Hybrid Scenario-IGDT-Based Congestion Management Considering Uncertain Demand Response Firms and Wind Farms

Abbas Tabandeh and M. J. Hossain, *Senior Member, IEEE*

***Abstract*— Demand response resources have been recently introduced as one of the most economic tools of congestion alleviation in power systems. Nevertheless, the severe uncertainty of multiple demand response resources constituting a demand response firm (DRF) is an indispensable issue to be considered for the resilient operation of future power systems. Consequently, the information gap decision theory (IGDT) technique is utilized for addressing the uncertainty of consumers' participation in demand response programs. This paper presents a novel hybrid scenario-IGDT-based framework, designated as SIGDT, for corrective transmission congestion management in the presence of large-scale uncertain wind farms and DRFs as well as the uncertainty of conventional generating units. A reliability network modeling of a repairable N-component wind turbine is presented, considering failure and repair rates of turbines' components, and then the uncertainty of wind farms' generation is handled using the scenario-based approach. The proposed framework is applied to the IEEE-RTS system to demonstrate its accuracy and capability. The results discuss the impact of failure and repair rates of wind turbines' components on the proposed SIGDT-based congestion management and emphasize the application of the proposed framework for decision makers to ensure the optimal operation of power systems under uncertainties of DRFs, wind farms, and conventional units.**

***Index Terms*— Congestion management, Demand response firm, Scenario-IGDT (SIGDT), Uncertainty, Wind farm.**

NOMENCLATURE

Indices and sets	
$f/i/d/j$	Wind farm/generator/DRF/involuntarily shed load index.
m, n	Bus indices.
$\Omega^{\mathrm{G/N}}$	Set of generators/buses.
$\Omega^{\mathrm{DRF/W}}$	Set of DRFs/wind farms.
Ω^{L}	Set of involuntarily shed loads.
$\Omega_n^{\mathrm{G/N}}$	Set of generators/buses connected to bus *n*.
$\Omega_n^{\mathrm{DRF/W}}$	Set of DRFs/wind farms connected to bus *n*.
Parameters	
$k_i^{up/down}$	Price offered by generator *i* to increase/decrease its power schedule.
π_d	Price of load curtailment by DRF *d*.
ξ_j	Price of load shedding respecting load *j*.
$\lvert Y \rvert / \delta_{nm}$	Magnitude/angle of the admittance matrix element.
$S_{nm}^{\max}$	Transmission capacity limit of line *nm*.
$\tilde{P}_{Gi}(w)$	Original scheduled output power of generator *i* in scenario *w*.
$P_{Gi}^{\min/\max}$	Lower/upper limit of production of generator *i*.
I_i	On/off status of generator *i*.
$\tilde{P}_{Ln}$	Original demand at bus *n*.
ϖ_C	Critical percentage of objective function.
Variables	
$CM_{RN}(w)$	RN-SIGDT CM cost in scenario *w*.
$\Delta P_{Gi}^{up}(w)$	Up power shift of generator *i* in scenario *w*.
$\Delta P_{Gi}^{down}(w)$	Down power shift of generator *i* in scenario *w*.
$P_{DRFd}(w)$	Power reduced by DRF *d* in scenario *w*.
$P_{SHDj}(w)$	Load shedding level respecting load *j* in scenario *w*.
$P_{Ln/Gn}(w)$	Total final active-power consumption/production at bus *n* in scenario *w*.
$Q_{Ln/Gn}(w)$	Total final reactive-power consumption/production at bus *n* in scenario *w*.
$V / \Phi_n(w)$	Voltage magnitude/angle of bus *n* in scenario *w*.
$P / Q_{Gi}(w)$	Final active/reactive power produced by generator *i* in scenario *w*.
P_{DRFd}^{AP}	Achievable potential of DRF *d* to curtail its consumption.
$P_{Wf}(w)$	Power production of wind farm *f* in scenario *w*.
$P_{DRFn}(w)$	Total consumption reduced by DRFs at bus *n* in scenario *w*.
$P_{SHDn}(w)$	Total involuntarily shed load at bus *n* in scenario *w*.
$\widehat{\upsilon}_1/\widehat{\upsilon}_2/\widehat{\upsilon}_3$	Maximum uncertainty radius of DRFs depending on different criteria.
$\upsilon(w)$	Uncertainty radius of DRFs in scenario *w*.
$\Gamma_C(w)$	Critical congestion management cost.
P_{DRFd}^{F}	Forecasted participation of DRF *d*.

I. INTRODUCTION

UNDER the smart electricity grid setting, wind power capacity installations have increased dramatically in recent years around the world. Wind energy plays an effective role in the future of power generation by comparison

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Abbas Tabandeh is with the Department of Electrical Engineering, Shahid Bahonar University of Kerman, Kerman, Iran, (e-mail: abbas.tabandeh@eng.uk.ac.ir).

Jahangir Hossain is with the Faculty of Engineering and Information Technology, University of Technology Sydney, Broadway, NSW 2007, Australia (e-mail: jahangir.hossain@uts.edu.au).

with other sorts of renewable energy. Utilization of wind farms as electricity generation resources can considerably keep the electricity production cost down and attenuate the pollutant emissions [1]. The sporadic nature of wind as well as unpredictable outage of wind turbines (WTs) makes power system operation and planning strategies extremely complicated. One of the most vital problems of the power system operation is the congestion management (CM) for which an independent system operator (ISO) is responsible [2], [3]. Congestion occurs on electric transmission facilities when actual or scheduled flows of electricity across a line or piece of equipment are limited below desired levels. These restrictions might be imposed either by the physical capacity of the line or by operational restrictions introduced and enforced so that the security and reliability of the grid can be protected [4].

In order to handle the CM problem in the presence of large-scale penetration of wind power generation, the uncertainty factors of wind turbines should be determined and modeled. There are several methods proposed in the literature for dealing with the uncertainty of wind power generation, including stochastic techniques, for example Monte Carlo simulation [5] and Point Estimate Method [6], fuzzy approach [7] and robust optimization [8]. A comprehensive model of wind farms considering turbines' outputs correlation, wind variability, and forced outages was presented in [9].

In literature, different methods have been adopted to the congestion management problem [10]. Multifarious studies have utilized in generation rescheduling and load shedding as powerful congestion management methods. In [11], congestion alleviation by redispatch of generations and loads was presented considering network uncertainties. In [12], following the selection of generators for congestion management according to their sensitivities to the power flow of congested lines, an algorithm based on particle swarm optimization was implemented to mitigate congestion. The authors in [13] presented a teaching-learning-based optimization algorithm to deal with the CM problem by rescheduling real power of generation units. A market-based CM framework in electric power systems by re-dispatching of generators, loads, and aggregators was addressed in [14]. To achieve the objective in [14], power transfer distribution factors, and topological generation and load distribution factors describing the relation between generators/loads/aggregators and line power flows were adopted. A stochastic programming framework for congestion mitigation by generators output power rescheduling, demand-side bidding, and load shedding was discussed in [15]. Reference [16] described a CM model considering voltage and transient stability of the power system in which altering the generators' and demands' powers was suggested. In [17], a multi-objective congestion management framework through generation rescheduling and load shedding was presented, considering realistic voltage-dependent load modeling. One of the most practical and economical congestion alleviation techniques compared to load shedding and generation rescheduling is the implementation of demand response resources (DRRs), which has been gaining a great deal of attention in recent years. In [18], flexible alternating current transmission system devices and an incentive/penalty-based demand response model were assigned to deal with the transmission congestion. In [19], a two-step CM by a linear model of demand response programs was presented. Reference [20] described a security-based congestion management by demand response implementation considering power system components' uncertainties, including transmission lines and generators outages. A CM framework through reinforcing collaboration between ISOs and retail electricity providers on the implementation of demand response programs was presented in [21]. The authors in [22] implemented a multi-objective particle swarm optimization method to relieve transmission congestion by means of demand response programs and generation rescheduling.

Despite the great contribution of the above studies on the role of demand response in congestion management, it is not considered that DRRs might fail to keep their promise whether unintentionally or deliberately to diminish their consumption as per their contract with ISOs. Nonetheless, in practice DRRs are uncertain and unpredictable. To the best of the authors' knowledge, only few studies have focused on the uncertainty modeling of DRRs. The authors in [23] presented a reliability model of a demand response resource considering customers' behaviors. In [24], after using a systematic method based upon the frequency and duration technique to introduce the multi-state model of multiple DRRs, called a demand response firm (DRF), considering repairable advanced metering infrastructures (AMIs), a probabilistic CM framework was addressed. An unfavorable feature of this probabilistic modeling of DRFs is that not only does it require some information about input parameters like the historical data on DRRs' load reduction, also the uncertainty of DRRs' participation is intimately bound up with several factors including weather patterns and humidity [25], consumers' profits [26], social circumstances, AMIs failure, etc. In this regard, due to the lack of sufficient historical data and severe uncertainty of DRRs' behavior, probabilistic methods for modeling the uncertainty of them appear to be less fruitful. In case of severe uncertainties, information gap decision theory (IGDT) has been reported to be the most appropriate technique to cope with the input parameters uncertainty [27], [28].

Also, previous studies have never paid attention to the impact of different uncertainty factors of wind farms including turbines' outputs correlation, wind speed variability, and forced outages on the CM problem, so the wind farm model presented in [9] motivates us to do so. However, in [9] neither a direct analytical expression for a perfect wind turbine's output power without considering failure and repair rates of a turbine was presented nor the relationship between a turbine and its constructing components was discussed. In fact, no detailed look at the network modeling of a turbine was taken into consideration [9]. Thus, it is important to extend the wind farm model presented in [9] for the CM purposes.

In the light of uncertainties of DRFs' power reduction and large-scale wind farms' output power, this paper first proposes a new reliability network modeling of repairable N-component wind turbines on a farm to develop a multi-state model of wind farms' output power. The availability, failure rate and mean time to repair (MTTR) of a turbine are introduced in terms of every single wind turbine's component. Then, a new IGDT-based model for DRFs' uncertainty is presented, and finally a novel hybrid scenario-information gap decision theory-based framework, designated as SIGDT, for the network CM in the presence of uncertain DRFs and wind farms is suggested. The key contributions of this paper are to:

- model the uncertainty of wind farms' output by developing a new reliability modeling of wind turbines' components.
- model and analyze the uncertainty of costumers' participation in demand response programs using the IGDT when they are under severe uncertainty.
- develop a hybrid SIGDT-based framework for CM in the presence of large-scale uncertain wind farms and DRFs. This model incorporates risk-neutral SIGDT (RN-SIGDT) and risk averse SIGDT (RA-SIGDT) strategies, which enables ISOs to evaluate the impacts of technical uncertainty factors of wind farms including correlation between outputs of individual wind turbines, wind variability, and wind turbines' components failure on decision-making. Moreover, this model allows ISOs to make the cost of CM robust against the unsatisfactory consequences of DRFs' output variability. The uncertainty of conventional generating units is also modeled using their failure/repair rates and the N-1 contingency concept, and is added to the proposed CM framework.

The rest of the paper is organized as follows. Section II presents a probabilistic multi-state modeling of output power of a wind farm considering repairable components of individual wind turbines. Uncertainty modeling of DRFs' participation using an IGDT technique is described in Section III. Detailed description and formulation of the SIGDT-based CM in the presence of both uncertain wind farms and DRFs are presented in Section IV while the proposed problem considering the uncertainty of conventional generating units is discussed in Section V. Simulation results are provided in Section VI, and finally section VII concludes the paper.

II. MULTI-STATE MODELING OF WIND FARMS' OUTPUT POWER CONSIDERING REPAIRABLE TURBINES' COMPONENTS

It is worthwhile to mention that although the underlying idea of the probabilistic model of output power of wind farms comes from [9], the modeling and impacts of repair and failure rates of individual turbines' components on the wind farms' output power were overlooked. Also, the formulation for a probabilistic model of a single perfect wind turbine without considering failure and repair rates of the turbine was not expressed. To address the above issues, an improved modeling is developed in this paper, which is discussed in detail below.

A. Reliability Network Modeling of Repairable N-Component Wind Turbines

As wind turbines consist of different parts, all the components must be operating without any failure to work properly and safely. This condition implies that all components can be modeled in such a way that they are connected in series from the reliability viewpoint. It should be appreciated that a turbine with a physically defined topological structure may have a considerably different reliability network topology. In this regard, as shown in Table I, several major subsystems or components are considered for a wind turbine modeling [29]. Fig. 1 shows the state space diagram for a wind turbine system to be equivalent to the multiple series components. The equivalent failure rate and mean repair time of a wind turbine with *NC* components in series can be deduced as:

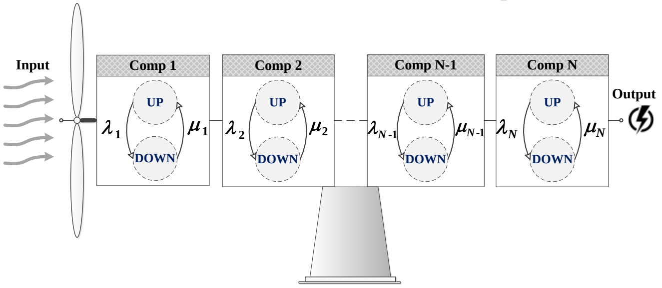

Fig. 1. Wind turbine state space diagram.

$$\lambda^T = \frac{1}{m^T} = \sum_{cp=1}^{NC} \lambda_{cp} \qquad \forall\ cp \in \Lambda_{Comp} \tag{1}$$

$$r^T = \frac{1}{\mu^T} = \frac{\sum_{cp=1}^{NC} \lambda_{cp} r_{cp}}{\sum_{cp=1}^{NC} \lambda_{cp}} \qquad \forall\ cp \in \Lambda_{Comp} \tag{2}$$

where λ^T and μ^T are failure and repair rate of a wind turbine, m^T and r^T are mean operating and repair time of a wind turbine, λ_{cp} and r_{cp} are failure rate and mean repair time of the wind turbine's component *cp*. Λ_{Comp} denotes a set of turbine's components. If m_{cp} is the mean operating time of a wind turbine's component, the probability of the turbine being in the operating state, i.e. the availability A^T, can be stated as:

$$A^T = \prod_{cp=1}^{NC} \left(\frac{m_{cp}}{r_{cp} + m_{cp}}\right) \tag{3}$$

Using concepts of the frequency and duration technique, the forced outage rate (FOR) of the wind turbine can be obtained in respect of the frequency of encountering the wind turbine up state, i.e. f^T, as follows:

$$FOR^T = f^T r^T = \frac{A^T}{m^T} r^T \tag{4}$$

B. Multi-State Modeling of the Output Power of Perfect Wind Turbines

In order to model the output power of a ***perfect turbine***, i.e. 100% reliable, first the wind turbine's output power, P_{real}^{WT}, is obtained in respect of wind speed, *V*, as follows:

TABLE I
WIND TURBINES' SUBSYSTEMS AND COMPONENTS

No.	Subsystem	Component
1	Electrical system	Converter, fuses, switches and cables/connections
2	Electronic control	Electronic control unit, relay, measurement cables and connections
3	Sensors	Anemometer/wind vane, vibration switch, temperature, oil pressure switch, power sensor and revolution counter
4	Hydraulic system	Hydraulic pump, pump motor, valves and hydraulic pipes/hoses
5	Yaw system	Yaw bearings, yaw motor, wheels and pinions
6	Rotor blades	Blade bolts, blade shell and aerodynamic brakes
7	Mechanical brake	Brake disc, brake pads and brake shoe
8	Rotor hub	Hub body, pitch mechanism, pitch bearings
9	Gearbox	Bearings, wheels, gear shaft and seals
10	Generator	Generator windings, generator brushes and bearings
11	Supporting structure/housing	Foundations, tower/tower bolts, nacelle frame, nacelle cover and ladder
12	Drive train	Rotor bearings, drive shafts and couplings

$$P_{real}^{WT} = \begin{cases} (A+B\times V+C\times V^2)P_r & V_{ci}<V\le V_r \\ P_r & V_r<V_{ci}\le V_{co} \\ 0 & otherwise \end{cases} \tag{5}$$

where V_{ci}, V_{co}, V_r, and P_r are the "cut-in", "cut-out" and "rated" speeds of the wind turbine and "rated" power of the turbine respectively. Parameters A, B, and C are extracted from [30]. Then, a number of arbitrary states depending on the required accuracy of the wind turbine probabilistic model can be considered for its output. If N_{step}^{WT} discrete output power states are required for a wind turbine with the rated power P_r, the real output power can be split into finite states as follows:

$$P_k^{WT} = (k-1)\frac{P_r}{N_{step}^{WT}-1} \qquad \forall\ k\in\left\{1,2,...,N_{step}^{WT}\right\} \tag{6}$$

where P_k^{WT} denotes the output power of the wind turbine in state *k*.

At this point, a data clustering technique [31] is deployed to cluster all real output power values into finite steps as follows:

$$\begin{aligned} &If \quad P_k^{WT}-\frac{1}{2}\frac{P_r}{N_{step}^{WT}-1}\le P_{real}^{WT}\le P_k^{WT}+\frac{1}{2}\frac{P_r}{N_{step}^{WT}-1} \\ &then \quad P_{real}^{WT}\rightarrow P_k^{WT} \end{aligned} \tag{7}$$

The probability of output state *k* of the wind turbine is

$$Pr_k^{WT} = \frac{\text{Time spent in state } k}{\text{Whole priod of observation}} = \frac{\Gamma_k}{\sum_{k=1}^{N_{step}^{WT}}\Gamma_k} = \frac{\Gamma_k}{\Gamma} \tag{8}$$

C. Probabilistic Wind Farm Modeling Considering Failure and Repair Rates of the Components of Wind Turbines

A set of wind turbines affected by the same wind regime in a windy region is designated as a wind farm. In this section, a probabilistic model of a wind farm containing N_{WT} repairable and similar wind turbines is presented. As shown in Fig. 2, the state space diagram for a wind farm with N_{WT} repairable wind turbines indicates that both "different output power states" and "failure and repair rates of wind turbines components" are prominent factors to be considered. Each circular shape in Fig. 2 represents the production of the wind farm in its relative state, so if there are ℓ operable wind turbines in a windy region, all possible output power states $O_{\ell,k}$ for this wind farm can be expressed as below:

$$O_{\ell,k} = P_k^{WT}\times\ell \quad \forall\ k\in\left\{1,2,...,N_{step}^{WT}\right\},\ \forall\ \ell\in\left\{1,2,...,N_{WT}\right\} \tag{9}$$

It follows that the number of possible output power states can become too large, provided the number of turbines increases. Thus, if N_{step}^{WF} arbitrary states are considered for the output of the wind farm, those possible states derived from (9) can be clustered into arbitrary output power states P_{∂}^{WF} as below:

$$P_{\partial}^{WF} = (\partial-1)\frac{N_{WT}P_r}{N_{step}^{WF}-1} \qquad \forall\ \partial\in\left\{1,2,...,N_{step}^{WF}\right\} \tag{10}$$

$$\begin{aligned} &If \quad P_{\partial}^{WF}-\frac{1}{2}\frac{N_{WT}P_r}{N_{step}^{WF}-1}\le O_{\ell,k}\le P_{\partial}^{WF}+\frac{1}{2}\frac{N_{WT}P_r}{N_{step}^{WF}-1} \\ &then \quad O_{\ell,k}\rightarrow P_{\partial}^{WF} \end{aligned} \tag{11}$$

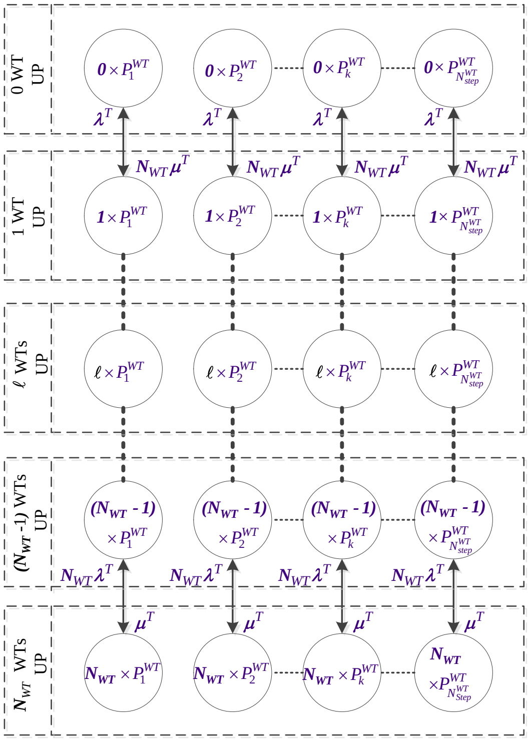

Fig. 2. Space diagram of a wind farm containing N_{WT} wind turbines.

If $Pr(O_{\ell,k})$ is the probability of all possible output power states for the wind farm,

$$Pr(O_{\ell,k}) = {}_{N_{WT}}C_{\ell}\ (FOR^T)^{N_{WT}-\ell}(A^T)^{\ell}\,Pr_k^{WT} \tag{12}$$

where ${}_{N_{WT}}C_{\ell}$ is the number of combinations of ℓ operable turbines from N_{WT}. Possible output states leading to the same output state ∂ for a wind farm can be cumulated, and the probability of residing in one of these cumulated states is evaluated by

$$Pr_{\partial} = \sum_{\ell}\sum_{k} Pr(O_{\ell,k}) \qquad \forall\ k,\ell\in\Lambda_{\partial} \tag{13}$$

where Λ_{∂} denotes the set of states approximated to state ∂.

III. UNCERTAINTY MODELING OF DRFS' PARTICIPATION USING IGDT TECHNIQUE

A set of DRRs with the potential of participating in demand response programs through communicating with a central demand response aggregator via AMIs is designated as a DRF. However, according to the report by the Federal Energy Regulatory Commission (FERC) [32], DRFs' behavior is unpredictable to high extent. It means that consumers might not honor their commitment to the demand response program contract. They might fail to reduce their loads due to several external factors including AMIs failure, temperature, human inertia, etc. Moreover, in most cases, historical data regarding DRFs' behavior is found hard to be collected or even there is no probability density function available. Given these points, an IGDT-based model is proposed to model and address the uncertainty of DRFs' participation. IGDT is a non-probabilistic method for modeling the risk of unknown parameters and does not require any historical data and probability density function [33]. There are different models to evaluate the uncertainty in a system using IGDT [27]. Herein, the fractional uncertainty model is adopted as follows:

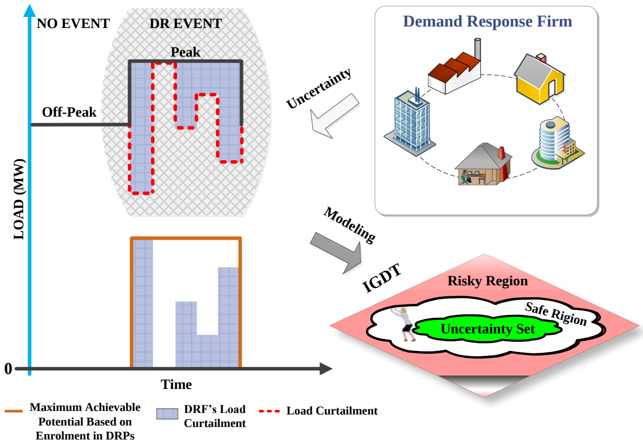

Fig. 3. Uncertainty modeling of DRFs' participation using IGDT technique.

$$\psi \in \Upsilon(\upsilon,\tilde{\psi}) = \left\{ \psi : \left| \frac{\psi - \tilde{\psi}}{\tilde{\psi}} \right| \le \upsilon \right\} \tag{14}$$

where $\tilde{\psi}$ shows the forecasted values of uncertain parameters ψ, υ is the radius of uncertainty, indicating the gap between the forecasted and violated values of uncertain parameters. Fig. 3 represents the description of the proposed uncertainty modeling of DRFs' behavior.

IV. CONGESTION MANAGEMENT USING SIGDT APPROACH

In this section, the SIGDT-based corrective CM framework in the presence of uncertain wind farms and DRFs, albeit with varying uncertainty intensity degrees, is explored. Fig. 4 depicts a hierarchical structure of the proposed SIGDT-based CM. In the real time, the ISO takes responsibility for mitigating transmission congestion in the case of congestion. Hence, after the uncertainty of wind farms is modeled, DRFs which have made a contract are requested by the ISO to reduce their demand for CM. Since DRFs are under severe uncertainty, ISOs can apply two strategies, i.e. RN-SIGDT and RA-SIGDT, to the CM problem as follows.

A. RN-SIGDT-Based Corrective Congestion Management

In this strategy, it is supposed that there are no forecast errors in predicting power reduction of DRFs under sever uncertainty, and only the uncertainty of wind farms' output power (probabilistic parameter) is taken into consideration. In this regard, once the probabilistic multi-state wind farms' production is determined, multiple scenarios are generated and the probability of each scenario, $\delta(w)$, is calculated as below:

$$\delta(w) = \prod_{f} \rho_f(\Omega_f) \qquad f \in \Omega^{\mathrm{W}} \tag{15}$$

where ρ_f indicates the probability of each output power state of wind farm f, and Ω_f is the set of states for wind farm f.

The following objective function represents the minimization of the CM cost for each scenario as there are no errors in forecasting the DRFs' participation.

$$CM_{RN}(w)\Big|_{P_{DRFd}^{AP}=P_{DRFd}^{F}} =$$

$$\min \;\; CM(w) = \sum_{i \in \Omega^{\mathrm{G}}} \left(k_i^{up} \Delta P_{Gi}^{up}(w) + k_i^{down} \Delta P_{Gi}^{down}(w) \right) \tag{16}$$

$$+ \sum_{d \in \Omega^{\mathrm{DRF}}} \left(\pi_d P_{DRFd}(w) \right) + \sum_{j \in \Omega^{\mathrm{L}}} \left(\xi_j P_{SHDj}(w) \right)$$

subject to

$$P_{Gn}(w) - P_{Ln}(w) =$$

$$V_n(w) \sum_{m \in \Omega^N} \left| Y_{nm} \right| V_m(w) \cos(\Phi_n(w) - \Phi_m(w) - \delta_{nm}) \quad \forall n \in \Omega^{\mathrm{N}} \tag{17}$$

$$Q_{Gn}(w) - Q_{Ln}(w) =$$

$$V_n(w) \sum_{m \in \Omega^N} \left| Y_{nm} \right| V_m(w) \sin(\Phi_n(w) - \Phi_m(w) - \delta_{nm}) \quad \forall n \in \Omega^{\mathrm{N}} \tag{18}$$

$$\left| S_{nm}(V_n, V_m, \Phi_n, \Phi_m, w) \right| \le S_{nm}^{\max} \qquad \forall n \in \Omega^{\mathrm{N}},\; m \in \Omega_n^{\mathrm{N}} \tag{19}$$

$$P_{Gi}(w) = \tilde{P}_{Gi}(w) + \Delta P_{Gi}^{up}(w) - \Delta P_{Gi}^{down}(w) \quad i \in \Omega^{\mathrm{G}} \tag{20}$$

$$I_i P_{Gi}^{\min} \le P_{Gi}(w) \le I_i P_{Gi}^{\max} \qquad i \in \Omega^{\mathrm{G}} \tag{21}$$

$$I_i Q_{Gi}^{\min} \le Q_{Gi}(w) \le I_i Q_{Gi}^{\max} \qquad i \in \Omega^{\mathrm{G}} \tag{22}$$

$$P_{Gn}(w) = \sum_{i \in \Omega_n^{\mathrm{G}}} P_{Gi}(w) + \sum_{f \in \Omega_n^{\mathrm{W}}} P_{Wf}(w) \qquad \forall n \in \Omega^{\mathrm{N}} \tag{23}$$

$$Q_{Gn}(w) = \sum_{i \in \Omega_n^{\mathrm{G}}} Q_{Gi}(w) \qquad \forall n \in \Omega^{\mathrm{N}} \tag{24}$$

$$0 \le P_{DRFd}(w) \le P_{DRFd}^{AP} \qquad d \in \Omega^{\mathrm{DRF}} \tag{25}$$

$$P_{Ln}(w) = \tilde{P}_{Ln} - P_{DRFn}(w) - P_{SHDn}(w) \quad \forall n \in \Omega^{\mathrm{N}} \tag{26}$$

$$Q_{Ln}(w) = P_{Ln}(w) \tan(\phi_{Ln}) \quad \forall n \in \Omega^{\mathrm{N}} \tag{27}$$

$$P_{DRFn}(w) = \sum_{d \in \Omega_n^{\mathrm{DRF}}} P_{DRFd}(w) \qquad \forall n \in \Omega^{\mathrm{N}} \tag{28}$$

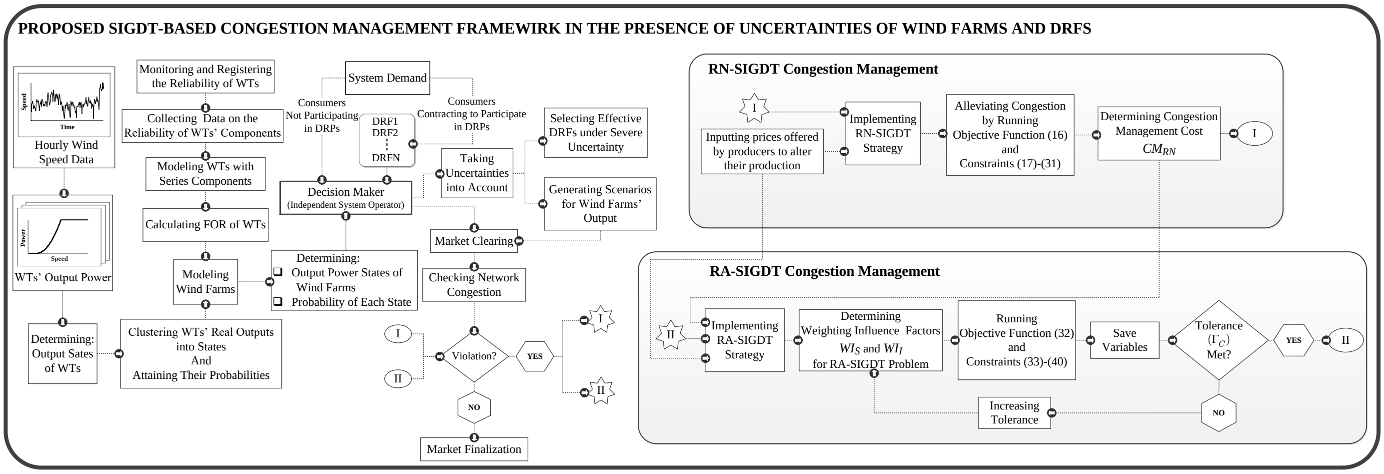

Fig. 4. SIGDT-based congestion management framework.

$$P_{SHDn}(w) = \sum_{j \in \Omega_n^{\mathrm{L}}} P_{SHDj}(w) \qquad \forall n \in \Omega^{\mathrm{N}} \tag{29}$$

$$V_n^{\min} \le V_n(w) \le V_n^{\max} \quad \forall n \in \Omega^{\mathrm{N}} \tag{30}$$

$$\Delta P_{Gi}^{up/down}(w) \ge 0,\ P_{SHDj}(w) \ge 0 \quad i \in \Omega^{\mathrm{G}},\ j \in \Omega^{\mathrm{L}} \tag{31}$$

The objective function (16) comprises three terms. The first one expresses payments to generation units for altering their output compared to the original schedule. The second term shows the total payments received by DRFs to curtail their loads whereas the third part represents the total cost of load shedding. Equations (17) and (18) specify the active and reactive power balance constraints respectively. Constraints (19) enforce branch flow limits. The final rescheduled generation of every unit is expressed by (20). Constraints (21) and (22) ensure that every unit runs between its active and reactive output limits. Constraints (23) and (24) refer to the total active and reactive power generation at every bus. DRFs' participation limits are represented by (25), whereas constraints (26) give the equivalent active power demand at every bus. Constraints (27) adjust reactive power demands considering a constant power factor. Equations (28) and (29) determine the total consumption reduced by DRFs and the total load compulsorily shed at every bus respectively. Constraints of bus voltage are provided in (30). Finally, constraints (31) state power shifts of units and the amount of loads shed are non-negative.

B. RA-SIGDT-Based Corrective Congestion Management

This strategy pertains to the cases in which uncertainties adversely affect the objective function; that is, uncertain parameters can pose a higher cost to system operators. In this strategy, there are uncertain parameters falling into two distinct types: scenario-based parameters (wind farms' output) and IGDT-based parameters (DRFs' participation). Thus, in this strategy uncertain parameters and their inevitable impact on decision variables are taken into consideration. However, based upon how influential each uncertainty type might be for decision makers, different criteria and weighting influence factors are proposed. These criteria are listed in Table II. WI_S and WI_I, designated as "Weighting Influence Factors", are binary input parameters that can take different values depending on the requirements of system operators.

Hence, the formulation of the proposed RA-SIGDT congestion management can be written as follows:

$$\upsilon_{\mathrm{RA}} = \Theta_1\hat{\upsilon}_1 + \Theta_2\hat{\upsilon}_2 + \Theta_3\hat{\upsilon}_3 \tag{32}$$

$$\begin{gathered} \Theta_1 = WI_S(WI_S - WI_I),\ \ \Theta_2 = WI_I(WI_I - WI_S) \\ \Theta_3 = WI_S WI_I, \quad WI_S \oplus WI_I = 1 \end{gathered} \tag{33}$$

TABLE II
POSSIBLE OPTIONS FOR SIGDT APPROACH

Criterion	Weighting Influence Factor		Uncertainty Type of More Importance	
	WI_S	WI_I	Scenario	IGDT
#1	1	0	✓	×
#2	0	1	×	✓
#3	1	1	✓	✓
#4	0	0	×	×

$$\hat{\upsilon}_1 = \left\{\max\ \upsilon(w')\right\}_{w' = \arg\max_w \left\{\delta(w)\right\}} \tag{34}$$

$$\hat{\upsilon}_2 = \min_{w=1:NW} \left\{X(w) = \max\ \upsilon(w)\right\} \tag{35}$$

$$\hat{\upsilon}_3 = \max\ \sum_w \delta(w)\upsilon(w) \tag{36}$$

$$\begin{aligned} \max\ &\left(\Theta_1 + \Theta_2\right)CM(w) + \Theta_3\sum_w \delta(w)CM(w) \\ &\le \left(\Theta_1 + \Theta_2\right)\Gamma_C(w) + \Theta_3\sum_w \delta(w)\Gamma_C(w) \end{aligned} \tag{37}$$

subject to

$$\Gamma_C(w) = (1 + \varpi_C)CM_{RN}(w) \tag{38}$$

$$\text{(17) to (31)} \tag{39}$$

$$P_{DRFd}^{AP}(w) = P_{DRFd}^{F}(1 - \upsilon(w)) \qquad d \in \Omega^{\mathrm{DRF}} \tag{40}$$

It can be noticed from (33) that only one of the three input parameters Θ_1, Θ_2, and Θ_3 equals unity at the same time and that each parameter stresses the respective criterion #1, #2, and #3, provided in Table II. These inputs are able to break the problem into three different optimization problems. Equations (34)-(36) result in an optimal solution with regard to each criterion. In the right-hand side of the inequality (37), the first and second terms are critical values concerning criterion #1/#2 and criterion #3 respectively, which are defined as a function of the RN-SIGDT objective function CM_{RN}. ϖ_C as a positive parameter is the degree of the tolerable increase in the RN-SIGDT objective function, specified by decision makers. When $\{WI_S,\ WI_I\}=\{1,\ 0\}$, only the most probable scenario play a significant role in making decisions, but in the case when $\{WI_S,\ WI_I\}=\{0,\ 1\}$, amongst the solutions set ($X(w)$) that maximizes the uncertainty radius of DRFs ($\upsilon(w)$), the scenario with the least size of uncertainty radius is selected as a final solution since this value can be feasible for all scenarios. On the other hand, when $\{WI_S,\ WI_I\}=\{1,\ 1\}$, decision makers take all scenarios into consideration and the expected value of the radius of uncertainty is of the interest. The immunity in each scenario is desirable when DRFs' participation is lower than what it has been forecasted to be, i.e. P_{DRFd}^{F}, specified by (25) and (40).

V. SIGDT-BASED CONGESTION MANAGEMENT CONSIDERING THE UNCERTAINTY OF CONVENTIONAL GENERATING UNITS

In practice, the failure rates of conventional generating units are comparable with the failure rates of wind turbines. Thus, the uncertainty of generating units can be assigned to the proposed SIGDT congestion management problem, along with variability of wind speed, turbines' availability, and uncertain behavior of DRFs. To model the uncertainty of generators, the outages of a single generating unit (N-1 contingency) is adopted using their forced outage rates [34]. Similar to wind farms' production, a scenario-based model is considered for generators outages based on their states (up/down) as follows:

$$\pi_g^w = \prod_i \left(\kappa_i^w(1 - FOR_i) + (1 - \kappa_i^w)FOR_i\right) \tag{41}$$

where π_g^w and κ_i^w represent the occurrence probability of each scenario and the state of each unit (1 if up/0 if down) in each scenario respectively. Assuming the uncertain parameters of wind farms and generating units are independent, the probability of each scenario, which was mentioned earlier in (15), is then reformed and calculated by combining different states of wind farms and generating units as follows:

$$\delta(w) = \pi_g^w . \ \pi_F^w$$
$$where \ \pi_F^w = \prod_f \rho_f(\Omega_f) \tag{42}$$

Modeling the RN_SIGDT and RA_SIGDT congestion management problems considering uncertainties of wind farms, DRFs, and conventional units is similar to the previous section, i.e. (16)-(31) and (17)-(40), thereafter.

VI. Results and Discussion

The proposed congestion management problem considering uncertainties of wind farms' output power, conventional generating units, and DRFs' participation is implemented in the IEEE-RTS system since the standard reliability data including failure/repair rates of generators are available for this network. This system is modified with a 20-MW wind farm and five DRFs. The wind farm consisting of ten identical "wt2000df TC IIA" wind turbines, designed by AMSC [35], is placed at bus B_2. The proposed algorithm is implemented in the general algebraic modeling system (GAMS) environment and solved by CONOPT solver.

A. *Impact of MTTR of Wind Turbines' Components*

In this paper, hourly wind speed data for a real wind farm [36] are utilized. The reliability characteristics of wind turbines' components are given in Table III. In order to analyze the impact of different MTTR values of components of a wind turbine on the forced outage rate of the turbine, the MTTR factor η is defined as $r_{cp}=(1+\eta)\,r_{cp}^{typical}$. The parameter $r_{cp}^{typical}$ indicates the MTTR of the typical wind turbine's components in Table III. As can be seen from Fig. 5, there is an adverse correlation between the availability of wind turbines and the mean repair times of their components. When the factor η increases from zero to 0.5, the MTTR value of the turbine's components goes up, which, in turn, increases the forced outage rate of the wind turbine.

B. *SIGDT-Based Congestion Management Analysis*

To investigate the proposed CM problem, the ratings of branches 3-24, 10-11 and 14-16 are assumed to reduce to 200, 150, and 300 MW respectively. After checking the possibility of network congestion, it is asserted that the aforementioned branches are congested, and the ISO needs to mitigate congestion. Information on the prices offered by generators to change their power schedule is extracted from [24]. In this study five DRFs located at buses B_1, B_2, B_3, B_7 and B_{13} are considered, with the forecasted participation of each DRF equaling 10 percent of the respective load. The price of consumption reduced by DRFs is 12 \$/MWh. The value of lost load for the aim of load shedding is also extracted from [24].

TABLE III
Characteristics of Components of A Typical Wind Turbine

Component	MTTR (day)	Failure Rate (f/year)
Electrical system	1.80	2.00
Electronic control	2.30	1.49
Sensors	1.80	0.89
Hydraulic system	1.40	0.85
Yaw system	3.30	0.66
Rotor blades	5.10	0.63
Mechanical brake	3.30	0.48
Rotor hub	4.40	0.40
Gearbox	7.90	0.36
Generator	9.30	0.33
Supporting structure	4.10	0.32
Drive train	7.10	0.19

TABLE IV
RN-Sigdt-Based Congestion Management Cost

Scenario	Output (MW)	Probability	CM Cost (\$/h)	Expected CM Cost (\$/h)
1	0	0.4264	97169.790	41433.198
2	5	0.1646	95354.590	15695.366
3	10	0.1032	93539.309	9653.257
4	15	0.0839	91723.994	7695.643
5	20	0.2219	89967.045	19963.687
				94441.151

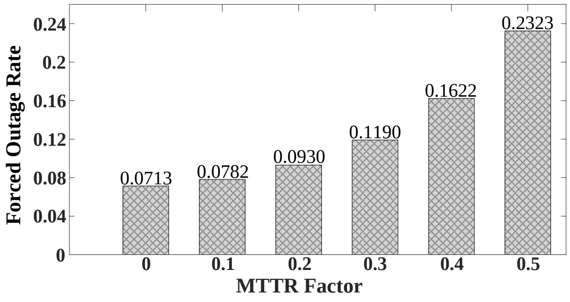

Fig. 5. FOR of a wind turbine for different MTTR values of its components.

In this problem, five states or scenarios are considered to model the uncertainty of the wind farm's output, and two strategies of SIGDT approach are studied as follows:

1) RN-SIGDT Strategy: In this strategy, which carries an underlying part in the SIGDT analysis, the radius of uncertainty of DRFs' participation is zero (no forecast errors exist), and the objective function is calculated for each scenario regarding the wind farm's production. Fig. 6 shows changes in the consumption of consumers, including power reduction of DRFs and involuntary load shedding. Table IV represents the CM cost in each scenario. As seen, with an increase in the wind farm's output power, the CM cost experiences a fall. A compelling justification is that less involuntary load shedding is required when more wind farm's production exists as depicted in Fig. 6.

2) RA-SIGDT Strategy: In this case, the problem is solved for different values of ϖ_C in each scenario. The parameter ϖ_C is varied in each scenario from zero to the extent to which the decision maker is no longer able to make the objective function more robust against the uncertainty of DRFs. It is

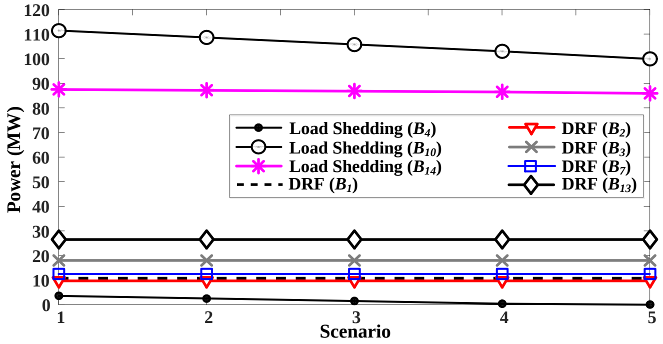

Fig. 6. Consumption adjustments in RN-SIGDT congestion management.

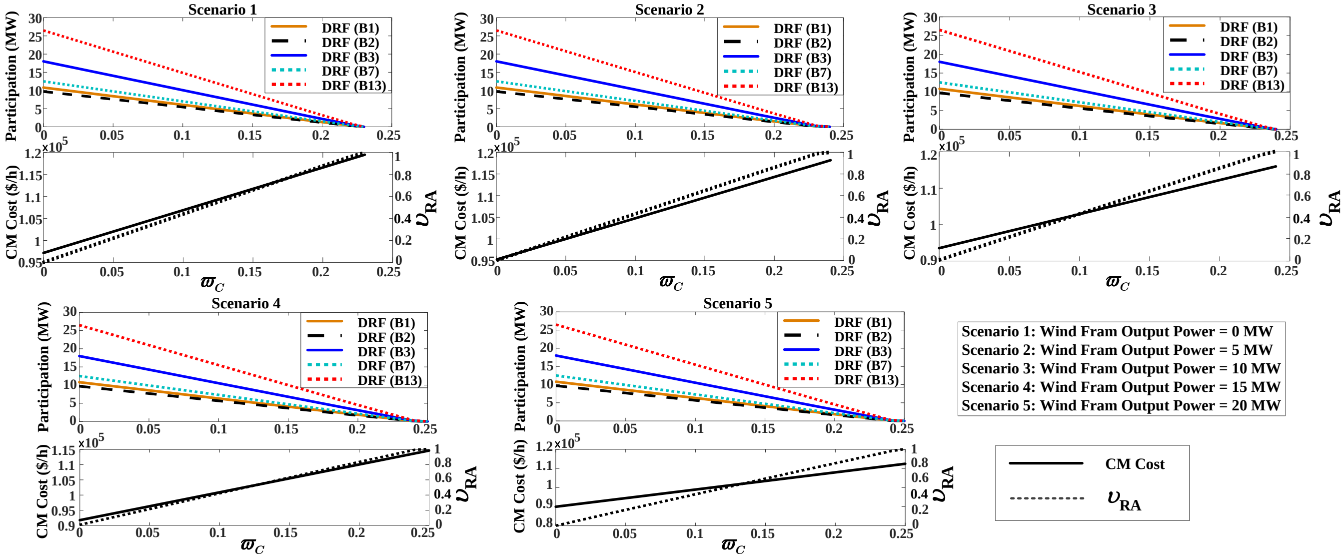

Fig. 7. Variation of DRFs' participation and CM cost versus ϖ_C in RA-SIGDT strategy for different output states of the wind farm.

TABLE VI
A COMPARISON BETWEEN THE PROPOSED METHOD AND A CM METHOD USING NO DRFS

Method	Strategy	DRFs'Participation Cost ($/h)	Generation Shifts Cost ($/h)	Load Shedding Cost ($/h)	CM Cost ($/h)
Without DRFs	Scenario-based	0	4499.527	112150.030	116649.557
Proposed Method	RN-SIGDT	930	5009.720	88501.431	94441.151
(With DRFs)	RA-SIGDT	730.482	4900.165	93532.561	99163.208

observed from Fig. 7 that by increasing the acceptable tolerance factor ϖ_C, the radius of uncertainty and CM cost increase in all scenarios, resulting from a drop in DRFs' participation. Interestingly, the maximum acceptable tolerance parameter in each scenario depending on different outputs of the wind farm is different from that of others. For instance, in scenario 1, the value of υ_{RA} rises from zero for ϖ_C = 0% to unity for ϖ_C = 23%, prior to remaining constant for $\varpi_C \geq$ 23%. It is also evident from Fig. 7 that as the radius of uncertainty increases the optimum value of participation of all DRFs in all scenarios falls.

The optimal solutions of the proposed RA-SIGDT problem for different values of weighting influence factors, when ϖ_C is 5%, are given in Table V. When $\{WI_S, WI_I\}=\{1, 0\}$, a scenario with the highest probability (0.4264), i.e. scenario 1, is the aim, and the radius of uncertainty of DRFs and CM cost equal 0.2201 and 102028.279 $/h respectively. When $\{WI_S, WI_I\}=\{0, 1\}$, the scenario with the smallest size of optimal uncertainty radius amongst the solutions set is the target, i.e. scenario 5. If $\{WI_S, WI_I\}=\{1, 1\}$, the expected radius of uncertainty and CM cost are equal to 0.2145 and 99163.208 $/h respectively.

C. Impact of MTTR of Wind Turbines' Components on the Proposed Congestion Management Problem

Fig. 8 shows the impact of different MTTR values of wind turbines' components on the CM cost and uncertainty radius of DRFs in the RA-SIGDT strategy when WI_S and WI_I are 1 and ϖ_C is assumed to be 5%. An increase in the MTTR of wind turbines' components increases the expected CM cost and the radius of uncertainty of DRFs.

TABLE V
OPTIMAL SOLUTIONS IN RA-SIGDT STRATEGY FOR ϖ_C = 5%.

Criterion	WI_S	WI_I	υ_{RA}	CM Cost ($/h)
#1	1	0	0.2201	102028.279
#2	0	1	0.2064	94465.397
#3	1	1	0.2145	99163.208

D. Comparison between CM without Demand Response Implementation and the Proposed Framework

This subsection investigates the benefits of the proposed SIGDT method for CM using DRFs compared to the CM without implementing demand response. In the former model, two strategies RN-SIGDT and RA-SIGDT are applied to CM through DRFs whereas in the latter method, only generation rescheduling and involuntary load shedding are implemented considering the uncertainty of the wind farm. As can be seen form Table VI, the CM cost related to the method in which no DRFs are used (116649.557 $/h) is higher in comparison with the proposed method in which DRFs even those under severe uncertainty are implemented. It is evident that the proposed method not only can keep the CM cost lower, also can enable decision makers to make the CM cost robust against the unsatisfactory consequences of DRFs' output variability.

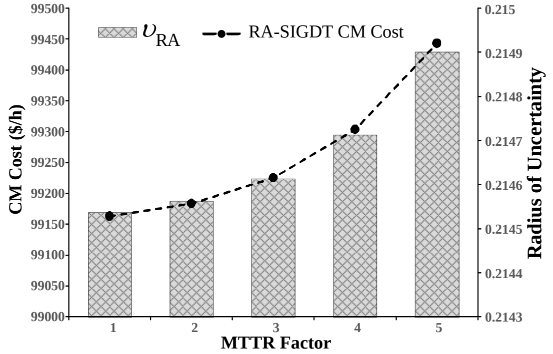

Fig. 8. Impact of MTTR of wind turbines' components on the RA-SIGDT CM.

TABLE VII
RESULTS OF THE SIGDT-BASED CONGESTION MANAGEMENT FOR SELECTED SCENARIOS CONSIDERING OUTAGES OF A SINGLE GENERATOR

Gen. Outage	Wind Farm's Production	Scenario Probability	RN-SIGDT	RA-SIGDT	
			CM Cost ($/h)	CM Cost ($/h)	υ_{RA}
G22	0%	0.0265	152246.59	159858.92	0.227
	25%	0.0102	150142.00	157649.1	0.224
	50%	0.0064	148037.64	155439.52	0.221
	75%	0.0052	145933.52	153230.19	0.218
	100%	0.0138	143829.64	151021.12	0.215
G23	0%	0.0265	151535.24	159112	0.226
	25%	0.0102	149431.22	156902.78	0.223
	50%	0.0064	147327.45	154693.82	0.220
	75%	0.0052	145223.91	152485.1	0.217
	100%	0.0138	143120.61	150276.64	0.214
G32	0%	0.0169	148337.49	155754.36	0.230
	25%	0.0065	146261.73	153574.81	0.227
	50%	0.0041	144188.55	151397.97	0.224
	75%	0.0033	142117.95	149223.84	0.221
	100%	0.0088	140049.90	147052.39	0.217
G14	0%	0.0102	144218.61	151429.54	0.313
	25%	0.0040	142425.77	149547.05	0.309
	50%	0.0025	140637.19	147669.05	0.305
	75%	0.0020	138847.88	145790.27	0.301
	100%	0.0053	137061.51	143914.58	0.297
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
G24	0%	0.0020	96279.33	101093.29	0.218
	25%	0.0008	94462.21	99185.32	0.214
	50%	0.0005	92644.85	97277.09	0.210
	75%	0.0004	90827.31	95368.67	0.206
	100%	0.0010	89071.79	93525.38	0.205

E. Influence of Uncertainties of Generating Units, Wind Farms and Demand Response Firms Together

This subsection intends to solve the proposed SIDGT congestion management problem and determine the optimal value of the radius of uncertainty of DRFs' participation considering the concurrent uncertainties of generating units, Wind Farms, and DRFs. To model the uncertainty of generators, the outages of a single generating unit (N-1 contingency) is applied using their forced outage rates. Accordingly, the SIGDT congestion management problem in the presence of uncertainty of the DRFs, wind farm including wind speed variability and turbines' forced outages, and generating units is solved for ϖ_C = 5%. The results for the five highest probable scenarios and the lowest one regarding generating units' contingencies are selected as samples from all scenarios and provided in table VII. The first three columns in this table represent the status of uncertainty of generating units and wind farm, and the probability of each system scenario respectively. The forth column shows the congestion management cost in RN_SIGDT strategy while the fifth and sixth columns specify the CM cost and radius of uncertainty of DRFs in the RA-SIGDT strategy. The expected CM cost and uncertainty radius in the RA_SIGDT strategy are equal to 116653.2 $/h and 0.2285 respectively. The CM cost (116653.2 $/h) is more than when there are no generating units outages (99163.208 $/h). Practically, this extra cost (116653.2-99163.208) pertains to the uncertainty costs of generating units for RA_SIGDT congestion management.

VII. CONCLUSION

This paper introduces a new hybrid SIGDT-based congestion management framework, in which uncertainties of large-scale wind farms' output power, DRFs' participation, and conventional generating units are taken into consideration on a simultaneous basis. To address the uncertainty of large-scale wind farms, a probabilistic multi-state modeling of the wind farm is developed considering correlation between outputs of individual wind turbines, wind speed variability, and wind turbines' components failure. In this context, a reliability network modeling for a wind turbine system incorporating series components is presented to elaborate upon the relationship between unavailability, MTTR, and failure rate of each wind turbine and its individual constructing components. On the other hand, granted that there are no sufficient historical participation data and probability density function for DRFs willing to participate in demand response events, the uncertainty of DRFs is handled using the IGDT technique. Uncertainty of conventional generating units is modeled using failure/repair rates of them on a basis of N-1 contingency concept.

The proposed CM framework incorporates two different strategies: RN-SIGDT and RA-SIGDT. To show the capability of this work, the proposed CM problem is solved and compared with another CM method in which no DRF is used. The Results indicate that the proposed method can keep the CM cost down compared to the other method. Moreover, the impact of MTTR values of each wind turbine's component on the FOR of the wind turbine, and the proposed CM problem are investigated. The results demonstrate that as the MTTR of components increases, the FOR of the wind turbine rises, having an adverse effect on the CM cost. The proposed CM is feasible and will assist ISOs to manage transmission congestion issues with improved performance and accuracy.

REFERENCES

[1] Y. Li, Z. Ni, T. Zhao *et al.*, “Coordinated Scheduling for Improving Uncertain Wind Power Adsorption in Electric Vehicles—Wind Integrated Power Systems by Multiobjective Optimization Approach,” *IEEE Trans. Ind. Appl.,* vol. 56, no. 3, pp. 2238-2250, 2020.

[2] S. R. Salkuti, “Congestion Management Using Optimal Transmission Switching,” *IEEE Syst. J.,* vol. 12, no. 4, pp. 3555-3564, 2018.

[3] A. Tabandeh, A. Abdollahi, and R. Abdollahi, "Congestion management using uncertain enrolled customers in emergency demand response programs," *2016 IEEE Int. Conf. Power Energy (PECon),* 2016, pp. 366-371.

[4] H. Khani, N. El-Taweel, and H. E. Z. Farag, “Power Congestion Management in Integrated Electricity and Gas Distribution Grids,” *IEEE Syst. J.,* vol. 13, no. 2, pp. 1883-1894, 2019.

[5] Z. Q. Xie, T. Y. Ji, M. S. Li *et al.*, “Quasi-Monte Carlo Based Probabilistic Optimal Power Flow Considering the Correlation of Wind Speeds Using Copula Function,” *IEEE Trans. Power Syst.,* vol. 33, no. 2, pp. 2239-2247, 2018.

[6] H. Saberi, H. Monsef, and T. Amraee, “Probabilistic congestion driven network expansion planning using point estimate technique,” *IET Gener. Transm. Distrib.,* vol. 11, no. 17, pp. 4202-4211, 2017.

[7] H. Wu, P. Dong, and M. Liu, “Random fuzzy power flow of distribution network with uncertain wind turbine, PV generation, and load based on random fuzzy theory,” *IET Renew. Power Gener.,* vol. 12, no. 10, pp. 1180-1188, 2018.

[8] S. Dehghan, N. Amjady, and P. Aristidou, “A Robust Coordinated Expansion Planning Model For Wind Farm-Integrated Power Systems With Flexibility Sources Using Affine Policies,” *IEEE Syst. J.,* vol. 14, no. 3, pp. 4110-4118, 2020.

[9] S. Sulaeman, M. Benidris, J. Mitra *et al.*, “A Wind Farm Reliability Model Considering Both Wind Variability and Turbine Forced Outages,” *IEEE Trans. Sustain. Energy,* vol. 8, no. 2, pp. 629-637, 2017.

[10] M. Khanabadi, Y. Fu, and C. Liu, “Decentralized Transmission Line Switching for Congestion Management of Interconnected Power Systems,” *IEEE Trans. Power Syst.,* vol. 33, no. 6, pp. 5902-5912, 2018.

[11] M. Hojjat, and M. H. Javidi, “Chance-constrained programming approach to stochastic congestion management considering system uncertainties,” *IET Gener. Transm. Distrib.,* vol. 9, no. 12, pp. 1421-1429, 2015.

[12] S. Dutta, and S. Singh, “Optimal rescheduling of generators for congestion management based on particle swarm optimization,” *IEEE Trans. Power Syst.,* vol. 23, no. 4, pp. 1560-1569, 2008.

[13] S. Verma, S. Saha, and V. Mukherjee, “Optimal rescheduling of real power generation for congestion management using teaching-learning-based optimization algorithm,” *J. Electr. Syst. Inf. Technol.,* vol. 5, no. 3, pp. 889-907, 2018.

[14] M. Pantoš, “Market-based congestion management in electric power systems with exploitation of aggregators,” *Int. J. Electr. Power Energy Syst.,* vol. 121, pp. 106101, 2020.

[15] M. Esmaili, N. Amjady, and H. A. Shayanfar, “Stochastic congestion management in power markets using efficient scenario approaches,” *Energy Convers. Manag.,* vol. 51, no. 11, pp. 2285-2293, 2010.

[16] Y. R. Sood, and R. Singh, “Optimal model of congestion management in deregulated environment of power sector with promotion of renewable energy sources,” *Renew. Energy,* vol. 35, no. 8, pp. 1828-1836, 2010.

[17] S. S. Reddy, “Multi-Objective Based Congestion Management Using Generation Rescheduling and Load Shedding,” *IEEE Trans. Power Syst.,* vol. 32, no. 2, pp. 852-863, 2017.

[18] A. Yousefi, T. T. Nguyen, H. Zareipour *et al.*, “Congestion management using demand response and FACTS devices,” *Int. J. Electr. Power Energy Syst.,* vol. 37, no. 1, pp. 78-85, 2012.

[19] E. Shayesteh, M. Moghaddam, A. Yousefi *et al.*, “A demand side approach for congestion management in competitive environment,” *Eur. Trans. Electr. Power,* vol. 20, no. 4, pp. 470-490, 2010.

[20] A. Tabandeh, A. Abdollahi, and M. Rashidinejad, "Security-based congestion management considering power system components' uncertainty," *2016 21st Electric. Power Distrib. Netw. Conf.,* 2016, pp. 172-179.

[21] M. H. Moradi, A. R. Reisi, and S. M. Hosseinian, “An Optimal Collaborative Congestion Management Based on Implementing DR,” *IEEE Trans. Smart Grid,* vol. 9, no. 5, pp. 5323-5334, 2018.

[22] F. Zaeim-Kohan, H. Razmi, and H. Doagou-Mojarrad, “Multi-objective transmission congestion management considering demand response programs and generation rescheduling,” *Appl. Soft Comput.,* vol. 70, pp. 169-181, 2018.

[23] H.-G. Kwag, and J.-O. Kim, “Reliability modeling of demand response considering uncertainty of customer behavior,” *Appl. Energy,* vol. 122, pp. 24-33, 2014.

[24] A. Tabandeh, A. Abdollahi, and M. Rashidinejad, “Reliability constrained congestion management with uncertain negawatt demand response firms considering repairable advanced metering infrastructures,” *Energy,* vol. 104, pp. 213-228, 2016.

[25] K. Mahmud, J. Ravishankar, M. J. Hossain *et al.*, “The Impact of Prediction Errors in the Domestic Peak Power Demand Management,” *IEEE Trans. Ind. Inf.,* vol. 16, no. 7, pp. 4567-4579, 2020.

[26] E. Fernandez, M. J. Hossain, and M. S. H. Nizami, “Game-theoretic approach to demand-side energy management for a smart neighbourhood in Sydney incorporating renewable resources,” *Appl. Energy,* vol. 232, pp. 245-257, 2018.

[27] A. Soroudi, A. Rabiee, and A. Keane, “Information gap decision theory approach to deal with wind power uncertainty in unit commitment,” *Electr. Power Syst. Res.,* vol. 145, pp. 137-148, 2017.

[28] A. Soroudi, and M. Ehsan, “IGDT Based Robust Decision Making Tool for DNOs in Load Procurement Under Severe Uncertainty,” *IEEE Trans. Smart Grid,* vol. 4, no. 2, pp. 886-895, 2013.

[29] Windmonitor, 2020. [Online] Available: http://windmonitor.iee.fraunhofer.de, [accessed 07.10.2020].

[30] M. Moeini-Aghtaie, A. Abbaspour, and M. Fotuhi-Firuzabad, “Incorporating Large-Scale Distant Wind Farms in Probabilistic Transmission Expansion Planning—Part I: Theory and Algorithm,” *IEEE Trans. Power Syst.,* vol. 27, no. 3, pp. 1585-1593, 2012.

[31] C. C. Aggarwal, and C. K. Reddy, *Data clustering: algorithms and applications*. London, UK: Chapman and Hall/CRC, 2013.

[32] "Demand response and advanced metering FERC report," Aug 2006 . Available at: http://www.ferc.gov/legal/staff-reports/demand-response.pdf; [accessed 11-11-2020].

[33] J. Zhao, C. Wan, Z. Xu *et al.*, “Risk-Based Day-Ahead Scheduling of Electric Vehicle Aggregator Using Information Gap Decision Theory,” *IEEE Trans. Smart Grid,* vol. 8, no. 4, pp. 1609-1618, 2017.

[34] C. He, L. Wu, T. Liu *et al.*, “Robust Co-Optimization Planning of Interdependent Electricity and Natural Gas Systems With a Joint N-1 and Probabilistic Reliability Criterion,” *IEEE Trans. Power Syst.,* vol. 33, no. 2, pp. 2140-2154, 2018.

[35] wt2000df wind turbine. [Online]. Available: https://www.amsc.com/wp-content/uploads/wt2000_DS_A4_0314_WEB.pdf.

[36] The wind speed series of Zabol wind farm. [Online]. Available: http://www.satba.gov.ir.