Congestion Management in Deregulated Power System by Optimal Choice and Allocation of FACTS Controllers Using Multi-Objective Genetic Algorithm

S. Surender Reddy *, M. Sailaja Kumari† and M. Sydulu**

Abstract – Congestion management is one of the technical challenges in power system deregulation. This paper presents single objective and multi-objective optimization approaches for optimal choice, location and size of Static Var Compensators (SVC) and Thyristor Controlled Series Capacitors (TCSC) in deregulated power system to improve branch loading (minimize congestion), improve voltage stability and reduce line losses. Though FACTS controllers offer many advantages, their installation cost is very high. Hence Independent System Operator (ISO) has to locate them optimally to satisfy a desired objective. This paper presents optimal location of FACTS controllers considering branch loading (BL), voltage stability (VS) and loss minimization (LM) as objectives at once using GA. It is observed that the locations that are most favorable with respect to one objective are not suitable locations with respect to other two objectives. Later these competing objectives are optimized simultaneously considering two and three objectives at a time using multi-objective Strength Pareto Evolutionary Algorithms (SPEA). The developed algorithms are tested on IEEE 30 bus system. Various cases like i) uniform line loading ii) line outage iii) bilateral and multilateral transactions between source and sink nodes have been considered to create congestion in the system. The developed algorithms show effective locations for all the cases considered for both single and multi-objective optimization studies.

Keywords: FACTS, Single objective optimization, Multi-objective optimization, Strength Pareto Evolutionary Algorithms (SPEA), SVC, TCSC, real parameter Genetic algorithms

1. Introduction

Transmission lines are often driven close to or even beyond their thermal limits in order to satisfy the increased electric power consumption and trades due to increase of the unplanned power exchanges. If the exchanges were not controlled, some lines located on particular paths may become overloaded, this phenomenon is called congestion. Political and environmental constraints make the building of new transmission lines difficult and restrict the electrical utilities from better use of existing network. It is attractive for electrical utilities to have a way of permitting more efficient use of the transmission lines by controlling the power flows.

FACTS devices have provided strategic benefits for better utilization of existing power systems. The parameter and variables of the transmission line, i.e., line impedance, terminal voltages, and voltage angles can be controlled by FACTS devices in a fast and effective way. FACTS devices are operated in a manner so as to ensure that the contractual requirements are fulfilled as far as possible by minimizing line congestion. The objective of this paper is to develop an algorithm to find the optimal location and size of multi-type FACTS devices in power system. The optimizations are performed on three parameters: the location of the devices, their types and rated values. The branch loading, voltage stability and line losses are applied as measures of power system performance.

Initially, the problem is formulated as a single objective optimization problem considering maxim-ization of branch loading, voltage stability and minimi-zation of loss independently. In the next step two objectives are optimized simultaneously considering i) maximization of branch loading and voltage stability, ii) maximization of branch loading and loss minimization, iii) maximization of voltage stability and loss minimization. In the third step, three objectives are optimized simultaneously. At each step, congestion is created in the system by uniform overloading, by line outage, by increasing bilateral and multi-lateral trans-actions between source and sink nodes[5]. This combinatorial optimization problem is solved using GA.

This paper is organized as follows: Static models of FACTS controllers are described in section 2. Real parameters GAs are described in section 3. Section 4 presents objectives of the optimization. In section 5 multi objective optimization and SPEA algorithm are presented. The simulation results are discussed in section 6. Finally, brief conclusions are deduced.

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2. Static Modeling of FACTS Controllers

This section focuses on the modeling of two kinds of FACTS, namely SVC and TCSC [14]. The power flows of the line connected between bus-i and bus-j having series impedance $r_{ij} + jx_{ij}\left(= 1/(g_{ij} + jb_{ij})\right)$ and without any FACTS controllers [1], can be written as,

$$P_{ij} = V_i^2 g_{ij} - V_i V_j (g_{ij}\cos\delta_{ij} + b_{ij}\sin\delta_{ij}) \quad (1)$$

$$Q_{ij} = -V_i^2 (b_{ij} + B_{sh}) - V_i V_j (g_{ij}\sin\delta_{ij} - b_{ij}\cos\delta_{ij}) \quad (2)$$

where V_i, V_j, δ_{ij} are the voltage magnitudes at bus-i and bus-j and voltage angle difference between bus-i and bus-j and

$$g_{ij} = \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2} \quad , \quad b_{ij} = \frac{-x_{ij}}{r_{ij}^2 + x_{ij}^2}$$

Similarly, the real power (P_{ji}) and reactive power (Q_{ji}) flows from bus-j to bus-i in the line can be written as

$$P_{ji} = V_j^2 g_{ij} - V_i V_j (g_{ij}\cos\delta_{ij} - b_{ij}\sin\delta_{ij}) \quad (3)$$

$$Q_{ji} = -V_j^2 (b_{ij} + B_{sh}) + V_i V_j (g_{ij}\sin\delta_{ij} + b_{ij}\cos\delta_{ij}) \quad (4)$$

2.1 Static Representation of TCSC

The basic idea behind power flow control with the TCSC is to decrease or increase the overall lines effective series transmission impedance, by adding a capacitive or inductive reactance correspondingly [14]. The TCSC is modeled as variable impedance, where the equivalent reactance of the line x_{ij} is defined as:

$$x_{ij} = x_{line} + x_{TCSC}$$

where, x_{line} is the transmission line reactance [12]. The level of applied compensation of the TCSC usually varies between 20% inductive and 70% capacitive. Fig 1.shows a controllable reactance $(-jx_{TCSC})$ placed in the transmission line connected between bus-i and bus-j.

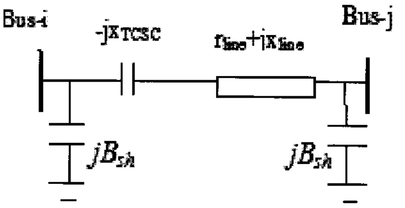

Fig. 1. Equivalent circuit of TCSC

The real and reactive power flows from bus-i to bus-j and bus-j to bus-i in the line can be written as (1) to (4) with modified $\boldsymbol{g_{ij}}$ and $\boldsymbol{b_{ij}}$ as given below.

$$g_{ij} = \frac{r_{ij}}{r_{ij}^2 + (x_{ij} - x_{TCSC})^2} \quad , \qquad b_{ij} = \frac{-(x_{ij} - x_{TCSC})}{r_{ij}^2 + (x_{ij} - x_{TCSC})^2}$$

2.2 Static Representation of SVC

SVC is a shunt connected static Var generator or consumer whose output is adjusted to exchange capacitive or inductive Var so as to maintain or control specific parameters of electrical power system, typically bus voltage [10,11]. Like the TCSC, the SVC combines a series capacitor bank shunted by thyristor controlled reactor. SVC structure is shown in fig.2. Also, shows SVC represented as a continuous variable shunt susceptance.

Fig. 2. SVC structure, SVC as variable shunt susceptance

The SVC load flow models can be developed treating SVC susceptance as control variable. Assuming that SVC is connected at node-p to maintain the bus voltage at V_p, the reactive power injected by the controller is given by (5).

$$Q_{pSVC} = -V_p^2 B_{pSVC} \quad (5)$$

The linearized load flow models make use of eqn. (5) to modify the corresponding Jacobian elements at SVC bus. The SVC load flow model can be developed treating SVC susceptance as control variable (B_{SVC}).

3. Genetic Algorithms (GA)

GAs are global search algorithms based on mechanisms of natural selection and genetics. GAs start with random generation of initial population and then the selection, crossover and mutation are performed until the best population is found. The goal of the present optimization is to find the best location of a given number of FACTS devices in accordance with a defined objective function within the equality and inequality constrains [13]. The configuration of FACTS devices is encoded by three parameters: the location, type and its rating. Each individual is represented by n_{FACTS} number of strings, where n_{FACTS} is the number of FACTS devices to be optimally located in the power system [3], as shown in fig.3.

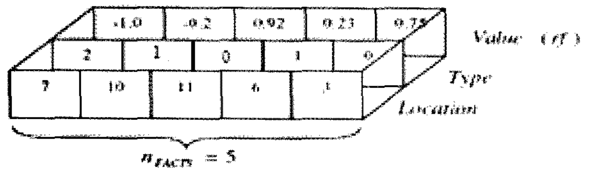

Fig. 3. Individual configuration of FACTS devices

The first value of each string corresponds to the location information. It must be ensured that on one transmission line there is only one FACTS device. The second value represents the types of FACTS device (n_{type}). The values assigned to FACTS devices are: "1" for SVC located at a bus; "2" for TCSC located in a line, "0" for no FACTS device. The last value *rf* represents the rating of each FACTS device. This value varies continuously between −1 and +1.If the selected FACTS device is TCSC, then this rated value generated between $-0.7X_{line}$ to $0.2X_{line}$. If it is SVC, the rated value is SVC susceptance (Bsvc) and this value is generated between -0.45p.u to +0.45p.u.

To obtain GA population, the above operations are repeated n_{Ind} times, where n_{Ind} is number of individuals of the population. The objective function is computed for every individual of the population and assigned fitness. In our case, the objective functions are defined in order to quantify the impact of the FACTS devices on the state of the power system and are presented in Section IV.

Then, the operators of reproduction, crossover and mutation are applied successively to generate the offsprings. Reproduction is a process where the individual is selected to move to a new generation according to its fitness. The present work employed tournament parent selection technique.

3.1 Blended (BLX-α) Crossover

The main objective of crossover is to reorganize the information of two different individuals and produce a new one. For two parent solutions $X_i^{(1,t)}$ and $X_i^{(2,t)}$ (assuming $X_i^{(1,t)} < X_i^{(2,t)}$), the BLX-α randomly picks a solution in the range $[X_i^{(1,t)} - \alpha(X_i^{(2,t)} - X_i^{(1,t)}), X_i^{(2,t)} + \alpha(X_i^{(2,t)} - X_i^{(1,t)})]$. If u_i is a random number between 0 and 1, the following (6) is an offspring [6]:

$$X_i^{(1,t+1)} = (1-\gamma_i)X_i^{(1,t)} + \gamma_i X_i^{(2,t)} \tag{6}$$

$where, \gamma_i = (1+2\alpha)u_i - \alpha$. If α is zero, this crossover creates a random solution in the range $(X_i^{(1,t)}, X_i^{(2,t)})$. It is reported that BLX-0.5(with α=0.5) performs better than BLX operators with any other α value.

3.2 Non-uniform mutation

In Non-uniform Mutation the probability of creating a solution closer to the parent is more than the probability of creating one away from it. However, as the generations (t) proceed, this probability of creating solutions closer to the parent gets higher and higher [6].

For a given parent $X = X_1, X_2, X_3, \ldots.. X_K, \ldots.. X_l$, if the gene X_K is selected for mutation and the range of X_K is $[U_{min}^K, U_{max}^K]$, then the result (7) $X_K^{'}$ is

$$X_K^{'} = \begin{cases} X_K + \Delta(t, U_{max}^K - X_K) & if\ random\ (0,1) = 0 \\ X_K - \Delta(t, X_K - U_{min}^K) & if\ random\ (0,1) = 1 \end{cases} \tag{7}$$

Where,

$$\Delta(t,y) = y\left[1 - r^{\left(1-\frac{t}{T}\right)^b}\right] \tag{8}$$

$\Delta(t,y)$ (y represents $X_K - U_{min}^K\ and\ U_{min}^K - X_K$) returns a value in the range [*0,y*]. In (8), *r* is a random value in the range of [*0, 1*] and *b* is a parameter determining the degree of non-uniformity. In this simulation, *b*=2 is used.

4. Objectives of the Optimization

The three objectives considered here are branch loading (BL) maximization, voltage stability (VS) maximization and loss minimization (LM).

4.1 Branch Loading (BL) maximization

The first objective is related to the branch loading and penalizes overloads in the lines [13]. This term, called BL, is computed for every line of the network. While the branch loading is less than 100%, its value is equal to 1; then it decreases exponentially with the load [6].

$$BL = \prod_{line} J_{line} \tag{9}$$

$$J_{line} = \begin{cases} 1 & ; if\ S_{pq}^{max} \geq S_{pq} \\ e^{\left[\lambda\left(1 - \frac{S_{pq}}{S_{pq}^{max}}\right)\right]} & ; if\ S_{pq} > S_{pq}^{mqx} \end{cases}$$

where, *BL* is Branch Loading factor, S_{pq} and S_{pq}^{mqx} are MVA flow and thermal limit of the line between buses p and q. λ is a small positive constant equal to 0.1.

4.2 Voltage Stability (VS) maximization

The second objective function concerns voltage levels. It favours buses voltages close to 1 p.u. The function is calculated for all buses of the power system. For voltage levels comprised between 0.95 p.u. and 1.05 p.u., the value of the objective function *VS* is equal to 1. Outside this range, the value decreases exponentially with the voltage deviation [13].

$$VS = \prod_{BUS} J_2 \quad (10)$$

$$J_2 = \begin{cases} 1 & ; if\ 1.05 \geq V_b \geq 0.95 \\ e^{[\mu(1-V_b)]} & ; \quad \text{otherwise} \end{cases}$$

where, V_b is Voltage at bus b and μ is a small positive constant equal to 0.1.

4.3 Loss Minimization (LM) minimization

For reactive power optimization, system transmission loss minimization is considered as the objective function. The converged load flow solution gives the bus voltage magnitudes and phase angles. Using these, active power flow through the lines can be evaluated. Net system power loss is the sum of power loss in each line.

$$J_3 = \sum_{i=1}^{Nl} LOSS_i = LM \quad (11)$$

where, Nl is the number of transmission lines in a power system.

5. Multi-Objective Optimization, Strength Pareto Evolutionary Algorithm (SPEA)

In multi-objective optimization we have two or more objective functions to be optimized at the same time, instead of having only one. As a consequence, there is no unique solution to multi-objective optimization problems, but we aim to find all of the trade-off solutions available (called as Pareto optimal set). The problem can be formulated as [6]:

$$maximize/minimize \quad J_i(X) \quad i = 1,2,\ldots.. N_{obj} \quad (12)$$

$$subjected\ to \quad g_j(X) = 0 \quad j = 1,\ldots.. M_{eq} \quad (13)$$
$$h_k(X) \leq 0 \quad k = 1,\ldots..., N_{ineq}$$

where J_i is the i^{th} objective function, x is a decision vector that represents a solution, and N_{obj} is the number of objectives.

For a multi-objective optimization problem, any two solutions x^1 and x^2 can have one of the two possibilities- one dominates the other or none dominates the other. In a minimization problem x^1 is said to dominate x^2 if following two conditions are satisfied.

$$\forall i \in \{1,2,\ldots N_{obj}\}: J_i(x^1) \leq J_i(x^2) \quad (14)$$

$$\exists j \in \{1,2,\ldots N_{obj}\}: J_j(x^1) < J_j(x^2) \quad (15)$$

If x^1 dominates x^2, x^1 is called the non-dominated solution. The solutions that are non-dominated within the entire search space are called Pareto Optimal Set.

In the present paper a strong dominated set of solutions is used to form pareto optimal set. The solution is a strong dominated solution if the following condition is satisfied.

$$\forall j \in \{1,2,\ldots N_{obj}\}: J_j(x^1) < J_j(x^2) \quad (16)$$

5.1 Multi-objective SPEA Algorithm

Step 1: Initialize a population of chromosomes 'N' and create an empty external Pareto Optimal Set $\overline{N}$.
Step 2: Search the population for non-dominated solutions and copy them to the external set.
Step 3: If the size of the external set exceeds its maximum size $\overline{N}$, apply clustering technique to reduce the size to maximum size.
Step 4: Assign fitness (called strength) to population members and external set members using SPEA fitness assignment technique. The strength of each external member is proportional to the number n_k of the current population members that an external member dominates.

$$S_k = \frac{n_k}{(N+1)} \quad (17)$$

The fitness of current population member j is assigned as one more than the sum of the strength values of all external members which weakly dominate j:

$$F_j = 1 + \sum_{k\epsilon\mu} S_k \quad (18)$$

This method of fitness assignment suggests that a solution with smallest fitness is better.
Step 5: Combine the external population and the population members. Use the assigned fitness values, apply tournament selection, a crossover and mutation operator to create new population of size N from combined population.
Step 6: Repeat steps 2 to 5 until stopping criterion is reached.
In step3 a hierarchical clustering algorithm is employed to reduce the pareto set to its maximum size. After obtaining the pareto optimal set, fuzzy min-max approach [15] is used to obtain the final optimal solution.Fig.4.shows the flow chart of SPEA GA [8] approach.

6. Results and Discussion

6.1 Single Objective Optimization

The proposed model is implemented using IEEE 30 bus system. Initially, BL, VS and LM are considered as single objective optimization problems. For case studies congestion is created in the lines by uniformly loading the system, by line outage and by increasing bilateral and multi-lateral transaction amount. Base case refers to the system normal operating condition, without any optimization objective. Table 1 presents the GA parameters used.

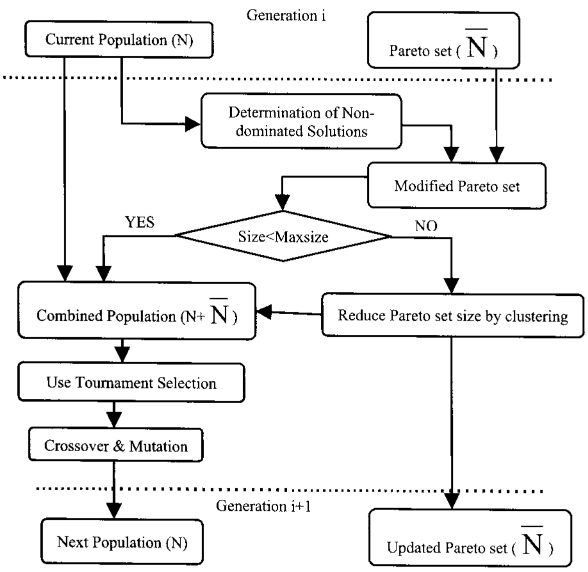

Fig. 4. SPEA GA flow chart

Case–i: when the system is uniformly loaded by 130% lines 1 and 10 are loaded by 126.036% and 110.97% respectively. For the BL objective function (9) is optimized using the real parameter GAs, the obtained objective function values are given in Table 2 and this overloading can be relieved by placing SVC at 25th bus with B_{SVC} of -0.005275p.u and TCSC in 40th line with X_{TCSC} of -0.118683p.u. From Table 2 it can be further inferred that, when VS is considered as optimization objective, BL is reduced from its base case value and the losses have also increased from its base case value. Considering LM as optimization objective reveals that a reduction in system transmission loss is associated with reduction in BL and VS values. This clearly demonstrates the conflicting nature of three objectives considered.

Case-ii: When the line 36 is given outage the lines 27, 30, 31 and 33 are loaded by 116.3357%, 103.8337%, 117.1324% and 127.7935% respectively. For BL objective function (9) is optimized using the real parameter GAs, the obtained objective function values are given in Table 3. This overloading can be relieved by placing SVC at 1st bus with B_{SVC} of 0.244239p.u and two TCSC devices in lines 31 and 33 with X_{TCSC} of -0.346388p.u and -0.325978p.u respectively. Table 3 also shows the objective function values when VS, LM are considered as independent single objectives. When VS is optimizing objective, the BL show an improvement from base case value, but not as much as is improved in the BL optimization case. The line losses are also increased from base case value. When LM is considered as optimization objective, both BL and VS increase but could not attain the values in BL, VS optimization case. This clearly shows the conflicting nature of the considered objectives. In both these cases congested lines are restricted to thermal limits and system voltage profile has been improved.

Table 1. GA Parameters

Population size	40
Reproduction operator	Tournament
Crossover operator, Crossover rate	Blended *(BLX-0.5),0.95*
Mutation operator, Mutation rate	Non-uniform,0.001
Maximum generations	200

Table 2. Comparison of Objective Function Values at Uniform Loading of 130% for Base Case and 130% loading with FACTS Devices

	Base case	*130% loading with FACTS devices*		
		BL	**VS**	**LM**
BL	2537.045	**2837.1096**	2289.215	2145.354
VS	1210.617	1329.8389	**1389.583**	1023.693
LM	0.190028	0.210257	0.193001	**0.179913**

Table 3. Comparison of Objective Function Values when Line 36 given Outage with and without FACTS Devices

	Line 36 is given outage	*Line 36 is given outage with FACTS devices*		
		BL	**VS**	**LM**
BL	60.8893	**621.8524**	601.7279	529.5170
VS	183.7809	302.0251	**309.2734**	282.9421
LM	0.12553	0.128988	0.127814	**0.120860**

Case-iii: Consider a bilateral transaction between the supplier at node 11 and the consumer at node 5. By increasing the transaction amount to 220% of base case, lines 1 and 8 get loaded by 137.8715% and 106.1109%.Objective function is taken as BL from (9). This congestion can be relieved by placing SVC at bus 5 with B_{SVC} of -0.547196p.u and three TCSC devices in lines 4, 25 and 32 with X_{TCSC} of -0.009161p.u,-0.33476p.u and -0.665461p.u respectively.

Case-iv: Consider a multi-lateral transaction between the supplier at node 2 and the consumer at nodes 8 and 21. The base case P_{gen} at supplier node 2 is 0.5756p.u., P_{load} at consumer nodes 8 and 21 are 0.3p.u, 0.175p.u respectively. By increasing the transaction amount by 170% at supplier node and drawing the same amount at consumer nodes then lines 10 and 27 get loaded by 102.2923% and 116.2234% respectively. Objective function is taken as BL from (9). This overloading can be relieved by placing two SVCs at buses 3 and 30 with B_{SVC} of -0.474376p.u,-0.302777p.u respectively and TCSC in line 16 with X_{TCSC} of -0.028801p.u.

6.2 Multi Objective Optimization

In view of the conflicting nature of these considered objectives, a multi-objective SPEA approach is proposed for optimal location of FACTS controllers. A set of strong dominated solutions is used to form the pareto optimal set. If the size of the pareto set exceeds its maximum value, a hierarchical clustering technique is used to limit its size. Tournament selection is applied on the ($N+\overline{N}$) combined population members, and Blend (BLX-α) crossover, non-uniform mutation are used in all optimization runs. Fast Decoupled load flow (FDLF) with real parameter GA is used as optimization tool to obtain the pareto optimal front. A fuzzy based approach [15] is used to select the best compromise solution [9] from the pareto optimal set. Table 4 presents the SPEA parameters used.

6.2.1 SPEA approach applied for uniform loading of 130%:

When the system is uniformly loaded by 130% lines 1 and 10 are loaded by 126.036% and 110.97% respectively. Multi-objective SPEA GA approach is considered for optimal FACTS location to relieve congestion and results presented in Table 5.

Case-i: BL and VS maximization as objective function

Fig.5 shows the pareto optimal front for BL and VS maximization. The best compromise solution [11] by using SPEA GA approach is 2765.9837 and 1360.63627, which shows 9.03% increase in BL and 12.39% increase in VS. This solution can be obtained by placing two SVC devices at buses 9 and 16 with B_{SVC} of -0.063133p.u, 0.009101p.u respectively and one TCSC in line no.39 with X_{TCSC} of -0.174865p.u.

Case-ii: BL maximization and LM as objective function

Fig.6 shows the pareto optimal front obtained with BL maximization and LM. The best compromise solution obtained is 2684.9562 and 0.18552, which shows 5.83% increase in BL and 2.38% reduction in loss. This solution can be obtained by placing two SVC devices at buses 12 and 21 with B_{SVC} of -0.094271p.u,-0.167034p.u respectively and one TCSC at line 40 with X_{TCSC} of -0.191707p.u.

Table 4. SPEA Parameters

Population size (N)	200
Pareto optimal set size ($\overline{N}$)	30
Reproduction operator	Tournament
Crossover operator, Crossover rate	Blended (BLX-0.5),1.0
Mutation operator, Mutation rate	Non-uniform, 0.006
Maximum generations	50

Case-iii: VS maximization and LM as objective function

Fig.7 shows the pareto optimal front obtained for VS maximization and LM. The best compromise solution obtained is 1357.1246 and 0.184572, which shows 12.10% increase in VS and 2.87% reduction in loss. This solution can be obtained by placing SVC at bus 18 with BSVC of -0.102711p.u and TCSC in line 19 with XTCSC of 0.009802p.u.

Table 5. Comparison of Best Compromise Solution for Uniform Loading of 130% with FACTS Devices Obtained using SPEA GA Approach

	Base case	*130% loading with FACTS devices*			
		BL & VS	**BL & LM**	**VS& LM**	**BL,VS & LM**
BL	2537.05	**2765.98**	**2684.96**	2347.65	**2709.72**
VS	1210.62	**1360.64**	1274.86	**1357.13**	**1297.55**
LM	0.19003	0.19907	**0.18552**	**0.18457**	**0.18637**

Case-iv: BL, VS maximization and LM as objectives

With simultaneous optimization of all the three objectives, BL is increased by 6.47%, the VS is increased by 7.909% and loss is reduced by 1.93% from the base case values. This solution can be obtained by placing SVC at bus 4 with B_{SVC} of -0.438717p.u and TCSC in line 19 with X_{TCSC} of -.041095p.u. Fig.8 shows the pareto optimal front for simultaneous optimization of three objectives.

6.2.2 SPEA approach applied for multi-lateral transaction

Consider a Multilateral transaction between the supplier at node 2 and the consumer at nodes 8 and 21. The base case P_{gen} at supplier node 2 is 0.5756 p.u., P_{load} at consumer nodes 8 and 21 are 0.3p.u., 0.175p.u respectively. By increasing the transaction amount by 170% at supplier node and drawing the same amount at consumer nodes, lines 10 and 27 get loaded by 102.2923% and 116.2234% respectively. Multi-objective SPEA GA approach is considered to relieve congestion. Table 6 presents the optimized objective function values for multi-lateral transaction.

Case-i: BL and VS maximization as objective function

Fig.9 shows the pareto optimal front for BL and VS maximization. The best compromise solution is 1127.9583 and 544.0825, which shows 7.23% increase in BL and 4.45% increase in VS. This solution can be obtained by placing SVC at bus 29 with B_{SVC} of -0.004393p.u and TCSC at line no.30 with X_{TCSC} of -0.09897p.u.

Case-ii: BL maximization and LM as objective function

Fig.10 shows the pareto optimal front obtained with BL maximization and LM. The compromise solution obtained is 1124.9685 and 0.11214, which shows 6.95% increase in BL and 6.54% reduction in loss. This solution can be obtained by placing one SVC at 1st bus with B_{SVC} of 0.058437p.u and two TCSC devices in lines 5 and 19 with X_{TCSC} of -0.374017p.u, 0.1871p.u respectively.

Case-iii: VS maximization and LM as objective function

Fig.11 shows the pareto optimal front obtained for VS maximization and LM. The best compromise solution obtained is 534.1102 and 0.11401, which shows 2.54% increase in VS and 4.97% reduction in loss. This solution can be obtained by placing two SVC devices at buses 5, 25 with B_{SVC} of -0.023498p.u,-0.493176p.u respectively and TCSC in line 19 with X_{TCSC} of 0.009802p.u.

Case-iv: BL, VS maximization and LM as objectives

With simultaneous optimization of all the three objectives, BL is increased by 5.18%, the VS is increased by 2.50% and loss is reduced by 5.25% from the base case values. Fig.12 shows the pareto optimal front for simultaneous optimization of three objectives. This solution can be obtained by placing two SVC devices at buses 2, 22 with B_{SVC} of 0.183417p.u and -0.054798p.u respectively and one TCSC in line 2 with X_{TCSC} of 0.212984p.u. This case presents, the line flows to be well within the limits, improved system voltage profile and minimized losses.

Table 6. Comparison of Best Compromise Solution for a Multilateral Transaction with FACTS using SPEA GA

	Base case	*Multi-lateral transaction with FACTS devices*			
		BL & VS	**BL & LM**	**VS & LM**	**BL,VS & LM**
BL	1051.89	**1127.96**	**1124.968**	1058.888	**1106.37**
VS	520.886	**544.083**	516.5130	**534.1102**	**522.190**
LM	0.11998	0.12351	**0.11214**	**0.111933**	**0.11178**

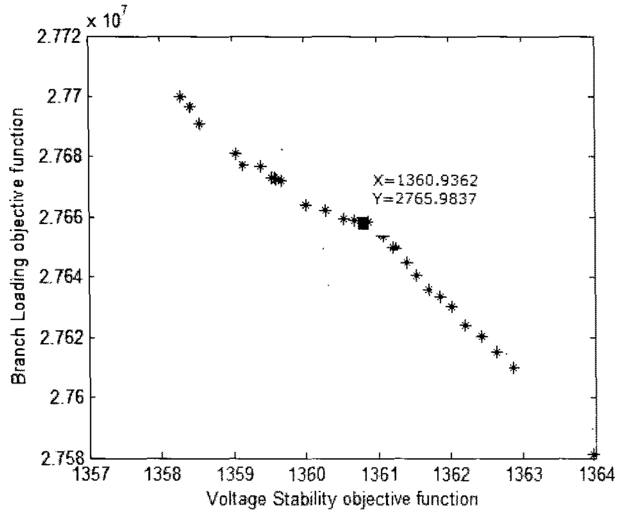

Fig. 5. Pareto optimal front of BL and VS for uniform loading of 130% with FACTS.

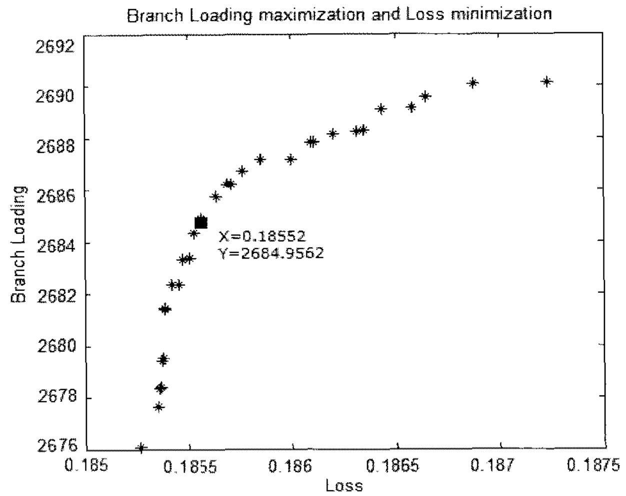

Fig. 6. Pareto optimal front of BL and LM for uniform loading of 130% with FACTS

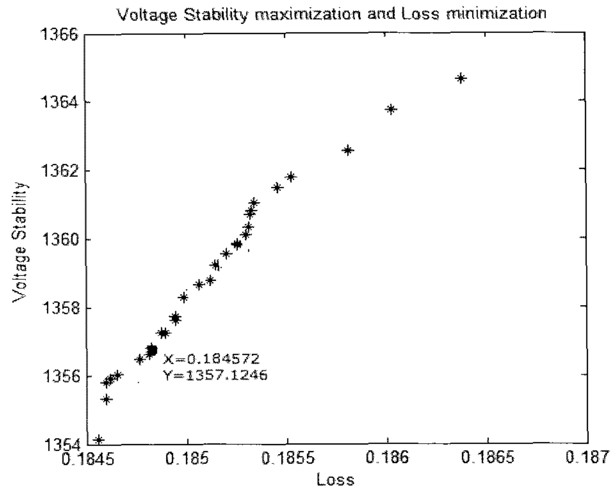

Fig. 7. Pareto optimal front of VS and LM for uniform loading of 130% with FACTS

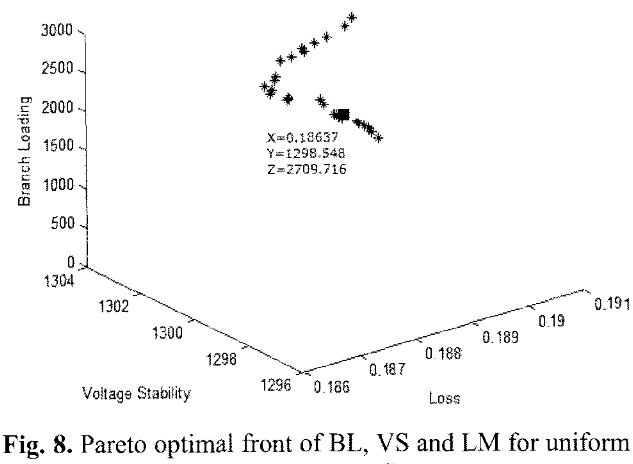

Fig. 8. Pareto optimal front of BL, VS and LM for uniform loading of 130% with FACTS

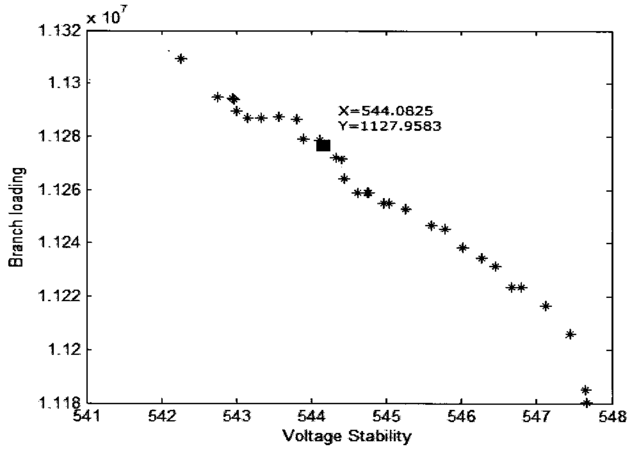

Fig. 9. Pareto optimal front of BL and VS for multi-lateral transaction

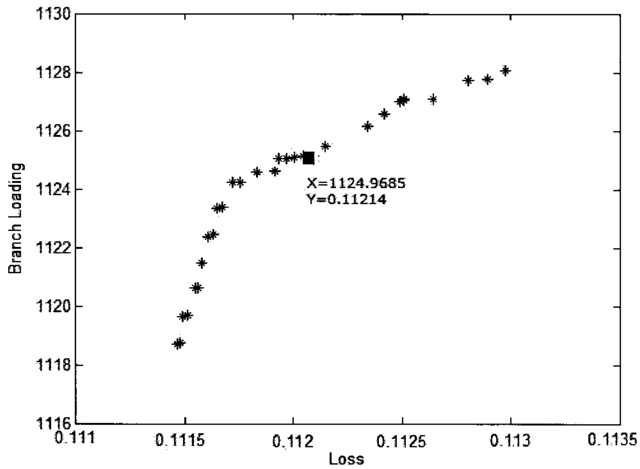

Fig. 10. Pareto optimal front of BL and LM for multi-lateral transaction

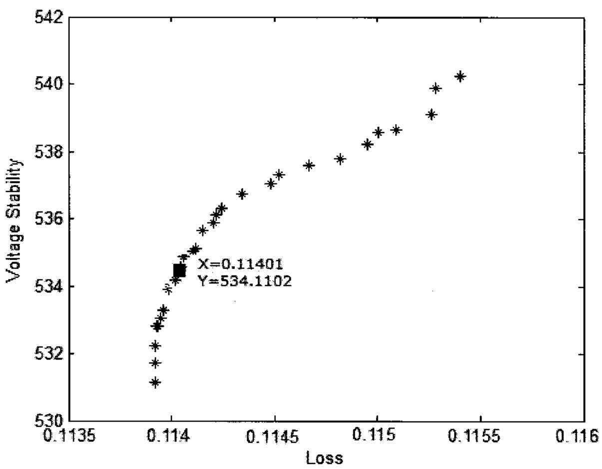

Fig. 11. Pareto optimal front of VS and LM for multi-lateral transaction

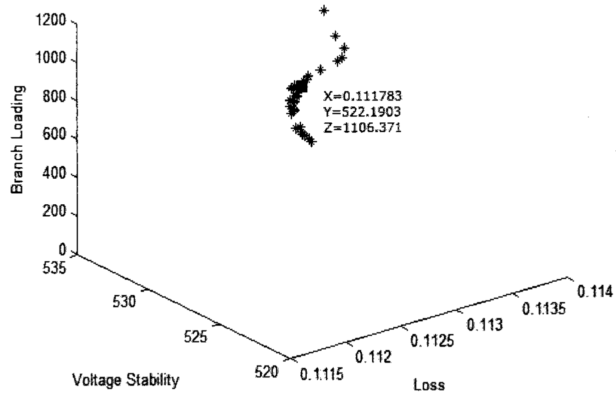

Fig. 12. Pareto optimal front of BL, VS and LM for multi-lateral transaction

7. Conclusions

In this paper an algorithm is developed for optimal choice and location of FACTS controllers for congestion management in deregulated power systems. Genetic Algorithms (GA) are best suitable for solution of combinatorial optimization and multi-objective optimization problems. In this work congestion is created in the system using i) uniform loading ii) line outage iii) bilateral transaction and iv) multilateral transactions. Optimal location of FACTS to relieve line congestion is treated as a single objective optimization problem considering i) BL ii) VS and iii) TL as objectives. It is observed that the locations which present favourable solution with respect to one of the objectives are not effective with respect to other objectives.

The results obtained for various cases studied for IEEE 30 bus system reveal that, single objective optimization algorithms do not provide attractive solutions when all objectives considered are to be given equal priority. Therefore, multi objective SPEA with GA is developed for simultaneous optimization of BL, VS and LM. The developed algorithm converges to a well distributed pareto optimal front in just 50 generations. Further, simultaneous optimization of three objectives considered presents optimal location of FACTS devices, which reduce line congestion, improved system voltage profile and reduce system losses. The proposed GA with SVC, TCSC models evolves as a good optimization algorithm for single objective optimization and SPEA for multi-objective optimization studies of optimal location of FACTS controllers' problem.

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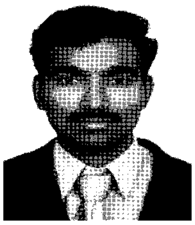

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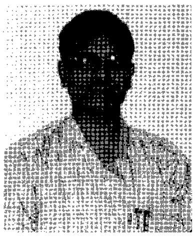

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