An Investigation on the Impacts of Low Probability and High Intensity Events on Wind Power Generator's Market Participation

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ABSTRACT This paper presents an extensive decision-making model for Wind Power Generators (WPGs) for profit maximization in an electricity market environment. This model has been presented at the intraday market stage due to the fact that WPGs can react according to the latest information and also they have less forecast errors in comparison to Day-ahead (DA) market. In addition, the Intraday Demand Response Exchange (IDRX) market is modelled with the aim of covering wind generation volatility so that the WPG can participate in it as a buyer. Note that, Demand Response (DR) uncertainty is modelled through Information Gap Decision Theory (IGDT) method so that the amount of financial resistance to the possible increase of the load is considered. In this article, the profitability of WPG in the event of High-Intensity and Low-Probability (HILP) events such as the hurricane, is also examined. In fact, the effects of hurricane on failure rate, reliability and aging of wind units are investigated. The Conditional Value at Risk (CVaR) is utilized to quantify the WPG risk as well. Several numerical analysis are conducted to show evidence of the approach efficacy.

INDEX TERMS Bidding strategy, demand response, HILP events, uncertainty modelling, wind power generators.

NOMENCLATURE

A. SETS AND INCCES

m	Index for bided block of Demand Response Providers (DRP)
p	Index for DRPs
s	Index for scenarios
t	Index for hours

B. VARIABLES

α	Uncertainty parameter
ξ	Value at risk
η_s	Auxiliary variable deployed for the computation of CVaR
ADR_{pt}	DRP power trade in the Demand Response Exchange (DRX)

$\text{Aging}^{\text{power plant}}_{\text{annual cost}}$	The annual aging cost of power plant
B	Profit in scenario s
$BLprofit$	Total revenue from the Balancing market
$DAprofit$	Total revenue from the DA market
$DRP\cos t_{pt}$	DR cost in relevance to the power traded by DRP
$delta_{ts}$	Overall deviation in wind power generation
$delta^{+}_{ts}$	Positive deviation
$delta^{-}_{ts}$	Negative deviation
$HILP_{\text{intraday cost}}$	Levelized intraday cost of HILP event on the power plant
$INprofit$	Total revenue from the Intraday market
P^{sch}_{ts}	The overall power scheduling of power of wind power generator
q^{m}_{pt}	The scheduled power of block m of DRP traded power
R	Reliability

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$RESP_{ts}$	The scheduled reserve power of wind power generator
$RESB_{pts}$	The amount of reserve as per the bilateral contract among DRP of the traded power and WPG
$REStotal_{ts}$	Total reserve scheduled
$RESprofit$	Total revenue from the Reserve market
$RISK$	Total revenue from the Risk
SP_{ts}^{DA}	Scheduled power generation of WPG at the DA market
SPS_{ts}^{IN}	WPG's selling potency in the intraday market
SPB_{ts}^{IN}	WPG's purchasing potency in intraday market
$SP_{pts}^{bilateral}$	The amount of power as per the bilateral contract among DRP of the traded power and WPG

C. PARAMETERS

ε	Confidence level
δ	Weight parameter to attain the exchange among the profit and CVaR
ρ	Occurrence probability of scenario s
π_{ts}^{DA}	Day-ahead (DA) market prices
π_{ts}^{IN}	Intraday market prices
$\pi_{pts}^{bilateral}$	The price of bilateral contract among DRP of the traded power and WPG
π_{ts}^{RES}	Reserve market prices
ADR_{pt}^{max}	Maximum bidding valency of DRP d
$Aging_{price}$	Aging cost factor
c_{pt}^m	Bidding cost of block of DRP p
CRP_t	Calling reserve probability
i	The monthly inflation rate
i'	The daily inflation rate
im_t^+	The ratio of positive DA market price imbalance
im_t^-	The ratio of negative DA market price imbalance
m	Number of bidded block of DRPs
n	The number of months in a year
n'	The number of days in a month
NP	The number of DRP blocks
P_{max}	The maximum capacity of wind power installations
PDT_{ts}	Wind power generation
$q_{pt}^{m,max}$	Maximum bidding valency of DRP d in block k
$\tilde{q}_{pt}$	Scheduled power forecast of block m of DRP of the traded power
SN	Number of scenario
T	Number of hours

D. FUNCTIONS

$\widehat{\alpha}(c_r)$	Robustness function
$\tilde{\beta}(c_o)$	Opportunity function
EP	Expected profit function of WPG

E. ABREVIATIONS

DP	DA market price
IP	Intraday market price
BP	Balancing market price
DSR	Down side risk
VC	Variance
SP	Stochastic programming
RD	Reserve development
RO	Robust optimization
vci	The cut-in speed of wind
vco	The cut-out speed of wind
vr	The nominal speed of wind
p_r	The maximum power generation

I. INTRODUCTION

A. LITERATURE REVIEW

The trends to use wind as a renewable resource for power generation, and as an inexpensive and zero-emission energy resource is developing swiftly over the last few years. For instance, it is expected that 20% of the total US electricity consumption serve through wind generation by the end of 2030 [1]. With the rapid advancement of wind farm technologies and the profitable economic value of this resource, Wind Power Generators (WPGs) have increased their involvement in the electricity market [2]. Among the parameters hat can grant a positive signal to WPGs and motivate them to make more profit from the electricity market are the choice of suitable wind farm location, creation of efficient multi-purpose portfolio (e.g wind, storage/wind, hydro, etc.), further precise prediction tools, and system equilibrium efficiency Heuristic search algorithms for allocating renewable energy systems are summarized in [3]. Integrating wind resources into the current grids poses some challenges due to the fact that wind generation is related to wind speed and the latter is of volatile nature. Therefore, it can be noted that the exploitation of wind resources has some risks for either WPGs or the grid operators [4]. Numerous references have addressed the issue of wind unit risk. Reference [5] has evaluated the risk of using wind resources from the perspective of WPG utilizing the Conditional Value at Risk (CVaR) measure. Down Side Risk is another alternative measure for risk evaluation [6]. Statical measurement of variance based on historical data is used to calculate risks related to market prices in [7].

In the current paper, the risk of wind generation from the perspective of WPGs is evaluated through CVaR index. In fact, the WPG must create a tradeoff between maximizing its profits and minimizing its risks in the face a various source of uncertainty [8]. There are many works that addressed the issue of bidding strategy of WPGs. Reference [9] proposed a multi-objective bidding strategy in the electricity market to improve the profits of WPG, though, the risk of using wind resources is not considered [9]. Reference [10] suggested a pairing methodology for Demand Response (DR) and wind renewable energy sources in the DA market via bilateral contracts. In [10], the DA market price is one of

the uncertainty parameters and also the risk of utilizing wind resources is evaluated by the Down Side Risk measure. Reference [11] has studied the tenders and bids for an affordable energy storage center in the electricity market. In [11], the uncertainty related to the upcoming market price has been considered and also the risk of using wind resources has been considered through the variance method. In [12], [13], load uncertainty has been examined by a set range, and the model of uncertainties of renewable energy and the prices of the market have been considered through independent scenarios. The authors in [14] have proposed a framework for modeling the uncertainties associated with generation companies in the electricity market through the Information Gap Decision Theory.

In the electricity market, major energy transactions are made in the DA market [15]. Therefore, wind units should provide offers in the DA market. Uncertainty of wind generation implies a possibility of selling some amount of power in the DA market but not being realized in actual time. Such deviations, whether positive or negative, will penalize the WPGs and thus reduce their anticipated profits. The authors in [16] assumed that WPG can participate in the intraday market which is close to real-time, and buy or sell energy in this market to modify its bids in the DA market and also compensate the imbalances.

Other references proposed several approaches to compensate the imbalance associated costs. In [17], [18], the utilization of storage devices along with wind farms is proposed to reduce the costs of imbalance. Reference [19] examined the effectiveness of different storage technologies for wind energy applications. Reference [20] considers not only wind farms but also hydro power plants, as an approach for the reduction in wind energy imbalances. Reference [21] utilized gas turbines besides compressed air energy storage to compensate WPG's imbalances. Reference [22] described the impacts of DR on the profits made by WPGs, however, there is not any risk management possibility in the proposed approach. Reference [5] examined the effects of implementation of Intra-day DR exchange on reducing the WPG imbalances and enhancing its profitability. Reference [23] considers DR scheduling in competitive market.

Reference [24] models DR programs with fuzzy method and uses IGDT to ensure the load responsiveness. The basis of IGDT is such that a period around the predicted value is considered and finally the confidence interval is announced to the decision maker.

Hurricane is a natural weather scenario of high wind speed. In such a HILP event, the profitability of wind units would be affected. Moreover, the issue can affect the physical infrastructure. With a possibility of accidents in wind farms, it is necessary to reveal the eventuality of HILP occurrence at a specific time and opt a proper strategy to reduce the economic impacts of these incidents [25]. One effective way to find the probability of such events is based on taking the advantages of historical data and predict possible weather conditions.

Despite the fact that the probability of occurrence of an HILP event is minimal, the commercial drawbacks of that HILP event could be significantly high and consequently, a high risk would be reflected back into WPG participating in the electricity market. For instance, the authors of [26] used a stochastic programming approach to investigate the impacts of severe weather events on smart grid planning.

In comparison to the above reviewed literature, the novelties of this paper are highlighted in Table 1.

B. CONTRIBUTIONS

In this article, a DR exchange market is considered to have formed in the intraday market. Uncertainty related to DR is modeled by IGDT method. DR sources behave as a seller in this market, while WPGs participate along with other buyers in this market to compensate the power imbalances and maximize their profits. In addition to the uncertainty associated with DR, the WPGs are facing with wind generation uncertainty as well as market price fluctuations. Therefore, an indicator can be used to consider the risk-taking and risk aversion of a WPG in its expected profit margin. In this paper, the CVaR index has been employed and different risk levels have been considered for WPG. The uncertainty of the DA and intraday market prices as well as the uncertainty related to wind generation are included to the model. One of the contributions of this paper is the assessment of the impacts of hurricane, weather condition with HILP events, on the profits of WPG. The parameters characterizing a hurricane such as historical data on central pressure, wind speed during hurricane and translation velocity of hurricane are involved for modeling the wind farm failure rate. The wind farm reliability model before and after the hurricane is obtained and compared. Furthermore, this paper investigates the possibility of WPG participation in the reserve market besides providing offers in the energy market. In summary, research innovations are described as follows:

- To evaluate the profitability of WPGs in the event of High-Intensity and Low-Probability events;
- To investigate the impacts of hurricane on the failure rate and aging of wind farms and developing a reliability model for wind farms based on fuzzy Markovian method;
- To develop a simultaneous risk-based offering strategy for WPG in energy and reserve markets at different time stages including DA and intraday;
- To model a DR exchange market in intraday stage with the aim of compensating the imbalances of WPG's offers considering DR uncertainty through IGDT.

C. PAPER STRUCTURE

This paper is structured as follows: Section II describes the WPG model. Mathematical model formulation is presented in section III. Section IV provides both the numerical studies and results. Section V concludes the paper.

TABLE 1. Classification of surveyed bidding strategy article.

Reference	Uncertainty parameters	Risk Modeling	Uncertainty Modeling	HILP Events (Modeling)
[14]	DP +IP +Wind	CVaR	Probabilistic	-
[20]	DP+BP+ Wind	-	Probabilistic	-
[21]	DP	DSR	Probabilistic	-
[22]	DP	VC	-	-
[24]	DP + Wind	-	SP + RO	-
[25]	DP + Wind	CVaR-VaR	Probabilistic	-
[26]	DP + Wind	-	SP + RO	-
Current paper	DP+ IP+ Wind+ DR+ HILP	CVaR	Probabilistic +IGDT	Hurricane (Fuzzy Markovian)

II. WPG MODEL DESCRIPTION

WPGs make their major offers in DA market. In DA market, WPGs can offer sales for the next 24 hours. Due to the forecasts in the DA market and uncertainty related to wind generation, WPGs will not be able to compete with other market players unless the conditions are right for them. Despite the undeniable improvements in wind forecasting, DA market forecasts can lead to significant uncertainty in power systems. Enabling WPGs to respond to the last information gains, in fact improved wind forecasts, is an essential to improve the market scheme and facilitate WPGs' involvement in the electricity market. The intraday market has beneficial impact on WPGs and the power systems' performance. As the period of wind forecast decreases, WPGs will adjust and update their proposals for this market, which is an advantage in the energy market [27]. In the intraday market, the WPGs can compensate their initial offers through purchasing DR with the aim of reducing their imbalances. This is modeled on an IDRX market. Note that the uncertainties regarding consumer participation in DR schedules has been taken into account through IGDT. Through the participation in IDRX market, WPGs can make up for unexpected windfall deficiencies to reduce their penalties' imbalance in the equilibrium market. Moreover, it could result in increasing WPGs' profitability in the electricity market and therefore encourage investors to invest in the development of wind power systems in the power sector.

In general, the proposed method is studied at four business levels. In the first level, forecast of the generated wind power and the prices of the DA market are considered for supply in the DA market. In the second level, WPGs can obtain new data by entering the intraday market, so they can update their DA market schedules. Also, WPGs must forecast the intraday market prices for minimization of the deviancies among the recent available forecast and the DA market forecast, as well as their financial risks. The third level describes a balanced market. Thus, if wind production exceeds the forecast in the second phase, WPGs will have to sell their production at lower price in comparison with the DA market. Conversely, with an event of wind power shortage, WPGs would have to

sell their deficits at higher price in comparison with the DA market price, and this strategy is logical. The fourth level is the reserve market. This market occurs if the previous three markets are realized. That is, when the WPG participates in DA, intraday and balancing markets, it can make offers in the reserve market as well. Figure 1 shows a schematic diagram summarizing the WPG problem.

III. MODEL FORMULATION

A. UNCERTAINTY CHARACTERAZATION

In general, there are three major sets of uncertainties in the WPG bidding strategy. These include those relevant to the prices of the electricity market, wind energy generation and responsive loads. The model of each set of the above-mentioned uncertainties are described below.
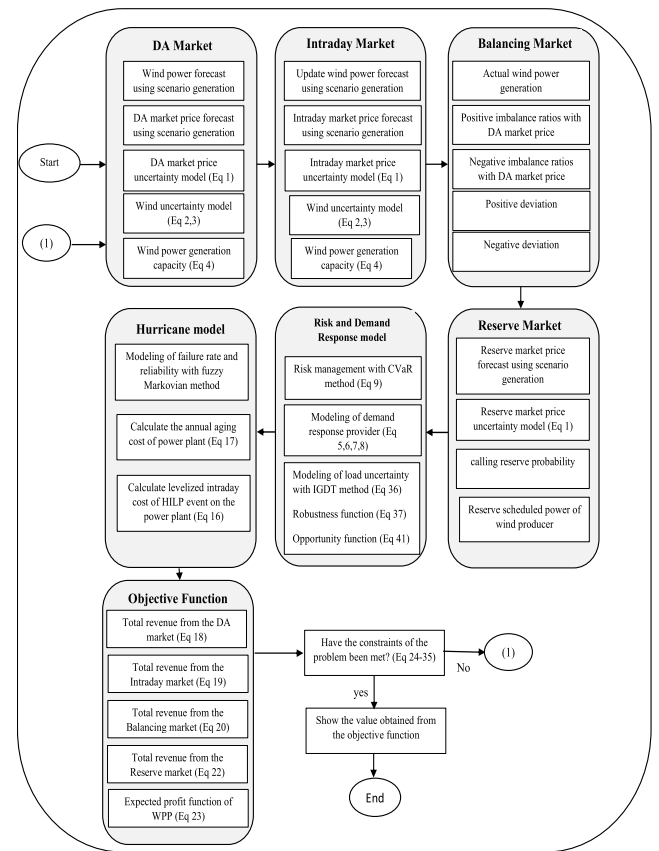

FIGURE 1. Schematic of the WPP profit problem.

1) MARKET PRICES UNCERTAINTY MODEL

WPGs must predict the price of the electricity market to succeed in the electricity market. A normal probability density function (PDF) is applied for modelling the uncertainty in the prices from DA, intraday and spinning-reserve markets. The PDF of market prices can be expressed as below:

$$f_p(\lambda_p, \mu_p, \sigma_p) = \frac{1}{\sigma_p\sqrt{2\pi}} \exp\left[-\frac{(\lambda_p - \mu_p)^2}{2\sigma_p^2}\right] \quad (1)$$

where λ_p is the distribution function parameter, μ_p is mean value and σ_p is standard deviation. For high accuracy, the distribution function should be divided into a number of parts per hour and a probability for the whole must be considered. In this paper, ''Roulette Wheel Mechanism (RWM)'' method is used for the purpose of generating scenarios. Obviously, the greater the number of scenarios, the more accurate model for uncertainty. But since too many scenarios make the optimization problem uncontrollable, the K-means clustering technique is employed to decrease the scenarios.

2) UNCERTAINTY IN WIND POWER GENERATION

The capacity of wind power generation valency is dependent on the wind speed. One of the first and most basic measures to be taken to check the presence of wind farms in power systems is to predict wind speed. The main feature of wind speed is its high fluctuations during the day and night. According to reference [28], the most suitable function for wind speed modeling is the Weibull distribution function. In this modeling method, for each wind farm, according to the historical data of regional wind speed, the PDF's parameters are obtained. The Weibull probability density function is represented according to Eq. (2) [5].

$$f_w(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \quad (2)$$

where f_w represents the probability density distribution functions, k is the shape parameter, c is the scale parameter and v is the wind speed random variable. The distribution function resulting from Eq. (2) is shown in Eq. (3) [5].

$$pro_i = \int_{ws_i}^{ws_{i+1}} f_w(v)dv \quad i = 1, 2, \ldots, s_N \quad (3)$$

where pro_i is the probability of each step and ws_i is the wind speed of ith scenario.

After the step of modelling wind speed, the power output of the wind farm can be estimated based on the non-linear relationship in Eq. (4). Note that, this type of relationship also depends on the type of turbine and its specifications. With the availability of wind speed and considering the power curve of the turbine, it is possible to determine the output power of wind turbines according to Eq. (4).

$$p_{GW} = \begin{cases} 0 & ws_i \geq vci \\ p_r\left(\dfrac{ws_i^2 - vci^2}{vr^2 - vci^2}\right) & vci \leq ws_i \leq vr \\ p_r & vci \leq ws_i \leq vco \end{cases} \quad (4)$$

B. MODELING OF DR PROVIDERS

DR is a change in the typical consumption of an electric customer in response to change in electricity tariffs or an incentive payment. Small customers are mainly reluctant for participation in the DR market to obtain more profits.

For such a situation, a player called Demand Response Provider (DRP) is introduced who can act as an intermediary between DR buyers and DR sellers (small customers). DRPs offer their DR to the intraday market in the pool-based DRX market. It is noteworthy that this paper considers a fully competitive pool-based DRX market, where WPGs participate in this market as DR buyers and loads participate as DR sellers. In this structure, both the buyers and sellers submits their offered packages to market operator and then, the market is cleared. On this basis, there is no need to communication between market participants. The constraints in equations (5)-(8) are related to modeling of DRPs that play the role of DR sellers in the DRX market. These formulas have been extracted directly from reference [5]:

$$ADR_{pt} = \sum_{m=1}^{x} q_{pt}^m \quad (5)$$

$$DRP\cos t_{pt} = \sum_{m=1}^{x} q_{pt}^m . c_{pt}^m \quad (6)$$

$$q_{pt}^m \leq q_{pt}^{m,\max} \quad (7)$$

$$ADR_{pt} \leq ADR_{pt}^{\max} \quad (8)$$

The maximum DR in each DRP block is specified in Eq. (7). The highest DR offer of DRP per hour in the intraday market is specified in Eq. (8). X describes the number of bidding block of DRPs. Parameter q is one of the parameters that has uncertainty in this issue, which will be modeled in the next section.

C. IGDT BACKGROUND

In power system, as a matter of the variability nature of data (e.g. load), it is necessary to account for the modelling of such parameters' uncertainty. The IGDT method can be used for such a modelling. The difference between this method and probabilistic methods is that there is no requirement for the PDF of uncertainty source, which can be very beneficial in cases where the decision maker has little knowledge of the parameters [29]. In fact, this method takes into consideration modelling the error among the actual parameters and the predicted ones. IGDT tackles both two conflicting issues utilizing two safety functions: (robustness and opportunity) [30]. The IGDT model contains three essential components: 1) system model; 2) performance requirements; and 3) uncertainty model [31].

1) SYSTEM MODEL

The input and the output system's configuration for which IGDT is deployed is described by E(q) where q is the parameter of load uncertainty.

2) PERFORMANCE REQUIREMENTS

The performance requirements can show the needs or predictions related to the objective function, which can be described

considering the profit or related functions. The performance requirements are assessed on the basis of performance of robustness and opportunity [31].

$\tilde{\alpha} = \text{Max}(\alpha)$ {The minimum profit generated from selling power and that is not beyond a provided profit goal} (9)

$\tilde{\beta} = \text{Min}(\beta)$ {The maximum profit generated from selling power and that is higher that a provided profit goal} (10)

The robustness function shows the highest uncertainty level of uncertainty as to how much the system can withstand a possible increase in load as well as the profit of electricity sales should not be below a certain amount. The robustness function describes the uncertainty resistance level to uncertainty and invulnerability to lower electricity sales profits [32]. Therefore, the mathematical description of the function via the optimization problem is described as follows [33].

$$\widehat{\alpha}(c_r) = Max_\alpha \{\alpha : Min\ EP(q) \geq c_r\} \quad (11)$$

The value of profit as a result of uncertainty is estimated through the opportunity function. This function indicates an opportunity to take advantage of the less uncertainty. Here is the minimum amount of that is possible to tolerate for increasing the profitability of electricity sales resulting from decisions made. The opportunity function represents the smallest value of that the profit from the sale of electricity can be as much as the given value. A higher value of demonstrates a condition that involves making profit during high load. Eq. (12) shows the mathematical representation of this function.

$$\bar{\beta}(c_0) = Min_\alpha \{\alpha : Max\ EP(q) \geq c_0\} \quad (12)$$

D. RISK MANAGEMENT
In this article, the value of the risk condition is included in the model to consider the risk associated with profit fluctuations in the WPG problem. CVaR calculation is possible through linear constraints modelling and is not mandating the involvement of binary variables.

$$Max\ \left(\xi - \frac{1}{1-\varepsilon}\sum_{s=1}^{S_N}\rho_s.\eta_s\right) \quad (13)$$

$$\text{Subject to } \xi - \eta_s \leq B_s \quad (14)$$

$$\eta_s \geq 0 \quad (15)$$

Note that, B_s is profit. Parameter ε is usually selected between 0.9 and 0.99. In this paper, ε is assumed to be 0.95. Due to the nature of the problem, when the profit has a value greater than ξ, the value of η_s would be zero; else, it would take a value between ξ and the profit.

E. MODELING OF HURRICANE AND HILP COST
Hurricane is one of the parameters that has low probability and high intensity. In the matter of biding strategy and of

WPG, hurricane is one of the issues that affect the profits of producers. For this reason, the WPG must predict the speed of the hurricane in order to reduce its losses in the electricity market. To predict the hurricane, historical data is considered and eventually these values will be broken in operation. The generated expected central pressure difference, generated expected approach angle, the generated expected landfall, and the generated expected translational velocity position are among the parameters affecting the storm, those are calculated by the Markov model.

A Markov decision process is an approach for describing a dynamic system evolving with respect to time as per to the concurrent impacts of the probability theoretical laws of movement and the decision-making series [34]. Using these parameters and based on [34], the failure rate as well as the reliability of the wind farm is calculated. Finally, a cost is defined as $HILP_{\text{intraday cost}}$ in this paper which is broken down into operation and added to the objective function.

$$HILP_{\text{intraday cost}} = \left[\left(\text{Aging}_{\text{annual cost}}^{\text{power plant}}\right) \times \left[\frac{i}{(1+i)^n - 1}\right]\right] \times \left[\frac{i'}{(1+i')^{n'} - 1}\right] \quad (16)$$

$$\text{Aging}_{\text{annual cost}}^{\text{power plant}} = \text{Aging}_{price} \times (1 - R_t) \quad (17)$$

F. OBJECTIVE FUNCTION
The goal of WPGs in the electricity market is to maximize their profits. In this paper, in addition to the WPGs' profit made in both the DA market and the intraday market, the risk of WPGs, the probability of recall and participation of WPGs in the reserve market as well as the impact of storms, which is one of the low probability events and high intensity are considered in the objective function. The objective function contains five parts.

Eq. (18) shows the first part of the objective function which is the revenue as a consequence of energy sold in the DA market.

$$DAprofit = \sum_{t=1}^{T}\sum_{s=1}^{SN}\rho_s.\pi_{ts}^{DA}.SPS_{ts}^{DA} \quad (18)$$

Eq. (19) shows the second part of the objective function. When the DA market price is cleared and these prices are determined, it is the turn of the intraday market, which includes energy selling in the intraday market, energy purchasing cost from the conventional intraday market and the energy purchasing cost from IDRX market.

$$INprofit = \sum_{t=1}^{T}\sum_{s=1}^{SN}\rho_s\left\{\begin{array}{l}\pi_{ts}^{IN}.SPS_{ts}^{IN} - \pi_{ts}^{IN}.SPB_{ts}^{IN} \\ -\sum_{p=1}^{NP}\pi_{pts}^{bilateral}.SP_{pts}^{bilateral} \\ -\sum_{p=1}^{NP}DRP\cos t_{pts}\end{array}\right\} \quad (19)$$

The third part of the objective function is relevant to the balancing market. This market is formed when the previous

two parts have taken place. Profits from this market depend on the positive and negative imbalances of the previous two markets. Eq. (20) represents the profits of this market.

$$BLprofit = \sum_{i=1}^{T} \sum_{s=1}^{SN} \rho_s \{\pi_{ts}^{DA} . im_t^+ . delta_{ts}^+ - \pi_{ts}^{DA} . im_t^- . delta_{ts}^-\}$$

$$(20)$$

The fourth part of the objective function is relevant to WPG's profit gained due to the participation in the reserve market, which includes the amount of power sales in the reserve market. The probability of a call in the reserve market is also considered in the objective function. Equations (21) and (22) show the profits of this market.

$$RES total_{ts} = \sum_{t=1}^{T} \sum_{s=1}^{SN} \rho_s \left\{ RESP_{ts} + \sum_{p=1}^{NP} RESB_{pts} \right\} \quad (21)$$

$$RES profit = \sum_{t=1}^{T} \sum_{s=1}^{SN} \rho_s \left\{ \begin{array}{l} \pi_{ts}^{RES} . REStotal_{ts} \\ + \pi_{ts}^{RES} . CRP_t . REStotal_{ts} \end{array} \right\} \quad (22)$$

The objective function, which is the expected WPG's profit, is obtained from Eq. (23). Risk is incorporated to objective function using CVaR.

$$EP = \left\{ \begin{array}{l} DAprofit + INprofit + BLprofit + RESprofit \\ + \delta \left(\xi - \dfrac{1}{1-\varepsilon} \displaystyle\sum_{s=1}^{SN} \rho_s . \eta_s \right) - HILP_{intraday \cos t} \end{array} \right\}$$

$$(23)$$

The goal is to maximize the objective function subject to the below constraints:

$$P_{ts}^{sch} = REStotal_{ts} + SP_{ts}^{DA} + SPS_{ts}^{IN} - SPB_{ts}^{IN}$$
$$- \sum_{p=1}^{NP} ADR_{pts} - \sum_{p=1}^{NP} SP_{pts}^{bilateral} \quad (24)$$

$$P_{ts}^{sch} \leq P_{\max} \quad (25)$$

$$SP_{ts}^{DA} + RESP_{ts} \leq P_{\max} \quad (26)$$

$$delta_{ts} = PDT_{ts} + P_{ts}^{sch} \quad (27)$$

$$delta_{ts} = \left(\begin{array}{l} delta_{ts}^{positive} - delta_{ts}^{negative} \\ - \displaystyle\sum_{t=1}^{T} \pi_{ts}^{DA} . SP_{ts}^{DA} + \pi_{ts}^{IN} . SPS_{ts}^{IN} \\ - \pi_{ts}^{IN} . SPB_{ts}^{IN} + \pi_{ts}^{DA} . im_{ts}^{positive} \\ . delta_{ts}^{positive} \\ - \pi_{ts}^{DA} . im_t^{negative} . delta_{ts}^{negative} \\ - \displaystyle\sum_{p=1}^{NP} DRP \cos t_{pt} \\ - \displaystyle\sum_{p=1}^{NP} \pi_{pts}^{bilateral} . SP_{pts}^{bilateral} \end{array} \right)$$

$$(28)$$

$$delta_{ts}^{positive} \leq PDT_{ts} \quad (29)$$

$$delta_{ts}^{negative} \leq P_{\max} \quad (30)$$

$$SPS_{ts}^{IN} \leq SP_{ts}^{DA} \quad (31)$$

$$SPB_{ts}^{IN} \leq SP_{ts}^{DA} \quad (32)$$

$$\sum_{p=1}^{NP} SP_{pts}^{bilateral} + \sum_{p=1}^{NP} RESB_{pts}$$
$$\geq 0 \quad (33)$$

$$\xi \leq \eta_s \quad (34)$$

$$\eta_s \geq 0 \quad (35)$$

Equation (24) calculates the total scheduled power for wind power producers including the power of DA, intraday and reserve markets. Equation (25) shows the total scheduled power limit. Equation (26) shows the value offered in the DA market and reserves that should not exceed the total valency designed for the wind farm. Equations (27) and (28) calculate the amount of total energy deviation with respect to the latest scheduled energy in both the DA market and the intraday market. Constraints (29) and (30) show the limits of positive/negative variations in the DA market and intraday market, respectively. Constraints (31) and (32) show the approximate WPG's sales/purchases of power in the intraday market, which should not exceed the scheduled potency in the DA market. Equation (33) shows the range of potency traded in bilateral contracts in DA, intraday as well as the reserve markets. Constraints (34) and (35) are also the formulas for WPG risk.

G. FURMOLATION OF THE IGDT METHOD FOR LOAD UNCERTAINTY MODELING

One method for reducing risk of using wind resources is to use DR in the electricity market which itself has uncertainty. The objective function of the problem has been examined from the perspective of the WPGs, so the load uncertainty must be investigated. In this paper, load uncertainty (q) is modeled by IGDT method.

$$U(\alpha, \tilde{q}_{pt}) = \left\{ q_{pt} : \dfrac{|q_{pt} - \tilde{q}_{pt}|}{q_{pt}} \leq \alpha \right\}, \quad \alpha \geq 0 \quad (36)$$

In Eq. (36), q_{pt} is the actual load value and $\tilde{q}_{pt}$ is the forecasted value of load. α represents an uncertainty parameter of the problem modelling the size of split among the identified parameter and the unidentified parameter. This parameter is the maximum possible deviation of the uncertain parameter from its prediction value, which is also called the uncertainty radius. This parameter could adjust according to risk averse or risk taker characteristics of the decision maker to provide a tolerable robustness region for the required target.

1) ROBUSTNESS FUNCTION
Function $\hat{\alpha}(c_r)$ related to the profit of electricity sales is lower than the minimum profit of that power plant, that means the highest degree of uncertainty in which the profit function of the power plant cannot be less than a value c_r. Therefore, it is expected that the value of c_r will increase as

$\widehat{\alpha}(c_r)$ decreases. Function $\widehat{\alpha}(c_r)$ is achieved while satisfying the relevant constraints. According to Equation (14), we have:

$$\widehat{\alpha}(c_r)$$
$$= Max_\alpha \tag{37}$$

Subject to:

$$Min \left\{ \begin{array}{l} DAprofit + INprofit + BLprofit \\ +RESprofit + \delta \left(\xi - \frac{1}{1-\varepsilon} \sum_{s=1}^{SN} \rho_s.\eta_s \right) \end{array} \right\}$$
$$\geq c_r \tag{38}$$
$$q_{pt} \leq \tilde{q}_{pt} + \alpha \tilde{q}_{pt} \tag{39}$$
$$q_{pt} \leq \tilde{q}_{pt} - \alpha \tilde{q}_{pt} \tag{40}$$

The parameter q is in Eq. (6), and since Eq. (6) is part of the objective function, the parameter q directly affects the objective function. Due to uncertainty α and due to Equation (38), this function should reach its minimum value. After constraints (39) and (40), constraint (39) is removed and only constraint (40) affects this issue.

2) OPPORTUNITY FUNCTION

The concept of uncertainty includes increasing or decreasing the burden. The opportunity function examines how to withstand a large increase in load. Therefore, a small amount of α is desirable. The opportunity function must reach a minimum value of c so that the profit from the sale of electricity is equal to C0. Naturally, the value of C0 is greater than β. The mathematical equation is a function of opportunity with respect to Eq. (15):

$$\bar{\beta}(c_o)$$
$$= Min_\alpha \tag{41}$$

Subject to

$$Max \left\{ \begin{array}{l} DAprofit + INprofit + BLprofit \\ +RESprofit + \delta \left(\xi - \frac{1}{1-\varepsilon} \sum_{s=1}^{SN} \rho_s.\eta_s \right) \end{array} \right\}$$
$$\geq c_0 \tag{42}$$
$$q_{pt} \leq \tilde{q}_{pt} + \alpha \tilde{q}_{pt} \tag{43}$$
$$q_{pt} \leq \tilde{q}_{pt} - \alpha \tilde{q}_{pt} \tag{44}$$

Due to uncertainty α and due to Equation (41), this function should reach its maximum value. After constraints (43) and (44), constraint (44) is removed and only constraint (43) affects this issue.

IV. NOMERICAL STUDY AND RESULT ANALYSIS
A. CASE STUDY

The suggested approach considers the risk of demand response uncertainty and is deployed on 50MW wind farm system. The DA, intraday, reserve markets and the data of wind data utilized in generating the scenarios are derived from the 2019 Spanish electricity market data [35]. For high accuracy, the division of the distribution function in 20 parts

for every hour and probability for the whole are considered. In this paper, the roulette wheel mechanism (RWM) is considered for the generation of scenarios. Since too many scenarios make the optimization problem uncontrollable, the KMEANS clustering technique is utilized for reducing scenarios, leading to a tree of scenarios with 10 scenarios that are independent of each other [36]. The mixed integer non-linear programming (MINLP) model of the bidding strategy problem is solved using the general algebraic modelling software (GAMS) and using a solver called ''COUENEE'', and the results are validated by SBB solver. The prices of the DA, intraday and reserve markets will be obtained through the mentioned methods.

B. RESULT ANALYSIS
In this paper, the issue of WPG bidding strategy has been investigated by considering the effects of hurricane occurrence on wind unit profit.
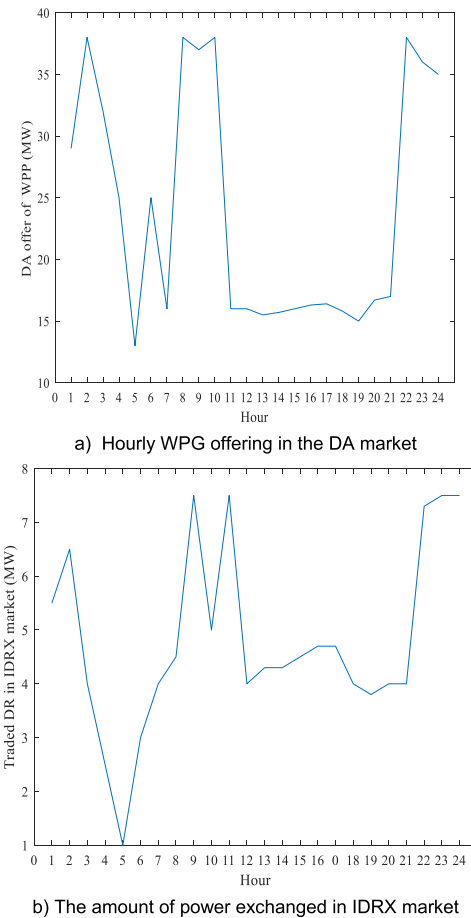

a) Hourly WPG offering in the DA market

b) The amount of power exchanged in IDRX market

FIGURE 2. Power exchanged in DA and IDRX market.

Figure 2 describes the amount of power exchanged in the IDRX market and hourly WPG's offers in the DA market. This exchange is both pool-based and bilateral contracts. Figures 3 show the total reserve scheduled. These proposals are made for the exchange of demand response in both pool-based and bilateral contracts.
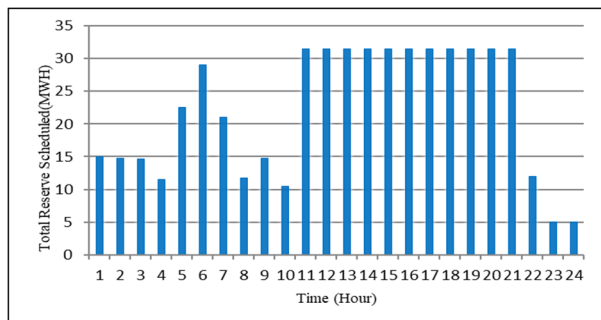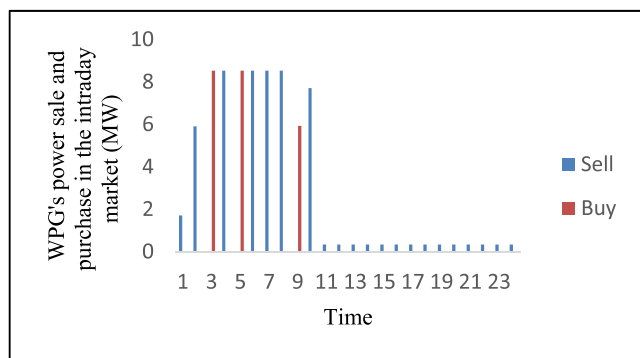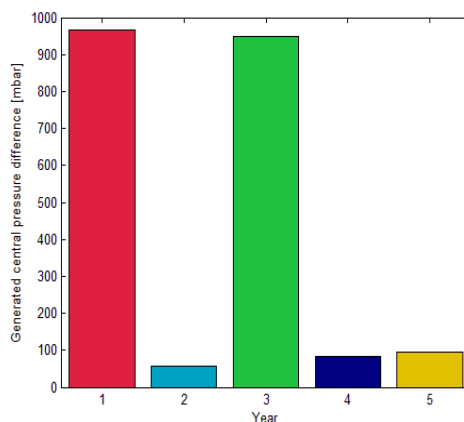
FIGURE 3. Total reserve scheduled.

FIGURE 4. Traded power of WPG in intraday market.

(a). Generated expected central pressure difference of hurricane

(b). Generated expected wind speed during hurricane

(C). Generated expected translation velocity of hurricane

FIGURE 5. Effective parameters of hurricane.

TABLE 2. The average hurricane data of the wind farm.

Unit	Average central pressure difference [mbar]	Average wind speed [m/s]	Average translation velocity [m/s]
Wind farm	429.60	22.40	14.20

With more wind energy being generated, wind power producers are not only participating in the IDRX market but can also increase their market offerings to increase their profits. In general, IDRX participation depends more on the availability of existing production than on the market specifications of IDRX. According to Figures 2 and 3, if the environment is ready for WPGs to manipulate the uncertainty in wind energy, it would generate the maximum possible power, because in this case, its profit will increase. This means that the introduction of IDRX will lead to a more competitive environment for producers. Figure 4 show WPG's traded power in the intraday market.
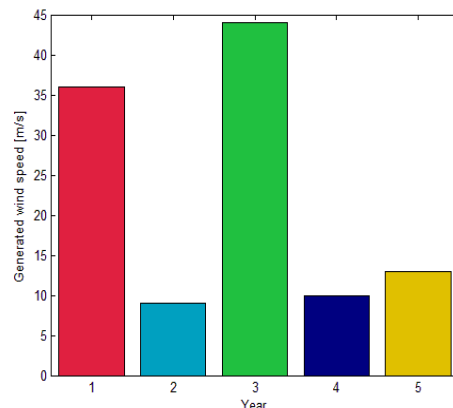
The generated expected central pressure difference, generated expected approach angle, the generated expected landfall and the generated expected translational velocity position by Markov model are shown in Figure 5. The fuzzy Markovian model applied in this paper is per the model in [34].

The average central pressure difference of hurricane, the wind speed during hurricane and the translation velocity of hurricane on the wind farm are presented in Table 2. The fuzzy value of the central pressure difference of hurricane, the wind speed during hurricane and the translation velocity on the wind farm is presented in Table 3.
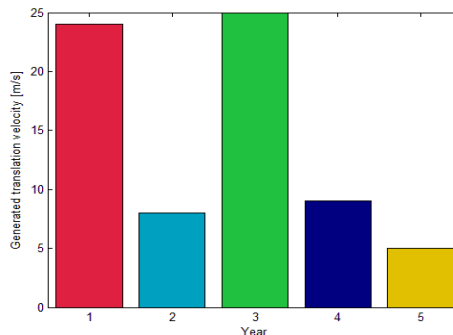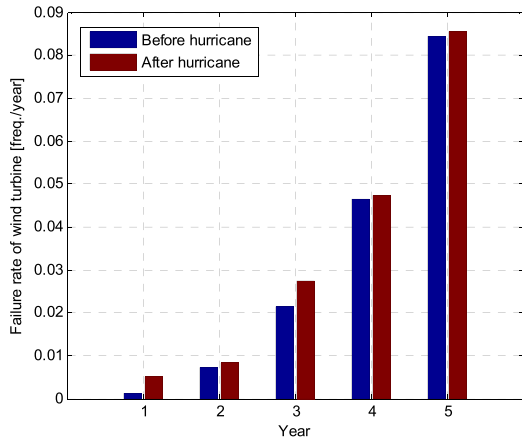
According to Figure 6 and Tables 2 and 3, using fuzzy Markovian method for hurricane modeling, it is observed that the failure rate of the wind unit as well as the reliability after the occurrence of the hurricane is reduced.

Table 4 shows the wind power generators profits in each market. Moreover, the profit of the WPG before and after hurricane occurrence are compared with each other in Table 5.
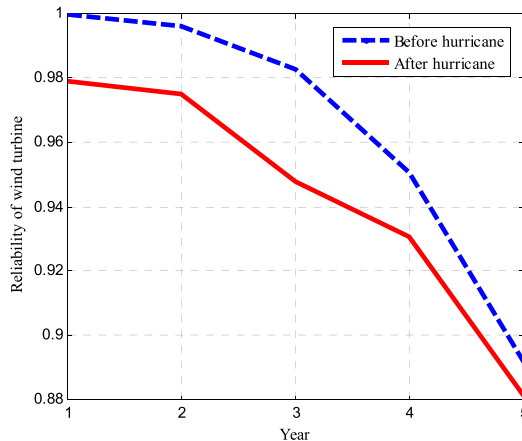
According to Table 5, the profit of the WPG in the scenario with the hurricane events will be reduced dramatically

TABLE 3. The fuzzy value of hurricane data on the wind farm.

Unit	Year	Central pressure difference	Wind speed	Translation velocity	Mean fuzzy value	Raised failure rate
Wind farm	1	2	2	3	2	0.004
	2	1	1	2	1	0.001
	3	2	3	3	3	0.006
	4	1	1	2	1	0.001
	5	1	2	1	1	0.001

(a). Failure rate

(b). Reliability

**FIGURE 6.** Failure rate and reliability of wind turbine before and after hurricane occurrence at each year.

TABLE 4. Revenues of WPG.

|	
Revenue made with the DA market(€)	21843.55
Revenue made with the intraday market(€)	298.69
Revenue made with the reserve market(€)	114.48
Positive imbalance revenue(€)	96.34
Negative imbalance cost(€)	4652.35
DRX cost(€)	1681.47
Expected profit (€)	16019.24

compared to the scenario without the hurricane events due to the decrease in the reliability of the wind turbine. As a result of such HILP events, the bidding strategy of the WPG will be

TABLE 5. Total profit of the WPG before and after hurricane occurrence.

Risk level (δ)	$\delta = 0$	$\delta = 0.5$	$\delta = 1$
Total profit of WPG before hurricane occurrence (€)	16019.24	13099.717	10772.252
CVaR(€)	6613.540	6726.985	6758.532
$HILP_{intraday\,cost}$ (€)		1204.88	
Total profit of WPG after hurricane occurrence (€)	14814.36	11894.83	9567.37
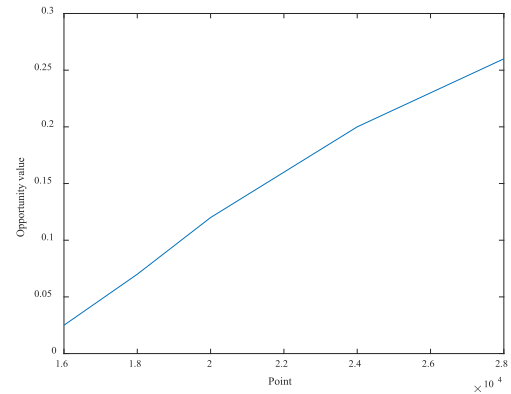
(a). Opportunity value
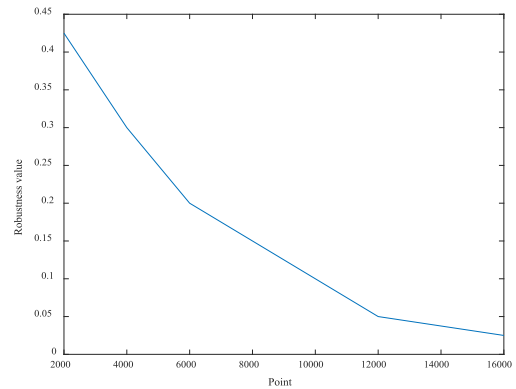
(b). Robustness value

FIGURE 7. Opportunity and robustness functions curve.

affected and changed. The amount of programmed power that DRPs are responsible for collecting is one of the parameters of problem uncertainty. This means that the greater the potential, the more responsive DRPs can enter the market. With the increasing level of DRPs' participation in the market, WPG prefer the participation in the IDRX market and refine their proposals. Therefore, wind power producers use demand response resources to compensate for their imbalance costs associated with wind energy uncertainties.

Figure 7 reveals the opportunity and robustness functions. The opportunity function indicates an opportunity to take advantage of the low uncertainty. The opportunity function can be described as the minimum α value that profit from the sale of electricity can be as much as the given value C0. All of this was for when hurricane did not occur.

The robustness function presents the undesired aspect of uncertainty and reveals the highest uncertainty level as to how much the system can withstand a possible increase in load. The robustness function can be described as the resistance level to uncertainty as well the immunity level to lower energy sales profits. As can be seen, Figure 7 show the amount of resistance to a possible increase in demand response. It also shows that the amount of wind energy sales cannot be less than the number obtained in the objective function.

V. CONCLUSION

This paper presents a new model for low HILP events such as the hurricane events and a model for WPG taking a role in the intraday market as a participant for maximizing his/her profits. The simulation results prove that a suitable IDRX market is motivating WPGs to supply further amount of power to the DA market. In the field of HILP, First, the effect of the hurricane on the reliability of wind turbine is investigated; then, the effect of it on the total profit of the WPG is studied and is compared with the scenario without the hurricane events. This paper also utilized the fuzzy Markovian method to the wind unit failure rate. Finally, to model the hurricane, levelized intraday cost of HILP event on the power plant is intended that his/her value is 1204.88. Results HILP revealed that the hurricane is one of the main parameters in the problem of bidding strategy for WPG, which affects the wind unit profit and should be considered. The CVaR value is also obtained for different levels of risk. The results show that the profit of the WPG in the scenario with the hurricane events will be reduced dramatically compared to the scenario without the hurricane events. The objective function is determined for different levels of risk. Finally, for a risk level zero ($\delta = 0$), the objective function is estimated to be 14814.36 considering the effects of hurricane.

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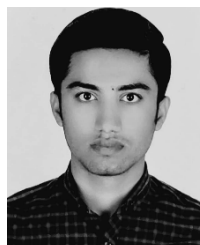
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