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Research Article

Multi Objective Genetic Algorithm for Congestion Management in Deregulated Power System Using Generator Rescheduling and Facts Devices

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Abstract: The problem of congestion management is more pronounced in deregulated environment as the participants of the energy market are market oriented rather than socially responsible-as exhibited by the government operated bundled system. Customers would like to purchase the electricity from the cheapest available sources. The seller in energy market would like to derive more benefit out of their investments, engages with contracts that may lead to overloading of the transmission elements of the power system. An Independent System Operator (ISO) who has no vested interest in the energy market, coordinates the trades and make sure that the interconnected power system always operates in a secure state at a minimum cost by meeting the all the load requirements and losses. In this proposed study, Congestion is mitigated by Generator Rescheduling and implementation of FACTS devices. Minimization of rescheduling costs of the generator and minimization of the cost of deploying FACTS devices are taken as the objectives of the given multi-objective optimization problem. Non-dominated sorting genetic algorithm II is used to solve this problem by implementing the series FACTS device namely TCSC and shunt FACTS device namely SVC. The proposed algorithm is tested on IEEE 30 bus system.

Keywords: Congestion management, generator rescheduling, multi objective optimization, NSGA II, Pareto optimality

INTRODUCTION

The electric utilities around the world have undergone changes in the way they are operated during the last three decades. As happened to many other industries, participation of the private entities in power sector are intended to bring-huge in flow of funding, newer technologies, enriched customer support services etc.. Unbundling of the vertically integrated power system also brings few challenges. The intensive usage of the transmission resources are the real bottlenecks of the deregulated power system. Most of the time power system is operated near to its rated capacity as both buyers and sellers in the market are trying to gain economically by full utilization of the existing resources. Congestion in transmission lines is bound to happen due to the lack of coordination between the generation and transmission utilities. Congestion is also created when contingencies like generation outages, sudden and huge variation in load demands and failure of branches or equipment become reality. In a vertically integrated system, congestion is treated in terms of steady state security and the basic objective was to control the generators' output so that system remains secure at the lowest cost as seen by the mutually agreeing electric utilities. Whereas in a deregulated environment, the sources of congestion are many, as every seller and buyer would like to exploit the transmission facility. The Independent System Operator (ISO) is responsible for mitigating the congestion in the deregulated power industry without compromising the system security and with minimum cost.

In the past, many works have been reported for congestion management in deregulated power system. Optimal Power Flow (OPF) is arguably the most significant technique for congestion management with existing transmission and operational constraints (Christie *et al*., 2000). However, OPF calculation is computationally expensive and time consuming. A genetic algorithm based congestion management using FACTS devices has been described in Deependra and Verma (2011). Market model based congestion management methods are proposed in Fang and David (1999). A method of overload alleviation by real power generation rescheduling based on the concept of Relative Electrical Distance (RED) has been presented in Yesuratnam and Thukaram (2007). Detailed analysis of different congestion management techniques used in different electricity markets and a general congestion relieving algorithm is reported in Bompard *et al*. (2003). Generator sensitivity factor based optimum generation rescheduling and/or load shedding schemes to relieve congestion of transmission lines are reported in Talukdar *et al*. (2005). Various evolutionary methods

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for multi objective optimization are discussed in Hazra and Sinha (2007) and Raghuwanshi and Wakde (2008). A congestion clusters based method has been proposed that groups the system users having similar effects on the transmission constraints in Kumar *et al*. (2004). The locational marginal prices based approach for eliminating congestion has been proposed in Joorabian *et al*. (2011). A strength Pareto evolutionary algorithm has been used for the optimal choice and allocation of FACTS controllers to relieve congestion in Reddy *et al*. (2009).

There are two means of mitigating the congestion and they are:

- Cost free
- Non-cost free

Literature works are found to be employing any one of these two types. As FACTS devices are playing a major role in eliminating congestion, in this study along with the application of FACTS devices, generation rescheduling is also being done to mitigate congestion. Both the cost free and non-cost free techniques are employed here.

In this study, congestion caused by a bilateral contract in the existing market is relieved by generator rescheduling and FACTS devices deployment. The generation sensitivity factors are calculated to identify the generators which contribute more to the congestion at the particular branches. The suitable location for the FACTS devices has been determined by an index called Line Overload Sensitivity Index (LOSI) (Banu and Devaraj, 2012). Non-dominated Sorting Genetic Algorithm (NSGA II) is used to minimize the cost of eliminating congestion by generation rescheduling and the cost of implementing the FACTS devices.

In multiple objective problems, the objectives are generally conflicting, preventing simultaneous optimization of all objectives. Optimizing one objective contradicts a favorable result with respect to the other objectives. Therefore, getting a perfect multi-objective solution that simultaneously optimizes each objective function is almost impossible. Two general approaches are employed to solve the multi objective problem, one is to combine all the individual objective functions into a single composite function by utility theory, weighted sum method etc., but the problem lies in the correct selection of the weights or utility functions to characterize the decision maker's preferences. Choice of weights or utility functions demands thorough technical expertise on the subject. Any small variation in the choice of weights can lead to a very different solution. The second approach is to explore all the trade-off solutions (Pareto Optimal set) available. A reasonable solution to a multi objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. The power system operators have the choice of electing a particular solution from the available non-dominated solution.

SENSITIVITY ANALYSIS

Line overload severity index: The severity of the system loading under normal and contingency cases can be described by the Line Overload Severity Index (LOSI). The LOSI_l for a branch *"l"* is calculated as the sum of the normalized power flow through branch *"l"* to all the considered contingencies 'C', expressed as:

$$\text{LOSI}_l = \sum_{C=1}^{N_c}\left(\frac{S_l^C}{S_l^{\max}}\right)^{2n} \tag{1}$$

where, S_l^C = MVA flow in line during contingency 'C'

The lines with higher LOSI values are where; the FACTS devices are to be employed.

Generation sensitivity factor: While rescheduling the generators for elimination of congestion, the impact on congested line's power flow by all the generators is not uniform and some of the generators will have negligible effect on relieving the congestion of a particular line, whereas some generators affect the congestion in a line heavily. A generator sensitivity factor is calculated to identify the generators which influence more on the congested line. The generators in the system under consideration have different sensitivities to the power flow on the congested line (Dutta and Singh, 2008). Generator sensitivity for line *k* can be written as:

$$Gg = \frac{\Delta P_{ij}}{\Delta P_g} \tag{2}$$

where,

ΔP_{ij} = The change in real power flow on the congested line *k* connected between *i* and *j*

ΔPG_g = The change in real power generated by generator *g*.

FACTS DEVICES FOR CONGESTION MANAGEMENT

FACTS devices based on power electronics technology are used to control the active power, reactive power flow on transmission systems based on the key control variables such as line impedance, phase angle and voltage. Series FACTS devices are used to improve the loadability of the branches, to reduce congestion and thereby better utilization of the existing grid infrastructure by minimizing the gap between the stability and thermal levels. The issues associated with the usage of FACTS devices are appropriate sizing, optimal location, setting, cost and modeling of the devices. For static application like congestion management FACTS can be modeled as Power Injection Model.

Static VAR Compensator (SVC) is an important first generation FACTS device, which is already widely

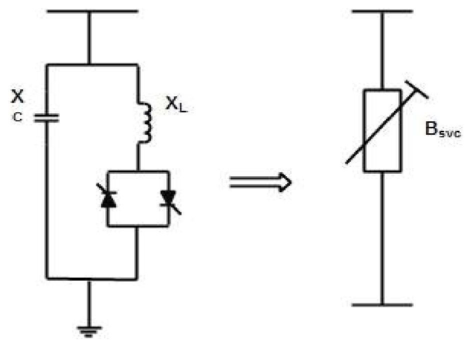

Fig. 1: Basic structure and model of SVC

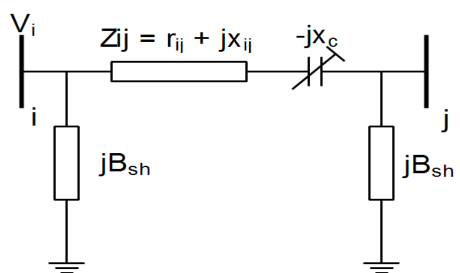

Fig. 2: TCSC located in transmission line

in use. It is a shunt reactive compensation controller consisting of combination of fixed capacitor or Thyristor switched capacitor in conjunction with Thyristor-controlled reactor (FC-TCR). SVC has been in use for the past three decades. In this study SVC has been modeled as an ideal reactive power injection at bus *"i"*:

$$\Delta Q_i = Q_{SVC} \tag{3}$$

The SVC has an operating range of -100MVAR to 100MVAR having a reference voltage of 0.95 pu to 1.05 pu. The basic structure and model of the SVC are depicted as in Fig. 1.

Thyristor Controlled Series Compensator (TCSC) is a second generation FACTS controller, which modifies the line reactance by connecting a variable reactance in series with the line. Variation in reactance is obtained by using fixed capacitor-thyristor controlled reactor combination with mechanically switched capacitor sections in series.

During steady state operation TCSC can be considered as an additional reactance $-jx_c$. Figure 2 shows the model of a branch with one TCSC, which is connected between bus-*i* and bus-*j*.

In order to identify the optimal placement of TCSC under varying system loading LOSI index defined in (4) is calculated at an increased load of 10% from the base values and at a decreased load of 10% from the base values as $LOSI^{IL}$ and $LOSI^{DL}$. The Base case LOSI is also calculated as $LOSI^{BL}$. The location of the TCSC to be placed is decided by taking the average of the three LOSI:

$$\mathrm{LOSI_l} = \left(\frac{LOSI^{BL} + LOSI^{IL} + LOSI^{DL}}{3} \right) \tag{4}$$

The branches are ranked as per their corresponding $\mathrm{LOSI_l}$ values. The TCSC are placed on the branches with the top rank and proceeding downward with as many branches as the number of available TCSC.

PROBLEM FORMULATION

The objectives of congestion management are to minimize the cost due to rescheduling of generators and the cost of utilizing SVC and TCSC devices. The fuel cost will be at minimum for a certain generator output combination-depending on the cost coefficients of the fuel cost equation and the generators' output to meet all the loads and losses. The congestion cost depends on the amount of generation change and the incremental and decremental bids of the generator. The cost for FACTS installation includes the fixed and variable cost of the FACTS devices. Sensitivity factors are calculated for the selection of the generators which have more impact on the congested line. Generators having higher GSF are considered for the rescheduling process.

Rescheduling cost: The generators offer bidding prices for their incremental as well as decremental production. In a deregulated environment some of the generators may opt out in participation to reduce the congestion and some of the generators contribution to reduce the congestion is considerably less due to their network location. Hence only the sensitive generators will be allowed to vary their production. The desirable point of operation is arrived from the OPF solution. Any overload in the transmission will be handled by rescheduling only the selected generators output. In this study, one of the objectives is to reduce such rescheduling cost. The rescheduling cost is determined by:

$$\mathrm{Min}\, C_C = \left(\sum_{i=1}^{N_g} C_{gi} \Delta P_{gi} \right) \tag{5}$$

where,

C_C = The congestion cost
N_g = The number of participating generators that are willing to adjust the output
C_g = The incremental and decremental price bids submitted by the generator
ΔP_g = The real power adjustment done by the generator 'g'.

The generators output should not make any violation of:

- The line flow constraints
- Real and reactive power limits of the generators
- Desired voltage limits at the buses

FACTS cost: The investment cost of FACTS devices are expressed as:

F_{SVCi} = 0.003S2-0.3051S+127.38 (US$/kVAr) (6)

F_{TCSCi} = 0.0015S2-0.713S+153.75 (US$/kVAr) (7)

where, F_{SVC} and F_{TCSC} are the fixed cost and variable cost for candidate FACTS device *i*, respectively. S is the reactive power supplied by the SVC and the reactance added to branches by the TCSC. The additional VAR of the selected FACTS devices is restricted to a maximum limit c_{It} for physical considerations. The constraints for c_{It} can be expressed as $-100 \leq c_{It} \leq 100$ and the reactance value of the TCSC is restricted to $X_{TCSC} = d^*(X_{li})$, where $-0.8<d<0.2$. X_{li} is the reactance of the branch.
Subject to:

$$P_{Gi} - P_{Di} - \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \cos(\delta_I - \delta_j - \theta_{ij}) = 0 \quad (8)$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \sin(\delta_I - \delta_j - \theta_{ij}) = 0 \quad (9)$$

where,

$$P_{Gi} = P_G^C + \Delta P_{Gi}^u + \Delta P_{Gi}^d, \text{ i = 1, 2, … NG} \quad (10)$$

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad (11)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, \quad (12)$$

$$V_b^{\min} \leq V_b \leq V_b^{\max}, \text{ b = 1, 2, …… NB} \quad (13)$$

$$|S_{ij}(\theta, v)| \leq S_{ij}^{\max} \quad (14)$$

where,

$P_G^{\min}, P_G^{\max}$ = Limits of the active power output of generators
ΔP_G = The change in generation for relieving
Q_g = The reactive power produced by the generators
$Q_G^{\min}, Q_G^{\max}$ = The reactive power limits of the generators, post congestion management
V_b = The voltage at the buses
V_{min}, V_{max} = The limits of bus voltages and their values are 0.95 and 1.05 p.u. respectively.

NON-DOMINATED SORTING GENETIC ALGORITHM

Concept of non-dominated solutions: A *Pareto optimal* solution is one which is not dominated by any other solution in the solution space. A Pareto optimal solution cannot be improved with respect to any objective without compromising at least one other objective. The set of all feasible non-dominated solutions is referred to as the *Pareto optimal set and* for a given Pareto optimal set, the corresponding objective function values in the objective space is called the *Pareto front*. Identifying the entire Pareto optimal set is practically impossible due to its size. In addition, for many problems, especially for combinatorial optimization problems, proof of solution optimality is computationally infeasible. Therefore, a practical approach to multi-objective optimization is to investigate a set of solutions (the best known *Pareto set*) that represent the Pareto optimal set as much as possible.

Working principle of NSGA II: Non-dominated Sorting Genetic Algorithm (NSGA) introduced by Srinivas and Deb (1993), differs in other multi-objective algorithm in the selection method based on classes of dominance of all solutions. NSGA derives non-dominated solutions in the population, ion, to form non-dominated fronts, based on the concept of non-dominance of Pareto. Other genetic operations like selection, crossover and mutation are performed as usual. Computational complexity, lack of elitism and choosing the optimal value for the sharing parameter σ_{share} are some of the difficulties found in NSGA. To sort out these difficulties NSGA II is developed with better sorting algorithm, incorporating elitism and no sharing parameter needed to be chosen a priori (Deb *et al*., 2002).

In NSGA-II algorithm the population with size N, is initialized randomly and is sorted based on non-domination in each front. The completely non-dominated set forms the first non-dominated front. The second front being dominated only by the first non-dominated front and so on. Each individual in each front are assigned rank values or based on the front in which they belong to. After ranking, a crowding distance is calculated for each individual to measure how close an individual is to its neighbors. Parents are selected from the population using binary tournament selection based on the rank and crowding distance. While selecting among the population, individuals with lesser rank and greater crowding distance are opted and such selected individuals generates the offspring by crossover and mutation operations. Existing population along with current offspring is sorted again based on non-domination and the best N individuals are selected as the parents for the next iteration.

Population initialization: The population is initialized randomly for all the decision variables. The population is generated within the decision variable range and constraints if any. All the variables are made in real form.

Non-dominated sorting: The initialized population is sorted based on non-domination. The fast sort algorithm is described as follows. For each individual *p* in main population P:

- Initialize S_p = Φ. This set would contain all the individuals that are being dominated by *p*.
- Initialize n_p = 0. This would be the number of individuals that dominate *p.*
- For each individual *q* in P, if p dominated *q* then add *q* to the set S_p, else if *q* dominated *p* then increment the dominated counter for *p. i.e.* $n_p = n_p+1$.
- If n_p = 0 i.e. no individual dominate p then p belongs to the first front, set rank of individual *p* to one *i.e.* p_{rank} = 1. Update the first front set by adding p to front one *i.e.* $F1 = F1 \cup \{p\}$
- This is carried out for all the individuals in main population P.
- Initialize the front counter to one, I – 1
- Following is carried out while the ith front is non-empty i.e., $Fi \neq \Phi$ and Q = Φ. The set for storing the individuals for (i+1)th front.
- For each individual *p* in front F_i. For each individual *q* in S_p (S_p is the set of individuals dominated by *p*) $n_q = n_q - 1$, decrement the domination count for individual *q*.
- If n_q = 0 then none of the individuals in the subsequent fronts would dominate *q*. hence set $q_{rank} = i+1$.
- Update the set *Q* with individual *q* i.e., $Q = Q \cup q$. Increment the front counter by one. Now the set *Q* is the next front and hence $Fi = Q$.

As this algorithm uses elitism by utilizing the information about the set that an individual dominate (S_p) and number of individuals that dominate the individuals (n_p).

Crowding distance: After the non-dominated sorting of the population the crowding distance is calculated. As the individuals are selected based on rank and crowding distance, all the individuals in the population are assigned a crowding distance value. Crowding distance is assigned front wise and comparing the crowding distance between two individuals in different front is meaningless. The procedure for calculating the crowding distance is as follows:

- For each front Fi, n is the number of individuals and initialize the distance to be zero for all the individuals i.e., Fi(dj) = 0, where j corresponds to th jth individual in front Fi
- For objective function m, sort the individuals in front Fi based on objective m i.e., i = sort (Fi, m)
- Assign infinite distance to boundary values for each individual in Fi i.e., I(d1) = ∞
- For k = 2 to (n-1):

$$I(d_k) = I(d_k) + \frac{I(k+1).m - I(k-1).m}{f_m^{\max} - f_m^{\min}} \tag{15}$$

- I(k).m is the value of the mth objective function of the kth individual in I

The idea behind the crowding distance is finding the Euclidian distance between each individual in a front based on their m objectives in the m dimensional hyper space. The individuals in the boundary are always selected since they have infinite distance assignment.

Selection: After non-dominated sorting of the population and with crowding distance assigned, the selection is carried out using crowded-comparison operator (a_n). The comparison is carried out as below:

- Non-domination rank p_{rank} i.e., individuals in front F_i will have their rank as $p_{rank} = i$
- Crowding distance *Fi*(*dj*)
  - P a_n q if
  - Prank<qrank
  - Or if p and q belong to the same front Fi then Fi(dp)>Fi(dq) i.e., the crowding distance is more
- The new individuals are then selected by using a binary tournament selection with crowd comparison operator

Genetic operators: NSGA II employs Simulated Binary Crossover (SBX) and polynomial mutation (Alawode *et al*., 2010). Then the offspring population is combined with the current generation population and selection is made to identify the next generation of the population. As all the previous and current best individuals are added in the new population, elitism is ensured. The new population then undergoes non-dominated sorting. The new generation is filled by each front subsequently until the population size exceeds the current size. If the population in a front Fj exceeds N then it will be limited to N by admitting only the individuals with lower crowding distance. The same process will be repeated to generate the new population for successive generations.

SIMULATION RESULTS AND DISCUSSION

The proposed NSGA II algorithm has been applied to solve the congestion management problem in IEEE 30 bus test system. The objectives are to minimize the generator rescheduling cost and to minimize the cost for implementation of FACTS devices. The data pertaining to the generator, transmission line and generator cost coefficients of IEEE 30 bus system are taken from Alsac and Scott (1974). MATPOWER package has been used to solve the power flow problems (Zimmerman *et al*., 2011). The LOSI has been calculated and two branches (5 and 36) have been identified for TCSC deployment. Two numbers of SVC are to be placed at buses (9 and12) where the voltage is found to be violating the limits. NSGA II has been developed using MATLAB 7.9 and has been run on Core i3 Pentium processor having 2.20 GHz clock. The optimal GA parameters are:

Number of Generation	: 50
Population size	: 50
Crossover rate	: 0.8
Mutation rate	: 0.5

NSGA II has been coded to minimize the cost required to eliminate the congestion. Minimization of the rescheduling cost and minimization of the FACTS cost are the two objectives. The algorithm is tested for two cases on IEEE 30 bus system. Rescheduling of all the six generators along with SVC and TCSC implementation is done in case 1. In case 2, only three generators which are having higher sensitivity factors for the congested line alone made to reschedule along with SVC and TCSC implementation cost.

Case (i): Congestion relieved by rescheduling all the generators and employing SVC and TCSC devices: Two numbers of SVC are placed in buses where voltage at the buses is low. Two numbers of TCSC are added to the branches having highest LOSI. All the six generators have been rescheduled to eliminate the congestion. The MVAR values of the SVCs, reactance value of the TCSCs and the rescheduled power output of the generator are the control variables to minimize the cost of rescheduling and to minimize the FACTS cost. A bilateral transaction of 15 MW is considered between bus 2 and bus 29 for creating congestion.

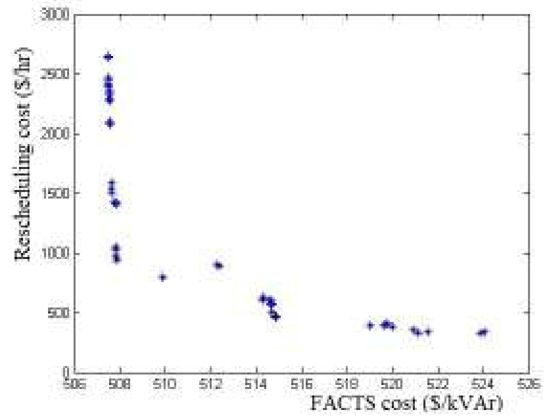

Fig. 3: Pareto optimal front for case (i)

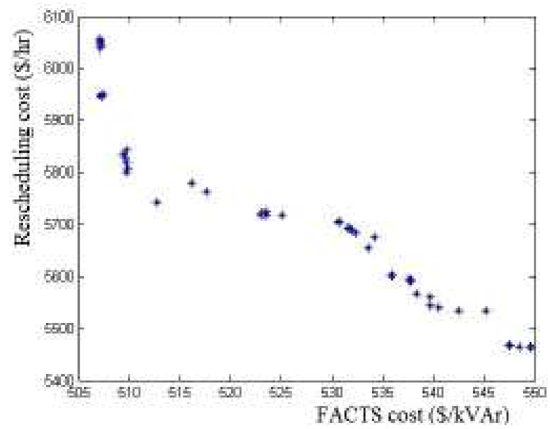

Fig. 4: Pareto front for case (ii)

The Pareto front for case (i) is in Fig. 3. The rescheduled power output and the values of the SVC and TCSC are given in Table 1. The independent system operator can opt for suitable decision among these Pareto solutions.

Case (ii): Congestion relieved by rescheduling sensitive generators and FACTS devices: The generator sensitivity factor has been calculated to identify the sensitive generators which affect the congested line. The generators at bus numbers 5, 11 and 13 are selected for rescheduling to eliminate the congestion. Two numbers each of SVC and TCSC are connected as above. The Pareto front for the case (ii) is in Fig. 4. The rescheduled power output and the values of the SVC and TCSC are given in Table 2.

Table 1: Generator rescheduling and FACTS values for case (i)

S. No	Extreme points	P_{g1}	P_{g2}	P_{g5}	P_{g8}	P_{g11}	P_{g13}
1	Left	94.2936	35.3	26.337	22.535	16.93	22.81
2	Right	174.99	44.80	20.93	18.17	12.87	12.00
S. No	Extreme points	X_{SVC1}	X_{SVC2}	X_{TCSC1}	X_{TCSC1}	Resched. cost	FACTS cost
1	Left	-99.22	-99.99	-0.1877	-0.1846	2608.2	507.70
2	Right	-44.54	-93.12	-0.4484	-0.384	333.55	524.1

Table 2: Sensitive generators' rescheduled output and FACTS values for case (ii)

S. No	Extreme Points	P_{g5}	P_{g11}	P_{g13}	X_{SVC1}	X_{SVC2}	X_{TCSC1}	X_{TCSC1}	Resched. cost	FACTS cost
1	Left	43.84	21.88	14.95	99.51	100	0.1858	-0.0604	6050.5	507.27
2	Right	50.00	29.99	21.53	96.18	-44.07	0.1312	-0.1366	5465.5	549.73

From the results, it is observed that generator rescheduling in all generators produces lesser cost of rescheduling and FACTS cost. In a deregulated environment there are occasions, when certain generators may not be available for rescheduling due to various reasons, in such conditions only selected generators are made to allow rescheduling.

CONCLUSION

In this study NSGA II based congestion management has been proposed to minimize the rescheduling cost and the FACTS cost. The simulation study has been conducted on IEEE 30 bus system for a bilateral transaction. Congestion created by such a transaction is eliminated so that the cost of rescheduling and the FACTS costs are minimized. While eliminating the congestion the rescheduled values of the generator and the FACTS parameters are tuned to have no violation in the voltage limits at the buses and the line flows are observed within limits. NSGA II has performed well to identify the various options available to the ISO to minimize the rescheduling cost and FACTS installation cost.

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