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A conservative framework for obtaining uncertain bands of multiple wind farms in electric power networks by proposed IGDT-based approach considering decision-maker's preferences

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A R T I C L E I N F O

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A B S T R A C T

Exploiting clean energy resources (CERs) is an applicable way to enhance sustainable development and have the cleaner production of electricity. On the other hand, variability and intermittency of these clean resources are the important disadvantages for determining the reliable operation of electrical grids. Thus, using the uncertainty modeling techniques seems necessary to have more practical values for the decision-making variables. The current paper demonstrates a novel architecture based on Information Gap Decision Theory (IGDT) to model the randomness of multiple Wind Farms (WFs) existing in electric power networks. Note that employing only the IGDT technique cannot consider the preferences defined by the decision-maker. In contrast, the proposed method tackles this issue by considering different values for radii of uncertainty related to the uncertain parameters. It has been proven that the presented approach is time-saving if compared with Monte Carlo Simulation (MCS) and the Epsilon-constraint-based-IGDT. Moreover, the execution time of the presented methodology does not considerably depend on the number of WFs for a power system. It means that if the number of WFs increases in a particular case study, consequently, the execution time does not noticeably rise if compared with the MCS and the Epsilon-constraint-based-IGDT. Furthermore, the equivalent Mixed Integer Linear Programming (MILP) of the original model is employed to guarantee the optimum solution. The performances of the presented methodology have been demonstrated by utilizing IEEE 30 BUS and IEEE 62 BUS systems.

1. Introduction

1.1. Motivation and literature review

To tackle the problems resulting from the emission pollutants released by the conventional generating units, employing Wind Farms (WFs) can be an applicable way for the cleaner production of electricity. It should be mentioned that the intermittent nature of the output power generated through the WFs is an important drawback (Sun et al., 2020). Consequently, modeling the uncertainty of active power injected into the electrical grids through the WFs is necessary to obtain more reliable values for the decision-making variables (Hemmati et al., 2020). Similarly, the importance of taking into consideration of the uncertainty of input parameters related to an electric power system has been highlighted in (Jordehi, 2018). There are several uncertainty modelling techniques to address the behavior of the stochastic input parameters described in (Ebeed and Aleem, 2021). In this section, several papers related to this research topic have been reviewed.

Information-Gap Decision Theory (IGDT) and stochastic approaches have been used to investigate the power system operation and planning considering the uncertain resources in the previous literature. For the first time, Ben-Haim suggested the IGDT technique to derive the decision-making variables, where the uncertain nature of parameters should be taken into account (Ben-Haim, 2006). As a result, this technique has been exploited to analyze the effect of uncertain parameters on the operation of power and energy systems (Mohammadi-ivatloo and Nazari-Heris, 2019).

In (Li et al., 2022), authors have presented a stochastic approach to derive the optimal scheduling of demand response for an isolated Micro Grid (MG), where the uncertain nature of Renewable Energy Resources (RERs) has been addressed. A bi-level framework was proposed based on

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Nomenclature

Sets, Indices

i, j	Index of buses
t	Index of time
g	Index of thermal power plants
τ	Set of hours
B	Set of buses
w	Index of wind farm unit
z	Index of piecewise linear segments
$\Omega_{(.)}$	Set of units

Parameters

$V_{\min}$	$V_{\max}$ Lower and upper limitations of voltage magnitude
$\delta_{\min}$	$\delta_{\max}$ Lower and upper limitations related to the phase of voltage
$P^G_{g,max}$	$P^G_{g,\min}$ Minimum and Maximum permitted real power for g^{th} generator
$Q^G_{g,\max}$	$Q^G_{g,\min}$ lower and upper permitted reactive power for g^{th} generator
RU_g	RD_g Ramp up and ramp down constraints of g^{th} conventional power plants
C^{sup}_g	C^{sdn}_g Start-up cost and shut-down cost of g^{th} conventional power plants
P^D_{dt}	Q^D_{dt} Active and reactive load demand
h	Number of tangent hyperplanes
P^{fr}_w	Forecasted real power strategy of w^{th} wind farm (WF)
PN_w	Penetration of w^{th} (WF)

Variables

α_{gt}	β_{gt} Binary variables showing the start of ramp-up and ramp-down rates for g^{th} conventional generating unit
V_{it}	Voltage magnitude
δ_{it}	Phase of voltage
TC	Operational cost of generating units in one day
n^G_{gt}	Turn-on and turn-off binary variables Related to g^{th} thermal power plant
P^G_{gt}	Real power of g^{th} thermal power plant
Q^G_{gt}	Reactive power of g^{th} thermal power plant
P_w	Active power generated through w^{th} wind farm
Q_w	Reactive power produced through w^{th} wind farm
$P^L_{ij,t}$	Exchanged real power between bus i and bus j at time t
$Q^L_{ij,t}$	Exchanged reactive power between bus i and bus j at time t
n_{gtz}	Index of z^{th} piecewise linear segment related to g^{th} conventional generating unit at time t
$\widehat{D}\ V$	The notification of each linear variable
$\cos_{ijt}$	Linear formulation of $\cos(\delta_{it} - \delta_{jt})$
P^{RA}_w	Robust strategy of real power for w^{th} WF
$\zeta^w_{\max}$	Maximum Conservativeness factor for w^{th} WF
AV_w	Average energy generated by the w^{th} WF
β^{RA}	Conservative level of satisfaction
Λ^c	Robust target of the IGDT
Γ	Uncertainty set
ψ	Set of equality/inequality constraints
ς^c	Critical percent of operational cost
ζ_W	Radius of uncertainty (conservativeness factor) of w^{th} WF

combining the Jaya algorithm and Interior Point Method (IPM) to solve the mathematical model. Likewise in (Li et al., 2021), to deal with the environmental issues, a Community Integrated Energy System (CIES) with Electric Vehicle Charging Station (EVCS) has been evaluated regarding the uncertainty of RERs. Note that the stochastic approach was employed to handle the uncertainty and a novel bi-level dispatching model has been presented for the CIES with an EVCS in multi-stakeholder scenarios.

Prior to review the IGDT-based frameworks to address the uncertainties in the electric power and energy systems, the reasons of using this technique need to be clarified. Firstly, the stochastic approaches cannot report the robust solution, meaning that only the expected values of the decision-making variables are determined (Aien et al., 2016). Secondly, in the Robust Optimization (RO) approach, the interval of the uncertain parameter is available, consequently, its predicted value is unknown. On the other hand, in the IGDT technique, the forecasted strategy is an input parameter and the maximum deviation from the forecasted value (robust solution) needs to be derived (Aien et al., 2016).

In Ref (Ahmadi et al., 2019), the IGDT technique has been served to implement the Security Constraint Unit Commitment (SCUC) problem in the presence of uncertain load demand and the intermittent active power generated by the WF. Another example of using the IGDT is (Ahmadi et al., 2018), which carries out the SCUC framework considering the uncertainty of load in a particular electric power network. Note that in (Chen et al., 2014), the restoration of a Distribution Network (DN) has been accomplished, where the load demand and generated power by Distributed Generators (DGs) are assumed as the uncertain input parameters. Likewise, in (Rabiee et al., 2016), the constrained voltage stability in the Optimal Power Flow (OPF) problem has been implemented based on the IGDT technique to determine the robust values for the decision-making variables, where the wind power is an uncertain parameter. Authors in (Ma et al., 2021) suggested a methodology based on the IGDT technique to make a robust decision against the uncertain power generated by the wind turbine in a Power to Gas (P2G) network. In (Nikkhah et al., 2020), an IGDT-based Energy Management System (EMS) was presented to address the immunized solution against the uncertainty of injected wind power into the DN. Note that in (Najafi et al., 2022), a methodology has been explained to consider the uncertainty of the power generated by the wind turbine based on the IGDT in a multicarrier energy system. It should be highlighted that the optimization procedure was coded in General Algebraic Modelling System (GAMS) platform. Risk-Averse based-IGDT has been employed in (Rawat and Niazi, 2020) to address the uncertainty of load and the intermittency of wind power generation in a MG. Another instance of using the IGDT technique is (Nikoobakht et al., 2016), where the SCUC problem was solved in the presence of the uncertain power generation through the WF. It should be added that the Transmission Switching (TS) action was considered in the power system. Similarly, in Ref (Nikoobakht and Aghaei, 2017), the authors proposed a methodology using the Bender Decomposition method to carry out the IGDT based-SCUC framework. This robust decision-making procedure was presented to address the stochastic nature of the generated power through the WF. Note that in (Soroudi et al., 2017), a robust solution for the UC problem has been achieved, where the intermittent behavior of wind power was addressed by exploiting the IGDT. Ref (Dai et al., 2020) attains the decision-making variables of the Economic Dispatch (ED) problem considering the uncertainties of wind power generation and Demand Response (DR) using the IGDT technique. Likewise, in (Rahmani and Amjady, 2019), a multi-objective IGDT technique was presented to address the uncertainties of wind, photovoltaic (PV), and load in a multi-carrier energy system based on the Normal Boundary Intersection method. In (Dai et al., 2019), the IGDT has been applied to implement the robust ED against the uncertainties of wind generation and DR.

Authors in (Yan et al., 2021) presented an architecture to derive an immunized operation of a multicarrier energy system against the uncertainty resulting from the stochastic nature of the market price. This robust framework is based on the IGDT technique. The optimization procedure was carried out in the GAMS and the mathematical formulation is Mixed Integer Non-Linear Programing (MINLP). In (Benyaghoob-Sani et al., 2021), a multi-objective RA-IGDT was proposed to obtain reliable operation of a multicarrier energy system considering the uncertainties of power generation related to the RERs, demand, and market price. This multi-objective approach was accomplished by employing the augmented epsilon constraint to have different radii of uncertainty. Furthermore, Ref (Akbari-Dibavar et al., 2021) used the IGDT to take into consideration the intermittent output power of three wind farms existing in a transmission power grid. Note that the mathematical formulation is Mixed Integer Linear Programming (MILP). The optimization procedure has been handled in the GAMS. An IGDT-based EMS was presented in (Nasr et al., 2019) to address the robust uncertain bands of load and generated electrical energy through the photovoltaic cell in an islanded MG. Furthermore, in Ref (Ayvaz and Genc, 2020), the authors exploited the IGDT technique to take into account the intermittency of wind energy resources based on making robust decisions. It is noteworthy that the constraints related to the OPF have been satisfied. Likewise, in (Saki et al., 2020), the immunized decision-making variables against the uncertainties of renewable-based energy resources have been achieved by using the IGDT technique in a MG. In (Ahrabi et al., 2021), authors suggested a hybrid stochastic-IGDT technique to evaluate the uncertainties. The intermittency of active power related the WF was considered based on the IGDT technique. On the other hand, the scenario-based decision-making method is exploited to address the stochastic behavior of Electric Vehicle (EV) owners. In (Rahmani and Amjady, 2018), an approach was explained to consider the intermittency of wind power generation and the randomness of demand in an electrical grid by employing the IGDT technique. To obtain the different radii of uncertainty for these parameters, a multi-objective optimization has been carried out based on the directed search domain scheme. Authors in (Mirzaei et al., 2020a) proposed a hybrid IGDT-stochastic method to accomplish the robust UC in the presence of the uncertain wind power in a multi-carrier energy system (electrical, gas, and heating energy). Likewise, in Ref (Mirzaei et al., 2020b), the hybrid stochastic-IGDT has been proposed to solve the Unit Commitment (UC) problem under uncertainty. The stochastic behavior of load is modeled by Monte Carlo Simulation (MCS), on the other hand, the IGDT reports the robust solution regarding the intermittency of the injected wind power into the grid. In (Daneshvar et al., 2020), the hybrid stochastic-IGDT framework was exploited to consider the uncertainties. It is worth mentioning that the uncertainty of market prices is taken into account by the IGDT and the randomness of RERs has been evaluated by the stochastic approach. Note that authors in (Mafakheri et al., 2020) discussed a two-level approach, where in the first level, the stochastic behavior of load, wind, and PV generation was evaluated by the probabilistic technique. In the second level, the IGDT has been used to obtain the robust strategy. In (Shojaei et al., 2021), a multi-objective IGDT method was proposed based on the epsilon-constraint to make robust decisions against the uncertainties of several WFs and load. In a similar way, authors in Ref (Eslahi et al., 2021a) presented an iterative IGDT-based approach to derive the conservativeness factors of multiple WFs and load demand. Note that the optimization process was coded in the GAMS.

1.2. Contributions and paper structure

It should be highlighted that if the IGDT technique is used to consider several WFs in the electric power network, one conservativeness factor is determined. Furthermore, the decision-maker's preferences cannot be addressed in this conventional technique.

In Ref (Li et al., 2022), the stochastic method was used to address the uncertainty, as a consequence, instead of obtaining the robust values of the decision-making variables, their expected values have been achieved. In a similar way, authors in (Li et al., 2021) evaluated the effect of the uncertainty related to the RERs on the electrical grid by using the stochastic method that the robust solution cannot be derived.

To demonstrate the novelty of the presented scheme, table (1) shows the research gap by providing related information about the previous studies using the IGDT. In (Ahmadi et al., 2019), a multi-objective IGDT technique was presented based on VIKOR method and the WFs have one value for the radius of uncertainty. Moreover, the decision-maker's preferences were not addressed. Authors in (Rabiee et al., 2016) implemented the multi-objective IGDT based on weighted sum theory to considered different radii of uncertainty for the WFs. Note that the impact of increasing the number of the WFs on the execution time was not analyzed, and the preferences of the decision-maker have not been satisfied. In Ref (Dai et al., 2020), only one value for radii of uncertainty related to the WFs was considered that is not practical. Furthermore, in (Rahmani and Amjady, 2019), the effect of the number of the WFs on the execution time has not been evaluated, and a unique value for radii of uncertainty was reported for the WFs. Authors in (Benyaghoob-Sani et al., 2021), different robust bands for the load demand and the market price have been reported without addressing the intermittency of wind power generation. Likewise, in (Nasr et al., 2019), the uncertainty of wind power was not considered. In (Rahmani and Amjady, 2018), the radii of uncertainty for the WFs have one value. As a consequence, the decision-maker's preferences have not been satisfied. Authors in (Shojaei et al., 2021) used epsilon-constraint-based IGDT to derive the different values for the radii of uncertainty related to the WFs and demand. To determine the final solution Pareto optimal front was needed, as a result, enough solutions should be obtained. Therefore, this method is time-consuming. It should be added that the preferences of the decision-maker were not taken into account. In contrast, in (Eslahi et al., 2021a), authors dealt with this issue, meaning that the decision-maker's preferences have been satisfied. Similarly, due to using the epsilon-constraint technique in (Eslahi et al., 2021a), to acquire a reliable solution, the number of iterations should be enough. Consequently, this method is computationally expensive.

In the other research works listed in Table 1, the IGDT technique has been employed to address the uncertainties, where the same conservativeness factor was reported for the uncertain parameters. In other words, for the parameters with different risks, a unique radius of uncertainty is reported, which is not practical.

In the current paper, different values of conservativeness factors for the WFs are obtained based on their average active power generation through a day (the decision-maker's criteria). It means that for the WF with higher risk, a greater radius of uncertainty is reported. Additionally, due to using the fuzzy sets for conservativeness factors during the optimization procedure, the proposed framework is considerably time-efficient.

It should be added that the MINLP-based optimization cannot guarantee the global optimal status in the GAMS (Karimi et al., 2019). Thus, the proposed framework is based on the linearized approximations of the non-linear mathematical expressions with reliable precision. The OPF problem has been linearized according to (Karimi et al., 2019). The assumptions of the linearization for cosine function are considered based on (Eslahi et al., 2021b). Moreover, the linearization of the quadratic fuel cost of the thermal power plants, and how the non-linear formulation can be converted to the MILP model is derived from (Eslahi et al., 2021b).

The contributions of this paper can be listed as follows:

— A novel RA- IGDT-based methodology has been presented to model the uncertainties of several WFs simultaneously considering the OPF problem in the electric power systems. Furthermore, the decision-maker's preferences are addressed based on the proposed architecture.

Table 1
Previous studies related to the operation of power and energy systems under uncertainty using the IGDT.

Ref	Uncertain phenomenon						Multi- Objective IGDT-based Uncertainty modelling		Decision-maker's preferences.	E	F	G	H
	A	B	C	PV	load	Price	Multi-Objective	Framework					
Ahmadi et al. (2019)	×	✓	×	×	✓	×	✓	VIKOR	×	×	×	×	×
Ahmadi et al. (2018)	×	×	×	×	✓	×	×	×	×	×	×	×	×
Chen et al. (2014)	×	×	×	×	✓	×	×	×	×	×	×	×	×
Rabiee et al. (2016)	✓	×	×	×	×	×	×	weighted sum	×	×	×	×	×
Ma et al. (2021)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Nikkhah et al. (2020)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Najafi et al. (2022)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Rawat and Niazi (2020)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Nikoobakht et al. (2016)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Nikoobakht and Aghaei (2017)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Soroudi et al. (2017)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Dai et al. (2020)	×	✓	×	×	✓	×	✓	Normal Boundary Intersection	×	×	×	×	×
Rahmani and Amjady (2019)	×	✓	×	×	✓	×	✓	Normal Boundary Intersection	×	×	×	×	×
Dai et al. (2019)	×	✓	×	×	✓	×	×	×	×	×	×	×	×
Yan et al. (2021)	×	×	×	×	×	✓	×	×	×	×	×	×	×
Benyaghoob-Sani et al. (2021)	×	×	×	×	✓	✓	✓	Augmented epsilon constraint	×	×	×	×	×
Akbari-Dibavar et al. (2021)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Nasr et al. (2019)	×	×	×	✓	✓	×	✓	Weighted sum	×	×	×	×	×
Ayvaz and Genc (2020)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Saki et al. (2020)	×	✓	✓	✓	×	×	×	×	×	×	×	×	×
Ahrabi et al. (2021)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Rahmani and Amjady (2018)	×	✓	×	×	✓	×	✓	Directed search domain	×	×	×	×	×
Mirzaei et al. (2020a)	×	✓	×	×	×	×	×	×	×	×	×	×	×
Mirzaei et al. (2020b)	×	✓	×	×	✓	×	×	×	×	×	×	×	×
Daneshvar et al. (2020)	×	✓	×	×	×	✓	×	×	×	×	×	×	×
Mafakheri et al. (2020)	×	✓	×	✓	×	✓	×	×	×	×	×	×	×
Shojaei et al. (2021)	✓	×	×	×	✓	×	✓	Epsilon-constraint	×	×	×	×	×
Eslahi et al. (2021a)	✓	×	✓	×	✓	×	✓	Epsilon-constraint	✓	✓	×	×	×
This paper	✓	×	✓	×	×	×	✓	D	✓	×	✓	✓	✓

A: Multiple WFs with different radii of uncertainty, B: One (or several) WF(s) having a unique value for the radii of uncertainty, C: Considering the different radii of uncertainty for all the RERs, D: Proposed multi-objective IGDT based on fuzzy sets of radii of uncertainty, E: Addressing the preferences after implementing the optimization problem for multiple WFs, F: Addressing the preferences during the implementation of the optimization problem for multiple WFs, G: Independence of execution time when the number of WFs increases in a power or energy system, H: Not requiring Pareto Optimal solutions.

— The suggested approach is noticeably more time-saving than the MCS and the epsilon-constraint based- IGDT. Furthermore, its accuracy has been proven.
— The execution time of the presented approach does not considerably depend on the number of WFs for a power system if compared with the MCS and the epsilon-constraint-based IGDT technique.
— According to the presented scheme, Pareto optimal solutions are not needed to obtain the final solution.

The structure of this paper can be expressed as follows: the original mathematical formulation is thoroughly presented in section 2. The mathematical architecture is suggested in section 3. Consequently, the numerical results are depicted and analyzed in section 4. The effectiveness of the proposed method is concluded according to the simulation results in section 5.

2. Problem formulation

2.1. Objective Function (OF)

The daily operational cost of thermal power plants is chosen as the Objective Function (OF) in the first level of the proposed approach. Note that the electricity generation cost (or the fuel cost), start-up cost and shut down cost make up the operational cost. Thus, it is formulated as follows:

$$TC = \sum_{t\in\tau}\sum_{g\in\Omega_g}\left(\begin{array}{l} a_g\left(P_{gt}\right)^2 + b_g P_{gt} + c_g n_{gt}^G \\ + C_g^{sup}\alpha_{gt} + C_g^{sdn}\beta_{gt}\end{array}\right) \quad (1)$$

As aforementioned, to guarantee the global optimal results, the equivalent MILP model has been used with reliable precision. Consequently, the linearized optimization problem in the first level of the presented method is mathematically expressed in (2).

$$\begin{cases} Min \quad \left\{\widehat{T}\,C\right\} \\ \widehat{G}(DV,\prod) = 0 \\ \widehat{H}(DV,\prod) \leq 0 \end{cases} \quad (2)$$

Where, $\widehat{T}\,C$, $\widehat{G}$, and $\widehat{H}$ are the linearized OF in the first level, the linearized equality constraints, and the linearized inequality constraints, respectively.

It is noteworthy that according to Table 1, a novel uncertainty modeling approach has been proposed, which is a multi-objective IGDT technique. It means that several radii of uncertainty (conservativeness factors) are optimized as the OFs (multi-objective optimization) in the second level of the presented framework. In other words, the optimization problem mentioned in (3) should be solved to determine the radii of uncertainty based on the Risk Averse (RA) strategy. According to this formulation, the maximum deviations from the forecasted values of active power generation related to the WFs are obtained by implementing (3). To solve (3), in this paper, a novel framework has been proposed considering the decision-maker's preferences, which is described in section 3. In (3), ζ_w is radius of uncertainty (conservativeness factor) of w^{th} WF, TC_b is the base value of the operational cost derived from the first level that is explained in section 3, P_w^{RA} is the robust active power generation of w^{th} WF, P_w^{fr} is the forecasted active power generation of w^{th} WF, N_w is the number of the WFs, and ς^c is the critical percentage of operational cost of the thermal power plants. It should be added that the linearization procedures have been completely explained in the appendix.

$$\begin{cases} \max\{\zeta_1, \ldots, \zeta_{Nw}\} \\ \widehat{G}(DV, \prod) = 0 \\ \widehat{H}(DV, \prod) \le 0 \\ \widehat{T}\,C \le TC_b + \varsigma^c |TC_b| \\ P_w^{RA} = (1-\zeta_w) P_w^{fr} \quad w = 1, \ldots, Nw \end{cases} \tag{3}$$

2.2. Network constraints

To implement the OPF problem, the limitations mentioned in (4) - (10) must be satisfied. The constraints related to the equations of real and reactive power for each bus and time duration are formulated in (4) and (5), respectively. Furthermore, the exchanged active and reactive power between the buses are mathematically modeled according to (5) and (6). It is noteworthy that the magnitude of voltage and its phase angle for each bus must be controlled within predetermined limitations, which these constraints are mentioned in (8) and (9), respectively. The allowable apparent power for a particular transmission line connecting i^{th} bus and j^{th} bus can is expressed in (10). It is highlighted that the WFs are equipped with the VAR compensators to have a unity power factor (Karimi et al., 2019).

$$\sum_{g \in \Omega_i^g} P_{gt}^G - \sum_{d \in \Omega_i^d} P_{dt}^D + \sum_{w \in \Omega_i^w} P_w = \sum P_{ij,t}^L \; \begin{matrix} j \in \Omega_i^j \\ (j \ne i) \end{matrix} \tag{4}$$

$$\sum_{g \in \Omega_i^g} Q_{gt}^G - \sum_{d \in \Omega_i^d} Q_{dt}^D + \sum_{w \in \Omega_i^w} Q_{wt}^W = \sum Q_{ij,t}^L \; \begin{matrix} j \in \Omega_i^j \\ (j \ne i) \end{matrix} \tag{5}$$

$$P_{ij,t}^L = B_{ij}\left(V_{it} V_{jt} \sin\left(\delta_{it} - \delta_{jt}\right)\right) - G_{ij}\left((V_{it})^2 - V_{it} V_{jt} \cos\left(\delta_{it} - \delta_{jt}\right)\right) \; \forall i,j \in B \quad \forall t \in \Omega_\tau \tag{6}$$

$$Q_{ij,t}^L = G_{ij}\left(V_{it} V_{jt} \sin\left(\delta_{it} - \delta_{jt}\right)\right) + B_{ij}\left((V_{it})^2 - V_{it} V_{jt} \cos\left(\delta_{it} - \delta_{jt}\right)\right) \; \forall i,j \in B \quad \forall t \in \Omega_\tau \tag{7}$$

$$V_{\min} \le V_{it} \le V_{\max} \; \forall i,j \in B \quad \forall t \in \Omega_\tau \tag{8}$$

$$\delta_{\min} \le \delta_{it} \le \delta_{\max} \; \forall i,j \in B \quad \forall t \in \Omega_\tau \tag{9}$$

$$\left(P_{ij,t}^L\right)^2 + \left(Q_{ij,t}^L\right)^2 \le \left(S_{ij}^{L,M}\right)^2 \; \forall i,j \in B \quad \forall t \in \Omega_\tau \tag{10}$$

2.3. Generating unit constraints

The injected real and reactive power into the grid by the generators must respect the constraints mentioned in (11) and (12), respectively. Similarly, ramp-up rate and ramp-down rate of generated power for each conventional power plant are formulated in (13) and (14), respectively. Note that the decision-making variables must not be contradicted, consequently, the constraints mentioned in (15) and (16) have been employed.

$$P_{g,\min}^G n_{gt}^G \le P_{gt}^G \le P_{g,\max}^G n_{gt}^G \; \forall g \in \Omega_g \quad \forall t \in \Omega_\tau \tag{11}$$

$$Q_{g,\min}^G n_{gt}^G \le Q_{gt}^G \le Q_{g,\max}^G n_{gt}^G \; \forall g \in \Omega_g \quad \forall t \in \Omega_\tau \tag{12}$$

$$P_{gt}^G - P_{g(t-\Delta t)}^G \le RU_i\left(1 - \alpha_{gt}\right) + \alpha_{gt} P_{g,\min}^G \; \forall g \in \Omega_g \quad \forall t \in \Omega_\tau \tag{13}$$

$$P_{g(t-\Delta t)}^G - P_{gt}^G \le RD_i\left(1 - \beta_{gt}\right) + \beta_{gt} P_{g,\min}^G \; \forall g \in \Omega_g \quad \forall t \in \Omega_\tau \tag{14}$$

$$\alpha_{gt} + \beta_{gt} \le 1 \; \forall g \in \Omega_g \quad \forall t \in \Omega_\tau \tag{15}$$

$$\alpha_{gt} - \beta_{gt} = n_{gt}^G - n_{gt-\Delta t}^G \; \forall g \in \Omega_g \quad \forall t \in \Omega_\tau \tag{16}$$

3. Methodology

3.1. IGDT technique

The IGDT is employed to handle an optimization process considering the uncertainty of parameters by reporting the robust strategy. In this technique, it is assumed that the following problem should be implemented (Soroudi et al., 2017):

$$\min_X \{f(X, \gamma)\}$$

Subject to

$$\begin{aligned} & H(X,\gamma) \le 0 \\ & G(X,\gamma) = 0 \\ & \gamma \in \Gamma \end{aligned} \tag{17}$$

Note that, in (17), the uncertain parameters belong to a vector called γ. In the above-mentioned optimization problem, X is the vector of decision-making variables. It is supposed that the values of uncertain parameters must belong to a space shown by Γ. The IGDT aims to obtain the radius of uncertain related to the input uncertain parameters, which can be defined as follows:

$$\forall \gamma \in \Gamma(\overline{\gamma}, \zeta) = \left| \frac{\gamma - \overline{\gamma}}{\overline{\gamma}} \right| \le \zeta \tag{18}$$

where $\overline{\gamma}$ is the forecasted strategy of the uncertain parameter existing in the system (electrical grid). Additionally, ζ is the decision-making variable, which is called "radius of uncertainty". The IGDT technique is a bi-level optimization procedure. In the first level (the base case), the problem (19) should be solved considering the forecasted value of the uncertain resources. The value of the OF derived in the first level is the "base value" noted by $\overline{f}$.

$$\overline{f} = \min f(X, \overline{\gamma})$$

Subject to:

$$\begin{aligned} & H(X,\overline{\gamma}) \le 0 \\ & G(X,\overline{\gamma}) = 0 \\ & \gamma \in \Gamma \end{aligned} \tag{19}$$

The second level can be accomplished based on two different strategies. The conservative decision-makers use the Risk-Averse (RA) framework to immunize the final solution against the uncertain phenomena. In contrast, the optimistic decision-makers present the approaches based on the Risk-Seeker strategy to derive the possible potential of having the best scenario (Soroudi et al., 2017). In this paper, the proposed methodology is conservative by employing the RA strategy. The second level of the RA-based IGDT technique is mathematically expressed in (20), where Λ^c is the critical value of the OF predetermined by the decision-maker. Note that γ is the vector of uncertain parameters (wind power generation in this paper), H_m and G_m are the inequality and equality constraints, respectively. As aforementioned, X is the vector of decision-making variables. According to this strategy, if the uncertain parameter has the inverse impact on the OF, the maximum reduction of this uncertain parameter needs to be determined by increasing the main OF. It means that increasing the value of the uncertain parameter leads the OF to reduce. For instance, if the injection of active wind power enhances, consequently, due to the decrease of power generation through the thermal power plants, the daily operational cost (OF) reduces. In (20), ζ is the radius of uncertainty (conservativeness factor), which shows the deviation from the forecasted profile. Based on determining the value of Λ^c, the maximum value of ζ can be attained by accomplishing (20). It is worth mentioning that the RA strategy can be implemented by defining a positive factor called the critical percentage of the OF (ς^c).

$$\begin{cases} \max_X \zeta \\ H_m(X,\gamma) \le 0 \quad m \in \psi^{inequ} \\ G_m(X,\gamma) = 0 \quad m \in \psi^{iequ} \\ f(X,\gamma) \le \Lambda^c \\ \Lambda^c = \bar{f}(X,\gamma) + \varsigma^c |\bar{f}(X,\gamma)| \end{cases} \tag{20}$$

3.2. Proposed RA-IGDT-based approach

Exploiting the IGDT technique determines one value for the conservativeness factor (radius of uncertainty) of WFs. Thus, it is can be practical to obtain different values of radii of uncertainty for the WFs based on their characteristics. For instance, according to their profiles through a day, an appropriate value for the radius of uncertainty is reported. It means that for the WF with a higher impact on providing the demand, a greater radius of uncertainty needs to be considered. In other words, it is the decision-maker's preference. In this paper, a Risk Averse (RA) strategy according to the IGDT has been presented to take into account simultaneously the randomness of multiple wind power plants regarding the predetermined criterion defined by the decision-maker. The presented scheme prioritizes the uncertainty of the WF with a greater effect on providing the load demand of the electric power network. Hence, several stages need to be accomplished according to the presented methodology. At the first stage, the base case value of operational cost related to the thermal generating units is determined considering the forecasted strategies of WFs based on solving the problem mentioned in (21).

$$\begin{cases} TC_b = \min\left\{\widehat{T}\,C\right\} \\ \widehat{H}_m(X,\gamma) \le 0 m \in \psi^{inequ} \\ \widehat{G}_m(X,\gamma) = 0 m \in \psi^{equ} \\ P_w = P_w^{fr} \quad w = 1,\dots,N_W \end{cases} \tag{21}$$

To take into account the decision-maker's preferences, the regulating factors are defined based on determining the WF with higher impact on providing the demand of the electric power system as follows:

$$\alpha_w' = \frac{AV_w}{AV^{\max}} \tag{22}$$

Where, AV_w is calculated using the equation expressed in (23).

$$AV_w = \frac{1}{T}\int_T P_w^{fr} dt \tag{23}$$

In (22), $AV^{\max}$ (maximum average wind energy) is determined as follows:

$$AV^{\max} = \max\{AV_1, AV_2, \dots, AV_{N_w}\} \tag{24}$$

At the next step, the conservativeness factor belonging to the WF having the highest value for $AV^{\max}$, noted by $\zeta'^{\max}_w$, is derived by implementing the optimization procedure according to (25).

$$\begin{cases} \zeta'^{\max}_w = \max\{\zeta_w\} \\ \widehat{H}_m(X,\gamma) \le 0 m \in \psi^{inequ} \\ \widehat{G}_m(X,\gamma) = 0 m \in \psi^{equ} \\ P_w^{RA} = (1-\zeta_w)P_w^{fr} \\ TC \le TC_b + \varsigma^c|TC_b| \end{cases} \tag{25}$$

Note that radii of uncertainty for other wind power plants can be regulated by employing (26).

$$\zeta_w^{\max} = \alpha_w' \zeta'^{\max}_w \tag{26}$$

According to (26), a greater conservativeness factor for the WF with higher average power in one day has been considered. In other words, the greatest deviation from the predicted profile of each WF should be regulated by addressing the decision-maker's preferences. To achieve simultaneously maximum deviation of nominal strategy related to each WF, a fuzzy membership function μ^{RA} for the radius of uncertainty has been formulated as follows:

$$\mu^{RA}(\zeta) = \begin{cases} 1 & \zeta \ge \zeta^{\max} \\ \dfrac{\zeta - \zeta^{\min}}{\zeta^{\max} - \zeta^{\min}} & \zeta^{\min} \le \zeta \le \zeta^{\max} \\ 0 & \zeta \le \zeta^{\min} \end{cases} \tag{27}$$

In this paper, according to (27), a linear fuzzy set is defined to accomplish the multi-objective optimization (radii of uncertainty). After determining the allowable deviation from the nominal pattern for all parameters according to (26), the proposed framework is implemented to derive simultaneously the robust uncertain band of random resources existing in the grid according to (28). In other words, this optimization procedure is the RA strategy based on IGDT technique, where β^{RA} indicates the conservative level satisfying the decision-maker. Due to addressing the decision-maker's preferences during the optimization problem in (28), Pareto optimal solutions are not needed. The presented architecture is illustrated in Fig (1).

$$\begin{cases} \max \beta^{RA} \\ \dfrac{\zeta_w - \zeta_w^{\min}}{\zeta_w^{\max} - \zeta_w^{\min}} \ge \beta^{RA} \\ \widehat{T}\,C \le TC_b + \varsigma^c|TC_b| \\ \widehat{H}_m(X,\gamma) \le 0 m \in \psi^{inequ} \\ \widehat{G}_m(X,\gamma) = 0 m \in \psi^{equ} \\ RA: P_w^{RA} = (1-\zeta_w)P_w^{fr} \end{cases} \tag{28}$$

4. Numerical example

4.1. Test system

The test systems in this study are IEEE 30 bus and IEEE 62 bus electrical grids. The suggested methodology is carried out by interfacing between MATLAB and GAMS. Note that the XPRESS solver has been used to optimize the OF in the GAMS. The load demand profile in Per Unit (PU) is illustrated in Fig (3). It should be mentioned that the base value of the power is 100 MVA. The number of linear segments for the generators has been determined according to the proposed approximation approach in (Eslahi et al., 2021b). Moreover, the difference of δ_{it} and δ_{jt} should be less than $\frac{\pi}{12}$ rad (Eslahi et al., 2021b). To linearize the inequality mathematically expressed in (10), a polygon with 16 sides is considered (Karimi et al., 2019). Several cases have been discussed in this section to demonstrate the performance of the presented framework. It is noteworthy that the daily wind power generation patterns and the installation sites of the WFs are arbitrary. In other words, the

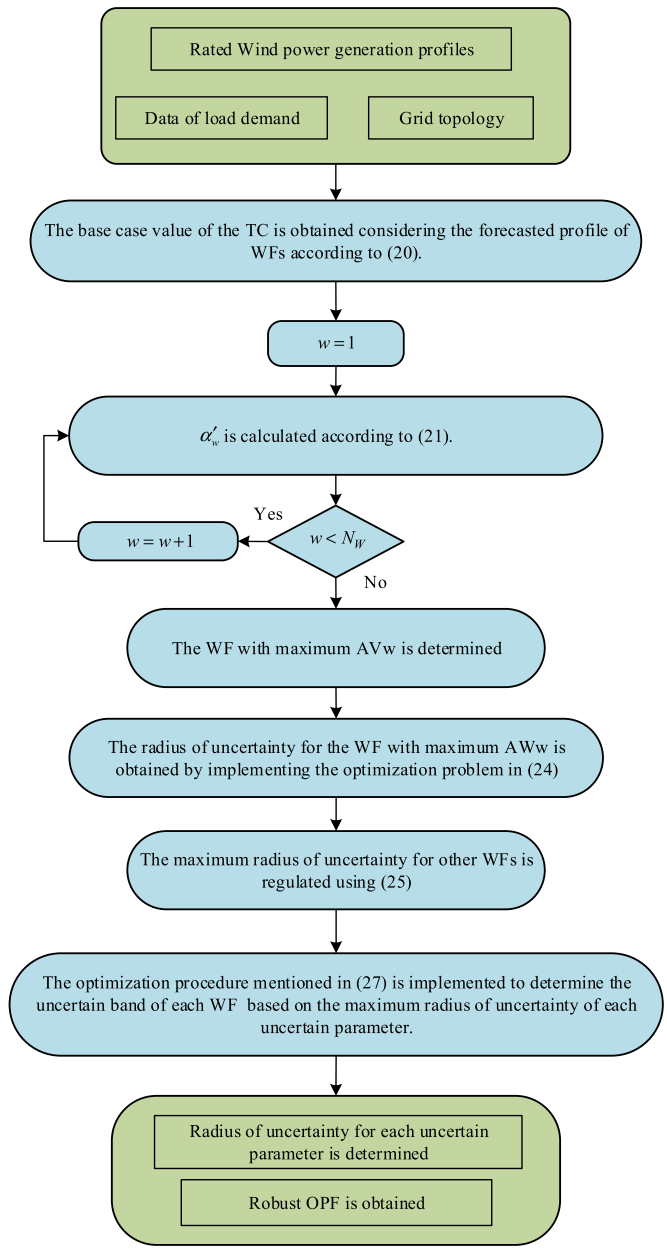

Fig. 1. Proposed architecture.

scope of this work is only to evaluate the impacts of the intermittency related to the WFs on the operation of the electric power network. It is assumed that the critical value of TC (ς^c) equals 20% in Cases C1, C2, and C3. Additionally, in cases C4 and C5, the value of ς^c is 3%.

4.2. Results obtained from the proposed approach

4.2.1. Case C1

In this case, the system under study is IEEE 30 Bus network shown in Fig (2) and it has been supposed that two wind power plants are located at bus 2 (70 MW, which is called WF1) and 30 (40 MW shown by WF2). Based on implementing the first stage of the proposed approach, the base value of *TC* is 11514.88 ($). The WF1 produces more active power in one day, therefore, the regulating factor of WF2 has been calculated 0.499 using (22). Note that the regulating factor of WF1 equals one. Consequently, the conservativeness factors for WF1 and WF2 are 0.543 and 0.267, respectively. The forecasted and robust strategies of active power generation through these WFs have been illustrated in Fig (4). As aforementioned, according to the conservative strategy, the WFs generate active power below the forecasted profile. The value of *TC* in the robust status is 13817.86 ($), meaning that the results related to the maximum deviation from the *TC* (20%) for the base case have been obtained. According to Fig (5), The total generation of these conventional power plants is on the increase from 2.171 (PU) to 0.95 (PU) belonging to the time in the interval [1h,5h] resulting from the rise of the electric demand. Since the shut-down cost of the thermal power plants is expensive, instead of shutting down these generation units, the generation of G1 (the generator with the highest capacity) is reduced in this period. The load of the electrical grid between the time interval [6h,10h] experiences a considerable increment, consequently, the total generation has risen from 1.096 (PU) to 2.486 (PU) in this period. It is worth mentioning that at $t = 9h$, G6 is turned on to meet the demand and it injects 0.12 (PU) into the power network. After a decrease of total generation through the conventional units from 2.387 (PU) to 2.026 (PU) between the period [11h, 14h], the total electricity production is raised to 2.815 (PU) at $t = 18h$. It should be noted that G4 turned on at $t = 17h$ and its electricity production (active power) is 0.2 (PU). During the on-peak period, all generators have not been turned off due to the expensive shut-down cost. The commitment of each thermal power plant is shown in Fig (5).

4.2.2. Case C2

According to this example, the IEEE 30 bus systems has been utilized and the WFs are located at bus 2 (WF1), 26 (WF2) and 30 (WF3), and the related capacities are 70 MW, 30 MW, and 20 MW, respectively. The daily operational cost is 12011.23 ($) derived from the fist level of the presented optimization framework. Note that AV_w belonging to WF1 is the greatest value, consequently, the regulating factors for WF2 and WF3 are 0.4737 and 0.3308, respectively. Due to the highest wind power generation belonging to WF1, its regulating factor equals one. Therefore, by considering the allowable radius of uncertainty according

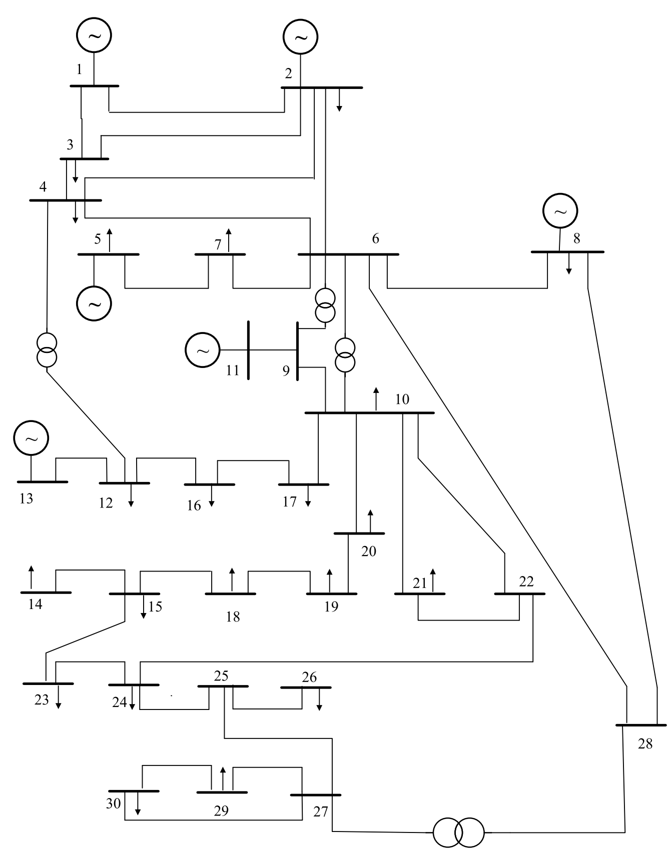

Fig. 2. IEEE 30 Bus system.

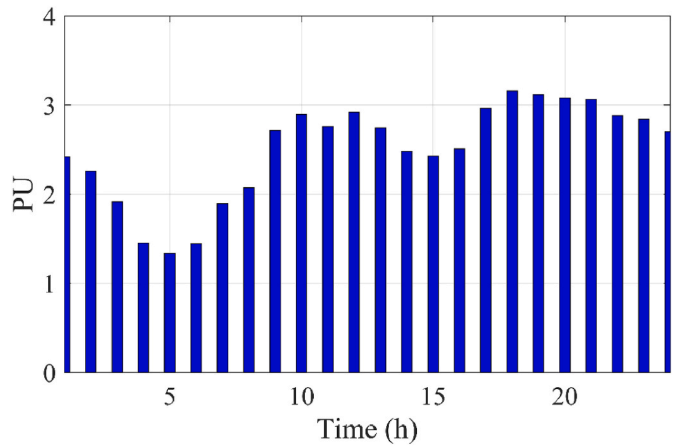

Fig. 3. Active load profile through a day.

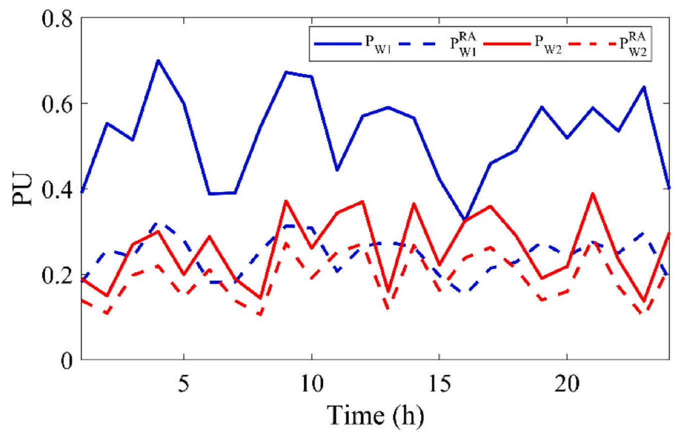

Fig. 4. Forecasted and robust patterns of active power generated by the WFs in scenario C1.

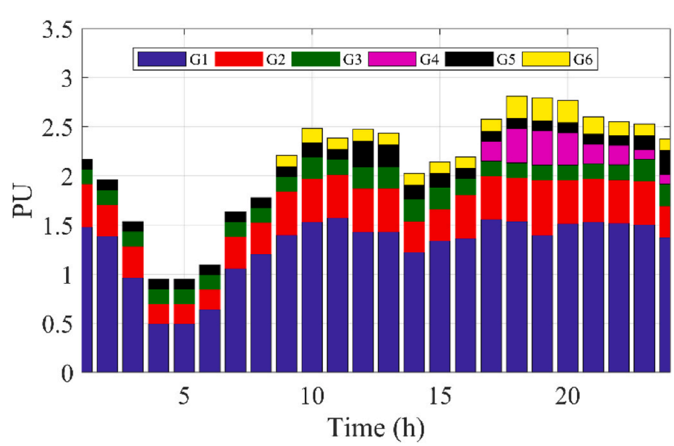

Fig. 5. Commitment of each thermal power plants considering robust strategy in the Case C1.

to (26) and carrying out the optimization process mentioned in (28), ζ_1, ζ_2, and ζ_3 are 0.763, 0.352, and 0.235, respectively. The forecasted and robust strategies of the WFs have been depicted in Fig (6). The operational cost of thermal power plants for the robust solution is 14413.47 ($). Furthermore, the radius of uncertainty for each WF is determined regarding the criterion predefined by the programmer, meaning that for the WF with higher risk, a greater robustness band has been acquired. In Fig (7), the active power generation for each conventional generating unit has been depicted through a day. It can be observed that due to the power plants G4 and G6 produce more expensive electricity, these generators have been turned on at the beginning of the first on-peak period ($t = 9h$), which the generated active powers are 0.1 (PU) and 0.12 (PU), respectively. Nevertheless, the load demand experienced a smooth reduction between the time interval [12h, 15h], the generators have remained active resulting from the expensive cost of turning off these units and the total electricity production by the thermal power plants reduced from 2.668 (PU) at $t = 13h$ to 1.968 (PU) at $t = 16h$. During the time interval between [17h, 24h], due to increasing the electrical demand, the production of the generators enhanced that the maximum generation is 2.925 (PU) at the 19th hour of the day. The base and robust strategies of the total power generation by the thermal generating units are illustrated in Fig (8). According to the proposed robust framework, the total generation of the worst scenario is derived to a make decision, which is immune against uncertainties existing in the system.

4.2.3. *Case C3*

In the current case, four WFs are considered to evaluate the performance of the proposed methodology. Table (2) provides information about the capacities and installation sites of WFs. Similarly, the electrical grid under study in this case is the IEEE 30 Bus network. The base case value of *TC* has been calculated 10225.21 ($) in the first step of the proposed algorithm. The average active power generation of WF4 is higher than other WFs, consequently, a wider radius of uncertainty is considered for this WF addressing the decision-maker's preference. The regulating factors for WF1, WF2, and WF3 are 0.8262, 0.7910, and 0.5221, respectively. As a consequence, the conservativeness factors for the WFs, in this case have been reported in Table 2. Moreover, Fig (9) shows the nominal and robust strategies of the generated power by these WFs. The robust operational cost obtained by carrying out the presented scheme is 12270.25 ($). Similarly, the robust active power injected into the grid through each thermal power plant has been shown in Fig (10). According to Fig (11), due to considering the conservative generation of the WFs, the total power of the generators is greater than this value related to the base case. As a result, it is useful to have the robust operation of the power system considering multiple WFs, where the decision-maker's preferences are taken into account. Note that this solution is achievable by employing the suggested framework.

4.2.4. *Case C4*

In this example, three WFs have been installed at bus 12 (WF1), 30 (WF2), and 44 (WF3). Note that their capacities are 110 (MW), 110 (MW), and 95 (MW), respectively. It should be highlighted that in this case, the electric power system under study is the IEEE 62 Bus transmission network. The operational cost derived from the first level of the

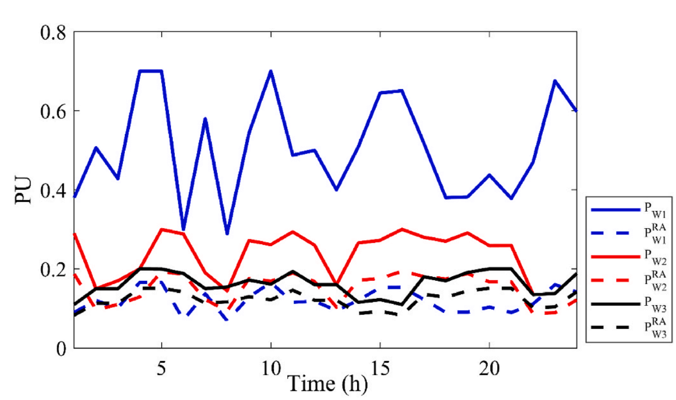

Fig. 6. Forecasted and robust patterns of active power generated by the WFs in Case C2.

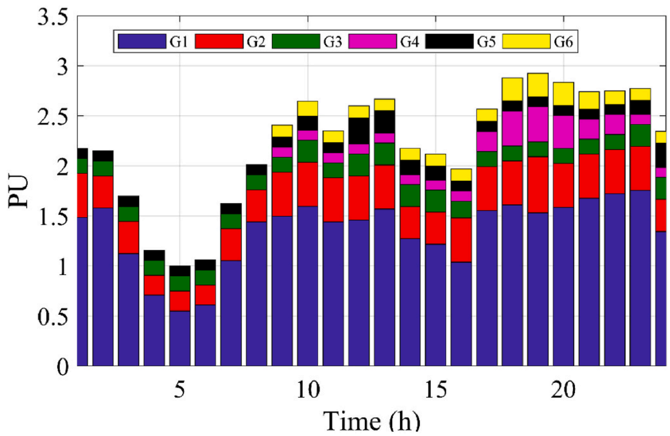

Fig. 7. Commitment of each thermal power plants considering robust strategy in the Case C2.

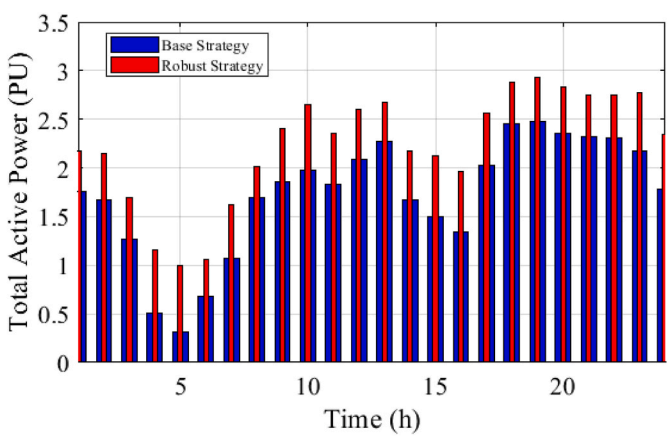

Fig. 8. Total power generation thermal power plants for the base and robust strategies in the Case C2.

Table 2
The initial information of WF and the derived conservativeness factor for each WF.

WF	Installation site	Capacity (MW)	Radius of uncertainty
WF1	BUS 2	30	0.322
WF2	BUS 26	30	0.309
WF3	BUS 30	20	0.201
WF4	BUS 28	40	0.395

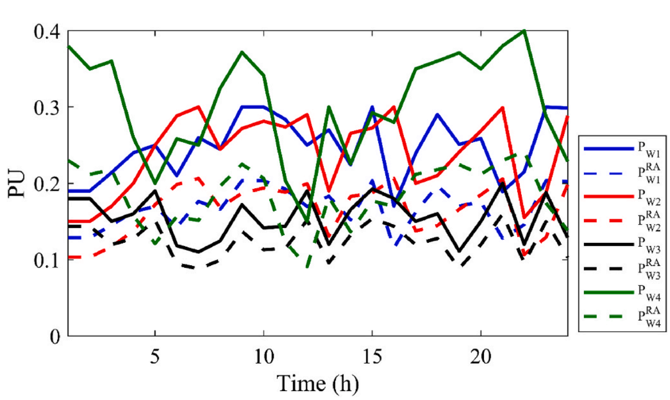

Fig. 9. Forecasted and robust patterns of active power generated by the WFs in Case C3.

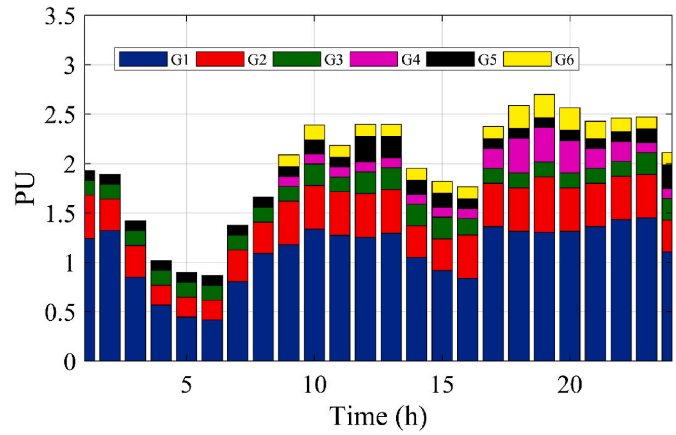

Fig. 10. Commitment of each thermal power plants considering robust strategy in Case C3.

proposed methodology is 220746.41 ($). Furthermore, the profiles of active power generation related to the WFs are available according to Fig (12). The greatest value for the radius of uncertainty has been obtained for the WF2, which is 0.531. It means that the average power generation of this WF is higher than other WFs. The radii of uncertainty for the WF1 and the WF3 are 0.489 and 0.477, respectively. For the robust solution, the value for the operational cost is 227368.80 ($). Consequently, the robust power profiles injected into the electric power network through the WFs have been plotted in Fig (12).

4.2.5. *Case C5*

In case C5, four WFs have been considered to obtain their radii of uncertainty. Similarly, the IEEE 62 Bus is employed to present the results of the proposed approach. The information about the capacities and installation sites of WFs and the obtained conservativeness factors have been presented in Table 3. The base value of the operational cost of thermal power plants is 219271.22 ($) determined by implementing (20). The highest daily active power generation (or AV^{max}) belongs to the WF3. As a result, the radius of uncertainty for this WF is wider than other wind power plants and it is derived 0.590. The value of operational cost for the robust (conservative) solution is 225849.35 ($). The predicted and robust profiles of active power profiles generated by the WFs are depicted in Fig (13).

4.3. *Assessing the effectiveness of the proposed approach*

In this subsection, the suggested architecture has been compared to

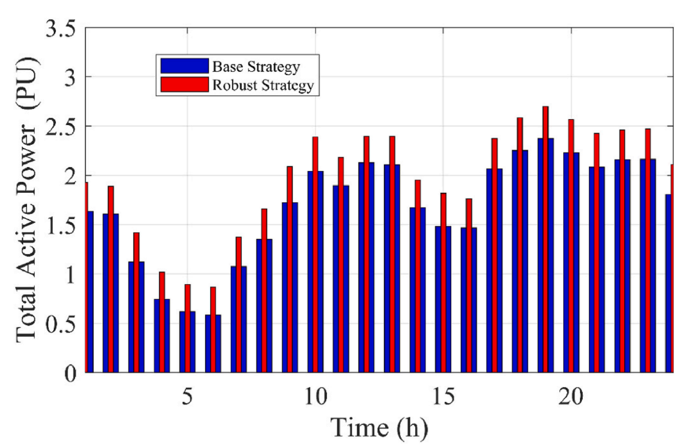

Fig. 11. Total power generation thermal power plants for base and robust strategies in Case C3.

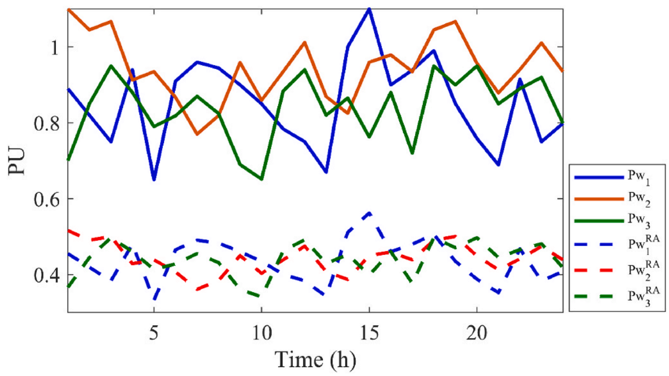

Fig. 12. Forecasted and robust patterns of active power generated by the WFs in Case C4.

Table 3
The initial information of WF and the derived conservativeness factor for each WF.

WF	Installation site	Capacity (MW)	Radius of uncertainty
WF1	BUS 12	100	0.556
WF2	BUS 30	90	0.465
WF3	BUS 44	90	0.590
WF4	BUS 60	70	0.449

the MCS and the epsilon constraint-based-IGDT approach introduced in (Eslahi et al., 2021a) to prove its efficiency. Firstly, to run the MCS, some scenarios related to the active power of the WFs are uniformly generated satisfying $\varsigma^c = 20\%$ for the IEEE 30 Bus system (or $\varsigma^c = 3\%$ for the IEEE 62 Bus network). Secondly, for each iteration, the deviation of real power from the nominal pattern of each WF is determined. Ultimately, the best solution is attained regarding the decision-maker's criterion. It means that the WF with greater active power generation should have a wider radius of uncertainty (conservativeness factor). Moreover, to accomplish the epsilon constraint-based-IGDT approach, according to (Yan et al., 2021), the number of iterations needs to be defined, and after that the algorithm is implemented. According to the results shown in Table 4, the effectiveness and performance of the presented approach is evident. It is important to be highlighted that the MCS is an iterative method, hence, to achieve a reliable solution, a great number of scenarios needs to be generated. To stop running the MCS, the expected value of the TC should fall into the permitted region of error predetermined by the decision-maker (Eslahi et al., 2021a). In other words, the stopping criterion is defined by the decision-maker to enhance the accuracy of the results. The appropriate number of scenarios to guarantee the precision of the solution in the cases C1, C2, and C3 are 329, 486, and 612, respectively, where the system under study is the IEEE 30 Bus electrical grid. Moreover, the number of generated scenarios for C4 and C5 are 459 and 643, respectively, where the IEEE 62 Bus system has been considered to implement the MCS.

It is noteworthy that if the number of WFs increases, then the execution time in the MCS and the epsilon constraint-based-IGDT dramatically rises for each system under study. In contrast, the presented algorithm is noticeably more time-efficient than these methods and its runtime does not considerably depend on the number of WFs in the same electric power system if compared with the MCS and the epsilon constraint-based-IGDT. Furthermore, according to Table (4), the accuracy of the proposed approach is reliable.

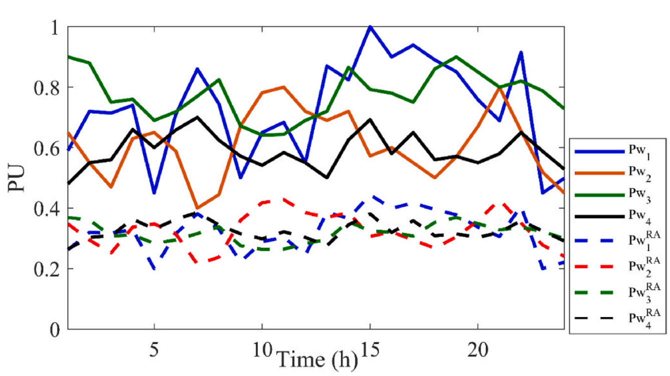

Fig. 13. Forecasted and robust patterns of active power generated by the WFs in Case C5.

5. Conclusion

Employing the RERs such as WFs is an applicable way to have cleaner production of electricity. To obtain the reliable and practical operation of the wind integrated power systems, taking into consideration the stochastic nature of WFs is necessary. This paper proposed a novel RA-IGDT-based framework to immunize the solution against the intermittent behavior of several WFs existing in the electric power network. Due to implementing the proposed architecture in the GAMS, to avoid local optimal solutions, the MILP equivalent of the original problem was exploited. The advantages of the suggested scheme can be addressed, firstly, the decision-maker's preferences (in this paper the average daily wind generation) were satisfied to derive a wider uncertain band for the WF with higher risk. Secondly, this method is noticeably more time-saving than the MCS and the epsilon constraint-based IGDT; moreover, its precision is reliable. Furthermore, the execution time of the proposed approach does not considerably depend on the number of WFs in the same electric power system if compared with the above-mentioned techniques. It should be added that the robust active power generations through the WFs were based on the conservative point of view, meaning that the derived patterns obtained by running the algorithm were below the nominal profile.

CRediT authorship contribution statement

Milad Eslahi: Conceptualization, Methodology, Writing. **Miadreza Shafie-khah:** Validation, Writing – review & editing, Investigation. **Pierluigi Siano:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A.1. Linearization.

As aforementioned, solving the non-linear family of optimization problems may lead to a local optimal solution (Karimi et al., 2019). As a result, in this paper, to achieve global optimal solutions, the MILP mathematical model of the original MINLP formulation has been used.

A.1.1. Linearization of the Quadratic Fuel Cost Function

The quadratic fuel cost function of each thermal power plant is linearized based on dividing a particular section of this curve into N linear piecewise segments (Wu, 2011).

Table 4
Comparison between the proposed method and the MCS.

System under study	Case	method	ζ_1	ζ_2	ζ_3	ζ_4	Execution time
IEEE 30 Bus	C1	Proposed approach	0.543	0.267	×	×	64.8 (Seconds)
		MCS	0.537	0.273	×	×	7009.1 (Seconds)
		Epsilon-constraint-based IGDT	0.541	0.291	×	×	291.8 (Seconds)
IEEE 30 Bus	C2	Proposed approach	0.763	0.352	0.235	×	79.6 (Seconds)
		MCS	0.768	0.346	0.231	×	10886.4 (Seconds)
		Epsilon-constraint-based IGDT	0.757	0.349	0.231	×	784.5 (Seconds)
IEEE 30 Bus	C3	Proposed approach	0.322	0.309	0.203	0.395	68.1 (Seconds)
		MCS	0.319	0.305	0.206	0.392	13341.6 (Seconds)
		Epsilon-constraint-based IGDT	0.320	0.311	0.206	0.389	2086.3 (Seconds)
IEEE 62 Bus	C4	Proposed approach	0.489	0.531	0.477	×	174.9 (Seconds)
		MCS	0.483	0.533	0.481	×	14952.4 (Seconds)
		Epsilon-constraint-based IGDT	0.484	0.535	0.474	×	1257.0 (Seconds)
IEEE 62 Bus	C5	Proposed approach	0.556	0.465	0.590	0.449	182.6 (Seconds)
		MCS	0.560	0.462	0.588	0.447	19338.1 (Seconds)
		Epsilon-constraint-based IGDT	0.552	0.468	0.591	0.446	5250.7 (Seconds)

$$\begin{cases} F\left(P_g^G\right) = a_g\left(P_g^G\right)^2 + b_g P_g^G + c_g \\ P_{g0}^G = P_{g,\min}^G \quad \forall P_g^G \in \left[P_{g,\min}^G, P_{g,\max}^G\right] \\ \widehat{P}_{gz}^G = P_{g,\min}^G + \left(P_{g,\max}^G - P_{g,\min}^G\right)\frac{z}{N} \\ z \in \Omega_z \quad \Omega_z = \{1, \ldots, N\} \end{cases} \tag{A1}$$

It is noteworthy that binary variables shown by n_{gz} have been employed to activate the z^{th} linear segment for g^{th} thermal power plant. Hence, the MILP approximation of the quadratic fuel cost can be formulated as follows (Eslahi et al., 2021b):

$$\widehat{F}\left(\widehat{P}_g^G\right) = \sum_{z\in\Omega_z}\left(SL_{gz}\widehat{P}_{gz}^G + B_{gz}n_{gz}\right) \ \forall z \in \Omega_z \quad \forall g \in \Omega_G \tag{A2}$$

In (A2), SL_{gz} and B_{gz} are calculated based on employing the equations mentioned in (A3) and (A4), respectively (Eslahi et al., 2021b).

$$SL_{gz} = \frac{F\left(\widehat{P}_{gz,\max}^G\right) - F\left(\widehat{P}_{gz,\min}^G\right)}{\widehat{P}_{gz,\max}^G - \widehat{P}_{gz,\min}^G} \ \forall z \in \Omega_z \quad \forall g \in \Omega_G \tag{A3}$$

$$B_{gz} = F\left(\widehat{P}_{gz}^G\right) - \frac{F\left(\widehat{P}_{g(z+1)}^G\right) - F\left(\widehat{P}_{gz}^G\right)}{\widehat{P}_{g(z+1)}^G - \widehat{P}_{gz}^G}\widehat{P}_{gz}^G \ \forall z \in \Omega_z \quad \forall g \in \Omega_G \tag{A4}$$

Likewise, the following constraints must be thoroughly respected according to (Eslahi et al., 2021b).

$$\widehat{P}_{gtz,\min}^G n_{gtz} \le \widehat{P}_{gtz}^G \le \widehat{P}_{gtz,\max}^G n_{gtz} \quad \forall z \in \Omega_z \quad \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A5}$$

$$\sum_z n_{gtz} \le 1 \quad \forall z \in \Omega_z \quad \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A6}$$

$$P_{gt}^G = \sum_z \widehat{P}_{gzt} \quad \forall z \in \Omega_z \quad \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A7}$$

$$Q_{gt}^G = \sum_z \widehat{P}_{gzt} \quad \forall z \in \Omega_z \quad \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A8}$$

Consequently, in (A9), the MILP mathematical model of the daily operational cost of the conventional generating units has been mathematically expressed (Eslahi et al., 2021b).

$$\widehat{T}C = \sum_{t\in\tau}\sum_{g\in\Omega_g}\left(\widehat{F}\left(\widehat{P}_{gt}^{G,s}\right) + C_g^{\sup}\alpha_{gt} + C_g^{sdn}\beta_{gt}\right) \tag{A9}$$

A.1.2. OPF Linearization

In this paper, the OPF problem has been approximated by the tangent hyperplanes of the cosine function. In other words, it is a linearization method, which can be applied to non-linearity related to the OPF problem. It is important to note that the small difference of phase angle of voltage for the connected buses is the initial assumption of this technique. The cosine function is linearized by implementing (A10) – (A18) (Coffrin and Van Hentenryck, 2014).

$$y \geq \cos(\overline{\nu}_{\Delta}) \tag{A10}$$

$$d = \frac{2\overline{\nu}_{\Delta}}{h+1} \tag{A11}$$

$$\begin{cases} y \leq -\sin(td - \overline{\theta}_{\Delta})(x - td + \overline{\theta}_{\Delta}) + \cos(td - \overline{\theta}_{\Delta}) \\ \qquad y = \cos_{\theta} \quad \forall t = 1, 2, ..., h \\ \qquad \forall t = 1, 2, ..., h \end{cases} \tag{A12}$$

In this linearization method, the approximations mentioned in (A13) – (A16) are employed, as a consequence, the linearized exchanged between the buses can be modeled according to (A17) and (A18), respectively (Karimi et al., 2019).

$$\left(V_{jt}\right)^2 \approx 2V_{jt} - 1 \ \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A13}$$

$$V_{it} + V_{jt} + \cos_{ijt} - 2 \approx V_{jt}V_{it}\cos\left(\delta_{it} - \delta_{jt}\right) \ \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A14}$$

$$\sin\left(\delta_{it} - \delta_{jt}\right) \approx V_{jt}V_{it}\sin\left(\delta_{it} - \delta_{jt}\right) \ \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A15}$$

$$\delta_{it} - \delta_{jt} \approx \sin\left(\delta_{it} - \delta_{jt}\right) \ \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A16}$$

$$\overset{\frown}{P}{}^{L}_{ij,t} = B_{ij}\left(\delta_{it} - \delta_{jt}\right) - G_{ij}\left(V_{it} - V_{jt} - \cos_{ijt} + 1\right) \ \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A17}$$

$$\overset{\frown}{Q}{}^{L}_{ij,t} = B_{ij}\left(V_{it} - V_{jt} - \cos_{ijt} + 1\right) + G_{ij}\left(\delta_{it} - \delta_{jt}\right) \ \forall g \in \Omega_G \quad \forall t \in \Omega_\tau \tag{A18}$$

A.1.3. Linearization of transmission line constraints

Due to the severe nonlinearities of the inequalities formulated in (9) describing the limitations of apparent power for each transmission line, these constraints should be linearized. Thus, according to (Karimi et al., 2019) a polygon surrounded by the circle, which its radius is the apparent power sent from i^{th} bus to j^{th} bus ($S^{L,M}_{ij}$) has been exploited in this paper. To implement this technique (A19) and (A20) need to be considered.

$$\alpha_n P + \beta_n Q + \gamma_n S \leq 0 \tag{A19}$$

$$\begin{cases} \alpha_n P + \beta_n Q + \gamma_n S = 0 \quad \forall n \in \{1, 2, ..., N\} \\ \qquad \alpha_n = \sin\left(\dfrac{\pi(2n-1)}{N}\right) \\ \qquad \beta_n = \cos\left(\dfrac{\pi(2n-1)}{N}\right) \\ \qquad \gamma_n = \cos\left(\dfrac{\pi(2n+2)}{2N}\right) \end{cases} \tag{A20}$$

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