, instantaneous steps are performed to sustain the power distribution system to restore its stability.

The intelligent detection system is based on an artificial neural network which uses back propagation learning algorithm. The ANN is trained on earlier events for instability or voltage collapse, to detect on-line instability or overload of power distribution system. An assumed power system was designed and simulated in MATLAB. Part of output voltage images were preprocessed to form patterns to be induced to the ANN for training and the rest for testing. Results of testing show the efficiency of the ANN in detecting instability and overload with high recognition rates and accuracy.

The voltage stabilizer which uses the decision of the intelligent system reacts in quick steps to restore the voltage stability of the distribution system or to clean the extreme voltage drop which caused by the overload state of the system. The organized steps to overcome the overload state are summarized in raising tap changer relays of distribution transformers, switching capacitor banks in steps and then if necessary shedding part of low voltage loads. If the voltage stabilizer is sensed for instability it goes directly to shed part of loads in the low voltage level to help in preventing the machines from switching off.

The stabilizer was tested with three overload cases and one instability case in which the main generator failed to feed the system with power forcing the other machines to sharply slow their speed. In the three cases of overload the stabilizer succeeded to raise the load voltage to allowed level in short time. Also, it succeeded to restore the stability of the system and to prevent the system to go to blackout.

The successful implementation of the intelligent detection system in detecting instability and overload of the PDS with high recognition rates and accuracy suggests that it could be efficiently used as a first phase of the intelligent voltage stabilizer to detect on-line instability and overload, which makes stability restoration quicker and more efficient. Also, the accurate performance of the second phase, which is the voltage stabilizer, in cleaning the voltage drop in the PDS and restoring the stability of a power system that was at the edge of instability danger preventing from blackout to the whole system, recommends using such a voltage stabilizer to work concurrently with SCADA system in keeping the PDS more stable.

The implementation of this work used an assumed power system with the following considerations:

- The power system parameters (generators, transmission lines, distribution transformers and buses variables) are not included in the design of the voltage stabilizer, thus the results of it were evaluated accordingly.
- The outputs of this program are not compared with any program available and the efficiency of the system was evaluated accordingly.
- The fault clearing duration for real power systems is 0.05 seconds but in simulation process it is set to 2 to 3 seconds.
- Single phase to ground faults contribute 80% of faults but in simulation of faults to achieve unstable cases, equal cases of three phases, two phases and single phase faults are performed.

Future work and future development of the proposed system include redesigning the voltage stabilizer to be fully intelligent by increasing the dependence on the intelligent system to find the direct optimal solution to clean the deep voltage drop or to find the optimal quantity of loads to be shed in order to restore stability quickly.

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APPENDIX A

MATLAB Programs

A.1 Neural Network Training and Testing Program

```
clear all
close all
clc
image_number = 3;
image_expression1 = 10;
image_expression2 = 3;
PATTERNS1 = [];
PATTERNS2 = [];
t = cputime;
cd( 'C:\Documents and Settings\Administrator\Desktop\new Voltage Outputs Train')
for k = 1:image_number
   for l = 1:image_expression1
      for m = 1:image_expression2
         IM = strcat(['image' int2str(k),'_' int2str(l),'_' int2str(m),'.jpg']);
         OI = imread(IM);
         GI = rgb2gray(OI);
         SI = imresize(GI,[400 202],'bicubic');
         for c = 2:201
            for d = 1:400
            n=401-d;
            if SI(n,c)<= 150
            vector_image = reshape(d,[],1);
            PATTERNS1 = [PATTERNS1 vector_image];
            break
            end
            end
         end
      end
   end
end
vector_image2 = reshape(PATTERNS1,[],(image_number*image_expression1));
PATTERNS2 = [PATTERNS2 vector_image2]/400;
Pre_Processing_Time = cputime - t;
disp(sprintf('PRE-PROCESSING TIME IS %8.4f',Pre_Processing_Time));% Display the
processing time
%%%%***** Neural Network *****%%%%
deserror = 0.002;                  % Desired Error
ETA = 0.001;                       % Learning Rate
ALP = 0.33;                        % Momentum Factor
```

```
maxiter=30000;                    % Maximum iteration
%%%% Training Patterns %%%%
PATTERNS2;
%%%% Desired Output %%%%
T1 = [1;0;0];
T2 = [0;1;0];
T3 = [0;0;1];
PATT = 30;                        % no of patterns
a = -0.31; b = 0.31;
for j= 1 : PATT
j;
hidw = a + (b-a) * rand(28,600);        % Selection the weights values between -0.31 and
0.31
outw = a + (b-a) * rand(3,28);
dhidw=0;                          % Initiate the change of hidden weight as zero
doutw=0;                          % Initiate the change of output weight as zero
hidb = a + (b-a) * rand(28,1);          % Selection the weights values Of Bias Neurons
between 0.31 and -0.31
outb = a + (b-a) * rand(3,1);
dhidb=0;                          % Initiate the change of hidden weight as zero
doutb=0;                          % Initiate the change of output weight as zero

TARGET = [T1 T1 T1 T1 T1 T1 T1 T1 T1 T1 T2 T2 T2 T2 T2 T2 T2 T2 T2 T2 T3 T3 T3
T3 T3 T3 T3 T3 T3 T3];
out1(:,j) = PATTERNS2(:,j);             % Forward pass, compute outputs out1
neth = (hidw * out1(:,j));
out2(:,j) = logsig( neth );             % Forward pass, compute outputs out2
neto = (outw*out2(:,j));
out3(:,j) = logsig( neto );             % Forward pass, compute outputs out3
out3(:,j);
end
e =TARGET - out3;                       % Calculate the error
error = 1/2*(mean(diag(e).*diag(e)));
iter=1;                                 % Initiate the iteration
t = cputime;                            % Begin processing time calculation
while error >= deserror & iter<maxiter    % Compare the error with goal error
   for j=1:PATTERN
dfout2 = dlogsig( neth , out2(:,j) ;
dfout3 = dlogsig( neto , out3(:,j) ;     % Calculate the signal error
dout = -2*diag(dfout3) * e(:,j);        % Adjustments at output layer
dhid = diag(dfout2) * outw'* dout;      % Adjustments at hidden layer
oldoutw = outw;
oldhidw = hidw;
oldoutb = outb;
oldhidb = hidb;
```

```
outw = outw - (1-ALP)*(ETA*dout*out2(:,j)' + ALP*doutw;  % Update Weight of output
layer
hidw = hidw - (1-ALP)*(ETA*dhid*out1(:,j)' + ALP*dhidw;  % Update Weight of hidden
layer
outb = outb - (1-ALP)*(ETA*dout) + ALP*doutb ;  % Update bias Weight of output layer
hidb = hidb - (1-ALP)*(ETA*dhid) + ALP*dhidb;  % Update bias Weight of hidden layer
dhidw = hidw-oldhidw;                % Calculate the change of hidden weight
doutw = outw - oldoutw;              % Calculate the change of output weight
dhidb = hidb - oldhidb;              % Calculate the change of hidden weight from Bias
Neuron
doutb = outb - oldoutb;              % Calculate the change of output weight from Bias
Neuron
out1(:,j) = PATTERNS2(:,j);              % Calculate the outputs again
neth = (hidw * out1(:,j))+hidb;
neto = (outw*out2(:,j))+outb;
out3(:,j) = logsig( neto );
   end
out3;
e = TARGET - out3;
error = 1/2*(mean(diag(e).*diag(e)));       % Calculate the mean sguare value of the error
disp(sprintf('ITER No.%6d       Mean Square Error =%10.5f%',iter,error));% Display the
error and the iteration
mse(iter)=error;
iter=iter+1;
end
Training_Time = cputime - t;                          % End processing time calculation
disp(sprintf('TRAINING TIME IS %8.4f',Training_Time));% Display the processing time
plot(mse,'k');
xlabel('ITERATION');
ylabel('MEAN SQUARE ERROR');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Test the patterns and default the output after training
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for i=1:PATT
PATTERNS2;
Train_out1 = PATTERNS2(:,i);
neth = (hidw * Train_out1)+hidb;
Train_out2 = logsig( neth );
neto = (outw * Train_out2)+outb;
Train_out3 = logsig( neto );
TRAIN_RESULTS = Train_out3
end
One_Forward_Run_Time = cputime - t;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%% This Part of Program is for Test
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
disp(sprintf('If You Want To Continue To Test Press Enter'));
pause
image_number = 3;
image_expression11 = 8;
image_expression12 = 3;
PATTERNS3 = [];
PATTERNS4 = [];
Tolirance = 0.8;
cd( 'C:\Documents and Settings\Administrator\Desktop\new Voltage Outputs Test')
for k = 1:image_number
  for l = 1:image_expression11
    for m = 1:image_expression12
      IM = strcat(['image' int2str(k),'_' int2str(l),'_' int2str(m),'.jpg']);
      OI = imread(IM);
      GI = rgb2gray(OI);
      SI = imresize(GI,[400 202],'bicubic');
      for c = 2:201
        for d = 1:400
          n=401-d;
          if SI(n,c)<= 150
          vector_image3 = (reshape(d,[],1))/400;
          PATTERNS3 = [PATTERNS3 vector_image3];
          break
          end
        end
      end
    end
  end
end
PATTEST = image_number*image_expression11;
vector_image4 = (reshape(PATTERNS3,[],(PATTEST)));
PATTERNS4 = [PATTERNS4 vector_image4];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for i=1:image_expression11
PATTERNS4;
Test_out1 = PATTERNS4(:,i);
neth = (hidw * Test_out1)+hidb;
Test_out2 = logsig( neth );
neto = (outw * Test_out2)+outb;
Test_out3 = logsig( neto );
TEST_RESULTS = Test_out3;
  if  Test_out3(1,:)>=Tolirance
  disp(sprintf('Stable Case    Recognition Percentage = %4.2f',Test_out3(1,:)*100));
  end
  if  Test_out3(1,:)<Tolirance
    max(Test_out3(j,:));
```

```
        if j==1
        disp(sprintf('Stable Case      Recognition Percentage = %4.2f',Test_out3(1,:)*100));
        elseif j==2
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
        elseif j==3
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
        end
    end
end
for i=(image_expression11+1):(image_expression11*2)
PATTERNS4;
Test_out1 = PATTERNS4(:,i);
neth = (hidw * Test_out1)+hidb;
Test_out2 = logsig( neth );
neto = (outw * Test_out2)+outb;
Test_out3 = logsig( neto );
TEST_RESULTS = Test_out3;

    if  Test_out3(2,:)>=Tolirance
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
    end
    if  Test_out3(2,:)<Tolirance
        max(Test_out3(j,:));
        if j==1
        disp(sprintf('Stable Case      Recognition Percentage = %4.2f',Test_out3(1,:)*100));
        elseif j==2
        disp(sprintf('Unstable Case     Recognition Percentage = %4.2f',Test_out3(2,:)*100));
        elseif j==3
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
        end
    end
end
for i=(image_expression11*2 +1):(image_expression11*3)
PATTERNS4;
Test_out1 = PATTERNS4(:,i);
neth = (hidw * Test_out1)+hidb;
Test_out2 = logsig( neth );
neto = (outw * Test_out2)+outb;
Test_out3 = logsig( neto );
TEST_RESULTS = Test_out3;
    if  Test_out3(3,:)>=Tolirance
        disp(sprintf('Overload Case     Recognition Percentage = %4.2f',Test_out3(3,:)*100));
    if  Test_out3(3,:)<Tolirance
        max(Test_out3(j,:));
        if j==1
        disp(sprintf('Stable Case      Recognition Percentage = %4.2f',Test_out3(1,:)*100));
```

```
        elseif j==2
        disp(sprintf('Unstable Case      Recognition Percentage = %4.2f',Test_out3(2,:)*100));
        elseif j==3
        disp(sprintf('Overload Case      Recognition Percentage = %4.2f',Test_out3(3,:)*100));
        end
    end
end
```

A.2 Voltage Stabilizer for Overload Cases program

```
Start
Vn = input('Inter Vn value = ');
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
QC = input('Inter maximum Reactive capacitor bank value (kVAR) = ');
Vta = 1.05*Va
Vtb = 1.05*Vb
Vtc = 1.05*Vc
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
   QC_bank = 0.2*QC
else
   disp('Stop  Actions');
   break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
   QC_bank = QC_bank + 0.2*QC
else
   disp('Stop  Actions');
   break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
   QC_bank = QC_bank + 0.2*QC
else
   disp('Stop  Actions');
   break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
```

```
    QC_bank = QC_bank + 0.2*QC
else
    disp('Stop  Actions');
    break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
    QC_bank = QC_bank + 0.2*QC
else
    disp('Stop  Actions');
    break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
    L7_1 = 0
else
    disp('Stop  Actions');
    break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
    L7_2 = 0
else
    disp('Stop  Actions');
    break
end
pause(2)
Va = input('Inter Va value = ');
Vb = input('Inter Vb value = ');
Vc = input('Inter Vc value = ');
if Va < 0.95*Vn & Vb < 0.95*Vn & Vc < 0.95*Vn
    L7_3 = 0
else
    disp('Stop  Actions');
    break
end
```

A.3 Voltage Stabilizer for Unstable Cases Program

```
Start
L1_1 = 0
L2_1 = 0
L3_1 = 0
L4_1 = 0
L5_1 = 0
L6_1 = 0
L7_1 = 0
L1_2 = 0
L2_2 = 0
L3_2 = 0
L4_2 = 0
pause(0.1)

L5_2 = 0
L6_2 = 0
L7_2 = 0
L1_3 = 0
L2_3 = 0
L3_3 = 0
L4_3 = 0
L5_3 = 0
L6_3 = 0
L7_3 = 0
pause(0.2)

L1_4 = 0
L2_4 = 0
L3_4 = 0
L4_4 = 0
L5_4 = 0
L6_4 = 0
L7_4 = 0
L1_5 = 0
L2_5 = 0
L3_5 = 0
L4_5 = 0
pause(0.5)
Va1 = input('Inter Va1 value = ');
Vb1 = input('Inter Vb1 value = ');
Vc1 = input('Inter Vc1 value = ');
F1 = input('Inter Frequency F1 value = ');
pause(0.5)
```

```
Va2 = input('Inter Va2 value = ');
Vb2 = input('Inter Vb2 value = ');
Vc2 = input('Inter Vc2 value = ');
F2 = input('Inter Frequency F2 value = ');
if F1 < F2
  disp('Stop  Actions');
  break
else
   if Va1<Va2 & Vb1<Vb2 & Vc1<Vc2
    disp('Stop  Actions');
    break
   else
      pause(4)
      Va3 = input('Inter Va3 value = ');
      Vb3 = input('Inter Vb3 value = ');
      Vc3 = input('Inter Vc3 value = ');
      F3 = input('Inter Frequency F3 value = ');
      if F3<F2
        disp('Stop  Actions');
        break
      else
        if Va3>Va2 & Vb3>Vb2 & Vc3>Vc2
         disp('Stop  Actions');
        break
        else
        disp('System is Stable');
        pause(4)
        L1_4 = 1
        L2_4 = 1
        L3_4 = 1
        L4_4 = 1
        L5_4 = 1
        L6_4 = 1
        L7_4 = 1
        L1_5 = 1
        L2_5 = 1
        L3_5 = 1
        L4_5 = 1
        disp('Stop  Actions');
        break
        end
      end
   end
end
```

APPINDEX B

INTELLIGENT SYSTEM DATABASE

B.1 Training Set Database


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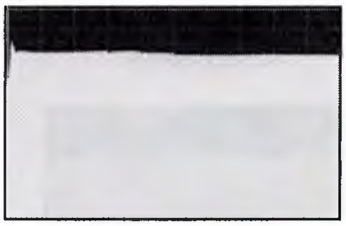
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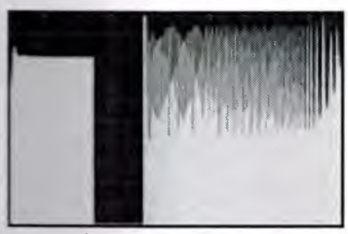
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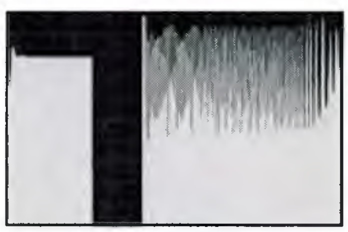
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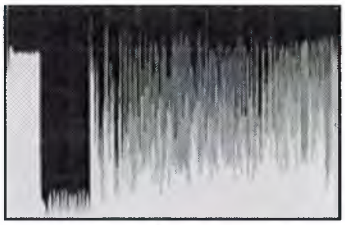
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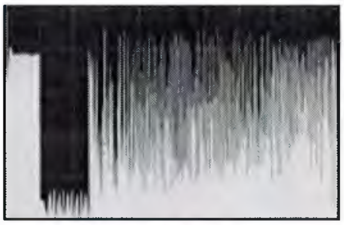
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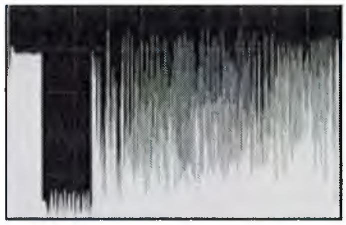
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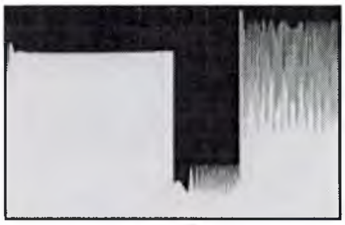
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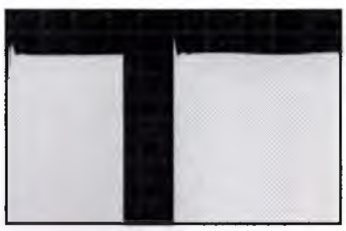
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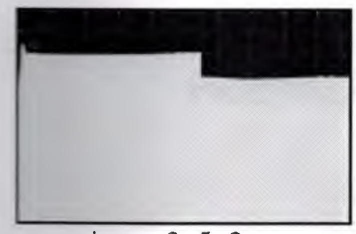
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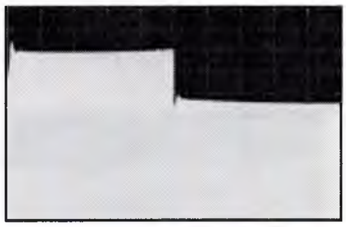
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B.2 Testing Set Database


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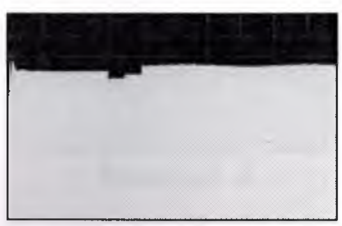
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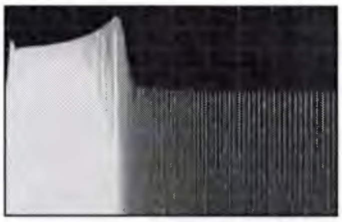
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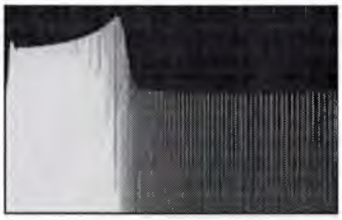
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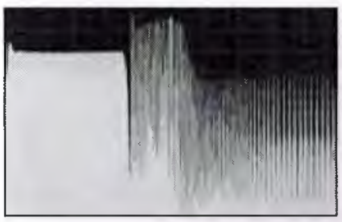
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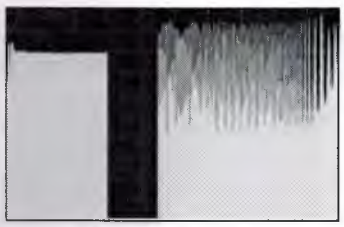
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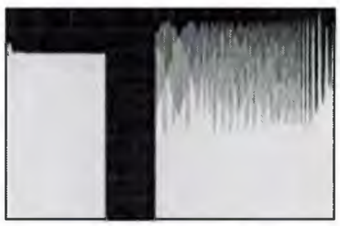
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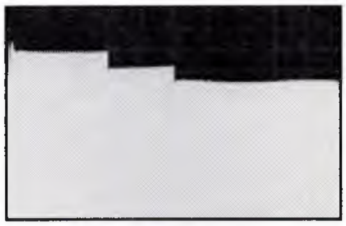
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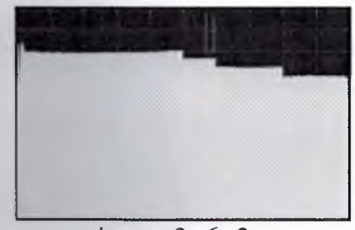
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image3_7_1


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image3_7_3


image3_8_1


image3_8_2


image3_8_3