OPTIMAL LOCATION OF FACTS DEVICES TO IMPROVE POWER SYSTEMS PERFORMANCE

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Abstract: Flexible Alternating Current Transmission Systems (FACTS) devices have been proposed as an effective solution for controlling power flow and regulating bus voltage in electrical power systems, resulting low system losses, and improved stability. Placement of these devices in suitable location can lead to control in line flow and maintain bus voltages in desired level and so improve power system security. This paper presents a novel algorithm for allocation of FACTS devices based on Elitist Non Dominated Sorting Genetic Algorithm (NSGA-II). The proposed algorithm is tested on IEEE 14 bus power system for optimal allocation of multi-type FACTS devices and results are presented.

Key words: Power System Security, FACTS Devices, Optimal Allocation, Multi objective Optimization, Multi Objective Genetic Algorithm.

1. Introduction

As the load increases, power utilities are looking for ways to maximize the utilization of their existing transmission systems, therefore controlling the power flow in the transmission lines is an important issue in planning and operating of power system.

In recent years, advances in the high power solid-state switches, e.g. Gate Turn Off (GTO) thyristors, have led to the development of transmission controllers that provide controllability and flexibility for power transmission. A new technology program is known as Flexible AC Transmission Systems (FACTS) [1].

The ability of FACTS devices to control those parameters like series impedance, shunt admittance, bus voltage, voltage drop and phase angle that govern the operation of transmission system, provides the possibility of improving such system operating issues as static/dynamic stability, system security, system loadability, total generation fuel cost and so forth. However, this potential depends mainly on the location, type and rating of F ACTS devices installed in the system.

The optimal allocation of FACTS devices has been investigated in several papers from different issues of system operation and performance. Sensitivity-based approaches have been used in [2-4] for this purpose. To enhance power system static security, the FACTS devices are located according to the sensitivity of security indices to line power flows or bus voltages or losses, and then the value of the sensitivity is used for sizing the device.

Although these approaches show acceptable results for some case studies, because of high nonlinearity of power system equations, there is no guaranty to the efficiency of first order sensitivities particularly for bulk and large scale power systems. Artificial Intelligence (AI) Based approaches like genetic [5-7], particle swarm algorithms [8-11], Simulated Annealing (SA) Algorithms [12], Low Discrepancy Sequences (LDS) [13], Bacterial Swarming Algorithm (BSA) [14], Differential Evolution (DE) technique [15] are successively used for optimal allocation of FACTS devices problems. The most attractive feature of these methods is their ability to find the global optimum solution.

For multiple-objective problems, there are two general approaches. One is to combine the individual objective functions into a single composite function (weighted sum method) such as [5]; this approach is very difficult to precisely and accurately select the weights. Compounding this drawback is that scaling amongst objectives is needed and small perturbations in the weights can sometimes lead to quite different solutions. An approach based on a fuzzy evaluation technique, combined with a genetic algorithm, is used to overcome these problems [16].

The second general approach is to determine a set of optimal solutions (an entire Pareto optimal solution set). [17] Presents a multi-objective genetic algorithm (MOGA) to determine the optimal allocation of FACTS devices into power systems, from both technical and economical point of view, in order to provide a better security level. [18] Non-dominated Sorting Particle Swarm Optimization (NSPSO) algorithm is used to solve a Multi-objective Optimization problem. [19] Proposes an approach based on the evolutionary algorithms (EA) to solve this problem. It is about the NSGA-II method (Elitist Non Dominated Sorting Genetic Algorithm).

In this paper, a new multi-objective optimization algorithm based on Elitist Non Dominated Sorting Genetic Algorithm (NSGA-II) is used to determine the optimal location and size of FACTS devices to enhance power system security considering power system losses.

Proposed method is tested on IEEE 14 bus system and results are presented.

2. FACTS devices model

2.1. FACTS devices

In this paper, three different FACTS devices have been selected to place in suitable location to improve security margins in power system. These are: TCSC (Thyristor Controlled Series Capacitor), SVC (Static VAR Compensator) and UPFC (Unified Power Flow Controller). These are shown in Fig. 1.

Power flow through the transmission line i-j namely P_{ij} is depended on line reactance X_{ij}, bus voltage magnitudes, V_i V_j, and phase angle between sending and receiving buses $\delta i - \delta j$. This is expressed by eq (1).

$$Pij = \frac{ViVj}{Xij} sin(\delta i - \delta j) \tag{1}$$

TCSC can change line reactance and SVC can be used to control reactive power in network. UPFC is the most versatile member of FACTS devices family and can be applied in order to control all power flow parameters (i.e. line impedance, bus voltage, and phase angle). Power flow can be controlled and optimized by changing power system parameters using FACTS devices, so optimal choice and allocation of FACTS devices can result in suitable utilization in power system.
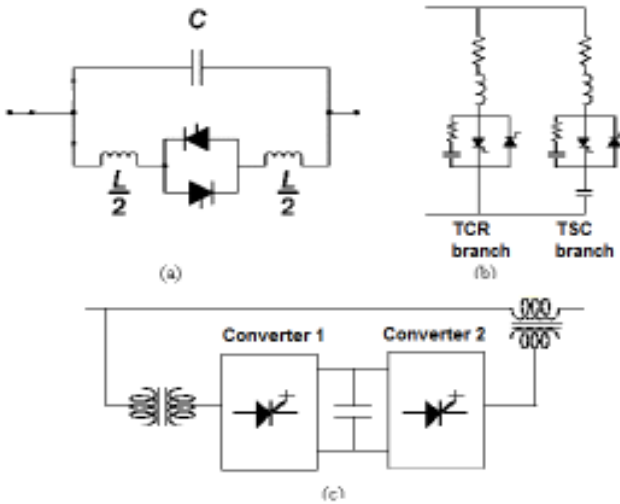

Fig. 1 Considered FACTS Devices (a) TCSC (b) SVC (c) UPFC

2.2. SVC model

SVC can be used for both inductive and capacitive compensation. In this paper SVC is modeled as an ideal reactive power injection at bus *i*:

$$\Delta Q_i = Q_{SVC} \tag{2}$$

The values are between -100 MVar and 100 MVar [6].

2.3. TCSC Model

TCSC acts as the capacitive or inductive compensator by modifying reactance of transmission line. This changes line flow due to change in series reactance. In this paper TCSC is modeled by changing transmission line reactance as below:

$$X_{ij} = X_{line} + X_{TCSC} \tag{3}$$
$$X_{TCSC} = r_{TCSC} . X_{line} \tag{4}$$

Where X_{line} is reactance of transmission line and r_{TCSC} is compensation factor of TCSC. Rating of TCSC is depended on transmission line where it is located. To prevent overcompensation, TCSC reactance is chosen between -0.8 X_{line} to 0.2 X_{line} [8].

2.4. UPFC Model

The unified power flow controller consists of two switching converters. These converters are operated from a common dc link provided by a dc storage capacitor (Fig. 1.c).

Converter 2 provides the main function of the UPFC by injecting an ac voltage with controllable magnitude and phase angle in series with the transmission line via a series transformer. The basic function of converter 1 is to supply or absorb the real power demand by converter 2 at the common dc link. It can also generate or absorb controllable reactive power and provide independent shunt reactive compensation for the line. Converter 2 supplies or absorbs locally the required reactive power and exchanges the active power as a result of the series injection voltage .

Since the series voltage source converter does the main function of the UPFC, it is appropriate to discuss the modeling of a series voltage source converter first, and then the shunt connected voltage source converter is incorporated [4, 20].

2.4.1 Model of series Voltage Source Converter

Suppose a series connected voltage source is located between nodes i and j in a power system. The series voltage source converter can be modeled with an ideal series voltage V_s in series with a reactance X_s.
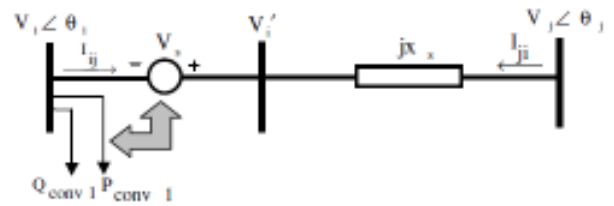

Fig. 2 Representation of a series connected VSC

In Fig. 2, V_s models an ideal voltage source and V_i' represents a fictitious voltage behind the series reactance. We have:

$$V_i' = V_s + V_i \tag{5}$$

The series voltage source V_S is controllable in magnitude and phase, i.e :

$$V_S = r V_i e^{j\gamma} \tag{6}$$

Where r and γ are the control variables of the series compensation ($0 < r < r_{max}$ and $0 < γ < 2π$).
The injection model is obtained by replacing the voltage source V_S by the current source $I_S = - jb_S\ V_S$, in parallel with the line where $b_S = 1/X_S$:
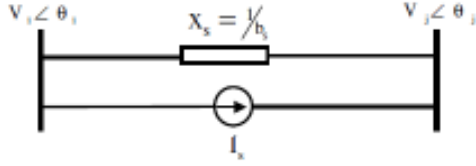

Fig. 3 Replacement of a series voltage source by a current source

The current source I_S corresponds to the injection powers S_{iS} and S_{jS}, (the injection power at bus i and j respectively), where:

$$S_{iS} = V_i\ (-I_S)^* \tag{7}$$
$$S_{jS} = V_j\ (I_S)^* \tag{8}$$

The injection power S_{iS} and S_{jS} are simplified to:
$$S_{iS} = V_i\ [\ jb_S\ r\ V_i\ e^{jγ}\ ]^*$$
$$= -b_S r\ v_i^2\ sin\ γ - jb_S\ r\ v_i^2\ cos\ γ \tag{9}$$

If we define: $θ_{ij} = θ_i - θ_j$, we have:
$$S_{jS} = V_j\ [\ -jb_S\ r\ V_i\ e^{jγ}\ ]^*$$
$$= b_S r\ v_i\ v_j\ sin(θ_{ij} + γ) + jb_S\ r\ v_i\ v_j\ cos(θ_{ij} + γ) \tag{10}$$

Based on the explanation above, the injection model of a series connected voltage source can be seen as two dependent loads as shown in Fig.4.
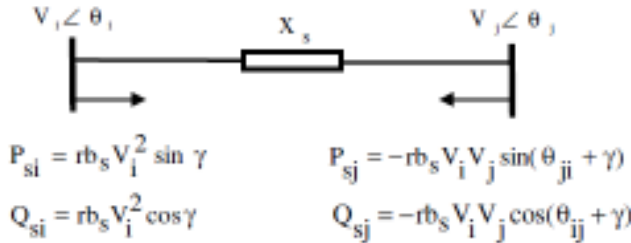

Fig. 4 Injection model for a series connected VSC

2.4.2. Insertion of shunt Voltage Source Converter in UPFC Model

In UPFC, the shunt connected voltage source (Converter 1) is used mainly to provide the active power which is injected to the network via the series connected voltage source. We have:

$$P_{CONV1} = P_{CONV2} \tag{11}$$

The equality above is valid when the losses are neglected. The apparent power supplied by the series voltage source converter is calculated from:

$$S_{CONV2} = V_s\ I^*_{ij} = r\ e^{jγ}\ V_i \left(\frac{V'_i - V_j}{jX_s} \right) \tag{12}$$

Active power supplied by Converter 1 is distinguished as:
$$P_{CONV1} = P_{CONV2} = Re\ (S_{CONV2})$$
$$= r\ b_S\ v_i\ v_j\ sin(θij + γ) - r\ b_S\ v_i^2\ sin\ γ \tag{13}$$

The reactive power delivered or absorbed by the converter 1 is independently controllable by UPFC and can be modeled as a separate controllable shunt reactive source, Q_{CONV1}. The UPFC injection model is constructed from the series voltage source (Fig. 4) with the addition of a power equivalent to $P_{CONV1} + j\ Q_{CONV1}$ to node i as shown in Fig. 5. The model can be incorporated to the power flow equations by adding the UPFC injection powers at buses i and j.
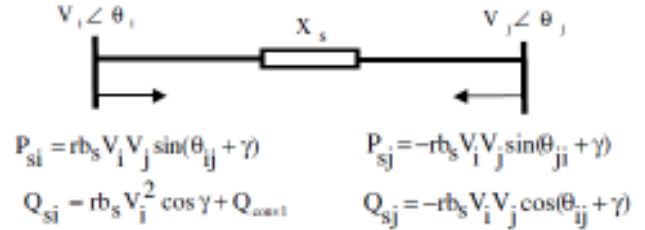

Fig. 5 UPFC injection model

3. Problem formulation

3.1. Objectives

The goal of optimization was the determination of optimal allocation of FACTS devices into a power system in order to enhance the systems security level, keeping in the same time low system losses. Therefore, the presented problem becomes a multi-objective optimization problem (MOP), and this can be expressed, in equation form, as:

$$Min\ F(x) = [\ F_V(x),\ F_S(x),\ F_{PL}(x)\ ] \tag{14}$$
$$Subject\ to\ x \in Ω$$
$$C_j(x) = 0 \quad j = 1....n$$
$$H_k(x) \leqq 0 \quad k = 1....p$$

Where F is known as the objectives vector, x represents a decision vector, $Ω$ is the solution domain and $C_j(x)$ and $H_k(x)$ are the equality and inequality problem constraints respectively. In this MOP, $F_V(x)$, $F_S(x)$, $F_{PL}(x)$ are objective functions represent the voltage deviation, system over load, and real power losses as follows:

$$F_V = \sum_i |V_i - V_i^{ref}|^2 \tag{15}$$

$$F_S = \sum_j \left(S_j \middle/ S_j^{max} \right)^2 \tag{16}$$

$$F_{PL} = \sum_i P_{Li} \tag{17}$$

Where:
V_i^{ref}: is Nominal voltage magnitude which is assumed to be 1pu for all load buses.
Vi: is the voltage magnitude for i_{th} load bus
S_j: is the apparent power for j_{th} line
S_j^{max}: is the max apparent power for j_{th} line
P_{Li}: is the real power at i^{th} line.

3.2. Constraints

The optimization problem is bounded by the following constraints

3.2.1. Equality constraints

These constraints represent the load flow equations corresponding to both real and reactive power balance equations, which can be written as:

$$P_{Gi} - P_{Di} - \sum_{j=1}^{N} V_j [G_{ij} cos(\theta ij) + B_{ij} sin(\theta ij)] = 0 \quad (18)$$
$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{N} V_j [G_{ij} sin(\theta ij) - B_{ij} cos(\theta ij)] = 0 \quad (19)$$

Where:
P_{Gi} and Q_{Gi}: generator real and reactive power at i_{th} bus, respectively;
P_{Di} and Q_{Di}: load real and reactive power at i_{th} bus, respectively;
G_{ij} and B_{ij} : transfer conductance and susceptance between buses i and j, respectively.

3.2.2. Inequality constraints

Generation reactive power constraints:
$$Q_{Gi}^{min} < Q_{Gi} < Q_{Gi}^{max} \quad for\ i = 1,...,N \quad (20)$$
FACTS constariants:
For SVC $\quad Q_c^{min} < Q_{SVC} < Q_c^{max} \quad (21)$
For TCSC $\quad r^{min} < r_{TCSC} < r^{max} \quad (22)$
For UPFC $\quad \gamma^{min} < \gamma < \gamma^{max} \quad (23)$
$\quad\quad\quad and \quad Q_c^{min} < Q_{conv1} < Q_c^{max} \quad (24)$

r is set at $r^{max} = 0.1$, because it is found that it gives best results at that value.

4. Solution algorithm

Seeing that the optimization process was oriented towards two parameters: FACTS location, and their rates, which can take discrete and continues values, the case discussed above becomes a *combinatorial optimization problem*. we chose to use local search (or *heuristic methods*), which is a robust way to obtain good solutions to real problems in a reasonable time. More particularly, from the class of the *heuristic methods*, we used the GAs [21] which are stochastic search techniques based on the mechanics of natural selection and natural genetics. They search for a solution inside a subspace of the total search space, being able to give a good solution in an acceptable computation time.

Furthermore to the aspects presented above, the problem multi-objective character imposes the consideration of suitable solving methods which are able to provide acceptable solutions.

4.1. Genetic Algorithms

GAs start with an initial set of random solutions called population. A population of candidate solutions, or individuals, is maintained, and individuals made to compete with each other for survival. Once evaluated, through the fitness function calculation, stronger individuals have a greater chance to contribute to the production of new individuals (the offspring) than weaker ones, which may not even contribute at all (selection procedure). Offspring are produced through recombination, whereby they inherit features from each of the parents, and through mutation, which can confer some truly innovative features as well. In the next selection step (next generation), offspring are made to compete with each other, and possibly also with their parents. Improvement in the population arises as a consequence of the repeated selection of the best parents, which are in turn more likely to produce good offspring, and the consequent elimination of low-performers. After several generations, the algorithm converges to the best individual, which hopefully represents the optimal solution to the problem. Fig. 6 shows the flow chart of GA with FACTS Allocation Problem.
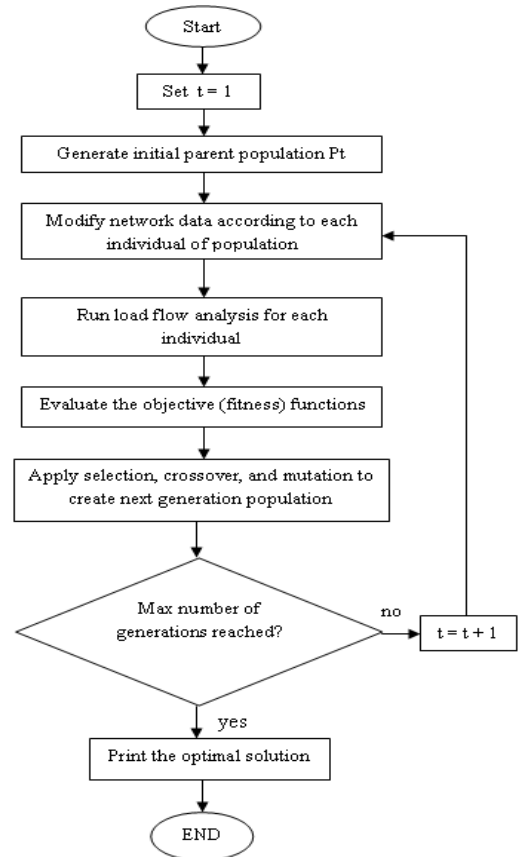

Fig. 6 flow chart of Genetic Algorithm

4.2. Multi-Objective Optimization

The problem described in Section (3) is a *multi-objective combinatorial optimization problem*, and thus it was necessary to use a multi-objective technique for solving it. The use of multi-objective techniques gives information on the consequences of the decision with respect to all the defined objective functions. While traditional optimization procedures result in one solution point only, the MOP usually has no unique, perfect (or utopian) solution, but a set of *non-dominated*, alternative

solutions, known as the Pareto-optimal set which define the POF. The principle of *dominance* can be defined in the following form: a solution is clearly better than (dominating) another solution, if it is better or equal in all objectives, but at least better in one objective. Using this principle, the set of best compromise solutions results by removing all solutions that are dominated by at least one other solution. The remaining solutions are all of equal quality (indifferent). For a given Pareto optimal set, and the corresponding objective function values in the objective space are called the Pareto front (Fig. 7).
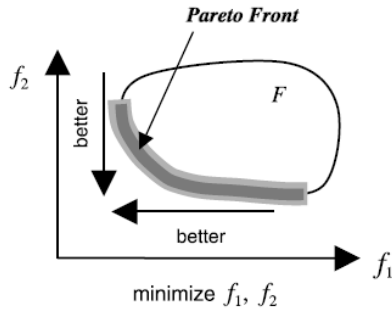

Fig. 7 Illustration of Pareto front for a bi-objective optimization problem

The POF offers complete information about the optimal solutions of the problem and becomes an important knowledge for the Decision Maker (DM). In this paper, the aim of the optimization is to determine the POF of the problem described in the section above. The choice of the optimal solution among the POF points remained to DM. For these types of problems the Genetic Algorithms (GAs) represent a standard tool. GAs can exploit the population-based feature and converge in parallel to the Pareto front. There are many EAs described in the literature, reviews of this can be found in [22]. For the present work, among the GAs, we choose to employ NSGA II technique.

4.3. Non-dominated Sorting Genetic Algorithm

NSGA (Non-dominated Sorting Genetic Algorithm) implements the idea of a selection method based on classes of dominance of all solutions. This algorithm identifies non-dominated solutions in the population, at each generation, to form non-dominated fronts, based on the concept of non-dominance of Pareto. After this, the usual selection, crossover, and mutation operators are performed.

However, there are some faults in NSGA. It has been generally criticized for its computational complexity, lack of elitism and for choosing the optimal parameter value for sharing parameter. A modified version, NSGA-II [23] wasdeveloped, which has a better sorting algorithm, incorporates elitism and no sharing parameter needs to be

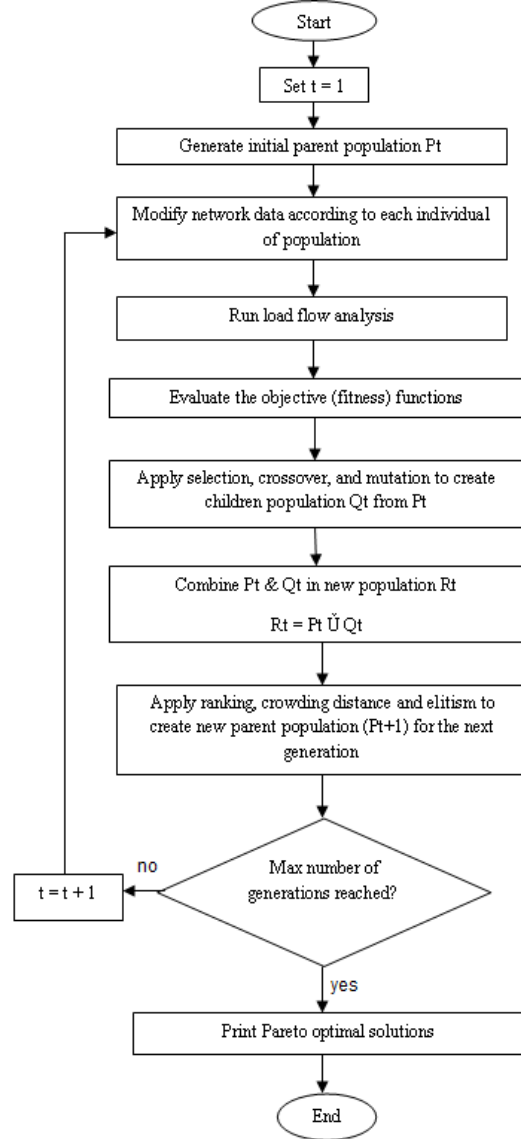chosen a priori. In this study NSGA-II is used.

Fig. 8 Proposed flow chart of NSGA II

One iteration of this algorithm procedure can be written as follows:

Step1: Initiate a random population with size N individuals (parent population (Pt))

Step 2: Evaluate Objective Values and assign Rank (level) Based on Pareto dominance sort

Step 3: Use crossover and mutation operators to create the offspring population Qt (with size N) from the parent population Pt

Step 4: Combine the two populations Qt and Pt to form new population R_t

Rt = Pt ∪ Qt   (Rt has size 2N)

Step 5: Perform Non-dominated Sort on Rt and assign ranks to each pareto front with fitness Fi

Step 6: Apply elitism as follows:

- Starting from Pareto front with fitness F1, add each pareto-front Fi to the new parent population Pt+1 until a complete front Fi cannot be included.

- From the current pareto-front Fi, Sort this front using the crowding distance in descending order and add the first individual members to new parent population Pt+1 until it reaches the size N.

Step 7: Apply selection, crossover and mutation to new parent population Pt+1 and obtain the new offspring population Qt+1

Where:

t: represent the generation number

i: represent the pareto front number

Fig. 8 shows the flow chart of the proposed implementation of NSGA II in FACTS allocation problem.

4.4. Individual (chromosome) structure and solution encoding

To apply multi objective GA to solve a specific problem, one has to define the solution representation and the coding of control variables. The goal of the optimization is to find the best location and size of FACTS devices, thus each chromosome consists of two geneses corresponding to the location and size of each FACTS device.
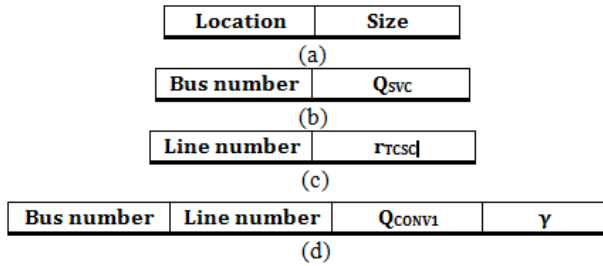

Fig. 9 chromosome structure of (a) general FACTS (b) SVC (c) TCSC (d) UPFC

5. Results

Simulation studies were done for different scenarios in IEEE 14 bus power system. Four different scenarios are considered:

- Scenario1: power system normal operation (without FACTS devices installation).

- Scenario2: the Genetic Algorithm with single objective function (power losses or Voltage deviation or power system over load) will be applied in case of:

a) One TCSC is installed

b) One SVC is installed

c) One UPFC is installed

- Scenario3: Then repeat scenario 2 but with the Multi-Objective Genetic Algorithm (using all objectives above)

- Scenario4: study the effect of optimal locations and sizes f TCSC, and SVC, and UPFC on the real power losses, voltage, and overload profiles of the electric power system.

Table 1 shows total power losses, system overload, and voltage deviation of IEEE 14 bus system without FACTS devices installation, then the Genetic Algorithm is applied to find the optimal location and size of FACTS devices (TCSC, SVC, and UPFC). GA is applied three times, one for power losses and other for system overload and for Voltage deviation as objective functions, and in each time the results are presented.

Table 1 Optimal location of FACTS devices using GA

Objective	Location		Size		Results		
					Loss	Overload	V. d
w/o FACTS	-		-		13.5929	10.5508	0.0289
TCSC	**Line number**		r_{TCSC}				
Losses	2		-0.226		13.4602	10.8840	0.0289
Overload	4		-0.725		15.7292	9.0784	0.0220
V. deviation	1		-0.624		14.5525	10.2696	0.0191
SVC	**Bus number**		Q_{SVC}				
Losses	9		30.3		13.3783	9.9068	0.0428
Overload	9		29.9		13.3784	9.9066	0.0426
V. deviation	7		-26.4		14.1266	10.7822	0.0095
UPFC	**Bus**	**line**	Q_{CONV1}	γ			
Losses	1	1	0	1.25	8.7846	9.0108	0.0328
Overload		4	-20	1.39	10.9264	8.1169	0.0346
V. deviation	7	15	29	1.559	14.2225	12.9588	0.0093

The main observation of table 1 is that the optimal solution for one objective function is not a good solution for other objectives.

Table 2, 3, and 4 present the pareto optimal set for FACTS allocation using NSGA II. Table 2 shows the pareto optimal set for TCSCS allocation, individuals (1, 2, and 4) are the optimal solutions corresponding to the losses, overload, and V. deviation respectively. The remaining individuals are the remaining non dominant solutions for TCSC allocation problem.

Table 2 Pareto optimal set for TCSC allocation

individual	Line No.	r_{TCSC}	Losses	Overload	V. dev
1	2	-0.2261	13.4602	10.8842	0.0289
2	4	-0.7243	15.7237	9.0780	0.0220
3	4	-0.7991	16.4766	9.3298	0.0209
4	1	-0.6411	14.5825	10.2619	0.0191
5	10	-0.7007	13.9254	14.1421	0.0259
6	10	-0.7935	14.0866	18.4620	0.0232
7	10	-0.7665	14.0485	16.5877	0.0233
8	2	-0.6392	14.5407	12.3880	0.0239
9	3	-0.7140	14.1856	9.3927	0.0291
10	10	-0.7995	14.0955	18.9803	0.0232
11	10	-0.7011	13.9259	14.1553	0.0259

Table 3 Pareto optimal set for SVC allocation

individual	Bus No.	Q$_{SVC}$	Losses	Overload	V. dev
1	9	29.90	13.3784	9.9066	0.0426
2	7	- 26.41	14.1267	10.7828	0.0095
3	9	30.29	13.3783	9.9068	0.0428
4	9	-18.45	14.0324	11.6059	0.0117
5	9	-14.46	13.9787	11.2270	0.0137
6	11	-17.78	14.1286	10.6504	0.0116
7	9	-10.21	13.8402	11.1142	0.0156
8	9	-18.05	14.0380	11.5304	0.0118
9	9	14.86	13.4218	10.1249	0.0366
10	9	30.29	13.3783	9.9068	0.0428
11	10	06.48	13.4780	10.4613	0.0339

Table 3 presents the pareto optimal set for SVC allocation, individuals (3, 1, and 2) are the optimal solutions corresponding to the losses, overload, and V. deviation respectively. The remaining individuals are the remaining non dominant solutions for SVC allocation problem.

Table 4 Pareto optimal set for UPFC allocation

Ind	Bus No.	Line No.	Q$_{CONV1}$	γ	Losses	Overload	V. dev
1	2	1	23.51	1.2441	8.7846	9.0118	0.0328
2	7	15	28.72	1.5506	14.2129	12.9351	0.0093
3	5	22	19.92	1.7465	19.1726	10.5198	0.0114
4	2	4	-25.92	1.3916	10.9264	8.1169	0.0346
5	7	15	21.72	1.7782	14.1442	13.6838	0.0115
6	5	25	19.29	1.7452	16.9638	10.0675	0.0161
7	1	2	23.54	1.7187	9.9045	11.4022	0.0291
8	7	14	25.26	1.6000	14.0560	15.9643	0.0103
9	5	25	17.87	1.7835	16.9638	9.7759	0.0120
10	5	22	10.78	1.5494	18.8828	10.3785	0.0120
11	3	3	21.48	1.7615	10.3543	8.7638	0.0229
12	4	26	14.11	1.7263	13.6898	11.5240	0.0142
13	2	4	-25.87	1.3916	10.9264	8.1169	0.0346
14	7	14	28.24	1.7137	14.0966	15.7097	0.0111
15	6	12	21.35	1.7228	14.6272	10.8755	0.0165
16	2	4	23.82	1.8055	11.2105	8.3058	0.0232

Table 4 presents the pareto optimal set for UPFC allocation, individuals (1, 4, and 2) are the optimal solutions corresponding to the losses, overload, and V. deviation respectively. The remaining individuals are the remaining non dominant solutions for UPFC allocation problem.

Fig. 10 shows the effect of FACTS devices in the optimal locations on the voltage profile of the power system, it is shown that the all FACTS improve the power system voltage profile but TCSC has less effectiveness on the voltage profile W.R.T SVC and UPFC.

Fig. 11 shows the effect of FACTS devices in the optimal locations on the power system losses of all transmission lines; it is shown that UPFC greatly reduces losses at lines (1, and 2) and slightly increases losses at lines (3, 4, and 5), so the overall system loss is greatly decreased using UPFC. SVC and TCSC have slightly affecting on the power system losses W.R.T UPFC.

Fig. 12 shows the effect of FACTS devices in the optimal locations on the system overloads, SVC has less effectiveness on the T.L overload W.R.T TCSC and UPFC.
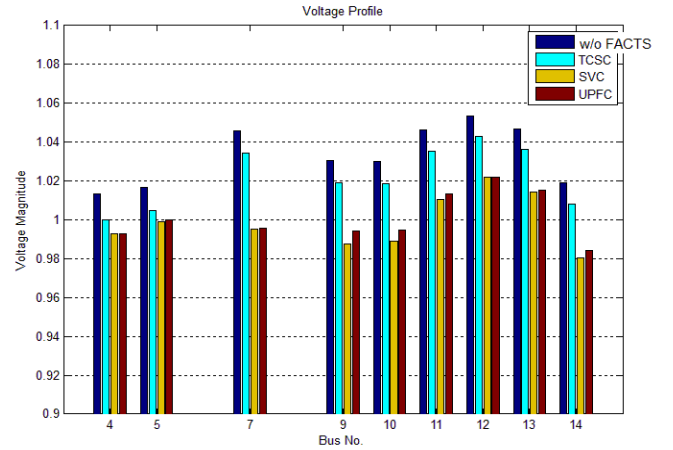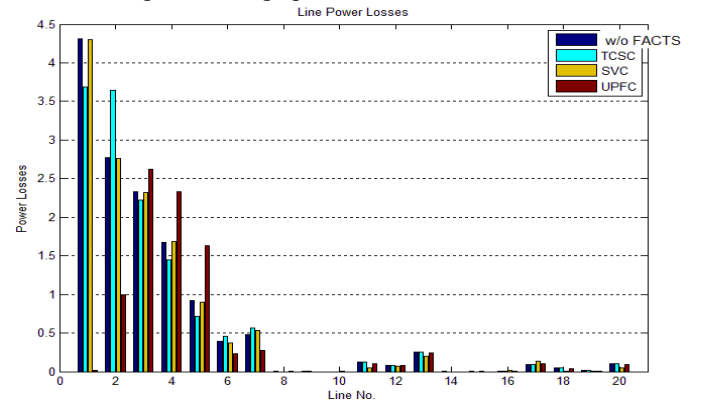

Fig. 10 Voltage profile of load buses

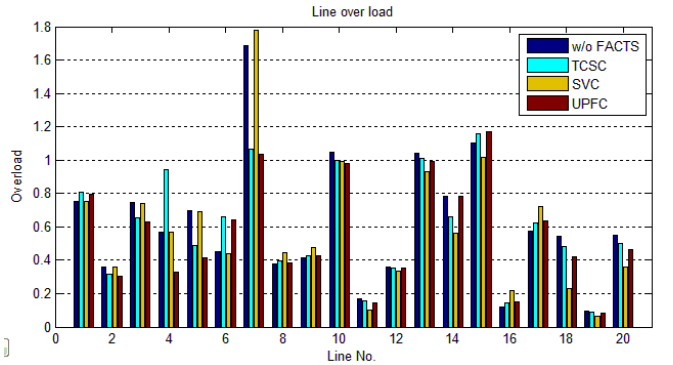Fig. 11 Power losses of Transmission lines

Fig. 12 Overloads of transmission lines

From fig. (10, 11, 12), Unified power flow controller (UPFC) is a versatile FACTS's device which can independently or simultaneously control the active power, the reactive power, and the bus voltages of power system networks.

6. Conclusions

The present paper makes use of recent advances in multi-objective evolutionary algorithms to develop a method for the combinatorial optimal allocation of FACTS into power systems. Optimizations were performed on two parameters: the locations of FACTS devices and their rates. It was considered as optimization criteria the maximization of the power system security and the minimization of power system losses. Implementation of

the proposed NSGA II has performed well when it was used to characterize POF of the FACTS optimal location problem. The results show that the proposed NSGA II can produce good solutions.

7. References

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