CHAPTER 4

MULTI OBJECTIVE PARTICLE SWARM ALGORITHM FOR REACTIVE POWER PLANNING INCLUDING VOLTAGE STABILITY

4.1 Introduction

Recently, voltage stability has become a major concern during the planning and operation of power system. The major cause of voltage instability is the inability of the power system to meet the reactive power requirement of the system. Hence it is essential to consider the voltage stability of the system during the reactive power planning stage. In this work Voltage stability level of the system is included as an additional objective of the RPP problem and Vector Evaluated Particle Swarm Optimization (VEPSO) algorithm is applied to solve this multi objective reactive power planning problem. VEPSO is a population-based multi objective stochastic optimization algorithm. It has been found that the VEPSO quickly finds the high-quality optimal solution for many power system optimization problems. The proposed approach has been examined and tested on the standard IEEE 30-bus system.

4.2 VOLTAGE INSTABILITY IN POWER SYSTEM

A system enters a state of voltage instability when a disturbance causes a progressive and uncontrollable decline in voltage. This change in voltage is so rapid that voltage control devices may not be able to take
corrective actions rapidly enough to prevent cascading outages. Voltage instability is typically associated with reactive power demands of load not being met because of limitation on the production and transmission of reactive powers. Contingencies such as unexpected line outages in stressed system may often result in voltage instability which may lead to voltage collapse. After a voltage collapse, the system becomes dismantled owing to the wide spread operation of protective devices.

4.2.1 Voltage Stability Analysis Methods

Research efforts have been made in understanding the phenomenon associated with the voltage instability and suggesting the remedial measures to protect the power system networks against such failures. Voltage stability analysis methods involve both static and dynamic factors.

Voltage stability is indeed a dynamic phenomenon and can be studied using extended transient/midterm stability simulations. However, such simulations do not readily provide sensitivity information or degree of stability. They are also time consuming in terms of CPU time and hence mathematical concepts are required for analysis of results. Therefore, the application of dynamic simulation is limited to investigation of specific voltage collapse situation, including fast or transient voltage collapse, and for coordination of protection and controls. Voltage stability analysis often requires examination of a wide range of system conditions and a large number of contingencies scenarios. For such application, the approach based on steady state analysis is more attractive and, if used properly, can provide much insight into the voltage/reactive power problem. Static analysis involves only the solution of algebraic equations and therefore is computationally much more efficient than dynamic analysis. The description of the static voltage stability analysis is presented below.
4.2.2 Static Voltage Stability Analysis

System dynamics influencing voltage stability are usually slow. Therefore, many aspects of the voltage stability problem can be effectively analyzed by using static methods, which examine the viability of the equilibrium point represented by a specified operating condition of the power system. The static analysis techniques allow examination of a wide range of system condition and, if appropriately used, can provide much insight into the nature of the problem and identify the key contributing factors.

4.2.2.1 Static voltage stability index

The static voltage stability analysis involves determination of a voltage stability index. This index will be an approximate measure of closeness of the system to voltage collapse. There are various methods of determining the voltage stability index. One such method is L-index proposed in (Kessel et al 1986). It is based on load flow analysis. Its value ranges from 0 (no load condition) to 1 (voltage collapse). The bus with the highest L-index value will be the most vulnerable bus in the system. The L-index calculation for a power system is briefly discussed below:

Consider a N-bus system in which there are \( N_g \) generators. The relationship between voltage and current can be expressed by the following expression:

\[
\begin{bmatrix}
I_G \\
I_L
\end{bmatrix} =
\begin{bmatrix}
Y_{GG} & Y_{GL} \\
Y_{LG} & Y_{LL}
\end{bmatrix}
\begin{bmatrix}
V_G \\
V_L
\end{bmatrix}
\]

(4.1)

where, \( I_G \), \( I_L \) and \( V_G \), \( V_L \) represent current and voltages at the generator buses and load buses.
Rearranging the above equation we get,

\[
\begin{bmatrix}
V_i \\
I_G
\end{bmatrix} =
\begin{bmatrix}
Z_{LL} & F_{LG} \\
K_{GL} & Y_{GG}
\end{bmatrix}
\begin{bmatrix}
I_L \\
V_G
\end{bmatrix}
\]  \hspace{1cm} (4.2)

where

\[
F_{LG} = -[Y_{LL}]^{-1}[Y_{LG}]
\]  \hspace{1cm} (4.3)

The L-index of the \( j^{th} \) node is given by the expression,

\[
L_j = \left| 1 - \sum_{i=1}^{N_g} F_{ji} \frac{V_i}{V_j} \angle (\theta_{ji} + \delta_i - \delta_j) \right|
\]  \hspace{1cm} (4.4)

where

- \( V_i \): Voltage magnitude of \( i^{th} \) generator bus
- \( V_j \): Voltage magnitude of \( j^{th} \) load bus
- \( \theta_{ji} \): Phase angle of the term \( F_{ji} \)
- \( \delta_i \): Voltage phase angle of \( i^{th} \) generator bus
- \( \delta_j \): Voltage phase angle of \( j^{th} \) load bus
- \( N_g \): Number of generating units

The values of \( F_{ij} \) are obtained from the matrix \( F_{LG} \). The L-indices for a given load condition are computed for all the load buses and the maximum of the L-indices (\( L_{\text{max}} \)) gives the proximity of the system to voltage collapse. The indicator \( L_{\text{max}} \) is a quantitative measure for the estimation of the distance of the actual state of system to the stability limit.

4.3 **PROBLEM STATEMENT**

The objectives of reactive power planning problem considered here is to minimize the total cost and L-index simultaneously subject to the equality and inequality constraints.
The first objective is given by

\[ \text{Minimize } f_1 = w_c + I_c \quad (4.5) \]

In the above equation, the first term represents the total cost of energy loss given by

\[ W_c = h \sum_{l \in N_i} d_{l} P_{\text{loss}}^l = h \sum_{l \in N_i} d_{l} \left[ \sum_{k \in n_{l}(k \neq l)} g_k (V_i^2 + V_j^2 - 2V_i V_j \cos \theta) \right] \quad (4.6) \]

Where \( P_{\text{loss}} \) is the network real power loss during the period of load level \( l \).

The second term represents the cost of reactive power source installation which has two components, the fixed installation cost and the purchase cost given by the equation.

\[ I_c = \sum_{i \in N} (c_i + C_{ci}|Q_{ci}|) \quad (4.7) \]

Here \( Q_{ci} \) can be either positive or negative corresponding to the installation of capacitance or reactance and so the absolute value is used to compute the cost.

The second objective is given by

\[ \text{Minimize } f_2 = L_{\text{max}} \quad (4.8) \]

The RPP problem is formulated as a nonlinear constrained multi-objective optimization problem where the cost and voltage stability index are treated as competing objectives. The above two objective functions (4.5) and (4.8) are subjected to the equality and inequality constraints given by the equations (3.4) to (3.11) in section 3.4. In this chapter, a multi-objective particle swarm optimization algorithm is proposed for solving the RPP problem. The effectiveness of this algorithm is demonstrated through IEEE 30 bus test system.
4.4 CONCEPT OF MULTI-OBJECTIVE OPTIMIZATION PROBLEM

When an optimization problem involves more than one objective function, the task of finding one or more optimum solutions are known as multi-objective optimization. Because of the presence of conflicting multi objectives, a multi objective optimization problem results in a number of optimum solutions, known as pareto-optimal solutions. In a multi-objective optimization, effort must be made in finding the set of trade-off optimal solutions by considering all objectives to be important.

There are two goals in a multi-objective optimization.

1. To find a set of solutions as close as possible to the pareto-optimal front.

2. To find a set of solutions as diverse as possible.

Multi-objective optimization problems can be solved by weighting functions, $\epsilon$ constraint and goal programming techniques. The important aspect of the weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. But weighting function cannot generate non-convex portions of the Pareto-front regardless of the weight contribution used. Also, the weight should be selected very intelligently, and this is difficult. To avoid this difficulty, the $\epsilon$-constraint method is used. This method is based on optimizing the most preferred objective and considering the other objectives as constraints bounded by some allowable levels. These levels are then altered to generate the entire Pareto–optimal set. This approach is time consuming and tends to find weak Pareto–optimal solutions. Goal programming requires that the decision makers
specify fairly detailed a priori information about the aspiration levels, preemptive priorities and the importance of goals in the form of weights. Hence, in this approach there is a tendency to generate inefficient solutions. The ability of particle swarm optimization algorithm to find multiple optimal solutions in one single simulation run makes it unique in solving multi-objective optimization problems.

4.5 MULTI OBJECTIVE PARTICLE SWARM OPTIMIZATION

PSO has been found to be quite successful in a wide variety of optimization tasks in power system including multi objective problems. Its high speed of convergence and its relative simplicity make PSO a highly viable candidate to be used for solving problems with several objectives. In this work, Vector Evaluated Particle Swarm Optimization (VEPSO) (Parsopoulos et al 2004) is applied to solve the multi objective RPP problem. It is a multi objective variant of particle swarm optimization. In VEPSO, the population is divided into number of sub populations based on the number of objective functions. Each swarm is evaluated using only one of the objective functions of the problem under consideration and the information it possess for this objective function is communicated to the other swarm through the exchange of their best experience. The relationships between the populations of two different swarms can be described considering all their possible types of interactions. Such interaction can be positive or negative depending on the consequences that such interaction produces on the population. The key issue in this algorithm is that the fitness of an individual in a population depends on the individual of a different population. The main features of VEPSO are given in Appendix 2.
4.6 VECTOR EVALUATED PARTICLE SWARM OPTIMIZATION ALGORITHM

The details of VEPSO algorithm is presented below:

Start

Generate two swarms and initialize particles

Evaluate the second Swarm using (4.5)

Evaluate the first Swarm using (4.8)

Set global best positions

\[ P_{gb}^{1} = \text{global best of } P_{i}^{1} \]

\[ P_{gb}^{2} = \text{global best of } P_{i}^{2} \]

While maximum number of iterations (Or any other convergence criterion) is not met.

Update the velocity using equation (A 2.1)

Update the position using equation (A 2.2)

Check the limits are enforced

Evaluate the swarm according to updated position

Update individual best

Update global best

End

Finish

4.7 VEPSO IMPLEMENTATION OF RPP PROBLEM

While applying VEPSO to solve the reactive power planning problem, the following issues need to be addressed.
1. Representation of the problem variables and
2. Formation of the evaluation function.

These two issues are described in this section.

4.7.1 Problem Representation

Each vector in the VEPSO population represents a candidate solution of the given problem. The elements of that solution consist of all the optimization variables of the problem. For the reactive power planning problem under consideration, generator terminal voltages \( V_{gi} \), the transformer tap positions \( t_k \) and the Capacitor settings \( Q_{Ci} \) are the optimization variables. Generator bus voltage is represented as floating point numbers, whereas the transformer tap position and reactive power generation of capacitor are represented as integers.

4.7.2 Evaluation Function

In the RPP problem under consideration, the objective is to minimize the total cost and voltage stability index \( L^{\text{max}} \) satisfying the constraints (3.4) to (3.11). The equality constraints given by equation (3.4) and (3.5) are satisfied by running the power flow program. The generator terminal bus voltage \( V_{gi} \), transformer tap settings \( t_k \) and the capacitor setting \( c \) are the control variables and they are self restricted by the optimization algorithm. The inequality constraints on the state variables are taken into consideration by adding a quadratic penalty function to the objective function. With the inclusion of penalty function, the overall penalty function becomes

\[
\text{PF} = \text{SP} + \sum_{j=1}^{N_{pq}} \text{VP}_j + \sum_{j=1}^{N_k} \text{QP}_j + \sum_{j=1}^{N_c} \text{LP}_j
\]  

(4.9)
Here SP, VP, QP, and LP are the penalty terms for the slack bus generator active power limit violation, load bus voltage limit violation, reactive power generation limit violation and line flow limit violation respectively. These quantities are defined by the equations (3.21) to (3.24) of section 3.9.2. The penalty function is added to each of the objective function to get the new objective functions.

4.8 BEST COMPROMISE SOLUTION

Upon having the pareto-optimal set of non-dominated solution, it is preferred to get the best compromise solution for implementation. Considering the imprecise nature of decision maker’s judgment, this work applies a fuzzy set-based approach to obtain the best compromise solution. Fuzzy set theory generalizes classical set theory to allow partial membership with a smooth boundary. The degree of membership in a set is expressed by a number between 0 and 1.0 means entirely not in the set, 1 means completely in the set, and a number in between 0 and 1 means partially in the set.

In this approach, the $i^{th}$ objective function $F_i$ is represented by a membership function $\mu_i$ defined by

$$\mu_i(F_i) = \begin{cases} 
1, & F_i \leq F_i^{min} \\
\frac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}}, & F_i^{min} < F_i < F_i^{max} \\
0, & F_i \geq F_i^{max}
\end{cases}$$

(4.10)

where $F_i^{min}$ and $F_i^{max}$ are the minimum and maximum value of the $i^{th}$ objective function respectively among all non-dominated solution.
The value of membership function suggests how far (in the scale from 0 to 1) a non-inferior (non-dominated) solution has satisfied the $F_i$ objective. The sum of membership function value $\mu(F_i)(i=1,2,3,...,M)$ for all the objectives can be computed in order to measure the accomplishment of each solution in satisfying the objectives. The accomplishment of each non-dominated solution can be rated with respect to all the N non-dominated solution by normalizing its accomplishment over the sum of the accomplishments of N non-dominated solution as follows:

$$\mu^k = \frac{\sum_{i=1}^{M} \mu(F_i^k)}{\sum_{k=1}^{N} \sum_{i=1}^{M} \mu(F_i^k)} \quad (4.11)$$

The solution that attains the maximum membership $\mu^k$ in the fuzzy set so obtained can be chosen as the best solution or the one having the highest cardinal priority ranking.

4.9 RESULTS AND DISCUSSION

The proposed MOPSO-based approach for solving the multi objective reactive power planning was applied to IEEE 30-bus system. The IEEE 30 bus system has 6 generators 24 load buses, 41 transmission lines, 4 transformer taps and 2 shunt elements. The generator active power generation was kept fixed except for the slack bus. The base power and parameters of costs are given in Table 3.1. The transmission line parameters and the system base load are taken from (Alsac et al 1974). The variable limits are given in Table 3.2. The real power settings of the generator are taken from (Alsac et al 1974). The real power settings of the generator are taken from (Alsac et al 1974). The possible locations for capacitor installation are buses 10, 12,15,17,20,21,23,24 and 29.
The MOPSO was applied with control parameters in order to get acceptable trade offs close to the pareto optimal front (POP). The pareto optimal front obtained in this case is plotted in Figure 4.2. It is observed that the proposed approach has produced 17 pareto optimal solution in a single run that have satisfactory diversity characteristics and span over the entire pareto optimal front. Out of these, two optimal solutions which are the extreme points of Figure 4.2 that represent the minimum total cost and minimum $L_{\text{max}}$ are given in Table 4.1. These solutions are very close to those of individual optimization in terms of objective function values. This demonstrates the effectiveness of the proposed approach, as the best solutions of both objectives along with a set of optimal solutions can be obtained in a single run. The distribution and the diversity of the optimal solution in the pareto optimal front are much better in terms of sharing the objective space. The membership function given in (4.16) and (4.17) are used to evaluate each member of the pareto optimal set. Then the best compromise solution that has the maximum value of membership can be extracted. The best compromise solution is given in Table 4.2.

Table 4.1 Optimal control variables for IEEE 30 – bus system

<table>
<thead>
<tr>
<th>Control variable settings</th>
<th>Minimum total cost</th>
<th>Minimum $L_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_1, V_2, V_5, V_8,$</td>
<td>1.05,1.04,1.03,</td>
<td>1.03,1.05,1.06,</td>
</tr>
<tr>
<td>$V_{11}, V_{13}$</td>
<td>1.06,1.05,1.04</td>
<td>1.05,1.04,1.05</td>
</tr>
<tr>
<td>$t_{6-9}, t_{6-10}, t_{4-12}, t_{28-27}$</td>
<td>0.95,1.05,1.025,1.00</td>
<td>1.05,1.025,1.00,0.95</td>
</tr>
<tr>
<td>$C_{10}, C_{12}, C_{15}, C_{17}, C_{20},$</td>
<td>1.5,4,3,5,3</td>
<td>5.4,3,4,2,5</td>
</tr>
<tr>
<td>$C_{21}, C_{23}, C_{24}, C_{29}$</td>
<td>5,4,3</td>
<td>5,3,1</td>
</tr>
<tr>
<td>Total Cost ($)</td>
<td>2,740,000</td>
<td>3,520,000</td>
</tr>
<tr>
<td>$L_{\text{max}}$</td>
<td>0.097</td>
<td>0.0944</td>
</tr>
</tbody>
</table>
Table 4.2 Best compromise solution

<table>
<thead>
<tr>
<th>Control variable</th>
<th>Optimal control variables settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_1, V_2, V_5, V_8, V_{11}, V_{13}$</td>
<td>1.09, 1.08, 1.05, 1.06, 1.04, 1.05</td>
</tr>
<tr>
<td>$t_{6-9}, t_{6-10}, t_{4-12}, t_{28-27}$</td>
<td>0.95, 1.05, 1.025, 1.00</td>
</tr>
<tr>
<td>$C_{10}, C_{12}, C_{15}, C_{17}, C_{20}, C_{21}, C_{23}, C_{24}, C_{29}$</td>
<td>1, 5, 5, 4, 5, 3, 5, 1</td>
</tr>
<tr>
<td><strong>Total Cost ($)</strong></td>
<td>2,880,000</td>
</tr>
<tr>
<td>$L_{\text{max}}$</td>
<td>0.095</td>
</tr>
</tbody>
</table>

Figure 4.1 Pareto optimal front for IEEE 30-bus system

4.10 CONCLUSION

The present work makes use of recent advances in multi objective particle swarm optimization algorithm to develop a method for optimal reactive power planning including voltage stability. The multi-objective reactive power planning problem has been solved using vector evaluated particle swarm optimization algorithm. It has considered the minimization of
operation and installation cost and voltage stability index – $L_{\text{max}}$ as the objectives. The algorithm has been tested on the standard IEEE-30 bus system. The result shows that the proposed algorithm is effective in solving the multi-objective reactive power planning problem. Moreover, a fuzzy based mechanism is employed to extract the best compromise solution over the trade-off front. This algorithm is general and can be applied to other multi-objective power system optimization problem also.