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FACTS Based Multi Objective Optimal Reactive Power Dispatch Using NSGA-II

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Abstract

This paper proposes the Shunt susceptance model of Static VAR Compensator (SVC) for Multi Objective Optimal Reactive Power dispatch (MOORPD) using the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II). The objectives considered are the minimization of transmission line losses and the bus voltage profile improvement. The standard IEEE 30-bus test system is considered to analyze the performance of NSGA-II for the SVC-MOORPD problem. The results depict the effectiveness of the proposed approach when compared to MOORPD with conventional capacitors.

Index Terms: Multi Objective Optimal Reactive Power Dispatch, Non-dominated Sorting Genetic Algorithm-II, FACTS, Static VAR Compensator, Conventional capacitors.

Introduction

Control of voltage and reactive power is required for efficient and reliable operation of power systems which can be accomplished by controlling the production, absorption and flow of reactive power at all levels in the system [14]. The devices used for this purpose are series capacitors, shunt capacitors, shunt reactors, synchronous condensers, tap changing transformers and Flexible AC Transmission Systems (FACTS) etc.,. Among these, series capacitors, shunt capacitors and shunt reactors, which are generally called as Conventional VAR sources, provide the discrete static compensation. They are either switched or permanently connected to the transmission system. They contribute to voltage control by modifying the network characteristics. FACTS devices provide continuous dynamic compensation by controlling the electrical parameters of the network. They reduce system losses and improve stability without generation rescheduling or topological changes [16].

Optimal Reactive Power Dispatch (ORPD) is an important problem in power system operational planning as it minimizes the transmission system line losses and improves the voltage profile of the system [3]. These objectives can be achieved by adjusting the generator terminal voltages (continuous), transformer tap settings (discrete), shunt capacitors/reactors (discrete) or FACTS devices (continuous). Due to the presence of continuous and discrete control variables, the problem of ORPD is a complex combinatorial optimization problem involving non-linear functions having multiple local minima [10].

In the literature, many methodologies have been proposed for ORPD and most of them employed the conventional VAR sources [1-10] and only a few have reported about FACTS based VAR sources for ORPD [19]. In this paper, both the conventional VAR sources (shunt capacitors) and the FACTS devices (Shunt susceptance model of SVC) are considered for the MOORPD.

To solve the ORPD problem, number of conventional optimization techniques have been proposed in the literature earlier [1-4]. They include Linear Programming, Non Linear Programming, Gradient based method, Integer Programming and quadratic programming methods. Recently, the ORPD problem is formulated as a multi objective optimization problem [7]. In the case of multi objective optimization also conventional and non conventional methods are reported in the literature. However, these works not treated the MOORPD problem as a true multi objective problem [7]. Instead, it was converted to a single objective problem by linear combination of different objectives as a weighted sum or considered only the most preferred objective and the other objectives as constraints bounded by some allowable levels of ε [5]. The most obvious weaknesses of these approaches are that they are time consuming and tends to find weakly non dominated solutions. In contrast, Evolutionary Algorithms (EAs) can find multiple optimal solutions in single simulation run due to their population approach [11]. Recently, some successful application of EAs to ORPD have been reported where minimizing voltage differences have been considered as an objective in addition to loss minimization [6]. This paper proposes the NSGA-II algorithm for the SVC-MOORPD problem.

ORPD With Conventional And Facts Devices

Conventional VAR Sources

In this paper, Shunt Capacitors are used for Conventional ORPD and the optimal settings of these devices are identified by using the NSGA – II Algorithm. Shunt Capacitors supply reactive power to compensate the reactive power absorption of transmission system to ensure satisfactory voltage levels during heavy loading conditions [14]. Advantages of shunt capacitors are low cost, flexibility of installation and operation. The principal disadvantage is the reactive power output being proportional to square of voltage. These are connected either directly to high voltage bus or to tertiary winding of the main transformer.

FACTS Devices

In this paper, Shunt susceptance model of SVC [15] is used for FACTS based ORPD and the optimal settings of these devices are identified by using the NSGA – II

Algorithm. SVC is a shunt connected static VAR generator or absorber whose output is adjusted to control the parameters of electrical power system [14].

Shunt Susceptance Model of SVC

Early SVC models treat SVC as a generator behind an inductive reactance [19]. The reactance accounts for SVC voltage - regulation characteristics. These generator models of SVC are invalid for operation outside limits because of the assumption of constant reactive power output of generator (IEEE Special Stability Controls Working Group 1995). To overcome this difficulty, the shunt susceptance model of SVC [15], as in Figure 1, is used for ORPD in this paper.

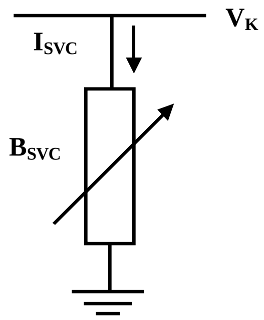

Figure 1: Shunt Susceptance Model of SVC

In this model, the reactive power drawn by SVC is a function of susceptance of SVC and nodal voltage magnitude. Since the nodal voltage magnitude is dependent on network operating conditions, the reactive power drawn by susceptance model varies with nodal voltage magnitude, whereas, it is constant for generator model [15].

With reference to Figure 1, current drawn by SVC is,

$$I_{SVC} = jB_{SVC}V_k \tag{1}$$

And, the reactive power injected by SVC at bus 'k' is,

$$Q_{SVC} = Q_k = -V_k^2 B_{SVC} \tag{2}$$

Where, V_K is the voltage at k^{th} bus and B_{SVC} is the susceptance offered by SVC.

Conventional and Facts Based Moorpd Problem Formulation

The problem of MOORPD is to optimize the steady state performance of a power system while satisfying several equality and inequality constraints. It is concerned with the attempt to minimize each objective function simultaneously. Meanwhile, the equality and inequality constraints of the system must be satisfied. Generally the problem can be represented as follows [10]:

Minimization of Transmission line losses

The primary goal of ORPD is to minimize the transmission line losses of the system [3]. An expression for transmission line losses in a power system is defined as,

$$P_{loss} = \sum_k G_k \left(V_i^2 + V_j^2 - 2V_i V_j \, Cos\,\theta_{ij} \right) \tag{3}$$

Where, P_{loss} is the network real power losses, G_k is the conductance of branch k. V_i and V_j are the voltage magnitudes of buses i and j and θ_{ij} is the voltage angle difference between buses i and j.

Minimization of Voltage Deviation

Another objective of ORPD is to improve the bus voltage profiles of the system. The reason for using this objective is that, the reactive power transfer is highly dependent on system bus voltage levels. By keeping load bus voltages close to their nominal values, less reactive power will be transferred to each load bus in the system. This has the effect of reducing line currents which also reduces the network real power losses. So, in this paper, a two fold objective function [6] is considered in order to minimize the losses and to improve the voltage profile by minimizing the load bus voltage deviations from 1.0 per unit which can be expressed through the following equation.

$$VD = \sum_{K=1}^{N_L} \left| V_K - 1.0 \right| \tag{4}$$

Equality Constraints

ORPD equality constraints are represented by the power flow equations [3]. These equations define the physical link between scheduled generation and load demand and cannot be violated as they define the state variable conditions for a given system operating point. The power flow equations that govern the physics of the system are given in the following equations:

$$\begin{aligned} 0 &= P_i - V_i \sum_{j \in N_i} V_j \left(G_{ij}\, Cos\,\theta_{ij} + B_{ij}\, Sin\,\theta_{ij} \right) \\ 0 &= Q_i - V_i \sum_{j \in N_i} V_j \left(G_{ij}\, Sin\,\theta_{ij} - B_{ij}\, Cos\,\theta_{ij} \right) \end{aligned} \tag{5}$$

Where, V_i and V_j are the voltage magnitudes of buses i and j. θ_{ij} is the voltage angle difference between buses i and j. P_i and Q_i are the real and reactive powers at bus i. G_{ij} and B_{ij} are the conductance and susceptance values of a branch connected between buses i and j.

Inequality Constraints

With respect to the ORPD, inequality constraints define the tolerable limits on both state variables and equipment usage. Important inequality constraints used in the ORPD problem are the transformer tap settings, bus voltage magnitudes, Capacitor and SVC outputs which can be expressed as follows [3], [15]:

$$\begin{aligned} &T_k^{min} \le T_k \le T_k^{max} && k \in N_T \\ &V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} && i \in N_G \end{aligned} \tag{6}$$

For Conventional MOORPD,

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max} \qquad i \in N_C \tag{7}$$

For SVC based MOORPD,

$$B_{SVCi}^{\min} \le B_{SVCi} \le B_{SVCi}^{\max} \qquad i \in N_{SVC} \tag{8}$$

Where, V_{Gi} is the generator bus voltage magnitude. T_k is the tap setting value of a transformer connected at branch k. Q_{ci} represents the reactive power injected by Conventional VAR sources. B_{SVCi} is the SVC susceptance value. N_C and N_{SVC} are the total number of Capacitor and SVC installments. N_G and N_T are the total number of generators and transformers.

In the above formulation, generator bus voltages, transformer tap settings and VAR source outputs, are the control variables, so they are self restricted. Load bus voltages and reactive power generations are the state variables which are restricted by the use of penalty terms.

Non-Dominated Sorting Genetic Algrithm-Ii (Nsga-II)

In NSGA-II, Simulated Binary Crossover (SBX) and polynomial mutation are used to generate new offspring and the tournament selection is used to select the population for next iteration [11-13].

Simulated Binary Crossover (SBX)

SBX puts the stress on generating offspring near the parents and guarantees that the extent of the children or offspring is proportional to the extent of the parents. It also favors that, near parent individuals are monotonically more likely to be chosen as children than individuals distant from the parents in the solution space [11]. The SBX operator simulates the working principle of Single Point Crossover in binary strings. It works with two parent solutions as,

$$\begin{aligned} x_i^{(1,t+1)} &= 0.5\left[\left(1+\beta_{qi}\right)x_i^{(1,t)} + \left(1-\beta_{qi}\right)x_i^{(2,t)}\right] \\ x_i^{(2,t+1)} &= 0.5\left[\left(1-\beta_{qi}\right)x_i^{(1,t)} + \left(1+\beta_{qi}\right)x_i^{(2,t)}\right] \end{aligned} \tag{9}$$

Where, $x_i^{(1,t)}$ and $x_i^{(2,t)}$ are the parent solutions. β_{qi} is the spread factor which can be calculated as,

$$\beta_{qi} = \begin{cases} 2\,rand_i^{\frac{1}{\eta_c+1}} & \text{if } rand_i \le 0.5 \\ \left(\dfrac{1}{2(1-rand_i)}\right)^{\frac{1}{\eta_c+1}} & otherwise \end{cases} \tag{10}$$

Where, $rand_i$ is a random number between 0 and 1. η_c is the crossover constant. A larger value of η_c gives a higher probability for creating 'near parent' solutions and a smaller value of η_c allows distant solutions to be selected as offspring. In this work, the crossover constant is considered as 5.

Polynomial Mutation

The probability of creating a solution near to the parent is higher than the probability of creating one distant from it. The shape of the probability distribution is directly controlled by an external parameter η_m and the distribution remains unchanged throughout the iterations. Like in the SBX operator, the probability distribution can also be a polynomial function, instead of a normal distribution [11].

$$\begin{aligned} y_i^{(1,t+1)} &= x_i^{(1,t+1)} + \left(x_i^U - x_i^L\right)\delta_i \\ y_i^{(2,t+1)} &= x_i^{(2,t+1)} + \left(x_i^U - x_i^L\right)\delta_i \end{aligned} \tag{11}$$

Where, x_i^U and x_i^L are the upper and lower limits of variable x_i. δ_i is the polynomial probability distribution parameter which can be calculated as,

$$\delta_i = \begin{cases} 2\,rand_i^{\frac{1}{\eta_m+1}} - 1 & if\ rand_i \le 0.5 \\ 1 - \left[2\left(1 - rand_i\right)\right]^{\frac{1}{\eta_m+1}} & if\ rand_i \ge 0.5 \end{cases} \tag{12}$$

Where, $rand_i$ is a random number between *0* and *1* and η_m is the mutation constant. The mutated individuals are called as offspring. Obtain the offspring fitness and form the combined population of parents and offspring.

Tournament Selection

Selection is made using tournament between two individuals. The individual with the lowest front number is selected if the two individuals are from different fronts. The individual with the highest Crowding Distance (CD) is selected if they are from the same front. i.e., a higher fitness is assigned to individuals located on a sparsely populated part of the front. In each iteration, the 'N' existing individuals (parents) generate 'N' new individuals (offspring). Both parents and offspring compete with each other for inclusion in the next iteration.

Step by Step Implementation of NSGA-II

The following steps are adopted for the implementation of NSGA-II algorithm. Figure 2 shows the flowchart of NSGA-II algorithm [10].

Step 1: Identify the control variables.

Step 2: Select the parameters such as number of population, maximum number of iteration, crossover and mutation probabilities.

Step 3: Generate initial population.

Step 4: Evaluate the objective functions (i.e., f1, f2) for initial population.

Step 5: Set the iteration count.

Step 6: Perform SBX and polynomial mutation for the set of individuals.

Step 7: Perform non-dominated sorting. (i.e., sort the population according to each of the objective function value in ascending order of magnitude).

Step 8: Calculate the Crowding Distance between the solutions.

Step 9: Perform the selection based on the tournament selection thereby a higher fitness is assigned to individuals located on a sparsely populated part of the front.

Step 10: Increment the iteration count and repeat the steps from 6 to 9 until the count reaches the specified maximum number of iterations.

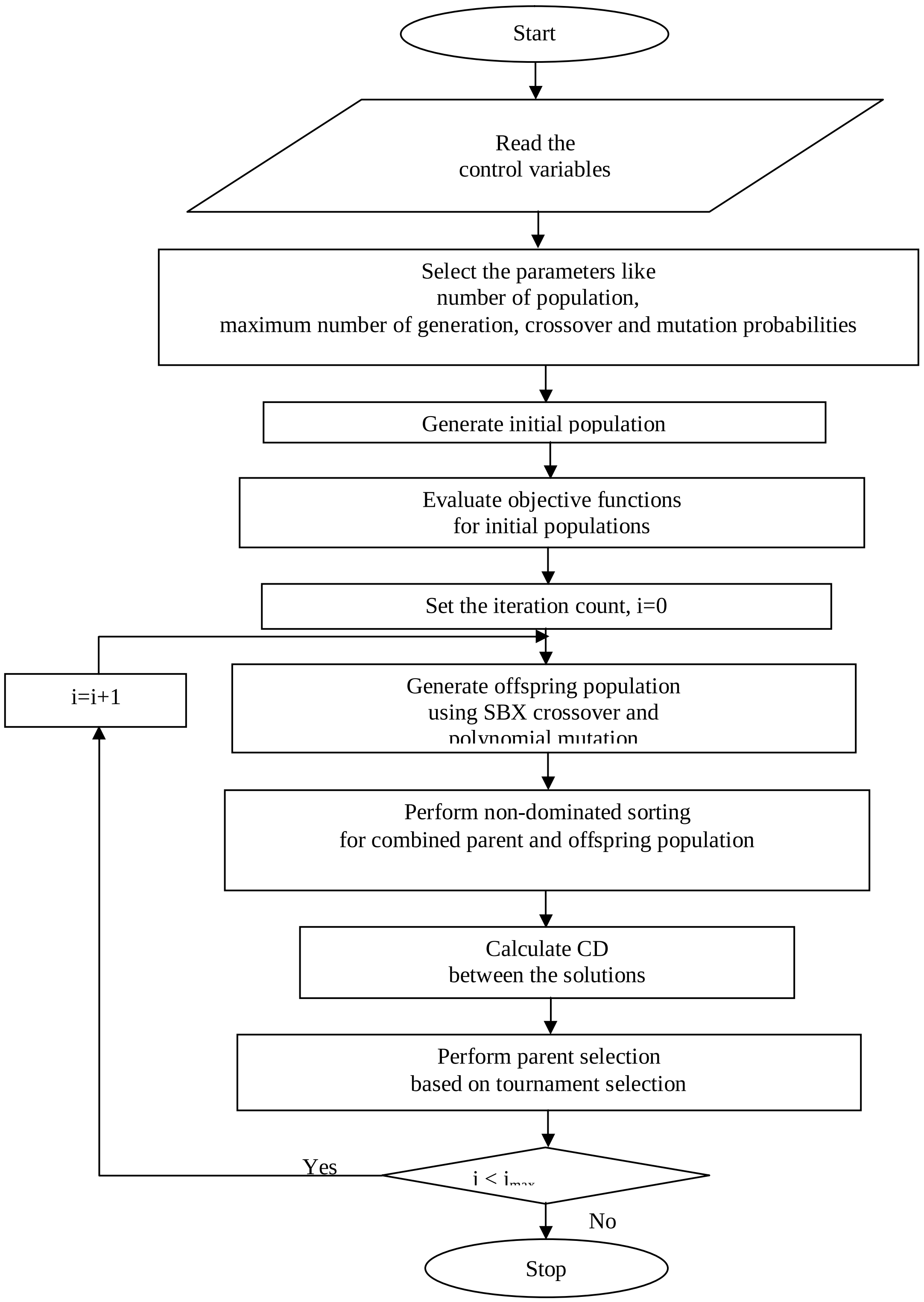

Figure 2: Flowchart of NSGA-II Algorithm

Simulation Results

IEEE 30-bus test system is used to analyze the performance of the proposed approach. The detailed data of this system are given in [1]. The system has 6 generator buses and 4 transformer branches. Bus numbers 1, 2, 5, 8, 11, and 13 are the generator buses. The voltage magnitude of these buses is varied from 0.95 p.u. to 1.1 p.u. Branches (6 - 9), (6 - 10), (4 - 12) and (28 - 27) are under load tap setting transformer branches with tap setting value 0.9 p.u. to 1.1 p.u. For this system, to eliminate voltage and reactive power violations, for Conventional ORPD [1], the shunt capacitors are installed at buses 10, 12, 15, 17, 20, 21, 23, 24, 29 and for SVC based ORPD, four SVC's are installed at buses 10, 12, 24 and 29 with rating 0 to 5 MVAr. Therefore, for Conventional ORPD using shunt capacitors, the number of variables to be optimized is 19 and for SVC based ORPD, the number of variables to be optimized is 14.

During the implementation of NSGA-II to MOORPD, the objective functions are subjected to power flow constraints and control variable (continuous and discontinuous) limits [10] with uniform population size of 40. Based on 50 trials of various combinations of parameters, it is concluded that, crossover probability of 0.9, mutation probability of 1/number of control variables, crossover index of 5 and mutation index of 10 yield better results for the MOORPD problem. Number of fitness function evaluations of 200 is used as a stopping criterion. Fifteen independent trials are conducted to select the better individuals from the NSGA-II algorithm. Figures 3 and 4 show the Pareto optimal front of Transmission line losses and Voltage Deviation obtained from the NSGA-II algorithm for the Conventional and SVC based ORPD.

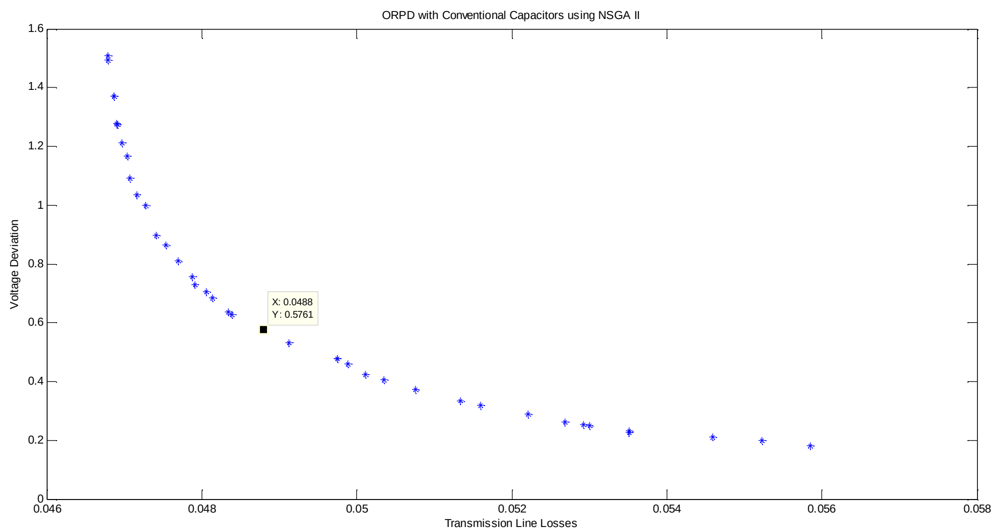

Figure 3: Pareto optimal front of Transmission line losses and Voltage Deviation for Conventional ORPD

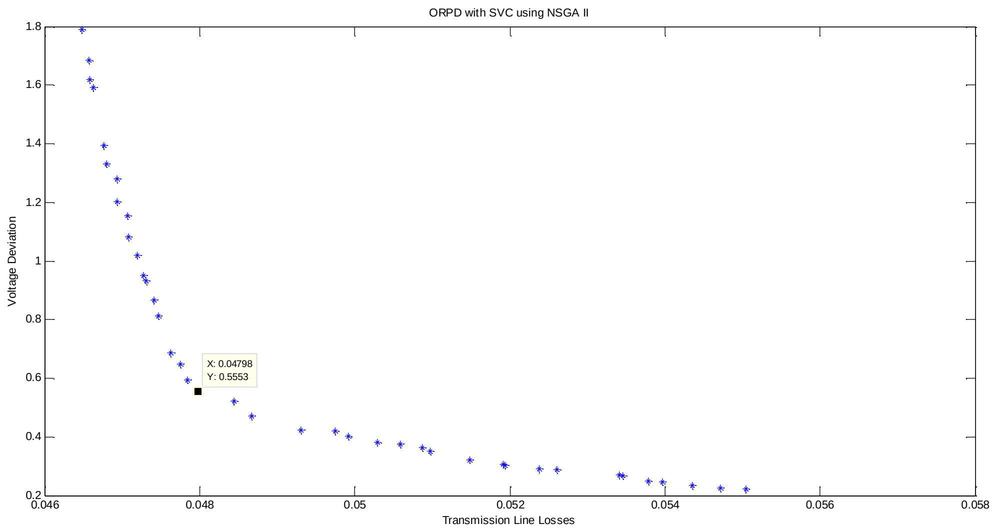

Figure 4: Pareto optimal front of Transmission line losses and Voltage Deviation for SVC based ORPD

From Figures 3 and 4, it is clear that, the optimal values of transmission line losses and Voltage Deviation for SVC based ORPD are **0.047979 p.u** and **0.5553 p.u** whereas, for Conventional ORPD, these values are **0.048795 p.u** and **0.5761 p.u** respectively. The optimal values obtained from the Pareto optimal fronts indicates that, the SVC based ORPD is better when compared to Conventional ORPD.

Optimal control variables obtained from NSGA-II for Conventional and SVC based ORPD are given in Table 1. From the Table, it is clear that, the minimum Transmission line losses from SVC based ORPD is **4.7979 MW** which is less by **0.0816 MW (i.e. 1.7 %)** when compared to Conventional ORPD. Also, the minimum Voltage Deviation from SVC based ORPD is **0.5553 p.u** which is less by **0.0208 p.u (i.e. 3.746 %)** when compared to Conventional ORPD.

Table 1: Optimal control variables obtained from NSGA-II for Conventional and SVC based ORPD

Control variables	SVC based ORPD	Conventional ORPD
V_1	1.0999	1.0947
V_2	1.0942	1.0848
V_5	1.0660	1.0638
V_8	1.0689	1.0659
V_{11}	1.0621	0.9564
V_{13}	1.0385	1.0389
$T_{6\text{-}9}$	1.1000	0.9821
$T_{6\text{-}10}$	1.0030	1.0369
$T_{4\text{-}12}$	1.0500	1.0206
$T_{28\text{-}27}$	1.0286	1.0441
$Q_{SVC\ 10}$	0.0221	-
$Q_{SVC\ 12}$	0.0181	-
$Q_{SVC\ 24}$	0.0139	-
$Q_{SVC\ 29}$	0.0134	-
$Q_{C\ 10}$	-	0.0200
$Q_{C\ 12}$	-	0.0500
$Q_{C\ 15}$	-	0.0500
$Q_{C\ 17}$	-	0.0500
$Q_{C\ 20}$	-	0.0200
$Q_{C\ 21}$	-	0.0100
$Q_{C\ 23}$	-	0.0400
$Q_{C\ 24}$	-	0.0500
$Q_{C\ 29}$	-	0.0300
RPL, MW	**4.7979**	**4.8795**
VD, p.u	**0.5553**	**0.5761**

Conclusion

In this paper, the Shunt susceptance model of SVC has been proposed for the MOORPD problem. Minimization of transmission line losses and the improvement of bus voltage profile via minimization of Voltage Deviation have been considered for the MOORPD. The optimal control variables have been obtained by using the NSGA-II algorithm. Simulation results from the IEEE 30-bus test system depict the effectiveness of the proposed approach when compared to the conventional MOORPD with conventional capacitors.

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