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Optimal Active Power Flow with Facts Devices Using Efficient Genetic Algorithm

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Abstract: This study presents an Efficient Genetic Algorithm (EGA) to solve the problem of optimal power flow with controllable FACTS devices. Two types of FACTS devices, Thyristor Controlled Series Compensator (TCSC) and Thyristor Controlled Phase Shifter (TCPS) are considered. The specified power flow control constraints due to the use of FACTS devices are included in the OPF problem in addition to the normal conventional constraints. The sensitivity analysis is carried out for the location of FACTS devices. In the solution process EGA is integrated with conventional OPF to select the best control parameters to minimize the total generation fuel cost and keep the power flows within the security limits. This method provides an enhanced economic solution with the use of controllable FACTS devices. Advanced and problem-Specific operators are introduced in order to enhance the algorithm's efficiency and accuracy. The probabilities of crossover and mutation are varied by adaptive algorithm. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

Key words: Optimal power flow, FACTS, TCSC, TCPS, Efficient (Enchanced) Genetic Algorithm (EGA),Simple Genetic Algorithm (SGA)

INTRODUCTION

One of the current researches on FACTS devices is on the power flow control and economic operation such as Optimal Power Flow (OPF). OPF is part of the standard tools of the Supervisory, Control and Data Acquisition (SCADA) and Energy Management System (EMS). It schedules power system controls to optimize an objective function while satisfying non-linear equality and linear equality constraints (Leung and Chung, 2000).

In steady state operation of power system, unwanted loop flow and parallel power flow between utilities are problems in heavily loaded interconnected power systems. These two power flow problems are sometimes beyond the control of generators or it may cost too much with generator regulations. However, with the FACTS controllers, the unwanted power flow can be easily regulated (Leung and Chung, 2000).

In OPF the main objective is to minimize the costs of meeting the load demand for the power system while satisfying all the security constraints (Chung and Li, 2001). Since OPF is a non-linear problem, decouple of the control parameter of the FACTS device is a highly non linear problem so that GA (Goldberg, 1989) is used as a methodology to solve. In this context, more control facilities may complicate the system operation. As control facilities influence each other, a good coordination is required in order to bring all devices to work together, without interfering with each other. Therefore, it becomes necessary to extend available system analysis tools, such as optimal power flow to represent FACTS controls. It has also been noted that the OPF problem with series compensation may be a non-convex and non-linear problem, which will lead the conventional optimization method stuck into local minimum (Janson and Wong, 1999).

GA has been applied to optimization problems. The objective of GA is to find the optimal solution to a problem. Since GAs are heuristic procedures, they are not guaranteed to find the optimum, but experience has shown that they are able to find very good solutions for a wide range of problems. GA approach to solve the optimal power flow control problem with FACTS is proposed. The control variables modeled are generator active power outputs and FACTS device constraint. The GA-OPF approaches overcome the limitations of the conventional approaches in the modeling of non-convex cost functions, discrete control variables and prohibited

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unit-operating zones. However, they do not scale easily to larger problems, since the solution deteriorates with the increase of the chromosome length (Anastasios and Pandel, 2002).

In this research, the conventional OPF problem is solved with SGA and EGA approaches along with 2 powers flow constraints. The probabilities of crossover and mutation are varied by adaptive algorithm (Anastasios and Randel, 2002; Srinivas and Patnaik, 1994). In addition to the basic genetic operators of the SGA used in Lai *et al.* (1997) and the advanced ones used in (Anastasios and Pandel, 2002) problem-specific operators, inspired by the nature of the OPF problem, have been incorporated in our EGA. With the incorporation of the problem-specific operators, the GA can solve larger OPF problems.

The approach minimize total cost as well as iteratively evaluates the control settings of TCSC and TCPS that are needed to maintain specified line flows. The sensitivity analysis is carried to position the TCSC and TCPS in test system (Singh and David, 2000). The results obtained shows that EGA is superior in convergence compared to SGA. Here EGA is used to obtain ED of generators such that these generations give minimum cost as well as does not result in line flow violation.

STATIC MODELING OF FACTS DEVICES

For injected-power model, it is a good model for FACTS devices because it will handle them well in load flow computation and OPF analysis (Leung and Chung, 2000). About load-equivalent method, actually it is only used when the control objectives of FACTS devices are known. In fact, the injected-power model is convenient and enough for power systems with FACTS devices.

Thyristor controlled series compensator: The effect of TCSC on the network can be seen as a controllable reactance inserted in the related transmission line. The model of the network with TCSC (Ge *et al.*, 1998) is shown in Fig. 1. The controllable reactance, x_c, is directly used as the control variable to be implemented in the power flow equation.

The power flow equations of the branch can be derived as follows:

$$P_{ij} = U_I^2 g_{ij} - U_i U_j (g_{ij} \cos\delta_{ij} + b_{ij} \sin\delta_{ij}) \qquad (1)$$

$$Q_{ij} = -U_I^2 b_{ij} - U_i U_j (g_{ij} \sin\delta_{ij} + b_{ij} \sin\delta_{ij}) \qquad (2)$$

Where

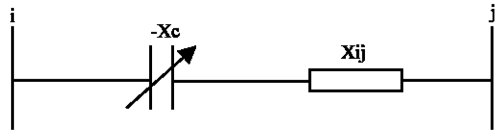

Fig. 1: Equivalent circuit of TCSC

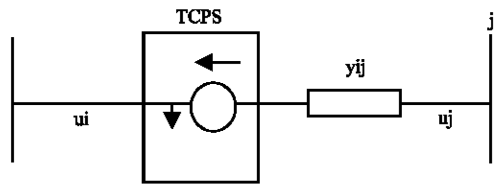

Fig. 2: Equivalent circuit of TCPS

$$g_{ij} = \frac{r_{ij}}{r_{ij} + (x_{ij} - x_c)^2} \qquad (3)$$

$$b_{ij} = x_{ij} - x_c / rij + (x_{ij} - x_{cj}) \qquad (4)$$

Here, the only difference between normal line power flow equation and the TCSC line power flow equation is the controllable reactance x_c (Chung and Li, 2001).

Thyristor controlled phase shifter: A series inserted voltage source $U_T$and a tapped current $I_T$can model the effect of TCPS on a network. Its equivalent circuit (Ge and Chung, 1998) is shown in Fig. 2. The additional voltage source changes the bus voltage from U_i to U_j corresponding to the shifting of the bus voltage U_I by an angle F.

$$\frac{U'_i}{U_i} = \frac{e^{j\theta}}{K} \qquad (5)$$

Where, K = cosΦ is the transformation co efficient of the voltage magnitude. We can derive the power flow equation of TCPS branch as follow:

$$P_{ij} = -U_I^2 g_{ij} / K^2 - U_i U_j [g_{ij} \cos (\delta_{ij} + \phi) + b_{ij} \sin(\delta_{ij} + \phi)] / K \qquad (6)$$

$$Q_{ij} = -U_I^2 g_{ij} / K^2 - U_i U_j [g_{ij} \sin (\delta_{ij} + \phi) + b_{ij} \cos(\delta_{ij} + \phi)] / K \qquad (7)$$

$$P_{ji} = -U_I^2 g_{ij} / K^2 - U_i U_j [g_{ij} \cos (\delta_{ij} + \phi) + b_{ij} \sin(\delta_{ij} + \phi)] / K \qquad (8)$$

$$Q_{ji} = -U_I^2 g_{ij}/K^2 - U_i U_j [g_{ij} \sin (\delta_{ij} + \phi) + b_{ij} \cos(\delta_{ij} + \phi)]/K \quad (9)$$

For TCPS, the controllable parameter is the voltage shift angle F. The injected active and reactive power at bus i and j can be derived as follows (Chung and Li, 2001):

$$P_{is} = -U_I^2 T^2 g_{ij} - U_i U_j T(g_{ij} \sin\delta_{ij} - b_{ij} \cos\delta_{ij}) \quad (10)$$

$$Q_{is} = -U_I^2 T^2 b_{ij} - U_i U_j T(g_{ij} \cos\delta_{ij} - b_{ij} \sin\delta_{ij}) \quad (11)$$

$$P_{js} = -U_i U_j T(g_{ij} \sin\delta_{ij} - b_{ij} \cos\delta_{ij}) \quad (12)$$

$$Q_{js} = -U_i U_j T(g_{ij} \cos\delta_{ij} - b_{ij} \sin\delta_{ij}) \quad (13)$$

Where

$$T = \tan\Phi. \quad (14)$$

PROBLEM FORMULATION

The optimal power flow problem in flexible AC transmission systems is expressed as follows (Chung and Li, 2001; Ge and Chung, 1999):

$$\min \sum_{i \in NG} (aiP_{gi}^2 + b_i P_{gi} + c_i) \quad (15)$$

$$\text{st.} P_{gi} + P_{is}(\phi) - P_d - \sum_{i \in NG} Wij\, Yij(x_c)\cos(\theta ij + \delta j - \delta i) = 0 \,\forall_1 = N \quad (16)$$

$$\text{st.} Q_{gi} + Q_{is}(\phi) - Q_d - \sum_{i \in NG} Wij\, Yij(x_c)\sin(\theta ij + \delta j - \delta i) = 0 \,\forall_1 = N \quad (17)$$

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \quad \forall i \in NG \quad (18)$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max} \quad \forall i \in NG \quad (19)$$

$$T_{gi}^{min} \le T_{gi} \le T_{gi}^{max} \quad \forall i \in NT \quad (20)$$

$$F_{ij}^{min} \le F_{ij} \le F_{ij}^{max} \quad \forall i \in NB \quad (21)$$

$$X_{ci}^{min} \le X_i \le X_{ci}^{max} \quad \forall i \in NP \quad (22)$$

$$\theta_i^{min} \le \theta_i \le \theta_i^{max} \quad \forall i \in NS \quad (23)$$

GENETIC ALGORITHM

Gas is a general-purpose optimization algorithm based on the mechanics of natural selection and genetics. GA operates on string structures (chromosomes), typically a concatenated list of binary digits representing a coding of the control parameters (phenotype) of a given problem. Chromosomes themselves are composed of genes. The real value of a control parameter, encoded in a gene, is called an allele.

GA is an attractive alternative to other Optimization methods because of their robustness.

In SGA (Leung and Chung, 2000; Anastasios and Pandel, 2002) assuming an initial random population produced and evaluated, genetic evolution takes place by means of three basic genetic operators Parent Selection, Crossover and Mutation.

One of the most important issues in the genetic evolution is the effective rearrangement of the genotype information. In the SGA crossover is the main genetic operator responsible or the exploitation of information while mutation brings new nonexistent bit structures. It is widely recognized that the SGA scheme is capable of locating the neighborhood of the optimal or near-optimal solutions, but, in general, requires a large number of generations to converge. This problem becomes more intense for large-scale optimization problems with difficult search spaces and lengthy chromosomes, where the possibility for the SGA to get trapped in local optimal increases and the convergence speed of the SGA decreases. At this point, a suitable combination of the basic, advanced and problem-specific genetic operators must be introduced in order to enhance the performance of the GA. Advanced and problem-specific genetic operators usually combine local search techniques and expertise derived from the nature of the problem. A set of advanced and problem-specific genetic operators has been added to the SGA in order to increase its convergence speed and improve the quality of solutions. Here the interest is focused on constructing simple yet powerful enhanced genetic operators that effectively explore the problem search space.

Hill climbing: In order to increase the GA search speed at smooth areas of the search space a hill-climbing operator is introduced, which perturbs a randomly selected control variable. The modified chromosome is accepted if there is an increase in FF value; otherwise, the old chromosome remains unchanged. This operator is applied only to the best chromosome (elite) of every generation (Anastasios and Pandel, 2002).

All problem-specific operators introduce random modification to all chromosomes of a new generation. If

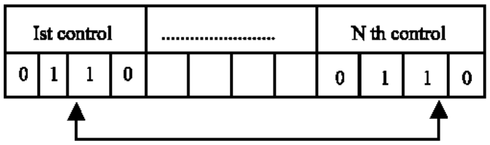

Fig. 3: Gene swap operator

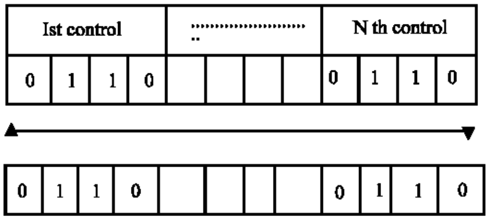

Fig. 4: Gene cross swap operator

the modified chromosome proves to have better fitness, it replaces the original one in the new population. Otherwise, the original chromosome is retained in the new population. All problem-specific operators are applied with a probability of 0.2. The following problem-specific operators have been used.

Gene Swap Operator (GSO): This operator randomly selects two genes in a chromosome and swaps their values, as shown in Fig. 3. This operator swaps the active power output of two units, the voltage magnitude of two-generation buses, etc. Swapping among different types of control variables is not allowed.

Gene Cross-Swap Operator (GCSO): The GCSO is a variant of the GSO. It randomly selects two different chromosomes from the population and two genes, one from every selected chromosome and swaps their values, as shown in Fig. 4. While crossover exchanges information between high-fit chromosomes, the GCSO searches for alternative alleles, exploiting information stored even in low-fit strings.

Gene Copy Operator (GCO): This operator randomly selects one gene in a chromosome and with equal probability copies its value to the predecessor or the successor gene of the same control type, as shown in Fig. 5. This operator has been introduced in order to force consecutive controls (e.g., identical units on the same bus) to operate at the same output level.

Gene Inverse Operator (GIO): This operator acts like a sophisticated mutation operator. It randomly selects one gene in a chromosome and inverses its bit-values from one to zero and vice versa, as shown in Fig. 6. The GIO

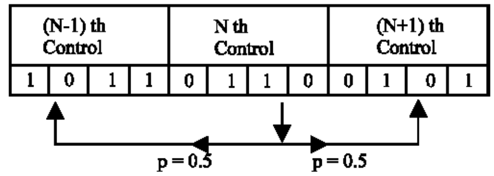

Fig. 5: Gene copy operator

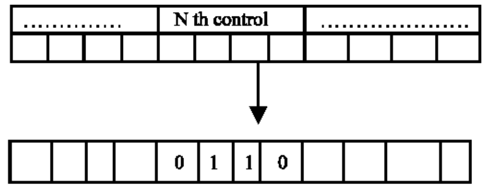

Fig. 6: Gene inverse operator

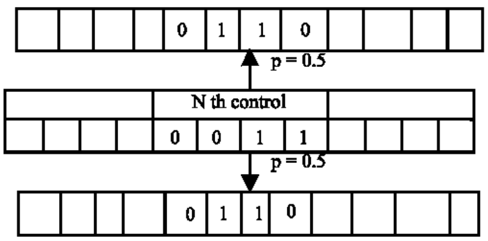

Fig. 7: Gene max-min operator

searches for bit-structures of improved performance, exploits new areas of the search space far away from the current solution and retains the diversity of the population.

Gene Max-Min Operator (GMMO): The GMMO tries to identify binding control variable upper/lower limit constraints. It selects a random gene in a chromosome and, with the same probability (0.5), fills its area with 1 s or 0 s, as shown in Fig. 7.

Efficient Genetic Algorithm (EGA): In the EGA, shown in Fig. 8, after the application of the basic genetic operators (parent selection, crossover and mutation) the advanced and problem-specific operators are applied to produce the new generation. All chromosomes in the initial population are created at random (every bit in the chromosome has equal probability of being switched ON or OFF).Due to the decoding process selected the corresponding control variables of the initial population satisfy their upper–lower bound or discrete value constraints.

Population statistics are then used to adaptively change the crossover and mutation probabilities (Srinivas and Patnaik, 1994). If premature convergence is detected the mutation probability is increased and the crossover

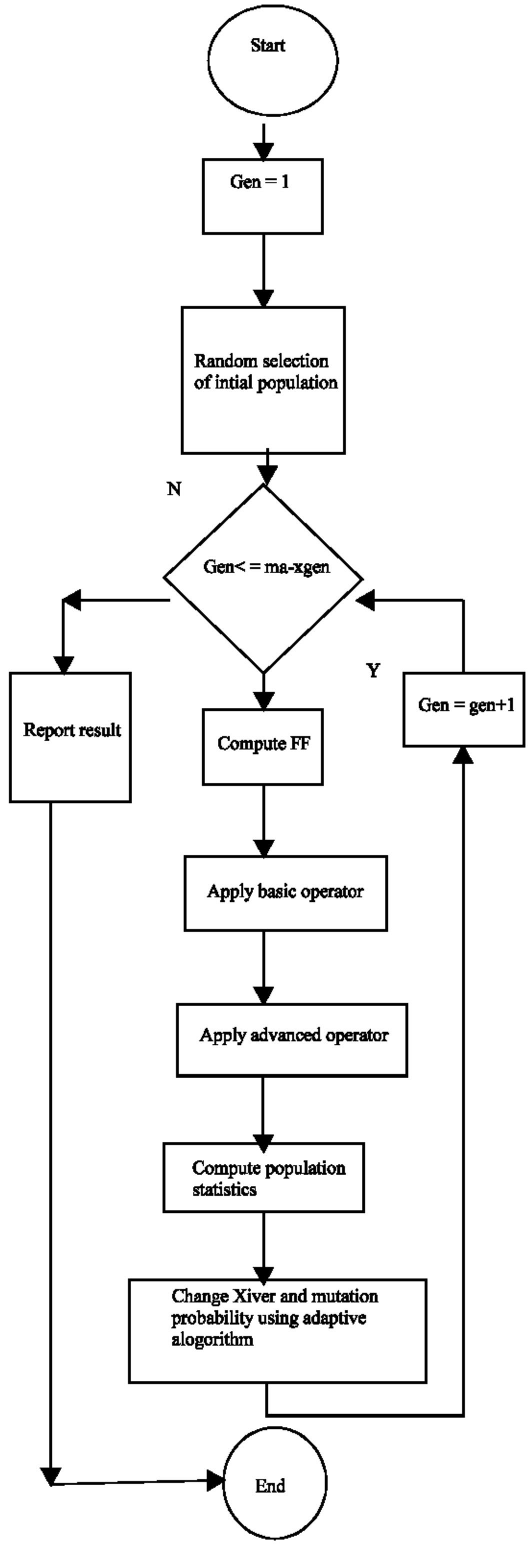

Fig. 8: Efficient genetic algorithm

probability is decreased. The contrary happens in the case of high population diversity.

OPTIMAL LOCATION OF TCSC AND TCPS

The severity of the system loading under normal and contingency cases can be described by a real power line flow performance index (Singh and Dawid, 2000), as given below in Eq. (24).

$$PI = \sum_{m=1}^{N} \frac{W_m}{2n} \left(\frac{P_{im}}{P_{im}^{max}} \right)^{2n} \tag{24}$$

Where P_{im}, is the real power flow and P_{im}^{max} is the rated capacity of line-m, n is the exponent and W_m a real nonnegative weighting coefficient which may be used to reflect the importance of lines. PI will be small when all the lines are within their limits and reach a high value when there are overloads. Thus, it provides a good measure of severity of the line overloads for a given state of the power system. In this study, the value of exponent has been taken as 2 and $W_i = 1$.

The real power flow PI sensitivity factors with respect to the parameters of TCSC and TCPS placed in line-k, one at a time, are defined as

$$a_k^c = \left.\frac{\partial PI}{\partial X_{ck}}\right| X_{ck} = 0 \tag{25}$$

$$a_k^s = \left.\frac{\partial PI}{\partial \phi_k}\right| \Phi_k = 0 \tag{26}$$

Using Eq. (24), the sensitivity of PI with respect to FACTS device parameter X_k, (X_{ck} for TCSC and ϕ_k for TCPS) connected between bus-i and bus-j for the case n = 2, can be written as

$$\frac{\partial PI}{\partial X_k} = \sum_{n=1}^{N} W_m P_{im}^{\ 3} \left(\frac{1}{P_{im}^{\ max}} \right)^4 \frac{\partial P_{im}}{X_k} \tag{27}$$

The real power flow in a line-m P_{lm} can be represented in terms of real power injections using DC power flow equations where s is slack bus, as or m ≠ k

$$P = \sum_{n=1}^{N} S_{nm} P_m$$

for m = k

$$P = \sum_{n=1}^{N} S_{nm} P_n + P_j$$

Where S_{mn} is the mn[th] element of matrix (S) which relates line flow with power injections at the buses without FACTS devices and N is the number of buses in the system.

Using (27), the following relationship can be derived,

$$\frac{\partial P_{im}}{\partial X_k} = S_{mi}\frac{\partial P_i}{\partial X_k} + S_{mj}\frac{\partial P_i}{\partial X_k} \text{ for } m \neq k$$

$$\frac{\partial P_{im}}{\partial X_k} = (S_{mi}\frac{\partial P_i}{\partial X_k} + S_{mj}\frac{\partial P_i}{\partial X_k}) + \frac{\partial P_j}{\partial X_k} \text{ for } m = k \quad (28)$$

The terms,

$$\left.\frac{\partial P_i}{\partial X_{ck}}\right|_{x_{ck}=0} \left.\frac{\partial P_j}{\partial X_k}\right|_{x_k=0} \left.\frac{\partial P_i}{\partial \phi_k}\right|_{\phi_k=0},$$

And

$$\left.\frac{\partial P_j}{\partial \phi_k}\right|_{\phi_k=0},$$

can be obtained using Eq. (29-32) and are given below:

$$\left.\frac{\partial P_i}{\partial X_k}\right|_{x_{ck}=0} \left.\frac{\partial P_{ic}}{\partial X_{ck}}\right|_{x_{ck}=0} = 2(V_i^2 - V_i V_j \cos\delta_{ij})G_0 B_0$$

$$\left.\frac{\partial P_i}{\partial X_k}\right|_{x_{ck}=0} V_i V_j \sin\delta_{ij}(B^2_{ij} - G^2_{ij}) \quad (29)$$

$$\left.\frac{\partial P_i}{\partial X_k}\right|_{x_{ck}=0} = \left.\frac{\partial P_i}{\partial X_k}\right|_{x_{ck}=0} = 2(V^2_i - V_i V_j \cos\delta_{ij})G_{ij} - B_{ij})$$

$$+\left.\frac{\partial P_i}{\partial X_k}\right|_{x_{ck}=0} V_i V_j \sin\delta_{ij}(B^2_{ij} - G^2_{ij}) \quad (30)$$

$$\left.\frac{\partial P_j}{\partial \phi_k}\right|_{\phi_k=0} \left.\frac{\partial P_{js}}{\partial \phi_k}\right|_{\phi_k=0} = V_i V_j (G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) \quad (31)$$

$$\left.\frac{\partial P_j}{\partial \phi_k}\right|_{\phi_k=0} \left.\frac{\partial P_{js}}{\partial \phi_k}\right|_{\phi_k=0} = -V_i V_j (G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) \quad (32)$$

The sensitivity factors a_k^c and a_k^s can now be found by substituting Eq. (29-31) in Eq. (28) (Singh and David, 2000).

Table 1: Sensitivity factor

Line-k		TCSC	TCPS
No:	I-j	(a_k^c)	(a_k^s)
1	1-2	2.8637	-20.5548
2	1-3	-0.0451	0.3140
3	2-4	-2.9016	-11.5733
4	3-4	-0.0784	1.0419
5	2-5	-3.4293	11.2810
6	2-6	-6.6653	-37.0595
7	4-6	0.2635	4.5995
8	5-7	0.1448	1.8885
9	6-7	-0.1602	1.5212
10	6-8	-2.1366	22.2651
11	6-9	0.0117	0.0820
12	6-10	-0.1726	4.4295
13	9-11	1.0316	-7.3835
14	9-10	-0.9427	6.6450
15	4-12	-0.2079	8.2213
16	12-13	2.8972	2.0427
17	12-14	0.2692	6.3608
18	12-15	0.8510	36.3020
19	12-16	0.8397	11.1163
20	14-15	-0.0395	2.2285
21	16-17	-1.0072	16.6773
22	17-18	0	0
23	18-19	-0.7089	10.3708
24	19-20	0.0813	0.9027
25	10-20	0.1181	1.8124
26	10-17	-0.0069	0.2409
27	10-21	-0.8743	12.5895
28	10-22	5.8480	41.0594
29	21-22	0.0195	0.1358
30	15-23	0.5250	8.2576
31	22-24	-2.2810	16.2996
32	23-24	-0.6831	10.7628
33	24-25	0.0300	0.2109
34	25-26	-0.2798	1.9994
35	25-27	0.0004	-0.0083
36	26-27	0	0
37	27-29	-0.6531	4.6597
38	27-30	-2.7140	19.4252
39	29-30	-0.4436	5.0815
40	8-28	0.0925	0.6493
41	6-28	0.9000	6.3184

Criteria for optimal location: The FACTS device should be placed on the most sensitive lines. With the sensitive indices computed for each type of FACTS device, TCPS should be placed in a line (k) having largest absolute value of the sensitivity factor. However, TCSC should be placed in a line (k) having largest negative value of the sensitivity factor.

It was found that the real power flows in lines were within the rating limit. Sensitivities were calculated for FACTS devices (TCSC and TCPS) placed in every line both at a time for this operating condition. The sensitivities of real power performance index with respect to TCSC and TCPS are presented in Table 1.The highest negative sensitivities in case-of TCSC and the highest absolute value of sensitivities in case of TCPS are presented in bold type.

CASE STUDIES

In this research, the standard IEEE 30-bus test system (Pai, 2006) has been used to test the effectiveness of the proposed method. It has a total of 8 control variables as follows: six unit active power outputs, TCSC constraints and TCPS constraints. The gene length for unit power outputs is 12 bits and for other parameter is 6 bits. They are both treated as continuous controls.

The reactance of the TCSC is between 0 and 0.20 (p.u), while the voltage shift angle limit of TCPS are between 0 and 0.07 (radian). The GA population size is taken equal to 20; the maximum number of generations is 75. In this problem the probabilities of crossover and mutation are varied depending on the fitness values of the solutions in the evolution process to prevent premature convergence and refine the convergence performance of genetic algorithm.

Three cases have been studied; Case 1 is the conventional OPF without FACTS devices and (N-I) security constraints using SGA. Case 2 is the conventional OPF with FACTS devices using SGA. Case 3 is the conventional OPF with FACTS devices using EGA. The main optimization results are listed in Table 2.

Without FACTS devices the cost of OPF is 805.0132 and cost of OPF with FACTS using SGA and EGA is 806.4227 and 805.3789, respectively. The results show that the generation cost increase with FACTS device since the parameter constraint of TCSC and TCPS are included. However, FACTS can change the power distribution effectively, reduce the system losses.

Two sets of test runs were performed, the first (SGA) with only the basic GA operators and the second (EGA) with all operators, including advanced and problem-specific operators. The FF evolution of the best of these runs is shown in Fig. 9. The operating costs of the SGA and EGA solutions are 806.6 4227 \$/h and 805.3789 \$/h, respectively. The operating cost of all EGA-OPF solutions is slightly less than the SGA. Figure 9 demonstrates the improvement achieved with the inclusion of the advanced and problem-specific operators.

Sensitivity factor of TCSC for line-6 is the most negative than the other lines and hence the most suitable for the TCSC placement. A branch 28 is the most sensitive for TCPS placement.

The specified branches flow constraint values are listed in Table 3.

Along with the conventional OPF, the power through line numbers 6 and 28 has been taken as additional constraints. The specified values of power are to be achieved by placing TCSC in line 6 and TCPS in line 28. Now the next step is to find the value of TCSC reactance and TCPS phase shift that are needed to maintain the specified power flow (Fig. 10 and 11).

Table 2: IEEE 30-bus system main results

P_{Gi} (MW)	Case 1	Case 2	Case
3P_{G1} (MW)	183.1800	192.5400	189.8200
P_{G2} (MW)	43.9700	48.6200	47.4100
P_{G5} (MW)	18.4400	19.5200	20.6200
P_{G8} (MW)	25.6200	11.7500	12.5500
P_{G11} (MW)	10.4300	10.2000	11.7400
P_{G13} (MW)	12.0000	12.1100	12.2100
ΣP_{Gi} (MW)	293.6400	294.7400	294.3500
Σcost (\$/hr)	805.0132	806.4227	805.3789

Table 3: IEEE 30-bus system specified line flow data

Line flows	F6	F28
Solution	0.4854	0.0749
Specified flow	0.3300	0.1800

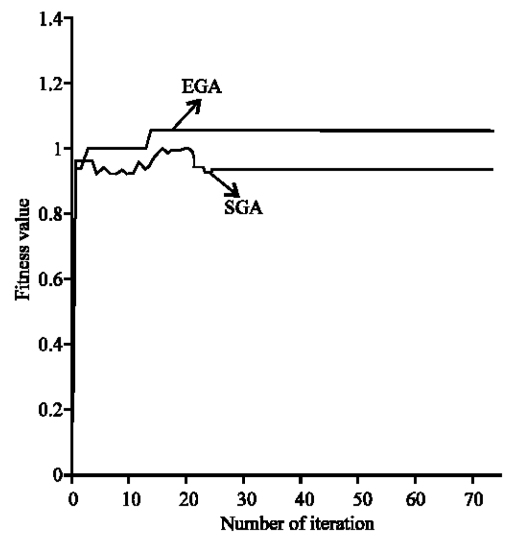

Fig. 9: FF comparison for IEEE 30-bus system

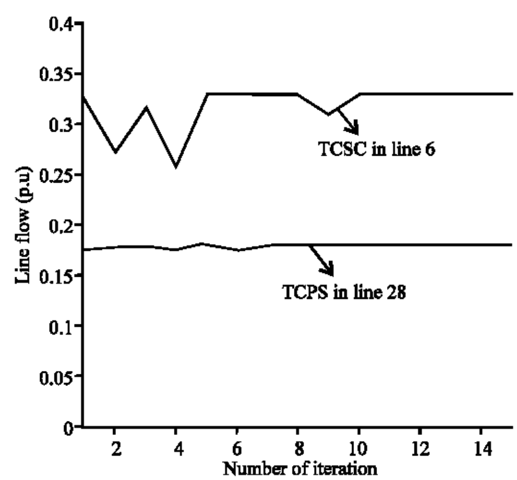

Fig. 10: Modified IEEE 30 bus system with specified line flows in case 2

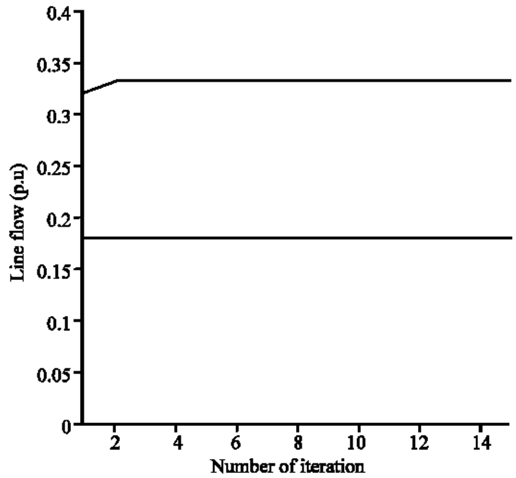

Fig. 11: Modified IEEE 30 bus system with specified line flows in case 3

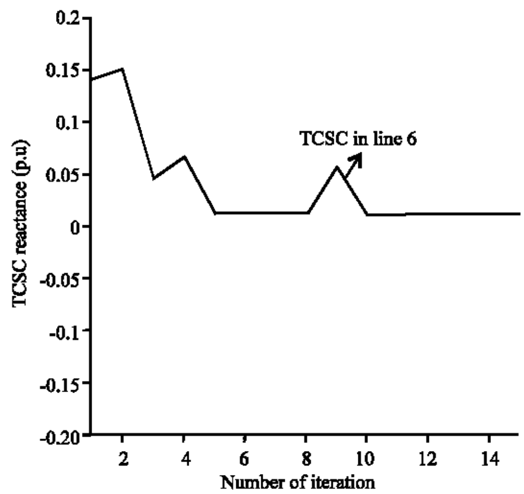

Fig. 12: Modified IEEE 30 bus system with TCSC value in case 2

These values are found by SGA and EGA method, with their convergence is shown in Fig. 12-15. The corresponding power flows found iteratively for SGA and EGA have been shown in Fig. 10 and 11, respectively.

With the SGA being optimization method used the power flow through line 6 converge to the required value flow through line 28 converge of 0.33 p.u approximately after 11 iterations, where as the power to the required value of 0.18 p.u approximately after 8 iterations. With the EGA being optimization method used, the power in the line 6 and 28 are converged very fast than SGA. This improvement is achieved with the inclusion of the advanced and problem specific operators. These show that the proposed approach is effective.

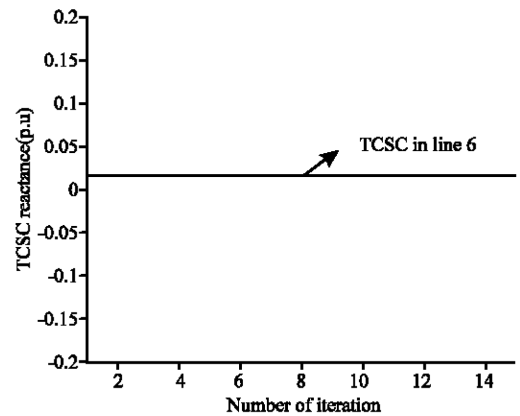

Fig. 13: Modified IEEE 30 bus system with TCSC value in case 3

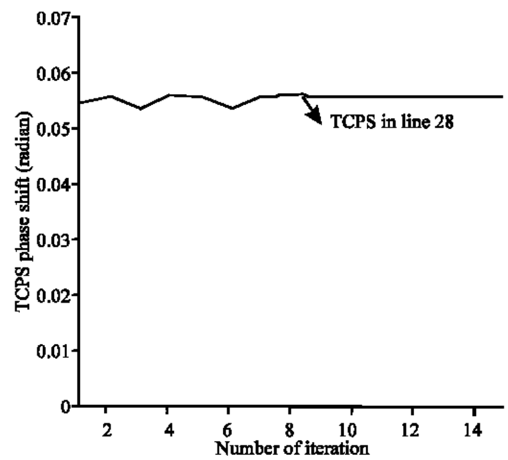

Fig. 14: Modified IEEE 30 bus system with TCPS value in case 2

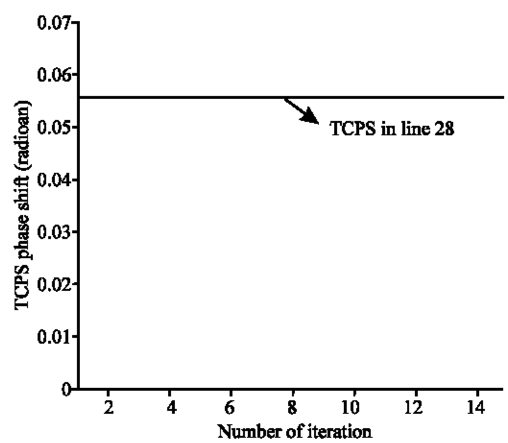

Fig. 15: Modified IEEE 30 bus system with TCPS value in case 3

If the power flow control constraints are not some specified values but some ranges, we can use the appropriate convergent threshold to achieve this. For example, suppose the power flow control value of one branch is between 0.5-0.6 p.u, it can be set the specified branch flow at 0.55 and set the convergent threshold at 0.05 p.u. Thus, when the problem converges, this branch power flow is between 0.5-0.6 p.u using this method and fulfills different power flow control needs.

CONCLUSION

In this study, sensitivity based an enhanced genetic algorithm method was presented to solve the optimal power flow problem of power system with Flexible AC Transmission Systems (FACTS). The proposed method introduces the injected power model of FACTS devices into a conventional AC optimal power flow problem to exploit the new characteristic of FACTS devices. Case studies on modified IEEE test system show the potential for application of EGA to determine the control parameter of the power flow controls with FACTS. It can be shown that the FACTS device cannot reduce the generation cost (i.e. it is not a cost saving device) compared with normal system OPF. However, it can increase the controllability and feasibility of the system and provide wider operating margin and higher voltage stability with higher reserve capacity.

In this method, EGA effectively finds the optimal setting of the control parameters by using the conventional OPF method. It also shows that EGA was suited to deal with non-smooth, non-continuous, non-differentiable and non-convex problem, such as the optimal power flow problem with FACTS.

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NOMENCLATURE

N	=	Set of bus indices.
NG	=	Set of generation bus indices.
NT	=	Set of transformer indices.
NP	=	Set of TCPS indices.
NS	=	Set of TCSC indices.
NB	=	Set of transmission line indices.
Yij and ⊖ij	=	Magnitude and phase angle of element in admittance matrix
P_{Gi} and Q_{gi}	=	Active and reactive power generation at bus i.
P_{di} and Q_{di}	=	Active and reactive power demands at bus i.
P_{is} and Q_{is}	=	Injected active and reactive powers at bus i due to TCPS.
V_i and d_I	=	Voltage magnitude and angle at bus i.
T_i	=	Tapping ratio at transformer i
I_i	=	Current magnitude at transmission line i.
Φ_I	=	Voltage shift angle of TCPS i.
X_{ci}	=	Reactance of TCSC i.
a_k^c	=	PI sensitivity factors for TCSC.
a_k^s	=	PI sensitivity factors for TCPS

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