Information Gap Decision Theory Based Preventive/Corrective Voltage Control for Smart Power Systems with High Wind Penetration

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***Abstract*— This paper proposes a new approach for preventive/corrective voltage control in smart power systems. Previous researches, which were based on deterministic methods, cannot be applied in the presence of high uncertainty caused by renewable generation and loads. Hence, new frameworks are required to handle the stochastic space of the problem. In this research, a robust approach based on the information gap decision theory (IGDT) is used to handle the uncertain space using the risk averse (RA) and opportunity seeker (OS) strategies. The RA strategy can provide an operation schedule for a given uncertainty budget in real time and with a required loading margin. The OS strategy helps to decrease the operating costs in view of possible uncertainties. The proposed method was implemented according to the IEEE reliability test system. The results of this approach give the flexibility to select a degree of robustness considering the desired uncertainty budget.**

***Index Terms* - Smart grid, Optimal power flow, Wind power, Preventive voltage control, Corrective voltage control, Information gap decision theory**

NOMENCLATURE

Sets:

NB Set of system buses

Indices:

i Bus index

j Bus index

G Generator index

W Wind farm

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Variables and Parameters:

D_i Load at bus *i*

P_i^W Wind power generation of wind farm *W* at bus *i*

C_{PG}^{+}/C_{QG}^{+} Cost of active/reactive power up re-dispatch

C_{PG}^{-}/C_{QG}^{-} Cost of active/reactive power down re-dispatch

P_i^{G+}/Q_i^{G+} Amount of active/reactive power up re-dispatch

P_i^{G-}/Q_i^{G-} Amount of active/reactive power down re-dispatch

$P_{i,sch}^{G}/Q_{i,sch}^{G}$ Amount of initial active/reactive power scheduled

C_{DR}/C_{DRQ} Cost of active/reactive demand response

C_{IL}/C_{ILQ} Cost of active/reactive interruptible load curtailment

DR_i/DRQ_i Active/Reactive demand response at bus *i*

IL_i/ILQ_i Active/Reactive interruptible load at bus *i*

P_i^G/Q_i^G Active/Reactive generation of generator *G* at bus *i*

V_i/θ_i Voltage Magnitude/Angle of bus *i*

Y_{ij}/φ_{ij} Magnitude/Angle of the *ij*th element of admittance matrix

$P_{i,max}^{G}/P_{i,min}^{G}$ Maximum/Minimum active power generation of generator at bus *i*

$Q_{i,max}^{G}/Q_{i,min}^{G}$ Maximum/Minimum reactive power generation of generator at bus *i*

$DR_{i,max}/DRQ_{i,max}$ Maximum active/reactive demand response at bus *i*

$IL_{i,max}/ILQ_{i,max}$ Maximum active/reactive involuntary load curtailment at bus *i*

$V_{i,max}/V_{i,min}$ Maximum/Minimum allowed voltage at bus *i*

$S_{ij}/\hat{S}_{ij}$ Apparent power of line between bus i and j for the base/loading case

$S_{ij,max}$ Maximum permitted apparent power of line between bus i and j

λ_s Loading margin of the system

λ_{des} Desired loading margin of the system

K_i^G/K_i^D Rate of change for generation/demand at bus i

$\hat{Q}_i^G$ Reactive power of generators for the loading case

$V_i^G/\hat{V}_i^G$ Voltage of generator buses for the base/loading case

I. Introduction

In recent years, the integration of wind generation in power systems has been significantly increased [1-2]. Two main aspects of wind farms including low cost of generation and environmental advantages make wind generation an interesting option for system operators. By the end of 2015 the global wind energy installations reached 432GW and by the end of 2030 these installations will reach 2000GW, which will supply 19% of the global energy [3-8]. While the Danish government is planning to produce 50% of its electricity from wind by 2050, the installed capacity of wind will reach 1TW in China by that year [9-10]. However, the intermittent characteristics of wind generation have to be considered to achieve economic and secure operation of the power system [11]. Smart grids give the operator many options to handle the intermittent operation of wind generation, including storage devices [12-13], and responsive loads [14-16]. Intermittency mitigation with storage devices includes pumped hydroelectric storage (PHS), compressed air energy storage (CAES), and battery energy storage systems [4]. Precise wind speed and power forecasting are the other methods which are used for intermittency alleviation [4].

Proper loading margin is one of the important factors for power system security [16]. Considering the volatility of wind generation [17], and also the load forecasting errors, an appropriate scheduling is required in order to provide the required loading margin while reducing operating costs in different circumstances. Preventive voltage control (PVC) actions are implemented to provide a certain margin for the loading of the system. Corrective voltage control (CVC) actions are used in order to recover the system from a negative loading margin caused by a severe contingency [18-19]. This control scheme finds a new equilibrium point for the post-contingency state.

The generation dispatch problem with high penetration of wind generation has been studied extensively. In [20], the dispatch problem was solved considering the emission tax. [21-22] provided novel methods for economic dispatch problem in smart grids. However, in these papers, the power system security aspects such as the loading margin were not considered. Providing power system security has been studied in many papers. In [23], a congestion management scheme was presented considering the loading margin (LM) of the system. In [18], a preventive/corrective control framework was introduced for the demand side participation. A hybrid preventive/corrective computational strategy for the security constrained optimal power flow problem, without considering the system loading margin, was presented in [24]. A market based optimal power flow scheme considering voltage security constraints was introduced in [25]. [26-27] introduced a voltage security pricing scheme for electricity markets. Reactive reserve procurement to improve the voltage stability margin was suggested in [28]. In all of these references, a deterministic framework was used and uncertain generation and consumption were neglected.

When a system faces multiple uncertainties, deterministic approaches are not efficient anymore. Hence, in recent years, many researchers have addressed different methods to handle the uncertain space caused by stochastic variables. In [29-30], samples taken from the Weibull distribution function were used to estimate the costs of wind spillage or wind deficiency penalties. References [31-32] handled the uncertain variables using the point estimate method. Yet, these studies focused only on the operating costs and the voltage security aspects were not studied. In [33], a stochastic framework was used for the corrective voltage actions in presence of wind power and demand response programs. [34-35] introduced a voltage security framework for microgrids, but without considering unit outages.

Recently, the information gap decision theory (IGDT) has been applied to many optimization problems with the aim of overcoming the uncertain space [36]. While probabilistic and stochastic approaches are dependent on precise information of the probability density functions and suffer from high computational burden, the IGDT method can be implemented with the least information about the uncertain variables and it has shorter execution times. The IGDT method has been examined for many power system optimization problems, including bidding strategy [37], unit commitment [38], generation expansion planning [39], transmission expansion planning [40], congestion management [41], and optimal power flow [42]. However, the preventive/corrective voltage control (PCVC) actions facing multiple uncertainties have not been studied using the IGDT method. In this paper, the stochastic space produced by the high wind power penetration and load uncertainty is handled using the IGDT method and nonlinear programming (NLP) formulation.

According to latest developments in smart grid infrastructure, demand response programs can be used as a proper solution for handling the volatility of renewable energy resources [43]. For incentive based demand response programs, incentives are paid to the demand response providers to decrease their load at required time. Emergency demand response to provide the required security margin was used in [44]. [18] and [45] used responsive loads, instead of involuntary load curtailment, in order to increase the voltage stability margin with a lower cost. In this paper, the demand response programs were used as a source to provide a portion of the required active and reactive power reserve.

In this work, a new robust model is presented for the preventive/corrective voltage control of power system. The information decision gap theory (IGDT) is used to provide a robust solution for this problem.

The main contributions of this paper are:

1. Providing a robust re-dispatch for the system in order to guarantee the required loading margin for a given uncertainty budget.
2. Proposing risk averse and opportunity seeker strategies for the preventive/corrective voltage control problem.
3. Demonstrating the effect of responsive and interruptible loads on increasing the robustness of the system and overcoming the uncertainty of the problem.

The rest of the paper is organized as follows: In Section II, preventive/corrective voltage control actions are described. In Section III, the IGDT approach is described. Section IV explains the application of IGDT to the PCVC problem. Section V presents simulation results and conclusions are given in Section VI.

II. Preventive/Corrective Voltage Control

According to the Western Electricity Coordinating Council (WECC) [46], in order to guarantee secure operation for power systems, a certain loading margin has to be provided for the base case and post contingencies.

Considering Fig. 1 (a), curve (1) is the pre-contingency curve with the operating point A. For different contingencies two different states can occur:

(i) After a severe contingency, the system can become unstable and the loading margin becomes negative (curve (2)). In this situation, a corrective voltage control is used to recover the system with a certain level of loading margin (curve (3)). In this figure, B2 is the new operating point and B1 is the point which leads to a zero loading margin.

(ii) After a contingency, the system can still be stable but the loading margin may not be adequate (curve (4) and $\lambda_1 < \lambda_{des}$). In this case, a preventive voltage control action is required to provide the required loading margin (curve (5) and $\lambda_{des} < \lambda_2$) [18], [33].

The above explained preventive/corrective voltage actions used for a deterministic space. For a system with stochastic variables, it is not guaranteed that, for a certain scheduling, the required loading margin will be satisfied or the system will remain stable. Therefore, in order to provide the required margin of the system for different stochastic variables, a proper level of active/reactive power re-dispatch has to be scheduled and deployed. The formulation presented in the next section is used to estimate the appropriate level of active/reactive power reserve that has to be provided by different sources while minimizing the operating costs.

III. Information Gap Decision Theory for Uncertainty Handling

Numerous power system problems in uncertain spaces were modeled and controlled with stochastic and probabilistic approaches [43], [47-50]. However, in addition to high computational burden that these methods require, they are dependent on the probabilistic density functions of the uncertain variables. Hence, these approaches are inapplicable when historical data are not available or not accurate [41].

Assume an optimization problem as follows:

$$min\ F(X,\gamma) \tag{1}$$

$$\boldsymbol{H}_i(X,\gamma) \le 0, \quad i \in S_{ieq} \tag{2}$$

$$\boldsymbol{G}_j(X,\gamma) = 0, \quad j \in S_{eq} \tag{3}$$

$$\gamma \epsilon \Omega \tag{4}$$

Where F is the objective function, γ and X are the uncertain and decision variables. $\boldsymbol{H}$ and $\boldsymbol{G}$ are the inequalities and equalities respectively. S_{ieq}, S_{eq}, and Ω are the sets of inequalities, equalities, and uncertainties.

The set of uncertainties can be defined as:

$$\forall \gamma\ \epsilon\ \Omega(\bar{\gamma},\alpha) = \left\{\gamma : \left|\frac{\gamma-\bar{\gamma}}{\gamma}\right| \le \alpha\right\} \tag{5}$$

Where $\bar{\gamma}$ indicates the forecasted value of the uncertain parameter. α is the radius of uncertainty and shows by how much the uncertain variable can diverge from its forecasted value.

For the base case, the optimization problem is solved using the forecasted values. According to the base case objective function, the risk averse (RA) and opportunity seeking (OS) strategies can be chosen by the decision maker. In the following sections, formulations for each strategy are provided.

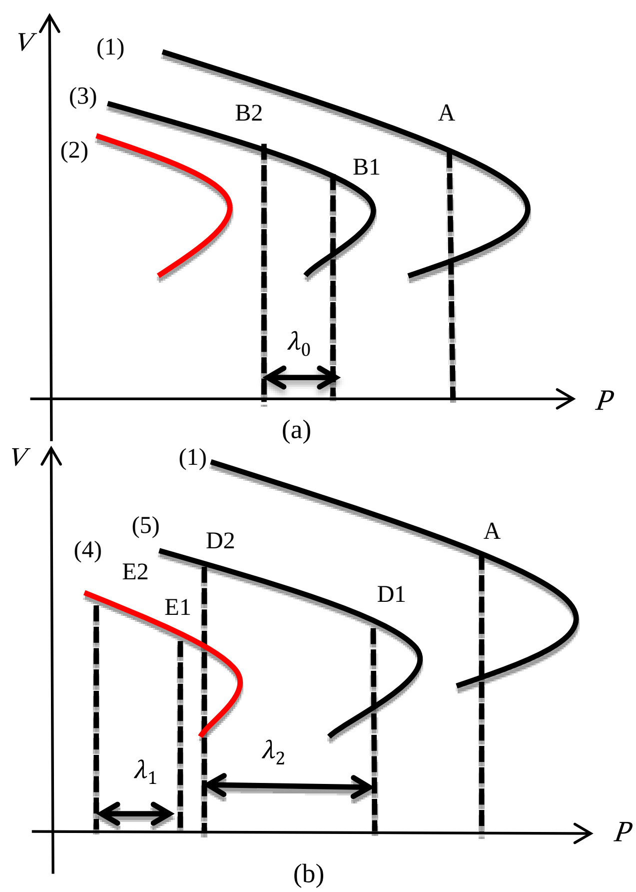

Fig. 1. Operating points for (a) Corrective voltage control (b) Preventive voltage control

A. Risk-averse strategy

The main goal of this strategy is to provide a decision which is robust against excursions of the uncertain variables from their forecasted values. In this strategy, the most conservative and robust decision occurs when the uncertain parameters have the greatest deviation from their expected values. This strategy can be formulated as follows:

$$Max\ \alpha \tag{6}$$

$$\boldsymbol{H}_i(X,\gamma) \leq 0, \quad i \in S_{ieq} \tag{7}$$

$$\boldsymbol{G}_j(X,\gamma) = 0, \quad j \in S_{eq} \tag{8}$$

$$F(X,\gamma) \leq (1+\sigma).F_0(X,\bar{\gamma}) \tag{9}$$

$$\gamma = (1+\alpha).\bar{\gamma} \tag{10}$$

In (9), σ is the deviation factor. $F_0(X,\bar{\gamma})$ is the objective function corresponding to the forecasted values of the uncertain variables $\bar{\gamma}$. Fig. 2 (a) illustrates the concept of the risk averse strategy for the IGDT method. In this figure, the solid lines are the forecasted variables and the base re-dispatch cost.

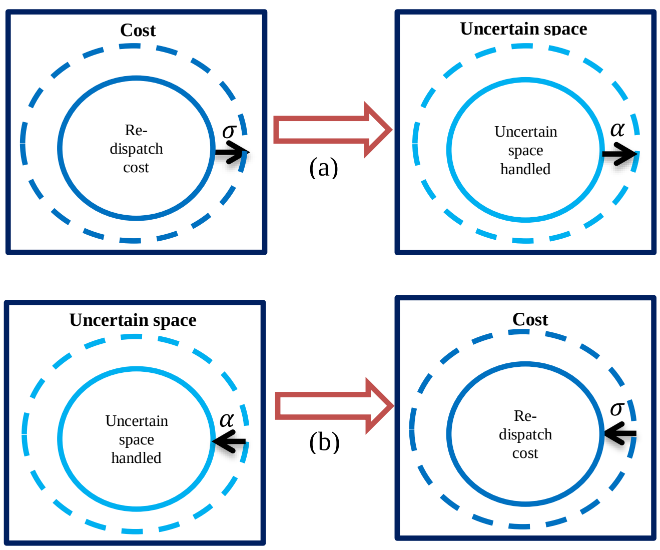

Fig. 2. Illustration of the IGDT concept, (a) Risk-averse strategy, (b) Opportunity seeking strategy

In Section IV, the PCVC formulation based on the risk averse strategy is presented.

B. Opportunity seeker strategy

In this strategy, the decision maker uses the uncertainty to increase the profit or decrease the total costs. In a single level optimization framework, this strategy can be formulated as follows:

$$Min\ \alpha \tag{11}$$

$$\boldsymbol{H}_i(X,\gamma) \leq 0, \quad i \in S_{ieq} \tag{12}$$

$$\boldsymbol{G}_j(X,\gamma) = 0, \quad j \in S_{eq} \tag{13}$$

$$F(X,\gamma) \leq (1-\sigma).F_0(X,\bar{\gamma}) \tag{14}$$

$$\gamma = (1-\alpha).\bar{\gamma} \tag{15}$$

In the above equations, (14) represents the profit or cost reduction that the decision maker is seeking for the uncertain variables modeled in (15). Fig. 2 (b) shows the concept of this strategy.

IV. Preventive/Corrective Voltage Control by IGDT Formulation

As mentioned in the previous sections, the IGDT is suitable for handling uncertainties without probability density functions. In this section, the risk averse and opportunity seeking formulations for the PCVC problem are presented.

A. Risk-averse PCVC

The main goal of the PCVC problem is to provide a new operation schedule which is able to increase the loading margin (preventive control) or recover the system (corrective control) after a severe contingency. In order to handle the uncertainty caused by the wind generation and load simultaneously, a net load NL is defined as:

$$NL_i = D_i - P_i^w, \qquad \forall i \in NB \tag{16}$$

The deviation coefficient factor $(1 \pm \alpha)$ is applied for the net load in the constraints.

The total re-dispatch cost, incorporating the costs of responsive and interruptible loads, is defined as (17).

$$\begin{aligned} TRC = \sum_{i \in NG} & C_{PG}^{+}\left((P_i^{G+}) - P_{i,sch}^{G}\right) \\ & + C_{PG}^{-}\left(P_{i,sch}^{G} - (P_i^{G+})\right) \\ & + C_{QG}^{+}\left((Q_i^{G+}) - Q_{i,sch}^{G}\right) \\ & + C_{QG}^{-}\left(Q_{i,sch}^{G} - (Q_i^{G+})\right) \\ & + \sum_{d \in ND}\left(C_{DR}DR_i + C_{DRQ}DRQ_i\right) \\ & + \sum_{L \in NL}\left(C_{IL}IL_i + C_{ILQ}ILQ_i\right) \end{aligned} \tag{17}$$

The objective function is limited by the constraints given in (18)-(27). These relations represent the normal operating state. Equalities (18) and (19) represent the power flow equations. The participation of responsive and interruptible loads is assumed as a percentage of the total demand. Moreover, the reactive powers of the wind farms are set to zero. Inequalities (20)-(27) are the constraints for the active power generation units, reactive power generation units, active responsive and interruptible loads, reactive responsive and interruptible loads, voltage buses, and line flows.

The relations for the loading margin are given in (28)-(40) ($\forall i \in NB$).

In the relations, (28) is the active power flow equation for the loading case. (29)-(32) define the net load, active power generation, responsive and interruptible loads for the loading state. (33)-(34) are the reactive power flows for this case. (35)-(37) are the limits for the active power generation, reactive power generation, and bus voltages. (38) indicates that the generators bus voltages are equal to the pre-contingency state [33]. Finally, (39)-(40) are the limits for the line flows and the desired loading margins.

$$P_i^G + (1+\alpha).(DR_i + IL_i) = (1+\alpha).NL + V_i \sum_{j\in NB} V_j Y_{ij} \cos(\theta_i - \theta_j - \varphi_{ij}) \quad (18)$$

$$Q_i^G - (1+\alpha).(DQ_i - DRQ_i - ILQ_i) = V_i \sum_{j\in NB} V_j Y_{ij} \sin(\theta_i - \theta_j - \varphi_{ij}) \quad \forall j \in NB \quad (19)$$

$$P_{i,min}^G \le P_i^G \le P_{i,max}^G \quad (20)$$

$$Q_{i,min}^G \le Q_i^G \le Q_{i,max}^G \quad (21)$$

$$0 \le DR_i \le DR_{i,max} \quad (22)$$

$$0 \le DRQ_i \le DRQ_{i,max} \quad (23)$$

$$0 \le IL_i \le IL_{i,max} \quad (24)$$

$$0 \le ILQ_i \le ILQ_{i,max} \quad (25)$$

$$V_{i,min} \le V_i \le V_{i,max} \quad (26)$$

$$|S_{ij}| \le S_{ij,max} \qquad \forall j \in NB \quad (27)$$

$$\hat{P}_i^G + (1+\alpha)(\widehat{DR}_i + \widehat{IL}_i) = (1+\alpha).\widehat{NL}_i + \hat{V}_i \sum_{j\in NB} \hat{V}_j Y_{ij} \cos(\hat{\theta}_i - \hat{\theta}_j - \varphi_{ij}) \quad (28)$$

$$\widehat{NL}_i = (1 + K_i^D \lambda_s) D_i - P_i^w \quad (29)$$

$$\hat{P}_i^G = \min(P_{i,max}^G, (1 + K_i^G \lambda_s) P_i^G) \quad (30)$$

$$\widehat{DR}_i = (1 + K_i^D \lambda_s) DR_i \quad (31)$$

$$\widehat{IL}_i = (1 + K_i^D \lambda_s) IL_i \quad (32)$$

$$\hat{Q}_i^G + Q_i^w - (1+\alpha).Q_i - (1+\alpha).\widehat{DQ}_i = \hat{V}_i \sum_{j\in NB} \hat{V}_j Y_{ij} \sin(\hat{\theta}_i - \hat{\theta}_j - \varphi_{ij}) \quad (33)$$

$$\widehat{DQ}_i = (1 + K_i^D \lambda_s)(DQ_i - DRQ_i - ILQ_i) \quad (34)$$

$$P_{i,min}^G \le \hat{P}_i^G \le P_{i,max}^G \quad (35)$$

$$Q_{i,min}^G \le \hat{Q}_i^G \le Q_{i,max}^G \quad (36)$$

$$V_{i,min} \le \hat{V}_i \le V_{i,max} \quad (37)$$

$$\hat{V}_i^G = V_i^G \quad (38)$$

$$|\hat{S}_{ij}| \le S_{ij,max} \qquad \forall j \in NB \quad (39)$$

$$\lambda_s \ge \lambda_{des} \ge 0 \quad (40)$$

Using the described equations, the risk averse strategy for the PCVC problem can be formulated as a single level optimization problem as follows:

$$Max\ \alpha \quad (41)$$

$$TRC \le (1+\sigma) TRC_0 \quad (42)$$

$$(16)\text{-}(40) \quad (43)$$

Where TRC_0 is the operating cost for the base case, using the forecasted parameters.

B. Opportunity seeking PCVC

In this strategy, it is presumed that the net load will decrease in real time. Hence, the decision maker can use this opportunity to decrease the costs of increasing the loading margin or recovering the system. Equations in this strategy are similar to the equations (17)-(40). The following equations are changed in this strategy ($\forall i \in NB$):

$$P_i^G + (1-\alpha).(DR_i + IL_i) = (1-\alpha).NL + V_i \sum_{j\in NB} V_j Y_{ij} \cos(\theta_i - \theta_j - \varphi_{ij}) \quad (44)$$

$$Q_i^G - (1-\alpha).(DQ_i - DRQ_i - ILQ_i) = V_i \sum_{j\in NB} V_j Y_{ij} \sin(\theta_i - \theta_j - \varphi_{ij}) \quad (45)$$

$$\hat{P}_i^G + (1-\alpha)(\widehat{DR}_i + \widehat{IL}_i) = (1-\alpha).\widehat{NL} + \hat{V}_i \sum_{j\in NB} \hat{V}_j Y_{ij} \cos(\hat{\theta}_i - \hat{\theta}_j - \varphi_{ij}) \quad (46)$$

$$\hat{Q}_i^G + Q_i^w - (1-\alpha)\widehat{DQ}_i = \hat{V}_i \sum_{j\in NB} \hat{V}_j Y_{ij} \sin(\hat{\theta}_i - \hat{\theta}_j - \varphi_{ij}) \quad (47)$$

Then, the opportunity seeking strategy is formulated as follows:

$$Min\ \alpha \quad (48)$$

$$TRC \le (1-\sigma) TRC_0 \quad (49)$$

$$(16\text{-}17), (20)\text{-}(27), (29)\text{-}(32), (34)\text{-}(40), (44)\text{-}(47) \quad (50)$$

V. Simulation Results

The proposed strategies were implemented for an IEEE Reliability Test System [51], and tested using the CONOPT solver [52] run in the GAMS environments on an *HP* Pavilion Computer with a 2.1GHz processor and 4GB RAM.

The IEEE reliability test system is composed of 32 generating units and a 2850MW load. The data for this system, including cost coefficients, active and reactive power limitations, are taken from [51]. In order to show the effect of wind power penetration on the system, two wind farms with a capacity of 350MW were placed at buses 17 and 24, accounting for 25% of the total load. 20% of each load is assumed to participate in the demand response programs, while the rest of the load at each bus can be curtailed. The costs of active and reactive power up (down) re-dispatch for generating units are \$25/MWh (\$5/MWh) and \$5/MWh (\$2/MWh) respectively. The prices of responsive loads and interruptible loads are changed for different scenarios.

Initially, the optimal power flow problem is solved for the base case. The required loading margin is assumed to be 15% for this case. The active and reactive power generations for each bus are depicted in Fig. 3.

The total generation cost is \$66,985. All generations are re-dispatched according to this initial state. In the next sections, the re-dispatch cost is calculated according to the forecasted values for each contingency. After obtaining the operation cost for the base case (TRC_0), the RA and OS problems are solved. In the next parts, the risk averse and opportunity seeking strategies are studied. For each case, preventive and corrective control actions are investigated.

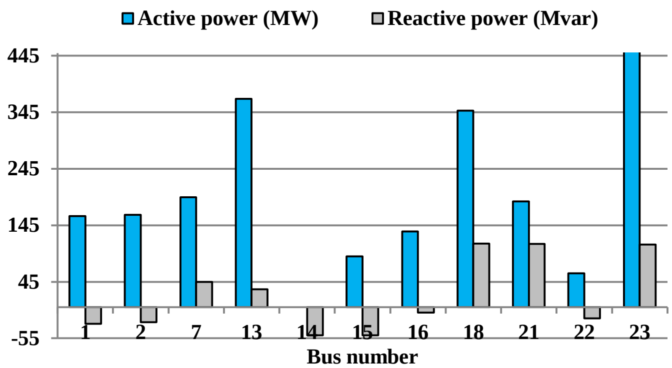

Fig. 3. Initial generation dispatch

1. Risk-averse strategy

In this case, the outage of unit 18 leads to a loading margin of -2.5% (with respect to the deterministic base case dispatch). The system has a negative loading margin, hence corrective control actions have to be implemented. It is assumed that, after a contingency, the loading margin has to be more than 10%. Therefore, the expected active and reactive powers procured by different sources, for reaching the desired amount of loading margin for any combinations of wind generation and load uncertainty, have to be calculated. These power re-dispatches are calculated for the generations obtained by solving the risk-averse strategy problem and considering the determined uncertainty budget. The re-dispatch cost for this case, considering the forecasted amounts, is $14,757.

Fig. 4 shows the robustness values versus the re-dispatch cost, for $\sigma = 0.05$ to $\sigma = 1$. The robustness value shown in Fig. 4 is the radius, as given in (5). It shows by how much the uncertain variable can deviate towards the worst case situation, while providing the desired loading margin and considering the uncertainty budget $((1+\sigma)TRC_0)$. This parameter is obtained by solving the optimization problem (41)-(43). Furthermore, it is obvious from Fig. 4 that the strategy is able to cover a larger uncertain space for a smaller loading margin, and for an identical uncertainty budget.
As indicated in Fig. 4, for a re-dispatch cost of $14,884 (an uncertainty budget of $615), if the net load increases to 2,448MW (17% increase) the operator will be able to provide the required loading margin by re-dispatching the procured active and reactive power resources. Additionally, for a loading margin of 7.5%, the net load can further increase to 2,580MW while satisfying the required loading margin.

Fig. 5 (a) shows the total active and reactive powers re-dispatch for a loading margin of LM=10% and $\sigma = 0.1$. Fig. 5 (b) shows the active and reactive power demand response participation for this case.

In order to demonstrate the importance of cost of responsive and interruptible loads for a specified amount of uncertainty budget ($\sigma = 1$), and a loading margin of 10%, the robustness value is calculated for different costs (the cost of reactive power is 10% of the active power).

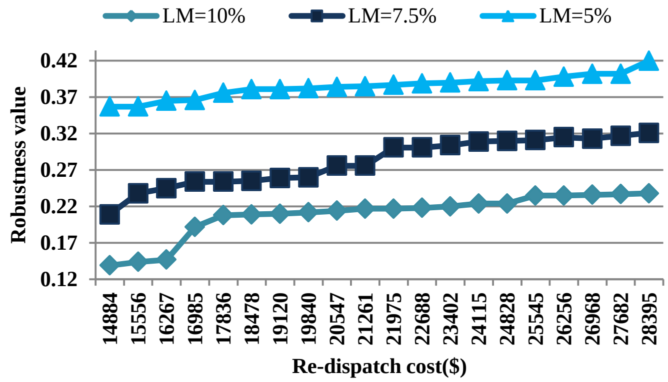

Fig. 4. Robustness curve for unit #18 outage

In Table I, the results for different costs of responsive and interruptible loads are given. As it can be concluded from Table I, by decreasing the cost of responsive loads, the participation of these loads increases, which results in increasing the robustness value. Hence, a larger portion of the uncertainty space can be covered by decreasing responsive load costs. It can be guaranteed that for different combinations of uncertain parameters (including wind and load), the required loading margin will be achieved (for a certain amount of uncertainty).

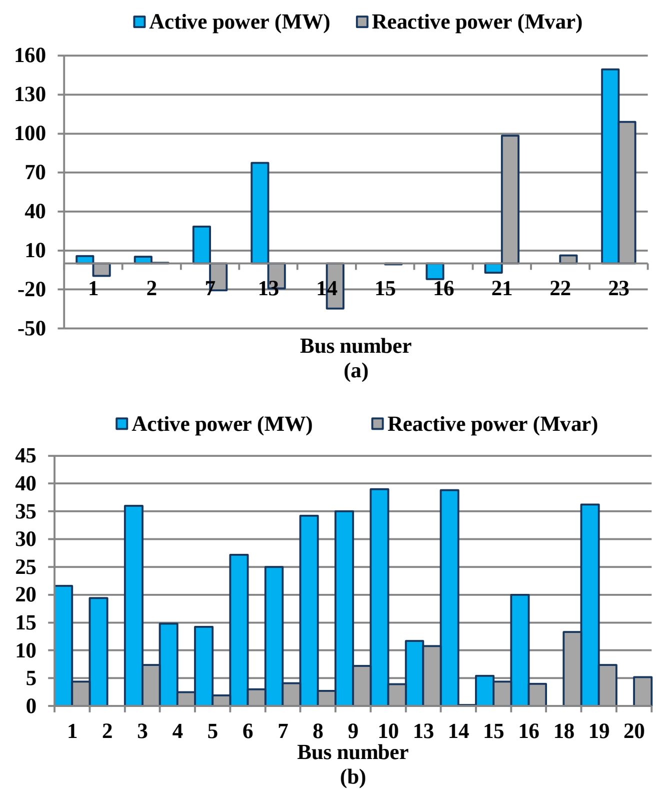

Fig. 5. (a) Active and reactive generation re-dispatch for unit 18 outage, (b) Active and reactive demand response participation (LM=10% and $\sigma = 0.9$)

Case B: Bus 23 unit outages

In this case, it is assumed that the unit at bus 23 is removed from the system. A robust re-dispatch is required to provide the required loading margin (10%) for different conditions of uncertainty. Similar to the previous case, the IGDT is used to provide a robust dispatch and guarantee the specified loading margin for different combinations of wind generation and load in real time. The re-dispatch cost for the base case, according to the forecasted parameters, is $24,000.

TABLE I
COMPARISON OF PARTICIPATION AND ROBUSTNESS VALUE FOR CORRECTIVE CONTROL

	Robustness value	Responsive loads active power (MW)	Responsive loads reactive power (Mvar)
DR cost=100$/MW IL cost=1500$/MW	0.103	22.3	48.2
DR cost=10$/MW IL cost=500$/MW	0.139	378.5	82.4

Fig. 6 illustrates the robustness values against the different uncertainty budgets for three different loading margins. Similar to the case of unit #18 outage, larger uncertainty levels can be handled for smaller loading margin values.

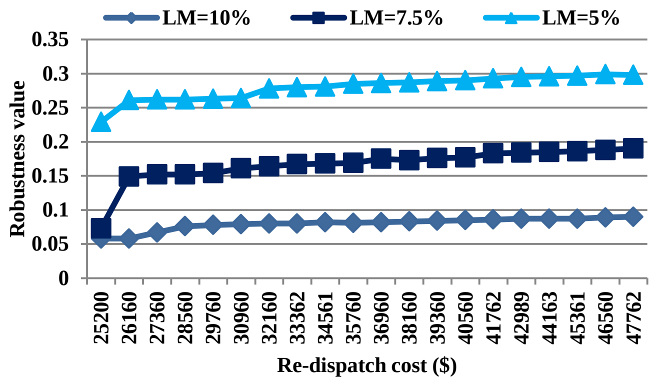

Fig. 6. Robustness curve for bus #23 unit outages

For a re-dispatch cost of $26,160 (additional $2,160 over the base case) the robustness value is close to 6%. For the outage of bus #23 unit, even if the total net load (2,150MW) increases to 2,279.5MW, the system security with the desired loading can be provided without requiring additional resources. Also, for a loading margin of 5%, an additional $1,200 re-dispatch cost (a total re-dispatch cost of $25,200) permits a 22.8% deviation of the net load by procuring the appropriate resources. The other points in this figure illustrate the cost of additional re-dispatch to handle each amount of uncertainty.

Fig. 7 presents the active and reactive power re-dispatches (LM=10%, $\sigma = 0.35$) for each bus. All re-dispatches are below the permitted amount and can be implemented during a short period.

Same as the corrective control case, to indicate the importance of the responsive load costs, the robustness value is shown in Table II (LM=10% and $\sigma = 0.35$).

The results in Table II demonstrate that, when the cost of responsive load decreases, the robustness value reaches higher values, which is equivalent to better control of the uncertain space.

2. Opportunity seeker strategy

In this section, an opportunity seeker strategy which allows the operator to benefit from an uncertain space is proposed. Unlike in the RA strategy, in this strategy the total cost has to be less than the base operating cost.

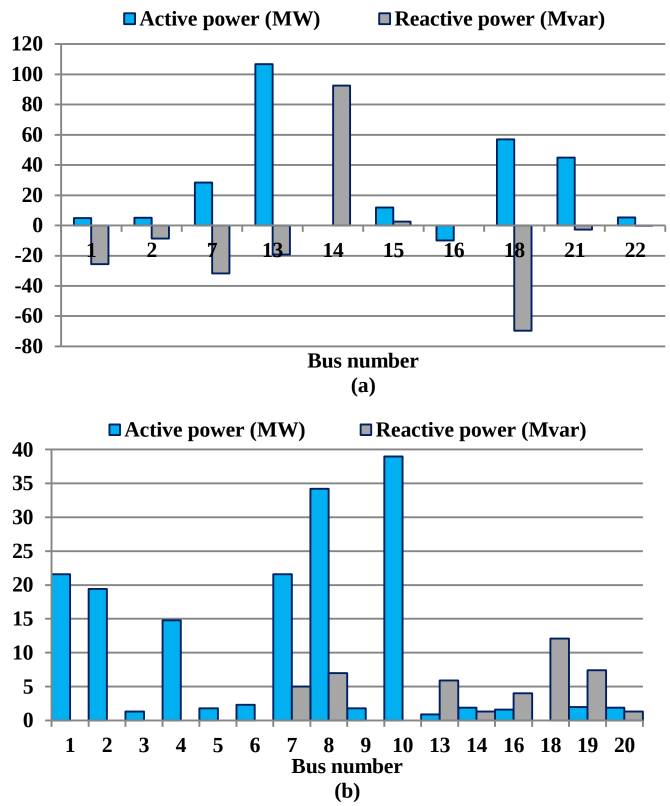

Fig. 7 (a). Active and reactive generation re-dispatch for bus 23 unit outages (b) Active and reactive demand response participation (LM=10% and $\sigma = 0.35$)

TABLE II
COMPARISON BETWEEN THE PARTICIPATION AND ROBUSTNESS VALUE FOR CORRECTIVE CONTROL

	Robustness value	Responsive loads active power (MW)	Responsive loads reactive power (Mvar)
DR cost=100$/MW IL cost=1500$/MW	0.08	166	41
DR cost=25$/MW IL cost=750$/MW	0.171	342	45.9

The outage of unit 18 is studied. In this case, the operator is optimistic that, in real time, the deviation of wind generation and load will lead to a lower re-dispatch cost as compared with the base cost obtained for forecasted values. For this contingency, the results for the opportunity value versus the re-dispatch cost are shown in Fig. 8, for LM=10%. The opportunity value α is minimized according to (48)-(50).

As illustrated in Fig. 8, if the net load decreases to 2,021MW (6% decrease), the re-dispatch cost will be $13,872, which results in $885 profit. The remaining opportunity values, which lead to lower re-dispatch costs, are shown in Fig. 7. Fig. 9 shows the active and reactive powers re-dispatch for $\sigma = -0.05$ and LM=10%.

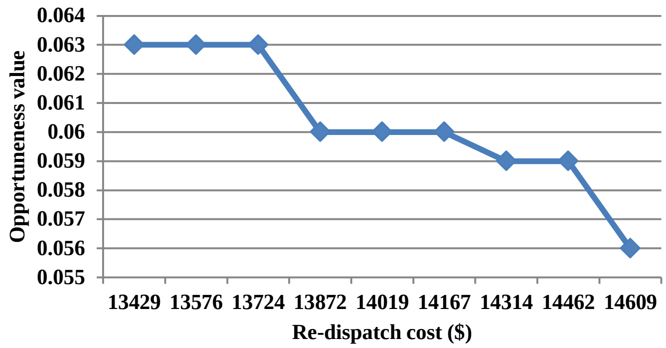

Fig. 8. Opportuneness values for different re-dispatch costs

3. Model validation and comparison with other benchmarks

In this section, the results obtained from the proposed model for two different preventive and corrective control actions are validated and compared with three main approaches, including deterministic, Monte Carlo simulation (MCS), and stochastic programming.

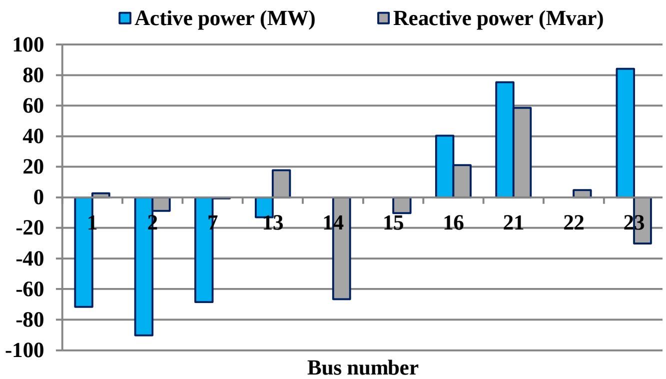

Fig. 9. Active and reactive generation re-dispatch for opportunity seeker strategy (LM=10% and $\sigma = -0.05$)

The base re-dispatch cost is obtained using the deterministic approach and calculated considering the forecasted amounts.

In the Monte Carlo simulation approach, 2000 scenarios are generated using the Gaussian probability density function for wind generation and loads. Table III compares results obtained from the IGDT (highlighted in the table) with the three other approaches.

Fig. 10 (a) indicates the distribution of re-dispatch costs for the bus #18 unit outages with an expected amount of $14,544, obtained by the MCS. The re-dispatch costs calculated by the IGDT are also shown. Comparing with the MCS, a decision can be made on how much robustness and at what expense can be obtained. For instance, while $\sigma = 0.1$ does not result in additional costs, $\sigma = 0.45$ is a completely robust solution.

Fig. 10 (b) shows the frequency of the re-dispatch costs for the bus #23 unit outages. While $\sigma = 0.1$ is an economic strategy, opting for $\sigma = 0.35$ can be a conservative strategy for the operator. Indeed, this is another advantage of the IGDT, it allows to select the desired strategy.

TABLE III
COMPARISON OF THE RESULTS OBTAINED BY THE IGDT WITH OTHER BENCHMARKS

	Deterministic [25]	MCS	Stochastic [33]	IGDT ($\sigma = 0.1$)
Unit #18 outage re-dispatch cost ($)	14,757	14,544	18,769	15,556
Unit #23 outage re-dispatch cost ($)	24,000	24,176	27,196	26,160

Table III shows the results calculated by the stochastic programming approach for the two studied outages. Utilizing the normal probability density function, 1000 scenarios are generated and reduced to a number of scenarios. For the outage of unit #18, this approach leads to a re-dispatch cost of $18,769. Fig. 11 (a) illustrates the re-dispatch cost for each scenario. The outage of units at bus 23 results in a re-dispatch cost of $27,196 and the results are depicted in Fig. 11 (b). For a better comparison, the results obtained by the IGDT, for different values of σ, are also shown in the same figure.

As illustrated in Table III, the results obtained by the IGDT method have lower re-dispatch costs for $\sigma = 0.1$. It is worth to mention that, unlike the IGDT which can be applied without precise static information, stochastic programming is dependent on generated scenarios and probability density functions of the uncertain variables.

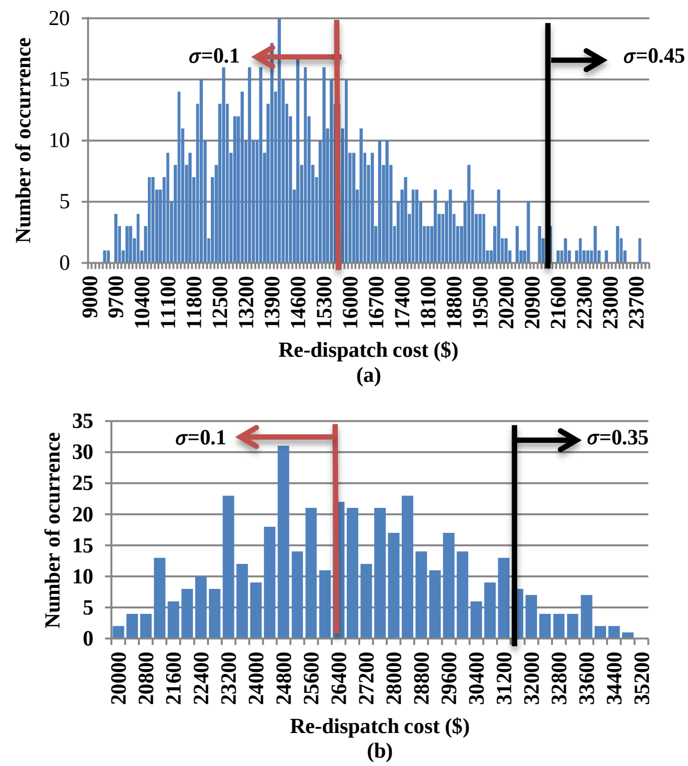

Fig. 10. Re-dispatch costs obtained by the MCS (a) unit #18 (b) bus #23 unit outages

VI. CONCLUSION

This paper proposed an information gap decision theory based approach for the preventive/corrective voltage control problem. A framework for two different strategies was presented. In the risk averse strategy, it was assumed that the net load increased in real time. A decision which accounted for the uncertain variable deviations for a given budget was proposed to the operator. The obtained results showed that, when the loading margin level increased, the level of uncertainty which can be covered by a given uncertainty budget decreased. Additional results revealed that by increasing the participation of responsive and interruptible loads, higher levels of uncertainty can be covered for a given level of the loading margin, for both the preventive and corrective control actions.

In the opportunity seeking strategy, the decision maker utilized the proposed framework with the presumption that the net load would decrease in real time and therefore the operating cost could be decreased (negative profit).

In this paper, the problem was solved using a single objective formulation. Nevertheless, other objective functions could be considered, resulting in a multi-objective framework. Moreover, all of the studies were formulated as a static framework. Procuring appropriate resources for providing the dynamic voltage stability of a system, facing multiple uncertainties, can be a great challenge for future studies. Utilizing the potential of other power system elements, such as a storage system in a multi-horizon framework, can be another direction for future research in this area.

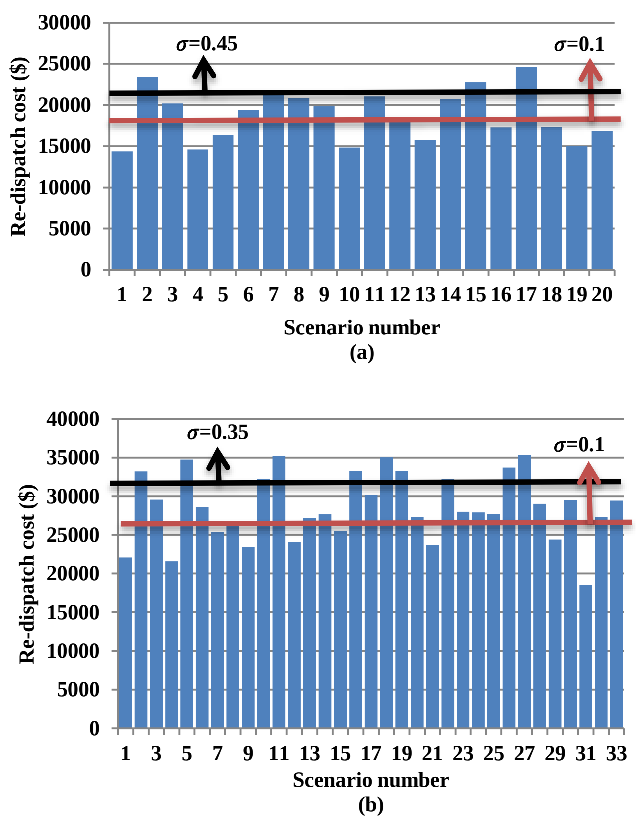

Fig. 11. Re-dispatch cost obtained by the stochastic programming (a) unit #18 outage (b) bus unit #23 outages

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