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Stochastic congestion management considering power system uncertainties: a chance-constrained programming approach

Mehrdad HOJJAT
Faculty of Electrical and Computer Engineering
Islamic Azad University, shahrood Branch
Shahrood, Iran
Me.hojjat@alumni.um.ac.ir

Mohammad Hossein JAVIDI
Department of electrical engineering
Ferdowsi university of Mashhad
Mashhad, Iran
H-javidi@ferdowsi.um.ac.ir

Mohamad Reza RAECY
Department of control on measuring instruments
Mashhad Electric Energy Distribution Company (MEEDC)
Mashhad, Iran
Raecyr@yahoo.com

Abstract— Considering system uncertainties in developing power system algorithms such as congestion management (CM) is a vital issue in power system analysis and studies. This paper proposes a new model for the power system congestion management, considering power system uncertainties based on the chance constrained programming (CCP). In the proposed approach, transmission constraints are taken into account by stochastic models instead of deterministic models. The proposed approach considers network uncertainties with a specific level of probability in the optimization process. Then, an analytical approach is used to solve the new model of the stochastic congestion management. In this approach, the stochastic optimization problem is transformed into an equivalent deterministic problem. Moreover, an efficient numerical approach based on a real-coded genetic algorithm and Monte Carlo technique is proposed to solve the CCP-based congestion management problem in order to make a comparison to the analytical approach. Effectiveness of the proposed approach is evaluated by applying the method to the IEEE 30-bus test system. The results show that the proposed CCP model and the analytical solving approach outperform the existing models.

Keywords— Congestion Management (CM); System Uncertainties; Chance constrained programming (CCP); Monte Carlo Simulation; Stochastic optimization.

1. Notations

The notations used throughout this paper are as follows:

Sets

$\mathbf{N_G}$	Set of generators
$\mathbf{N_L}$	Set of dispatchable loads
$\mathbf{N_{cont.}}$	Set of probable contingencies

Variables

ΔP_{Gi}	Re-dispatch power of generator i
ΔP_{Lj}	Re-dispatch power of load j
$\Delta P_t^{int.}$	Interruption power for contingency t
P_{line_l}	Flow of line l
ΔP_{line_l}	Change in flow of line l
$\Delta P^{+}_{Gi}, \Delta P^{-}_{Gi}$	Increment and decrement re-dispatch power of generator i

Constants

$\overline{P_{line_l}}$	The expected value of P_{line_l}
$Var(P_{line_l})$	The variance of P_{line_l}
$P_{line_l}^{max}$	Maximum allowed flow in line l
ΔP_{Gi}^{min} , ΔP_{Gi}^{max}	Maximum allowed re-dispatch power for generator i
ΔP_{Lj}^{min} , ΔP_{Lj}^{max}	Maximum allowed re-dispatch power for load j
α_l	Confidence level of the l-th line flow
$a_{l,i}$	Transmission congestion distribution factor (TCDF) for line l with respect to injection in bus i
$\overline{a_{l,i}}$	Mean value of $a_{l,i}$
E_l	Standard normal variable related to α_l

2. Introduction

During the past decade, open access to transmission networks in the restructured power systems has resulted in the emergence of the bilateral contracts. This trend together with the growth of the electricity consumption has increased the possibility of the congestion in the transmission network. Congestion is essentially referred to the violation in the physical, operational and policy constraints of the network. Both vertically integrated and unbundled power systems have experienced such problems [1, 2]. Congestion generally arises from 2 main sources: the occurrence of the system contingencies and ignorance of the generation location in market clearing mechanism [3]. Congestion may occur in day-ahead, hour-ahead and real-time dispatch. The system operator is responsible for the necessary preventive or remedial actions to prevent or relieve congestion. The set of the remedial activities performed to relieve violated limits is referred to as congestion management. In order to alleviate network congestion, cheaper generators may be replaced by more expensive ones in primary market dispatch. Therefore Managing network congestions may impose additional cost on the operation of the system. Transmission congestion may result in market power for some participants or endanger the stability of the system [4]. Therefore, preventive or corrective actions are necessary to relieve congestion and decrease system risks.

Recently, many researchers have investigated the congestion management techniques. The basic differences among the CM approaches arise from the modeling of power market, available controls to relief congestion and algorithms applied to the proposed CM problems. Kumar et al. [1] categorized the congestion management approaches into 4 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 has been reviewed. A unified framework for different congestion management schemes has been presented in [2]. In the presented framework in [2], two distinct stages have been considered for the operation of an electricity market, including market dispatch and congestion re-dispatch. The second stage will only be performed if the first stage cannot achieve a feasible operating state with no constraint violation. In most congestion management methods, the general concept of the congestion re-dispatch problem implies the minimization of the market re-arrangement cost to alleviate congested lines [5-7].

The network uncertainties may be related to different sections of the power system, including generation, transmission and distribution [8]. Therefore, considering the system uncertainties in power system operation and control actions, such as congestion management, is of prime importance in power system analysis and studies. Applying the uncertainties to the congestion management models and algorithms may seriously improve the feasibility of the resulted operating point and improve the power system security level. As an example, Esmaili et al. in [9], proposed a stochastic congestion management technique using a scenario-based approach. In their technique, scenarios are produced for the power system operating point to deal with power system uncertainties. Moreover, they reduced the generated scenarios to include the most probable and non-repetitive ones. Finally, the congestion management is performed for the reduced scenarios. The Final solution of the CM problem was obtained by computing the expectation of the solutions associated with each scenario.

In this paper, we proposed a new formulation for congestion management considering network uncertainties. In our proposed method, probability density functions (PDF) of line flows are employed to model the stochastic CM problem. The new model of stochastic congestion management is formulated based on the chance constrained programming (CCP) in which deterministic transmission constraints are replaced by the stochastic ones with respect to PDFs of line flows. Therefore, the proposed method can have a better accuracy compared with scenario based methods, which generally select a set of most important scenarios and eliminate the others. In our proposed approach, a stochastic optimization problem based on PDF of line flows will be formulated to handle the system uncertainties in congestion management process. The PDF of line flows can be obtained using a Monte Carlo simulation considering the uncertain model of the system variables. Moreover, an analytical approach is used to solve the new model of the stochastic congestion management. In this method, stochastic optimization problem will be transformed to an equivalent deterministic problem. Effectiveness of the proposed approach is evaluated by applying the method to the IEEE 30-bus test system.

The rest of this paper is organized as follows. Section 3 presents the deterministic congestion management model. The stochastic congestion management based on CCP is described in section 4. The results of simulation on IEEE 30-bus test system are presented in section 5. Finally, the concluding remarks are summarized in section 6.

3. Deterministic congestion management model

In this paper, a day-ahead pool electricity market is used as the framework to implement the proposed congestion management algorithm. In the market, suppliers and consumers submit their bids to market operator, who is responsible for the clearing procedure [10]. The time framework for the market-clearing procedure is 24 hours. On the other hand, congestion management is performed on an hourly basis, if necessary.

In this environment, the deterministic congestion management can be formulated as follows:

$$Min \quad \sum_{i=1}^{N_G} \mathrm{C}_i\,(\Delta P_{Gi}) + \sum_{j=1}^{N_L} \mathrm{C}_j\,(\Delta P_{Lj}) \qquad (1)$$

$s.t.$

$$\left| P_{line_l} + \sum_{i=1}^{N_G} a_{l,i}\,\Delta P_{Gi} - \sum_{j=1}^{N_L} a_{l,j}\,\Delta P_{Lj} \right| \le P_{line_l}^{\max} \qquad \forall l \in N_{Line} \qquad (2)$$

$$\Delta \mathrm{P}_{Gi}^{\min} \le \Delta P_{Gi} \le \Delta \mathrm{P}_{Gi}^{\max} \qquad \forall i \in N_G \qquad (3)$$

$$\Delta \mathrm{P}_{Lj}^{\min} \le \Delta P_{Lj} \le \Delta \mathrm{P}_{Lj}^{\max} \qquad \forall j \in N_L \qquad (4)$$

$$\sum_{i=1}^{N_G} \left(\Delta P_{Gi}\right) = \sum_{i=1}^{N_L} \left(\Delta P_{Lj}\right) \qquad (5)$$

The objective function of the CM problem is the minimization of the total cost of the re-dispatch step in day-ahead market. The objective function in (1) consists of 2 distinct terms, related to the costs imposed by generators and loads for congestion re-dispatch. In (1), $\mathrm{C}_i\,(\Delta P_{Gi})$ is the re-dispatch cost function related to the generators which can be expressed as,

$$\mathrm{C}_i\,(\Delta P_{Gi}) = C_i^{up} \times \Delta P_{Gi}^{+} + C_i^{down} \times \Delta P_{Gi}^{-} \qquad (6)$$

Where, C_i^{up} and C_i^{down} are the bids of generator i for the power increment and decrement, respectively. The re-dispatch cost function related to the loads is similar to that of the generators. Constraint (2) explains the changes in line flows in which $a_{l,i}$ stands for transmission congestion distribution factor (TCDF), described in detail in [11]. Constrains (3) and (4) express the maximum allowed changes in the power of generators and loads. Moreover, constraint (5) models the power balance equation. In this paper, transmission losses in CM formulation are ignored.

4. Stochastic congestion management model

Power system behavior involves various types of uncertainties, which should be considered in the modeling process of the power system problems to have dependable analyses and studies on the power system [12]. Power system uncertainties may be categorized into loads forecasting errors, the availability of the equipments and the price uncertainties in the power market. The modeling of the power system uncertainties is the first step in the stochastic CM.

The main steps for the proposed stochastic CM can be expressed as follows:

- Determining PDFs of output variables such as line flows using a primary Monte Carlo simulation considering the model of the network uncertainties in section 4.1.

- Formulating the stochastic CM based on CCP in section 4.2 with respect to PDFs of line flows.

- Identifying the equivalent deterministic problem for CCP based stochastic CM as it will be explained in sections 4.3 and 4.4.

4.1. Modeling of Power System Uncertainties

Power system loads follow a random pattern and therefore, load forecasting errors are inevitable. Hence, load in power systems is modeled as a random variable (ξ) with normal distribution as the probability density function (PDF) [12]. These uncertain loads may have correlations with each other [13]. In this paper, short term load forecasting is considered and therefore, the order of σ_i / μ_i should be smaller than 0.15 [12]. Availability of the system equipments, including generators and transmission lines can be modeled using forced outage rate (FOR) [14]. The uncertainties related to market prices have been neglected in this paper. In order to model system uncertainties, we have used a Monte Carlo simulation utilizing the PDF of input variables. Using Monte Carlo simulation, the PDFs of output variables, such as line flows (P_{line_l}), are achieved. In each iteration of Monte Carlo, the samples of uncertain variables are generated. The primary market dispatch is generated using these samples and therefore, the values of line flows are obtained. The PDFs of line flows are extracted from the obtained values in Monte Carlo iterations. These PDFs are effectively used to formulate the stochastic CM.

4.2. Formulating the Stochastic CM Based on CCP

Chance-constrained programming is a special type of the optimization problems which is useful for problems involving uncertain variables in their objective function or constraints. In this type of optimization, the fulfillment of constraints is guaranteed with a specific level of probability instead of being treated as hard constraints. A typical CCP can be formulated as follows [15]:

$$\begin{aligned} &Min.\ f(x) \\ &\Pr\{g_i(x,\xi) \le 0\} \ge \alpha_i \quad \forall i \end{aligned} \tag{7}$$

where, x is the decision vector of the optimization problem and ξ stands for a set of uncertain variables. Furthermore, α_i which identifies the level of constraints satisfaction, is called confidence level.

Based on the CCP formulation in (7), the probabilistic version of the CM problem in (1)-(5) can be written as follows:

$$Min \quad \sum_{i=1}^{N_G} C_i(\Delta P_{Gi}) + \sum_{j=1}^{N_L} C_j(\Delta P_{Lj}) \tag{8}$$

$s.t.$

$$\Pr\left[\left|P_{line_l} + \sum_{i=1}^{N_G} a_{l,i}\,\Delta P_{Gi} - \sum_{j=1}^{N_L} a_{l,j}\,\Delta P_{Lj}\right| \le P_{line_l}^{\max}\right] \ge \alpha_l \quad \forall l \in N_{Lin} \tag{9}$$

$$\Delta P_{Gi}^{\min} \le \Delta P_{Gi} \le \Delta P_{Gi}^{\max} \qquad \forall i \in N_G \tag{10}$$

$$\Delta P_{Lj}^{\min} \le \Delta P_{Lj} \le \Delta P_{Lj}^{\max} \qquad \forall j \in N_L \tag{11}$$

$$\sum_{i=1}^{N_G}(\Delta P_{Gi}) = \sum_{i=1}^{N_L}(\Delta P_{Lj}) \tag{12}$$

Constrains (9) express the line flow limitations which should be satisfied with the minimum probability of α_l . In the CCP-based congestion management, α_l identifies the probability of the constraints satisfaction for the flow in the line *l*. As an example, for $\alpha_l = 0.9$, stochastic constraints of the transmission branches must be satisfied for at least 90% of system states, which are modeled in the primary Monte Carlo simulation. In (9), P_{line_l} is an uncertain variable which its PDF has been determined in the primary Monte Carlo simulation. Also, ΔP_{Gi} and ΔP_{Lj} are the decision variables for the optimization problem in (8)-(12).

The stochastic optimization problem stated in (8)-(12) is very complicated and difficult to be solved since it includes a set of stochastic constraints in (9). In [12], a sequential approach has been proposed to solve this type of the optimization problems, which includes a simulation layer together with an optimization layer. A numerical method using Genetic Algorithm (GA) and Monte Carlo technique has been presented in [16] to solve the stochastic transmission expansion planning modeled by CCP. In fact, real-coded GA generates the suggested solution for stochastic CM, while Monte Carlo evaluates the satisfaction of the probabilistic constraints. Rao has developed an analytical approach to solve the stochastic optimization problems in [17].

Stochastic congestion management problem, formulated by CCP, is solved in [18] using a combined approach including real-coded genetic algorithm and Monte Carlo simulation same as that in [16]. The real-coded genetic algorithm has been incorporated into Monte-Carlo simulation to solve the proposed stochastic congestion management. In fact, real-coded GA generates the suggested solution for stochastic CM while, Monte-Carlo evaluates the satisfaction of the probabilistic constraints. In this paper, we utilize the analytical approach, proposed by Rao [17], while the other proposed methods in [9] and [18] are also implemented to perform a comprehensive study.

4.3. Equivalent Linear Model for Stochastic Congestion Management

If the variation of the shift factors under stochastic modeling are neglected ($Var(a_{l,i}) \cong 0$), the stochastic optimization problem in (8)-(12) would be equal to the deterministic optimization problem, expressed below [17],

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

$$\left| \overline{P_{line_l}} + \sum_{i=1}^{N_G} \overline{a_{l,i}} \Delta P_{Gi} - \sum_{j=1}^{N_L} \overline{a_{l,j}} \Delta P_{Lj} \right| \le P_{line_l}^{max} + E_l \sqrt{Var(P_{line_l})} \quad \forall l \in N_{Line} \tag{14}$$

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

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

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

Where, E_l is the standard normal variable, obtained from the standard normal distribution $\rho(E_l)$ with respect to the value of the confidence level α_l , as expressed in (18),

$$\rho(E_l) = 1 - \alpha_l \Rightarrow E_l = \rho^{-1}(1-\alpha_l) = -\rho^{-1}(\alpha_l) \tag{18}$$

It should be noted that in this study, it is assumed that $\alpha_l > 0.5$ and consequently $1-\alpha_l < 0.5$, therefore, $E_l < 0$ [17]. For example, if $\alpha_l = 0.99$ then we have $E_l = -\rho^{-1}(0.99) = -2.33$ using standard normal distribution with probability of 99%. Deterministic optimization problem in (13)-(17) is a linear problem which can be easily solved using linear programming.

4.4. Equivalent Nonlinear Model for Stochastic Congestion Management

Considering the variance of the shift factors, the stochastic optimization problem in (8)-(12) would be equal to a nonlinear deterministic optimization problem, expressed below [17].

$$Min \quad \sum_{i=1}^{N_G} C_i(\Delta P_{Gi}) + \sum_{j=1}^{N_L} C_j(\Delta P_{Lj}) \tag{19}$$

$$\left| \overline{P_{line_l}} + \sum_{i=1}^{N_G} \overline{a_{l,i}} \Delta P_{Gi} - \sum_{j=1}^{N_L} \overline{a_{l,j}} \Delta P_{Lj} \right| \le P_{line_l}^{max} + E_l \sqrt{Var(h_l)} \quad \forall l \in N_{Line} \tag{20}$$

$$\Delta P_{Gi}^{min} \le \Delta P_{Gi} \le \Delta P_{Gi}^{max} \quad \forall i \in N_G \tag{21}$$

$$\Delta P_{Lj}^{min} \le \Delta P_{Lj} \le \Delta P_{Lj}^{max} \quad \forall j \in N_L \tag{22}$$

$$\sum_{i=1}^{N_G} (\Delta P_{Gi}) = \sum_{i=1}^{N_L} (\Delta P_{Lj}) \tag{23}$$

Where,

$$h_l = P_{line_l} + \sum_{i=1}^{N_G} a_{l,i} \Delta P_{Gi} - \sum_{j=1}^{N_L} a_{l,j} \Delta P_{Lj} - P_{line_l}^{max} \tag{24}$$

$$Var(h_l) = \sum_{i=1}^{N_G} Var(a_{l,i}) \Delta P_{Gi}^2 + \sum_{j=1}^{N_L} Var(a_{l,j}) \Delta P_{Lj}^2 + Var(P_{line_l}) \tag{25}$$

Constraints (14) and (20) are the set of equivalent constraints for the stochastic constraints in (9) [17]. These equivalent constraints transform the stochastic optimization to a deterministic one. Therefore, the solution of the stochastic congestion management in (8)-(12) can be obtained by solving the deterministic optimization problem in (13)-(17) or (19)-(25). The equivalent deterministic problem in (19)-(25) is a non-linear optimization which can be solved by sequential quadratic programming (SQP) algorithm.

A primary Monte Carlo simulation is carried out to identify mean and variance values of the line flows and shift factors ($\overline{a}_{l,i}$,$Var(a_{l,i})$). The uncertain model of loads and network equipments are utilized in primary Monte Carlo simulation. The main difference between the results produced by the linear and nonlinear methods arises from the modeling of the shift factors variations, which are considered by the nonlinear approach.

The flow chart for the solution of CCP-based stochastic CM can be described by Figure 1. The flow chart consists of 2 main steps: primary Monte Carlo simulation to model the system uncertainties and produce PDF for line flows, solving the equivalent deterministic problem for the proposed stochastic CM.

5. Simulation Results

To evaluate the proposed probabilistic congestion management approach, both deterministic and probabilistic congestion management models have been applied to the IEEE 30-bus test system. IEEE 30-bus test system includes 6 generators and 41 transmission lines. A primary Monte Carlo simulation is performed based on the test system data to model the system uncertainties and obtain the distribution function of line flows. Mean and variance values related to the shift factors are also determined by the primary Monte Carlo simulation. Probability distribution function (PDF) for the power flow in line 14 is shown in Figure 2.

In this case study, 9 market participants, including generators installed at buses 5,8,11 and dispatchable loads at buses 7, 8, 10, 15, 20, and 21 have been selected to contribute in the congestion re-dispatch step. 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 [9] utilize the deterministic values of TCDFs, while the stochastic method presented in [18] and the proposed approach in this paper use the mean values of the TCDFs. Figure 3 shows the deterministic and expected values of the TCDFs, which are used in deterministic and stochastic CM, respectively.

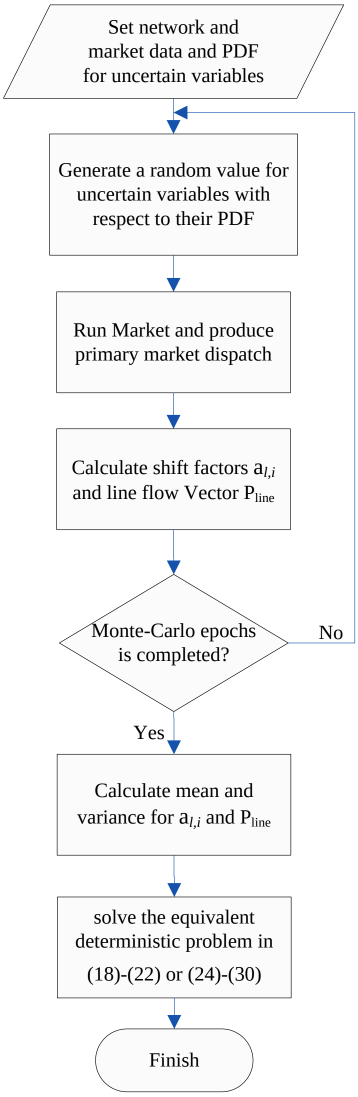

Fig. 1. Flow chart for the solution of CCP-based stochastic CM

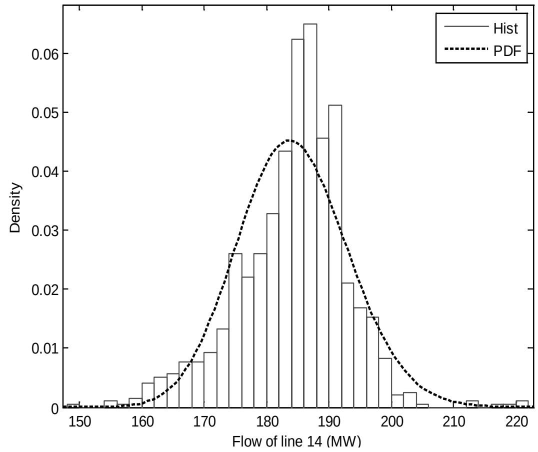

Fig. 2. Probability Distribution Function of 14th line flow

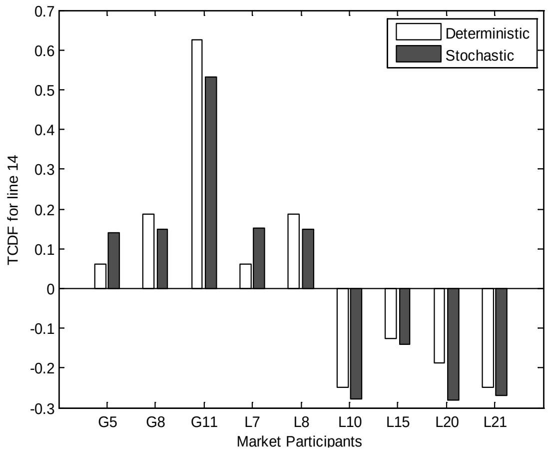

Fig. 3. Shift factors of line 14 related to selected market participants

To simulate the proposed method on the case study, 5 different methods are implemented and compared to each other. The first method is a deterministic approach which has been introduced in [11], while the second approach is a stochastic CM method presented in [9]. This method uses scenario generation and reduction in order to solve the stochastic CM. The other 3 approaches are the proposed CCP-based congestion management technique with different solving algorithms, including Monte Carlo based real-coded genetic algorithm (RCGA) [18] and the 2 models of analytical approach [17]. The results of managing congestion on the 30-bus test system using the mentioned methods are shown in table I.

TABLE I. RE-DISPATCH RESULTS WITH DIFFERENT METHODS

Method	Algorithm	Cost($/h)	ΔP_L (MW)	$\Delta P_{line_{14}}$ (MW)	$\overline{\Pr}(P_{line})$
Deterministic [11]	-	121.2	-16.38	-14.33	0.4897
Stochastic [9]	Scenario generation and reduction	142.8	-19.28	-16.30	0.4065
Stochastic [18]: ($\alpha = 0.6$)	Monte Carlo based RCGA	159.9	-20.60	-17.26	0.3615

Proposed Method: ($\alpha = 0.6$)	Linear model	150.8	-20.38	-16.55	0.3919
Proposed Method: ($\alpha = 0.6$)	Non-linear model	151.3	-20.45	-16.60	0.3896

In this table, the total cost of re-dispatch, total load decrement, changes in power flow in line 14 and the probability of the network constraints violation are presented for each method. If the deterministic method is applied to relieve congestion, the probability of constraint violation will be 50% approximately with respect to the PDF of the line flows. This figure decreases to 40% in the method presented in [9]; however, the total cost of re-dispatch increases by 30 $/h to promote the probability of constraint satisfaction. To have a same situation, α_l is set to 0.6 in the stochastic CM which means the maximum allowed constraint violation is 0.4. The same value is employed for α_l to have a better comparison between the stochastic CM approaches. The proposed stochastic CM is solved by 3 methods, including proposed method by [18], and linear and nonlinear analytical approaches. It is clear that the solution of the analytical method has the prominence over the solution obtained by the numerical method because the proposed method not only has the flexibility to set the confidence level, but also it uses fewer approximations compared to the method in [9]. Moreover, the proposed method imposes less computational burden than numerical method. In contrast with the scenario based approach proposed in [9], which selects the most important scenarios and eliminates the others, our proposed approach is an analytical method which utilizes the distribution function of output variables such as line flows. The PDF of line flows can be generated using Monte Carlo simulation or any other methods such as Cumulant or 2 point estimate method.

Re-dispatch power of each market participant for the methods presented in table I, are shown in Figure 4. The pattern of re-dispatch strategy in stochastic CM differs from the deterministic one since the probability of the constraint violation in the stochastic approach is reduced. The flexibility of the proposed CCP-based congestion management is more than the other methods since the confidence level α_l is introduced in this method. Change in α_l causes the changes in the relief strategy to meet the satisfaction level which is defined for the stochastic constraints. The results of stochastic congestion re-dispatch with the proposed linear and nonlinear methods under different confidence levels are shown in table II. As it can be seen in table II, firstly, the costs of congestion re-dispatch rise along with increasing α_l in both linear and nonlinear methods. This is due to the decrease in the probability of constraint violation, i.e. $\overline{\Pr}(\Delta P_{line})$. It should be noted that, $\overline{\Pr}(\Delta P_{line})$ is almost equal to $1-\alpha_l$ which is quite reasonable. Secondly, the cost of re-dispatch in the non-linear method is more than that in the linear approach since *the* non-linear method considers the variation of shift factors in stochastic optimization. In fact, in the non-linear method, the level of system uncertainties is larger in comparison to the linear approach and consequently, the amount of re-dispatched power increases to provide the level of constraint satisfaction.

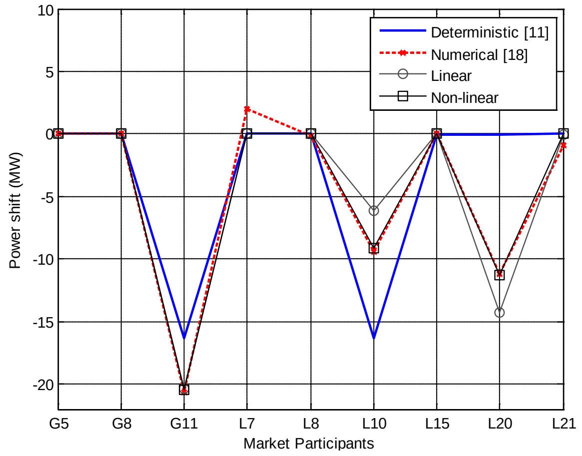

Fig. 4. Re-dispatch power of market participants using different approaches

TABLE II. RE-DISPATCH RESULTS WITH DIFFERENT CONFIDENCE LEVELS

Method	Cost($/h)	ΔP_L (MW)	$\Delta P_{line_{14}}$ (MW)	$\overline{\Pr}(P_{line})$
Linear ($\alpha = 0.8$)	197.7	-26.69	-21.69	0.2001
Linear ($\alpha = 0.9$)	232.9	-31.46	-25.54	0.1060
Linear ($\alpha = 0.99$)	316.0	-42.71	-34.68	0.0148
Non-linear ($\alpha = 0.8$)	200.4	-27.08	-21.98	0.1925
Non-linear ($\alpha = 0.9$)	238.4	-32.21	-26.15	0.0947
Non-linear ($\alpha = 0.99$)	335.6	-45.36	-36.81	0.0086

Three different confidence levels, including $\alpha_l = 0.8$ *or* 0.9 *or* 0.99 are simulated. As can be seen in Figure 5, change in the confidence level α_l leads to the change in the re-dispatch pattern. The re-dispatch power of the selected participants rises by increase of α_l to achieve the required satisfaction probability.

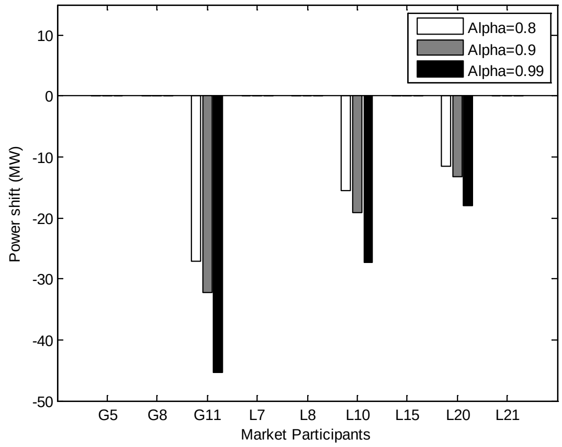

Fig. 5. Re-dispatch power of market participants with different α_l in the non-linear method

6. Conclusion

This paper proposed a new approach for probabilistic congestion management based on the chance-constrained programming. Introducing the confidence level in congestion re-dispatch step promotes the flexibility of congestion management approach. CCP-based probabilistic CM is a complicated problem and difficult to solve since it includes a set of stochastic constraints. In this paper, the analytical approach, developed to solve the stochastic optimization problems, was employed to find the solution of the CCP-based CM problem. Moreover, a numerical method, based on a real-coded genetic algorithm and a Monte Carlo simulation, was also implemented for comparison to the analytical approach. The real-coded GA was used to find the optimum solution for the CM problem while the Monte Carlo simulation was implemented to investigate the fulfillment level of the stochastic constraints. The analytical method is more proper to apply in real power systems since it transforms the CCP based CM problem to an equivalent deterministic problem. In fact, this approach not only converges during a limited time but also has an acceptable accuracy level. The obtained simulation results showed that the probability of the constraints satisfaction identifies the re-dispatch strategies in different market conditions. The costs of the market re-dispatch increases when the system operator intends to have a higher probability of the constraints fulfillment. In such conditions, there will be larger changes in the primary arrangement of the market and more reduction in the flow of the congested lines compared to the other situations with less fulfillment probabilities. In fact, the new formulation of the probabilistic congestion management models the probable system conditions and consequently, the proposed strategy for congestion relief will have an acceptable confidence level as decided by the system operator. The main contribution of this paper is proposing a new formulation for stochastic CM using CCP which allows the system operator to have a desirable level for system security and reliability in contrast with the proposed method in [9], which uses the expectation of the selected scenarios. Furthermore, an analytical solving approach for the CCP-based stochastic CM has been proposed in this paper. The analytical approach has less complexity and computation burden compared with the proposed algorithms in [12] and [18] to solve the CCP-based problems.

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