Preamble

Accurate and precise estimation of voltage instability has been a great concern of the power engineers over the last few decades. The inevitable effects of instability can only be avoided by fast and exact prediction and corresponding preventive action. Classical methods of voltage instability determination have been analyzed to be accurate but not prompt enough for real time instability computation and prevention. The objective of this chapter is to develop an Artificial Neural Network based model to predict the voltage instability in real time. The developed model is accurate, sensitive and faster responsive with the alteration of the active and reactive power demand.
3.1 INTRODUCTION

Voltage control and stability problems are very much familiar to the electric utility industry but are now receiving special attention by power system analysts and researchers. With growing size of a power system along with economic and environmental pressures, the possible threat of voltage instability is becoming increasingly pronounced. Several factors contribute to voltage collapse such as rise of loading on transmission line, reactive power constraints, on load tap changer dynamics and load characteristics. Truly, voltage instability implies an uncontrolled decrease in voltage triggered by a disturbance, leading to voltage collapse and it is primarily caused by system dynamics. It is also believed among professionals that the existing transmission systems will be more and more utilized due to socio-economic concern, which makes it difficult to build new power plants and/or transmission lines. As a result the stress on the existing system will increase. Researches are going on for long to study the voltage instability in an interconnected system. In this context, it has been found that classical calculations of voltage stability index or point of voltage collapse has been discussed in many literatures. On the other hand, Artificial Neural Network (ANN) has attracted a great deal of attention because of its pattern recognition capabilities and its ability to handle corrupted data. ANN has been successfully applied in numerous power-engineering problems. It is a massively parallel-distributed information-processing unit that has been inspired by the biological nervous system. It reflects a practical classification approach that can draw the experience and knowledge of an engineer. An ANN is trained it with a set of input and output patterns from which it then learn the linking association of input and output. But, its ability to perform well is affected by the chosen training data as well as network topology and training scheme.

The stability indices for recognizing voltage instability or collapse have been depicted in first part of the following sections. The second part, however, focuses on the Artificial Neural Network technique for pattern recognition. In this respect, the classical calculation of voltage stability indices and implementation of an ANN based model to predict voltage stability to relieve System Operator from the tedious calculation have been discussed to establish the applicability of ANN in modern power network.

3.2 THEORETICAL DEVELOPMENT OF VOLTAGE STABILITY AND VOLTAGE COLLAPSE

One of the most fundamental concepts in AC power transmission is stability. It is the property of the power system that enables its operation in the intended mode where power flows through entire network and the power angles have their magnitude within specified
limits. It maintains synchronism between the synchronous machines (chief sources of power generation) and also ensures that the system voltage and currents do not exceed the rated values. Stability of an AC power system is also denoted by its capability to recover from planned and unplanned electrical disturbances and outages, viz. switching operation, faults, and variation in load demand etc.

Hence the stability studies are an integral part of power system planning and should be carried out in order to assure appropriate operation of the system. The study of stability is broadly categorized into two parts viz. angle and voltage stability. Stability, depending upon the disturbance can be of three different types: steady state, transient and dynamic. The steady state stability is the ability of a system to return to its normal operation after being subjected to slow and continuous disturbance or increase in load. The transient stability, however, is the capability of a system to restore its operation to a stable point on occurrence of a fast and sudden disturbance like load pull out. The time scale of dynamic stability lies in between steady state and transient stability. The voltage stability, however, is the ability of the system to sustain its voltage under variable operating conditions. In the following subsections the causes of voltage instability have been discussed.

### 3.2.1 Theoretical Background of Voltage Instability and its Causes

The voltage decline is often monotonous and small at the onset of the collapse and difficult to detect. A sudden and probably unexpected increase in the voltage decline often marks the start of the actual collapse. It is not easy to distinguish this phenomenon from angle (transient) stability where voltages also can decrease in a manner similar to voltage collapse (Figure 3.1). Only careful post-disturbance analysis may in those cases reveal the actual cause.

During the last decades there have been one or several large voltage collapses almost every year somewhere in the world. The main reason may be higher degree of utilization of the power system, leading to a decreasing system security. Also, the changing load characteristics, increased use of air conditioners and electrical heating appliances may other causes for loosing system stability radically. The incidents that lead to a real breakdown of the system are rare, but when they occur they have large repercussions on society.

Due to the continuous increase in reactive power demand, power systems will be used with a smaller margin to voltage collapse. The reasons are: the need to use the invested capital efficiently and difficulties in supervising a deregulated market. In this view, voltage stability is believed to be of greater concern in the future and if not proactively analyzed and controlled, can be incredibly erratic to cause failure of synchronism of the different parts of the network.
Nearly all types of contingencies and even slowly increased load could cause a voltage stability problem. The time scale for the course of events, which develops into a collapse, may vary from around a second to several tens of minutes. This makes voltage collapse difficult to analyze since there are many phenomena that interact during such a time span (Figure 3.2). Important processes that interact during a voltage decline lasting several minutes are among others: generation limitation, behavior of on-load tap changers and load alteration. The actions of these components are often studied in long-term voltage stability studies.

Voltage instability is a very frequent problem that can arise in a power system. A typical property of voltage stability is that the system frequency usually is fairly constant until the very end of its collapse. This indicates that the balance is kept between production and active load demand. Power oscillations between different areas in the system can be a limiting phenomenon on its own but may also appear during a voltage instability mixing voltage instability issues with electro-mechanical oscillations.
The followings are the formal definitions according to IEEE, of terms related to voltage stability:

- **Voltage Stability** is the ability of a system to maintain voltage so that when load admittance is increased, load power will increase, and both power and voltage are controllable.

- **Voltage Security** is the ability of a system, not only to operate stably, but also to remain stable (as far as the maintenance of system voltage is concerned) following any reasonably credible contingency or adverse system change.
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- **Voltage Collapse** is the process by which voltage instability leads to loss of voltage in a significant part of the system.

In the following sub-section, the voltage stability indices and analytical methods required for the identification of voltage instability, collapse and security have been furnished. The system operator, by the determination of these indices will be able to predict the stability of the system in terms of voltage.

### 3.2.2 Few Relevant Analytical Methods and Indices for Voltage Stability Assessment

The typical quasi-steady state description of a power system applicable to voltage stability analysis is given by the differential algebraic equations (3.1)

\[
\begin{align*}
\dot{x} &= f(x, y, \lambda) \\
0 &= g(x, y, \lambda)
\end{align*}
\]  

(3.1)

where \( x \) corresponds to the system state variables and \( y \) represents the 'algebraic' variables. The variable \( \lambda \) stands for a parameter or a set of parameters that change 'slowly' with time so that the system moves from one equilibrium point to another until reaching the collapse point. Another way of representing the system is by defining \( z = [x, y]^T \), so that (3.1) can be rewritten as

\[
\begin{bmatrix}
\dot{x} \\
0
\end{bmatrix} = F(z, \lambda)
\]  

(3.2)

If we assume that the Jacobian \( D_x g(\cdot) [\partial g/\partial y] \) in (3.1) is nonsingular along some system trajectories of interest, these equations can be reduced to

\[
\dot{x} = f\left(x, y^{-1}(x, \lambda), \lambda\right) = s(x, \lambda)
\]  

(3.3)

This reduction requires that \( D_x g(\cdot) [\partial g/\partial y] \) is locally nonsingular along these trajectories.

An equilibrium point \((z_0, \lambda_0)\) of (3.1) is defined by \( F(z_0, \lambda_0) = 0 \). Hence based on the non-singularity assumption of the algebraic equations, an equilibrium point \((z_*, \lambda_*)\), where \( D_x F(z_*, \lambda_*) \) [or, \( \partial F(z_*, \lambda_*)/\partial z \)] is singular, is mathematically known as a 'singular' bifurcation point [271]. This equilibrium point in power systems has been directly related with voltage collapse problem. Thus in power system one is usually interested in determining the singularity of the 'Jacobian' associated with the system dynamic equations. Different
models of the system element, particularly generators and loads affect the location of these collapse points [272, 273]. In addition to that, changing various parameters in the system one can produce different types of bifurcating phenomena [274].

A typical power flow model of a set of nonlinear equations defining the active and reactive power mismatches at system buses is used here to obtain and compare different voltage stability indices as given below:

\[
\begin{bmatrix}
F(u, \lambda) \\
Q(u, \lambda)
\end{bmatrix} = F(u, \lambda) = 0
\]

where \( F(u, \lambda) \) is subset of \( F(z, \lambda) \), with \( u \) typically representing \( V \) and \( \delta \) i.e., the magnitude and angle of system bus voltages. In this particular power flow or load flow model of power system the variations of constant active and reactive power at system buses are assumed to be the main parameter driving the system towards a singularity (or voltage collapse). Although this simple system model is certainly not adequate to thoroughly study the voltage collapse phenomenon, for certain particular dynamic models, the load flow equations yield adequate results as singularities in the related load flow Jacobian can be associated with actual singular bifurcations of the corresponding dynamical system [271]. Moreover, regardless of the direct relation between singularities of the load flow Jacobian and actual bifurcations of full dynamical system, it is always of interest to determine system conditions where the load flow problem is not solvable. However, with the help of numerical techniques currently available, (3.4) can be used to compute other system variables besides \( V \) and \( \delta \) so that system controls and its limit may be readily handled by swapping variables in \( u \) without the need for changing the structure and number of the equations used in the computational process. For example, generator reactive power injection \( Q \) can be part of \( u \) including reactive power mismatch equations at \( PV \) buses in (3.4), so that when a \( Q \)-limit is reached, or released, the corresponding bus voltage magnitude \( V \) is swapped for \( Q \) in \( u \), or vice versa. Automatic transformer taps or any other control variables can be handled in similar fashion. It may be noted that \( F(u, \lambda) \) and \( u \) for that matter, could be modified to include more detailed models of certain system devices such as generators (including AVR s and other controls) and loads, or other devices such as HVDC links and FACTS, making power flow equations more accurate for computing equilibrium points of the full system model represented by the nonlinear function \( F(u, \lambda) \).

The \( \lambda \) variable typically represents a scalar parameter or loading factor used to simulate the system load changes that drive the system to collapse in the following way:
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\[ P_{\text{load}_j} = P_{j_p} (1 + k_{p,p} \lambda) + P_{j_z} \left( \frac{V}{V_0} \right) \left( 1 + k_{z,p} \lambda \right) + P_{j_z} \left( \frac{V}{V_0} \right)^2 (1 + k_{z,\lambda}) \]

\[ Q_{\text{load}_j} = Q_{j_0} \left( 1 + k_{q,q} \lambda \right) + Q_{j_z} \left( \frac{V}{V_0} \right) \left( 1 + k_{q,z} \lambda \right) + Q_{j_z} \left( \frac{V}{V_0} \right)^2 (1 + k_{q,\lambda}) \]

where \( P_{\text{load}_j} \) and \( Q_{\text{load}_j} \) represent the active and reactive load at bus-\( j \). \( P_{j_p}, P_{j_z}, k_{p,p}, k_{z,p}, k_{q,q}, k_{q,z}, Q_{j_z}, k_{q,\lambda}, k_{z,q}, k_{z,\lambda}, Q_{j_0}, Q_{j_z} \) and \( V_0 \) are all pre-defined constants that determine the composition of constant power, constant current, constant impedance load [272]. The analytical derivations in this thesis are derived assuming constant power loads in PQ buses and hence we can write for \( j^{th} \) load bus,

\[ P_{\text{load}_j} = P_{j_p} (1 + k_{p,p} \lambda) \]

\[ Q_{\text{load}_j} = Q_{j_0} \left( 1 + k_{q,q} \lambda \right) \]

(3.6)

For constant power loads \( \lambda \) represents a net MVA change in the total system load.

**A. The PV- and the VQ-curves for the small system**

The active power-voltage function for the small system has a characteristic form usually called the 'PV-curve' (Figure 3.3). As can be seen there is a maximum amount of power that can be transmitted by the system. Another property of the system is that a specific power can be transmitted at two different voltage levels. The high-voltage/low-current solution is the normal working mode for a power system due to lower transmission losses. One way to write the equations describing this power-voltage relation is:

\[ V = \sqrt{\alpha \pm \sqrt{\alpha^2 - \beta}} \]

(3.7)

\[ \alpha = \frac{E^2}{2} - RP - XQ \quad \text{and} \quad \beta = (P^2 + Q^2)Z^2 \]

(3.8)

where \( E \) is the sending end voltage, \( V \) is the receiving end voltage and \( R, X \) are the line resistance and reactance respectively.

The point, "Point of Maximum Loadability" (maximum power transfer capability) is indicated in Figure 3.3. This point can be calculated by either solving 'PML' from the relation \( \alpha^2 = \beta \) from (3.7), by implicit derivation of \( \frac{dP}{dV} = 0 \) in (3.7) or by evaluating the load-flow Jacobian singularity.
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Figure 3.3 The PV-curve with different load characteristics

Figure 3.4 The VQ-curve for two different active loads
Another possibility to demonstrate the capacity of the small system is to show the V-Q relation. The necessary amount of reactive power in the load end for a desired voltage level $V$ is plotted in Figure 3.4.

B. Singular Values

Singular values have been employed in power systems because of the useful orthonormal decomposition of the Jacobian matrices. For the real $n \times n$ square Jacobian matrix, $[J] = D_z F(z_0, \lambda_0)$ [or, $\frac{\partial F(z_0, \lambda_0)}{\partial z}$] at the equilibrium point $(z_0, \lambda_0)$ of (3.2), we have

$$[J] = R \Sigma S^T = \sum_{i=1}^{n} r_i s_i^T$$

(3.9)

where the singular vectors $r_i$ and $s_i$ are the $i^{th}$ columns of the unitary matrices $R$ and $S$ and $\Sigma$ is a diagonal matrix of positive real singular values $\sigma_i$, such that $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n$. The diagonal entries of $\Sigma^2$ correspond to the eigenvalues of matrix $JJ^T$.

This singular value decomposition is typically used to determine the rank of a matrix, which is equal to the number of non zero singular values of $J$. Hence its application to voltage collapse analysis focuses on monitoring the smallest singular value up to the point when it becomes zero at the collapse point [275].

In general the Jacobian $[J]$ contains the first derivatives of the reactive power mismatch equations $Q(z, \lambda)$ with respect to the voltage magnitude. Hence linearizing the steady state equations $F(z, \lambda) = 0$ at equilibrium point $(z_0, \lambda_0)$,

$$[\Delta F(z, \lambda)] = [J][\Delta z]$$

(3.10)

or,

$$[\Delta P(z, V, \lambda)] = \begin{bmatrix} \frac{\partial P(z_0, \lambda_0)}{\partial z} & \frac{\partial P(z_0, \lambda_0)}{\partial V} \end{bmatrix}[\Delta z]$$

(3.11)

$$\begin{bmatrix} \Delta Q(z, V, \lambda) \end{bmatrix} = \begin{bmatrix} \frac{\partial Q(z_0, \lambda_0)}{\partial z} & \frac{\partial Q(z_0, \lambda_0)}{\partial V} \end{bmatrix}[\Delta V]$$

(3.12)

For the typical load flow model, $\Delta P(z, V, \lambda)$ represents the active power mismatches, $\Delta Q(z, V, \lambda)$ represents the reactive power mismatches and $z$ represents the bus voltage.
angles $\delta$. From (3.12) it can be valid for any equilibrium point other than voltage collapse point, as

$$\begin{bmatrix} \Delta x \\ \Delta V \end{bmatrix} = [J]^{-1} \begin{bmatrix} \Delta P(z, V, \lambda) \\ \Delta Q(z, V, \lambda) \end{bmatrix}$$

$$\begin{bmatrix} \Delta x \\ \Delta V \end{bmatrix} = [J]^{-1} \begin{bmatrix} \Delta P(z, V, \lambda) \\ \Delta Q(z, V, \lambda) \end{bmatrix}$$

$$\begin{bmatrix} \Delta x \\ \Delta V \end{bmatrix} = \sum_{i=1}^{n} r_{i} s_{i}^T \begin{bmatrix} \Delta P(z, V, \lambda) \\ \Delta Q(z, V, \lambda) \end{bmatrix} \quad \therefore [J] = \sum_{i=1}^{n} r_{i} s_{i}^T$$

(3.13)

It may be noted that minimum singular value is a relative measure of how close the system is to the voltage collapse or singular point. Furthermore, near this collapse point, since $\sigma_{n}$ is close to zero, (3.13) can be rewritten as

$$\begin{bmatrix} \Delta x \\ \Delta V \end{bmatrix} = [J]^{-1} \begin{bmatrix} \Delta P(z, V, \lambda) \\ \Delta Q(z, V, \lambda) \end{bmatrix}$$

(3.14)

Hence, the associated left and right singular vectors $r_{n}$ and $s_{n}$, contain important information. The maximum entries in $s_{n}$ indicate the most sensitive voltage magnitudes (critical buses or weak buses) and the maximum entries in $r_{n}$ correspond to the most sensitive direction for changes of power injections.

Assuming that $\Delta P(z, V, \lambda) = 0$, which in the standard power flow model corresponding to only reactive power injections changes, (3.13) yields

$$\begin{bmatrix} \Delta Q(z, V, \lambda) \end{bmatrix} = \left([J_{4} - J_{3}J_{1}^{-1}J_{2}] \right)[\Delta V] = [J_{QV}][\Delta V]$$

(3.15)

At voltage collapse point $J_{v}$ is not singular even though $[J]$ is singular. Thus $[J_{QV}]$ become singular at collapse point since

$$|J_{QV}| = |J|/|J_{v}|$$

(3.16)

where $|J|$ is the determinant of $[J]$, similarly $|J_{1}|$ and $|J_{QV}|$ are the determinants of $[J_{1}]$ and $[J_{QV}]$ respectively. The singular values of this reduced matrix $[J_{QV}]$ can then be used to determine proximity to voltage collapse. Furthermore, these singular values show better profiles than the ones of $[J]$ as has been demonstrated in literature [276, 277].

It is interesting to highlight the fact that the sub-matrix $[J_{3}]$ is quasi-symmetric, for small values of transmission system resistances. Therefore, one expects a similar attribute for
$[J_{qp}]$, making the singular values and eigen values for this matrix practically identical [276], as symmetric matrices have similar singular value and eigen value decomposition.

C. Eigenvalue Decomposition

Eigen values, as singular value, are also often used to determine the proximity to the voltage collapse point [278, 272]. The eigen value decomposition for the Jacobian matrix $[J]$ is given by

$$[J] = [\xi][U][\eta]$$

(3.17)


$[J_{qp}]$ as defined in (3.16), is quasi-symmetric and therefore diagonalizable. This decomposition may be applied directly to assess voltage stability [276]. In addition to that due to its quasi-symmetric structure a set of only real eigen values and eigenvectors can be expected which are very similar in value to the corresponding singular values and singular vectors. Thus for $[J_{qp}]$, the eigenvectors associated with eigen values closest to zero have the same interpretation as the singular vectors near the collapse point. Therefore the maximum entries in the right eigenvector correspond to the critical buses (most sensitive buses) in the system and the maximum entries in the left eigenvector pinpoints the most sensitive direction for change of power injections [279, 280]. Comparing the singular value and eigen value based indices to the sensitivity factors, somewhat similar information can be obtained with these indices but at higher computational cost than in case of sensitivity factors.

D. Modal Analysis

The static voltage stability analysis is based on the modal analysis of the power flow Jacobian matrix that can be rewritten as follows

$$
\begin{bmatrix}
\Delta P_{PQ, PV} \\
\Delta Q_{PQ} 
\end{bmatrix} =
\begin{bmatrix}
J_{PQ} & J_{PV} \\
J_{QQ} & J_{QV}
\end{bmatrix}
\begin{bmatrix}
\Delta \theta \\
\Delta V_{PQ}
\end{bmatrix}
$$

(3.18)

where, $\Delta P_{PQ, PV}$ is the incremental changes in active power of PQ and PV buses; $\Delta Q_{PQ}$ is the incremental changes in reactive power of PQ buses; $\Delta \theta$ is a vector that contains the incremental changes in bus voltage angle; $\Delta V$ is a vector that contains the incremental changes in bus voltage magnitude.
The elements of the Jacobian matrix represent the sensitivities between power flow bus voltage changes. According to the classical static voltage stability analysis, power system voltage stability is largely affected by the reactive power. Therefore, keeping active power as constant at each operating point, the Q-V analysis can be carried out.

Assuming $\Delta P_{pq,pr} = 0$, it follows from (3.18) that

$$
\Delta Q_{pq} = \left[ J_{pq} - J_{ga}J_{pq}^{-1}J_{pr} \right] \Delta V_{pq} = J_{r} \Delta V_{pq}
$$

(3.19)

and

$$
\Delta V_{pq} = J_{r}^{-1} \Delta Q_{pq}
$$

(3.20)

Based on the $J_{r}^{-1}$, which is reduced V-Q Jacobian matrix, the Q-V modal analysis can be carried out. Therefore, the bus, branch and generator participation factors on the static voltage stability can also be obtained. Moreover, the stability margin and the shortest distance to instability will be determined.

**E. Voltage Stability Index ‘L’**

For a system, where, $n$ is the total number of buses, with $1, 2, \ldots, g$ generator buses, $g + 1, g + 2, \ldots, g + s$ SVC buses, $g + s + 1, \ldots, n$ the remaining buses ($r = n - g - s$) and $t$ is the number of OLTC transformer, a load flow result can be evaluated for a given operating condition. The load flow algorithm incorporates load characteristics and generator control characteristics. Using load flow result, $L$-index [281] can be computed as

$$
L_j = 1 - \sum_{m=1}^{rs} F_{jm} \frac{Y_{jm}}{Y_j}
$$

(3.21)

where $j = g + 1, \ldots, n$ and all the terms within sigma on RHS of (3.21) are complex quantities. The values $F_{jm}$ are obtained from $Y$ bus matrix as follows

$$
\begin{bmatrix}
I_o \\
I_L
\end{bmatrix} =
\begin{bmatrix}
Y_{gg} & Y_{gl} \\
Y_{lg} & Y_{ll}
\end{bmatrix}
\begin{bmatrix}
V_o \\
V_L
\end{bmatrix}
$$

(3.22)

where, $I_o, I_L, V_o, V_L$ represent current and voltages at the generator nodes and load nodes. Rearranging (3.22), it can be written as

$$
\begin{bmatrix}
V_L \\
I_o
\end{bmatrix} =
\begin{bmatrix}
Z_{ll} & F_{lg} \\
K_{gl} & Y_{gg}
\end{bmatrix}
\begin{bmatrix}
I_L \\
V_o
\end{bmatrix}
$$

(3.23)
where, \( F_{lo} = [Y_{lo}] \) are the required values. The L-indices for a given load condition are computed for all load buses.

The equation for the L-index for \( j^{th} \) node can be written as

\[
L_j = \left| 1 - \sum_{i=1}^{m} \frac{F_{ij} V_i}{V_j} \angle \theta_i + \delta_i - \delta_j \right|
\]  

(3.24)

where, \( \delta_i \) and \( \delta_j \) are the voltage angles of \( i^{th} \) and \( j^{th} \) bus w. r. to slack bus and \( \theta_i \) is the power factor angle.

For stability, the index \( L_j \) must not be violated for any of the nodes \( j \). Hence the global indicator \( L \) describing the stability of the complete subsystem is given by \( L \) is the maximum of \( L_j \) for all \( j \) (load nodes). The indicator \( L \) is a quantitative measure for the estimation of the distance of the actual state of the system to the stability limit. The local indicators permit the determination of those nodes from which a collapse may originate. The stability margin in this case is obtained as the distance of \( L \) from a unit value i.e. \( (1 - L) \). The advantage of this method lies in the simplicity of the numerical calculation and expressiveness of the results.

**F. Fast Voltage Stability Index (FVSI) and Line Quality Factor (LQF)**

The Fast Voltage Stability Index and Line Quality Factor [51] are quite efficient in predicting the voltage collapse of power network. But their proper formulation is quite imperative, as that will determine the dynamic restoration of stability under disturbance. For that purpose, an interconnected system is reduced to a single line network and applied to assess the overall system stability. Utilizing the same concept, a criterion for stability can be developed. Let us consider a single line of an interconnected network as shown in Figure 3.5.

![Figure 3.5 Typical single-line diagram of transmission line](image)

The sending end bus voltage \( (V_1) \) is actually the summation of line drop and receiving end bus voltage \( (V_2) \).

\[
V_1 = V_2 - \left( \frac{P_2 - jQ_2}{V_2} \angle \delta \right) (R + jX) = V_1 < 0
\]
\[ V_2^2 + P_2R + Q_2X + j\left(XP_2 - Q_2R \right) = V_1V_2 \cos\delta + jV_1V_2 \sin\delta \] (3.25)

After separating the real and imaginary parts and eliminating \(\delta\), (3.25) reduces to

\[ V_2^4 + V_1^2 \left(2Q_2X - V_2^2\right) + X^2 \left(P_2^2 + Q_2^2\right) = 0 \] (3.26)

To have real solutions for voltage (3.25) must have real roots. Thus the following conditions, which can be used as stability criterion, need to be satisfied:

\[ \left(2Q_2X - V_2^2\right)^2 - 4X^2 \left(P_2^2 + Q_2^2\right) \geq 0 \] (3.27)

Again from (3.25), substituting the value of \(P_2\)

\[ V_2^2 + Q_2X + V_1V_2 \left[ \frac{\sin\delta}{\tan\theta} - \cos\delta \right] = 0 \] (3.28)

where, \(Z \sin \theta = X\)

For getting real solution of voltage, (3.28) should have real roots and at limiting condition, the following criterion must be satisfied:

\[ FVSI = \frac{4XQ_2}{V_1^2 \left[ \sin (\delta - \theta) \right]^2} \leq 1.00 \] (3.29)

The stability criteria (3.27) and (3.29) are used to find the stability index for each line connected between two bus bars in an interconnected power network. Based on the stability indices of the lines, voltage collapse can be accurately predicted. As long as the stability indices are less than 1, the system is stable.

**G. Global Voltage Stability Indicator**

For a two-bus system, the sending end and receiving end active and reactive powers being represented as \(P_s, Q_s\) and \(P_r, Q_r\) respectively, the power flow equations can be represented as

\[ P_s = P_L + P_r \] (3.30)
\[ Q_s = Q_L + Q_r \] (3.31)

The active and reactive power losses are given by
where, \( V \) being the voltage at sending end, \( R \) and \( X \) being equivalent resistance and reactance of the network.

The power flow equation can be then modified as follows:

\[
P_s = \frac{R \left( P_s^2 + Q_s^2 \right)}{V^2} + P_R \tag{3.33}
\]

\[
Q_s = \frac{X \left( P_s^2 + Q_s^2 \right)}{V^2} + Q_R \tag{3.34}
\]

On simplification, the sending end active power expression becomes

\[
P_s = P_R + \frac{R \left\{ P_s^2 \left( R^2 + X^2 \right) - \left( 2X^2P_R - 2XRP_Q \right)P_s + \left( X^2 + P_R^2 - 2XRP_Q + R^2 + Q_R^2 \right) \right\}}{V^2} \tag{3.35}
\]

To have real solution of active power, the discriminant part must be greater than or equal to zero. This gives the following condition:

\[
4 \left\{ (XP_R - RQ_R)^2 + XQ_R + RP_R \right\} \leq 1 \tag{3.36}
\]

This term has been named as global VSI [282] and to maintain the global stability, the criterion is \( VSI \leq 1 \).

**H. Voltage Collapse Proximity Indicator (VCPI)**

With the aid of Thevenin’s theorem, a general conclusion can be drawn about the condition for maximum power transfer to a node in a system. The maximum power transfer to a bus takes place when the load impedance becomes the driving point impedance as seen from the load bus under consideration. Any network of linear elements and energy sources can be represented by a series combination of an ideal voltage and impedance. For a network, the Thevenin’s equivalent impedance looking into the port between bus \( i \) and the ground is \( Z_a \). Therefore, at load bus \( i \), with load impedance \( Z_i \), for permissible power transfer to the load
at bus $i$, $\left| \frac{Z''}{Z_i} \right| \leq 1$. The Voltage Collapse Proximity Indicator (VCPI) [283] for all nodes is computed as

$$VCPI_i = \left| \frac{Z''}{Z_i} \right|$$

(3.37)

The stability margin in this case is obtained as the distance of VCPI from unity. The bus having the maximum value of VCPI is the weakest bus in the system.

1. **Proximity Indices of Voltage Collapse**

It has been observed that with increase in load at bus $i$, value of diagonal elements of Jacobian matrices $\frac{\partial Q_i}{\partial V_i}$ and $\frac{\partial P_i}{\partial \delta_i}$ get reduced. Thus, the deviation in value of $\frac{\partial Q_i}{\partial V_i}$ and $\frac{\partial P_i}{\partial \delta_i}$ from its no-load value to the value at any particular loading condition can be used as an index of voltage stability for the load bus $i$. Using these criteria two voltage stability indices can be defined as follows [283]:

$$I_{P_i} = \frac{\frac{\partial P_i}{\partial \delta_i} (\text{loading condition})}{\frac{\partial P_i}{\partial \delta_i} (\text{no load condition})}$$

(3.38)

$$I_{Q_i} = \frac{\frac{\partial Q_i}{\partial V_i} (\text{loading condition})}{\frac{\partial Q_i}{\partial V_i} (\text{no load condition})}$$

(3.39)

2. **Identification of weak bus of Power Network**

The governing equation of Load Flow analysis used in N-R method is given by

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \left| V \right| \frac{\partial P}{\partial |V|} \\ \frac{\partial Q}{\partial \delta} & \left| V \right| \frac{\partial Q}{\partial |V|} \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta |V| \end{bmatrix}$$

(3.40)

Hence the real and reactive power sensitivities of the $i^{th}$ bus can be written as [284]

$$\frac{\partial P_i}{\partial |V_i|} = \left[ J_{2i} \right]_i ; \frac{\partial Q_i}{\partial |V_i|} = \left[ J_{4i} \right]_i$$

(3.41)
Equation (3.41) represents the real and reactive power sensitivities of the \(i\)th bus.\[\frac{\partial Q_i}{\partial |V_i|}\] also indicates the degree of weakness for the \(i\)th bus as \[\frac{\partial |V_i|}{\partial Q_i}\] is high, \[\frac{\partial |V_i|}{\partial Q_i}\] becomes low indicating minimum change in voltage for variation of \(Q\) (reactive power) of the bus. Thus higher value of \[\frac{\partial Q_i}{\partial |V_i|}\] represents lesser degree of weakness of the \(i\)th bus. With the help of this indicator, weakest bus of a power network can be evaluated.

**K. Diagonal Element Ratio**

This index is given as the ratio of the maximum to minimum values of diagonal elements of the Jacobian matrix [283]. Mathematically, it can be expressed as

\[I_d = \frac{J_{\text{max}}}{J_{\text{min}}}\]  

(3.42)

where, \(J_{\text{max}}\) and \(J_{\text{min}}\) are maximum and minimum values of diagonal elements of Jacobian matrix.

**L. Line Voltage Stability Index**

The complex power injected at bus \(k\) consists of an active and a reactive component and may be expressed as a function of nodal voltage and the injected current at the bus:

\[S_k = P_k + jQ_k = E_k^* I_k^* = E_k (Y_{kk} E_k + Y_{km} E_m)^*\]  

(3.43)

where \(I_k^*\) is the complex conjugate of the current injected at bus \(k\) and the other terms are carrying their usual meanings. The expressions for \(P_k\) and \(Q_k\) can be determined by using the expressions of \(E_k, Y_{kk}, Y_{km}\)

\[P_k = V_k^2 G_{kk} + V_k V_m \left[ G_{km} \cos(\theta_k - \theta_m) + B_{km} \sin(\theta_k - \theta_m) \right]\]  

(3.44)

\[Q_k = -V_k^2 B_{kk} + V_k V_m \left[ G_{km} \sin(\theta_k - \theta_m) - B_{km} \cos(\theta_k - \theta_m) \right]\]  

(3.45)

With the help of these expressions Jacobian matrix for load flow analysis can be developed and the point of voltage instability being coincident with the singularity of the Jacobian, the condition of voltage stability can be obtained from following condition

\[\Delta[J] = 0\]  

(3.46)
Thus at voltage collapse point, by using (3.44-3.46) Line Voltage Stability Index can be formulated as

\[ LVSI = \frac{V_m \cos \theta_m}{V_k} = \frac{1}{2} \]  

(3.47)

**M. Local Load Margin**

This index is based on physical quantities of a power flow model. T. Nagao et al [285] has proposed the index for bus-\(i\) as follows

\[ P_{LLM_i} = \frac{P_{\text{max},i} - P_{\text{initial},i}}{P_{\text{max},i}} \]  

(3.48)

where \(P_{\text{initial},i}\) is the initial load in MW and \(P_{\text{max},i}\) (in MW) is the load at the nose of the PV curve when the load at bus-\(i\) is increased at a fixed power factor.

The local load margin \(P_{LLM_i}\) has a value between 1 and 0 (at the collapse point). Here the loads at other buses are assumed to remain constant. However, equation (3.48) allows for the computation of a voltage stability margin for each load point. As the voltage may be on a lower solution domain depending on the system conditions, it is convenient to present the value \(P_{LLM_i}\) as a negative number when the system voltage is in this particular state.

As \(P_{LLM_i}\) is defined with respect to a specific bus, its computation is relatively easy. However, a voltage stability margin should be evaluated for the entire power system; thus, the index \(P_{LLM_i}\) should be computed for all load buses. This index can be utilized to monitor the worst possible contingencies in the system for stability point of view and can be used to prepare a ranking table according to the severity of line contingencies. Hence this index can be employed as a Contingency Factor in contingency analysis of a power network.

**N. Voltage Ratio Index**

The \(V/V_0\) index is rather simple to define and compute. Thus assuming the bus voltage values \((V)\) to be known from load flow or state estimation studies, new bus voltages \((V_0)\) are obtained by solving a load flow for the system at an identical state but with all loads set to zero. The ratio \(V/V_0\) at each node yields a voltage stability map of the system, allowing for immediate detection of weak and effective countermeasure spots. A problem with this index is that it presents a highly nonlinear profile with respect to changes on the system parameter \(\lambda\), not allowing for accurate predictions of proximity to collapse [278]. Nevertheless when
used together with operating experience, it has turned out in practice to be an effective tool against voltage collapse. Thus the $V_j/V_0$ index has been successfully used since 1982 in Belgium for off-line studies, particularly in seasonal operation planning; it was then added in 1995 to the on-line security assessment unit of the new Belgium dispatch center.

3.3 THEORY OF ARTIFICIAL NEURAL NETWORK (ANN)

Research in the field of neural networks has been attracting, increasing attention in recent years. Since 1943, when Warren McCulloch and Walter Pitts presented the first model of artificial neurons, the study of neurons, their interconnections, and their role as the brain's elementary building blocks has become one of the most dynamic and important areas of exploration of the modern research fields. The earlier trends followed in the technological fields got enriched after the incorporation of ANN based models. In quite a few cases, application of ANN could even produce better solutions in respect of the classical techniques available. Apart from that ANN has projected quite a few drawbacks of classical approaches to increase the adoption of Artificial Intelligence (AI) in the engineering fields:

1. Classical Techniques impose restrictions on the number of input data: one is limited to a few inputs among dozens or hundreds available, imposing a priori variable selection, with all the inherent pitfalls.

2. Regressions are performed using simple dependency functions that are not very realistic. The hypothesis is made that there is only one dependency function over the whole data set, instead of many distinct niches.

3. Other hypotheses imposed by their underlying theories (normal distributions, equi-probabilities, uncorrelated variables) known to be violated, but that are necessary for their good operation.

In all the cases one has to call on an expert of the method and perform many weeks, even a few months' worth of work. In comparison of classical techniques, ANN offers the following advantages:

1. Neural nets need less constraining hypotheses (the dependency must be a function, nothing more).

2. Qualitative (enumerative) data are straightforwardly handled.

3. No preprocessing, simplification or reduction of quantitative variables is necessary.

It has been demonstrated that linear regression and logistic regression are particular cases of neural nets (with one layer and a linear threshold function). The same thing happens with
Principal Component Analysis (PCA) whose values are contained in the weights of the neurons of a one-layer, linear-threshold function network performing self-association.

### 3.3.1 Attributes of Artificial Neural Networks (ANN)

Artificial Neural Networks are a form of computation inspired by the structure and function of brain. A common topology used is the weighted directed graph. The nodes, known as neurons, in the graph can be 'on' or 'off' and time is discrete. At each time instant, all the 'on' nodes send an impulse along their outgoing arcs to their neighboring nodes. All nodes sum their incoming impulses, weighted according to the arc. All the nodes at which this sum exceeds a threshold turn on at the next time instant; all others turn off. Computation proceeds by setting nodes, waiting for the network to reach a steady state, and then reading the output nodes. Nodes can be trained to recognize certain pattern, for instance to classify objects by their features. In this section, building blocks of ANN and different networks have been discussed which are very much imperative for application of ANN in voltage stability analysis of power networks.

#### A. Building block of ANNs

First attempts at building Artificial Neural Networks (ANN) were motivated by the desire to create models for natural brains. Much later it was discovered that ANN are a very general statistical framework for modeling posterior probabilities given a set of samples (the input data). This simple element consists of the components given below:

1. A set of inputs
2. A set of weights
3. A threshold
4. An activation function
5. A single neuron output or set of outputs

**Inputs:** Typically, these values are external stimuli from the environment or come from the outputs of other artificial neurons. They can be discrete values from a set, such as \(\{0,1\}\), or real-valued numbers.

**Weights:** These are real-valued numbers that determine the contribution of each input to the neuron's weighted sum and eventually its output. The goal of neural network training algorithms is to determine the best possible set of weight values for the problem under consideration. Finding the optimal set is often a trade-off between computation time and minimizing the network error. Apart from that the weights incorporated depends upon the type of input.
The basic building block of a (artificial) neural network (ANN) is a neuron shown in the Figure 3.6, which is a processing unit with some (usually more than one) inputs and only one output.

At the outset, each input $x_i$ is weighted by a factor $w_i$ and the whole sum of input is calculated as $\sum_{i} w_i x_i = a$. Then an activation function $f$ is applied to the result $a$ and the neuronal output is taken to be $f(a)$.

Threshold: The threshold is a real number that is added algebraically to the weighted sum of the input values. Sometimes the threshold is referred to as a bias value.

Activation Function: The activation function for the original McCulloch-Pitts neuron was the unit step function. However, the artificial neuron model has been expanded to include other functions such as the sigmoid, piecewise linear, Gaussian etc, the most popular of which is the sigmoidal function.

The effect of threshold and shape modifier can be explained by the figures (Figure 3.7), which are self-expounding.

In accordance with the working environment and inputs, the threshold and shape modifier makes the activation function more reliable. This also assists to achieve optimal weight values of the inputs of each neuron.
Generally the ANNs are built by putting the neurons in layers and connecting the outputs of neurons from one layer to the inputs of the neurons from the next layer (Figure 3.8).

**B. Building layers of ANN**

Generally the ANNs are built by putting the neurons in layers and connecting the outputs of neurons from one layer to the inputs of the neurons from the next layer (Figure 3.8).

![Figure 3.7 Threshold and shape modifier used in ANN](image)

![Figure 3.8 The general layout of a Neural Network](image)
The depicted network is also named as feedforward (a feedforward network does not have feedbacks, i.e. no loops) network. In fact, there is no processing on the layer 0, its role is just to distribute the inputs to the next layer (data processing really starts with layer 1); for this reason its representation will be omitted most of the time.

Generally, the output of one neuron may go to the input of any neuron, including itself; if the outputs of neuron from one layer are going to the inputs of neurons from previous layers then the network is called recurrent, this providing feedback; lateral feedback is done when the output of one neuron goes to the other neurons on the same layer. So, to compute the output, an “activation function” is applied on the weighted sum of inputs.

\[
\text{total inputs } a = \sum w_i x_i \quad \text{(3.49)}
\]

\[
\text{output} = \text{activation function} \left( \sum w_i x_i \right) = f(a) \quad \text{(3.50)}
\]

Neural nets have two fundamental advantages:

1. It has the ability to represent any function, which may be linear or not, simple or complicated. Neural nets are what mathematicians call “universal approximators” (Kolmogorov’s Theorem, 1957).

2. The ability to learn from representative examples. Model building is automatic.

However, building neural model belongs to data analysis and not to magic (even though, to quote Arthur C. Clarke, “sufficiently advanced technology is indistinguishable from magic”). The data must be explicative and in sufficient amount.

C. Structures of Neural Networks

A neural network comprises the neuron and building blocks. The behavior of the network depends largely on the interaction between these building blocks. There are three types of neuron layers: input, hidden and output layers. Two layers of neuron communicate via a weight connection network. There are different types of weighted connections, among which some are discussed below:

(i) Feed-Forward Neural Network

For this kind of neural models, data from neurons of a lower layer are propagated forward to neurons of an upper layer via feed forward connections networks. The Feed-forward Neural Network shown in Figure 3.9, has an input vector \( X \) consisting of components \( x_1, x_2, \) and \( x_n \), a hidden layer \( Y \) having the components of \( y_1, y_2, \) and \( y_m \) and an output vector \( Z \) having
the components of $x_1, x_2, \text{and } x_k$. The synaptic links carrying weights connects every input neuron to output neuron. The function of hidden neurons is to intervene between the external input and the network output in some useful manner \cite{286}. By adding one or more hidden layers, the network is enabled to extract higher order statistics. The set of output signals of the neurons in the output layer of the network constitutes the overall response of the network to the activation pattern supplied by the source nodes in the input layer.

(ii) **Recurrent Neural Network**

The back propagation neural networks are strictly feed-forward networks in which there are no feedbacks from the outputs of one layer to the inputs of same layer or earlier layers of neurons. However such networks have no memory, since the output at any instant depends entirely on the inputs and the weights at that instant.

There are situations (e.g. When dynamic behavior is involved) where it is advantageous to use feedback in neural networks. When the output of a neuron is fed back into a neuron in an earlier layer, the output of that neuron is a function of both the input from the previous layer at time $t$ and its own output that existed at an earlier time, that is, at time $t - \Delta t$, where $\Delta t$ is the time for one cycle of calculation. Hence, such network exhibits characteristics similar to short-term memory, because the output of the network depends on both the correct and prior inputs.

Neural networks that contain such feedback are called recurrent neural networks. Although virtually all the neural networks that contained feedback could be considered as recurrent
networks, the discussion here will be limited to those that use back-propagation for training (often called recurrent backprop networks). Let us consider an elementary feed forward network with the input, middle, and output layers each having only one neuron, and where the neuron \( h \) is a buffer neuron that instantaneously sends the input \( x \) to neuron \( p \). When the input \( x(0) \) (at time \( t = 0 \)) is applied to the input, the outputs of neuron \( p \) and \( q \) at time \( t = 0 \), \( v(0) \) and \( y(0) \) respectively, are

\[
v(0) = \phi(W_{p}x(0)) \\
y(0) = \phi(W_{q}v(0)) = \phi(W_{q}\phi(W_{p}x(0)))
\]

where, \( \phi \) is the activation function operator (usually a sigmoidal function).

(iii) Elman Backpropagation Neural Network

An Elman Backpropagation Neural Network (EBNN) is a two-layer backpropagation network, with the addition of a feedback connection from the output of the hidden layers to its input as shown in Figure 3.10. This feedback path allows an Elman Network to learn to recognize and generate temporal as well as special patterns.

Since there is a feedback connection from the first-layer output to the first layer-input, a recurrent connection is established, which allows the Elman network to both detect and generate time varying patterns (Fausett 1999). The delay in this connection stores values from the previous time step, which can be used in the current time step. Here, a specific group of units called context units receives feedback signals from the previous time step. The weights on the feedback connection to the context units are fixed, and information processing is sequential in time. Therefore, training in this network is more difficult than for a standard backpropagation network.

At time \( t \), the activation of the context units implies the activation of the hidden units at the previous time step. The weights of the context units to the hidden units are trained in exactly the same manner as the weights from the input units to the hidden units. Thus at any time step the training algorithm is same as for standard backpropagation.

Let \( W_{1} \) be the weight matrix between the input layer and hidden layer, \( W_{2} \) be the weight matrix between the hidden layer and output layer, and \( W_{3} \) be the weight matrix between the context layer and hidden layer. \( i, h, o \) and \( c \) indicate the number of input nodes, hidden nodes, output nodes and context layer nodes. In terms of weight matrix in neural structure, each
weight coefficient can be defined as an element of these matrices; e.g., $W_{ih} \in W_1$, $W_{oh} \in W_2$, and $W_{hc} \in W_3$.

Figure 3.10 An Elman Backpropagation Neural Network

The outputs of the neuron in the hidden and output layers are given as
Updated weight coefficient can be assigned to minimize the approximation error $E$ in the output layers as follows:

$$W_{\text{new}} = W_{\text{old}} + \eta \Delta W$$

where $\eta$ is the learning rate.

$$E(W) = (1/2) \sum_{s=1}^{p} \sum_{\omega=1}^{c} [T_{\omega}^{(s)} - Z_{\omega}^{(s)}]$$

where $T_{\omega}^{(s)}$ is the target value, $p$ is the length of training sequence, and $W_1$ and $W_3$ are the target coefficient matrices.

$$\Delta W_{3hc} = \sum_{\omega=1}^{c} [T_{\omega}^{(s)} - Z_{\omega}^{(s)}] W_{2oh} f\left( Y_{h}^{(s)} Y_{h}^{(s-1)} \right)$$

This value is used to update the weight coefficients between the context layer and the hidden layer of the training procedure of Elman Backpropagation Neural Network.

**Input delay Feed-Forward Backpropagation Neural Network**

The input delay feed-forward backpropagation neural network is a time delay neural network whose hidden neurons and output neurons are replicated across time. As shown in Figure 3.11, the delay is taken from the top of the input nodes.

Hence, here the network has tapped delay line that senses the current signal, previous signal and the delayed signal before it is connected to the network weight matrix through delay time units such as 0, 1 and 2. These are added in ascending order from left to right to correspond to the weight matrix. All other features are similar to the feed-forward neural network, except that the input given to the network is delayed. In this network, memory is limited by the length of the tapped delay line.

Let us consider a non-uniform sampling

$$X_i(t) = X(t - W_i)$$
where $W_i$ is the integer delay associated with the component $i$. Each input really be a convolution of the original input sequence,

$$X_i(t) = \sum_{l=1}^{i} C_i(t - l)$$

(3.58)

In case of delay time memories,

$$C_i(t) = \begin{cases} 1 & t = W_i \\ 0 & \text{otherwise} \end{cases}$$

(3.59)

**Figure 3.11 Input Delay Feed-Forward Backpropagation Neural Network**

**D. Training algorithms of Neural Network**

Above discussed neural networks are commonly categorized in terms of their corresponding training algorithms: Fixed-weights Networks, Unsupervised Networks, and Supervised
Networks. There is no learning required for the Fixed-weight Networks (e.g. Hamming Net) [287]. In other networks, the learning mode is either unsupervised or supervised.

**Unsupervised Learning**

For an unsupervised learning rule, the training set consists of input training patterns only. Therefore, the network is trained without the benefit of any teacher. The network learns to adapt, based on the experiences collected through the previous training patterns. A typical unsupervised system is Kohonen's Self-organizing Feature Map.

**Supervised Learning**

Supervised learning networks represent the main stream of the development in neural network. The convergence property and accuracy of training process is heavily dependent upon the scaling of the input output data. In supervised training, the training patterns must be provided in input/teacher pattern pairs. Depending on the nature of the teacher's information, there are two approaches to supervised learning. One is based on the correctness of the decision and the other based on the optimization of a training cost criterion. Of the later, the least square error approximation based formulation represents the most important special case.

**Phases of Supervised Network**

Two phases are involved in a supervised learning network: training phase and retrieving phase.

In the training phase, a training data set is used to determine the weight parameters that define the neural model. This trained neural model will be used later in the retrieving phase to process real test patterns and yield classification results.

Real-world applications may face two very different kinds of real-time processing requirements. One requires real-time retrieving but off-line training speed. The other demands both retrieving and training in real-time. These two lead to very different processing speeds, which in turn affect the algorithm and hardware adopted.

**3.4 Analysis of Voltage Stability of Multi-bus Power Network**

Ascertaining voltage stability of a large interconnected network is the primary approach of power system planning. As discussed earlier, monitoring stability and standardizing the same is imperative to insulate the system from sudden and steady state disturbances. In this section, a comprehensive study on voltage stability surveillance by classical methods has been
presented along with a novel ANN based stability assessment technique. It has been established that the ANN based analytical tool can provide fairly accurate result as compared to the classical method.

### 3.4.1 Classical Analysis of Voltage Stability

In the classical technique, the foremost step is to determine the weakest bus of the system using the assistance of a standard technique (using (3.41)). Once the weakest bus has been determined, the study concentrates on the effect of the increased load (active or reactive) at that particular bus and this study is quite capable of revealing a scenario of the whole system stability at stressed condition. The stability indices have been determined for both IEEE 30 bus system as well as a 203 bus-265 lines practical power network (Eastern Grid of India). Table 3.1 and 3.2 enumerates the summarized description of the afore-mentioned systems. The SLDs have been provided in the appendix.

**TABLE 3.1**

**SYSTEM DESCRIPTION OF IEEE 30 BUS SYSTEM**

<table>
<thead>
<tr>
<th>Si No</th>
<th>Particulars</th>
<th>Provision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Buses</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>Branches</td>
<td>41</td>
</tr>
<tr>
<td>3</td>
<td>Generators</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>Total active demand (MW)</td>
<td>283.6</td>
</tr>
<tr>
<td>5</td>
<td>Total reactive power demand (MVAr)</td>
<td>126.2</td>
</tr>
</tbody>
</table>

**TABLE 3.2**

**DESCRIPTION OF EASTERN GRID OF INDIA**

<table>
<thead>
<tr>
<th>Si No</th>
<th>Particulars</th>
<th>Provision</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Buses</td>
<td>203</td>
</tr>
<tr>
<td>2</td>
<td>Branches</td>
<td>265</td>
</tr>
<tr>
<td>3</td>
<td>Generators</td>
<td>24</td>
</tr>
<tr>
<td>4</td>
<td>Total active power demand (MW)</td>
<td>7619</td>
</tr>
<tr>
<td>5</td>
<td>Total reactive power demand (MVAr)</td>
<td>4808.35</td>
</tr>
</tbody>
</table>

For IEEE 30 bus system, it has been found that bus number 26 is the weakest one (Figure 3.12) followed by bus numbers 30 and 29. However bus number 26 has only one interconnecting line with rest of the system and an outage of this line will cause complete isolation of bus number 26 from the network. Hence in the present work the second weakest
bus, i.e. bus 30 has been considered and its loading impact on steady state voltage stability has been observed.

![Graph](image1.png)

**Figure 3.12 Weak bus determination of IEEE 30 bus system**

The same procedure has been repeated for the practical network and as shown in Figure 3.13, bus number 168 is the weakest bus followed by 169 (weaker bus) and 173 (weak bus) for the considered practical system.

![Graph](image2.png)

**Figure 3.13 Weak bus determination of Eastern Grid of India**

After determining the weakest bus for both the systems, classical analysis has been carried out to study the stability with the continuous increase in reactive demand as voltage magnitude intensely depends on reactive power. Few results are shown in following tables.
(Table 3.3 and 3.4). The referred tables also demonstrate the effect of load-intensification on voltage magnitude and angle of the weakest bus. The limiting values of the indices have been depicted in section 3.2.2, and with the increase of the demand the indices are approaching towards their marginal values. These data sets can be provided to the ANN based model as training data for the concerned systems.

### Table 3.3

#### COMPARISON OF DIFFERENT INDICES FOR VOLTAGE STABILITY ANALYSIS OF IEEE 30 BUS SYSTEM

<table>
<thead>
<tr>
<th>Reactive Load (p.u.)</th>
<th>LQF (27-30)</th>
<th>LQF (29-30)</th>
<th>L= J(<em>{\text{max}}) J(</em>{\text{min}}) FVSI (27-30)</th>
<th>FVSI (29-30)</th>
<th>(I_q(30))</th>
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</thead>
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<td>0.019</td>
<td>0.0087</td>
<td>0.04624</td>
<td>0.03614</td>
<td>49.91698</td>
<td>0.07901</td>
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<td>0.025</td>
<td>0.09769</td>
<td>0.06135</td>
<td>0.04801</td>
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<td>0.06832</td>
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<td>0.14069</td>
<td>0.11022</td>
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<td>0.22363</td>
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<td>0.065</td>
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<td>0.16984</td>
<td>0.13348</td>
<td>50.36802</td>
<td>0.27633</td>
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<td>0.075</td>
<td>0.06097</td>
<td>0.19740</td>
<td>0.15674</td>
<td>50.47355</td>
<td>0.32054</td>
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<td>0.085</td>
<td>0.05399</td>
<td>0.22699</td>
<td>0.18085</td>
<td>50.67962</td>
<td>0.36529</td>
</tr>
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<td>0.095</td>
<td>0.04521</td>
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<td>0.20586</td>
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<td>0.41060</td>
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<td>0.105</td>
<td>0.03713</td>
<td>0.28885</td>
<td>0.23182</td>
<td>51.26670</td>
<td>0.45653</td>
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<td>0.120</td>
<td>0.02459</td>
<td>0.33776</td>
<td>0.27271</td>
<td>51.73433</td>
<td>0.52668</td>
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<tr>
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### TABLE 3.4

COMPARISON OF DIFFERENT INDICES FOR VOLTAGE STABILITY ANALYSIS OF EASTERN GRID OF INDIA

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<th>LQF</th>
<th>Bus voltage</th>
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Thus through classical analysis different stability indices can be calculated to predict the
condition of the system at different loading stresses. In the next part, the work has focused on
the realization of ANN in predicting the system instability during different loading
conditions. This will assist to avoid complex classical calculation even in very large practical
system for both on-line and off-line monitoring.

3.4.2 Application of ANN on Voltage Stability Analysis

As discussed earlier, the Elman network based model can be trained to predict the stability
for a particular loading stress. The methodology has been summarized in the following flow
chart (Figure 3.14).

![Flow chart of solution methodology]

Referring to the above flow chart, the immediate step after obtaining stability indices through
classical analysis with different loading stresses is the training procedure of ANN based
model with the same data set of input training vector to meet convergence Criteria. The
convergence criterion for the application has been achieved in 5000 iterations with a training
goal of 0.0001. All the other parameters of the described model have been tabulated in Table 3.5.

**TABLE 3.5**

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<td>Testing Vector</td>
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</table>

After achieving the training goal, the network gets fully trained with the correlation between the changing load pattern and the corresponding values voltage magnitudes, angles and stability indices. The generalizing capability of the trained Elman model is tested by 50 sets of unknown test data. A few samples of the test results are presented in Table 3.6 and 3.7. These tables demonstrate the high degree of coherence with which the results obtained from the classical analysis tally with the results obtained from analysis of the practical networks using the depicted ANN based model.

**TABLE 3.6**

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TABLE 3.7

COMPARISON OF RESULTS OBTAINED BY CLASSICAL CALCULATION AND ANN BASED MODEL (EASTERN GRID OF INDIA)

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<th>LQF</th>
<th>Voltage mag (p.u.)</th>
<th>L Index</th>
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</table>

The training performance of the developed methodology also has been shown in Figure 3.15 for ready reference.
It is also evident from the above tables that the classical analysis and the neural network analysis agree to a high degree with a few minor ignorable departures. However, the spectrum of advantages of the developed ANN based model significantly scores over the negligible inaccuracy in its performance. The successful agreement of this aforesaid neural network methodology with classical results envisages the possibility of real time prediction and correction of voltage stability.

3.5 SUMMARY

A system enters a state of voltage instability when a disturbance causes a progressive uncontrollable decline in voltage. Growing demand without matching expansion of generation and transmission facilities, contribute to increase of the frequency of these disturbances to continuously jeopardize the stability of the system. Hence, in the present day power market scenario, it is quite imperative to maintain a constant surveillance on the system voltage profile and new methods are to be harnessed to control the same. The classical approaches of stability estimation require cumbersome and tedious off-line calculation for their inherent complexity. Thus, for fast and accurate estimation of control parameters, the classical approaches of stability determination are not suitable and hence cannot be adopted for online correction. Effective uses of ANN in this respect have been depicted in this chapter for real time assessment of voltage instability. The simulation results of the adopted methodology are quite encouraging and optimistic.

Annotating Outlines

- Voltage instability is one of the most frequent problems encountered by power networks.
- Investigation of voltage instability should be carried out on the weakest link of the network, so that the same methodology can be implemented in weaker or weak zones.
of the network. The weak buses have been identified employing a standard technique (Figure 3.12 and 3.13).

➢ The classical methods of voltage instability determination require cumbersome and tedious calculation involving high degree of time complexity (Table 3.3 and 3.4).

➢ Instead of determining the voltage stability directly with different indices as proposed in classical method, an Artificially Intelligent system has been developed to predict the same almost instantaneously with the training of the classical data set (Figure 3.14).

➢ The ANN based model developed in this pursuit, can be utilized for faster and accurate prediction of voltage instability to avoid its inevitable consequences (Table 3.6 and 3.7).

CONTRIBUTIONS IN THIS CHAPTER LEAD TO THE FOLLOWING PUBLICATIONS:


