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Risk-averse Pre-Extreme Weather Events Self-Scheduling of a Wind Power Plant: A Hybrid Possibilistic-Scenario Model

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ABSTRACT

This paper develops a new possibilistic-scenario model for a wind power plant to determine its optimal self-scheduling (SS) in the presence of high-impact low-probability events uncertainty. Nowadays, in the context of the power system, examining the effects of extreme weather events in the category of high-impact low-probability (HILP) events has become one of the most important issues for researchers all around the world. There are so many reports of HILP events which acknowledge that these incidents can directly affect the power plants and cause them to fail. Generally, the self-scheduling of generating units in the pre-extreme weather conditions would be different from normal conditions. In such manners, this paper tries to address the self-scheduling problem of a wind power plant in pre-extreme weather conditions. For this purpose, there are numerous uncertainty sources in the SS problem that could affect the final results which include electricity prices, wind power production and contingency-based lack of production in the face of HILP events. In this regard, this paper proposes an efficient hybrid probabilistic-possibilistic assessment tool for dealing with these uncertainties. Additionally, CVaR evaluation was used as the intrinsic risk management tool of both probabilistic and possibilistic parameters in the SS problem.

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I. INTRODUCTION

Contrary to the power system with integrated structure, key parts of the power system including generation, transmission and distribution are not managed by one company in the deregulated environment. In the deregulated environment, market players are required to submit their offers for each time step. The day-ahead (DA) markets are one of the most important markets that are being used to implement the competitive electricity market. In general, many parameters affect Self-Scheduling (SS) problem, which most of the effective parameters have uncertainty. Various market prices are the most significant uncertain parameters in the SS problem. On the other hand, the power output of renewable generations as well as contingency-based lack of production in the face of HILP events will affect the producers benefit.

Nowadays, the power system resilience has changed to one of the most significant issues for the scholars all around the world. Indeed, resilience deals with the capability to make the power system strong against HILP evens[1]. HILP events like extreme weather events can have a considerable consequence on the electrical power equipment worldwide[2]. In order to reconcile to the impacts of extreme weather events through the redesign of some strategy to diminish the impacts, it is essential to characterize the likelihood of an extreme event happening in particular time and locations[3]. Note that, in extreme weather conditions, the probability of unit failure in comparison with the normal operation condition is much higher. For this purpose, the power producers should benefit from the experience, historical information, insight and weather forecasts[3]. Sometimes low probability of HILP events persuade us to ignore them, but, the research shows that the cost of these incidents may be very great, thus they should consider in any kind of problem. Hence, the power producer should execute the self-scheduling problem with more confidence in pre-disaster situations. Thus, when we make effort to propose a pre-extreme weather events self-scheduling framework for a typical wind power plant, one of the most common questions that may appear is: Do these events have a direct effect on wind power plants in terms of that effects of these incidents on transmission and distribution network is more remarkable?

The answer to this question for wind power plants depends on various factors such as the location of wind farms, type of HILP events and their intensity. in this regard, multiple reports from different events have been reported that could potentially face wind power plants to the lack of production. Power plants and substations

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Nomenclature

Indices and symbols

t	Index of time periods (1 to T).
s	Index of scenarios (1 to N_s).

Constants

π_s	The probability of scenario s.
κ	Per unit confidence level.
J	A large positive number that exceeds installed capacity of wind power plant.
C_{WP}^{Max}	Installed capacity of wind power plant, MW.
β	Weighting parameter for profit versus risk tradeoff.
a^{WP}, b^{WP}	Shape parameters of Beta PDF.
τ	The coefficient for positive and negative imbalances.

Variables

$\pi^E(t,s)$	Market clearing price for the energy market in period t and scenario s, $\$/MW$.
$\pi^{up}(t,s)$	Positive imbalance price in period t and scenario s, $\$/MW$.
$\pi^{down}(t,s)$	Negative imbalance price in period t and scenario s, $\$/MW$.
$bid^E(t,s)$	Power of wind power plant sold in the energy market in period t and scenario s.
$\tilde{\pi}_{HILP}(t)$	The possibility of lack of production in the face of HILP events in period t.
$q_{WP,t,s}$	A binary value (0 or 1), indicates the states of wind plant in period t and scenario s (1 =available, 0 =unavailable).
η_s	Auxiliary variable related to the scenario s and used to compute the CVaR.
ζ	The auxiliary variable used to compute the CVaR.
$k_{t,s}$	Binary variables used for the definition of positive and negative energy imbalances (equals 1 to negative energy imbalance).
$FP(t,s)$	Forecasted wind power production in period t and scenario s.

(which in some cases the ownership of the primary substation is with generation companies) are at risk from storm surge and coastal flooding, especially in locations along the U.S. East Coast and Gulf of Mexico[4]. In these coastal areas, a hurricane or other large coastal storm can push water inland in a large and damaging storm surge. On the other hand, some incidents such as cyber-attacks are intended to target substations or power plants[5]. Hence, increasing dependence on automation and remote controlling is another source of vulnerability. According to Wired Magazine[6], control systems of wind farms are another source of vulnerability which had been targeted by hackers. Reference[5] has been reported that offshore wind turbines are in danger of destroying by severe storms. In this regard, it was mentioning that seven wind turbines were destroyed confronting to a typhoon in 2003, Japan. For this issue, the researchers have been proposed to install wind turbines in areas with the lowest risk of hurricane damage. One another problem is that wind turbines cannot produce power before, during, and immediately after violent hurricanes[5]. During severe storms, inspectors should shut down wind generators in order to reduce the risk of damage. In particular, when a hurricane strikes, operators will shut off and lock down turbines when winds reach about 125 km/h (78 mph)[7]. The survival speed range of wind turbines is between 144 km/h (89 mph) and 259 km/h (161 mph) which demonstrates us most turbines will not be harmed in the face of hurricane categories number 1-4[8]. All in all, we realize that it is necessary to take into account the likelihood of damaging extreme weather events in the pre-disaster self-scheduling of wind power plants. In the following, we would review a few studies in the context of wind power plants self-scheduling.

The problem of participating wind power plants in the electricity markets have been studied in the literature[9–14]. Reference[9] proposed a new strategy for wind power producers in LMP-based markets. The authors benefit from conditional value-at-risk to consider the risk of wind power producer (WPP) participating. The problem of a price maker WPP in short-term electricity market has been investigated in[10]. The electricity market prices and wind power output are considered as the uncertain parameters. Baringo and Conejo[11] focused

on the risk-based multistage offering strategy of a price maker WPP. Authors in[12] presented a coordinated offering strategy for a group of wind farms through an extended agent. Reference[13] used robust optimization for optimal bidding strategy of a wind farm coordinated with energy storage. At last, authors in[14] focused on the optimal bidding strategy of a WPP. The authors benefit from bilevel stochastic programming to achieve the optimal WPP strategy. Given this framework, the contributions of this work are threefold:

1. To address a new framework for self-scheduling of WPPs in pre-HILP events conditions.
2. To deal with uncertainties in the SS problem of a typical WPP in a Possibilistic-scenario way.
3. To propose a risk-constrained SS framework in the presence of both fuzzy and probabilistic parameters.

As mentioned in (1), the main contribution of this work is to examine the SS problem of a typical WPP in bad weather conditions. To the best of our knowledge, there is no relevant work in the literature. The considered uncertain sources are electricity prices, wind power production and contingency-based lack of production in the face of HILP events. As pointed out in (3), the conditional value-at-risk (CVaR) is being used as the risk controlling tool for both fuzzy and probabilistic parameters.

The rest of this paper is organized as follows. Section II describes the methodologies for tackling uncertainties. Section III is assigned to the problem formulation. Section IV introduces the solution procedure used for the proposed problem. Section V presents the study case and results and finally, Section VI presents a conclusion.

II. UNCERTAINTY CHARACTERIZATION

There are a number of uncertainty sources that could impress the self-scheduling problem. These uncertainties are mainly from the electricity prices, wind power production, and accidental lack of production in the face of HILP events (forced outages)[15]. Where in this paper the last uncertainty is appointed due to the possibility of occurring HILP events in the sites. In this regard, we will introduce all uncertain parameters with their corresponding modeling techniques in the following.

A. Electricity prices: Probabilistic Approach

The first uncertainty emanates from day-ahead (DA) energy prices and imbalance energy prices which are described via scenarios. Although other techniques such as fuzzy and IGDT could be useful for price uncertainty, according to the reviewed papers in this context, the most common way for dealing with price uncertainty is to describe it via a set of scenarios. To this aim, the DA energy price scenarios will be derived from historical data. The method used to predict the hourly imbalance energy prices based on the realized DA energy prices is as follows:

$$\pi_{t,s}^{up} = (1-\tau)\pi_{t,s}^{E}$$
$$\pi_{t,s}^{down} = (1+\tau)\pi_{t,s}^{E} \quad (1)$$

B. Wind power production: Probabilistic Approach

Several scenario Generation techniques have been already utilized for characterization of wind power uncertainty and variability[16]. The most usual way to describe the uncertainty in wind power production is the probabilistic approach. For this purpose, numerous probability density functions (PDFs) have been used. In this paper, Beta distribution is used for scenario generation.

C. Contingency-based lack of production in the face of HILP events: Possibilistic Approach

Last uncertainty is contingency-based lack of production in the face of high-impact low-probability events. This uncertainty is considered via the prediction associated with high-impact events. The term "high-impact"dedicates to incidents with such a great consequence that cause lack of production and the term "low-probability" represents incidents that rarely happen within a certain period. As described in[17], several days or hours before a hurricane strikes a power plant, forecasting data such as the hurricane track and radius are known from weather forecasting. With this information, the WPP can quantitatively appraise the impact of the coming hurricane on the sites, which is outlined by the failure probabilities of the wind power plant. Similarly, some other relevant weather incidents which may affect power plants can be forecasted few days before damaging them. It assumed that no relevant historical data is available for these incidents. In this kind of conditions, one of the efficient ways to model the uncertainty of lack of production due to HILP events in the sites is to describe them with fuzzy numbers[18]. It is assumed that the WPP can describe the characteristic of HILP events with a fuzzy membership function. For this purpose, a fuzzy triangular number (FTN) (Fig. 1) is used to handle this uncertainty.

As mentioned above, the uncertain parameters are divided into two groups: probabilistic and Possibilistic parameters. According to the above descriptions, it would be necessary to explain each way of modeling. Possibilistic, probabilistic and joint possibilistic-probabilistic uncertainty modeling techniques will be defined in the following subsections.

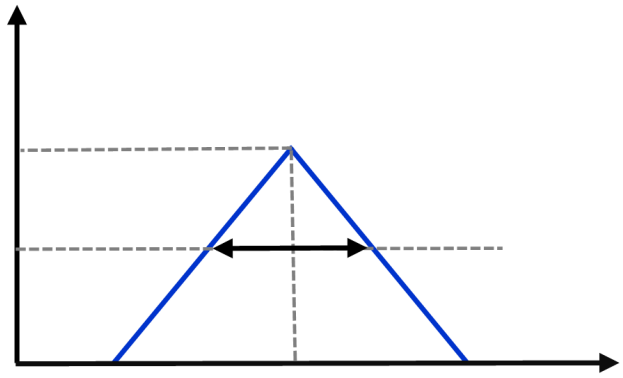


FIG. 1. Fuzzy triangular number.

1. Possibilistic Uncertainty Modelling

In possibilistic uncertainty modeling, a fuzzy number is applied to represent the vague information. In possibilistic theory, a fuzzy set can be formed by assigning a membership function ($\mu_{PB}(x)$) to each uncertain value ($\tilde{p}_B$) in the interval of $[0,1]$[19] where B is the possibilistic parameter (B=HILP). Membership function represents the degree to which an uncertain value belongs to a fuzzy set. Let X define the universe of discourse, where X represents an element of the universe, X, and $\mu_{PB}(x)$ denotes a fuzzy set $\mu_{PB}(x)$. Membership function can be manifested by different shapes and some of the common shapes are triangular, Gaussian and trapezoidal numbers. In this paper, we benefit from a triangular fuzzy number $\tilde{p}_B = (p_{L,B}, p_{M,B}, p_{R,B})$ to handle the uncertain parameters as shown in Fig. 1.

Consider that an objective function is $\tilde{y} = f(\tilde{x})$, where vector $\tilde{x}$ represents the possibilistic uncertain parameters. For a certain membership function of the possibilistic input variable $\tilde{x}$, it is possible to acquire the membership function of output variable $\tilde{x}$ by -cut method[20].

1. *α-cut Method*: P_B^α of a fuzzy set $\tilde{p}_B$ is a crisp set that contains all the elements of a universal set X, whose membership degree in is 'greater than or equal to' the given value of α, as:

$$p_B^\alpha = x \in \bigcup | \mu_{p_B} \geq \alpha = (\underline{p_B^\alpha}, \overline{p_B^\alpha}) \tag{2}$$

where $\underline{p_B}$ and $\overline{p_B}$ are the lower and upper bounds of the α-cut set, respectively. After obtaining α-cut of input variables, we can determine the output α-cuts using the following equations.

$$\begin{aligned} \underline{y^\alpha} &= min f(p_B^\alpha) \\ \overline{y^\alpha} &= max f(p_B^\alpha) \\ y^\alpha &= (\underline{y^\alpha}, \overline{y^\alpha}) \end{aligned} \tag{3}$$

where p_B^α represents the α-cut of the possibilistic input variable. Furthermore, for each α-cut of output, lower and upper bounds of Y are obtained. According to the decomposition theorem, a fuzzy set can be represented by the union of all its α-cuts, weighted by their value α[20], as shown in 4.

$$y = \bigcup_{\alpha \in [0,1]} \alpha y^\alpha \tag{4}$$

2. *Defuzzification Process*: In various engineering problems, we will finally find a need to defuzzify the fuzzy results[21]. In this paper, the centroid method[21] is being used for defuzzification of the fuzzy results according to the following equation.

$$A^* = \frac{\int \mu_A(x).x dx}{\int x dx} \tag{5}$$

2. Probabilistic Uncertainty Modelling

Assume the objective function $y = f(v)$, where vector v represents the probabilistic uncertain parameters. There are numerous techniques to deal paper with probabilistic uncertain parameters in the literature[18]. For this purpose, in this paper, the probabilistic uncertain parameters are described using a probabilistic-scenario approach. As mentioned above, our probabilistic parameters are wind power output and electricity prices. In this method the value of y is calculated as follows:

$$y = \sum_{s \in N_S} \pi_s \times f(v_s) \tag{6}$$

where π_s is the probability of each scenario and N_S is the set of all considered scenarios.

3. Joint Probabilistic-Possibilistic Uncertainty Modelling

Define Assume the objective function $y = f(v, \tilde{x})$, where vectors v and $\tilde{x}$ indicate the probabilistic and possibilistic uncertain parameters, respectively. According to the introduced assessment tool in[22], the uncertain parameters are decomposed into two categories and are dealt with separately as follows.

1. Determining the final scenario set of probabilistic uncertain parameters v, N_S.
2. Calculate the output α-cuts using the following equations:

$$\begin{aligned} \underline{y^\alpha} &= \min \sum_{s \in N_\Omega} \pi_\omega \times f(v, x^\alpha) \\ \overline{y^\alpha} &= \max \sum_{s \in N_\Omega} \pi_\omega \times f(v, x^\alpha) \\ x^\alpha &= (\underline{x^\alpha}, \overline{x^\alpha}) \end{aligned} \tag{7}$$

3. Calculate the crisp value of output variable using Eq. (4).

III. PROBLEM FORMULATION

The goal of a wind power plant in the self-scheduling problem is to maximize its profit while participating in the target markets. According to the reviewed papers in the introduction section, some WPPs participate in both day-ahead and real-time energy market and some only participate in the day-ahead energy market. However, this paper only focuses on the second model. The objective function of a typical WPP for participating in day-ahead energy market within a daily scope is shown in Eq. (8).

$$\begin{aligned}\max \quad \tilde{EP} = &\sum_{s=1}^{N_S} \tilde{\pi}_s \sum_{t=1}^{T} \pi^E(t,s) bid^E(t,s) \\ &+ \pi^{up}(t,s)(FP(t,s) - bid^E(t,s))(1-k_{t,s}) \\ &- \pi^{down}(t,s)(bid^E(t,s) - FP(t,s))(k_{t,s}) \\ &- \beta(\zeta - \frac{1}{1-\kappa}\sum_{s=1}^{N_S} \pi_s \eta_s)\end{aligned} \tag{8}$$

where in (8), $bid^E(t,s)$ is for the energy offer at each hour of scenarios. $FP(t,s)$ stands for the probable production of wind power plant in each scenario. $\pi^{up}(t,s)$ and $\pi^{down}(t,s)$ indicate the positive and negative imbalance energy prices, respectively. Also, $k_{t,s}$ is utilized for definition of positive and negative energy imbalances. In fact, the expression $-\pi^{down}(t,s)(bid^E(t,s) - FP(t,s))(k_{t,s})$ is a penalty term for WPP if it does not generate as much as it offers. Consequently, equations (9)-(13) show the problem constraints.

$$\begin{aligned}\eta_s \geq \zeta - \textstyle\sum_{t=1}^{T} &\pi^E(t,s) bid^E(t,s) + \pi^{up}(t,s) \\ &(FP(t,s) - bid^E(t,s))(1-k_{t,s}) - \pi^{down}(t,s) \\ &\left(bid^E(t,s) - FP(t,s)\right)(k_{t,s}), \forall s\end{aligned} \tag{9}$$

$$\eta_s \geq 0, \forall s \tag{10}$$

$$\left(bid^E(t,s) - FP(t,s)\right) \leq j \cdot k_{t,s}, \forall t, \forall s \tag{11}$$

$$\left(FP(t,s) - bid^E(t,s)\right) \leq j \cdot (1-k_{t,s}), \forall t, \forall s \tag{12}$$

$$0 \leq bid^E(t,s) \leq C_{WP}^{\max}, \forall t, \forall s \tag{13}$$

The objective function (7) compromises two terms: the expected profit from participating in the day-ahead energy market and risk term (CVaR) multiplied by the weighting parameter β. The parameter β would let us achieve a proper tradeoff between the expected profit and profit variability. Constraints (8) and (9) are used to compute conditional value-at-risk (CVaR). Equations (10) and (11) are used to specify the value of binary variable $k_{t,s}$ in each scenario. For more clarification, the state $k_{t,s} = 1$ in a certain scenario shows that the wind production is lower than the offered energy, while the state $k_{t,s} = 0$ indicates that the offered energy is lower than the predicted wind power output. Constraint (12) bounds below and above the offered power based on the installed capacity of wind power plant. It should be noted that according to the reviewed studies in the introduction section, no operation cost is considered for the WPP.

IV. SOLUTION PROCEDURE

The proposed solution procedure for WPP self-scheduling is shown in the appendix. First WPP forecast energy prices. For this purpose, WPP educed 5 scenarios for day-ahead energy prices using historical data. In the next step, the WPP acquire beta parameters by relevant weather forecasts. At this stage, the WPP generates 4000 scenarios representing wind power output. Then, a useful methodology named probability distance algorithm is utilized to diminish the number of scenarios to 5[23]. Therefore, the final scenario set for WPP include 25 scenarios with the structure of 5×5 (5 for day-ahead energy prices and 5 for wind power).

After defining the scenario set of probabilistic parameters (wind power and energy price), it is time to benefit from α-cut method to consider the possibilistic parameter ($\tilde{\pi}_s$) in the problem. In this step, three α-cuts at levels $\alpha = 0$, $\alpha = 0.5$ and $\alpha = 1$ are used for the possibilistic parameter. These three α-cuts are based on the background knowledge of authors from fuzzy theory. Here, according to the descriptions in section II (Eq. 7), the membership function of output variables will be obtained.

Finally, by taking advantage of centroid method (Eq. 5), the crisp values of optimal WPP self-scheduling will be calculated.

The only remaining part of the proposed framework for WPP self-scheduling is the calculation of each scenario probability by taking into account the uncertain nature of HILP events. For this purpose, at each hour of every final scenario set, random values in the range of $[0,1]$ are generated. If each of these random values is less than the α-cut of HILP parameter (π_{HILP}^{α}) ($q_{wp,t,s} = 0$) at a specified hour then the power of wind power plant is considered zero at that hour. But if the random value is greater than the (π_{HILP}^{α}) ($q_{wp,t,s} = 1$) then the power of wind power plant is considered as its forecasted power.

As the uncertainty sources are independent, the prob-

ability of each scenario can be calculated as follows:

$$\tilde{\pi}_s = \Big(\prod_t^T \underbrace{prob(\pi^E_{t,s})}_{\frac{1}{5}=0.2}\Big) \times \Big(\prod_t^T prob(FP(t,s))\Big) \times \Big(\prod_t^T \Big[q_{PW,t,s} \times (1-\tilde{\pi}^{\alpha}_{HILP}(t)) + (1-q_{PW,t,s}) \times \tilde{\pi}^{\alpha}_{HILP}(t)\Big]\Big) \quad (14)$$

The optimal WPP self-scheduling problem has been formulated as a mixed-integer nonlinear (MINLP) problem which is solved using DICOPT under general algebraic modeling system (GAMS)[24].

V. NUMERICAL RESULTS

In this section, the proposed framework is implemented in the optimal self-scheduling problem of a typical WPP over a 24-hour time interval. This framework tries to obtain the optimal participation of WPP in extreme weather events situations. The day-ahead energy market prices are given in Fig. 2. A statistical analysis of NYISO for 5 days was executed to take into account a realistic energy price. As another source of uncertainty, imbalance energy prices should be considered in the problem. In order to take into account this uncertainty, the value of τ for all hours is assumed to be 0.1. As also mentioned in the second section, the uncertainty of HILP events is considered through a possibilistic approach. These fuzzy parameters based on the relevant weather forecasts are provided in Table I. The authors in[25] noticed that the power producer can approximately estimate the severity and duration of extreme weather events.

In order to investigate the impact of various distribution shapes pertaining to the selective PDF of wind power output (Beta), three different distribution shapes named high-mean ($a > b$), mid mean ($a = b$) and low-mean ($a < b$) distributions based on the information in[26] are chosen for the SS problem. Generally, the Beta distribution is characterized by two parameters (a^{WP}, b^{WP}). The information on the considered distribution shapes is reported in Table II. For more clarifications, these three distinct distribution shapes are shown in Fig. 3.

As described in the second section, the uncertainty associated with wind power production is considered through a probabilistic-scenario approach. A beta distribution has been used to generate a sufficient number of wind power scenarios (4000). In order to make our simulation tractable, the initial scenarios are reduced to five using a fast forward selection algorithm based on the Kantorovich distance[23]. The reduced scenarios are in per unit, i.e., wind power output divided by wind power capacity (50 MW). The reduced wind power production scenarios pertaining to set 1 are depicted in Fig. 4.

As described in the second section, the uncertainty associated with wind power production is considered

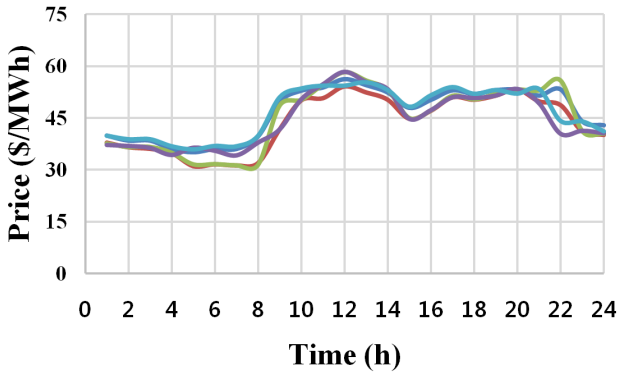


FIG. 2. Energy price scenarios.

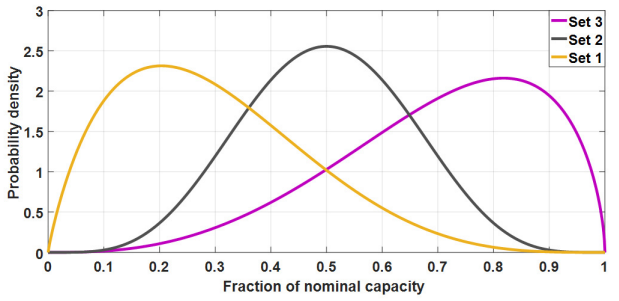


FIG. 3. Wind power distributions.

through a probabilistic-scenario approach. A beta distribution has been used to generate a sufficient number of wind power scenarios (4000). In order to make our simulation tractable, the initial scenarios are reduced to five using a fast forward selection algorithm based on the Kantorovich distance[23]. The reduced scenarios are in per unit, i.e., wind power output divided by wind power capacity (50 MW). The reduced wind power production scenarios pertaining to set 1 are depicted in Fig. 4. The possibilistic-probabilistic self-scheduling of WPP (8)-(13) is solved for two different cases. For this purpose, the confidence level to calculate CVaR is 0.95. The first case is dedicated to the WPP self-scheduling without taking into account the effects of HILP parameters. The second case is related to the WPP self-scheduling by considering the effects of HILP parameters. These two cases will let us know how the coming HILP events can affect the outcome of the self-scheduling problem. It should be noted that each case of the self-scheduling problem includes three different shapes of Beta distribution, namely, set 1, set 2 and set 3.

The results of the self-scheduling problem for case 1 are provided in Table III. As it can be seen from this table, set 3 has the largest expected profit in comparison with two other sets. This issue is due to the higher level of wind power production with respect to the other sets as shown in Fig. 3. According to this table, for all sets, the maximum profit obtains in risk-neutral condition ($\beta = 0$). By increasing the risk controlling parameter , the

TABLE I. HILP event parameters for wind power plant

t	$\tilde{\pi}_{HILP}(t)$ $(P_{L,HILP}, P_{M,HILP}, P_{R,HILP})$	t	$\tilde{\pi}_{HILP}(t)$ $(P_{L,HILP}, P_{M,HILP}, P_{R,HILP})$
1	(0.025, 0.025, 0.050)	17	(0.000,0.0025,0.005)
2	(0.180, 0.210, 0.240)	18	(0.045, 0.050, 0.055)
3	(0.360, 0.390, 0.420)	19	(0.160, 0.200, 0.240)
4	(0.180, 0.210, 0.240)	20	(0.320, 0.360, 0.400)
5	(0.025, 0.025, 0.050)	21	(0.160, 0.200, 0.240)
		22	(0.045, 0.050, 0.055)
		23	(0.000, 0.0025, 0.005)

TABLE II. Shape parameters of beta distributions

Shape parameters	Set 1 $a < b$	Set 2 t $a = b$	Set 3 $a > b$
(a^{WP}, b^{WP})	(1.89,4.48)	(5.37,5.37)	(3.78,1.62)

TABLE III. The result of SS problem versus different risk factors in case 1

Case 1	Risk factors (β)	Expected Profit ($)	CVaR ($)
Set 1	0.0	15394.52	14541.58
	0.5	15361.30	14637.78
	1.0	15330.05	14725.15
	2.0	15180.21	14913.75
Set 2	0.0	26324.71	25073.56
	0.5	26268.62	25223.16
	1.0	26200.45	25384.79
	2.0	25945.29	25715.04
Set 3	0.0	37254.73	35607.19
	0.5	37166.28	35607.19
	1.0	37060.27	35843.54
	2.0	36710.82	36308.99

TABLE IV. The result of SS problem versus different risk factors in case 2

Case 1	Risk factors (β)	Expected Profit ($)	CVaR ($)
Set 1	0.0	14714.87	13621.74
	0.5	14613.00	13730.19
	1.0	14512.26	13837.31
	2.0	14382.88	13955.78
Set 2	0.0	24515.34	23014.99
	0.5	24347.21	23201.71
	1.0	24168.65	23390.24
	2.0	23964.22	23560.45
Set 3	0.0	33024.77	30825.51
	0.5	32780.47	31175.45
	1.0	32536.74	31492.14
	2.0	32149.27	31895.14

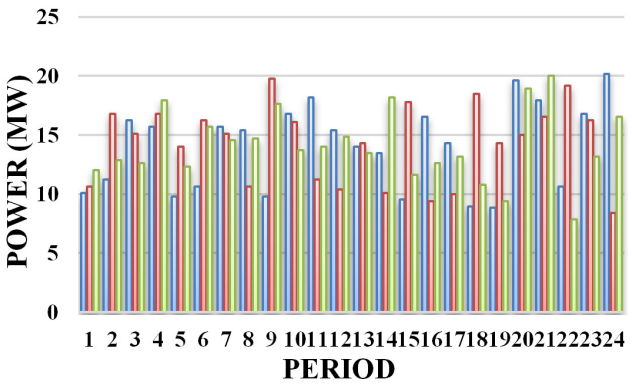


FIG. 4. Wind power scenarios for set 1.

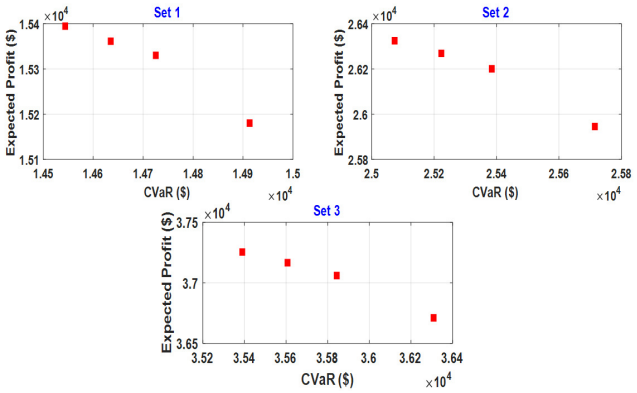


FIG. 5. Efficient frontier in case 1.

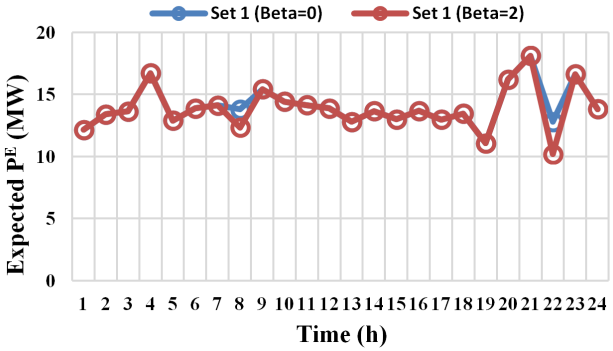


FIG. 6. Expected production bids in case 1.

expected profit reduces and as a result the CVaR will be increased which indicated the risk-averse solutions.

The expected profit versus the CVaR for different values of Beta is shown in Fig. 5. As it can be seen from this figure, the solutions with low expected profit and high CVaR indicate the low-risk solutions.

The expected production bids for case 1 pertaining to set 1 are depicted in Fig. 6. As it can be seen from this figure, only the result of self-scheduling at hours 8 and 22 depends on the risk-aversion of WPP.

The results of self-scheduling problem related to the second case are provided in Table IV. According to this table, considering the uncertainty of HILP events will make a loss in expected profit and CVaR of WPP in all sets. This fact is due to the zero power output of WPP in some scenarios. Also, the efficient frontier, representing the expected profit versus the CVaR for different values of weighting parameter β is The expected production bids of WPP in case 2 for set 1 are shown in Fig. 8. As illustrated in this figure, for the risk-neutral conditions, the expected production bids during the HILP events period will be reduced in comparison with case 1. In the risk-averse conditions ($\beta = 2$) the expected production bids at hours 3, 20 and 22 have been affected. These results show that the power producer tries to reduce its production offers during HILP events period in order to reduce the risk.

VI. CONCLUSIONS AND FUTURE WORKS

This paper proposed a new possibilistic-scenario framework for a wind power producer to specify its optimal self-scheduling in pre-disaster situations. Also, in order to take into account the risk of uncertain parameters in the proposed model, a risk-aversion methodology named conditional value-at-risk (CVaR) is considered in the model. Energy prices, wind power generation and contingency-based lack of production in the face of HILP events are the considered sources of uncertainty. The uncertainty associated with electricity prices and wind power production is modeled via scenarios. On the other hand, a possibilistic approach is implemented to take into account the uncertainty of lack of production due to HILP incidents. The proposed framework is able to consider the risk of the concurrent presence of both probabilistic and possibilistic parameters. Appropriate numerical studies are conducted to assess the impact of uncertainty sources on the SS problem. The results demonstrate the change in the production strategies in the presence of HILP events uncertainty. Further work is needed to examine the coordinated operation

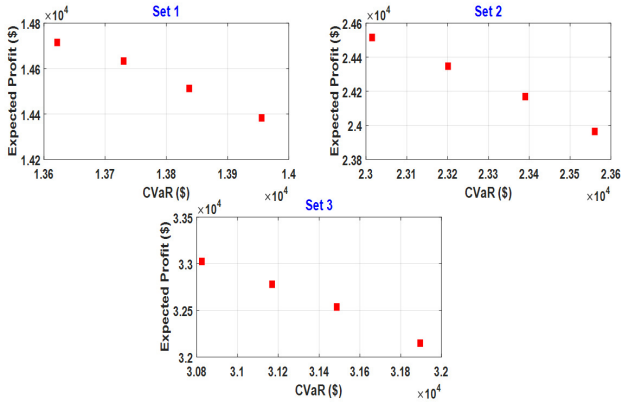


FIG. 7. Efficient frontier in case 2.

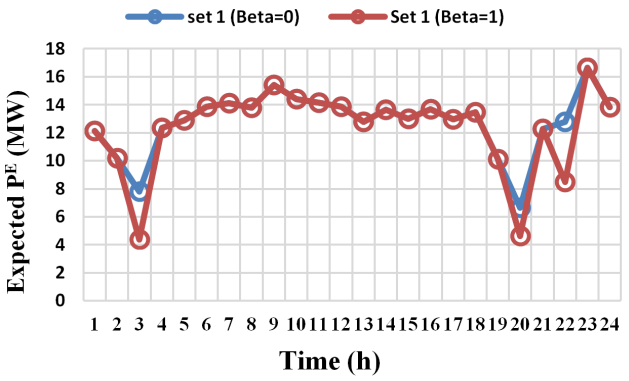


FIG. 8. Expected production bids in Case 2.

of wind power plants with other market players and producers such as energy storage and demand response resources in extreme weather events conditions. The authors acknowledge that the coordinated operation of wind power plants with other resources in this kind of conditions not only increase the expected profit of both resources, but it can potentially reduce the economic risk of WPPs in electricity markets.

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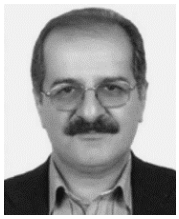


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