CHAPTER 3

VOLTAGE STABILITY ENHANCEMENT

3.1 INTRODUCTION

Voltage stability analysis can be done in several ways. One methodology is analyzing analytically on small networks by means of mathematical bifurcations as stability criterion. Analysis of minimum eigen value is an extraordinary case of this method. Eigenvectors of the system is used occasionally in modal analysis. For larger networks modal analysis and the smallest singular value can be used.

This chapter presents the identification of weak bus using modal analysis technique. Index method is also used to find the weak buses such that we can implement the FACTS devices for voltage stability enhancement. The location for connecting the STATCOM is identified from the weak bus for voltage stability enhancement.

Optimal location of TCSC and UPFC using GA, EGA and PSO is also done for IEEE 14 bus system.

3.2 VOLTAGE STABILITY

Voltage stability is concerned with the ability of the power system to maintain acceptable voltages at all buses in the system under normal conditions and after being subjected to disturbance [2]. Power system will enter instability state if a large disturbance or increase in load demand, or change in system condition causes a progressive and unmanageable reduction in voltage. The main cause causing instability is the inability of the power system to congregate the requirement of reactive power.
The following section deals with the various techniques available for performing voltage stability analysis.

Various techniques exist in the literature for implementation of voltage stability analysis. Some of the conventional methods widely used are classified into the following types.

1. Q-V curve method.
2. P-V curve method.
3. Modal analysis
4. Continuation power flow method.
5. Index method.
6. Compensators

3.2.1 Q-V curve method

The Q-V curve technique is one among the popular methods to examine voltage instability problems during the post transient period in power systems. Two-bus equivalent representation is not required in Q-V curve method. Reactive power at the bus is plotted against critical Voltage at that bus. Generator bus is considered as test bus and power-flow program is run for specified voltage ranges and the reactive power of a bus is found from the power flow solutions and a curve is plotted against the specified voltage [2].

3.2.2 P-V curve method

P-V curve method is one of the extensively used methods for voltage stability analysis. Active power margin exists before the point of voltage instability can be calculated. Changes in real power consumption for change in voltage are monitored in a radial system. In huge meshed networks, real
power is the total active load in an area and \( V \) is the voltage of the critical bus. Real power transferred throughout a transmission line is also studied by this method [2].

### 3.2.3 Continuation Power flow

At the voltage collapse point, it is hard to obtain the power flow solution because the Jacobian matrix becomes singular. To solve this problem continuation power flow is used, where the power flow solution closer to voltage collapse point is obtained. The varying parameter is the loading factor; however, if system gets nearer to bifurcation the classical power flow Jacobian fails. At the voltage collapse point the power flow Jacobian is made nonsingular. Thus this method obviously goes around the collapse point, such that the user traces the unstable side of the branch.

### 3.2.4 Modal Analysis

The modal analysis primarily depends on Jacobian matrix of the power flow. Flowchart for the modal analysis method used is shown in Figure 3.1

At a given operating condition the voltage is stable for a system if for all the buses in the system, the reactive power injection is increased at a bus then voltage magnitude also increases in the same bus. A system is voltage unstable; if the voltage magnitude decreases at a bus as the reactive power injection is increased at the same bus. In other words, if \( Q-V \) sensitivity is positive then the system is voltage stable for all bus and if \( Q-V \) sensitivity is negative then it is unstable for at least one bus.
3.2.5 Index Method

The slow variation in reactive power loading towards its maximum point causes the traditional load flow solution to reach its non-convergence point. Beyond this point, the ordinary load flow solution does not converge, which in turn forces the systems to reach the voltage stability limit prior to bifurcation in the system. The margin measured from the base case solution to the maximum convergence point in the load flow computation determines the maximum loadability at a particular bus in the system. Some of the indices are FVSI, $L_{mn}$ and $L_{QP}$

3.2.6 Compensators

Various compensators such as series and shunt compensators are used for analysing the voltage stability. Nowadays FACTS devices are widely used for compensation.
3.3 MODAL ANALYSIS AND WEAK BUS IDENTIFICATION

3.3.1 Participation factors

The participation factor of the $j^{th}$ variable in the $i^{th}$ mode is defined as the product of the $j^{th}$'s components of the right and left eigenvectors corresponding to the $i^{th}$ mode. The magnitude of participation factors is dimensionless. They are independent state variables. In a mode the sum of the participation factors of all variables and the sum of the participation of all modes in a variable are equal to one [9].

The suitable description and purpose as to which load bus participates in the selected modes become more important. This requires a tool, called the participation factor, for classifying the weakest load buses that are making major contribution to the selected modes.

For the eigen value $\lambda_i$ of the matrix $J_R$, if $\xi_i$ and $\eta_i$ correspond to the right and left eigenvectors respectively, then the participation factor measuring the participation of the $k^{th}$ bus in $i^{th}$ mode is defined as

$$P_{ki} = \xi_ki\eta_{ki}$$ (3.1)

V-Q sensitivity at $i^{th}$ mode is determined by the bus with highest $P_{ki}$. The area close to voltage instability is determined by bus participation factor provided by the smallest eigen value of $J_R$.

3.3.2 Location of STATCOM by Modal Analysis Technique

By Modal analysis technique the location of the STATCOM can be identified using the subsequent procedure [8].

1. Using N-R method Voltage profile for base case is determined.
2. Modal analysis is done to predict the voltage collapse.
3. Calculate Participation factor and identify weak bus.

4. Incorporating the STATCOM into the affected area.

3.3.3 Voltage Profile of IEEE 14 bus and 30 bus System

Power flow analysis is done for the base case for the test system. The test system considered is IEEE 14 bus and IEEE 30 bus system. The Voltage Profile graph which shows the voltages of all the buses in the system after the load flow analysis is represented in the graph as shown in Figure 3.2 for 14 bus and Figure 3.3 for 30 bus system.

Figure 3.2 Voltage profile for 14 bus

Figure 3.3 Voltage profile for 30 bus
3.4.4 Eigen value and participation factor

Using MATLAB programming the eigen value and participation factor for the respective buses are calculated. The Eigen value and the Participation factor tabulation are shown in Table 3.1 and 3.2.

Table 3.1: Eigen Value for 30 Bus

<table>
<thead>
<tr>
<th>Load Buses</th>
<th>Eigen Value</th>
<th>Load Buses</th>
<th>Eigen Value</th>
<th>Load Buses</th>
<th>Eigen Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>110.2056</td>
<td>15</td>
<td>19.12576</td>
<td>23</td>
<td>1.023776</td>
</tr>
<tr>
<td>4</td>
<td>100.6465</td>
<td>16</td>
<td>19.78167</td>
<td>24</td>
<td>1.726683</td>
</tr>
<tr>
<td>6</td>
<td>65.95407</td>
<td>17</td>
<td>18.07852</td>
<td>25</td>
<td>8.785738</td>
</tr>
<tr>
<td>7</td>
<td>59.54311</td>
<td>18</td>
<td>16.37527</td>
<td>26</td>
<td>7.436012</td>
</tr>
<tr>
<td>9</td>
<td>37.81878</td>
<td>19</td>
<td>13.72794</td>
<td>27</td>
<td>3.580842</td>
</tr>
<tr>
<td>10</td>
<td>35.38626</td>
<td>20</td>
<td>13.63338</td>
<td>28</td>
<td>4.050713</td>
</tr>
<tr>
<td>12</td>
<td>23.42376</td>
<td>21</td>
<td>11.04466</td>
<td>29</td>
<td>6.020716</td>
</tr>
<tr>
<td>14</td>
<td>23.07394</td>
<td>22</td>
<td>0.50603</td>
<td>30</td>
<td>5.452661</td>
</tr>
</tbody>
</table>

Table 3.2(a): Participation Factor For 14 Bus

<table>
<thead>
<tr>
<th>Load Bus Numbers</th>
<th>Participation Factor</th>
<th>Load Bus Numbers</th>
<th>Participation Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.00907</td>
<td>11</td>
<td>0.110</td>
</tr>
<tr>
<td>5</td>
<td>0.00454</td>
<td>12</td>
<td>0.0225</td>
</tr>
<tr>
<td>7</td>
<td>0.0691</td>
<td>13</td>
<td>0.0351</td>
</tr>
<tr>
<td>9</td>
<td>0.191</td>
<td>14</td>
<td>0.325</td>
</tr>
<tr>
<td>10</td>
<td>0.232</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 3.4 IEEE 30 bus system

Table 3.2(b): Participation Factor For 30 Bus

<table>
<thead>
<tr>
<th>Load Bus Numbers</th>
<th>Participation Factor</th>
<th>Load Bus Numbers</th>
<th>Participation Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0.0004</td>
<td>19</td>
<td>0.0179</td>
</tr>
<tr>
<td>4</td>
<td>0.0005</td>
<td>20</td>
<td>0.0172</td>
</tr>
<tr>
<td>6</td>
<td>0.0005</td>
<td>21</td>
<td>0.0176</td>
</tr>
<tr>
<td>7</td>
<td>0.0002</td>
<td>22</td>
<td>0.0189</td>
</tr>
<tr>
<td>9</td>
<td>0.0037</td>
<td>23</td>
<td>0.0238</td>
</tr>
<tr>
<td>10</td>
<td>0.0121</td>
<td>24</td>
<td>0.0395</td>
</tr>
<tr>
<td>12</td>
<td>0.0037</td>
<td>25</td>
<td>0.1055</td>
</tr>
<tr>
<td>14</td>
<td>0.0081</td>
<td>26</td>
<td><strong>0.1729</strong></td>
</tr>
<tr>
<td>15</td>
<td>0.0111</td>
<td>27</td>
<td>0.1028</td>
</tr>
<tr>
<td>16</td>
<td>0.0079</td>
<td>28</td>
<td>0.0025</td>
</tr>
<tr>
<td>17</td>
<td>0.0115</td>
<td>29</td>
<td><strong>0.1934</strong></td>
</tr>
<tr>
<td>18</td>
<td>0.0165</td>
<td>30</td>
<td><strong>0.2118</strong></td>
</tr>
</tbody>
</table>
The graphical representation of the Participation factor for the buses in the test system is represented in Figure 3.5(a) and Figure 3.5(b)

Figure 3.5(a) Participation Factor for 14 Bus

Figure 3.5(b) Participation Factor for 30 Bus
From the modal analysis calculation and the load flow analysis it is found that the participation factor is more for the Bus 14, (Participation value = 0.325) hence the bus is more sensitive to voltage collapse for 14 bus system.

For 30 bus system the participation factor is more for buses 26, 29 and 30 (Participation value = 0.1729, 0.1934 and 0.2118 respectively) compared to other buses. Therefore the buses 26, 29 and 30 is more sensitive to voltage collapse in a 30 bus system.

3.4 LINE STABILITY INDICES

The main objective of this section is to develop indices based algorithm for analysing voltage stability and find the maximum loadability, critical line and the critical voltage for all the load buses. The most sensitive bus is identified based on the maximum loadability. To develop an algorithm for line outage contingency analysis based on indices for finding the most critical line outage and maximum loadability of all the buses. Contingency ranking is done based on the severity of all the line outages.

3.4.1 Fast Voltage Stability Index

The FVSI is derived from the voltage quadratic equation at the receiving bus on a two- bus system [18]. FVSI can be defined by

\[
FVSI_{ij} = 4 \frac{Z^2 Q_j}{V_i^2 X}
\]

(3.2)

where \(Z\) is the line impedance, 
\(X\) is the line reactance, 
\(Q_j\) is the reactive power flow at the receiving end and 
\(V_i\) is the sending end voltage.
The line that gives index value closest to 1 will be the most critical line of the bus and may lead to system wide instability scenario. This index can also be used to determine the most sensitive bus on the system.

3.4.2 Line Stability Index (L_{QP})

Line Stability Index, L_{QP} is given as follows

\[ L_{QP} = 4 \left( \frac{X_{ij}}{V_i^2} \right) \left( \frac{X_{ij}}{V_j^2} P_i^2 + Q_j \right) \]  \hspace{1cm} (3.3)

where

\( X_{ij} \) is the line reactance,
\( Q_j \) is the reactive power flow at the receiving bus,
\( V_i \) is the voltage on sending bus and
\( P_i \) is the active power flow at the sending bus.

Operating at secure and stable conditions requires the value of L_{QP} index to be maintained less than 1.

3.4.3 Line Stability Index (L_{mn})

This index was derived based on a two machine model of the power system connected by a single transmission. This is represented mathematically as

\[ L_{mn} = \frac{4Q_j X_{ij}}{V_j^2 \sin(\theta - \delta)} \]  \hspace{1cm} (3.4)

Lines that represent L_{mn} close to 1 reaching their stability limits while those near zero are stable.
3.5 VOLTAGE STABILITY ANALYSIS (VSA)

The loading pattern is chosen so that each time the load is changed in only one particular node, keeping the load at other nodes fixed at base case. Several combinations of real and reactive load pattern are selected to achieve this and they are listed as follows

Case 1: Change with reactive power loading
Case 2: Change with real power loading
Case 3: Change with both real and reactive power

The analysis is conducted on the IEEE 30 bus system. Load buses are selected in order to investigate the effect of reactive power loading on FVSI values which in turn identifies the most critical line with respect to a bus. Reactive power at load buses are gradually increased from the base case until their highest permissible load or maximum loadability limit which is the maximum load that could be injected to a load bus previous to the power flow solution diverges.

The impact of line outage can be done by contingency analysis in the system. It is done by removing the lines in the system, in succession for all pre-determined case. This is done in order to delay the divergence of the load flow calculation; otherwise the load flow divergence will be faster and produce an inaccurate outcome of contingency ranking. The process is similar to voltage stability analysis. The only variation is that load flow calculation is done with a line outage at a time and there is no need to raise the reactive power load in the system. The buses are chosen in progression manner to validate the severity of outages that could occur in the system. FVSI are calculated on outage for every case. Output from all outage is sorted in descending order. The outage that results the highest index is the most severe contingency.
Table 3.3 Voltage stability analysis based on FVSI for case 1

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>( Q_{\text{max}} ) (MVAR)</th>
<th>Bus Voltage (p.u)</th>
<th>Critical Line connecting bus</th>
<th>FVSI</th>
<th>Bus No.</th>
<th>( Q_{\text{max}} ) (MVAR)</th>
<th>Bus Voltage (p.u)</th>
<th>Critical Line connecting bus</th>
<th>FVSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>286</td>
<td>0.776</td>
<td>1-3</td>
<td>0.998</td>
<td>19</td>
<td>92.5</td>
<td>0.6135</td>
<td>10-20</td>
<td>0.9995</td>
</tr>
<tr>
<td>4</td>
<td>470</td>
<td>0.7391</td>
<td>2-4</td>
<td>0.973</td>
<td>20</td>
<td>88.5</td>
<td>0.6903</td>
<td>10-20</td>
<td>0.9941</td>
</tr>
<tr>
<td>6</td>
<td>680</td>
<td>0.7864</td>
<td>6-8</td>
<td>0.983</td>
<td>21</td>
<td>159</td>
<td>0.6245</td>
<td>6-10</td>
<td>0.9915</td>
</tr>
<tr>
<td>7</td>
<td>280</td>
<td>0.7573</td>
<td>5-7</td>
<td>0.99</td>
<td>22</td>
<td>148</td>
<td>0.6181</td>
<td>6-10</td>
<td>0.9846</td>
</tr>
<tr>
<td>9</td>
<td>175</td>
<td>0.8288</td>
<td>9-11</td>
<td>0.981</td>
<td>23</td>
<td>88.2</td>
<td>0.6713</td>
<td>23-24</td>
<td>0.9794</td>
</tr>
<tr>
<td>10</td>
<td>173</td>
<td>0.7491</td>
<td>6-10</td>
<td>0.992</td>
<td>24</td>
<td>105</td>
<td>0.6571</td>
<td>22-24</td>
<td>0.9918</td>
</tr>
<tr>
<td>12</td>
<td>206</td>
<td>0.8187</td>
<td>12-13</td>
<td>0.988</td>
<td>25</td>
<td>60.8</td>
<td>0.672</td>
<td>24-25</td>
<td>0.9942</td>
</tr>
<tr>
<td>14</td>
<td>82.2</td>
<td>0.7788</td>
<td>14-15</td>
<td>0.998</td>
<td>26</td>
<td>28.5</td>
<td>0.7079</td>
<td>25-26</td>
<td>0.9936</td>
</tr>
<tr>
<td>15</td>
<td>149</td>
<td>0.6776</td>
<td>12-15</td>
<td>0.99</td>
<td>27</td>
<td>57.1</td>
<td>0.7486</td>
<td>28-27</td>
<td>0.9971</td>
</tr>
<tr>
<td>16</td>
<td>112</td>
<td>0.7219</td>
<td>12-16</td>
<td>0.986</td>
<td>28</td>
<td>292</td>
<td>0.7368</td>
<td>8-28</td>
<td>0.9923</td>
</tr>
<tr>
<td>17</td>
<td>154</td>
<td>0.588</td>
<td>6-10</td>
<td>0.979</td>
<td>29</td>
<td>34.5</td>
<td>0.6514</td>
<td>27-29</td>
<td>0.9916</td>
</tr>
<tr>
<td>18</td>
<td>86.5</td>
<td>0.6686</td>
<td>15-18</td>
<td>0.976</td>
<td>30</td>
<td>31.05</td>
<td>0.6606</td>
<td>27-30</td>
<td>0.9931</td>
</tr>
</tbody>
</table>

3.6 SIMULATION RESULTS

Voltage stability analysis is done on IEEE 30 bus system with line stability index indicated by FVSI and the results are shown in Table 3.3. For this purpose MATLAB software package has been used for coding. FVSI are calculated for all line in the system for every load increase. The line which has the biggest index with respect to increase in load is determined as the most critical line. Further increase in the load will cause the line to contain an index value larger than 1.00 resulting in whole system instable. The lines are called critical lines that exhibit the maximum FVSI values for each test bus. The greatest reactive load at FVSI value nearer to 1.00 is assigned as the maximum permissible load. The maximum loadability of all the load buses is referred in the Table 3.4. It is obvious that the line index increases as the reactive power loading increased. Line 34 is the most critical line corresponds
to any load change at bus 26. Bus 26 has the least maximum permissible load of 0.028589p.u and it is ranked the highest in the system and also the buses 29 and 30 have the lowest maximum loadability, these buses also consider as critical buses and marked as bold in Table.. Since the bus 3, 4 and 6 have a maximum permissible load of 2.85768p.u, 3.00089p.u and 3.1546p.u respectively. These buses are the most secure buses in the system according to the large maximum loadability.

Table 3.4 Bus Ranking based on Maximum loadability (VSA)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>26</td>
<td>26</td>
<td>30</td>
<td>13</td>
<td>22</td>
<td>15</td>
</tr>
<tr>
<td>2</td>
<td>30</td>
<td>30</td>
<td>29</td>
<td>14</td>
<td>15</td>
<td>22</td>
</tr>
<tr>
<td>3</td>
<td>29</td>
<td>29</td>
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<td>15</td>
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<td>4</td>
<td>27</td>
<td>25</td>
<td>18</td>
<td>16</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>5</td>
<td>25</td>
<td>27</td>
<td>14</td>
<td>17</td>
<td>10</td>
<td>12</td>
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<td>19</td>
<td>25</td>
<td>19</td>
<td>12</td>
<td>9</td>
</tr>
<tr>
<td>8</td>
<td>23</td>
<td>23</td>
<td>20</td>
<td>20</td>
<td>7</td>
<td>3</td>
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<td>19</td>
<td>20</td>
<td>23</td>
<td>22</td>
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<td>7</td>
</tr>
<tr>
<td>11</td>
<td>24</td>
<td>24</td>
<td>15</td>
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</tr>
<tr>
<td>12</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>24</td>
<td>6</td>
<td>6</td>
</tr>
</tbody>
</table>

3.7 VOLTAGE STABILITY ENHANCEMENT IN DEREGULATED ENVIRONMENT

The objective of this section is to apply an algorithm and simulate to find the power allocated for each of the generators and find the optimal and best location for the FACTS controllers such that overall system cost are minimized. The algorithm used is enhanced Genetic Algorithm to find the
type of the controller to be connected and conventional Newton-Raphson power flow analysis to find the optimal location of the devices and its rating.

3.8 COST FUNCTION

The objective of this work is to find simultaneously the optimal generation, choice and location of FACTS controllers so as to minimize the overall cost function, which comprises of generation cost and investment cost of FACTS controllers.

3.8.1 Generation Cost Function

The generation cost function is represented by a quadratic polynomial as follows [70].

\[ C_2(P_G) = \alpha_0 + \alpha_1 P_G + \alpha_2 P_G^2 \]  

(3.5)

Whereas \( P_G \) is the output of the generator (MW), and \( \alpha_0, \alpha_1 \) and \( \alpha_2 \) are cost coefficients.

3.8.2 FACTS Controller Cost Function

Based the Siemens AG Database the cost function for the controller that has been selected to use are as follows

The cost function for UPFC is:

\[ C_{1UPFC} = 0.0003s^2 - 0.2691s + 188.22 \text{ (US$ / kvar)} \]  

(3.6)

The cost function for TCSC is:

\[ C_{1TCSC} = 0.0015s^2 - 0.7130s + 153.75 \text{ (US$ / kVar)} \]  

(3.7)
The rating of the device is given by

\[ R_{TCSC} = rf \times 0.45 - 0.25 \text{ (Mvar)} \]  
(3.8)

\[ R_{UPFC} = rf \times 180 \text{ (MVar)} \]  
(3.9)

Where

\[ C_{1UPFC} \text{ and } C_{1TCSC} \] are in US$ / kVar, \( rf \) – rating factor and \( s \) is the operating range of the FACTS controller in MVar.

### 3.9 OPTIMAL POWER FLOW (OPF) WITH FACTS CONTROLLERS

The formulation of the optimal allocation of FACTS controllers can be expressed as follows [70]

Minimize \( C_{Total} = C_1(f) + C_2(P_G) \)  
(3.10)

Subjected to \( E(f,g) = 0 \)  
(3.11)

\[ B_1(f) < b_1, B_2(g) < b_2 \]  
(3.12)

Where

\( C_{Total} \): the overall cost objective function which includes the average investment costs of FACTS devices \( C_1(f) \) and the generation cost \( C_2(P_G) \).

\( E(f,g) \): the conventional power flow equations.

\( B_1(f) \) and \( B_2(g) \): are the inequality constraints for FACTS controllers and the conventional power flow respectively.

\( f \) and \( P_G \): are vectors that represent the variables of FACTS controllers and the active power outputs of the generators.

\( g \): represents the operating state of the power system.
The unit for generation cost is US$/Hour and for the investment cost of FACTS controllers are US$. They must be unified into US$/Hour. Normally the FACTS controllers will be in service for many years. However only a part of its life time is employed to regulate the power flow. In this work three years is employed to evaluate the cost function.

The average value of the investment costs are calculated as follows [70]

$$C_1(f) = \frac{C(f)}{8760 \times 3} \quad (3.13)$$

As mentioned above, power system parameters can be changed using FACTS controllers. These different parameters derive different results on the objective function in Equation 3.10. Also, the variation of FACTS locations and FACTS types has also influences on the objective function. Therefore, using the conventional optimization methods is not easy to find the optimal location of FACTS devices, types and control parameters simultaneously.

To solve this problem, optimization technique such as Genetic Algorithm, Enhanced Genetic Algorithm and Particle Swarm Algorithm are employed in conjunction with conventional NR power flow method.

3.10 GENETIC ALGORITHM

Genetic Algorithms are general purpose optimization algorithms [34] based on the mechanics of natural selection and genetics. They operate on string structures (chromosomes), typically a concatenated list of binary digits representing a coding of the control parameters (phenotype) of a given problem. Chromosomes themselves are composed of genes. The real value of a control parameter, encoded in a gene, is called an allele.

GA’s are an attractive alternative to other optimization methods because of their robustness. There are three major differences between
Genetic Algorithm and conventional optimization algorithms. First, Genetic Algorithm operates on the encoded string of the problem parameters rather than the actual parameters of the problem. Each string can be thought of as a chromosome that completely describes one candidate solution to the problem. Second, Genetic Algorithm uses a population of points rather than a single point in their search. This allows the Genetic Algorithm to explore several areas of the search space simultaneously, reducing the probability of finding local optima. Third, Genetic Algorithm do not require any prior knowledge, space limitations, or special properties of the function to be optimized, such as smoothness, convexity, unimodality, or existence of derivatives. They only require the evaluation of the so-called fitness function (FF) to assign a quality value to every solution produced.

Assuming an initial random population produced and evaluated, genetic evolution takes place by means of three basic genetic operators:

1) Parent selection
2) Crossover
3) Mutation

Parent selection is a simple procedure whereby two chromosomes are selected from the parent population based on their fitness value. Solutions with high fitness values have a high probability of contributing new offspring to the next generation. The selection rule used in this approach is a simple roulette-wheel selection.

Crossover is an extremely important operator for the Genetic algorithm. It is responsible for the structure recombination (information exchange between mating chromosomes) and the convergence speed of the Genetic algorithm and is usually applied with high probability (0.6–0.9). The chromosomes of the two parents selected are combined to form new
chromosomes that inherit segments of information stored in parent chromosomes. Until now, many crossover schemes, such as single point, multipoint, or uniform crossover have been proposed in the literature. Uniform crossover has been used in our implementation.

While crossover is the main genetic operator exploiting the information included in the current generation, it does not produce new information.

Mutation is the operator responsible for the injection of new information. With a small probability, random bits of the offspring chromosomes flip from 0 to 1 and vice versa and give new characteristics that do not exist in the parent population. In this approach, the mutation operator is applied with a relatively small probability (0.0001-0.001) to every bit of the chromosome.

Figure 3.6 Simple genetic algorithm (SGA)
The FF evaluation and genetic evolution take part in an iterative procedure, which ends when a maximum number of generations is reached, as shown in Figure 3.6.

When applying Genetic algorithms to solve a particular optimization problem (OPF in this case), two main issues must be addressed

1) The encoding, i.e., how the problem physical decision variables are translated to a Genetic Algorithm chromosome and its inverse operator, decoding;

2) The definition of the FF to be maximized by the Genetic Algorithm is formed by an appropriate transformation of the initial problem objective function augmented by penalty terms that penalize the violation of the problem constraints.

3.10.1 Encoding

In the SGA, shown in Fig. 3.7, after the application of the basic genetic operators (parent selection, crossover, and mutation) the advanced and problem-specific operators are applied to produce the new generation. All chromosomes in the initial population are created at random (every bit in the chromosome has equal probability of being switched ON or OFF).

Due to the decoding process selection, the corresponding control variables of the initial population satisfy their upper–lower bound or discrete value constraints. Population statistics are then used to adaptively change the crossover and mutation probabilities. If premature convergence is detected the mutation probability is increased and the crossover probability is decreased. The contrary happens in the case of high population diversity.
3.10.2 Fitness Function

GAs is usually designed so as to maximize the FF, which is a measure of the quality of each candidate solution. The objective of the OPF problem is to minimize the total operating cost.

Therefore, a transformation is needed to convert the cost objective of the OPF problem to an appropriate FF to be maximized by the GA. The OPF functional operating constraints are included in the GA solution by augmenting the GA FF by appropriate penalty terms for each violated functional constraint. Constraints on the control variables are automatically satisfied by the selected GA encoding/decoding scheme.

Therefore, the GA FF is formed as follows [71]

\[
FF = \frac{A}{\sum_{i=1}^{N_G} F_i(P Gi) + \sum_{i=1}^{N_C} w_j Pen_j}
\]  

(3.14)

\[
Pen_j = |h_j(x,u)|.H(h_j(x,u))
\]  

(3.15)

Where

- \( FF \)-fitness function;
- \( A \)- constant;
- \( F_i(P Gi) \) - fuel cost of unit i
- \( H(.) \)-Heaviside (step) function;
- \( N_G \)-number of units;
- \( N_C \)-number of functional operating constraints.
- \( Pen_j \)- penalty function for functional operating constraint j
- \( w_j \)- weighting factor for functional operating constraint j
3.11 ENHANCED GENETIC ALGORITHM (EGA)

In the EGA, [37] after the application of the basic genetic operators (parent selection, crossover, and mutation) the advanced and problem-specific operators are applied to produce the new generation.

All chromosomes in the initial population are created at random (every bit in the chromosome has equal probability of being switched ON or OFF). Due to the decoding process selected, the corresponding control variables of the initial population satisfy their upper–lower bound or discrete value constraints. However, the initial population candidate solutions may not satisfy the functional operating constraints or even the load flow constraints since the random, within limits, selection of the control variables may lead to load flow divergence.

Population statistics computed for the new generation include maximum, minimum, and average fitness values and the 90% percentile.

Population statistics are then used to adaptively change the crossover and mutation probabilities. If premature convergence is detected the mutation probability is increased and the crossover probability is decreased. The contrary happens in the case of high population diversity.
3.11.1 Advanced and Problem-Specific Genetic Operators

One of the most important issues in the genetic evolution is the effective rearrangement of the genotype information. In the Simple Genetic Algorithm, crossover is the main genetic operator responsible or the exploitation of information while mutation brings new non-existent bit structures. It is widely recognized that the Simple Genetic Algorithm scheme is capable of locating the neighborhood of the optimal or near-optimal solutions, but in general, requires a large number of generations to converge. This problem becomes more intense for large-scale optimization problems with difficult search spaces and lengthy chromosomes, where the possibility for the Simple Genetic Algorithm to get trapped in local optimal increases and the convergence speed of the Simple Genetic Algorithm decreases.
At this point, a suitable combination of the basic, advanced, and problem-specific genetic operators must be introduced in order to enhance the performance of the Genetic Algorithm. Advanced and problem-specific genetic operators usually combine local search techniques and expertise derived from the nature of the problem.

A set of advanced and problem-specific genetic operators has been added to the Simple Genetic Algorithm in order to increase its convergence speed and improve the quality of solutions. Our interest was focused on constructing simple yet powerful enhanced genetic operators that effectively explore the problem search space. The advanced features included in this GA implementation are as follows.

1) **Fitness Scaling**: In order to avoid early domination of extraordinary strings and to encourage a healthy competition among equals, a scaling of the fitness of the population is necessary. In this approach, the fitness is scaled by a linear transformation.

2) **Elitism**: Elitism ensures that the best solution found thus far is never lost when moving from one generation to another. The best solution of each generation replaces a randomly selected chromosome in the new generation.

3) **Hill Climbing**: In order to increase the GA search speed at smooth areas of the search space a hill-climbing operator is introduced, which perturbs a randomly selected control variable. The modified chromosome is accepted if there is an increase in FF value; otherwise, the old chromosome remains unchanged. This operator is applied only to the best chromosome (elite) of every generation.

In addition to the above advanced features, which are called “advanced” despite their wide use in most recent GA implementations to
distinguish between the Simple genetic algorithm and our EGA, operators specific to the OPF problem have been added.

All problem-specific operators introduce random modification to all chromosomes of a new generation. If the modified chromosome proves to have better fitness, it replaces the original one in the new population. Otherwise, the original chromosome is retained in the new population. All problem-specific operators are applied with a probability of 0.2. The following problem-specific operators have been used.

**Gene Swap Operator (GSO)** This operator randomly selects two genes in a chromosome and swaps their values. This operator swaps the active power output of two units, the voltage magnitude of two-generation buses, etc. Swapping among different types of control variables is not allowed.

**Gene Cross-Swap Operator (GCSO)** The GCSO is a variant of the GSO. It randomly selects two different chromosomes from the population and two genes, one from every selected chromosome, and swaps their values. While crossover exchanges information between high-fit chromosomes, the GCSO searches for alternative alleles, exploiting information stored even in low-fit strings.

**Gene Copy Operator (GCO)** This operator randomly selects one gene in a chromosome and with equal probability copies its value to the predecessor or the successor gene of the same control type. This operator has been introduced in order to force consecutive controls (e.g., identical units on the same bus) to operate at the same output level.

**Gene Inverse Operator (GIO)** This operator acts like a sophisticated mutation operator. It randomly selects one gene in a chromosome and inverses its bit-values from one to zero and vice versa. The GIO searches for
bit structures of improved performance, exploits new areas of the search space far away from the current solution, and retains the diversity of the population.

**Gene Max-Min Operator (GMMO)** The GMMO tries to identify binding control variable upper/lower limit constraints. It selects a random gene in a chromosome and, with the same probability (0.5), fills its area with 1s or 0s.

### 3.12 PARTICLE SWARM OPTIMIZATION (PSO)

PSO is a population-based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the social behavior of bird flocking or fish schooling. These phenomena can also be observed on insect colonies, e.g. bees. It is applicable to solving a number of problems where local methods fail or their usage is ineffective as in this case. One of the most important features of PSO is the ability of optimizing large complex multi-criterial combinatorial problems where the problem with the design of criterial function occurs, for example, it is hard to derive or is not continuous.

PSO however does not need this as it only requires the evaluation of each solution by the fitness function depending on the set of optimized parameters. This function is also used by GA and so is the idea of the initialization of parameter setup as a random generation. The main advantage of PSO compared to GA is the simpler method of providing new solutions based only on two variables - velocity and position related by two linear equations. Each possible solution is represented by a particle, which flies through the searched space, which is limited by restrictive maximum and minimum values, toward the current optimal position. The particle has its direction and speed of movement (velocity) but it can also randomly decide to move to the best position of all positions or to its own best position. Each
particle holds information about its own position (which represents one potential solution), the velocity and the position with the best fitness function it ever has flown through.

A. Implementation

The program was implemented in the MATLAB environment. The position here represents one potential solution, the velocity shows the trend of this particle, and both parameters are represented by a vector in the program implementation. The particles were coded by natural numbers. The position of each element in the vector space represents the number of the node in which a shunt capacitor should be placed whose value designates the capacitor type. The whole set of particles at a time is called the population. The subset made of newly born particles is called the generation.

The first generation of particles is produced with random position and velocity. Particle velocity is checked whether it is within the limits. The top speed can be different for each unit of velocity vector. If the velocity component exceeds the maximum allowed value, then it is set to the top value. After this correction, the solution is evaluated by the fitness function. The fitness function plays a key role in the program; therefore it is necessary to describe it in more details.

B. Fitness and penalization functions

The fitness function evaluates the quality of solutions and it incorporates numerous parameters, such as the capital cost of capacitors, expenses covering the power losses in the network per year, and function $\gamma$. The power losses are calculated by steady state analysis of the network. The output of the fitness function is total yearly operational costs of the network. The lower the fitness function value, the better the solution. The fitness function is calculated by the following equation [71]
\[ FF = \frac{A}{\sum_{i=1}^{N_G} F_i(P_{Gi}) + \sum_{i=1}^{N_C} \omega_j \cdot Pen_j} \]  

(3.16)

Where

- \( FF \) - fitness function;
- \( A \) - constant;
- \( F_i(P_{Gi}) \) - fuel cost of unit \( i \);
- \( H(.) \) - Heaviside (step) function;
- \( N_G \) - number of units;
- \( N_c \) - number of functional operating constraints (2).

\[ Pen_j = |h_j(x,u)| \cdot H(h_j(x,u)) \]  

(3.17)

C. **Next population**

After evaluation, the solutions can be sorted with respect to their fitness functions and it is possible to develop a new generation.

The first cycle ends after the creation of a new velocity vector and the calculation of the new position of the particular particle.

The new vector of velocity is calculated by the formula:

\[ \ddot{v} = \dot{v}_0 + c_1 \cdot n_1 \cdot (\vec{P}_{best} - \vec{P}_{pos}) + c_2 \cdot n_2 \cdot (\vec{g}_{best} - \vec{P}_{pos}) \]  

(3.18)
Figure 3.8. The principle of PSO

Where $\vec{v}$ denotes the new vector of velocity, $\vec{v}_0$ is the original vector of velocity, $c_1$ and $c_2$ are the constants which are set to the weight of differences of positions, $n_1$ and $n_2$ are the random variables, $\vec{P}_{best}$ is the best position of particle, $\vec{P}_{pos}$ is the current position of particle, and best $\vec{G}_{best}$ is the best position of all particles.

The new position is determined by the formula:

$$\vec{P}_{best} = \vec{P}_{pos} + \vec{v}$$  \hspace{1cm} (3.19)

D. Border

Each particle should be kept in a confined space corresponding to the parameter limitations. This problem is solved in this program by one of four methods. In the first case, the particle arriving in the forbidden area returns to its previous position. In the second case, the particle is held on the border. In the third case, the particle is bounced back to the allowed space. Bouncing back to the allowed space can be perfect or imperfect. Regarding the imperfect bounce, it is possible for the particle to end up in a random position.

In the fourth case, the particle can fly through the forbidden area back to the allowed space, but on the other side of the allowed space. This approach can be used in the case of a very specific limited space.
E. Parallel operation

One of the advantages of PSO utilization is the possibility to introduce parallel operations with mutual coupling, which enables searching in a larger area of feasible solutions and thereby finding the optimum solution more quickly. Parallel operation means that instead of a single branch of evolution several branches are created. These branches influence one another during the evolution only after a given number of generations when the temporary best solution of all the branches is transferred to the other branches. Thus the evolution of the branches is independent, but they can also use the results of the other branches. This modification limits a potential deadlock of the algorithm in the local minimum.

A MATLAB coding is developed for each algorithm inter linked with the conventional Newton Raphson’s method for load flow study. IEEE 14-bus system is taken to verify the effective operation of the algorithm. The Figure 3.9 shows the line diagram of IEEE 14-bus system.
The total population size in each algorithm is selected as 30, the mutation probability as 0.01 and crossover probability as 1.0.

Table 3.5 Result obtained for Genetic Algorithm

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Controller Type</th>
<th>Rating (p.u)</th>
<th>nl</th>
<th>nr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>UPFC</td>
<td>-0.681</td>
<td>9</td>
<td>14</td>
</tr>
<tr>
<td>2</td>
<td>TCSC</td>
<td>-0.977</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>UPFC</td>
<td>-0.353</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>UPFC</td>
<td>0.6501</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>TCSC</td>
<td>0.7654</td>
<td>4</td>
<td>9</td>
</tr>
</tbody>
</table>

From the coding results obtained with genetic algorithm it is found that each time the coding is executed a new result is obtained as tabulated in Table 3.5. From the observation made from the Table 3.5 we could say that with genetic algorithm analysis the use of TCSC controller with rating of 1.0p.u to -1.0p.u at the line connecting the bus 4 to bus 9.

Table 3.6 Result obtained for Enhanced Genetic Algorithm

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Controller Type</th>
<th>Rating (p.u)</th>
<th>nl</th>
<th>nr</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>TCSC</td>
<td>-0.277</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>TCSC</td>
<td>-1</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>UPFC</td>
<td>0.9989</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>UPFC</td>
<td>-0.251</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>TCSC</td>
<td>0.5972</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>
From the result obtained shown in Table 3.6, it is found that the use of UPFC controller will be more efficient with a rating of 1.0p.u to -0.25p.u at the line connecting the bus 1 to bus 5. Though the TCSC controller is repeated more number of times than UPFC controller the bus location for TCSC controller is different in each time when TCSC controller is selected.

Table 3.7 Result obtained for Particle Swarm Optimization

<table>
<thead>
<tr>
<th>SI</th>
<th>Controller Type</th>
<th>Rating (p.u)</th>
<th>bus</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>nl</td>
</tr>
<tr>
<td>1</td>
<td>UPFC</td>
<td>-0.0496</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>UPFC</td>
<td>-0.2579</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>UPFC</td>
<td>-0.1543</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>TCSC</td>
<td>-0.1129</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>UPFC</td>
<td>-0.9757</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 3.7 shows the coding result obtained for particle swarm optimization. The controller selected by this algorithm is UPFC with a rating ranging from 0.5p.u to -0.5p.u at the line connecting bus 5 to bus 6.

3.13 VOLTAGE STABILITY ENHANCEMENT

To improve the voltage stability of the system, the Voltage Stability Index (FVSI) which estimates the stability margin of the system is included into the objective function. The value of FVSI varies between 0 and 1 corresponds to no load and voltage collapse. Reduction in FVSI value indicates voltage stability improvement.
FVSI has to lie between 0 and 1 to maintain stability in power system. It has to be minimized to imply voltage stability improvement. Lower the index higher is the stability of the system.

From the Bus ranking from Voltage stability analysis and Line outage contingency analysis, it is evident that the optimum locations of the STATCOM are bus 26, 29 and bus 30. Buses 26, 29 and 30 has been identified as weak bus through Maximum loadability as well as modal analysis, hence we can conclude that the FACTS device STATCOM can be placed at buses 26, 29 and 30 and to improve the voltage stability.

**Table 3.8 STATCOM at Bus 30 (Q=31.09 MVAr)**

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>Voltage</th>
<th>Line No.</th>
<th>FVSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>With FACTS</td>
<td>Without FACTS</td>
<td>With FACTS</td>
</tr>
<tr>
<td>30</td>
<td>0.9836</td>
<td>0.7896</td>
<td>38</td>
</tr>
<tr>
<td>29</td>
<td>0.8941</td>
<td>0.6993</td>
<td>36</td>
</tr>
<tr>
<td>26</td>
<td>0.9925</td>
<td>0.8671</td>
<td>39</td>
</tr>
</tbody>
</table>

From table 3.8, it is clear that after connecting a STATCOM at bus 30 with reactive power of 31.09MVAR, the voltages at buses 26, 29 and 30 is increased. The voltage is increased from 0.8671p.u to 0.9925p.u at bus 26. after connecting STATCOM at bus 26. The FVSI values at the corresponding buses are reduced from 0.5824 to 0.4315 indicating that the loadability of buses 26,29 and 30 is increased.
Table 3.9 STATCOM at Bus 26 (Q=28.58 MVAr)

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>Voltage</th>
<th>Line No.</th>
<th>FVSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>With FACTS</td>
<td>Without FACTS</td>
<td>With FACTS</td>
</tr>
<tr>
<td>30</td>
<td>0.9732</td>
<td>0.9021</td>
<td>34</td>
</tr>
<tr>
<td>29</td>
<td>0.9625</td>
<td>0.8732</td>
<td>36</td>
</tr>
<tr>
<td>26</td>
<td>0.9869</td>
<td>0.7156</td>
<td>33</td>
</tr>
</tbody>
</table>

From table 3.9, after connecting a STATCOM at bus 26 with reactive power of 28.58MVAR, the voltages at buses 26, 29 and 30 is increased. Further it is concluded after connecting STATCOM at bus 26 the FVSI values at bus reduced from 0.3967 to 0.2302 and voltage increased from 0.7156p.u to 0.9869p.u indicating that the loadability of buses 26 and other weak bus is increased.

3.14 SUMMARY

Voltage stability analysis has been carried out by modal analysis and indices method. The test system considered for performing the studies are IEEE 14 bus and IEEE 30 bus system.

In modal analysis technique, the eigen values are estimated from the Jacobian matrix formed by N-R power flow method. The participation factor is estimated by using the eigen value. The bus corresponding to the highest participation factor is considered as weak bus. For IEEE 14 bus system 14th bus is identified as weak bus and for IEEE 30 bus system buses 26, 29 and 30 are the weak buses.

In the indices method the relation between Q and V has been used for formulation of different indices. Based on the indices value the critical bus
and critical lines have been estimated for IEEE 30 bus system in the critical
buses are 26, 29 and 30.

To improve the stability in a deregulated environment TCSC and
UPFC devices have been implemented in IEEE 14 bus system. The rating,
location and the cost function of FACTS devices have been developed. The
cost minimization of TCSC and UPFC has been optimized using GA, EGA,
and PSO.

By connecting STATCOM at bus 30 and 26 the voltage profile as well
as loadability of the weak bus is enhanced.