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Stochastic Congestion Alleviation with a Trade-off between Demand Response Resources and Load Shedding

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Abstract

Under the smart grid environments, Demand Response Resources (DRRs) as power system resources can effectively participate in and improve performance of electric systems. Congestion management is one of the technical challenges in which DRRs can play a significant role. Previously, congestion management is applied without considering the power system uncertainties. Therefore, a stochastic congestion management by means of a trade-off between DRRs and load shedding is proposed so that the outage of transmission lines and generating units are considered. In order to investigate the proposed framework, two types of Monte Carlo simulation methods, namely 1) ordinary and 2) lattice rank-1, are utilized and compared. Hence, Independent System Operator (ISO) can be able to relieve the existing transmission line congestion considering the uncertain network configuration. The proposed model is applied to the 24-bus Reliability Test System (RTS) and simulation studies are performed to examine the effectiveness and capability of the proposed framework.

Keywords: *Demand response resource (DRR); congestion management; Monte Carlo simulation; load shedding; uncertainty; power system outages*

Nomenclature

B_j^u	Bid price of generation unit *j* to increase its output power
B_j^d	Bid price of generation unit *j* to decrease its output power
$\Delta P_j^{u,\zeta}$	Up generation shift of generation unit *j* under scenario ζ
$\Delta P_j^{d,\zeta}$	Down generation shift of generation unit *j* under scenario ζ
π_{ls}	Value of lost load *ls* for involuntary load shedding
ΔP_{ls}^{ζ}	Amount of involuntary load shedding related to load *ls* under scenario ζ
$price_{dr}$	Price of reducing consumption for demand response participant *dr*
ΔP_{dr}^{ζ}	Power reduction for demand response participant *dr* under scenario ζ
j	Index of generating unit
ls	Index of load shedding
dr	Index of demand response resource
p_j^{Min}, p_j^{Max}	Minimum and maximum limits of generating unit *j*, respectively.
B_k, F_{mn}^{Max}	Susceptance and capacity limit of in service line connected to buses *m* and *n*, respectively

1. Introduction

Transmission lines in a competitive market environment are often driven at or beyond their capacity limits due to an increase in electric power consumption, trades and also unplanned power exchanges [1]. Moreover, if these trades are not controlled, transmission lines may get overloaded and it can be really said that congestion occurs in the power systems. Therefore, one of the most important issues in electric power network is congestion management. Independent System Operator (ISO) has the significant responsibility of relieving the transmission lines congestion using different market tools and techniques so that the system is maintained secure. There are mainly two types of congestion management techniques which ISO can utilize them. One is cost-free tools such as out-ageing of congested lines, FACT devices transformer taps and phase shifters. Another one is non-cost-free techniques such as rescheduling generators output power, involuntary load shedding and transaction curtailment.

In the literature, many methods are reported for congestion management in power systems. Some papers are presented rescheduling the generators output and or involuntary load shedding methods [2-4]. In [5] optimal transmission switching as a congestion management tool is utilized to change network topology. In [6], wind power curtailment and energy storage as transmission congestion mitigation measures are analyzed. Reference [7] presented a generalized optimal model of congestion management for deregulated power sector that dispatches the pool in combination with privately negotiated bilateral and multilateral contracts. Authors proposed the congestion management in distribution networks using electric vehicles in [8]. Reference [9] described a congestion management model considering voltage security and dynamic voltage stability of the power system in which altering the generators and demands power is used.

Under the smart grid environment, Demand response Resources (DRRs) as a consequence of demand response programs (DRPs) can play a significant role for congestion management. Many papers have done studies on demand response programs [10-13] which can be efficient for network reliability enhancement, controlling the electricity price spikes and congestion management [14-16]. The impact of load elasticity on congestion management was investigated in [17]. Reference [15] demonstrated that appropriate invocation of interruptible loads by the independent system operator (ISO) can aid in relieving transmission congestion in power systems.

In previous frameworks [15, 17], congestion management has been implemented without considering the power system uncertainties but in realistic power systems, the status of electric networks such as generating units, transmission lines and loads are not deterministic. In other words, power system components are no fully reliable and may be failed. Hence, it is considerably efficient and pragmatic that ISO carries out the stochastic congestion management considering outage of components. In order to determine the power system reliability, different methods such as N-1 contingency criteria and Monte Carlo simulation can be applied. Instead of applying N-1 or other deterministic contingency criteria, it is better to apply the Monte Carlo method to simulate two or more contingencies together in the stochastic problem.

In this framework, the existing transmission congestion is alleviated at the lowest cost using DRRs and involuntary load shedding as well as generators output rescheduling and also implementing Monte Carlo simulation techniques. The demand response formulation is extended considering simultaneously incentive and penalty programs in order to consumers participate in congestion management as DRRs. Consequently, a trade-off between DRRs and load shedding is carried out and the effect of DRRs' participation on involuntary load shedding and finally the congestion management cost is assessed. In addition, the power system components uncertainty including outage of transmission lines and generating units in this context is considered. For this reason, two types of Monte Carlo simulation methods, namely ordinary and lattice rank-1 Monte Carlo simulation, are applied to stochastic congestion management in presence of DRRs and are also compared. Computation time for solving scenario-based congestion management depends on the number of scenarios in which the congestion cost is minimized. In this paper scenario reduction as a trade-off between accuracy and computational time is performed and the propose problem is solved for accepted scenarios. It should be noted that the results obtained from solving the optimization problem are expected solutions. Here, CPLEX as a sophisticated and computationally efficient MIP solver is applied for solving the proposed model under General Algebraic Modeling System (GAMS) software package.

The rest of paper is organized as follows. The elastic load modeling based on incentive and penalty is explained in section II. Section III provides the power systems uncertainty modeling using Monte Carlo simulation. The formulation of stochastic congestion management considering DRRs and load shedding is presented in section IV. Section V conducts the numerical simulations and finally the conclusion is drawn in section VI.

2. Price sensitive loads

In this context, an elastic load modeling based upon the both incentive and penalty according to customers' benefit function is presented such that DRR's capacity can be estimated. Also, this DRR model makes formulation of bidding curve submitted to the system operator possible. After implementation of DRP, demand change of customers at i-th node can be presented as:

$$\Delta D(i) = D_o(i) - D(i) \tag{1}$$

Where $D_o(i)$ and $D(i)$ are amounts of demand before and after the DRP, respectively. If $\lambda(i)$ is an incentive payment to customers who reduce their consumption 1 MW, whole incentive payment to participating customers can be determined in (2).

$$Incentive(\Delta D(i)) = \lambda(i).(D_o(i) - D(i)) \tag{2}$$

It is worthwhile that if the customers participating in DRPs do not reduce their minimum output power in the contract, they should make a payment as a penalty. Also, if $R(\mathrm{i})$ and $\rho(\mathrm{i})$ are the asking load reduction by system operator and the penalty, respectively, whole penalty $Penalty(\Delta D(i))$ could be expressed as:

$$Penalty(\Delta D(i)) = \rho(i).[R(i) - (D_o(i) - D(i))] \tag{3}$$

It should be noted that the asking load reduction $R(\mathrm{i})$ is limited to enrolled maximum amount $R^{En}(i)$ in the contract between consumer and system operator. The customers' benefit for each period will be:

$$\begin{aligned} Ben &= Rev(D(i)) - \pi(i).D(i) \\ &+ Incentive(\Delta D(i)) - Penalty(\Delta D(i)) \end{aligned} \tag{4}$$

Where $\pi(i)$ and $Rev(D(i))$ are price of electricity after implementing DRP and customer's income, respectively. So, according to the classical optimization rules, to maximize the customer's benefit, $\frac{\partial Ben}{\partial D(i)}$ should be equal to zero. Hence,

$$\begin{aligned} &\frac{\partial Ben}{\partial D(i)} = \frac{\partial Rev(D(i))}{\partial D(i)} - \pi(i) \\ &+ \frac{\partial Incentive(\Delta D(i))}{\partial D(i)} - \frac{\partial Penalty(\Delta D(i))}{\partial D(i)} = 0 \end{aligned} \tag{4}$$

It can be obtained from (5) that

$$\frac{\partial Rev(D(i))}{\partial D(i)} = \pi(i) + \lambda(i) + \rho(i) \tag{5}$$

The most commonly used structural forms for customer's income include quadratic, potential, exponential, and logarithmic functions so that in this paper a logarithmic function is utilized and describes as:

$$\begin{aligned} &Rev(D(i)) = Rev_o(D_o(i)) \\ &+ \frac{\pi_o(i) D(i)}{1 + E(i)^{-1}} \left[\left(\frac{D(i)}{D_o(i)} \right)^{E(i)^{-1}} - 1 \right] \end{aligned} \tag{6}$$

$$\begin{aligned} &\frac{\partial Rev(D(i))}{\partial D(i)} = \frac{\pi_o(i)}{1 + E(i)^{-1}} \left[\left(\frac{D(i)}{D_o(i)} \right)^{E(i)^{-1}} - 1 \right] \\ &+ \frac{\pi_o(i).D(i)}{1 + E(i)^{-1}} \left[\left(\frac{E(i)^{-1}}{D_o(i)} \right) \left(\frac{D(i)}{D_o(i)} \right)^{E(i)^{-1}} \right] \end{aligned} \tag{7}$$

In (7), $E(i)$ and $\rho_o(i)$ are self-elasticity demand and market price before implementing DRP, respectively. Differentiating (7) with respect to D(i) and substituting the result in (6) yields

$$\begin{aligned} &(1 + E(i)^{-1}).\frac{\pi(i) + \lambda(i) + \rho(i)}{\pi_o(i)} \\ &= \left(\frac{D(i)}{D_o(i)} \right)^{E(i)^{-1}} - 1 + E(i)^{-1}.\left(\frac{D(i)}{D_o(i)} \right)^{E(i)^{-1}} \end{aligned} \tag{8}$$

Rearranging (9) leads to

$$\frac{\pi(i) + \lambda(i) + \rho(i)}{\pi_o(i)} = \left(\frac{D(i)}{D_o(i)} \right)^{E(i)^{-1}} - \left(\frac{1}{1 + E(i)^{-1}} \right) \tag{9}$$

The second part of equation (10) can be neglected for small amount of elasticity and finally, demand response modeling can be shown as:

$$D(i) = D_o(i).\left(\frac{\pi(i) + \lambda(i) + \rho(i)}{\pi_o(i)} \right)^{E(i)} \tag{10}$$

3. Power system uncertainties modeling with Montecarlo simulation

The power system uncertainties modeled in stochastic congestion management contain the outage of transmission lines and generators. According to Markov chain model [18], Forced Outage Rate (FOR) of each component is utilized in order that probability of components outage is obtained. A set of scenarios based upon the Monte Carlo simulation is generated in order to model the uncertainties in the congestion management problem. Herein, different scenario generation approaches and scenario reduction technique is presented.

A. *Random Number by Ordinary and Lattice Monte Carlo Simulation*

Implementation of Monte Carlo simulation is convenient because of being independent of system size. In this paper, two different Monte Carlo simulation, i.e. ordinary Monte Carlo simulation and lattice Monte Carlo simulation are employed to simulate availability and unavailability of generators and transmission lines and also be compared with each other. The random numbers by ordinary Monte Carlo simulation are uniformly distributed such that random numbers are generated for each component (generators and transmission lines) between 0 and 1. In lattice Monte Carlo simulation, an n-point lattice rule of rank-r in dimension-d is defined as:

$$\sum_{z=1}^{r}\frac{k_z}{n_z}*v_z \mod 1 \qquad \{k=1,2,...,n_z\} \tag{11}$$

where v1, v2,…, vr are linearly independent vectors with d-dimension of integers which are randomly generated between 0 and 1. In the congestion management problem, d indicates the number of overall components (generators and transmission lines). Figs. 1 and 2 delineate two different aforementioned random number series. In these figures, it is assumed that d is equal to one. Random numbers in Fig.1 are generated by the ordinary Monte Carlo simulation and those ones in Fig.2 are generated by lattice Monte Carlo simulation rank-1. As depicted, the random numbers by Lattice Monte Carlo simulation are more uniformly distributed than ordinary Monte Carlo simulation.

After generating random numbers by ordinary Monte Carlo simulation and or lattice Monte Carlo simulation, in order to obtain scenarios, if the value of generated number for each component is smaller than the components' FOR, that component is considered to be out of service, otherwise, the component will be in service under the scenario. After that, the probability of all scenarios should be calculated as:

$$Prob_s=\prod_{e=1}^{NE}\left(status_{e,s}.(1-FOR_e)+\left(1-status_{e,s}\right).FOR\right. \tag{13}$$

Where NE and status signify the number of all components (generators and transmission lines) and the status of component e under scenario s, respectively. Also Probs and FORe are the probability of scenario s and FOR of component e, respectively.

B. Scenario Reduction Technique

The computational requirements for a scenario-based optimization model depend on the number of scenarios. Thus an effective scenario reduction method could be very essential for solving large scale systems [19].

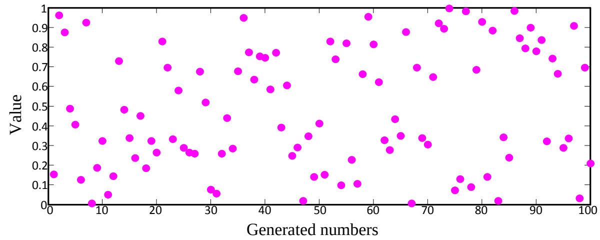

Fig. 1. Random numbers by ordinary Monte Carlo simulation

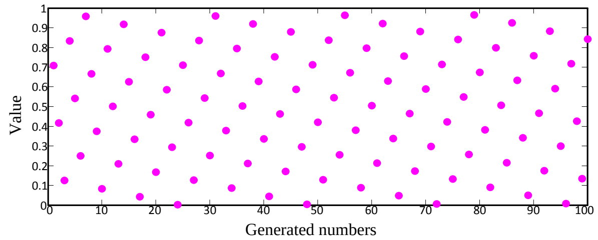

Fig. 2. Random numbers by lattice rank-1 Monte Carlo simulation

The scenario reduction is a scenario approximation with a smaller number of scenarios. Furthermore, scenario reduction is performed by a reasonably approximation of original system. On other hand, this scenario reduction is carried out with respect to computation time and accuracy. In this paper, a large number of scenarios are needed by using ordinary Monte Carlo simulation and lattice Monte Carlo simulation is needed. However, this makes computation of the problem intractable. Hence, after generating initial scenarios, solving the congestion management for each scenario, and implementing scenario reduction, NS scenarios are preserved which are identified by the estimated standard deviation of congestion alleviation cost. In order to obtain acceptable scenarios based on estimated standard deviation of congestion cost, i.e. cost of mitigating congestion, the following stopping criterion can be calculated as:

$$\sigma_{COST^{CM}}=\frac{1}{\overline{COST^{CM}}.NS}.\sqrt{\frac{1}{NS-1}\sum_{s=1}^{NS}\left(COST^{CM}-\overline{COST^{CM}}\right)} \\ \sigma_{COST^{CM}}<\sigma_{FIX} \tag{14}$$

Where $\overline{COST^{CM}}$ and NS are the mean value of congestion management cost and the number of scenarios, respectively. Additionally, $\sigma_{COST^{CM}}$ in (14) is the normalized standard deviation of the congestion cost for all the accepted scenarios and this equation identifies that $\sigma_{COST^{CM}}$ should be less than threshold σ_{FIX}. The fixed value of σ_{FIX} as an input data is usually selected in the range of [0.01-0.05] which can influence the scenario reduction results [20]. Finally, after scenario reduction, NS deterministic scenarios are obtained so that each scenario has a corresponding probability and is considered for the congestion management problem analysis. Solving the congestion management for accepted scenarios, the results such as generation shifts, DRRs' participation, load shedding and congestion cost are expected values which are described in next section.

4. Stochastic congestion management formulation

In this paper, after ISO has cleared the electricity market without taking into account the network constraints and with the aim of maximizing social welfare, he/she should analyze the electricity network congestion using results of market clearing. Therefore, ISO should relieve congestion if transmission line limit violation is monitored. Herein, the uncertainty of generating units and transmission lines is considered. For this reason, Monte Carlo simulation is implemented to generate different scenarios. After that, the rescheduling of generating units, load shedding and DRRs are used together for accepted scenarios with the purpose of minimizing the congestion cost.

The objective function (15) consists of different parts. The first part is the payment that ISO pays to generation units for varying their output as compared to initial market clearing schedule. The second term denotes the payment to customers who are involuntary shed by ISO, and the third part is the payment to the demand response participants because of reducing their consumption. *SG*, *SD* and *SHED* are sets of generating units, DRRs which are committed (in service) and loads which are involuntary shed, respectively. Equations (16)-(25) are describing how to implement this aforementioned model.

$$Min:\left\{\begin{aligned}&\sum_{j\in SG} B_j^u.\Delta P_j^{u,\zeta}+B_j^d.\Delta P_j^{d,\zeta}+\sum_{ls\in SHED}\pi_{ls}.\Delta P_{ls}^{\zeta}\\&+\sum_{dr\in SD} price_{dr}.\Delta P_{dr}^{\zeta}\end{aligned}\right\} \tag{12}$$

$$P_j^{Min}\le P_j^{\zeta}\le P_j^{Max} \qquad \{j\in SG\} \tag{13}$$

$$0\le \Delta P_{dr}^{\zeta}\le P_{dr}^{Max} \qquad \{dr\in SD\} \tag{14}$$

$$P_{Gn}^{\zeta}=\sum_{j\in SGn} P_j^{\zeta} \qquad \{n\in SN\} \tag{15}$$

$$P_{DRn}^{\zeta}=\sum_{dr\in SDRn}\Delta P_{dr}^{\zeta} \qquad \{n\in SN\} \tag{16}$$

$$P_{SHn}^{\zeta}=\sum_{ls\in SHEDn}\Delta P_{ls}^{\zeta} \qquad \{n\in SN\} \tag{17}$$

$$P_{Gn}^{\zeta}-P_{Dn}^{\zeta}=\sum_{\substack{m\in SN,\\ k\in SL}} B_k(\delta_m^{\zeta}-\delta_n^{\zeta}) \qquad \{n\in SN \tag{18}$$

$$-F_{mn}^{Max}\le B_k(\delta_m^{\zeta}-\delta_n^{\zeta})\le F_{mn}^{Max} \quad \{n\in SN\},\{k\in S \tag{19}$$

$$P_j^{\zeta}=P_j^{o}-\Delta P_j^{d,\zeta}+\Delta P_j^{u,\zeta} \qquad \{j\in SG\} \tag{20}$$

$$P_{Dn}^{\zeta}=P_{Dn}^{o}-P_{DRn}^{\zeta}-P_{SHn}^{\zeta} \qquad \{n\in SN\} \tag{21}$$

$$\begin{aligned}&\Delta P_j^{u,\zeta}\ge 0,\ \Delta P_j^{u,\zeta}\ge 0, \quad \{j\in SG\},\{dr\in SD\},\\&\Delta P_{dr}^{\zeta}\ge 0,\ \Delta P_{ls}^{\zeta}\ge 0 \qquad \{ls\in SHED\}\end{aligned} \tag{22}$$

Where SN and SL are sets of nodes and in service transmission lines, respectively. In addition, SGn, SDRn and SHEDn express sets of in service generating units, DRRs and involuntary shed loads connected to node n, respectively. Constraint (16) ensures that the rescheduled generators stay within the respective maximum and minimum power outputs under each scenario. Equation (17) specifies the capacity of DRRs' output power reduction. Constraints (18) and (19) represent the total power generation at node n as the sum over generation units when multiple units are connected to node n and the power reduction of each DRR placed at node n, respectively.

Similarly, equation (20) determines involuntary load shedding at node n and DC power flow equation is presented in (21). The constraint (22) enforces transmission lines capacity limit for DC power flow under each scenario. Equation (23) indicates final rescheduled power generation of each generator under scenario ζ. The constraint (24) represents equivalent demand at node n under each scenario and also (25) confines all up and down power changes to positive values.

5. Test results

The proposed congestion management in presence of DRRs is applied to the 24-bus IEEE Reliability Test System (RTS). The market data is given in appendix A. As shown in Table VI, generation units 22-29 don't participate in relieving congestion because units 22 and 23 are nuclear power plants and also units 24-29 are hydro generators operating at their maximum output of 50 MW. The other required system characteristics can be obtained from [21].

The single diagram of 24-bus RTS with DRRs is depicted in Fig. 3. As an additional assumption in this paper, the capacity limit of lines 3-24, 10-11 and 14-16 are reduced to 120, 100 and 200 MVA, respectively. According to market clearing data in appendix A, market is not feasible and lines 3-24, 10-11 and 14-16 are congested. Here, all simulations are solved using CPLEX under the fast software with very optimal solutions, namely General Algebraic Modeling System (GAMS) software package because the time horizon of alleviating congestion is near the real-time operation. In the following, in order to study the impact of DRRs on the load shedding and congestion cost, at first, deterministic congestion management is performed and then, the results of stochastic congestion management by means of ordinary and lattice Monte Carlo simulations are compared in presence of both DRRs and load shedding.

A. Impact of DRRs on Costs of Load Shedding and Relieving Congestion in Deterministic Congestion Management

In order to investigate the effect of DRRs on deterministic congestion management cost compared to load shedding, simulations are run for different DRRs' capacities. In fact, there is a trade-off between load shedding and DRRs. As it was shown in fig. 3, five DRRs on nodes #1, #2, #7, #13 and #14 are selected to participate in deterministic congestion management.

Table I shows the impact of DRRs' capacity on involuntary load shedding and also congestion management cost. It can be seen that when DRRs' capacity increases, the load shedding cost and also congestion management cost are decreasing, though, the cost of DRRs' participation becomes greater.

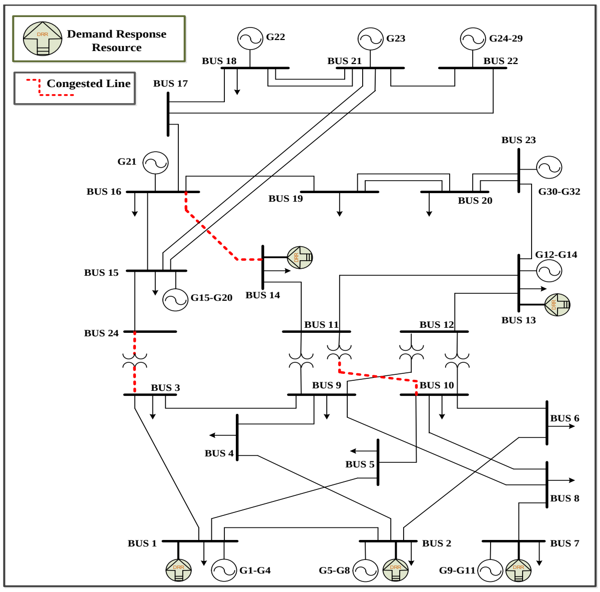

Fig. 3. Single line diagram of stochastic congestion management with DRRs.

As presented in Table I, when deterministic congestion management is implemented without any DRRs the total congestion management cost ($87279.223) is more than DRRs participate in this major issue. Therefore, it is worthwhile that ISO employs more DRRs instead of implementation of involuntary load shedding, singly.

Table I
Impacts of DRRs' capacity on load shedding and congestion cost

Capacity of each DRR(= % of the related bus load) (MW)	Cost of load shedding ($)	Cost of DRRs' participation ($)	Cost of generation shifts ($)	Cost of congestion management ($)
No DRRs	63682.221	0	23597.002	87279.223
2%	60282.331	189.400	23415.256	83886.987
4%	56922.453	378.799	23231.774	80533.026
6%	53562.576	568.199	23048.292	77179.067
8%	50202.698	757.598	22864.810	73825.106

B. Stochastic congestion management using DRRs and load shedding

Here, in order to evaluate the stochastic congestion management, two types of Monte Carlo simulation methods are applied, i.e. ordinary Monte Carlo simulation and lattice rank-1 Monte Carlo simulation. Hence, according to uncertainty of generating units and transmission lines, 100 scenarios are generated by using two aforementioned types of Monte Carlo simulation. The sets of scenarios generated are not similar and, really, each of them has its own probable contingencies. Since this number of scenarios is large and it own makes computational time of solving the problem increase so that an effective scenario reduction technique is required, as discussed in section III.A.

In order that ordinary Monte Carlo simulation and lattice rank-1 Monte Carlo simulation can be compared for congestion management problem, the threshold value is chosen in a way that both methods consist of similar number of accepted scenarios. So, 20 scenarios are selected for each type of Monte Carlo simulations after scenario reduction. Then, the objective function (15) along with constraints (16)-(25) are carried out under each scenario.

The results of mitigating congestion for 20 accepted scenarios for both Monte Carlo simulation methods, including the failed components, scenario probability and individual congestion management cost for each scenario are presented in the second, third and fourth columns of Table II, respectively. In this table, "G" and "T" denote the failed generating unit and transmission line, respectively. For instance, scenario 7 indicates that generating unit #7 is out of the service with probability of 0.0159 for both stochastic methods. Referring to Table II, the first scenario for both methods which no components are failed (out of service) has the greatest likelihood value. In other words, the congestion cost under this scenario denotes deterministic congestion management in presence of

DRRs and load shedding which no contingency occurs. Moreover, the probability of this scenario is just equal to 0.1429 in stochastic congestion management while the probability of deterministic state is 1. Indeed, the deterministic congestion management cannot give a pragmatic solution.

As presented in Table II, sets of scenarios for two types of stochastic congestion management are not similar, though, the 9 scenarios with higher probability are common in two methods. As seen, the last scenario in ordinary Monte Carlo simulation has a probability of 0.0022 for two contingencies occurrence (simultaneous outage of G2 & G23) while in lattice rank-1, the probability is 0.0060 for only outage of G31.

This means that lattice rank-1 Monte Carlo simulation is more realistic than another one as two contingencies occurred in ordinary Monte Carlo simulation and this own made its probability value more less than probability of one contingency occurrence. In fact, lattice rank-1 Monte Carlo simulation can give ISO more probable scenarios than ordinary one. It can be seen that the uncertainty probability, i.e. sum of accepted scenarios' probabilities, related to lattice rank-1 Monte Carlo simulation (0.3699) is greater than ordinary Monte Carlo simulation (0.3422). In other words, lattice rank-1 Monte Carlo simulation includes more uncertainties of electrical network for congestion management problem and is more realistic than ordinary Monte Carlo simulation. It should be noted that all scenarios have a role for determining the value of total variables. For this reason, the expected value of solutions should be obtained. The optimal output power of DRRs along with amount of involuntary load shedding and expected change in output power of conventional units are shown in Table III and Table V, respectively.

Table IV indicates the total congestion cost, generation shifts cost, load shedding cost and the payment to DRRs who reduce their consumption for deterministic situation and both Monte Carlo methods.As seen, the congestion cost in the ways of ordinary and lattice Monte Carlo are \$80076.630 and \$83025.767, respectively which are more than the deterministic congestion management cost (\$78856.047). In fact the extra costs \$80076.630-\$78856.047 and \$83025.767-\$78856.047 are related to uncertainty costs for stochastic congestion management with ordinary and lattice Monte Carlo methods, respectively.

Furthermore, it can be obviously concluded that value of uncertainty cost in lattice rank-1 is greater than the uncertainty cost in ordinary method so that this makes the lattice rank-1 more realistic than another one for proposed congestion management.

6. Conclusion

Congestion management is one of the most important responsibilities of ISO which is traditionally carried out without considering the power system uncertainties. This paper proposed a stochastic congestion management with a trade-off between DRRs and load shedding in which the uncertainties in generating units and transmission lines were considered. It is concluded that presence of DRRs can make the relieving congestion cost much lower rather than just use load shedding. Therefore, it is economical to increase DRRs' capacity for participating in this vital power system operation. The components outages are simulated by two different Monte Carlo simulation methods, i.e. ordinary and lattice rank-1. Numerical results present that sum of accepted scenario probabilities in ordinary simulation is less than lattice rank-1. In other words, lattice rank-1 includes more probable contingencies than ordinary one. The congestion cost in stochastic congestion management is higher than deterministic simulation. Besides, the value of uncertainty cost in congestion management is greater than ordinary Monte Carlo and even deterministic congestion alleviating cost. Therefore it is more realistic and efficient to applied lattice Monte Carlo simulation rather than ordinary Monte Carlo simulation.

Appendix

The information about market clearing results and also generating units bids are provided in Table VI. Pj corresponds to power generation of units obtained from market clearing without taking account to transmission lines limit.

Table V
Optimal change in output power of generating units

Unit#	Ordinary Monte Carlo		Lattice Rank-1 Monte Carlo	
	Δp_j^u	Δp_j^d	Δp_j^u	Δp_j^d
1	9.4711	0	9.5702	0
2	9.0064	0	9.1403	0
5	9.5354	0	9.5702	0
6	9.5354	0	9.5702	0
7	60.8	0	60.8	0
8	18	0	18	0
9	20	0	20	0
10	13.616	0	13.7338	0
11	20	0	19.6756	0
12	101.194	0	98.1857	0
13	96.3617	0	95.1324	0
14	54.4313	0	56.4341	0
15	0	10.4781	0	10.7348
16	0	10.4781	0	10.7348
17	0	10.4781	0	10.7348
18	0	10.4781	0	10.7348
19	0	10.3764	0	10.7348
20	0	92.5551	0	90.6159
21	0	100.75	0	100.75
30	0	82.0581	0	82.5699
31	0	90.6655	0	90.9603
32	0	187.7236	0	194.6322

Table II
Stochastic congestion management for 20 accepted scenarios in ordinary and lattice Monte Carlo simulations

Scenario No#	Ordinary Monte Carlo			Lattice rank-1 Monte Carlo		
	Outage of Component	*Scenario Probability*	*Congestion Cost ($/h)*	*Outage of Component*	*Scenario Probability*	*Congestion Cost ($/h)*
1	-	0.1429	78856.047	-	0.1429	78856.047
2	G22	0.0195	30258.138	G22	0.0195	30258.138
3	G23	0.0195	30260.405	G23	0.0195	30260.405
4	G1	0.0159	86846.422	G1	0.0159	86846.422
5	G2	0.0159	86846.422	G2	0.0159	86846.422
6	G5	0.0159	86732.161	G5	0.0159	86732.161
7	G6	0.0159	86727.161	G6	0.0159	86727.161
8	T14	0.0137	112186.387	T14	0.0137	112186.387
9	T15	0.0137	104838.700	T15	0.0137	104838.7
10	T17	0.0137	130539.474	T16	0.0137	65813.245
11	G32	0.0124	66966.420	T17	0.0137	130539.477
12	G13	0.0075	107853.795	T7	0.0137	181943.896
13	G14	0.0075	107802.295	G32	0.0124	66966.420
14	G10	0.0060	111735.985	G12	0.0075	107905.295
15	G30	0.0060	70588.921	G10	0.0060	111735.985
16	G31	0.0060	70635.687	G11	0.0060	111745.985
17	G19	0.0029	78538.047	G20	0.0060	62185.527
18	G3	0.0029	109903.473	G21	0.0060	64323.057
19	G1,G23	0.0022	36404.610	G30	0.0060	70588.920
20	G2, G23	0.0022	36404.610	G31	0.0060	70635.687

Table IV
Congestion management cost for different deterministic and stochastic methods

Different payments	Ordinary Monte Carlo	Lattice rank-1 Monte Carlo	Deterministic
Total Congestion Cost ($)	80076.630	83025.767	78856.047
Generation Shifts Cost ($)	20702.977	20822.773	23140.033
DRRs' Participation Cost ($)	450.021	445.073	473.499
Load Sheding Cost ($)	58923.632	61757.921	55242.515

Table III
Optimal DRRs' output and amount of involuntary load shedding

Bus#	Ordinary Monte Carlo		Lattice rank-1 Monte Carlo	
	DRR's Output	*Load Shedding*	*DRR's Output*	*Load Shedding*
1	5.4010		5.4010	
2	4.8450		4.8450	
3		51.1520		50.8987
7	6.2560		6.2560	
10		68.9836		70.8980
13	13.2530		13.2530	
14	7.7476	10.3585	7.3353	15.4413

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