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ORIGINAL PAPER

Optimum allocation of FACTS devices under load uncertainty based on penalty functions with genetic algorithm

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Abstract This paper presents genetic algorithm optimization method with a suitable objective function to determine optimum location and rated values of FACTS devices by taking into account changes in the power system load over time. In this study, annual daily load profile is considered as a whole instead of an instant load profile while looking for optimum size and location of FACTS devices. For this reason, to simplify the optimization procedure, a graph-based panelized objective function is developed, which can be used in a mixed integer search heuristic optimization technique. This paper focuses on the evaluation of the simultaneous use of thyristor controlled series capacitor and static VAR compensator. The proposed method allows including, in a simple way, the long term load profile in the planning stage to improve the power system performance using FACTS devices. After the optimization process, the performance of the proposed method has been tested on the IEEE-30 bus system with several annual test load profiles. The planning horizon is included in the optimization framework and the impact of planning horizon result is presented to compare with that of single load profile. The optimization strategy is shown to lead a significant reduction in the voltage and line violations under the long term test load profiles.

Keywords FACTS · Genetic algorithm · Penalized objective function · Long-term load profile · Optimization

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1 Introduction

As the use of electricity penetrates into every area of life, the power delivery network is becoming more complex in terms of efficiently managing the growing power network. The transmission lines are difficulty in catching up with the growth in generation capacity [1]. Therefore, the overall system is obliged to operate under stress due to the voltage profile and thermal capacity problems. On the other hand, distributed generation increasingly becomes an attractive concept for meeting load demands in the future grid. However, the voltage regulation is one of the primary problems to be dealt in distributed generation integrated power systems [2,3]. Transmission lines might reach their thermal limits that endanger the energy security or the blackout events might occur because of the voltage collapse. As a result, the consequences of large blackouts have vital impacts in terms of very high costs, depending on duration of the outage and load types. In that manner, the flexible AC transmission system (FACTS) devices are playing important role for the system security and power quality. These devices have the ability to control active and reactive power flow within their operating limits [4]. The existing power system can be operated effectively using FACTS devices. Thus, the construction of new infrastructure can be postponed. However, the high cost concern has limited the widespread deployment of FACTS solutions. Thus, the problem of determining the size and location of FACTS devices is essential due to the technical and economical reasons.

Optimal FACTS allocation problem has been solved using various optimization techniques and different objective functions. The methods on the allocation FACTS studies in the literature can be categorized into three main headlines, which are sensitivity based, classical optimization based, and intelligence based techniques [5]. In [6], a method based on hybrid group search optimization technique is presented to enhance the power system security through eliminating or minimizing the over loaded lines and the bus voltage limit violations under single line contingencies. Another hybrid evolutionary algorithm is used for increasing total transfer capability and minimizing the system real power loss [7]. System loadability is increased using genetic algorithm (GA) with the consideration of thermal and voltage limits [8]. In [9], a mathematical objective function is used to derive objective function for GA by including voltage stability, cost of FACTS devices, and power losses. On the other hand, in [10], a similar objective function is reconstructed using weighted coefficients for voltage stability, costs, and power losses. These weighted coefficients are optimized by trial and error method. So, it is very important to derive an objective function without being too specific so that it limits the algorithm needlessly. In [11], the FACTS devices based on SVC can be utilized with microgrid AC/DC systems to improve the overall performance of a typical hybrid microgrid. Reference [12] proposes a GA based optimization strategy and includes directly in its formulation both the reactive power capability from wind turbines and the reactive power injection from SVC units. In [13], an easy static synchronous series compensator model based on the power injection approach is presented to reduce the code complexity of load flow algorithms. In [14,15], only the investment cost of FACTS is considered as an objective function while allocating the FACTS devices. In another study, a multi-objective genetic algorithm (MOGA) procedure is used for solving the problem of optimal allocation of FACTS devices by considering maximization of system security and minimization of investment cost [16]. The main difference between a conventional GA and a MOGA is based on the assignment of fitness function which is a particular type of objective function in GA [17]. In [18], an algorithm is developed for optimal choice and location of FACTS controllers for congestion management in deregulated power systems for comparison of optimization results with different objectives. It is observed that the obtained results which present favorable solution according to one of the objectives, are not suitable according to other objectives. The most difficult and most important concept of genetic programming is the objective function, because it determines how well a program is able to solve the problem. In [19], three objective functions such as active power loss, investment cost, and peak point power generation are considered using MOGA optimization technique. Despite its effectiveness, the implementation of this technique is more difficult than a traditional GA programming. Reference [20] presents a GA to seek the optimal location, types, and values of multi-type FACTS devices in terms of branch loading and voltage levels. It is observed that there is a maximum number of FACTS devices beyond which the loadability of the system cannot be improved.

It is well understood from the literature that different objective functions have been considered to solve the optimal placement of FACTS devices problem by different techniques. However, the improvement in one objective does not guarantee the same improvement in others [18,19]. This can make difficult a fair comparison between the methods. In [21,22], different optimization methods are compared to observe which one shows better performance for optimal allocation of FACTS devices. However, the comparison results show that there is no optimization method that universally outperforms all others [22,23]. The selection of an algorithm is problem dependent. On the other hand, simplifying the formulation in the FACTS optimization problem is challenging [13] while including uncertainty in the power network such as load demand, because the most difficult task of an optimization problem is to find a suitable objective function in GA programming. The objective function needs to accurately describe the problem and should include all possible combinations of data available during the simulation runs. On the other hand, most of the existing studies are developed on the assumption that there is no change in the power system load over time. These optimizations are performed under a constant load profile or overloaded conditions. It is assumed that the optimization results obtained using single load profile cover different load conditions. It is not possible to get the same performance obtained from single load profile under different load profiles. On the other hand, it is very difficult to include the long-term load profile into the optimal power flow programming because of the complexity of problem. The mathematical optimization methods may not converge with a huge number of constraint functions. In that manner, the decomposition techniques are used to overcome this kind of problem in the optimization formulations. Nevertheless, the load variability profile in a long term perspective should be included into optimization of FACTS integrations in power systems since the load profile changes over time. The including long term load profile in the optimization process is a challenging issue.

The heuristic search algorithms, based on the evolutionary ideas of natural selection and genetics, have promising potential for solving non-convex optimization problems [30–33]. In this study, to simplify the optimization procedure when determining optimum location and rated values of FACTS devices by taking into account changes in the power system load over time, a graph based panelized objective function is developed, which can be used in a mixed integer search heuristic optimization technique with classical power flow calculations. The proposed approach are conducted with GA and NOMAD (Nonlinear Optimization by Mesh Adaptive Direct Search) to test the optimization strategy. Matlab environment is used for both optimization processes. NOMAD is a useful derivative-free algorithm and an open source optimization solver within Matlab environment [34–36].

NOMAD can handle mixed integer variables optimization problems using the variable neighborhood search option and it is able to escape from local minima [37].

This paper focuses on the evaluation of the simultaneous use of thyristor controlled series capacitor (TCSC) and static VAR compensator (SVC). The proposed approach merges heuristic mixed integer programming with classical power flow calculations. So that, the proposed approach allows including, in a simple way, the long-term load profile in the optimization stage to improve the power system performance under various load profiles using FACTS devices. The performance of the proposed method has been tested on the IEEE-30 bus test system with different annual load profiles that are not used in the optimization process.

This paper is organized as follows: Sect. 2 describes the model of SVC and TCSC devices. Section 3 presents objectives and procedure of the optimization. The simulation results by applying the proposed method on the IEEE-30 bus test system are presented in Sect. 4. The impact of long-term load profile result is presented to compare with that of single load profile. The conclusion of this paper is presented in Sect. 5.

2 FACTS devices and modeling

FACTS devices are high power electronic devices that can control the power flow and voltage profile in power systems [4]. The flow in heavily loaded transmission lines can be reduced by controlling line impedance, bus voltage and angles. So, the existing transmission system can be utilized more effectively using FACTS devices [24,25]. In literature, the existing steady-state models of FACTS devices can be classified into two categories: power injection and variable reactance modeling techniques [13,19,20,26]. In this study, two main types of FACTS devices, SVC and TCSC, are considered as described below.

SVC is a bus reactive power controller. It can adjust injected reactive power to control the voltage magnitude at the point of connection of power network [27]. The working range of SVC is set −100 to 100 MVAr [20,28]. SVC is a shunt FACTS device that can be modeled as an ideal source of rapidly controllable reactive power compensator at the point of connection as given in Fig. 1a. The injected reactive power at bus i is:

$$\Delta Q_{i.inj.} = Q_{\mathrm{SVC}} \tag{1}$$

where Q_{SVC} is the SVC size.

The TCSC is a series connected device and incorporated into the transmission line model by simply adding the variable reactance X_{TCSC} to the line reactance as shown in Fig. 1b [29,30]. It mainly controls the active power flow in a line

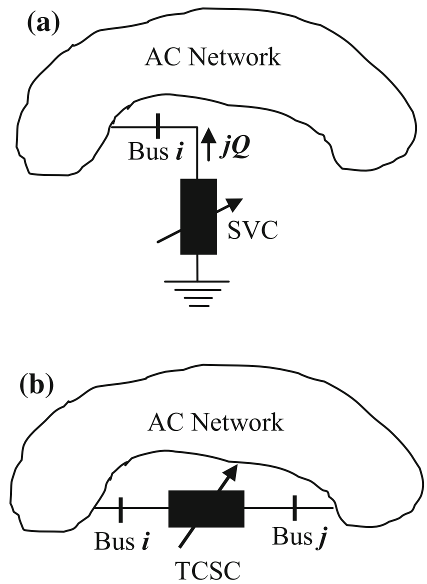


Fig. 1 Model of FACTS devices **a** SVC, **b** TCSC

by adjusting the line reactance and is modeled as variable reactance. The equivalent reactance of the transmission line X_{ij} is defined as:

$$X_{ij} = X_l + X_{\mathrm{TCSC}} \tag{2}$$

where X_l is the original transmission line reactance, X_{TCSC} is TCSC controllable reactance placed in the transmission line connected between bus i and bus j. The operation value of TCSC is a function of line reactance X_l as follows:

$$X_{\mathrm{TCSC}} = k_{\mathrm{TCSC}} \cdot X_l \tag{3}$$

where k_{TCSC} is variable and it varies continuously between −0.7 and 0.2. It means that the compensation of the TCSC varies between 70 % capacitive and 20 % inductive. The working range of TCSC is adjusted by k_{TCSC} and its typical operation range is selected between $-0.7X_l$ and $0.2X_l$ to avoid overcompensation [18,20].

The SVC operating values are modeled as reactive power injection in the bus data that is used in classical newton raphson based power flow calculations. So, the reactive power coming from SVC size is included into reactive power balance equations in a simple way. The TCSC values are embedded into the line data by updating the reactance of the corresponding transmission line. The updated bus data and line data using design variables coming from the optimization framework will be used in the classical power flow calculations. This approach can allow us to use long term load profile in the optimization process in a simple way.

3 Problem description and formulation

In this study, instead of considering single load profile, a graph based panelized objective function is developed to determine the size and location of FACTS devices considering long term load profile. The proposed approach is suitable for mixed integer heuristic optimization techniques. In that manner, the proposed approach is applied with Genetic Algorithm. And then, another heuristic search algorithm called NOMAD that can handle mixed integer variables to observe the performance of the proposed methodology under long term load profiles. Both optimization processes were conducted using Matlab software. The optimization process is carried out with classical power flow calculations. By this way, the long-term load profile can be integrated into the optimization process without increasing the number of constraints. It is well known that the long term planning is a very difficult issue for electric power system. In that manner, the novelty of this paper lies in considering long term load profile while looking for size and location of FACTS devices using a simple approach. The planning horizon is included in the optimization framework and the impact of planning horizon result is presented to compare with that of single load profile in this study.

3.1 Genetic algorithm

The GA optimization method is used with a suitable objective function, which allows simplify the optimization problem of allocation FACTS devices for a long term load profile. The GA is one of the popular heuristic methods because of its effectiveness and simple structure. It is based on principles of natural genetics and natural selection [38]. It has some difference from the traditional optimization techniques, which is: in starting process it uses a population of initial points rather than single initial point. If the population size is too large, genetic algorithm will take a long running time to find the optimal solution. The GA uses actual objective function instead of derivative of it. This feature allows optimizing non derivative functions. Binary number is the most common approach for representing the design variables for crossover and mutation processes. In this study, the location and size of FACTS devices are integer and continues variables, respectively. The fundamental terms of natural genetics are reproduction, crossover and mutation operators which work like probabilistic procedure. They are used in The GA process to find best objective value. The GA optimization problem solution starts with creating initial population. Specified number of population contains random strings related to design variable. Each string is evaluated to find its fitness value. In this study, the classical power flow calculations are utilized when evaluating the fitness values. New population is produced by reproduction, crossover and mutation operators. They are evaluated again to find the fitness value then stop criteria is checked. Each iterative process is called generation. Iteration stops if the difference between new and old fitness values is smaller than the specified value or the generation number reaches its specified number. Reproduction aims to choose good string of the population to generate a mating pool. It chooses better strings in population and replaces multiple copies in the mating pool by probabilistic procedure. Therefore, good ones go their ways but bad ones do not, like natural selection. After reproduction, the crossover operator is performed. Aim of this operator is composing new strings in the mating pool. It is done by swapping information between strings. Mostly, two individual strings are selected randomly from mating pool and exchange some portions of their strings. It is the main operator for creating new generation to achieve better fitness value. Last operator is mutation that performed for creating new population. It changes string information in bitwise with a specific small mutation probability. All these operations are worked in probabilistic procedure. It is important to state that, the GA method is operated in iterative procedure to get best results.

3.2 Optimization strategy and objection function

One of the most important issues of genetic programming is the objective function, because it determines how well a program is able to solve the problem in a simple manner. In [39], an algorithm is presented to create more randomness for efficient handling of integer restrictions on decision variables and to increase the possibility of getting global optimal solution. This procedure is based on penalty function methods which have been the most popular approach because of their simplicity and ease of implementation. So, the penalized objective function can be used as an objective function in GA optimization [40]. The genetic algorithm attempts to minimize a penalty function, not the fitness function. In this study, static penalty function is utilized for objective function and a general formulation is as follows for a minimization problem:

$$F = \sum_{i=1}^{m} \delta_i \begin{cases} \delta_i = 1 & \text{if constraint is violated} \\ \delta_i = 0 & \text{if constraint is satisfied} \end{cases} \tag{4}$$

where m is the number of cases. In this paper, this basic formulation is adapted for finding the best locations and rated values of FACTS to minimize system operating risks at bus voltages and lines by taking into account of long term load profile instead of a specific single load condition. Here the number of cases will be the load variations in a year. This approach allows dealing only with the total violation number for a long period of time. The violations can be observed simply in the optimization framework using newton raphson based classical power flow calculations. The planning studies considered long term is a very difficult problem in terms of optimization process with optimal power flow formulation. In this study, the objective function is based only on the number of interested operating conditions over time, which is presented in the following sections.

3.3 Penalized objective function in terms of violations in voltages and line flows

In a power system, the electricity generation and consumption must balance at all times. Difference in load and power supply could cause grid instability or severe voltage variations, and cause failures in power systems. Unfortunately, unexpected load changes might cause a blackout. When power lines are overloaded, the transmission lines exceed their thermal limits. With the existing infrastructure, over or under voltage situations may occur due to the limited control capability of synchronous generators and limited static reactive power resources. In that manner, suitable located FACTS devices allow better utilization of existing grid infrastructure. The SVC and TCSC are the most commonly used FACTS devices in controlling the voltage and active power, respectively.

Power system operators must take technical precaution to hold bus voltages in permissible levels according to the acceptable voltage variations in the grid voltage. However, there might be unexpected situation where the conventional solutions are not feasible, and some bus voltages would exceed their permissible limits. So, bus voltage violation (V_v) occurs. It is expected that SVC minimize these violations. Besides the bus voltages, transmission lines may reach their thermal limits at different load conditions. This is called as line violations (L_v). TCSC maintains active power flow in the branch of the network at a specified level under a wide range of load conditions. In this study, annual daily load profile is considered in the optimization process as a whole instead of an instant load profile while looking for optimum size and location of FACTS devices. For this reason, to simplify the GA optimization procedure, a graph based panelized objective function is developed as shown in Fig. 2. If the bus voltage exceeds the permitted value, the return value of '1' indicates that a violation occurs. In contrast, the return value of '0' that indicates that there is no problem in terms of voltage profile. The same methodology is applied for power flow in the transmission line in terms of overloaded lines. Here, the specified voltage variation and line overloaded limits are ±5 % and 95 %, respectively. The main aim of the proposed methodology is to find the optimum location and rated values of SVC and TCSC devices for reducing the number of violations for a long period of time.

If total number of buses and lines in a network are n_b and n_l, respectively, and n_d is the number of pairs of active and

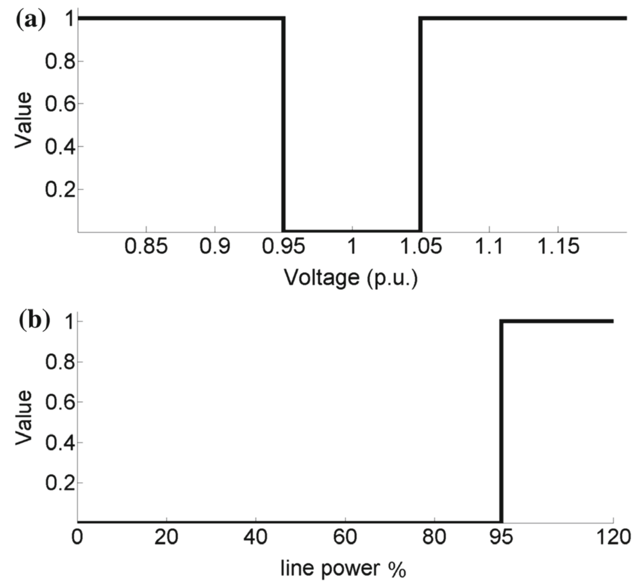


Fig. 2 Graph based objective function **a** for voltage violation, **b** for transmission line violation

reactive load demand, which can be given daily or hourly, $n_b \times n_d$ and $n_l \times n_d$ cases should be considered as a whole while allocating the FACTS devices to minimize the total number of violations for a long term. The violation number in bus voltages and overloaded lines are determined to be used in the optimization using graph based objective function easily. Consequently, the penalized objective function to be minimized is expressed as below:

$$\min : F_{\text{obj}} = \sum_{j=1}^{n_d} \left(\sum_{i=1}^{n_b} V_v^{ij} + \sum_{i=1}^{n_l} L_v^{ij} \right) \tag{5}$$

$$V_v^{ij} = \begin{cases} 0 & 0.95\ pu \le V^{ij} \le 1.05\ pu \\ 1 & 0.95\ pu \ge V^{ij} \quad 1.05\ pu \le V^{ij} \end{cases} \tag{6}$$

$$L_v^{ij} = \begin{cases} 0 & 0.95\ pu \ge L^{ij} \\ 1 & 0.95\ pu \le L^{ij} \end{cases} \tag{7}$$

where n_d is the number of pairs of active and reactive load demand for a long period time. n_b and n_l are the number of buses and lines, respectively. L^{ij} is branch loading of every line of the network and V^{ij} is voltages of all buses of the network for each load profile.

The proposed methodology is summarized in Fig. 3. The design variables are locations and rated values of FACTS devices which have specified upper and lower bounds. The SVC rated values (Q_{SVC}) are between −100 and 100 MVAr. The TCSC rated values are limited between $-0.7X_l$ and $0.2X_l$, where X_l is the corresponding line reactance. The candidate locations of SVC are all buses except slack and PV buses. It is also noted that TCSC rated value depends on connected line reactance, thus its operation interval is

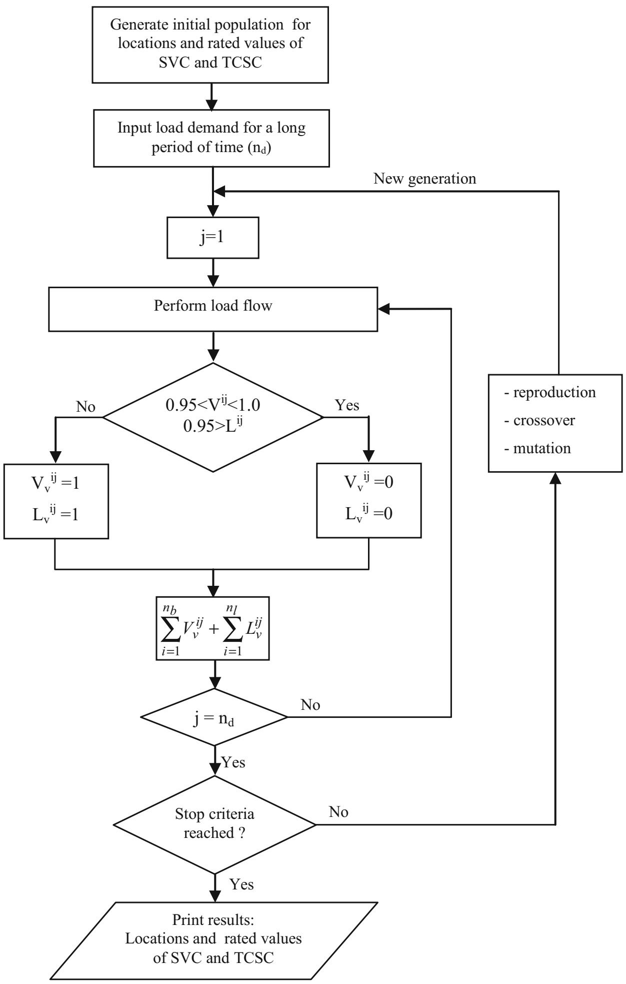


Fig. 3 Flow chart of the optimization procedure

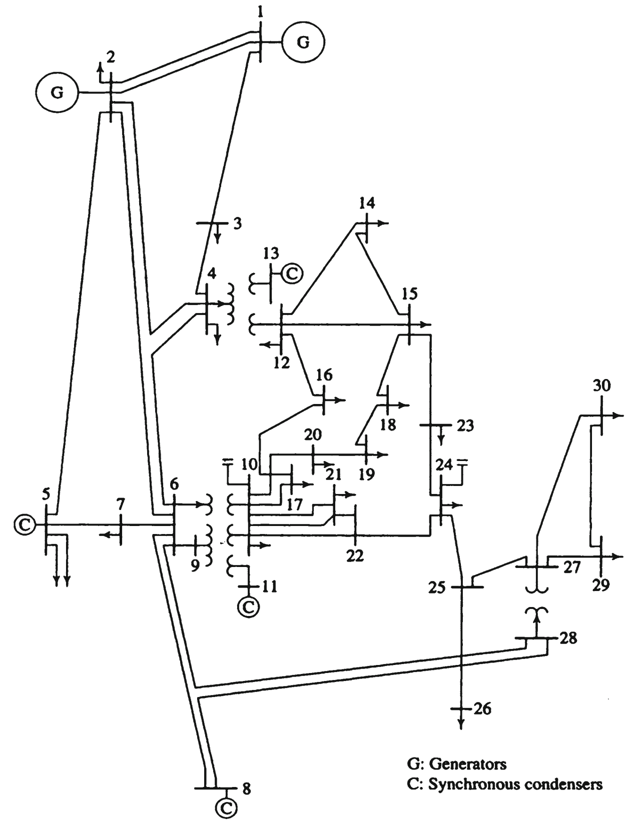


Fig. 4 The IEEE-30 bus test system

changeable. The allocation of more than one SVC and TCSC unit into the same bus and line is not allowed in the optimization process.

There are some criteria to stop the GA process. The efficient value of maximum generation is problem dependent. The GA stop criteria adopted here is that the process stops when the maximum number of iterations, here is 100 iterations, are reached or when no significant changes are observed in the objective function.

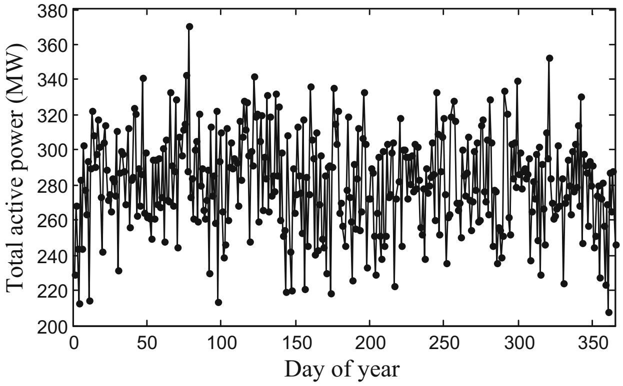
4 Simulation studies and results

Several test load profiles have been conducted to evaluate effectiveness of the proposed method by simulation with the IEEE-30 test system [13] as shown in Fig. 4. The design variables are locations and rated values of SVC and TCSC devices. The annual daily load curve is generated using Eqs. (8) and (9) to include the load uncertainty over time as shown in Fig. 5. The mostly used IEEE-30 bus network has total real and reactive load of 283.4 MW and 126.2 MVAr, respectively. There are 24 load buses (PQ buses) and 41 lines. Different load profiles can be generated by a uniform random number generator [41–44]. Each load bus in the network has different level of real and reactive power. Under normal operating condition, load demand is taken as original real and reactive load data (P_{org}, Q_{org}) of the test system [45]. In this paper, the variability of the loads are modeled based on n_d randomly generated values using as follows:

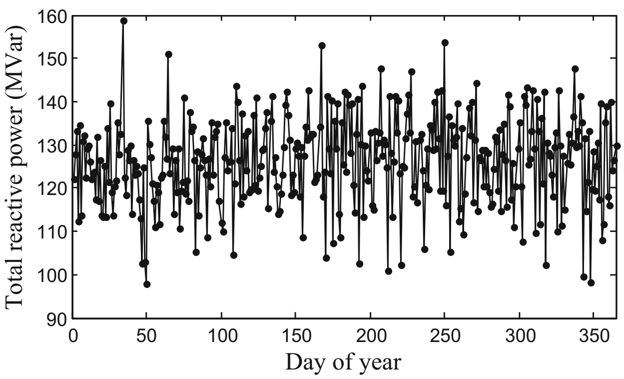
$$[P]_{\mathrm{mxn}_d} = [P_{\mathrm{org}}]_{mx1} \cdot [1]_{1xn_d} + \alpha \cdot [P_{\mathrm{org}}]_{mx1} \cdot [\mathrm{randn}]_{1\mathrm{xn_d}} \tag{8}$$

$$[Q]_{\mathrm{mxn}_d} = [Q_{org}]_{\mathrm{mx1}} \cdot [1]_{1xn_d} + \alpha \cdot [Q_{\mathrm{org}}]_{mx1} \cdot [\mathrm{randn}]_{1\mathrm{xn_d}} \tag{9}$$

where m is the number of load buses in the network, n_d is the number of pairs of active and reactive load demand for a long period time, α is index of standard normal distribution, *randn* is normally distributed pseudorandom numbers, P and Q are randomly generated real and reactive powers, respectively. The m and n_d are the dimension of [P] and [Q] matrixes. The generated load data are obtained using the original loads (P_{org} and Q_{org}). These data profiles are integrated with the GA optimization procedure with the proposed objective function.



(a) Total active power



(b) Total reactive power

Fig. 5 Annual daily load profile for the optimization process of the IEEE 30 bus system. **a** Total active power. **b** Total reactive power

The randomly generated load conditions are simulated based on power flow to calculate the number of violations in the voltage of buses and the branch loading in the network. In each generation process in GA, the objective function takes into account the annual load profiles. Thus, the optimization is performed for annual load profile instead of single load level.

4.1 Optimization results of the proposed method

The aim of the optimization is to minimize violations in bus voltages and line power flow by considering load variations for a long term period. In that manner, three different cases are investigated for testing the proposed method. In the first case, 1 SVC and 1 TCSC are handled for looking for optimum allocation simultaneously. In the second, 2 SVC and 2 TCSC devices are considered. Finally, the optimum sizes and rates are investigated for 3 SVC and 3 TCSC devices. Population sizing is one of the important topics in evolutionary computation. Small population size may cause to poor solutions. On the other hand, large population size causes to increase the computation time significantly. The GA algorithm here is started by creating 100 random initial populations. In the opti-

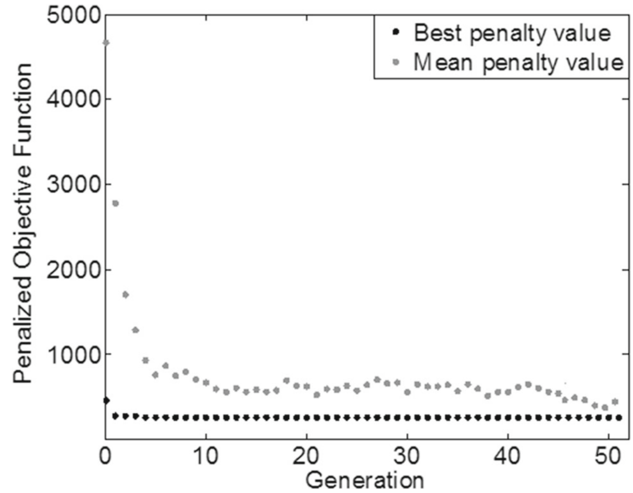


Fig. 6 Penalized objective function versus generation for 1 SVC and 1 TCSC

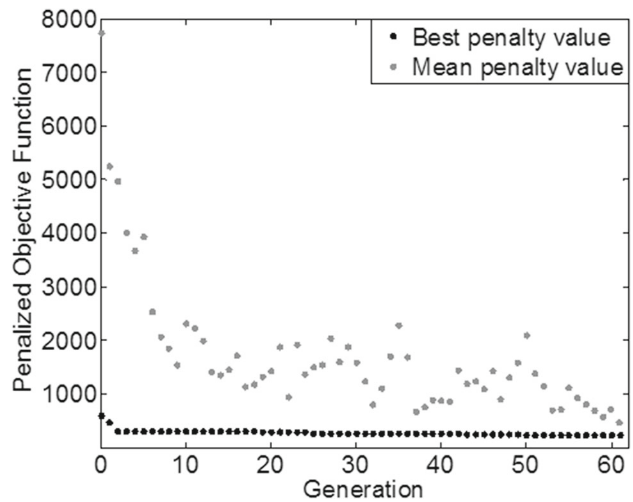


Fig. 7 Penalized objective function versus generation for 2 SVC and 2 TCSC

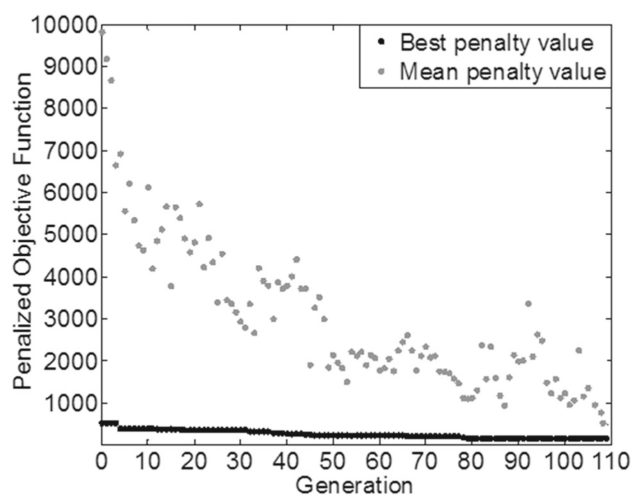


Fig. 8 Penalized objective function versus generation for 3 SVC and 3 TCSC

Table 1 Comparative optimization results using annual and single load profiles with the proposed method (Ann.: annual, Sng.: single, cap.: capacitive, ind.: inductive)

Cases						Voltage violation number		Line violation number	
Case 0: Without FACTS under annual load profile						556		441	
		Location		Rated value					
		Ann.	Sng.	Ann.	Sng.	Ann.	Sng.	Ann.	Sng.
Case 1	SVC 1	15th bus	12th bus	19.42 MVAr cap.	15.60 MVAr ind.	5	48	256	421
	TCSC 1	5th line (buses 2–6)	4th line (buses 3–4)	$-0.395X_l$ cap.	$-0.395X_l$ cap.				
Case 2	SVC 1	15th bus	7th bus	21.20 MVAr cap.	17.38 MVAr cap.	4	11	243	306
	SVC 2	21st bus	17th bus	1.00 MVAr cap.	29.28 MVAr ind.				
	TCSC 1	5th line (buses 2–6)	3th line (buses 2–4)	$-0.421X_l$ cap.	$-0.414X_l$ cap.				
	TCSC 2	3rd line (buses 2–4)	5th line (buses 2–5)	$-0.377\ X_l$ cap.	$-0.494\ X_l$ cap.				
Case 3	SVC 1	15th bus	10th bus	21.51 MVAr cap.	16.60 MVAr ind.	0	2	151	394
	SVC 2	3rd bus	4th bus	51.83 MVAr ind.	92.96 MVAr cap.				
	SVC 3	17th bus	12th bus	12.83 MVAr cap.	64.51 MVAr ind.				
	TCSC 1	41st line (buses 29–30)	10st line (buses 6–8)	$-0.691X_l$ cap.	$0.069X_l$ ind.				
	TCSC 2	25th line (buses 12–16)	33rd line (buses 24–25)	$-0.362X_l$ cap.	$-0.554X_l$ cap.				
	TCSC 3	5th line (buses 2–6)	1st line (buses 1–2)	$-0.421X_l$ cap.	$0.172X_l$ ind.				

mization process, the parameters of m, n_d, and α are 24, 365, and 0.25, respectively. To show the effectiveness of proposed method, the graph based GA optimization procedure is also performed using an instant load profile which is original load of IEEE 30 bus system. The comparative optimization results using the single load profile and annual load profile are given in Table 1. The performances of the GA are given in Figs. 6, 7, and 8. The number of violations without using FACTS devices under the annual load profile are also given in Table 1. If the FACTS devices are not used under the annual load profile given in Fig. 5, the number of violations in bus voltages and lines are 556 and 441, respectively. Results show that long term load profiles should be considered when allocating FACTS devices to enhance the power system performance. The best locations and rated values of FACTS devices when using the annual load profile are different than that of the single load profile. The number of violations can be reduced with increasing the number of FACTS devices. The problematic buses, lines, and corresponding violation numbers are given in Tables 2 and 3 in detail. The results show that the number of TCSC devices should be increased to forestall line overloading violations. The penalized objective function with GA optimization method, as the one presented in this paper, can effectively solve this problem in a simple manner.

Table 2 The number of voltage violations and corresponding bus numbers

Cases		Bus number	Violation number	Total violation number
Case 0	Without FACTS	9	181	556
		10	9	
		12	362	
		16	4	
Case 1	1 SVC 1 TCSC	9	4	5
		30	1	
Case 2	2 SVC 2 TCSC	9	3	4
		30	1	
Case 3	**3 SVC 3 TCSC**	0	0	0

4.2 Comparative optimization results with the GA and the NOMAD

In this section, the results obtained from the GA have been compared to those obtained using the NOMAD [34–37] with various scenarios. The NOMAD has been obtained from [46] and can be used for solving mixed integer optimization problems. It is also a derivative-free optimization algorithm. The NOMAD algorithm generates a trial point on the mesh that improves the current best solution at each iteration. The next iteration is initiated for a finer mesh, if an iteration is not successful [46].

First, the annual load profile presented in Fig. 5 is used in the optimizations process. The comparative optimization results using the NOMAD method and the GA method are shown in Table 4. The optimum rated values and locations are presented in Table 4. The simulation results proves the efficiency of the proposed method and shows that the GA method is able to find better solutions than the NOMAD for

Table 3 The number of line violations and corresponding lines

Cases		Lines	Violation number	Total violation number
Case 0	Without FACTS	From bus 1 to 2	1	441
		From bus 2 to 6	1	
		From bus 3 to 4	185	
		From bus 4 to 6	26	
		From bus 6 to 7	198	
Case 1	1 SVC 1 TCSC	From bus 1 to 2	1	256
		From bus 2 to 6	21	
		From bus 3 to 4	21	
		from bus 4 to 6	1	
		From bus 6 to 7	212	
Case 2	2 SVC 2 TCSC	From bus 1 to 2	2	243
		From bus 2 to 6	19	
		From bus 4 to 6	10	
		From bus 6 to 7	212	
Case 3	3 SVC 3 TCSC	From bus 1 to 2	1	151
		From bus 2 to 6	25	
		From bus 3 to 4	13	
		From bus 4 to 6	1	
		From bus 6 to 7	111	

Table 4 Comparison of the proposed method and NOMAD results using annual load profile of the IEEE 30 bus test system.(PM: Proposed Method, NMD: NOMAD, cap.: capacitive, ind.: inductive)

Cases		Location		Rated value		Voltage violation number		Line violation number	
		PM	NMD	PM	NMD	PM	NMD	PM	NMD
Case 1	SVC 1	15th bus	3th bus	19.42 MVAr cap.	19.47 MVAr cap.	5	36	256	385
	TCSC 1	5th line (buses 2–5)	5th line (buses 2–5)	$-0.395X_l$ cap.	$-0.451X_l$ cap.				
Case 2	SVC 1	15th bus	15th bus	21.20 MVAr cap.	24.53 MVAr cap.	4	22	243	245
	SVC 2	21st bus	3th bus	1.00 MVAr cap.	35.70 MVAr ind.				
	TCSC 1	5th line (buses 2–5)	6th line (buses 2–6)	$-0.421X_l$ cap.	$0.199X_l$ ind.				
	TCSC 2	3rd line (buses 2–4)	10th line (buses 6–8)	$-0.377\ X_l$ cap.	$0.198\ X_l$ ind.				
Case 3	SVC 1	15th bus	10th bus	21.51 MVAr cap.	37.56 MVAr cap.	0	3	151	225
	SVC 2	3rd bus	4th bus	51.83 MVAr ind.	53.83 MVAr cap.				
	SVC 3	17th bus	12th bus	12.83 MVAr cap.	8.11 MVAr ind.				
	TCSC 1	41st line (buses 29–30)	9th line (buses 6–7)	$-0.691X_l$ cap.	$0.200X_l$ ind.				
	TCSC 2	25th line (buses 12–16)	18th line (buses 12–15)	$-0.362X_l$ cap.	$0.003X_l$ ind.				
	TCSC 3	5th line (buses 2–5)	6th line (buses 2–6)	$-0.421X_l$ cap.	$0.197X_l$ ind.				

the cost of a lower number of violations especially in the branch overloading.

Second, three different test load profiles having 8760 random values are generated based on Eqs. (8) and (9). Here, the value of n_d is 8760 that resembles hour of year. Statistical information of the load profiles are given in Table 5. From Table 6, it is seen that significant reduction in the number of violations is achieved by the GA method compared to the NOMAD method. It is worth noting that minimizing the number of violation is very important for long period of time to prolong the life of power system components. In that manner, long term performance evaluations should be taken into account when determining optimum allocation of FACTS devices to improve the performance of existing

Table 5 Statistical information of randomly generated test load profiles

		Mean	Max.	Min.	Standard deviation	Variance
Load profile 1	Active load (MW)	283.360	311.728	255.065	16.312	266.1
	Reactive load (MVAr)	126.172	138.815	113.581	7.283	53.0
Load profile 2	Active load (MW)	283.320	340.056	226.73	32.625	1064.4
	Reactive load (MVAr)	126.152	151.431	100.962	14.567	212.2
Load profile 3	Active load (MW)	283.280	368.384	198.395	48.938	2395.0
	Reactive load (MVAr)	126.128	164.047	88.343	21.851	477.4

Table 6 Violation numbers under the randomly generated load profiles in Table 5 (Case 1: 1 SVC and 1 TCSC, Case 2: 2 SVC and 2 TCSC, Case 3: 3 SVC and 3 TCSC)

Cases		Load profile 1		Load profile 2		Load profile 3	
		Voltage violation number	Line violation number	Voltage violation number	Line violation number	Voltage violation number	Line violation number
Case 0: Without FACTS		13,683	8484	15,511	9769	17,825	10,970
Case 1	Proposed method	0	4411	1539	6432	5825	8629
	NOMAD	929	8760	4895	10,156	12,132	12,868
Case 2	Proposed method	0	4407	954	5256	5869	10,347
	NOMAD	220	2086	2073	7348	5062	10,570
Case 3	Proposed method	0	415	462	3884	3987	7322
	NOMAD	0	3423	1100	6669	6408	9351

network infrastructures. It is not possible to get the same performance under different load profiles. However, the optimization results are consistent if we observe the results when dealing with only single load profile. In a general, the optimization results should be tested in different long-term load profiles. As seen in Table 5, the standard deviation and variance of Load Profile 3 are higher than those of in Load Profiles 1 and 2. The main aim of the comparison given in Table 6 is to point out that the obtained optimization results using a load condition may not be give the same performance under a different load condition. The performance of obtained optimization results can change with different load conditions. So, the test results strongly depend on the load conditions.

5 Conclusion

This paper has presented an effective and simple approach for determining the optimal capacity and location of FACTS devices in power systems. The objective functions considered in the study were minimization of the violation number of bus voltages and line overloading as well as the profit of the system security and power quality. In this study, annual daily load demand is considered as a whole instead of an instant load profile while looking for optimum size and location of FACTS devices. For this reason, to simplify the optimization procedure, a graph based panelized objective function is developed. The effectiveness of the proposed method is examined by applying it to the IEEE 30-bus test system. The results show that appropriate size and location of FACTS devices are highly crucial by considering long term load profile to maximize the benefits, and to operate the system safely through minimizing the violations in bus voltage and transmission line thermal limits. This method can facilitate to take into account of long term load variations while looking for optimum location and size of multiple FACTS devices.

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