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Multi-objective Evolutionary Algorithm for Security Enhancement

This paper reports an application of Multi-objective Evolutionary algorithm for solving the security enhancement problem. Generation rescheduling and adjustment of TCSC are used to alleviate the line overload. The probable locations of TCSC are pre-selected based on Line overload Sensitivity (LOS) index which ranks the system branches according to their severity. The security enhancement problem is formulated as a multi-objective optimization problem with minimization of investment cost of Thyristor Controlled Series Capacitor (TCSC) and minimization of control variable adjustment cost as objectives. Non-dominated sorting algorithm is applied to solve this multi-objective optimization problem. The proposed approach has been evaluated on the IEEE 30-bus test system. Simulation results show the effectiveness of the proposed approach for solving the multi-objective optimal power flow problem

Keywords: Power system security, Flexible AC transmission system (FACTS) devices, Thyristor Controlled Series Capacitors (TCSCs), Genetic Algorithm, Non –dominated sorting genetic algorithm, Pareto optimal frontier.

1. Nomenclature

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.

2. Introduction

In any power system, unexpected outages of transmission lines occur due to faults or other disturbances. These events referred to as contingencies, may cause significant overloading of transmission lines, which in turn may lead to total or partial blackout. Transmission line overload can be alleviated by re-routing power flows in the system. A change in line flow can be caused by an appropriate change in phase angles and magnitude

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of bus voltages, which are usually referred to as state variables. The state variables can, in turn, be modified by a variation in generated power [1-3].

Optimal Power Flow (OPF) is the important tool used in Energy Management System for security enhancement. The OPF problem aims to optimize one or more objectives by adjusting the power system control variables while satisfying a set of operational and physical constraints. It is a mixed-integer non-linear optimization problem with a large number of variables. The integer variables appear in the mathematical formulation owing to the discrete nature of the transformer tap positions and the capacitor bank. A wide variety of optimization techniques have been applied to solve the OPF problem. These include gradient method [4-5], Newton method, linear programming [6] and Interior Point Method (IPM). Unfortunately, an OPF problem is a highly nonlinear optimization problem.

Therefore, conventional optimization methods that make use of derivatives and gradients, in general, are not able to locate or identify the global optimum. Further, many mathematical assumptions such as analytic and differential objective functions have to be given to simplify the problem. Hence, it becomes essential to develop optimization techniques that are efficient to overcome these drawbacks and difficulties. Evolutionary Computation techniques like Genetic Algorithm (GA) [7-8] and Evolutionary Programming [9,10] have been proposed to overcome these difficulties. Evolutionary Computation techniques do not require any space limitations such as smoothness, convexity or uni-modality of the function to be optimized. This feature makes it suitable for many real-world applications, including the OPF problem.

FACTS devices [11-17] based on power electronics technology represents an active tool for the control of active power as well as reactive power or voltage control. A good coordination between FACTS devices and the conventional power system control devices is necessary to make the power systems operating in a more secure and economic way. Therefore, it becomes necessary to extend the available power system analysis tools such as optimal power flow to include the FACTS devices. Several papers [18-19] have been published in dealing with OPF incorporating FACTS devices. For a large-scale power system, more than one FACTS device may have to be installed in order to achieve the desired performance. Studies have been conducted to find suitable location for FACTS devices to improve power system security. In [16], optimal location of multi type FACTS devices was presented. Here, the system loadability was employed as a measure of power system performance. In [17], the authors presented a systematic procedure to place and operate TCSCs in a power system.

While using FACTS devices for the performance of power system, the installation costs need to be taken in to account. In addition, the limited amount of time to alleviate the overload is itself a security concern and it is further complicated by the fact that controls can not move instantaneously. Generator ramp rates can significantly restrict the speed with which active power is rerouted in the network. Hence, during the rescheduling of the generators to alleviate overload in the contingency state one of the objectives should be to minimize the deviation of the control variables from the base case value. This objective has not been considered in many of the literatures. This paper focuses on the rescheduling of generator power and adjustment of TCSC for security enhancement taking minimization of installation cost and control variables deviation as the objectives .The presence of multiple objectives in a problem gives rise to a set of optimal solutions, known as Pareto-optimal solutions. In the absence of any further information, one of these Pareto-optimal solutions can not be said to be better than the other. This demands a user to find as many Pareto-optimal solutions as possible.

Generally, the multi-objective optimization problems are converted to a single objective problem by linear combination of different objectives as a weighted sum [20] .The important aspect of this weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used to find Pareto-optimal solutions in problems having a non-convex Pareto-optimal front. To avoid this difficulty, the Є-constraint method [21-22] is used for multi-objective optimization problem. This method is based on optimizing the most preferred objective and considering the other objectives as constraints bounded by some allowable levels. These levels are then altered to generate the entire Pareto-optimal set. It is obvious that this approach is time-consuming and tends to find weakly non-dominated solutions.

The recent research direction is to handle both objectives simultaneously as competing objectives. The studies on evolutionary algorithms [23-26] have shown that these methods can be efficiently used to eliminate most of the difficulties of classical methods. Since they are population-based techniques, multiple Pareto-optimal solutions can, in principle, be found in one single run.

In this paper, Non-dominated sorting genetic algorithm (NSGA) [27] is proposed for solving the multi-objective security optimization problem. The dual objectives in a multi-objective optimization algorithm are maintained by using a fitness assignment scheme which prefers non-dominated solutions and by using a sharing strategy which preserves diversity among solutions of each non-dominated front.

The main advantage of an NSGA is the assignment of fitness according to non-dominated sets. Since, better non-dominated sets are emphasized systematically, an NSGA progresses towards the Pareto-optimal region front-wise. Moreover, performing sharing in the parameter space allows phenotypically diverse solutions to emerge when using NSGAs. If desired, the sharing can also be performed in the objective space.

The effectiveness and potential of the proposed approach to solve the multi-objective OPF problem has been demonstrated using IEEE 30-bus system

3. Severity Index

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

$$SeverityIndex\,(SI_l) = \sum_{l=1}^{L_0} \left(\frac{S_l}{S_l^{\max}} \right)^{2m} \tag{1}$$

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.

Larger the severity index value a contingency has, the more severe it will be. The line flows in (1) are obtained from Newton-Raphson load flow calculations. While using the above severity index for security assessment, only the overloaded lines are considered to avoid masking effect.

4. Modeling and placement of 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. This changes the line flow due to change in series reactance. The equivalent circuit of TCSC module is shown in Fig.1.

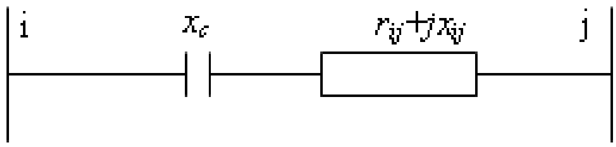

Fig.1. Equivalent circuit of TCSC

The TCSC reactance is given by

$$x_c = x_{TCSC} x_{line} \tag{2}$$

where,

x_{line} is the reactance of the transmission line.

x_{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}).

The power flow equations of a transmission line with TCSC can be written as

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

$$Q_{ij} = -V_i^2 b_{ij} - V_i V_j (g_{ij} \sin\delta_{ij} - b_{ij} \cos\delta_{ij}) \tag{3}$$

where,

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

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

The only difference between normal line power flow equation and the TCSC line power flow equation is the presence of the controllable reactance x_c which is varied by adjusting the value of TCSC reactance.

To enhance the security of the system, the TCSC has to be placed at the suitable locations. To determine the best location of TCSC, an index called Line overload sensitivity (LOS) index is calculated for all considered contingencies. The LOS_j for branch "j" is defined as the sum of the severity index of branch "j" to all considered contingencies '*l*', expressed as,

$$LOS_j = \sum_{l=1}^{m} SI_j^l \tag{4}$$

To identify the suitable location for placement of TCSC, first the LOS values are calculated for all branches using (4). Then the branches are ranked by their corresponding LOS values. The locations of the TCSCs are determined according to the ranking of branches and system topology. The locations are chosen starting from the top of the ranking list and proceeding downward with as many branches as the number of available TCSCs.

5. Problem Formulation

In general, the OPF problem is formulated as an optimization problem in which one or more objective functions are minimized while satisfying a number of equality and inequality constraints. In the security enhancement problem considered here the goal is to determine the optimal values of TCSCs and generator active power that enhance the systems security level while minimizing the investment cost of TCSC and the control variable movement. The mathematical formulation of the security enhancement problem is given below:

5.1 Objective functions

Control variable adjustment (F_C):

While enhancing the security of the systems, it is preferred to have minimum deviation of the generator real power from the base value [28]. This is stated as,

$$F_C = \sum_{i=1}^{N_C} w_i \left| \frac{u_i - u_i^0}{u_i^{\max} - u_i^{\min}} \right| \tag{5}$$

where N_C is the number of control variables; u_i and u_i^0 are the new and initial settings of the i^{th} control variable respectively; and w_i is a weighting factor to reflect the relative cost of the i^{th} control variable. u_i^{max} and u_i^{min} are the maximum and minimum limits of the i^{th} control variable.

TCSC cost function (F_E)

It is important to take the economical aspects of the FACTS devices present in the power systems due to high investment and operating costs. The cost function for TCSC [29, 30] is given by,

$$F_E = 0.0015S^2 - 0.71S + 153.75 \text{ (US\$/KVAR)} \tag{6}$$

Where,

S = Operating range of TCSC=$|S_2-S_1|$

S_1=Apparent power flow through branch before placing TCSC

S_2=Apparent power flow through branch after placing TCSC

Multi-objective function

The multi-objective optimization problem is therefore formulated as:

Minimize $F_T = [F_C, F_E]$ (7)

Problem Constraints

- **Load flow constraints**

$$P_i - V_i \sum_{i=1}^{N_B} V_j (G_{ij} \cos\Theta_{ij} + B_{ij} \sin\Theta_{ij}) = 0,\ i = 1,2,.......N_{B-1} \tag{8}$$

$$Q_i - V_i \sum_{i=1}^{N_B} V_j (G_{ij} \sin\Theta_{ij} - B_{ij} \cos\Theta_{ij}) = 0,\ i = 1,2,.......N_{PQ} \tag{9}$$

- **Voltage constraint**

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad i \in N_B \tag{10}$$

- **Real Power Generation limit**

$$P_g^{\min} \le P_g \le P_g^{\max}, \quad g \in N_g \tag{11}$$

- **Generator reactive power generation limit**

$$Q_g^{\min} \le Q_g \le Q_g^{\max}, \quad g \in N_g \tag{12}$$

- **Limit on reactance of TCSC**

$$X_{TCSC,i}^{\min} \le X_{TCSC,i} \le X_{TCSC,i}^{\max}, \quad i \in N_{TCSC} \tag{13}$$

- **Transmission line flow limit**

$$S_l < S_l^{\max}, \quad l \in N_l \tag{14}$$

6 Multi-objective Genetic Algorithm

Genetic algorithms (GA) [25] are generalized search algorithms based on the mechanics of natural genetics. 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. They combine solution evaluation with stochastic genetic operators namely, selection, crossover and mutation to obtain optimality. Being a population-based approach, GA is well suited to solve multi-objective optimization problems. A generic single-objective GA can be modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for problems with non-convex, discontinuous and multi-model solution spaces. This paper applies Non-dominated Sorting Genetic Algorithm (NSGA) to solve the multi-objective OPF problem. The details of NSGA are presented below:

6.1 Non-dominated Sorting Genetic Algorithm (NSGA)

NSGA differs from simple genetic algorithm only in the way the selection operator works. The crossover and mutation operators remain the same. Before the selection is performed, the population is ranked on the basis of an individual's non-domination. The non-dominated individuals present in the population are first identified from the current population. Then, all these individuals are assumed to constitute the first non-dominated front in the population and assigned a large dummy fitness value. The same fitness value is assigned to give an equal reproductive potential to all these non-dominated individuals. In order to maintain diversity in the population, these classified individuals are then shared with their dummy fitness values. Sharing [27] is achieved by performing selection operation using degraded fitness values which are obtained by dividing the original fitness value of an individual by a quantity proportional to the number of individuals around it. This causes multiple optimal points to co-exist in the population.

After sharing, these non-dominated individuals are ignored temporarily to process the rest of population in the same way to identify individuals for the second non-dominated front. These new set of points are then assigned a new dummy fitness value which is kept smaller than the minimum shared dummy fitness of the previous front. This process is continued until the entire population is classified into several fronts. The population is then reproduced according to the dummy fitness values. A tournament selection is used in this work. Individuals in the first front have the maximum fitness value, they always get more copies than the rest of population. This was intended to search for non-dominated regions or Pareto-optimal fronts. This results in quick convergence of the population towards non-dominated regions and sharing helps to distribute it over this region. By emphasizing non-dominated points, NSGA is actually processing the schemata representing Pareto-optimal regions. The efficiency of NSGA lies in the way multiple objectives are reduced to a dummy fitness function using non-dominated sorting procedure. Fig. 2 shows a flow chart of this algorithm. The algorithm is similar to a simple GA except the classification of non-dominated fronts and the sharing operation. The sharing in each front is achieved by calculating a sharing function value between two individuals in the same front as

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\dfrac{d_{ij}}{\sigma_{share}} \right)^2 , & if \quad d_{ij} < \sigma_{share} \\ 0 & Otherwise \end{cases} \tag{15}$$

In the above equation, the parameter d_{ij} is the phenotypic distance between two individuals i and j in the current front and share is the maximum phenotypic distance allowed between any two individuals to become members of a niche. Some guidelines to set these parameters are given in [27]. A parameter niche count is calculated by adding the above sharing function values for all individuals in the current front. Finally, the shared fitness value of each individual is calculated by dividing its dummy fitness value with its niche count.

7. Genetic Algorithm Implementation

While applying GA for solving the OPF problem, the following issues need to be addressed:

- Solution Representation and
- Fitness evaluation.

7.1 Solution Representation

Implementation of GA for a problem starts with the parameter encoding (i.e., the representation of the problem). Each individual in the genetic population represents a candidate solution. 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 variable, each variable is represented by a substring and all the substrings are concatenated to form a bigger string. In the OPF problem under consideration, generator active-power $P_{gi,}$ and TCSCs settings are the optimization variables.

7.2 Evaluation Function

GA searches for the optimal solution by maximizing a given fitness function, and therefore an evaluation function which provides a measure of the quality of the problem solution must be provided. In the OPF problem under consideration, the objective is to minimize the investment cost of TCSC and control variable adjustment cost satisfying the constraints. The equality constraints given by equations (8) & (9) are satisfied by running the power flow program. The active power generation (P_{gi}) (except the generator at the slack bus) and generator terminal bus voltages (V_{gi}) are the control variables and they are self-restricted by the optimization algorithm. The limit on active power generation at the slack bus (P_{gs}), load bus voltages (V_{load}), reactive power generation (Q_{gi}) and line flow (S_l) are satisfied through penalty function approach. With the inclusion of the penalty function the new objective function becomes,

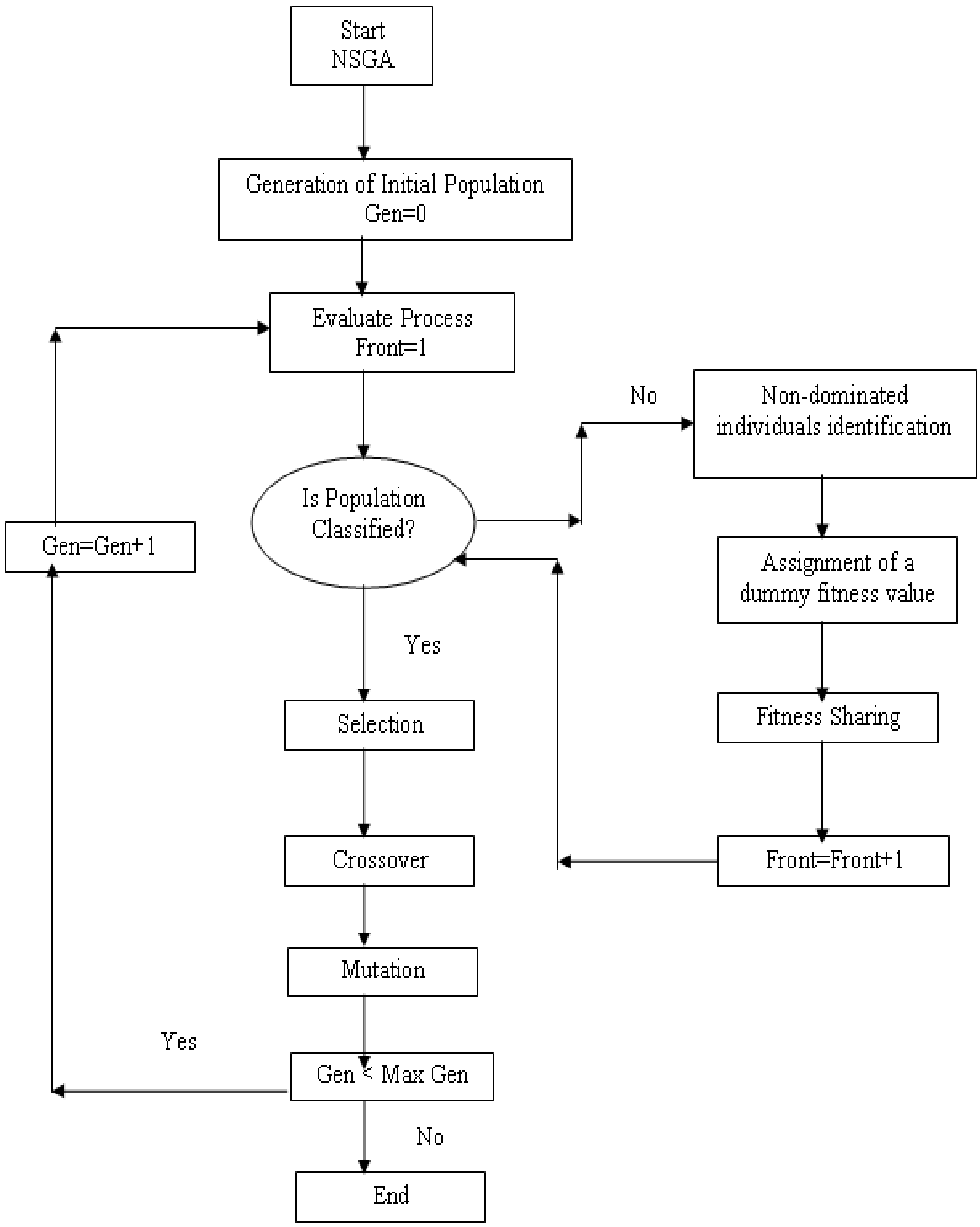

Fig.2. Flowchart of NSGA

$$Min\, f = F_T + SP + \sum_{j=1}^{N_l} VP_j + \sum_{j=1}^{N_g} QP_j + \sum_{l=1}^{N_l} LP_l$$

(16)

where,

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:

$$SP = \begin{cases} K_S\left(P_S - P_S^{\max}\right) & if \quad P_S > P_S^{\max} \\ K_S\left(P_S^{\min} - P_S\right) & if \quad P_S < P_S^{\max} \\ 0 & otherwise \end{cases}$$

$$VP_j = \begin{cases} K_V\left(V_j - V_j^{\max}\right)^2 & if \quad V_j > V_j^{\max} \\ K_V\left(V_j - V_j^{\min}\right)^2 & if \quad V_j < V_j^{\min} \\ 0 & otherwise \end{cases}$$

$$QP_j = \begin{cases} K_q\left(Q_j - Q_j^{\max}\right)^2 & if\ Q_j > Q_j^{\max} \\ K_q\left(Q_j - Q_j^{\min}\right)^2 & if\ Q_j < Q_j^{\min} \\ 0 & otherwise \end{cases}$$

$$LP_l = \begin{cases} K_l\left(S_l - S_l^{\max}\right)^2 & if \quad S_l > S_l^{\max} \\ 0 & otherwise \end{cases}$$

GA is usually designed to maximize the fitness function which is a measure of the quality of each candidate solution. Hence in this work, we employed as GA's fitness the inverse of the objective function

8. Simulation Results

The proposed genetic algorithm approach has been applied to solve the optimal power flow problem in IEEE-30 bus test system which is shown in Fig. 3. The IEEE 30-bus system has 6 generator buses, 24 load buses and 41 transmissions lines of which 4 branches (6-9), (6-10), (4-12) and (28-27) are with tap setting transformers. The upper and lower voltage limits at all the bus bars except slack are taken as 1.10 p.u and 0.95p.u respectively. The slack bus bar voltage is fixed to its specified value of 1.06 p.u.

The generator cost coefficients and the transmission line parameters are taken from [5]. It is assumed that the impedance of all TCSCs can be varied within 50% of the corresponding branch impedance.

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

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

Case 2: Multi objective optimal Power flow for security enhancement.

Case 1: Base case OPF

In this case, fuel cost objective is optimized in order to explore the extreme points of the trade-off surface and evaluate the diversity characteristics of the pareto optimal solutions obtained by the proposed approach. Generator real power output and voltage magnitude of generator buses are taken as the control variables.

The initial population was randomly generated between the variable's lower and upper limits. Tournament selection was applied to select the members of the new population. Two point crossover and uniform 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, P_c and P_m, respectively. The performance of GA for various crossover and mutation probabilities in the range of 0.6–1.0 and 0.001–0.1 respectively was therefore evaluated. The best result of the GA was obtained with the following control parameters:

- No of generations : 70
- Population size : 45
- Crossover probability : 0.9
- Mutation probability : 0.01

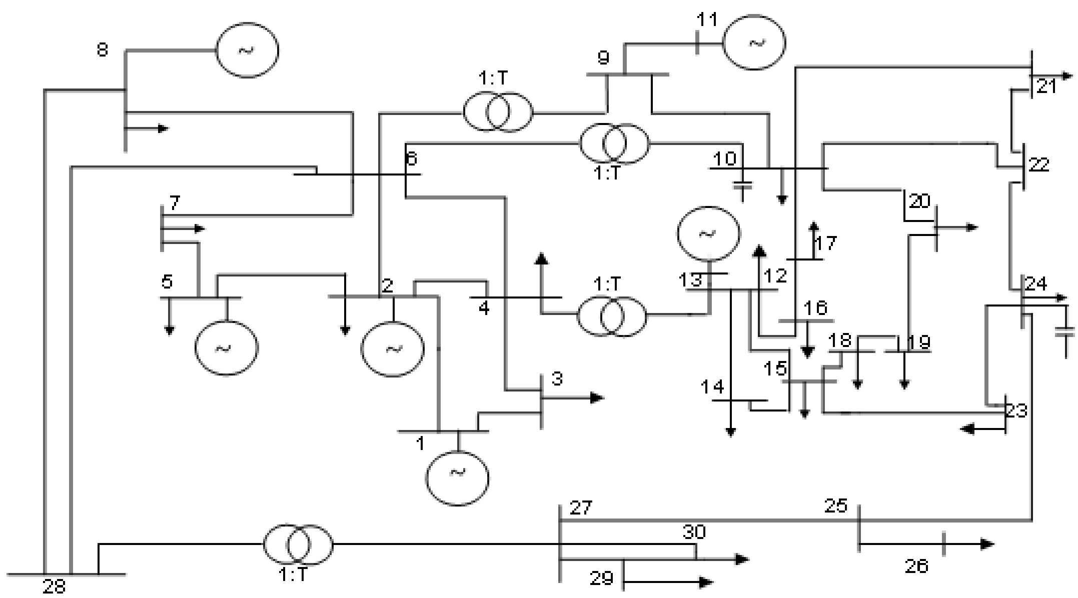

Fig.3. IEEE-30 bus test system

Fig. 4 shows the variation of fitness during the GA run for the best case. 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.

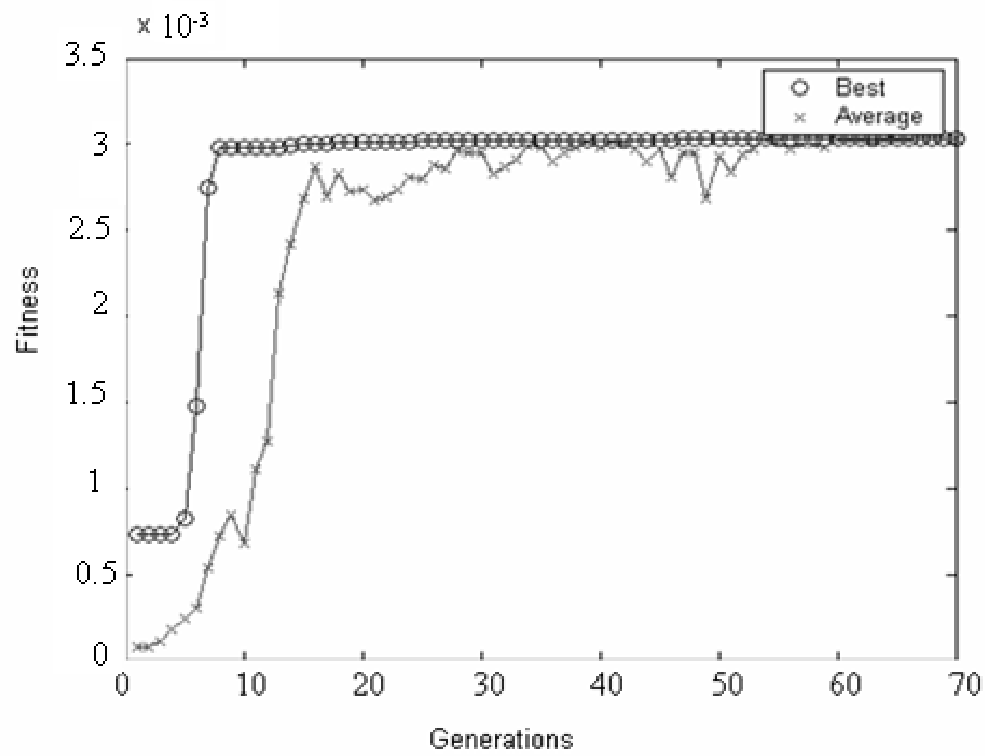

Fig.4. Convergence of the GA-OPF algorithm for IEEE 30-bus test system

Table 1: Result of Single Objective OPF Algorithm

Control Variables	**Variable Setting**
P_1	173.6
P_2	50.2
P_5	21.8
P_8	23.8
P_{11}	10.8
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}	0.9802
Generation Cost	801.7165 ($/hr)

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.

Table 2: Comparison of Fuel cost

Method	**Minimum Cost**
Gradient approach [5]	802.43$/hr
Hybrid evolutionary programming [9]	802.62$/hr
Improved Evolutionary programming [10]	802.465 $/hr
Proposed Method	**801.7165 *$/hr***

Case 2: Multi-objective OPF

Contingency analysis was carried out on the system to identify the severe contingencies. The list of severe contingencies along with their severity index value is given in table 3. From this table, it is found that line outage 1-2 is the most severe contingency in the system.

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 3-4 4-6	191.58 174.13 103.37	130 130 90	5.262	1
1-3	1-2 2-6	181.17 66.482	130 65	3.010	2
3-4	1-2 2-6	178.43 65.558	130 65	2.9011	3
2-5	2-6 5-7	76.285 101.08	65 70	1.3777	4
28-27	22-24 24-25	19.062 17.781	16 16	2.1979	5
4-6	1-2 2-6	132.63 69.921	130 65	0.6327	6

The GA based algorithm was applied for corrective control under the contingency state taking the generator real power and generator bus voltage magnitude as control variables and minimum severity index as the objective function. The GA based approach was able to alleviate the overload in all cases except for the contingency 1-2. Table 4 shows the control variable settings for contingency 1-2. This shows that generation rescheduling alone is not sufficient to alleviate the overload under some contingency cases.

Table 4: Control Variable setting for contingency 1-2

Line outage	P_1	P_2	P_5	P_8	P_{11}	P_{13}	V_1	V_2	V_5	V_8	V_{11}	V_{13}	SI value
1-2	145.49	57.36	24.42	34.82	18.03	17.2	1.035	0.998	0.959	0.967	1.02	0.9500	2.473

Next, TCSC was included in addition to generation rescheduling to alleviate the overload. The LOS indices are calculated using equation (4) for each branch of the studied system for the severe contingencies. The branches which have high values of LOS for the severe contingency are listed in table 5.

Table 5: LOS Values for IEEE 30 bus test system

S.No	**Branches**	**LOS value**	**Rank**
1	2-4	0.4770	1
2	2-5	0.3421	2
3	2-6	0.1643	3

The TCSCs are placed in these three lines. Generator active power, generator bus bar voltages and the reactance values of TCSCs are taken as the control variables and the problem was handled as a multi-objective optimization problem with TCSC installation cost and control variable adjustment as objectives to be minimized simultaneously with the NSGA.

In all simulation, the following parameters were used

- Number of generation =90
- Population size = 40
- Cross over probability =0.9
- Mutation probability =0.01
- Distribution index for cross over =10
- Distribution index formulation =20

The diversity of the pareto optimal set over the trade off optimal set over the trade off surface is shown in Fig. 5.

It is worth mentioning that the proposed approach produces 25 pareto optimal solutions in a single run that have satisfactory diversity characteristics and span over the entire pareto optimal front. Out of these two non-dominated solutions which are the extreme points of Fig. 5 that represent the best installation cost and best control variable adjustment are given in tables 6 and 7. In both cases the value of SI is zero, which shows that the proposed approach is able to enhance the security of the system.

Table 6: Minimum Installation cost solution

$P_1,P_2,P_5,P_8,P_{11},P_{13}$	124.73810 45.0758 32.122 34.5764 19.8657 29.1128
$V_1,V_2,V_5,V_8,V_{11},V_{13}$	0.9661, 0.9987, 0.9590, 0.9688, 1.0266, 0.9560
TCSC settings	0.4677, -0.1129, 0.3387
Installation cost (US$/KVAR)	$1.25*10^7$
Control variable adjustment	5.5369

Table 7: Minimum control variable adjustment solution

$P_1,P_2,P_5,P_8,P_{11},P_{13}$	134.7507, 53.9003, 34.7752, 24.1251, 21.3001, 27.8201
$V_1,V_2,V_5,V_8,V_{11},V_{13}$	0.9935, 0.9865,0.9743, 0.9813, 1.0074,1.0009
TCSC settings	-0.1452, 0.3387, -0.2419
Installation cost (US$/KVAR)	$5.712*10^7$
Control variable adjustment	3.098

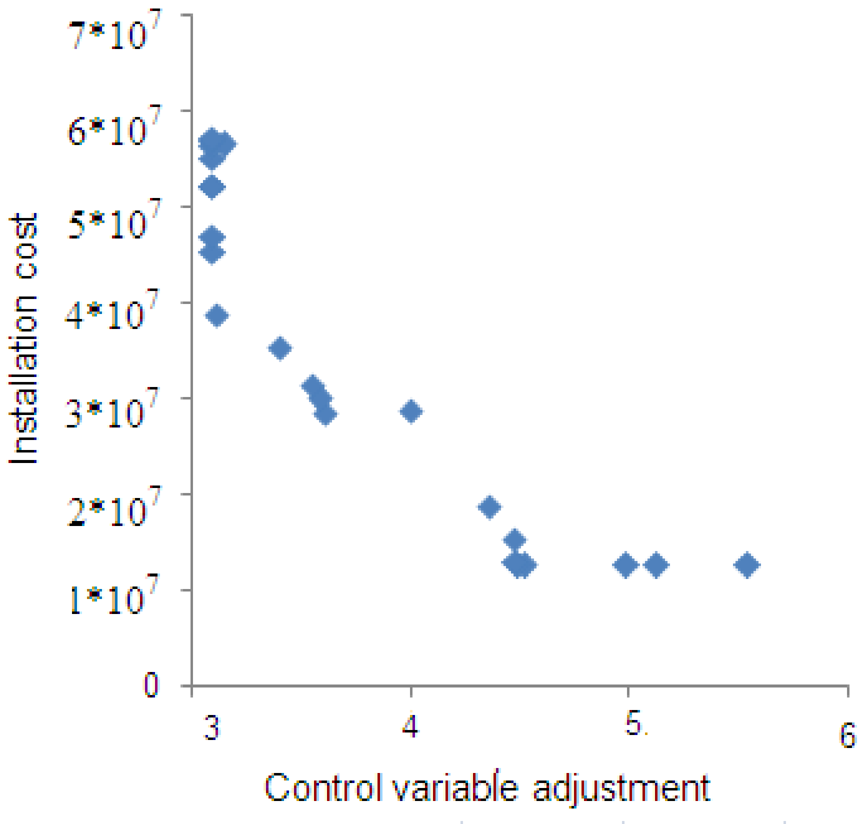

Fig.5. Pareto-optimal front of the MOGA problem

9. Conclusion

In this paper, the multi-objective optimal power flow problem has been solved using non dominated sorting genetic algorithm. The present paper makes use of recent advances in multi-objective evolutionary algorithms to develop a method for the optimal allocation of FACTS in to power systems. It has considered as optimization criteria, the minimization of control variable adjustments and installation cost of TCSCs. The algorithm has been tested on the standard IEEE-30 bus system .The result shows that the proposed algorithm is applicable and effective in the solution of OPF problems that consider nonlinear characteristics of power system with different objective functions. It is shown that TCSCs can enhance the power system security through their optimal allocation. Implementation of the proposed Multi-objective GA has performed well when it was used to characterize POF of the multi-objective optimal power flow problem. NSGA can generate an efficiently high quality solution with more stable convergence characteristics than simple genetic algorithm.

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