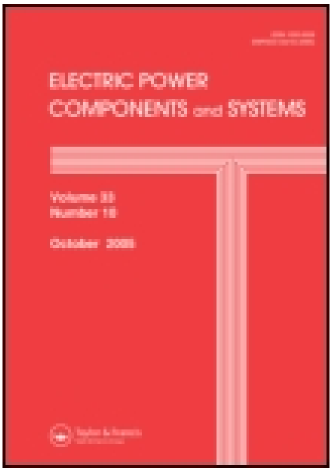

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Probabilistic Congestion Management Considering Power System Uncertainties Using Chance-constrained Programming

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Abstract *In this article, a new model for stochastic congestion management considering system uncertainties has been developed. The model utilizes chance-constrained programming to propose the stochastic formulation for the congestion management problem. In this approach, transmission constraints are considered with stochastic models instead of deterministic models. Indeed, this approach considers network uncertainties with a specific level of probability in the optimization process. Moreover, an efficient numerical approach based on the real-coded genetic algorithm and Monte Carlo technique has been proposed to solve the chance-constrained programming based congestion management scheme. Effectiveness of the proposed algorithm has been evaluated by applying the method to the IEEE 30-bus test system.*

Keywords chance constrained programming, congestion management, Monte Carlo simulation, real-coded genetic algorithm, system uncertainties

1. Introduction

Open access to transmission networks in the restructured power system has resulted in developing bilateral contracts during the past decade. This trend together with the growth of electricity consumption has increased the possibility for the occurrence of transmission congestion in one or more transmission lines when transferring electrical energy between two buses or two zones in the power system. Congestion essentially means the violation in one or some of the physical, operational, and policy constraints of the network. Both vertically integrated and unbundled power systems have experienced such problems [1, 2]. Congestion arises from two main resources: the occurrence of system contingencies and ignoring generation locations in the market clearing mechanism [3]. Congestion may occur in day-ahead, hour-ahead, and real-time market dispatch. When congestion does happen, the system operator is responsible for necessary preventive actions to relieve it. The set of the remedial activities performed to relieve violated limits is referred to as congestion management (CM). Managing network congestion may impose some additional cost on the operation of the system. This is due to the fact

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Nomenclature

Sets

N_G	set of generators
N_L	set of dispatchable loads
N_p	set of chromosomes

Functions

C	re-dispatch function for market participants
ρ	normal distribution function

Variables

P_{line_l}	flow of line l
ΔP_{Gi}	re-dispatch power of the generator i
ΔP_{Gi}^{+}, ΔP_{Gi}^{-}	increment and decrement re-dispatch power of generator i
ΔP_{Lj}	re-dispatch power of the load j
ΔP_{line_l}	change in flow of line l

Constants

$a_{l,i}$	transmission congestion distribution factor for line l with respect to injection at bus i
$MTTF$	mean time to failure
$MTTR$	mean time to repair
$P_{line_l}^{\max}$	maximum allowed flow in line l
r_{ij}	correlation coefficient between ith and jth random variables
s	number of random variables in random vector
α_l	confidence level for flow of line l
$\Delta P_{Gi}^{\min}$, $\Delta P_{Gi}^{\max}$	maximum allowed re-dispatch power for generator i
$\Delta P_{Lj}^{\min}$, $\Delta P_{Lj}^{\max}$	maximum allowed re-dispatch power for load j
μ_i	mean value for random variable i
σ_i	standard deviation for random variable i

that to alleviate network congestion, cheaper generators may become replaced by more expensive ones in the primary market dispatch. Transmission congestion may result in market power for some participants or threaten the stability of the system [4]. Therefore, preventive or corrective actions are necessary to relieve congestion and decrease system risk.

Recently, many researchers have been investigating CM techniques. The basic differences among CM approaches arise from modeling of the power market, available controls to relieve congestion, and solving algorithms for the proposed CM problems. Kumar *et al.* [1] categorized CM approaches into four distinct methods, including sensitivity-factor-based, re-dispatch-based, auction-based, and pricing-based methods. In [1], a wide range of literature on the mentioned approaches was reviewed. A unified framework for different CM schemes was presented in [2]. In this framework, two distinct stages for the operation of an electricity market, namely market dispatch and congestion re-dispatch, were considered. The second stage will only be performed if the first stage cannot achieve a feasible operating state with no constraint violation. The general concept of the congestion re-dispatch problem, in most CM methods, implies minimizing the cost of market rearrangement to alleviate congested lines [5–7]. Sensitivity of line flows to a change of power injection at different buses is the original basis for market re-dispatch to manage network congestion [8]. Utilizing flexible AC transmission systems (FACTS) devices to maximize the use of transmission facilities, as well as employing distributed resources to remove the network congestion, has been also considered recently [9, 10].

Uncertainties in physical aspects of the network may be one of the most challenging features of a power system, especially in the restructured environment. These uncertainties may be related to different power system sections, including generation, transmission, and distribution [11]. Therefore, incorporation of system uncertainties in the modeling of such power system algorithms as CM is becoming a vital issue in power system analysis. Considering these uncertainties in CM can seriously improve the feasibility of the operating state and the power system security level. As an example, system uncertainties were incorporated into a CM algorithm in [12]. At first, possible scenarios of power system operating states were generated, and then these scenarios were reduced to include only those that were the most probable and non-repetitive. CM is performed for all of the final scenarios and related solutions for each one calculated. The final solution is obtained from the average of CM solutions for the selected scenarios.

In this article, a new model for stochastic CM using chance-constrained programming (CCP) has been developed. In this approach, stochastic, rather than deterministic, models have been used for transmission constraints. This approach considers network uncertainties with a specific level of probability in the optimization process. Moreover, an efficient numerical approach based on the real-coded genetic algorithm (GA) and Monte Carlo technique has been proposed to solve the CCP-based CM scheme. The effectiveness of the proposed algorithm has been evaluated by applying the method to the IEEE 30-bus test system.

2. Deterministic CM Model

The system operator intends to maximize the use of network assets regarding network security. Voltage instability and the thermal limit are the most common barriers in utilizing the full capacity of transmission networks [13]. In fact, such limitations may lead to network congestion, which affects the power market arrangement. In this article, a day-ahead electricity market has been used as the framework for the implementation of the CM algorithm. In this market, suppliers and consumers submit their bids to the market operator, who is responsible for the clearing procedure [14]. The time framework for a market clearing procedure is 24 hours; however, CM will be performed hour by hour if necessary.

Deterministic CM in this environment is formulated as follows:

$$\text{minimize} \qquad \sum_{i=1}^{N_G} C_i(\Delta P_{Gi}) + \sum_{j=1}^{N_L} C_j(\Delta P_{Lj}), \tag{1}$$

$$\text{subject to} \qquad P_{line_l} + \sum_{i=1}^{N_G} a_{l,i}\,\Delta P_{Gi} - \sum_{j=1}^{N_L} a_{l,j}\,\Delta P_{Lj} \le P_{line_l}^{\max} \quad \forall l \in N_{Line}, \tag{2}$$

$$\Delta P_{Gi}^{\min} \le \Delta P_{Gi} \le \Delta P_{Gi}^{\max} \quad \forall i \in N_G, \tag{3}$$

$$\Delta P_{Lj}^{\min} \le \Delta P_{Lj} \le \Delta P_{Lj}^{\max} \quad \forall j \in N_L, \tag{4}$$

$$\sum_{i=1}^{N_G} (\Delta P_{Gi}) = \sum_{i=1}^{N_L} (\Delta P_{Lj}). \tag{5}$$

Here, the objective function of the CM problem is to minimize the total cost of re-dispatch steps in a day-ahead market. The objective function in Eq. (1) consists of two distinct items that correspond to the cost imposed by generators and loads for congestion re-dispatch, respectively. In this equation, $C_i(\Delta P_{Gi})$ is the re-dispatch cost function related to generators, which can be written in the form of Eq. (6), where C_i^{up} and C_i^{down} are the bids for the power increment and decrement by generator i, respectively; the re-dispatch cost function related to the loads is similar to that of generators:

$$C_i(\Delta P_{Gi}) = C_i^{up} \times \Delta P_{Gi}^{+} + C_i^{down} \times \Delta P_{Gi}^{-}. \tag{6}$$

Equation (2) explains the changes in line flows. In this equation, $a_{l,i}$ stands for the transmission congestion distribution factor (TCDF), which was described in [15]. The TCDF is defined as the change in the flow of transmission line l due to the unit increment in the power injection at bus i,

$$a_{l,i} = \frac{\Delta P_{line_l}}{\Delta P_{Gi}}. \tag{7}$$

Equations (3)–(5) illustrate the allowed range of changes for the injection power of generators and loads; moreover, the constraint in Eq. (5) models the power balance equation.

3. Stochastic CM Model

There are many intrinsic uncertainties that must be considered in modeling power system problems in order to have a comprehensive analysis [16]. Some of the major power system uncertainties are load forecasting error, availability of equipment, and price uncertainties in the power market. The modeling of these uncertainties can be considered as the first step in stochastic CM.

3.1. Modeling of Power System Uncertainties

Due to the fact that system loads follow a random pattern, an error in load forecasting is inevitable, and therefore, the amount of system loads is modeled as a random variable (ξ). The probability density function (PDF) of this variable may be assumed to have a normal distribution form [16] and can be written as follows:

$$\rho(\xi) = \frac{1}{\sqrt{(2\pi)^s |\Sigma|}} \exp\left(-\frac{1}{2}(\xi - \mu)^T \Sigma^{-1} (\xi - \mu)\right), \tag{8}$$

where μ and Σ are the mean vector and covariance matrix in the forms

$$\mu = [\mu_1, \mu_2, \ldots, \mu_s]^T, \tag{9}$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2 r_{12} & \cdots & \sigma_1\sigma_s r_{1s} \\ \sigma_2\sigma_2 r_{21} & \sigma_2^2 & \cdots & \sigma_2\sigma_s r_{2s} \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_s\sigma_1 r_{s1} & \sigma_s\sigma_2 r_{s2} & \cdots & \sigma_s^2 \end{bmatrix}. \tag{10}$$

In this article, short-term load forecasting is used, and therefore, the scale of $\frac{\sigma_i}{\mu_i}$ should be smaller than 0.15 [16].

Availability of system equipment, including generators and transmission lines, can be modeled with a forced outage rate (FOR) [17]:

$$FOR = \frac{MTTR}{MTTR + MTTF}. \tag{11}$$

The necessary information to calculate *MTTR* and *MTTF* is extracted from the transmission lines history, which is available in dispatching center of the network. The uncertainties related to market prices have been neglected in this article.

This study employs Monte Carlo simulation to model the mentioned system uncertainties in stochastic CM. Performing Monte Carlo considering the PDF of input variables generates the PDF of output variables, such as line flows (P_{line_l}). These PDFs are effectively used to formulate the stochastic CM.

3.2. Stochastic Optimization Using CCP

CCP is a special type of optimization problem that is useful for problems with uncertain variables in their objective function or constraints. In this type of optimization, constraints are guaranteed to be satisfied with a specific level of probability instead of being considered firmly. Typical CCP can be formulated as follows [18]:

$$\begin{aligned} \text{minimize} \quad & f(x) \\ & \Pr\{g_i(x, \xi) \le 0\} \ge \alpha_i \quad \forall i. \end{aligned} \tag{12}$$

In this equation, x is the decision vector of the optimization problem; ξ stands for the set of uncertain variables; and α_i, referred to as the confidence level, identifies the level of constraints satisfaction.

Considering CCP formulations in Eq. (12), probabilistic CM can be formulated as follows:

$$\text{minimize} \quad \sum_{i=1}^{N_G} C_i(\Delta P_{Gi}) + \sum_{j=1}^{N_L} C_j(\Delta P_{Lj}), \tag{13}$$

$$\text{subject to} \quad \Pr\left[P_{line_l} + \sum_{i=1}^{N_G} a_{l,i}\Delta P_{Gi} - \sum_{j=1}^{N_L} a_{l,j}\Delta P_{Lj} \le P_{line_l}^{\max} \right] \ge \alpha_l \quad \forall l \in N_{Line}, \tag{14}$$

$$\Delta P_{Gi}^{\min} \leq \Delta P_{Gi} \leq \Delta P_{Gi}^{\max} \quad \forall i \in N_G, \tag{15}$$

$$\Delta P_{Lj}^{\min} \leq \Delta P_{Lj} \leq \Delta P_{Lj}^{\max} \quad \forall j \in N_L, \tag{16}$$

$$\sum_{i=1}^{N_G}(\Delta P_{Gi}) = \sum_{i=1}^{N_L}(\Delta P_{Lj}). \tag{17}$$

Equation (14) shows the line flow constraints that should be satisfied with the least probability of α_l. In CCP-based CM, α_l identifies the probability of constraints satisfaction for the flow of line l. For instance, if $\alpha_l = 0.7$, the stochastic constraints of transmission branches must be satisfied for at least 70% of system states, while in the case where $\alpha_l = 1$, a CCP solution must be guaranteed for all system states. These possible system states should be determined before performing stochastic CM.

It should be noted that P_{line_l} in Eq. (14) is an uncertain variable, the PDF of which is identified in the primary Monte Carlo simulation. Indeed, uncertain line flows (P_{line_l}) are the reflection of the system uncertainties in the formulation of the stochastic CM. A secondary Monte Carlo simulation is also utilized to check the satisfaction of stochastic constraints in Eq. (14).

3.3. A Numerical Solving Algorithm

The optimization problem in Eqs. (13)–(17) includes a set of stochastic constraints in Eq. (14). Therefore, solving this problem is very complicated. In [16], a sequential approach was proposed to solve this type of optimization problem. The approach consists of a simulation layer beside an optimization layer. Also, a numerical method using the GA and Monte Carlo technique was presented in [19] to solve the stochastic transmission expansion planning that is modeled by CCP.

In this article, the real-coded GA has been incorporated into Monte Carlo simulation to solve the proposed stochastic CM. In fact, the real-coded GA generates the suggested solution for stochastic CM, while Monte Carlo evaluates the satisfaction of the probabilistic constraints in Eq. (14). The PDFs of line flows, which are required in the formulation of Eq. (14), have been already computed using a primary Monte Carlo.

The real-coded GA, which has been widely used in CM problems, can be formulated as follows [20]; in a real-coded system, chromosome m will be in the form

$$C_m = [\Delta P_{m1}, \Delta P_{m2}, \ldots, \Delta P_{mn}], \qquad m = 1, 2, \ldots, N_p.$$

The fitness function with respect to the re-dispatch cost function in Eq. (13) can be written as

$$Fit_m = \sum_{i \in N_G}(\Delta P_{mi} \times Bid_i) + \sum_{j \in N_L}(\Delta P_{mj} \times Bid_j) + \sum_{k \in N_T}(\Delta P_{mk} \times Bid_k), \qquad m = 1, 2, \ldots, N_p, \tag{18}$$

where ΔP_{mi} is the re-dispatch power of generator i, and Bid_i is the bid price offered by generator i. If chromosomes $C_v = [\Delta P_{vi}, \Delta P_{v2}, \ldots, \Delta P_{vn}]$ and $C_w = [\Delta P_{w1},$

$\Delta P_{w2}, \ldots, \Delta P_{wn}]$ from generation e are crossed, two possible children will be created in the form

$$\begin{aligned} C_1^{g+1} &= \omega C_w^e + (1-\omega) C_v^e, \\ C_2^{g+1} &= (1-\omega) C_w^e + \omega C_v^e, \end{aligned} \tag{19}$$

where ω is a constant parameter chosen to be equal to 0.3 [20]. The mutation function alters the bit ΔP_{mi} from chromosome $C_m = [\Delta P_{m1}, \Delta P_{m2}, \ldots, \Delta P_{mn}]$ in the form

$$\Delta P_{mi}^{mut} = \begin{cases} \Delta P_{mi} + \psi\left(P_{mi}^{\max} - P_{mi}\right) & \text{if } r = 0 \\ \Delta P_{mi} + \psi\left(P_{mi} - P_{mi}^{\min}\right) & \text{if } r = 1 \end{cases}, \tag{20}$$

$$\psi(y) = y \cdot (1 - \zeta^{(1-e/E)^b}), \tag{21}$$

where r is a random bit to identify the course of changes, and $\psi(y)$ is a function that generates a number in the range $[0, y]$. Also, E is the total number of generations, and b is the dependence factor to the number of generations, which is chosen equal to 5 [20]. When e is small, the function generates an output near y, while increasing e will decrease the generated value.

The main steps to solve the CCP-based stochastic CM problem using a combined algorithm including the Monte Carlo simulation and real-coded GA can be expressed as follows.

1. Produce the first generation of decision variables C_m for the real-coded GA and their fitness function Fit_m from Eq. (18).
2. Calculate line flow changes that resulted from one of the decision variables C_m using TCDFs, *i.e.*,

$$\Delta P_{line_l} = \sum_{i=1}^{N_G} a_{l,i} \Delta P_{Gi} - \sum_{j=1}^{N_L} a_{l,j} \Delta P_{Lj} \quad \forall l \in N_{Line}.$$

3. Select one of the line flow vectors P_{line} that resulted from primary Monte Carlo.
4. Check the satisfaction of probabilistic constraints. For this purpose, ΔP_{line_l}, which resulted from the selected strategy in Step 2, will be added to the selected line flow vector in Step 3. If the inequality constraint in Eq. (22) is satisfied, n_l will be increased by one:

$$P_{line_l} + \Delta P_{line_l} \leq P_{line_l}^{\max} \quad \forall l \in N_{Line}. \tag{22}$$

5. Steps 3 and 4 will be repeated for all of the other line flow vectors in the primary Monte Carlo using the same value for ΔP_{line}.
6. The probabilistic constraint is satisfied if the inequality in Eq. (23) is satisfied. N is the total number of line flow vectors in the primary Monte Carlo, and n_l is the successful epochs in the above-mentioned process:

$$\frac{n_l}{N} \geq \alpha_l. \tag{23}$$

7. If Eq. (23) is not established, add the penalty value to the fitness function Fit_m.
8. Steps 2–7 will be repeated for all C_m.

9. Produce the next generation of C_m using elitism, mutation, and cross-over in Eqs. (19)–(21) and return to Step 2.
10. When the number of generations is completed, propose the final decision variable (relief strategy).

The suggested algorithm for probabilistic CM using the Monte Carlo-based real-coded GA is presented in Figure 1.

4. Simulation Results

To evaluate the proposed probabilistic CM method, both deterministic and probabilistic CM models have been applied to the IEEE 30-bus test system. Figure 2 shows the single-line diagram for the IEEE 30-bus test system. This system is composed of 6 generators and 41 transmission lines [21].

To evaluate the efficiency of the stochastic CM, two different cases have been investigated:

- Case 1: only load uncertainties have been considered and
- Case 2: all three uncertainties mentioned in Section 3.1 have been modeled.

Deterministic and probabilistic CM methods have been applied to the above-mentioned cases, and the results have been compared with each other. It is assumed that there are nine participants, including generators at buses 5, 8, and 11 and dispatchable loads at buses 7, 8, 10, 15, 20, and 21, which contribute in the congestion re-dispatch step in the market. The main information about IEEE 30-bus test system and market participants is included in the Appendix.

The deterministic and expected values of the TCDFs for line 14, related to the market participants who contribute in the re-dispatch market, are shown in Figure 3. The deterministic approach and the proposed method in [12] utilize the deterministic values of TCDFs, while the proposed approaches in this article use the mean values of the TCDFs.

Table 1 shows the data for power flow in line 14. It is assumed that the thermal limit for line 14, calculated by the system operator, is 170 MW; therefore, line 14 has a great overload probability. The probability of lines overload, *i.e.*, $\overline{\Pr}(P_{line})$, has been calculated based on the PDF of line flows, which are computed from the primary Monte Carlo. As it can be seen in this table, the probability of line overload in Case 2 is greater than that in Case 1; this is because of considering all of system uncertainties in simulations of Case 2. Furthermore, in Case 2, the value of the standard deviation for flow in line 14 is greater than that in Case 1 for the same reason.

System uncertainties are modeled using a primary Monte Carlo simulation. For this purpose, the probability distribution function of uncertain variables in a power system is determined based on its behavior, which is described in Section 3.1. A sample of each uncertain variable is generated with respect to its PDF, and the power market is simulated using the generated values of uncertain variables in a deterministic manner. This process is performed for a sufficient number of iterations to compute the PDF of the output variables, such as line flows. The number of Monte Carlo iterations depends on the system size, number of uncertain variables, and also the severity of uncertainties. An independent Monte Carlo simulation is performed for each of the two mentioned cases. To evaluate the sufficiency of the Monte Carlo samples, the convergence diagram for one of the output variables was presented in [22]. Figure 4 shows the convergence of

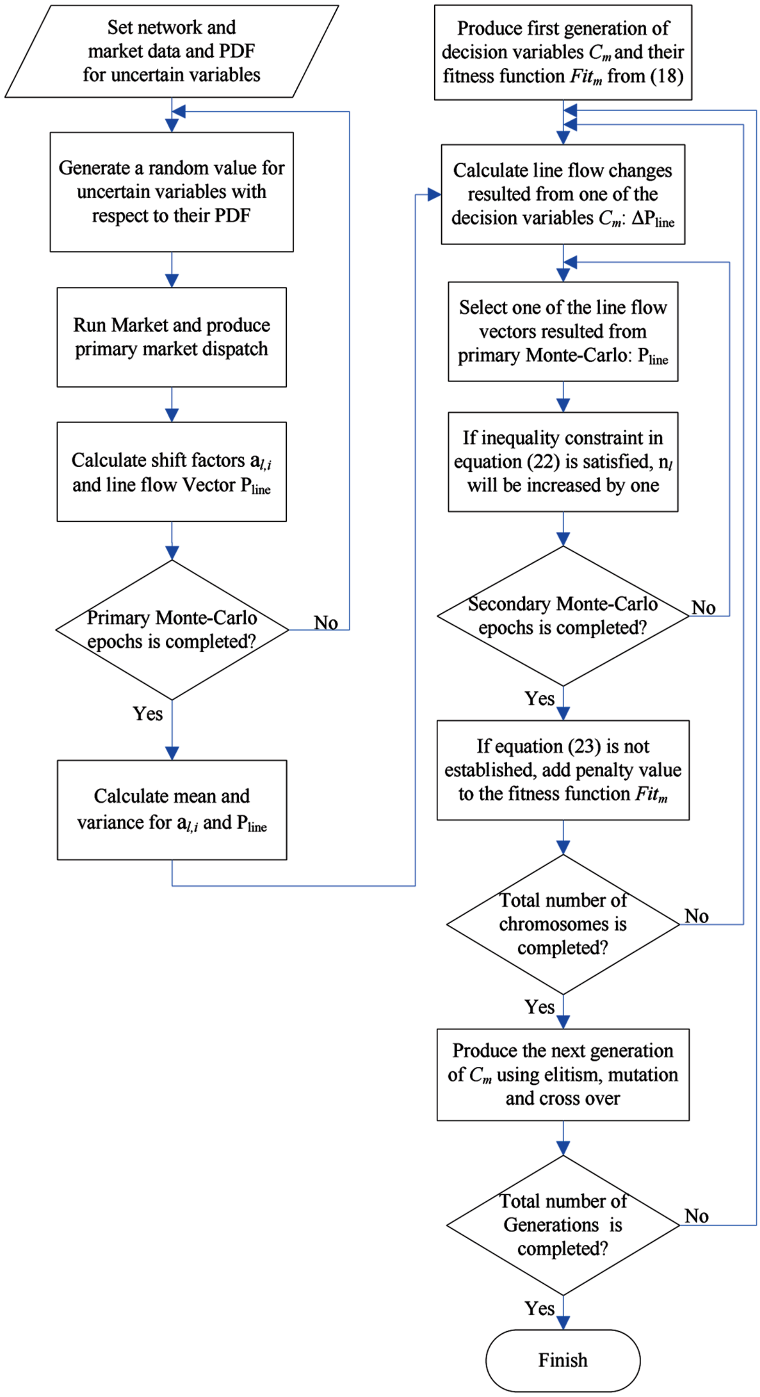

Figure 1. Solving algorithm for proposed probabilistic CM. (color figure available online)

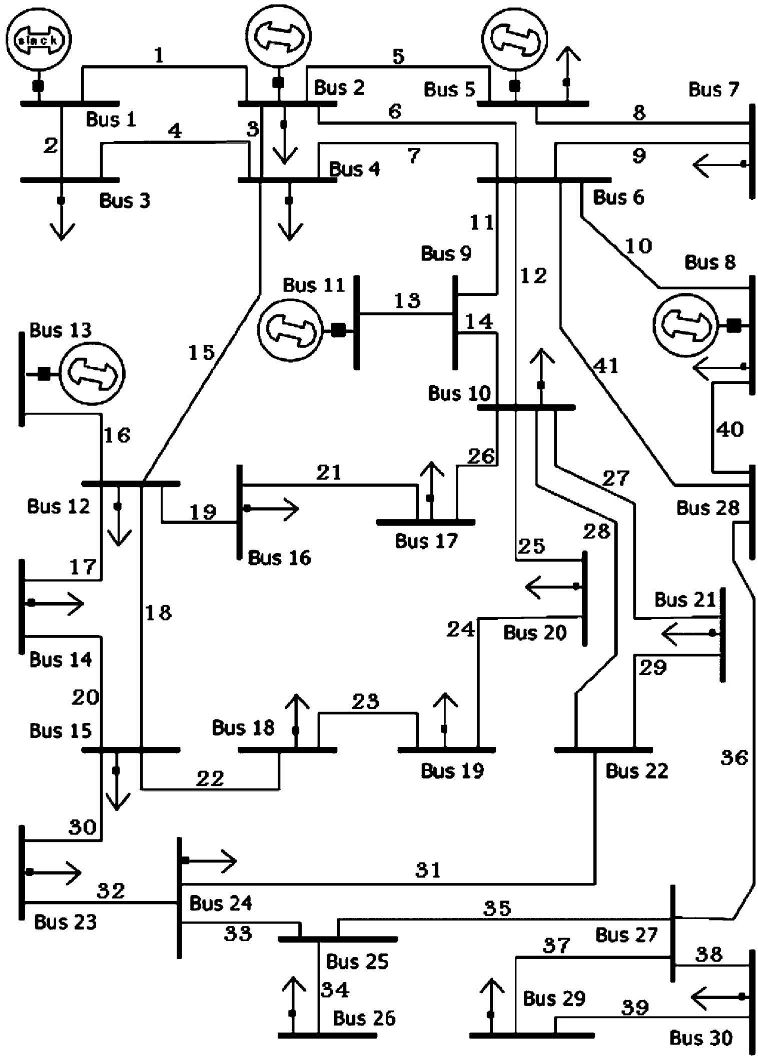

Figure 2. Single-line diagram for IEEE 30-bus test system.

flow for line 14 along with simulation iterations. The percentage of variable changes in Case 2 is more than that in Case 1, because Case 2 models all of the system uncertainties while Case 1 considers only load uncertainties. Therefore, the number of Monte Carlo iterations needed for convergence of the output variables in Case 2 is greater.

The results of CM for Case 1 are shown in Table 2. In this table, the cost of relieving congestion, total amount of load interruption (ΔP_L), changes in flow of line 14 ($\Delta P_{line_{14}}$), and probability of line overload for deterministic and probabilistic models have been compared with each other. It should be reminded that $\alpha = 0.6$ means that the line flow constraints must be satisfied for at least 60% of total states that are simulated in primary Monte Carlo simulation.

The deterministic approach reduces the overload probability to 48.97%, while this figure declines to 40.65% in the scenario-based stochastic CM. To have the same situation,

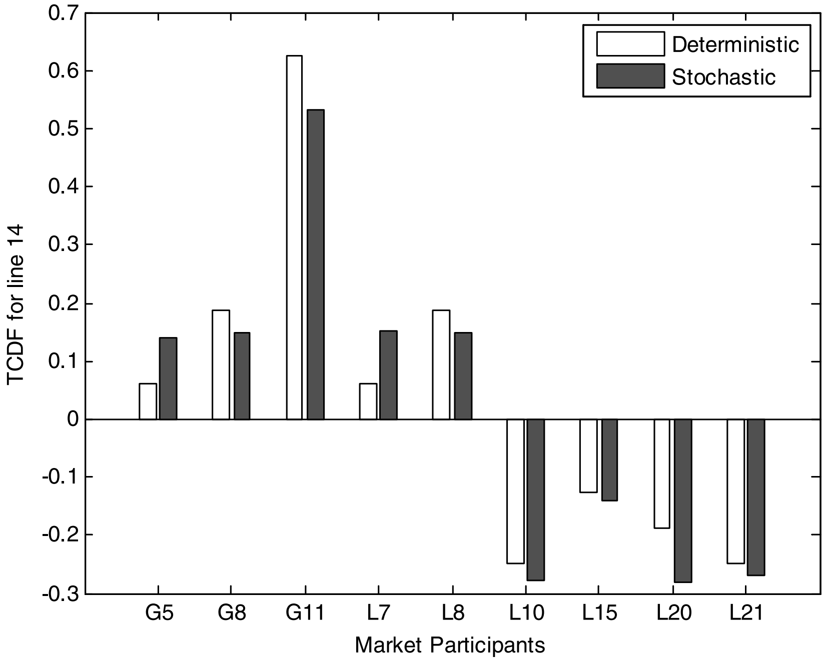

Figure 3. TCDFs for line 14 in IEEE 30-bus test system.

Table 1
Basic results for the flow of line 14 in two simulation cases

Case	μ_{14} (MW)	σ_{14}	Maximum (MW)	$\overline{\Pr}(P_{line})$
1	184.2	8.43	202.7	0.936
2	184.3	11.79	224	0.968

Table 2
Redispatch results for Case 1 within different approaches

Method	Algorithm	Cost ($/hr)	ΔP_L (MW)	$\Delta P_{line_{14}}$ (MW)	$\overline{\Pr}$ (P_{line})
Deterministic	—	121.2	−16.38	−14.33	0.4897
Stochastic [12]	Scenario generation and reduction	142.8	−19.28	−16.30	0.4065
Proposed method ($\alpha_l = 0.6$)	RCGA	150.1	−20.28	−16.46	0.3929

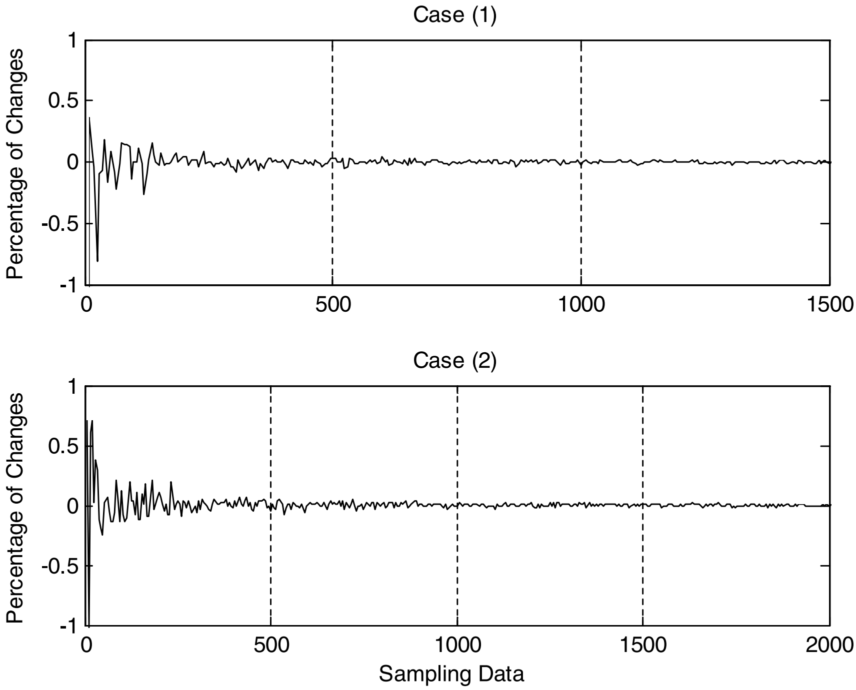

Figure 4. Convergence of output variable during Monte Carlo simulation.

α is set to 0.6 in the proposed stochastic CM, and therefore, it is expected that the overload probability decreases to about 40%. Consequently, in the proposed method to solve probabilistic CM, the system operator can specify the level of network security using parameter α in CCP. In fact, the flexibility of the proposed method is higher than other methods, since it utilizes the confidence level in the CM process. Furthermore, in contrast to the method introduced in [12], which uses some approximations to reduce the number of scenarios, the proposed method of this study has fewer approximations because it employs the PDF of line flows in the stochastic CM. It is clear that the cost of market re-dispatch is increased due to the reduction of overload probability, with the main reason being that to reduce the flow of line 14, the amount of re-dispatched power is increased. The amount of re-dispatched power in CCP-based CM is more than that in the deterministic approach to meet the satisfaction level for the stochastic constraints.

Table 3 shows the simulation results for both cases utilizing the proposed CCP-based CM with 90% of confidence level. In Case 2, all of the power system uncertainties have been modeled. Consequently, in this case, the amount of reduction in flow of line 14 is

Table 3
Redispatch results of the proposed approach with $\alpha = 0.90$

Case	Cost ($/hr)	$\Delta P_{line_{14}}$ (MW)	$\overline{\Pr}(P_{line})$
1	263.3	−25.13	0.1072
2	340.8	−29.33	0.1057

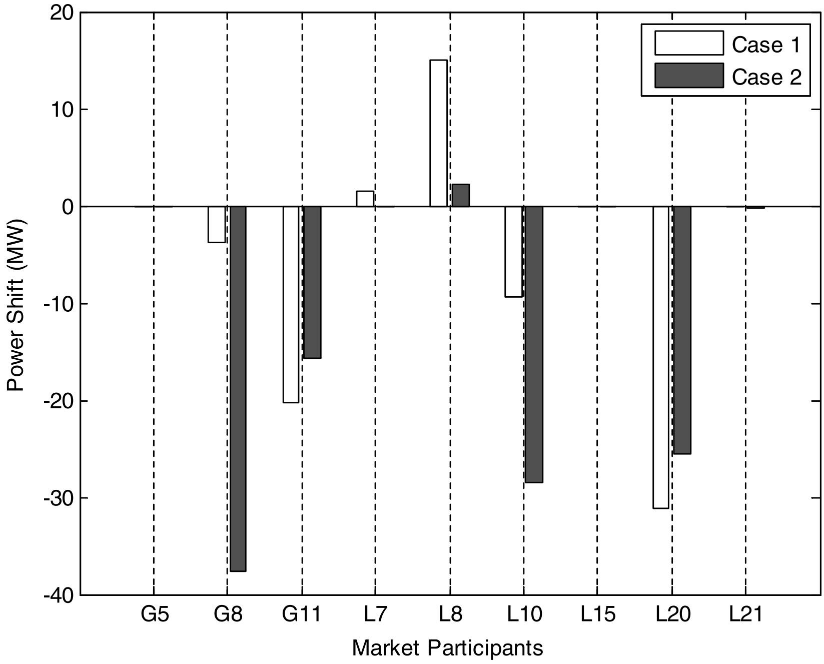

Figure 5. Re-dispatch power for different participants with $\alpha = 0.90$.

bigger than that in Case 1 to have 10% overload probability. Therefore; the re-dispatch costs are bigger than that of the previous case with the same confidence level (α).

Figure 5 shows the rescheduled power of different market participants for both cases with 90% of confidence level. The difference between re-dispatch strategies arises from the difference between line flow PDFs in two cases.

Line flow changes that resulted from CM strategies in Figure 5 are compared with those in the scenario-based approach in Figure 6. Case 2 imposes the most severe changes in the flow of line 14 compared with Case 1, because this case has the greater overload probability and 90% of confidence level.

The cost of congestion re-dispatch within different confidence levels is shown in Figure 7. It is obvious that re-dispatch cost in Case 2 is more than that in Case 1. Moreover, increasing the confidence level will result in an ascending trend for re-dispatch costs. When α is raised, the overload probability decreases, and consequently, network security level increases. Therefore, it can be said that this cost is spent to preserve network security.

Reviewing the results shows that the new formulation proposed here for stochastic CM effectively models system uncertainty and provides an efficient measure for the system operator to handle system security. The proposed method may be more proper for the modern power system, the uncertainty sources of which are growing dramatically because of introducing renewable energies and distributed resources.

5. Concluding Remarks

Considering power system uncertainties is inevitable to have a comprehensive analysis of network operation. Most of the electricity markets include two distinct stages in

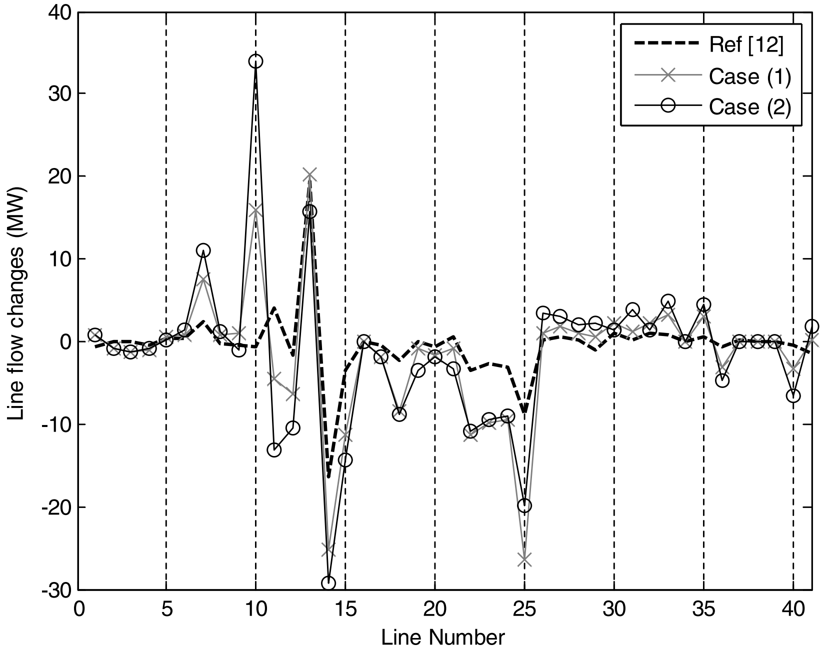

Figure 6. Line flow changes resulting from the proposed method with $\alpha = 0.90$.

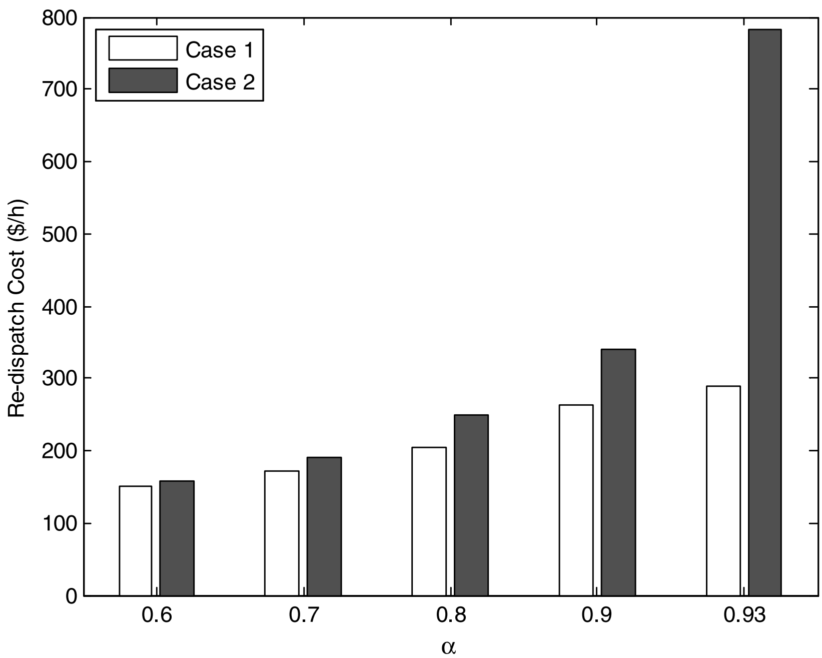

Figure 7. Re-dispatch cost of stochastic CM within different confidence levels.

operation: market dispatch and congestion re-dispatch. As discussed in the literature, the second stage will be performed when a network constraint is violated. Modeling system uncertainties in the congestion re-dispatch step may have a great impact on network constraints satisfaction within different probable conditions.

In this article, a new formulation for probabilistic CM based on CCP has been presented. Applying CCP in probabilistic CM allows stochastic—instead of deterministic—constraints to be defined. Therefore, transmission constraints can be formulated with a specific confidence level, which will be decided by the system operator. Introducing the confidence level in the congestion re-dispatch step promotes the flexibility of the CM approach.

Due to complexity of the CCP-based probabilistic CM, a numerical method is utilized in this study to solve the proposed problem. The numerical method consists of a real-coded GA and a Monte Carlo simulation. The real-coded GA is used to find the optimum solution for the CM problem, while Monte Carlo simulation is implemented to investigate the satisfaction of stochastic constraints.

Simulation results show that the probability of constraints satisfaction identifies the re-dispatch strategies in different market conditions. The costs of market re-dispatch increases when the system operator intends to have a higher probability of constraints satisfaction. In such a situation, changes in the primary market arrangement will be bigger, and therefore, the flow of congested lines will be reduced more than that in the other situations with less satisfaction probability. In fact, the new formulation of probabilistic CM models the probable system conditions, and consequently, the proposed strategy to relieve congestion will have an acceptable confidence level as decided by the system operator. It should be noted that the purpose of this study is not to determine the optimum amount of confidence level in the CM process; rather, it introduces a new model to carry system uncertainties for which the system operator can identify its desirable confidence level.

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Appendix: Information of the IEEE 30-bus Test System

Table A1
Generator data for IEEE 30-bus system

	Cost coefficients		Output limits		
Bus no.	C^{up} ($/MWh)	C^{down} ($/MWh)	$P_{\min}$	$P_{\max}$	FOR
5	6	5.4	0	300	0.005
8	5.475	1.2	0	300	0.008
11	4.275	3	0	300	0.008

Table A2
Load data for IEEE 30-bus system

Bus no.	Load quantity (MW)	C^{up} ($/MWh)	C^{down} ($/MWh)	$\Delta P_{Lj}^{\max}$ (MW)	$\Delta P_{Lj}^{\min}$ (MW)
2	9	—	—	—	—
3	18	—	—	—	—
4	22.5	—	—	—	—
5	13.5	—	—	—	—
7	27	1.25	4.4	15	−27
8	18	1.2	4	15	−18
10	27	1.1	4.4	15	−27
12	13.5	—	—	—	—
14	27	—	—	—	—
15	31.5	1.2	4.4	15	−31.5
16	31.5	—	—	—	—
17	9	—	—	—	—
18	27	—	—	—	—
19	58.5	—	—	—	—
20	63	1.2	4.4	15	−63
21	45	1.1	4.8	15	−45
23	4.5	—	—	—	—
24	40.5	—	—	—	—
26	27	—	—	—	—
29	36	—	—	—	—
30	36	—	—	—	—

Table A3
Branch data for IEEE 30-bus system

Branch	From	To	r (p.u.)	x (p.u.)	b (p.u.)	Rate (MW)	FOR
1	1	2	0.0192	0.0575	0.0528	170	0.0047
2	1	3	0.0452	0.1652	0.0408	170	0.0038
3	2	4	0.057	0.1737	0.0368	170	0.0037
4	3	4	0.0132	0.0379	0.0084	170	0.0059
5	2	5	0.0472	0.1983	0.0418	170	0.005
6	2	6	0.0581	0.1763	0.0374	170	0.0044
7	4	6	0.0119	0.0414	0.009	170	0.0058
8	5	7	0.046	0.116	0.0204	170	0.0052
9	6	7	0.0267	0.082	0.017	170	0.004
10	6	8	0.012	0.042	0.009	170	0.0063
11	6	9	0	0.208	0	170	0.0053
12	6	10	0	0.556	0	170	0.0065
13	9	11	0	0.208	0	170	0.0061
14	9	10	0	0.11	0	170	0.0043
15	4	12	0	0.256	0	170	0.0037
16	12	13	0	0.14	0	170	0.0049
17	12	14	0.1231	0.2559	0	170	0.0047
18	12	15	0.0662	0.1304	0	170	0.0042
19	12	16	0.0945	0.1987	0	170	0.0055
20	14	15	0.221	0.1997	0	170	0.0065
21	16	17	0.0524	0.1923	0	170	0.0045
22	15	18	0.1073	0.2185	0	170	0.0042
23	18	19	0.0639	0.1292	0	170	0.0048
24	19	20	0.034	0.068	0	170	0.0057
25	10	20	0.0936	0.209	0	170	0.0041
26	10	17	0.0324	0.0845	0	170	0.0038
27	10	21	0.0348	0.0749	0	170	0.0049
28	10	22	0.0727	0.1499	0	170	0.0049
29	21	22	0.0116	0.0236	0	170	0.0055
30	15	23	0.1	0.202	0	170	0.0044
31	22	24	0.115	0.179	0	170	0.0049
32	23	24	0.132	0.27	0	170	0.0046
33	24	25	0.1885	0.3292	0	170	0.0049
34	25	26	0.2544	0.38	0	170	0.0065
35	25	27	0.1093	0.2087	0	170	0.0044
36	28	27	0	0.396	0	170	0.0037
37	27	29	0.2198	0.4153	0	170	0.0055
38	27	30	0.3202	0.6027	0	170	0.0041
39	29	30	0.2399	0.4533	0	170	0.005
40	8	28	0.0636	0.2	0.0428	170	0.0044
41	6	28	0.0169	0.0599	0.013	170	0.0055