Smart Grid Congestion Management Through Demand Response

J. Hazra, Kaushik Das, and Deva P Seetharam
IBM India Research
Email:{jahazra1,kausdas8,dseetharam}@in.ibm.com

***Abstract*—This paper proposes a novel cost-effective congestion management (CM) scheme for smart grids through demand response(DR). In this congestion management, two objectives i.e. acceptable congestion and congestion cost including DR are optimized by choosing optimal mix of generation rescheduling and DR of participating buses by minimizing the impact on revenues and customer satisfaction. Participating generators for rescheduling and loads for DR are selected using an sensitivity index which combines both biding cost and sensitivity to alleviate the congestion. The scheme employs a meta-heuristic optimization technique called Ant Colony Optimization to optimize the individual options and uses a fuzzy satisfying technique to choose the best compromise solution from the set of Pareto optimal solutions. The proposed system has been evaluated on benchmark IEEE 30 bus test systems and the results of this evaluation are presented in this paper.**

I. Introduction

Congestion in smart grid is a very common problem mainly because of increased penetration of intermittent renewable sources and diminishing spare capacity of the grid due to extensive usuage of transmission system. In a competitive energy market, most of the time grid operates very close to it's capacity. Therefore, congestions may occur frequently due to unexpected line outage, generator outage, sudden increase of demand, failures of equipments, lack of co-ordination among generation and transmission, etc. Sometimes, such congestions are not alleviated intentionally due to economic reasons which not only decreases asset life time, but also triggers the large blackouts. In fact, several blackouts have happened from congestion [1]. Hence, network congestion has become a major concern for smart grids and there is a growing demand for fast, transparent, and cost effective congestion management solutions for smart grids.

In the literature, many methods are reported for congestion management in power systems. For example, in references [2], [3] congestions are managed through cost-free means such as network reconfiguration, operation of transformer taps and operation of flexible alternating current transmission system (FACTS) devices. Generation rescheduling and load shedding are used in [4], [5] for alleviation of congestion. In these methods system operator has no choice of selecting the participating generator and/or load buses. Reference [6] proposed a mathematical model of bus Sensitivity Factors (SFs) which relate the bus injections to change in line currents. These SFs are used to alleviate the congestion by selecting high sensitive generator and/or load buses. However, this method does not consider the cost of generation rescheduling and/or load shedding. Reference [7] proposed a direct method for alleviation of congestion where both cost of load shedding and generation rescheduling are considered. Considering slow dynamics of the grid, a congestion management method has been proposed in [8]. Reference [9] proposed a congestion management technique considering the risk of cascading failures due to malfunctioning of protection system.

Most these methods manage congestion by either generation scheduling and/or by load shedding which is determined by Independent System Operators (ISOs) where loads have no options to act. Recently several pricing schemes such as real time pricing, time of use pricing, peak pricing, peak reduction credit, etc are proposed for demand response which enables loads to directly participate in managing the grid. Demand response shows to have several benefits including better utilization of renewable resources, network reliability enhancement, improving the loadability of the transmission lines, etc. Recently, a combination of demand response and FACT control is proposed in [10] for congestion management. However, this method may not provide optimal solution as it does not consider cost sensitivity while selecting DR participants.

In this paper, a novel congestion management scheme is proposed through demand response. In this method, a trade-off has been made between tolerable congestion and the cost of operation while managing the congestion. A Sensitivity Index (SI) which combines the cost and sensitivity is proposed to use for selection the participating loads for DR and generators for rescheduling. Congestion is managed through optimal mix of generation scheduling and demand response. A multi objective Ant Colony Optimization (ACO) method has been used to generate the trade-off solutions and a fuzzy satisfying method has been used to select the best compromise solution from the set of Pareto optimal solutions.

Rest of the paper is organized as follows. Section II briefly presents the congestion management formulation. Section III describes the sensitivity index used for load and generation selection in CM and Section IV describes the ant colony optimization method. Section V presents the fuzzy approach for selecting the best compromise solution, and section VI describes the congestion management strategy. Section VII presents the simulation results whereas Section VIII concludes the proposed work.

II. System Architecture

Electric power market is considered to have three categories of participants i.e. the bidders, the scheduling coordinators and the independent system operator. Responsibility of each of these participants is described as follows:

A. The Bidders

Generation and distribution companies form this group. This group encompasses both the load and generation side of the market. Bidders may have their own physical assets, or act as aggregators for other producers or consumers. During congestion in power network they offer their bid price to the scheduling coordinator to manage the congestion.

B. The Scheduling Coordinator

The function of the scheduling coordinator is to match load and generation bids to produce a balanced transaction for submission to the system operator. By aggregating the curves on the supply and demand side, the scheduling coordinator calculates a market clearing price which is awarded to all accepted bids.

C. The Independent System Operator

Scheduling coordinators pass on balanced load generation transactions to the system operator. The ISO then carries out congestion management, before returning the revised schedules to the scheduling coordinators.

III. Problem formulation

The objective of the proposed congestion management is to minimize the congestion as well as the cost of operation. Mathematically it can be represented as follows:

Objective 1: Minimize congestion

$$Minimize\, OL = \sum_{i=1}^{nl} (S_i - S_i^{max})^2 \tag{1}$$

where, OL is cumulative overload, nl is number of overloaded line, S_i is MVA flow on line i, and S_i^{max} is MVA capacity of line i.

Objective 2: Minimize cost of operation

$$\begin{aligned} Minimize\, TC \quad &= \quad \sum_{i=1}^{ng} [(a_i + b_i.\Delta P_{gi} + c_i.\Delta {P_{gi}}^2) \\ &+ \quad |e_i \times \sin(f_i \times (P_{gi} - P_{mini}))|] \\ &+ \quad \sum_{k=1}^{pl} (a_k^{'} + b_k^{'}.\Delta D_k + c_k^{'}.\Delta {D_k}^2) \end{aligned} \tag{2}$$

where, TC is total operation cost, ng is number of participating generators, pl is number of participating loads, ΔP_{gi} is the amount of generation change at bus i generator, P_{mini} is minimum generation of i^{th} generator, ΔD_k is amount of load change at bus k, a_i, b_i, c_i are cost coefficients of generator i, $a_k^{'}, b_k^{'}, c_k^{'}$ are cost coefficients demand response at load bus k and e_i, f_i are coefficients of generator i reflecting valve point loading effect.

Constraints

Equality constraints

Network power flow equations:

$$P_{gi} - P_{di} = \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \cos(\delta_i - \delta_j - \theta_{ij}) \tag{3}$$

$$Q_{gi} - Q_{di} = \sum_{j=1}^{NB} |V_i||V_j||Y_{ij}| \sin(\delta_i - \delta_j - \theta_{ij}) \tag{4}$$

where,

P_{gi}, Q_{gi}	real and reactive power generation at bus i;
P_{di}, Q_{di}	real and reactive power demand at bus i;
NB	number of buses;
$\|V_i\|, \|V_j\|$	voltage magnitude at bus i and j respectively;
Y	network admittance matrix;
δ_i, δ_j	voltage angle of bus i and bus j respectively;
θ_{ij}	admittance angle of line between buses i and j.

Inequality constraints

Inequality constraints are operating and physical limits of each transmission line, transformer and generator as follows:

$$Flow_i \leq Capacity_i \tag{5}$$

$$V_{mini} \leq V_i \leq V_{maxi} \tag{6}$$

$$P_{mini} \leq P_{gi} \leq P_{maxi} \tag{7}$$

$$Q_{mini} \leq Q_{gi} \leq Q_{maxi} \tag{8}$$

where,

V_{mini}, V_{maxi}	minimum and maximum voltage limit
$Flow_i, Capacity_i$	power flow on line and line capacity
P_{mini}, P_{maxi}	minimum and maximum active power generation limits of generator i;
Q_{mini}, Q_{maxi}	minimum & maximum reactive power generation limits of generator i.

IV. Selection of participation nodes

For any congestion, utilities interested in participating congestion management may not be be equally cost effective and/or sensitive in managing congestion. For example, in any congested place, local utilities are expected to be more effective than remote ones in alleviating it. On the other hand, remote utilities may be cheaper than local utilities. Hence, it is essential to select the optimal mix of utilities so that total operation cost is minimized. In this paper, a sensitivity index called SI is used to select the participating buses where SI is defined as follows:

$$SI = f_i \times IC \tag{9}$$

where IC is incremental cost of generation (IC_g) or load (IC_l) defined as follows:

$$
\begin{aligned}
IC_g &= b_i + 2c_iP_{gi} + |e_if_i \times \cos(f_i \times (P_{gi} - P_{mini}))|] \\
IC_l &= b_k^{'} + 2c_k^{'}D_k
\end{aligned}
$$

and (f_i) is the sensitivity of the change in line flow with respect to injection defined as follows [11]:

$$
\begin{aligned}
f_i = \frac{\Delta I_{km}}{\Delta P_i} &= \frac{\partial I_{km}}{\partial \delta_k}\frac{X_{ki}}{|V_i|} + \frac{\partial I_{km}}{\partial \delta_m}\frac{X_{mi}}{|V_i|} \\
&+ \beta_i\left(\frac{\partial I_{km}}{V_k}\frac{Y_{ki}}{|V_i|} + \frac{\partial I_{km}}{V_m}\frac{Y_{mi}}{|V_i|}\right) \quad (10)
\end{aligned}
$$

where, ΔI_{km} is change in line current from bus k to m, ΔP_i is change in real power injection at bus i, X/Y is element of admittance matrix, V is voltage magnitude and δ is voltage phase angle.

Participating generators are selected on the basis of SI values. As the power output from a generating station can be increased or decreased (within the operating limits) according to requirements, generator buses with high positive or negative SI value can be selected as a participating generator in congestion management. On the other hand as demand is assumed to be decreased only, buses with high negative sensitivity values are considered for DR. For non-participating buses the sensitivity values are assigned as zero.

V. Ant Colony Optimization (ACO)

In this paper a multi-objective ant colony optimization technique proposed in [12] is used. The algorithm consists of four stages i.e. solution construction, pheromone update, local search and pheromone re-initialization as described follows:

1) Solution Construction: In this method, initial position of each ant i.e. initial solution vectors are generated randomly in the feasible search region. In each iteration artificial ant construct the solution by generating a random number for each variable using the normal distribution $N(\mu_i, \sigma_i^2)$. Mean (μ_i) and standard deviation (σ_i^2) for each variable i changes with iteration number based on the experience of the colony.

2) Pheromone update: For multi-objective the real difficulty lies in the definition of the best solutions of the candidate set. In this paper the best solutions with respect to each objective are selected to update the pheromone information. Then, when multiple pheromone information is considered, each pheromone matrix associated with each objective is updated by the solution with the best objective value for the respective objective. Pheromone matrix for any objective is updated as follows:

$$
\begin{aligned}
\mu_i(t) &= \mu_i(t) + \rho_2 x^{gb} \\
\sigma_i(t) &= \sigma_i(t) + \rho_2|x^{lb} - \mu_i(t-1)|
\end{aligned} \quad (11)
$$

where $\rho_2 \in [0, 1]$ is the intensification parameter, a uniform random number between 0 and 1 and x^{lb} is the local best solution (Pareto optimal) found in last (t-1) iteration.

3) Local Search: In this paper Pareto Local Search (PLS) proposed in [13] is implemented. PLS starts from a solution and examines its neighborhood. Next, any nondominated solution found is added to an archive and the dominated ones are removed from it. PLS terminates when all the neighboring solutions of all solutions in the archive have been explored.

4) Pheromone Re-initialization: To avoid premature convergence or getting trapped into local minima pheromone re-initialization is done looking at a convergence factor cf defined as follows [14]:

$$
cf = \frac{\sum_i^n \frac{2\sigma_i}{b_i - a_i}}{n} \quad (12)
$$

The pseudo code for ACO is shown in Table I.

TABLE I
PSEUDO CODE FOR ACO

```
Randomly generate initial solutions within search space
and initialize pheromone trails
Repeat
    Construct solution for each ant using normal distribution
    Identify global best and local best ant
    Conduct local search on them
    Update pheromone
    Check the convergence factor. If below
    threshold re-initialize pheromone
Until some convergence criteria is satisfied
    Provide the set of Pareto optimal solutions
```

VI. Selection of compromise solution

In order to chose a suitable solution from the set of pareto optimal solutions, a fuzzy satisfying method is used to find the best compromise solution from a set of Pareto optimal solutions. For each objective fuzzy membership is defined by linear function as follows:

$$
\mu_i = \begin{array}{ll} 1 & if \quad f_i \leq f_i^{min} \\ \frac{f_i^{max} - f_i}{f_i^{max} - f_i^{max}} & if \quad f_i^{min} < f_i < f_i^{max} \\ 0 & if \quad f_i \geq f_i^{max} \end{array} \quad (13)
$$

where

μ_i is membership value of objective i;
f_i^{min} is the value of objective i which is completely satisfactory;
f_i^{max} is the value of objective i which is completely unsatisfactory.

For each Pareto solution normalized membership function is found as follows:

$$
\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M}\sum_{i=1}^{N_{obj}} \mu_i^k} \quad (14)
$$

where,

N_{obj} is the number of objective functions;
M is number of Pareto optimal solutions;
μ^k is membership value of non dominated solution k.

The non-dominating solution that attains the maximum membership μ^k is chosen as the best compromise solution.

VII. Congestion Management Strategy

In this method set of participating loads and generators is selected based on sensitivity index as described in Section III. With the selected participants congestion is managed by optimal mix of generation rescheduling and/or demand response based on required level of congestion alleviation. In case of multiple line overloads, congestions are solved simultaneously to avoid oscillatory solution and non-convergence due to conflict. Per unit values of load and generation are taken as state variables. Computational steps of the proposed congestion management scheme is summarized as follows:

1) Identify the congested lines and transformers in the grid.
2) Collect bidding from generators and loads interested in congestion management.
3) Calculate sensitivity Indices (SIs) for interested generators and loads with respect to change in current flow on each congested line.
4) Select high sensitive generators and loads for CM.
5) Minimize cost of operation and congestion using Ant Colony Optimization.
6) Check whether congestion is managed.
   a) If not, select more participants and goto step 5.
   b) Else, go to step 7.
7) Select the best compromise solution from the set of Pareto optimal solutions using fuzzy approach.
8) Present the solution to the decision maker.

VIII. Simulation Results

Proposed congestion management method is evaluated on benchmark IEEE 30 bus test systems. For simulation purpose, cost coefficients as given in Appendix were chosen for DR while cost coefficients for generators were chosen from reference [11]. With the given cost functions, an experiment was done to optimize the colony size while optimizing the pre-congestion generation cost. Convergence characteristics with different size of colony are given in Figure 1. From this figure, it is clear that colony of 10 ants provides satisfactory convergence characteristic. From this experiment it seems that optimal number of ants in the colony is proportional to the dimension of the optimization problem. Hence, for congestion management, colony size was chosen as the number of variables to be optimized. In order to evaluate the proposed congestion management technique, congestions were simulated by setting reduced value for the line limits of a few lines. Detailed simulated cases are given in Table II.

TABLE II
SIMULATED CASES

Test system	Simulated cases	
IEEE 30 Bus	1A	Overload simulation by reducing capacity of line 1-2 to 70 MVA
	1B	Overload simulation by reducing capacity of lines 10-21 to 10 MVA respectively
	1C	Overload simulation by reducing capacity of lines 2-5 and 5-7 to 40 MVA and 10 MVA respectively

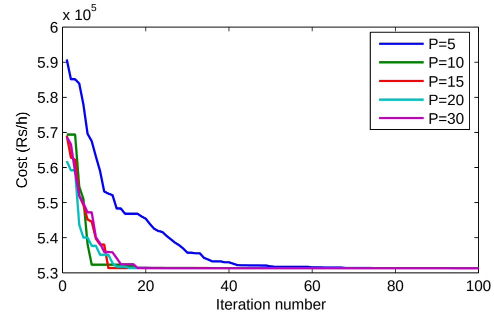

Fig. 1. Convergence characteristics with different colony size

For case 1A, congestion was created by reducing capacity of line 1-2 from 130 MVA to 70 MVA. Sensitivity indices of generators and loads with respect to change in flow on line 1-2 are given in Table III and Table IV, respectively. In this case all the sensitivities are negative which indicate congestion can be alleviated either by increasing the generation or by reducing load. As generator sensitivities are more or less equal, all the generator buses are selected for CM. In this case, there are several load buses having high sensitivity index. All the load buses having sensitivity index $SI \geq 0.036$ are selected for congestion management. In this case, though few loads such as buses 2, 5 and 7 are highly sensitive to alleviate the congestion, got lower rank in the SI table as their incremental costs are very high. With the selected participants ACO was run and obtained Pareto optimal solutions are presented in Figure 2. Figure 2 clearly shows Pareto solutions are uniformly distributed accrross the Pareto font. Non-dominated solutions with minimum cost, minimum congestion and a trade-off from these Pareto optimal solutions are presented in Table V. From Table V it is clear that in this case demand response participation is not economical and hence congestion is managed only with generation rescheduling. In this case, if the operator wants to alleviate the overload completely he will choose the solution 1 and for this case congestion cost will be as high as Rs/h 113925. But if the operator allows some overload ($\simeq 10\%$) and chooses solution 2, congestion cost will be as low as Rs/h 31701. This motivates utilities to allow some overload. However, sometime such overload may not be acceptable due to reliability threat. In such case utilities always can chose a compromise solution where tradeoff is made between cost and congestion. Solutions 1, 2 and 3 clearly show that if the operator wants to alleviate the over load completely he has to sacrifice the cost a lot.

TABLE III
GENERATOR SENSITIVITIES W.R.T CONGESTED LINES

Bus	1-2	10-21	2-5	5-7
2	-0.0304	0.00006	0.0015	-0.0011
5	-0.0279	0.0001	-0.0266	-0.0199
8	-0.0245	0.0002	-0.0067	0.0064
11	-0.0246	0.0021	-0.0065	0.0060
13	-0.0237	-0.0003	-0.0056	0.0051

TABLE IV
LOAD SENSITIVITIES W.R.T CONGESTED LINES

Bus	Sensitivity Index w.r.t				Bus	Sensitivity Index w.r.t			
	1-2	10-21	2-5	5-7	Bus	1-2	10-21	2-5	5-7
2	-0.0374	0.0001	0.0018	-0.0014	17	-0.0370	0.0072	-0.0094	0.0099
3	-0.0282	0.0002	-0.0057	0.0064	18	-0.0371	0.0007	-0.0092	0.0090
4	-0.0343	0.0003	-0.0069	0.0072	19	-0.0369	0.0028	-0.0092	0.0092
5	-0.0255	0.0001	-0.0243	-0.0182	20	-0.0374	0.0038	-0.0094	0.0094
7	-0.0313	0.0003	-0.0180	0.0233	21	-0.0362	-0.0489	-0.0093	0.0099
8	-0.0293	0.0002	-0.0080	0.0076	23	-0.0371	-0.0120	-0.0092	0.0093
10	-0.0374	0.0071	-0.0096	0.0097	24	-0.0371	-0.0290	-0.0095	0.0103
12	-0.0357	-0.0007	-0.0084	0.0085	26	-0.0377	-0.0171	-0.0098	0.0107
14	-0.0365	-0.0015	-0.0087	0.0084	29	-0.0379	-0.0087	-0.0100	0.0104
15	-0.0365	-0.0026	-0.0088	0.0086	30	-0.0370	-0.0070	-0.0098	0.0098
16	-0.0370	0.0032	-0.0090	0.0092					

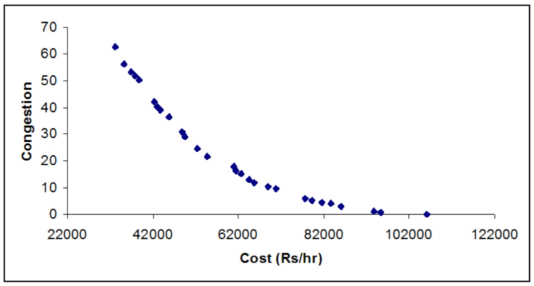

Fig. 2. Pareto optimal solutions for congestion case 1A

For congestion case 1B, generator sensitivities are very low as shown in Table III and hence are not very effective in managing the congestion. This is not surprising because generators are far away from the congestion location. On the other hand, loads at buses 21, 23, 24 and 26 are highly sensitive and hence, are selected for demand response in this congestion management. In this particular case at least one generator needs to be selected as slack because if congestion is managed by load reduction through DR, at least one generator should reduce the generation to balance the total load and generation. In this case generator at bus 11 is selected as slack as it has the highest sensitivity index and is close to the congestion location. Pareto optimal solutions with selected participants are presented in Table V. In this case if the operator wants to alleviate the congestion completely he needs to reduce total 12.07 MW load through DR. In this case 9.75MW, 0.45 MW, 0.81 MW and 1.06 MW loads are reduced at buses 21, 23, 24 and 26, respectively. In response to 12.07 MW of DR, 12.37 MW of generation is backed down at bus 11 to balance the grid. Though load is reduced by 12.07 MW, generator needs to be reduced by 12.37 MW because transmission loss is reduced by 0.3 MW due to load reduction in the grid. For the given scenario, operator needs to pay Rs 14623 as DR incentive and Rs 43450 for generation back down incentive. Hence total congestion cost becomes Rs 58073. It is interesting to note that for the given scenario demand response cost is much lower than the incentive given to the generator only for balancing the grid. Even though high incentive is paid to one generator, overall congestion cost through DR is better than the congestion management through generation rescheduling. It is also obvious that congestion cost can be low if some overload is tolerated. These simulation results clearly show that demand response could be an efficient means of managing congestion in smart grid.

For case 1C, congestion was created on two lines i.e. 2-5 and 5-7. In this case, sensitivity indices with respect to each line are conflicting. For example, for bus 2 generation SI is positive (0.0014) w.r.t. flow on line 2-5 whereas it is negative (-0.0011) w.r.t. flow on 5-7. On both the line power flow is towards bus 5. If generation at bus 2 is increased flow on line 2-5 increases whereas flow on 5-7 decreases and vice versa. In order to achieve a trade-off generators and loads are selected based on absolute value of SI. In this congestion case, it is assumed that most sensitive generator at bus 5 is not interested to participate in the congestion management. Hence, remaining generators and high sensitive loads (at buses 5, 7, 26 and 29) are selected for congestion management. Pareto optimal solutions for this case are presented in Table V. Table V shows that in this case congestion can not be alleviated by generation rescheduling only. Therefore, demand response has to be carried out on participating loads. To alleviate the overload completely operator needs to reduce 28.91 MW load only at bus 5 where 28.91 MW of load reduction is compensated by generation reducing of 26.17 MW at bus 2, 1.08 MW at bus 8, 2.19 MW at bus 11, and 1.03 MW at bus 13. For this case congestion cost becomes as high as Rs 137796 including demand response cost of Rs 53172 and generation rescheduling cost of 84623. As expected, for subsequent solutions congestion cost reduces with higher tolerable overload. All these case studies clearly shows that a combination of DR and generation scheduling could be very effective for alleviating the congestion in smart grid.

IX. CONCLUSION

In the era of grid restructuring, congestion in power network is quite common. This paper proposes a congestion management method through demand response. Simulation results presented in this paper clearly show that with demand response, congestion management becomes more flexible and

TABLE V
SIMULATED CASES FOR IEEE 30 BUS SYSTEM

Case	Over loaded condition			Initial generation/ load* at Participating buses			Pareto optimal solutions								
							Min congestion			Min cost			Compromise		
	Line	MVA Flow	MVA Cap.	Bus code	Pg/ Pd MW	Cong. Cost Rs/h	MVA Flow	Pg/ Pd MW	Cong. Cost Rs/h	MVA Flow	Pg/ Pd MW	Cong. Cost Rs/h	MVA Flow	Pg/ Pd MW	Cong. Cost Rs/h
1A	1-2	79.43	70	1	115.0	550374	70.00	97.80	113925	78.81	113.4	31701	75.88	109.0	47391
				2	69.50			77.33			69.31			74.80	
				5	24.99			32.69			24.91			25.03	
				8	26.70			26.74			26.12			26.67	
				11	27.15			27.25			25.39			27.25	
				13	26.29			26.98			30.33			26.51	
1B	10-21	17.79	10	11	27.15	550374	9.99	14.78	58073	10.84	15.81	54980	10.5	15.11	56554
				21*	17.50			7.75			9.26			8.26	
				23*	3.20			2.75			2.72			2.78	
				24*	8.70			7.89			7.50			8.00	
				26	3.50			2.44			2.17			2.03	
1C	2-5	56.67	40	1	115.0	550374	40.00	115.2	137796	44.79	112.5	121582	41.85	115.2	128894
	5-7	14.21	10	2	69.50		5.26	43.33		9.03	51.96		5.69	45.28	
				8	26.70			25.62			25.64			25.28	
				11	27.15			24.96			24.93			25.44	
				13	26.29			25.26			23.97			25.87	
				5*	94.20			65.29			77.58			69.48	
				7*	22.8			22.80			18.56			22.80	
				26*	3.50			3.50			3.06			3.50	
				29*	2.40			2.40			1.03			1.48	

economical as loads can directly participate in congestion management. Simulation results also show that proposed sensitivity index could be very effective in selecting appropriate participation generation and demand for managing the congestion most economic way. It was also identified that sometimes little overload could reduce the congestion cost significantly.

REFERENCES

[1] R. C. Hardiman, M. Kumbale, and Y. V. Makarov, "An advanced tool for analyzing multiple cascading failures," in *Proc. Intl Conf. Probabilistic Methods Applied to Power Systems*, 12-16 Sept. 2004, pp. 629–634.

[2] N. Acharya and N. Mithulananthan, "Locating series facts devices for congestion management in deregulated electricity markets," *Electr Power Syst Res*, vol. 77, pp. 352–60, 2007.

[3] T. Nguyen and V. Nguyen, "Application of wide-area network of phasor measurements for secondary voltage control in power systems with facts controllers," in *in Proc. Power engineering society general meeting*, vol. 3, 2005, pp. 2927–34.

[4] T. K. P. Medicherla, R. Billinton, and M. S. Sachdev, "Generation rescheduling and load shedding to alleviate line overloads-analysis," *IEEE Trans. Power Apparatus and Systems*, vol. PAS 98, no. 6, pp. 1876–1884, Nov. 1979.

[5] A. Shandilya, H. Gupta, and J. Sharma, "Method for generation rescheduling and load shedding to alleviate line overloads using local optimisation," *IEE Proc. C Gener. Trans. and Dist.*, vol. 140, no. 5, pp. 337–342, Sept. 1993.

[6] D. Hazarika and A. K. Sinha, "Method for optimal load shedding in case of generation deficiency in a power system," *Int. J. Electr. Power Energy Syst.*, vol. 20, no. 6, pp. 411–420, Aug. 1998.

[7] B. K. Talukdar, A. K. Sinha, S. Mukhopadhyay, and A. Bose, "A computationally simple method for cost-efficient generation rescheduling and load shedding for congestion management," *Int. J. Electr. Power Energy Syst.*, vol. 27, no. 5-6, pp. 379–388, June-July 2005.

[8] J. Hazra and A. K. Sinha, "Congestion management using multiobjective particle swarm optimization," in *IEEE Trans. Power Systems*, vol. 22, no. 4, 2007, pp. 1726–1734.

[9] J. Hazra and D. P. Seetharam, "A network congestion management approach considering the risk of cascading failures," in *Proc. PEDES & POWER INDIA CONF*, 2010.

[10] A. Yousefi, T. T. Nguyen, H. Zareipour, and O. P. Malik, "Congestion management using demand response and facts devices," *Electrical Power and Energy Systems*, 2012.

[11] J. Hazra, A. K. Sinha, and Y. Phulpin, "Congestion management using generation rescheduling and/or load shedding of sensitive buses," in *Proc. Third International Conference on Power Systems*, 2009.

[12] M. Lpez-Ibez, "Multiobjective ant colony optimization," Master's thesis, Technische Universitat Darmstadt, Germany, 2004.

[13] L. Paquete and T. Stutzle, "A study of local search algorithms for the biobjective qap with correlated flow matrices," *European Journal of Operational Research*, 2004.

[14] M. Kong and P. Tian, *Ant Colony Optimization and Swarm Intelligence*. Springer-Verlag, 2006, vol. 4150/2006, ch. A Direct Application of Ant Colony Optimization to Function Optimization Problem in Continuous Domain, pp. 324–331.

APPENDIX

TABLE VI
DR COST COEFFICIENTS

Amount of load in the bus(MW)	p' Rs/h	q' Rs/MWh/h	r' Rs/MW^2/h
$\leq$10	0.0	1200	1.00
$\leq$20	0.0	1200	1.50
$\leq$30	0.0	1500	1.25
$\leq$40	0.0	1500	1.35
$\leq$50	0.0	1575	1.25
$\leq$60	0.0	1575	1.5
$\leq$75	0.0	1650	1.25
$\leq$100	0.0	1800	1.35
$\leq$125	0.0	1875	1.425
$>$125	0.0	2025	1.5