Optimal Power Flow for Steady State Security Enhancement using Enhanced Genetic Algorithm with FACTS Devices

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Abstract – This paper presents an enhanced Genetic Algorithm (EGA) based approach to solve the Optimal Power Flow (OPF) with FACTS devices to eliminate line over loads in the system following single line outages. The optimizations are performed on two parameters: the location of the devices, and their values. Two different kinds of FACTS controllers are used for steady state studies: Thyristor Controlled Series Capacitors (TCSCs) and Thyristor controlled Phase shifting Transformers (TCPSTs). The proposed approach uses an index called the single contingency sensitivity (SCS) index to rank the system branches according to their suitability for installing TCSC and TCPST. Once the locations are identified, the problem of determining the optimal TCSC and TCPST parameters is formulated as an optimization problem and a GA based approach is applied to solve the Optimal Power Flow (OPF) problem. Simulations are done on IEEE 30 bus system for a few harmful contingencies.

Keywords – Power system security, flexible AC transmission system (FACTS) devices, security enhancement, thyristor controlled series capacitors (TCSCs), thyristor controlled phase shifting transformers (TCPSTs).

NOTATIONS

G_{ij} ,B_{ij}	Mutual conductance and susceptance between bus *i* and bus *j*
G_{ii}, B_{ii}	Self-conductance and susceptance of bus *i*
G_k	Conductance of branch *k*
F_T	Total Fuel cost
N_B	Total number of buses
N_{B-1}	Total number of buses excluding slack bus
N_{PQ}	Number of PQ buses
N_g	Number of generator buses
N_l	Number of branches in the system
P_i,Q_i	Real and reactive powers injected into network at bus *i*
P_{gi}, Q_{gi}	Real and reactive power generation at bus *i*
S_l	Apparent power flow through the l^{th} branch
S_l^{max}	Apparent power flow limit through the l^{th} branch
V_i	Voltage magnitude at bus *i*
V_j	Voltage magnitude at bus *j*
θ_{ij}	Voltage angle difference between bus *i* and bus *j*

I. INTRODUCTION

The principle role of power system control is to maintain a secure system state, this is to prevent the power system, moving from secure state into emergency state over the widest range of operating conditions. In any power system, unexpected outages of lines or transformers occur due to faults or other disturbances. These events, referred to as contingencies, may cause significant overloading of transmission lines or transformers, which in turn may lead to a viability crisis of the power system. Several publication deals with the optimization techniques for corrective control of power system security [5, 15]. The various formulation aim at minimizing the total fuel cost or minimizing /alleviating the line overloads with system security constraints [7-8].

The OPF solution gives the optimal settings of all controllable variables for a static power system loading condition. A number of mathematical programming based techniques [6-8] have been proposed to solve the OPF problem. They have the common weakness of requiring differentiable objective function, convergence to local optima and difficulty in dealing with discrete variables like transformer tap setting and shunt capacitor bank. Also, difficulties are encountered in incorporating directly the discrete variables related to the TCSC and TCPST values. It does not provide a continuous fabric over the solution space. Recently global optimization techniques such as the genetic algorithm have been proposed to solve the optimal power flow problem [10-13]. A genetic algorithm [9] is a stochastic search technique based on the mechanics of natural genetics and natural selection. It works by evolving a population of solutions towards the global optimum through the use of genetic operators: selection, crossover and mutation.

The possibility of operating the power system at the minimal cost while satisfying specified transmission constraints and security constraints is one of main current issues in stretching transmission capacity by the use of controllable flexible AC transmission system (FACTS)[1-2, 17-18]. The conventional OPF program must undergo some changes such as inclusion of new control variables belonging to FACTS devices and the corresponding load flow solutions to deal with the above said problem.In applying the FACTS devices, one must address the issue of identifying the proper location, number, type, setting, and installation cost of the FACTS devices. The method in [3] is applied to allocate a maximum number of FACTS devices but alleviating overloads on the transmission lines under contingencies are not addressed. In [4], the allocation of thyristor controlled phase shifting transformer (TCPST) and thyristor controlled series capacitor (TCSC) is done using sensitivity analysis. This method only provides an approximate location and setting of the control devices. This approach is tested on IEEE 14-bus network and once again alleviating overloads under contingencies are not addressed. In [5], the authors

The paper first received 2 July 2009 and in revised form 27 June 2010.
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presented a systematic procedure to place and operate TCSCs in a power system. In this paper, we look for the optimal location of multi-type FACTS devices. Two different devices, with specific characteristics, have been selected for steady state analysis. They are used to maximize the power transmitted by the network by controlling power flows. The proposed approach is illustrated through corrective action plan for a few harmful contingencies in the IEEE 30bus system.

II. MODELS OF FACTS DEVICES

A. Thyristor Controlled Series Capacitor (TCSC)

Thyristor Controlled Series Capacitor (TCSC) consists of a fixed capacitor in parallel with a thyristor controlled reactor. The primary function of the TCSC is to provide variable series compensation to a transmission line [14]. This changes the line flow due to change in series reactance.

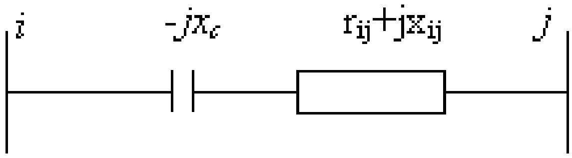

Fig. 1: Equivalent circuit of TCSC

Fig. 1 show a model of transmission line with TCSC connected between buses ‘i’ and ‘j’. For steady state analysis, the TCSC can be considered as a static reactance $-jx_c$. The controllable reactance x_c is directly used as the control variable in the power flow equations. The power flow equations of a transmission line with TCSC can be written as

$$P_{ij} = V_i^2 g_{ij} - V_i V_j (g_{ij} \cos \delta_{ij} + b_{ij} \sin \delta_{ij})$$

$$Q_{ij} = -V_i^2 b_{ij} - V_i V_j (g_{ij} \sin \delta_{ij} - b_{ij} \cos \delta_{ij}) \qquad (1)$$

where

$$g_{ij} = r_{ij} /(r_{ij}^2 + (x_{ij} - x_c)^2)$$

$$b_{ij} = x_{ij} - x_c /(r_{ij}^2 + (x_{ij} - x_c)^2)$$

Here, the only difference between normal line power flow equation and the TCSC line power flow equation is the controllable reactance x_C where TCSC acts as the capacitive or inductive compensation respectively. In this study, the reactance of the transmission line is adjusted by TCSC directly. The rating of TCSC depends on the reactance of the transmission line where the TCSC is located.

$$X_{ij} = x_{line} + x_{t\,csc} \qquad (2)$$

$$x_{t\,csc} = r_{t\,csc} . x_{line} \qquad (3)$$

where, x_{line} is the reactance of the transmission line and r_{tcsc} is the coefficient which represents the degree of compensation by TCSC.

To avoid overcompensation, the working range of the TCSC is chosen between ($-0.5.X_{line}$ and $0.5.X_{line}$). By optimizing the reactance values between these ranges, optimal setting of reactance values can be achieved.

B. Thyristor Controlled Phase Shifting Transformer (TCPST)

In general, phase shifting is obtained by adding a perpendicular voltage vector in series with a phase. This vector is derived from the other two phases via shunt connected transformers. The perpendicular series voltage is made variable with a variety of power electronics topologies. A circuit concept that can handle voltage reversal can provide phase shift in either direction. This Controller is also referred to as Thyristor-Controlled Phase Angle Regulator (TCPAR).

A phase shifter model can be represented by an equivalent circuit, which is shown in Fig 2. It consists of admittance in series with an ideal transformer having a complex turns ratio $K\angle\varphi$.

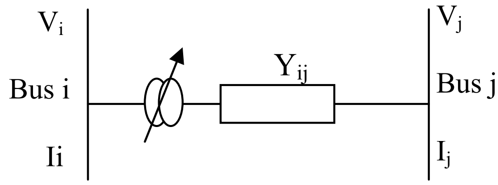

Fig. 2: Circuit diagram of the phase shifter

The injected active power at bus-‘i’ (P_{is}) and bus-j (P_{js}) of a line having a phase shifter can be written

$$P_{is} = -V_i^2 K^2 G_{ij} - V_i V_j K\left[G_{ij} \sin \delta_{ji} - B_{ij} \cos \delta_{ij}\right] \qquad (4)$$

$$P_{js} = -V_i V_j K\left[G_{ij} \sin \delta_{ji} + B_{ij} \cos \delta_{ij}\right] \qquad (5)$$

where K=tanΦ

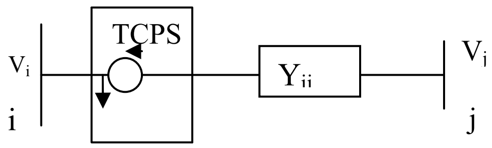

Fig. 3: Equivalent circuit of TCPST

The mathematical model of TCPST [1] can be derived from Fig. 3.

i.e

$$\begin{bmatrix} \bar{I}_i \\ \bar{I}_j \end{bmatrix} = \begin{bmatrix} Y_{ij}' + Y & -Y_{ij}' \\ -Y_{ij}' & Y_{ij}' + Y_i \end{bmatrix} \begin{bmatrix} \bar{V}_i \\ \bar{V}_j \end{bmatrix} \qquad (6)$$

where

$$Y_j = Y_{ij}'\left[\left(1 - \frac{1}{k\angle\varphi}\right)\frac{V_i}{V_j}\right]$$

III. METHOD FOR OPTIMAL LOCATION OF FACTS DEVICES

The severity of a contingency to line overload may be expressed in terms of the following severity index (12), which express the stress on the power system in the post contingency period.

Severity Index (SI)

$$SI_l = \sum_{l=1}^{L_O} \left(\frac{S_l}{S_l^{\max}} \right)^{2m} \qquad (7)$$

where
S_l =MVA flow in line l
S_l^{max} = MVA rating of the line l.
L_0=set of overloaded lines.
m=integer exponent.

The line flows in (1) are obtained from Newton-Raphson load flow calculations. While using above severity index for security assessment, the overloaded lines are only considered to avoid masking effect. For IEEE 30 bus system considered in this work, we have fixed the value of m as 1.To determine the best location of TCSC & TCPST, an index called Single contingency sensitivity (SCS) index is calculated for all considered contingencies.
The SCS_j for branch "j" is defined as the sum of the sensitivities of branch "j" to all considered contingencies, expressed as,

$$SCS = \sum_{i=1}^{m} SI_l \tag{8}$$

where, SCS values are calculated for every branch using (8). Branches are then ranked by their corresponding SCS values. In general a SCS value a branch has, the more sensitive it will be. The branch with the largest SCS is considered as the best location for one FACTS device. For a large-scale power system, more than one FACTS device may have to be installed in order to achieve the desired performance. However, obvious budgetary constraints force the utilities to limit the number of TCSCs & TCPSTs to be placed in a given system. Given such a limit on the total number of TCSCs & TCPSTs to be installed in a power system, the locations of these FACTS devices can be determined according to the ranking of branches and system topology. They will be chosen starting from the top of this ranked list and proceeding downward with as many branches as the number of available TCSCs & TCPSTs. In order to avoid redundant placements, no TCSC or TCPST will be placed in a branch that forms a loop with branches of already assigned TCSCs or TCPSTs

IV. Problem Formulation

The aim of the optimization is to enhance the security level of the system. The FACTS devices are located in order to remove and prevent overloads .The objective function is based on indexes quantifying the severity of the contingencies in terms of branch loading. Thus, for a given system load, we look for the best configuration of TCSC & TCPST devices minimizing the following objective function

$$J = \sum_{k} \left(\frac{S_k}{S_{\max k}} \right)^n \tag{9}$$

where S_k is the apparent power in line k and S_{maxk} is the apparent power rate of the line k. The weight 'w_k' is calculated in order to have the same index value for a branch loading of 100%. They could also be used to give more or less importance to specific elements of the system. The exponent n is equal to 4 on order to give more importance to overload minimization.

A. Problem Constraints

The conventional formulation of OPF problem determines the optimal setting of control variables such as real power generations, generator terminal voltages, transformer tap setting, and reactance values of TCSCs and phase shifting angles of TCPSTs while minimizing an objective function such as fuel cost given in (10)

$$F_T = \sum_{i=1}^{N_g} \left(a_i P_{gi}^2 + b_i P_{gi} + c_i \right) \ \$/hr \tag{10}$$

where a_i , b_i , and c_i are the cost coefficients of generator at bus *i*.

During security control, the prime task of the power system operator would be to remove the line overload. Hence the minimum severity index defined below is taken as the objective function in this paper.

Equality constraints

These constraints represent load flow equation
Such as

$$\begin{aligned} &P_i - V_i \sum_{\substack{j=1 \\ i \in N_b - 1}}^{N_B} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0, \\ &Q_i - V_i \sum_{\substack{j=1 \\ i \in N_{PQ}}}^{N_b} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0 \end{aligned} \tag{11}$$

The minimization problem is subjected to the following constraints
Inequality constraint

Voltage limits:

$$V_i^{\min} \le V_i \le V_i^{\max} \ ; i \in N_B \tag{12}$$

Unit limits**:**

$$\begin{aligned} &P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \ ; i \in N_B \\ &Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max} \ ; i \in N_B \end{aligned} \tag{13}$$

Transmission line flow limit:

$$S_l \le S_l^{\max} \ ; i \in N_l \tag{14}$$

TCSC reactance constraint

$$X_{ci}^{\min} \le X_{ci} \le X_{ci}^{\max} ; i \in N_{TCSC} \tag{15}$$

TCPST constraint

$$\phi_i^{\min} \le \phi_i \le \phi_i^{\max} \ i \in N_t \tag{16}$$

The power flow equations are used as equality constraints and the inequality constraints are the limit on active and reactive power generations, TCSC reactance settings, TCPSTs phase angle settings, bus bar voltage magnitudes and apparent power flows

V. Review of Genetic Algorithm

Genetic algorithms (GA) [9-10] are essentially search algorithms based on the mechanics of nature (e.g. natural selection, survival of the fittest) and natural genetics. They combine solution evaluation with randomized, structured exchanges of information between solutions to obtain optimality. Genetic algorithms are considered to be robust methods because no restrictions on the solution space are made during the process. The power of this algorithm comes from its ability to exploit historical information structures from previous solution guesses in an attempt to increase performance of future solution structures.

GA maintains a population of individuals that represent the candidate solutions. Each individual is evaluated to give some measure of its fitness to the problem from the objective function. In each generation, a new population is formed by selecting the more fit individuals based on particular selection strategy. Some members of new population undergo genetic operations to form new solutions. Two commonly used genetic operators are crossover and mutation. Crossover is a mixing operator that combines genetic material from selected parents. Mutation acts as a background operator and is used to search the unexplored search space by randomly changing the values at one or more positions of the selected chromosome.

VI. GENETIC ALGORITHM IMPLEMENTATION

When applying GAs to solve a particular optimization problem, two main issues must be addressed

(i) representation of the decision variables and

(ii) formation of the fitness function

A Problem Representation

Each individual in the genetic population represents a candidate solution [9]. In the binary coded GA, the solution variables are represented by a string of binary alphabets. The size of the string depends on the precision of the solution required. For problems with more than one decision variables, each variable is usually represented by a substring. All substring are concatenated together to form a bigger string. In the OPF problem under consideration, variables need to be determined by the optimization algorithm are generator active-power $P_{gi,}$ generator terminal voltages Vgi , the TCSC reactance values X_{TCSC} and TCPST phase shifting angles ϕ_{TCPST} .These variables are represented in their natural form,i.e P_{gi} ,Vgi ,the $X_{TCSC}$and φ_{TCPST} values are represented as real numbers. The use of floating point numbers in the GA representation has a number of advantages over binary encoding. The efficiency of the GA is increased as there is no need to convert the solution variables to binary type. Moreover, less memory is required and there is no loss in precision by discretisation to binary or other values. Also, there is greater freedom to use different genetic operators

B. Fitness Function

The objective is to minimize the severity index value under contingency case satisfying the constraints (11)-(16). For each individual, the equality constraints (11) are satisfied by running Newton Raphson algorithm and the constraints on the state variables are taken in to considerations by adding penalty function to the objective function.

Thus the new objective function becomes,

$$Min\, f = SI + SP + \sum_{j=1}^{N_l} VP_j + \sum_{j=1}^{N_g} QP_j + \sum_{l=1}^{N_l} LP_l \quad (17)$$

Here, SP, VP_j, QP_j and LP_l are the penalty terms for the reference bus generator active power limit violation, load bus voltage limit violation; reactive power generation limit violation and the line flow limit violation respectively. These quantities are defined by the following equations:

$$SP = \begin{cases} K_s(P_s - P_S^{\max}) & if \;\; P_S \rangle P_s^{\max} \\ K_S(P_S - P_S^{\min}) & if \;\; P_S \langle P_S^{\min} \\ 0 & \text{otherwise} \end{cases}$$

$$VP_j = \begin{cases} K_v(V_j - V_j^{\max})^2 & if \;\; V_j \rangle V_j^{\max} \\ K_V(V_j - V_j^{\min})^2 & if \;\; V_j \langle V_j^{\min} \\ 0 & \text{otherwise} \end{cases}$$

$$QP_j = \begin{cases} K_q(Q_j - Q_j^{\max})^2 & if \;\; Q_j \rangle Q_j^{\max} \\ K_q(Q_j - Q_j^{\min})^2 & if \;\; Q_j \langle Q_j^{\min} \\ 0 & \text{otherwise} \end{cases}$$

$$LP_l = \begin{cases} K_l(S_l - S_{\max})^2 & S_l \rangle S_{\max} \\ 0 & \text{otherwise} \end{cases}$$

GAs is usually designed to maximize the fitness function, which is a measure of the quality of each candidate solution. In the OPF under consideration, the objective is to minimize the severity in the post contingency state satisfying the equality and inequality constraints (11-16).Therefore a transformation is needed to convert the objective of the OPF problem to an appropriate fitness function to be maximized by GA. Therefore the GA fitness function is formed as follows

F=*k*/(1+*f*)

where, *k*= a large constant. In the denominator a value of 1 is added with f in order to avoid division by zero in case of complete overload alleviation

C. Selection Strategy

The selection of parents to produce successive generations plays an important role in the GA. The goal allows the fittest individuals to be selected more often to reproduce. There are a number of selection methods proposed in the literature [9-11] fitness proportionate selection, ranking and tournament selection. Fitness proportionate selection is used in this work. In this selection, individual strings are copied according to their objective function values (fitness function values). Copying strings according to their fitness values means that strings with a higher value have a higher probability of contributing one or more offspring in the next generation. This operator is an artificial version of natural selection, as Darwinian survival of the fittest among string creatures.

D. Crossover

Crossover is an important operator of the GA. It is responsible for the structure recombination (information exchange between mating chromosomes) and the convergence speed of the GA and it is usually applied with high probability (0.6-0.9).After selection operation, gene cross swap operation proceeds. It is an enhanced genetic operator, which promotes the exploration of new regions in search space.

E. Mutation

Mutation is a background operator, which produces spontaneous changes in various chromosomes. In artificial genetic systems the mutation operator protects against some irrecoverable loss. It is the occasional random alteration of the value in the string position. Mutation is needed because even though reproduction and crossover effectively search and recombine extent notions, occasionally they may become over zealous and lose some potentially useful genetic material.

VII. SIMULATION RESULTS

The proposed method has been tested on IEEE 30 bus system, which consists of six generators and 41 transmission lines. The generator and transmission-line data relevant to the system are taken from [5]. The upper and lower voltage limits at all the bus bars except slack were taken as 1.10 p.u and 0.95p.u respectively. The slack bus bar voltage was fixed to its specified value of 1.06 p.u. It is assumed that the impedance of all TCSCs can be varied within 50% of the corresponding branch impedance and the limits of the phase shifting angles of TCPSTs were taken as $\pm 20^0$.

To demonstrate the effectiveness of the proposed approach, two different cases have been considered as follows:

Case 1: Base case Optimal Power Flow problem with minimization of fuel cost as objective.

Case 2: Overload alleviation through FACTS devices

Case 1:

In this case, generator real power output, the generator bus terminal voltages and transformer tap settings are taken as the control variables. The initial population was randomly generated between the variable's lower and upper limits. Fitness proportionate selection was applied to select the members of the new population. Gene cross Swap and bit wise mutation were applied on the selected individuals. The performance of GA generally depends on the GA parameters used, in particular, the crossover and mutation probabilities, Pc and Pm, respectively. The performance of GA for various crossover and mutation probabilities in the range of 0.6–0.9 and 0.001–0.01 respectively was therefore evaluated. The best result of the GA was obtained with the following control parameters:

No of generations: 100, Population size: 45,
Crossover probability: 0.9, Mutation probability: 0.01

The minimum cost obtained by the GA based approach along with the optimal control variables are given in Table 1. Corresponding to this control variable, it is found that there is no limit violation in any of the state variables in the base case. Table 2 gives a comparison between the proposed approach and the other algorithms reported in the literature in the case of fuel cost minimization as objective. From this comparison, it is evident that the proposed approach has produced the solution with lowest fuel cost. This shows the effectiveness of the proposed GA approach in solving the OPF problem. Figure 4 shows the variation of fitness during the GA run for the best case. After 100 generation it was found that all the individuals have reached almost the same fitness value. This shows that GA has reached the optimal solution.

Table: 1 Result of OPF Algorithm

P_1	163.6
P_2	50.2
P_5	26.8
P_8	24.08
P_{11}	13.8
P_{13}	12.3
V_1	1.0145
V_2	1.0068
V_5	0.9698
V_8	0.9688
V_{11}	0.9670
V_{13}	0.9820
T_{11}	0.9205
T_{12}	1.075
T_{15}	1.02
T_{36}	0.9
Generation Cost	801.1485($/hr)

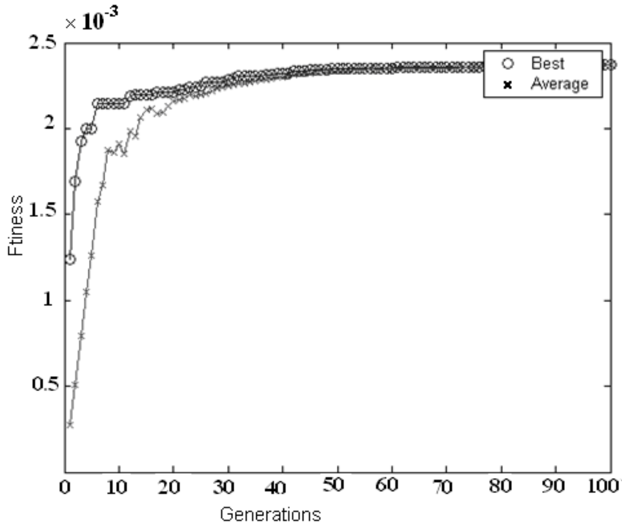

Fig 4: Convergence of the GA-OPF algorithm (Case 1)

Table: 2 Comparison of Fuel cost

Method	Minimum Cost
Gradient approach [7]	802.43 $/hr
Improved Evolutionary programming [16]	802.465 $/hr
Hybrid evolutionary programming [19]	802.62$/hr
Proposed Method	***801.1485 $/hr***

Case 2:

In this method, the GA based algorithm is used for corrective control under a contingency case. As a preliminary computation, the contingency analysis was carried out. From the contingency analysis, the most

severe contingencies were the outages of lines (1–2), (1–3) and (3–4).
The power flow on the overloaded lines and the calculated value of severity index for each contingency are given in Table 3.
From the Table 3, it is found that line outage 1-2 is the most severe one, and the results in overloading on three other lines. Calculation of SCS indices was carried out to identify the suitable locations of the TCSCs and TCPSTs to alleviate the line overload. In general, the larger s SCS value a branch has, the more sensitive it will be. The four locations identified for each contingency along with the SCS values are given in Table 4.The GA based OPF algorithm was applied to alleviate the line overload in all four severe contingency cases.

Table 3: Line Outage Ranking using Severity Index

Outage Line No.	Over loaded lines	Line flow (MVA)	Line flow limit (MVA)	Severity Index (SI)	Rank
1-2	1-3	191.58	130	54.7791	1
	3-4	174.13	130		
	4-6	103.37	90		
1-3	1-2	181.17	130	22.4650	2
	2-6	66.482	65		
3-4	1-2	178.43	130	20.1648	3
	2-6	65.558	65		
2-5	2-6	76.285	65	2.2911	4
4-6	1-2	132.63	130	0.6327	6
	2-6	69.921	65		
28-27	22-24	19.062	16	1.0962	5
	24-25	17.781	16		

Table 4: TCSCs & TCPSTs Locations in IEEE 30-Bus System

Line outage	1-2	1-3	3-4	2-5
TCSC & TCPST location	1-3	(SCS value : 0.0082)		
	3-4	(SCS value : 0.0078)		
	28-27	(SCS value: 0.0067)		
	2-5	(SCS value :0.0031)		

Generator active power and the reactance values of TCSCs are taken as the control variable. The minimum severity index is taken as the objective function of GA. The algorithm was run for a maximum of 150 generations. The best results of the GA were obtained with the following control parameters: GA control parameters: Generation: 150, Population size: 45 Crossover probabilities: 0.85, Mutation probability: 0.01. After 70 generation it was found that all the individuals have reached almost the same fitness value. This shows that GA has reached the optimal solution. Figure 5 shows the variation of the fitness during the GA run for the best case. Table 5 presents the optimal control variable settings for all four cases, along with the final values of severity index. Corresponding to these control variables, it was found that all the state variables satisfy the lower and upper limits and also the secured optimal solution obtained by this algorithm does not violate any constraints.

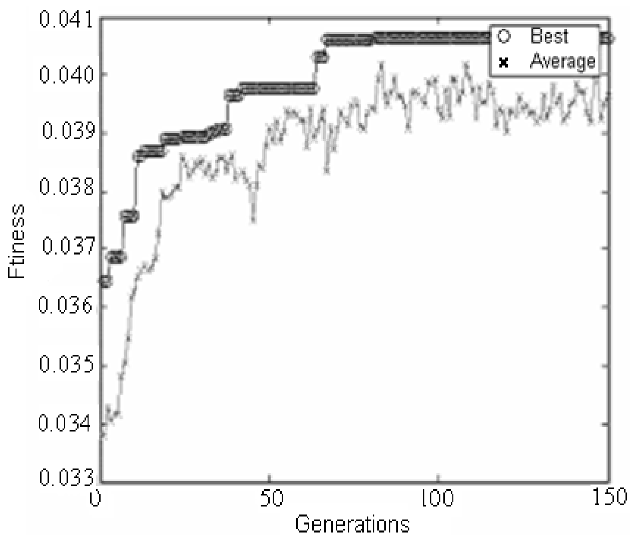

Fig 5: Convergence characteristics (Case 2)

Table: 5 Control Variable Settings for IEEE 30- Bus System

Line outage	P1	P2	P5	P8	P11	P13	TCSC 1	TCSC 2	TCPST1	TCPST2	SI without TCSC & TCPST	SI value with TCSC TCPST
1-2	174.68	60.99	41.9	27.9	20.5	38.1	-0.37	0.27	-4.51	13.54	54.77	0
1-3	192.38	68.17	32.2	29.6	11.8	34.1	-0.15	0.34	5.8	-3.22	22.46	0
3-4	127.91	54.09	40.6	33.3	27.9	26.6	0.37	-0.05	-10.9	-5.86	20.16	0
2-5	132.74	30.75	39.6	28.0	27.8	23.9	0.12	0.02	-18.70	9.67	2.29	0

VIII. CONCLUSION

Simulation studies using MATLAB programming code, on IEEE 30 bus system are presented to illustrate the methodology and to demonstrate the benefit of the proposed approach. In this paper, optimal locations of TCSCs and TCPSTs are identified using an index named as SCS. From the simulation results, it is clear that, the line overloads are alleviated for all severe contingencies. The application of this approach for scheduling the power system during normal operation and to schedule the power system controls during contingencies have been presented. In this method, the problem of representing the decision variables in the binary coded GA has been alleviated by employing floating point numbers to represent the generator loading. An improved form cross over and mutation operations to deal with the real and integer variable has been presented.

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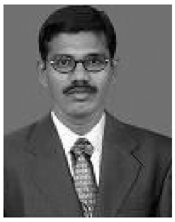
BIOGRAPHIES



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