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Optimal Allocation of SVC for Minimization of Power Loss and Voltage Deviation using NSGA-II

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Abstract

Modern this paper proposes non dominated sorting genetic algorithm (NSGA-II) which has feature of adaptive crowding distance for finding optimal location and sizing of Static Var Compensators (SVC) in order to minimize real power losses and voltage deviation and also to improve voltage profile of a power system at the same time. While finding the optimal location and size of SVC, single line outages are considered as contingencies and voltage limits for the buses are taken as security constraints. To demonstrate the effectiveness of the proposed approach, NSGA-II has been applied for finding optimal location and sizing of SVC on IEEE 30-bus test system. The obtained results are highly encouraging and reveal the capability of the NSGA-II to generate well-distributed non-dominated Pareto front.

Keywords*-Multi-objective optimization; NSGA-II; SVC; power losses (PL); voltage deviations (VD)*

1. Introduction

One of the major problems in the operation and control of emerging power system is to sustain the voltage profile with optimal operating and the security of the system while minimizing system power losses. A suitable voltage profile can be maintained while minimizing two objective functions related to the power losses and load voltage deviation using FACTS devices. Installation of FACTS devices is matter of huge capital investment and therefore an intensive exploration is required at planning stage to acquire maximum benefit of these devices.

Different approaches, algorithms and methods have been reported in the literature to solve the dispatch problems. They can be broadly classified under following headings:

Based on the evolutionary techniques [1] as the NPGA method (Niched Pareto Genetic Algorithm) [2-3], NSGA (Non Dominated Sorting Genetic Algorithm) [4], SPEA (Strength Pareto Evolutionary Algorithm) [5], ISPEA-II (Improving Strength Pareto Evolutionary Algorithm) [6], an Improved Hybrid Evolutionary Programming Technique [7] and Ant Colony Optimization Method [8].

Based on the classic methods as the non linear programming technique [9], the weights method [10] and the ϵ-constraints method [11]. The classic methods reported in the literature provides some inconveniences like the long time execution, the non security of convergence, the complexity of algorithmic and the generation of a weak number of non dominated

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solutions. Due to these inconveniences, the evolutionary algorithms are more popular nowadays as they have ability to exploit huge spaces of research and don't require a pre identification of the problem. In [21], the optimal location and size of SVC has been searched in a power system using outage of critical contingencies and GA for minimization of power loss, voltage deviation and size of SVC. The Optimal location of TCSC has been obtained using PSO and PSO-TVAC for voltage stability enhancement. It has been found that PSO-TVAC provides faster convergence and better solution quality as compare to PSO [22]. The problem of minimization of real power loss and load bus deviation has been combined to form a multi-optimization function. NSGA-II has been used for minimization of this multi-objective function. The capability of NSGA-II has been explored in handling multi-objective function has been explored by the authors [23].

In this paper, multi-objective optimization problem is formulated as mixed continuous-discreet problem by combining two objective functions. These two objective functions are minimization of real power loss and load bus voltage deviation. The evolutionary optimization method implemented for optimization of multi-objective problem is non dominated sorting genetic algorithm-II (NSGA-II). The optimization has been performed for minimization of the formulated multi-objective function considering constraints.

2. Problem Formulation

In this paper, single line outages in a power system are considered as contingencies for optimal placement of SVC. The severity of a contingency (i.e. single line outage) is evaluated using Voltage Power Index (*VPI*) [17] as:

$$VPI = \sum_{i=1}^{NB} (\Delta|V_i|/\Delta|V_i^{max}|)^{2m} \tag{1}$$

where, $\Delta|V_i|$ is difference between the voltage magnitude under line outage and base case condition; $\Delta|V_i^{max}|$ is bus voltage magnitude chosen by the utility engineers to indicate how much they think is tolerable limit for an outage case. In this paper, the value of the exponent m has been taken as 2 and $\Delta|V_i^{max}|$ has been considered as 0.2 p.u.

A. Minimization of Real Power Loss

The real power loss (P_L) as first objective function $F_1(u,v)$ is defined as:

$$P_L = \sum_{k=1}^{NTL} [g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \tag{2}$$

where, NTL and g_k are the number of transmission lines and conductance of k^{th} line; the bus voltages at the both ends of k^{th} line are $V_i \angle\delta_i$ and $V_j \angle\delta_j$, respectively .

B. Minimization of Voltage Deviations

The load voltage deviation (VD) as second objective function $F_2(u,v)$ is defined as:

$$VD = \sum_{k=1}^{NL} |(V_k - V_k^{ref})| \tag{3}$$

where, NL represents number of load buses. In this paper, V_k^{ref} is taken as 1.0 p.u. In a power system, unless specified, it is accustomed to maintain the load bus voltages within ±5% of its nominal value.

In both objective functions $F_1(u,v)$ and $F_2(u,v)$, u is the vector of dependent variable consisting of load bus voltages ($V_{L_1} \; . . . \; V_{L_{NL}}$), generators' reactive powers ($Q_{g_1} \ldots Q_{g_{NG}}$) and transmission lines' loadings (S_{L_1} . . . $S_{L_{NTL}}$), and v is the vector of independent variables consisting of generators' voltages (V_{g_1} …$V_{g_{NG}}$), transformers' tap settings (T_1 . . .T_{NT}) and reactive power injections (Q_{c_1} . . . $Q_{c_{NC}}$).Therefore u and v can be expressed as:

$$u = [V_{L_1} \ldots V_{L_{NL}}; Q_{g_1} \ldots Q_{g_{NG}}; \; S_{L_1} \ldots S_{L_{NTL}}] \quad (4)$$

$$v = [V_{g_1} \ldots V_{g_{NG}}; T_1 \ldots \; T_{NT}; \; Q_{c_1} \ldots Q_{c_{NC}}] \quad (5)$$

C. Multi- Objective function

The objective function for the optimization problem can be obtained by combining all objectives mentioned above as:

$$Ƒ\,(u,v) = F_1(u,v) + F_2(u,v) + \eta \quad (6)$$

where, η is penalty factor (pf) which is taken into account for violation of load voltage deviation. Lower the value of η is an indication of fissile solution and vice-a-versa. Now, the optimization can be performed for minimizing the objective function Ƒ (u,v), subject to equality and inequality constraints.

D. Constraints

1) Equality Constraints

The equality constraints represent the typical load flow equations as follows:

$$P_{Gi} - P_{Di} = V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) B_{ij} \sin(\delta_i - \delta_j))] \quad (7)$$

for i = 1,……., *NB*

$$Q_{Gi} - Q_{Di} = V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] \quad (8)$$

for i = 1,……., *NB*

where, NB represents number of buses. P_{Gi},, Q_{Gi} are the generator real and reactive powers and P_{Di}, Q_{Di} are the active and reactive power load at bus *i and j* respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance of the line between bus *i* and bus *j*, respectively.

2) Inequality Constraints

Inequality constraints are the upper and lower limits of reactive power of a generator. The reactive power of i^{th} generator must lie within its minimum ($Q_{g_i}^{min}$) and maximum ($Q_{g_i}^{max}$) limits as:

$$Q_{g_i}^{min} \le Q_{g_i} \le Q_{g_i}^{max} \qquad i = 1,2 \ldots NG \quad (9)$$

3. Implementation of NSGA-II

A. Initial Population

As a first step an initial population *P* is generated. The size of initial population is *N'*× *n'*, where *N'* represents the number of individuals (chromosomes) while *n'* represents the number of both variables i.e. continuous and discrete variables. Initially a gene of each individual is determined by setting its value randomly such that its value lies between the upper and lower limits.

B. Non-dominated Sort

After generating the initial population *P*; a non-dominated sorting of the population is done into different fronts. Detail discussion regarding the theory of non-dominated sorting is accessible in ref. [18].

C. Density Estimation

To obtain an approximation of the density of solutions nearby a particular solution in the population, the average distance of two points of either side on the point under consideration is calculated for each of the objectives. A cuboid is thus obtained created by considering the nearest solutions on either side. The magnitude $i_{distance}$ provides as an estimate of the perimeter of the cuboid and is called the crowding distance. For details of crowding distance ref. [18] may be referred.

D. Selection Algorithm

The Non-dominated sorting based selection approach as given in [20] has been used for selecting the population for the next generation. In the selection process, as a first step, a combined population $R_t = P_t \cup Q_t$ is created, where P_t represents the parent population while Q_t stands for the new population formed with implementation of genetic operators. The size of population R_t is as 2N. The population R_t is sorted in accordance to non-domination. Thereafter crowding distance is calculated for each individual. As the only N chromosomes are selected for next generation P_{t+1} from 2N chromosomes of population R_t, an ensured elitism may be predicted. Now, solutions subjected to the non-dominated set F_1 can be considered as the best solutions of the combined population and same must be given higher priority than any other solution during the process of selection. During the process of selection of N solutions from non-dominated set *i.e.*, from F_1 starting fronts the following cases are considered for selecting a front:

a) There should be attest more than one chromosome having zero crowding distance and/or

b) The different solutions that have a crowding distance which is less than $\in$ the threshold value.

The Case 1 is a suggestion of duplicate chromosomes and in case 2 where chromosomes are having a crowding distance less than $\in$ is an indication of close proximity of solutions *i.e.*, threshold value which, if accepted, may result into cluster of solutions which are not desired. The algorithm selects only one solution in case of duplicate chromosomes and rejects all that chromosomes which have crowding distance less than $\in$. If the number of solutions so selected from front F_1 is less than N, the remaining (y) members of the population P_{t+1} are chosen from next succeeding non-dominated fronts in the order of their ranking. As a result, solutions from the set F_2 are chosen next to F_1, followed by solutions from the set F_3 and so on till N number of solutions is selected. During the selection, the solutions are received from best to worst front (F_1, F_2, …..), but due to non acceptance of all solutions of any particular front, there may be a chance for not getting all N chromosomes even from all the fronts (having 2N chromosomes). In all these cases, population will be filled up by duplicating the acceptable solutions. The new population size N of P_{t+1} will now used for genetic operator like selection, crossover, and mutation to create a new population Q_{t+1} of size N.

E. Adaptable threshold for crowding distance

The threshold value for crowding distance is adapted as proposed in [17] for creating prospective solutions like creating diverse solutions, avoiding too proximate solutions etc. If, for a particular value of $\in$, all N solutions are selected from F_1 only, it may happen that all N accepted solutions are clustered in a particular region. In that case the algorithm adapts the value of $\in$ to a greater value so that, to have a total of N solutions, the algorithm is bound to go to at least F_2, if not to F_3. Going to F_2 guarantees that all solutions of F_1 are accepted, which are spread over the Pareto Front. However, if *N* solutions are not obtained even after accepting non-violated chromosomes from all the fronts, $\in$ value will be decreased to enable the algorithm to have more solutions from F_1, F_2 *etc*.

F. Creation of offspring

In this paper, real-coded GA (SBX- Simulated Binary Crossover) has been used for crossover and Polynomial mutation is used for mutation. Details are in accordance to ref. [19].

G. Stopping Rule

The iterative procedure for generating new trials by selecting those having minimum function values from the set of competing pool is terminated when there is no considerable improvement in the solution. The procedure can also be terminated when a given maximum number of generations are reached. In this paper, the maximum number of generations has been considered as the stopping criterion.

4. Simulations Results

NSGA-II has been implemented for finding optimal location and sizing of SVC in IEEE 30-test bus system [16] to minimize real power losses and load bus voltage deviation. The test bus system consists of one slack bus, 5 *PV* buses, 24 *PQ* buses and 41 transmission lines. For optimal placement of SVC, single line outages are considered as contingencies in the test power system and to determine the severity of a contingency, *VPI* is calculated for all possible line outage. It has been observed that developed NR load flow program converges only for 37 line outages out of 41 line outages. The objective function (6) is formulated as a multi objective optimization problem. The placement of SVC is considered as a discreet decision variable, where 24 *PQ* buses may be the possible optimal location for SVC placement.

For some of the single line outage contingencies, the voltage of some buses violated the permissible voltage limit in viewpoint of voltage security, which is indicated by *VPI* in this paper. On the basis of *VPI*, the ranking of critical contingencies is done as 36, 5, 15, 37, 38, and 25 and so on. In this paper, only first three severe contingencies *i.e.*, outage of line nos. 36, 5, and 15 have been considered for SVC placement.

A. Outage of line no. 36

The highest value of *VPI* is obtained for outage of line no. 36 as 0.1541, therefore, from the viewpoint of voltage security it is the most severe line outage. NSGA II is implemented for outage of line no. 36, with a population size of 10 and 180 generations to determine the optimal location and sizing of SVC. The simulation results of five trials are shown in Table 1.

These results provide two optimal locations i.e. bus no. 27 for three times and bus no. 30 for two times with a penalty factor of 3.37 and 11.67 respectively. The rating of SVC for bus no. 27 is 0.1180 p.u. while it is found 0.1093 p.u. for bus no. 30. The power loss and voltage deviations are 0.1930 p.u. and 0.6562 p.u., when SVC was placed at bus no. 27 whereas power loss and voltage deviations are 0.1943 p.u., and 0.6207 p.u, when SVC is placed at bus no. 30. The best optimal location for SVC may be considered as bus no. 27 due to lowest penalty factor and minimum power loss. Figure 1 show the Pareto optimal front for outage of line no. 36, when SVC is placed at bus no. 27. It provides several solutions to multi objective optimization problem (6) and permits the operator to select adequate one. The best compromising solution for optimal values of power loss and voltage deviation are given in Table IV. Figure 2 illustrates the voltage profile of the test system without and with SVC at bus no. 27. It is observed from Figure 2 that with outage of line no. 36, the voltage magnitude at bus nos. 25, 26, 27, 29 and 30 was below 0.95 p.u., which after placement of SVC at bus no. 27 significantly increased.

Table 1. SVC Placement Results for LO 36

Trials	Optimal Location	Optimal Size (p.u)	Real Power Loss (p.u)	Voltage Deviation in p.u	Penalty Factor
T1	27	0.1180	0.1930	0.6562	3.37
T2	30	0.1093	0.1943	0.6207	11.67
T3	27	0.1180	0.1929	0.6562	3.37
T4	27	0.1180	0.1929	0.6562	3.37
T 5	30	0.1093	0.1943	0.6207	11.67

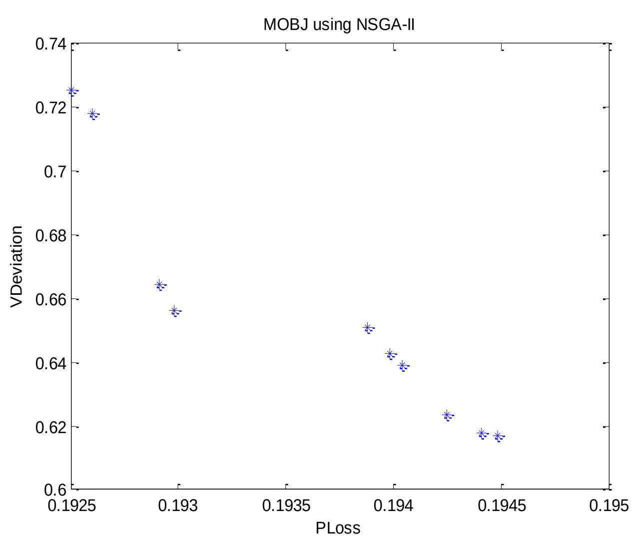

Figure 1. Pareto Front for LO 36 when SVC placed at bus no 27

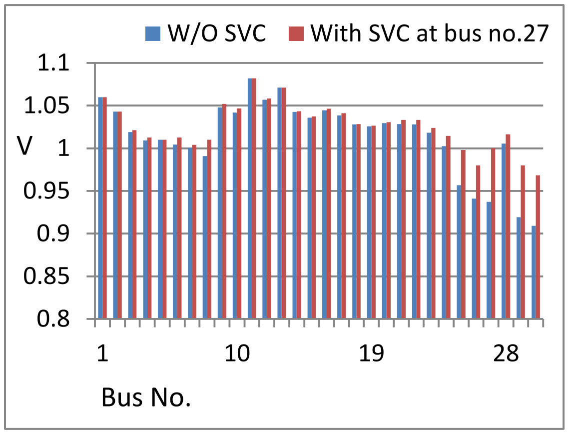

Figure 2. Voltage Profile for Outage of Line No. 36 without and with SVC at Bus No. 27

B. Outage of line no. 5

The value of *VPI* is 0.0063 for second most severe contingency which is outage of line no. 5. NSGA II is implemented to find the optimal location and sizing of SVC following the outage of line no. 5 for five trials keeping the same fixed number of generations and population size *i.e.*, 180 and 10 respectively. The simulation results obtained are compiled in Table 2. It is observed from Table 2 that bus no. 6 is repeatedly obtained optimal location for four trials of SVC placement. The Pareto optimal front obtained for simulations of NSGA II, when SVC is placed at bus no. 6 is shown in Figure 3 which provides several solutions for power loss and voltage deviation for multi-objective function (6). The best compromising solution for optimal values of power loss and voltage deviation are shown in Table 4.

Table 2. SVC Placement Results for LO 5

Trials	Optimal Location	Optimal Size (p.u)	Real Power Loss (p.u)	Voltage Deviati on (p.u)	Penalty Factor
T1	6	0.4269	0.3192	0.6013	90.26
T2	6	0.4269	0.3192	0.6013	90.26
T3	6	0.4269	0.3192	0.6013	90.26
T4	12	-0.9205	0.1472	0.7450	96.25
T 5	6	0.4269	0.3192	0.6013	90.26

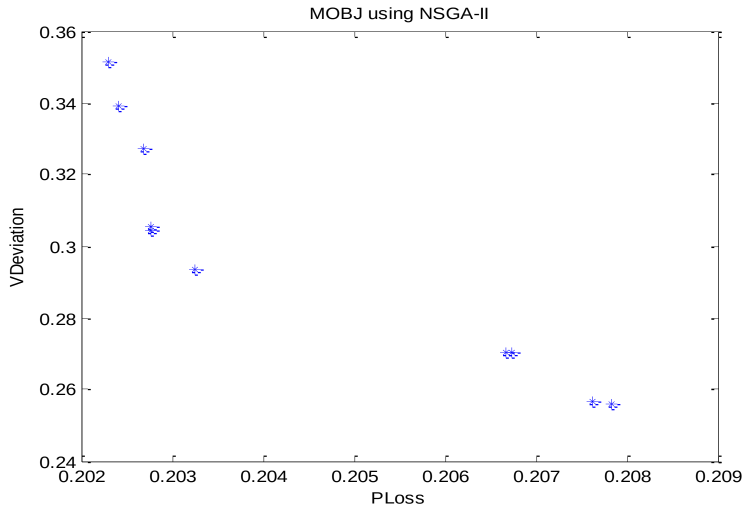

Figure 3. Pareto Front for LO 5 when SVC Placed at Bus no 6

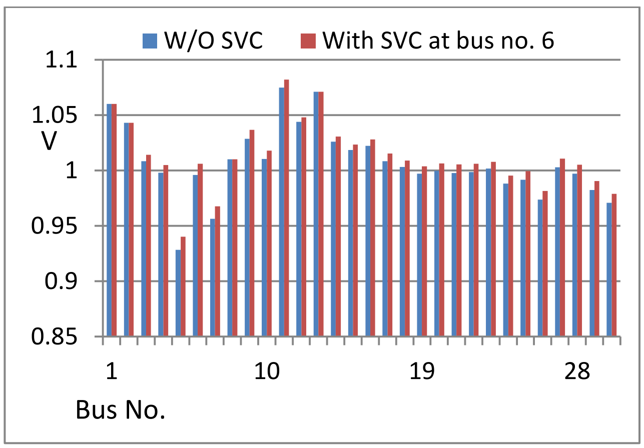

Figure 4. Voltage Profile for Outage of Line No. 5 without and with SVC at Bus No. 6

The voltage profile before and after placement of SVC at bus no. 6 is shown in Figure 4.

C. Outage of line no. 15

The developed NSGA II algorithm has been implemented maintaining the same population size and generations *i.e.*, 10 and 180 respectively for third most severe contingency i.e. outage of line no. 15 having *VPI* value as 0.0023. The simulation results for five trials are summarized in Table 3. The optimal location for SVC placement is found to be bus no. 24 with rating of -0.2033 p.u. for three trials with least penalty factor. Figure 5 shows the Pareto optimal front obtained as a result of NGSA II implementation when line number 5 is out and SVC is placed at bus no. 24. The best compromising solution for optimal values of power loss and voltage deviation are given in Table IV. The voltage magnitude of all the buses with and without SVC is illustrated in Figure 6.

Table 3. SVC Placement Results for LO 15

Trials	Optimal Location	Optimal Size (p.u)	Real Power Loss (p.u)	Voltage Deviation(p.u)	Penalty Factor
T1	24	-0.2033	0.2933	0.2935	3.6
T2	21	-0.6936	0.1685	0.3288	98.06
T3	10	-0.7805	0.1640	0.2556	9.67
T4	10	-0.7805	0.1640	0.2556	9.67
T 5	24	-0.2033	0.2933	0.2935	3.6

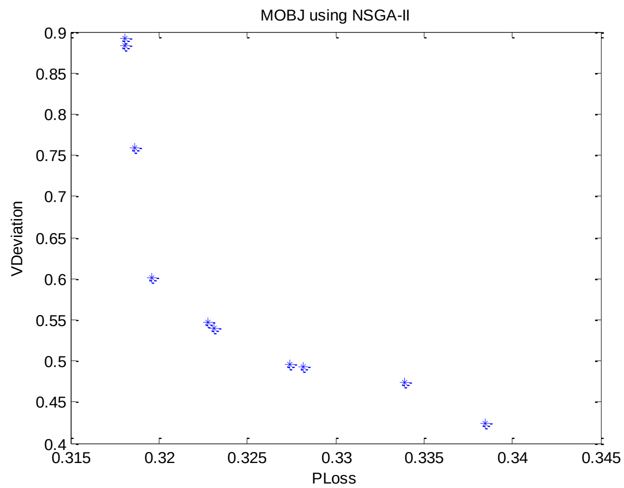

Figure 5. Pareto Front for LO 15 when SVC placed at bus no 24

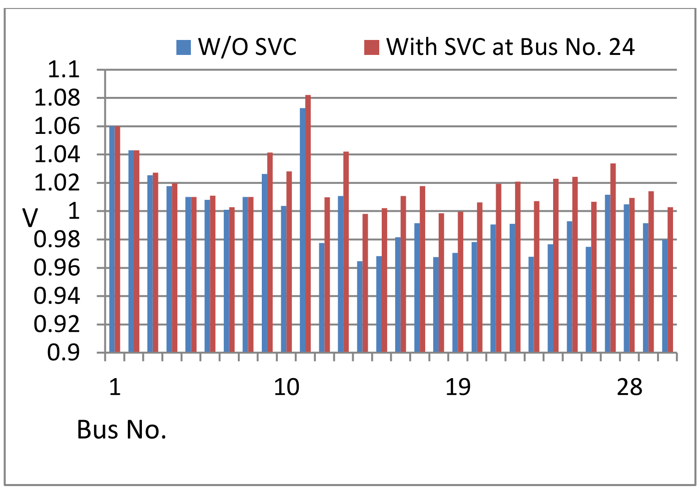

Figure 6. Voltage Profile for Outage of line no. 15 without and with SVC at bus no. 24

Table 4. Best Compromising Results of NSGAII for Base Load with Contingency

LO	Optimal Location	Optimal Size in p.u	Real Power Loss in p.u	Voltage Deviation in p.u	Penalty factor
Base case	-	-	0.1803	0.6001	-
LO 36	27	0.1180	0.1930	0.6562	3.37
LO 5	6	0.4269	0.3192	0.6013	90.26
LO 15	24	-0.2033	0.2933	0.2935	3.6

The optimal location and sizing of SVC computed for outage of line no. 36 is found to be self-sufficient for maintaining voltage security of the test power system when outage of the first three most critical lines occur one at a time. Table 5 presents voltage scenario of test power system without placement of SVC. It is observed from Table 5, there is no need of SVC placement for base case condition. Table 6 presents voltage profile of the test system when SVC of 0.1180 p.u. is placed at bus no. 27 and outage of line no. 36, 5, 15 are simulated considering one by one.

Table 5. Voltage Profile Without SVC

Bus No.	Base Case	LO 36	LO 5	LO 15
1	1.06	1.06	1.06	1.06
2	1.043	1.043	1.043	1.043
3	1.0215	1.0201	1.0111	1.0274
4	1.0129	1.0112	1.0012	1.0199
5	1.01	1.01	0.9323	1.01
6	1.0121	1.0115	0.9993	1.0112
7	1.0034	1.0031	0.9601	1.0029
8	1.01	1.01	1.01	1.01
9	1.051	1.0461	1.0437	1.0454
10	1.0444	1.0354	1.036	1.0362
11	1.082	1.082	1.082	1.082
12	1.0574	1.053	1.0524	1.0097
13	1.071	1.071	1.071	1.0419
14	1.0424	1.0353	1.0371	0.997
15	1.0378	1.027	1.0317	1.0002
16	1.0447	1.0382	1.0381	1.014
17	1.0391	1.0309	1.0312	1.0242
18	1.0279	1.0177	1.021	1.0001

19	1.0253	1.0154	1.0178	1.0035
20	1.0293	1.0196	1.0215	1.0109
21	1.0321	1.0182	1.0237	1.0225
22	1.0327	1.0173	1.0243	1.0227
23	1.0272	1.0045	1.0202	0.9984
24	1.0216	0.9835	1.0133	1.0052
25	1.0189	0.9246	1.0093	1.0124
26	1.0012	0.9051	0.9915	0.9946
27	1.0257	0.8999	1.0155	1.0254
28	1.0107	1.0153	1.0009	1.0088
29	1.0059	0.877	0.9955	1.0056
30	0.9945	0.8637	0.9839	0.9942

Table 6. Voltage Profile With SVC at Bus No. 27

Bus No.	LO 36	LO 5	LO 15
1.	1.06	1.06	1.06
2.	1.043	1.043	1.043
3.	1.0213	1.0124	1.0285
4.	1.0126	1.0027	1.0212
5.	1.01	0.9344	1.01
6.	1.0127	1.0011	1.0131
7.	1.0038	0.9621	1.0041
8.	1.01	1.01	1.01
9.	1.052	1.0463	1.0495
10.	1.0467	1.0405	1.0433
11.	1.082	1.082	1.082
12.	1.0586	1.0548	1.0195
13.	1.071	1.071	1.0515
14.	1.0435	1.0403	1.0072
15.	1.0373	1.0358	1.0107
16.	1.0463	1.0413	1.0228
17.	1.0413	1.0353	1.0319
18.	1.0285	1.0252	1.0096
19.	1.0264	1.0221	1.0123
20.	1.0307	1.0259	1.0193
21.	1.0333	1.0295	1.0312
22.	1.0335	1.0305	1.0318

23.	1.0238	1.0275	1.0109
24.	1.0147	1.0249	1.0203
25.	0.9985	1.0356	1.0408
26.	0.9805	1.0183	1.0235
27.	1.0009	1.0508	1.0618
28.	1.0162	1.0058	1.0139
29.	0.9806	1.0315	1.0428
30.	0.9688	1.0204	1.0317

5. Conclusion

In this paper, Non Dominated Sorting Genetic Algorithm has been successfully implemented for finding optimal location and sizing of SVC to minimize real power loss and load bus voltage deviation. The voltage security of the system is also examined with all placements of SVCs. It is concluded that optimal placement of SVC can enhance voltage security significantly in a power system. Implementation performed on IEEE 30-bus test system indicates that proposed NGSA-II is capable to provide optimal location and sizing of FACTS devices. Though, the proposed approach has been implemented on IEEE 30-bus test system, the same can be implemented on practical power system as well.

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