IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 27 April 2023, accepted 25 May 2023, date of publication 2 June 2023, date of current version 16 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3282575

RESEARCH ARTICLE

Pricing Wind Power Uncertainty in the Electricity Market

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The work of Luis Ramirez-Burgueno and Yuanrui Sang was supported in part by the UTEP University Research Institute (URI) Award.

ABSTRACT The volatile and intermittent nature of renewable energy sources (RES) has a critical impact on electric power grid operations. However, there still lacks a model to price the uncertainty of renewable energy in electricity markets. This paper aims to propose a model to quantify the impact of the uncertainty of RES on the power system operating costs in an electricity market environment considering the use of flexible ramping (FR) products, compensation for wind power curtailment, and the cost for flexible load curtailment, and thus offer a method to price the uncertainty of RES. The model is based on a stochastic optimization model for power system operations considering FR products, and the uncertainty cost is calculated by comparing the dispatch cost as well as the compensation for wind power curtailment and load curtailment with and without uncertainties. The method was implemented on a modified RTS-96 test system with a high penetration of wind energy, and the uncertainty of wind power output was represented using three different distributions, namely, Gamma, Weibull, and Rayleigh. Results show that the uncertainty of wind power increases power system operating costs, and different uncertainty modeling can affect the pricing of wind power uncertainty by up to 5%. This shows that there is a need for system operators to choose the appropriate distribution to model wind power uncertainty when pricing wind power uncertainty.

INDEX TERMS Electricity market, gamma distribution, stochastic optimization, rayleigh distribution, renewable energy sources, uncertainty price, weibull distribution, wind power.

NOMENCLATURE

Indices

b	Bus.
g	Generator.
l	Transmission Line.
s	Scenario.
seg	Segments for the piece-wise linear cost function.
t	Time.
w	Wind farms.
ϕ	Distribution Type.

Sets

NL_b^+	Transmission lines with their "to" bus connected to node n.
NL_b^-	Transmission lines with their "from" bus connected to node n.
NG_b	Generators connected to node n.
NW_b	Wind Farms connected to node n.

The associate editor coordinating the review of this manuscript and approving it for publication was Ali Raza.

Variables

C_t^d	Dispatch cost of the base case at time t.
$C_{t,\phi}^d$	Dispatch cost of distribution ϕ at time t.
P_{gt}	Real power generation of generator g at time t.
P_{gt}^{seg}	Real power generation of generator g at time t in segment seg.
$P_{wt,s}^W$	Wind generation of wind farm w in scenario s at time t.
P_t^{WC}	Total wind curtailment of the base case at time t.
$P_{wt,s}^{WC}$	Wind curtailment of wind farm w in scenario s at time t.
$P_{t,\phi}^{WC}$	Total wind curtailment of distribution ϕ at time t.

P_t^{FLC}	Total flexible load curtailment of the base case at time t.
$P_{bt,s}^{FLC}$	Flexible load curtailment of bus b in scenario s at time t.
$P_{t,\phi}^{FLC}$	Total flexible load curtailment of distribution ϕ at time t.
$PL_{lt,s}$	Real power flow through transmission line l at time t in scenario s.
SR_{gt}^D	FR down available through generator g at time t.
SR_{gt}^U	FR up available through generator g at time t.
$sr_{gt,s}^D$	FR down deployment by generator g at time t in scenario s.
$sr_{gt,s}^U$	FR up deployment by generator g at time t in scenario s.
$\theta_{1t,s}$	Voltage angle at the slack bus at time t in scenario s.
$\mu_{t,\phi}^{UNC}$	Uncertainty price of distribution ϕ at time t.

Parameters

G	Total number of generators.
P_{bt}^D	Load at bus b at time t.
P_{rate}	Rated output of the wind farm.
PL_l^{max}	Upper real power flow limit of transmission line l.
N	Number of piece-wise linear segments for the generators.
P_g^{max}	Upper generation limit of generator g.
P_g^{min}	Lower generation limit of generator g.
RD_g	Per minute ramp-down rate for generator g.
RU_g	Per minute ramp-up rate for generator g.
S	Total number of scenarios.
T	Length of investigated time period.
$P_g^{seg,max}$	Upper generation limit of generator g in segment seg.
μ_g^{seg}	Linear cost of generator g in segment seg.
μ_g^{sr}	FR deployment cost of generator g.
μ_g^{SR}	FR capacity cost of generator g.
μ_w^{WC}	Wind curtailment compensation rate for wind farm w.
μ_b^{FLC}	Flexible load curtailment compensation rate for bus b.
v	Wind speed.
$f(v)$	The frequency rate of wind speed.
v_{ci}	The cut-in speed of the wind turbine.
v_{co}	The cut-out speed of the wind turbine.
v_{rated}	The rated speed of the wind turbine.
μ	Mean value.
σ	Standard deviation.
k	Shape parameter of Weibull/Rayleigh distribution.
c	Scale parameter of Weibull/Rayleigh distribution.
α	Shape parameter of Gamma distribution.
β	Scale parameter of Gamma distribution.
Γ	The Gamma function.
$\gamma_{t,s}$	Probability of scenario s at time t.

I. INTRODUCTION

Currently, electric power generation contributes more than 30% of greenhouse emissions in the U.S. It is expected that the electricity demand will grow by 56% from 2010 to 2040 [1], raising an extended concern about the environmental impact caused by power systems. To reduce greenhouse gas emissions, the usage of renewable energy systems (RES) plays a critical role. Among different types of RES, wind energy has been leading in both growth and total consumption. In 2017, 52% of global renewable energy consumption is from wind energy, while only 21% is from solar energy. The massive increase in wind energy usage compared to other RES is mainly due to its wide availability and low cost. Wind farms can be deployed not only on land but also onshore and offshore with large capacities, thus alleviating the need for large areas of land. However, the wide usage of RES, such as wind energy, causes a challenge to power system operations due to its risks, which can compromise their economic benefits and negatively affect the reliability of the system if not addressed properly. The risks of renewable energy mainly include two aspects: variability and uncertainty. The variability of renewable energy is relatively easy to accommodate because dispatchable energy resources could be properly scheduled to accommodate the fluctuation of renewable energy supply if the fluctuations can be accurately forecasted. To accommodate the uncertainty of renewable energy, however, is a true challenge.

To mitigate the impact of the uncertainty, renewable energy output forecasting is the first step. Forecasting methods have evolved during the past years, intending to reduce error and improve accuracy. The first type of methods are physical method, which utilize mainly physical data to produce a weather and wind forecast over a period of time [2]. A more sophisticated version of physical methods includes the usage of spatial correlation models, which uses the spatial relationship of different wind speed data and physical properties. The data obtained from specific sites are used to predict the wind speed at such sites by analyzing the patterns and important parameters of such data [3], [4]. To analyze the data, statistical methods are commonly used. These methods are based on probability density functions (PDF), which can portray the patterns of future wind speed and wind power output. Wind power output scenarios can be created through Monte Carlo simulations based on the PDFs, allowing power system operators to take the uncertainty into consideration [5]. The advantage of the statistical methods is their easiness to implement, however, they have relatively large prediction errors as the forecasted time increases [6]. Facilitated by the recent development in artificial intelligence (AI), modern techniques take full advantage of the computational power to perform forecasting tasks. AI algorithms such as artificial neural networks (ANN) can detect complex nonlinear relations utilizing historical data to determine the dependence between different variables affecting the wind speed forecast with a high accuracy level [7].

Despite the improvement of renewable energy output forecasting methods, forecasting errors are unavoidable. Forecasting error is a major source of uncertainty for renewable energy. One of the most prevailing methods to address such uncertainty is to use fast-response flexible ramp (FR) [8]. FR, or "flexiramp", allows the generators to rapidly reduce their generation when the wind power supply increases and increase their generation when the wind power supply decreases. It provides the flexibility needed by power systems to accommodate the uncertainties of renewable energy resources [9], [10], [11]. California Independent System Operator (CAISO) and Midcontinent Independent System Operator (MISO) have both adopted FR to manage the variability and uncertainty caused by renewable energy in their systems [12]. The scheduling of FR can be performed using stochastic programming [9], which considers different realizations of the uncertainty, or robust programming [13], which considers the worst-case scenario of the uncertainty. Including FR in the operating schedule can induce an increase in the power system operating cost, which is an opportunity cost that could have been avoided had the FR not been scheduled. In the electricity market, this opportunity cost is often used to determine the price of ancillary services such as FR [13], [14], [15]. With the procurement of FR due to the integration of renewable energy, the operating costs of the power system will increase inevitably.

The impact of wind power uncertainty on the electricity market has been discussed in multiple studies. The impact of wind power on operating reserves is analyzed from a unit commitment and market point of view in [16] and [17]. In the case of [18], the impact of wind power uncertainty on electricity prices was examined. FR products are used to mitigate the impact of wind power uncertainty in [9], [10], [11], [12], [13], [14], [15], [19], [20], [21], and [22], using either robust optimization [13], [19], which considers the worst-case scenario, or stochastic optimization [9], [10], [19], [20], [21], which considers a number of uncertainty scenarios. Despite existing studies on the scheduling of ancillary services considering the uncertainty of wind power, there is still a gap in studying the impact of wind power uncertainty on the increase of power system operating costs, and there lacks a comprehensive approach that evaluates the prices of wind power uncertainty with a high time resolution and a large number of representative scenarios.

With the increasing penetration of wind energy, there is a growing need to quantify the impact of its uncertainty in monetary terms. This study aims to fill the above-mentioned gaps and tackle this challenging problem by proposing an approach to evaluate the impact of wind power uncertainty on the electricity market in monetary terms. Since FR products are the most commonly used ancillary service to accommodate wind power uncertainty, the proposed model is based on a power system optimization model with FR products in a stochastic optimization framework. The contributions of this paper are listed as follows:

1) A method to quantify and price wind power uncertainty is proposed based on the increases in dispatch cost as well as the compensation for wind power curtailment and load caused by the uncertainty of wind power. The wind power uncertainty prices generated from this method can provide references for electricity market operators to design new market mechanisms and incentivize wind energy builders to mitigate the impact of such uncertainties.
2) A stochastic optimization model is proposed to evaluate the impact of wind power uncertainty on FR scheduling. This model avoids producing overly conservative results for scheduling FR products while ensuring that the FR scheduling is representative to show the impact of wind power uncertainty.
3) The uncertainty of wind power generation is simulated with different models, and the impact of the wind power uncertainty modeling method on FR scheduling, and thus, the wind power uncertainty price, is analyzed.
4) The method was implemented on a modified RTS-96 test system with high penetration of wind energy and a large number of wind power scenarios from different uncertainty models. The uncertainty of wind power is priced under different uncertainty models, and results show that the proposed method can effectively price the uncertainty of wind power.

The rest of the paper is organized as follows. Section II presents the wind power uncertainty pricing model, and Section III specifies the parameters used for the case studies. Simulation results and discussion is presented in section IV, followed by the conclusions in section V.

II. THE UNCERTAINTY PRICE MODEL

The proposed uncertainty pricing model includes two steps. The first step is to optimally schedule FR in the system using a scenario-based stochastic optimization model. Using this model, the generation dispatch costs for two cases are obtained: (1) the case considering wind power uncertainty, and (2) the case that assumes wind power is accurately forecasted without uncertainty. In the second step, the difference between the generation dispatch costs obtained in the two cases is calculated, and an average cost increase induced by the uncertainty of wind power over the studied period of time is calculated, and this average cost increase is considered as the uncertainty price for wind power. The evaluation process is shown in FIGURE 1.

A. THE OPTIMAL FR SCHEDULING MODEL

The optimal FR scheduling model is based on a multi-period stochastic generation dispatch model with 5-minute intervals. This model considers a large number of renewable power gen-

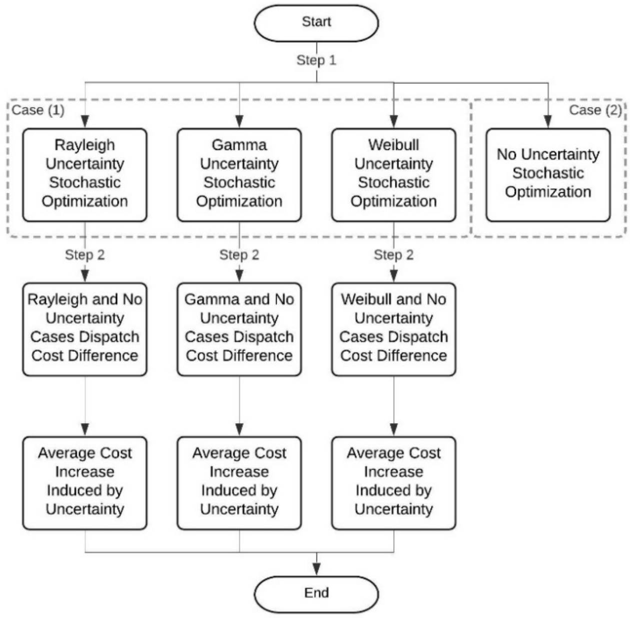

FIGURE 1. Uncertainty price model flowchart.

eration scenarios and tries to accommodate different scenarios using FR. The curtailment of renewable energy and flexible load is allowed but penalized in the objective function.

The formulation of the model is presented with Equations (1)-(16). The model objective function shown in (1) minimizes power system operating costs, including piecewise linear generation costs, FR capacity cost, FR deployment cost, as well as the penalties for wind energy curtailment and flexible load curtailment. Equations (2) and (3) are the generation constraints, (4) describes the power balance constraint at each node of the system, (5) sets the transmission line thermal limit constraints, (6) and (7) are the FR availability constraints from each generator, (8) sets the limit for flexible load curtailment, (9) sets the limit for wind power curtailment from each wind farm, (10) and (11) are the 5-minute ramping constraints for each generator, (12) is the flexible ramp up constraint for each generator, while (13) corresponds to the flexible ramp down constraint for each generator, (14) and (15) are the flexible ramp up and down deployment constraints, and (16) sets Bus 1 as the reference bus.

$$\begin{aligned} min \Bigg\{ & \sum_{t=1}^{T}\sum_{g=1}^{G}\left(\mu_g^{SR} SR_{gt}^{U} + \mu_g^{SR} SR_{gt}^{D} + \sum_{seg=1}^{N} \mu_g^{seg} P_{gt}^{seg}\right) \\ & + \sum_{t=1}^{T}\sum_{g=1}^{G}\sum_{s=1}^{S} \gamma_{t,s}\left(\mu_g^{sr} sr_{gt,s}^{U} + \mu_g^{sr} sr_{gt,s}^{D}\right) \\ & + \sum_{t=1}^{T}\sum_{b=1}^{B}\sum_{s=1}^{S} \gamma_{t,s}\left(\mu_b^{FLC} P_{bt,s}^{FLC}\right) \\ & + \sum_{t=1}^{T}\sum_{w=1}^{W}\sum_{s=1}^{S} \gamma_{t,s}\mu_w^{WC} P_{wt,s}^{WC} \Bigg\} \end{aligned} \tag{1}$$

$$P_{gt} = \sum_{seg=1}^{N} P_{gt}^{seg} \quad \forall g, t \tag{2}$$

$$0 \le P_{gt}^{seg} \le P_{gt}^{seg,max} \quad \forall g, t, seg \tag{3}$$

$$\begin{aligned} & \sum_{i \in NG_b} (P_{gt}^{seg} + sr_{gt,s}^{U} - sr_{gt,s}^{D}) \\ & + \sum_{w \in NW_b} (P_{wt,s}^{W} - P_{wt,s}^{WC}) + \sum_{l \in NL_b^+} PL_{lt,s} \\ & - \sum_{l \in NL_b^-} PL_{lt,s} = P_{bt}^{D} - P_{bt,s}^{FLC} \quad \forall b, t, s \end{aligned} \tag{4}$$

$$-PL_l^{max} \le P_{lt,s} \le PL_l^{max} \quad \forall l, t, s \tag{5}$$

$$SR_{gt}^{U} + P_{gt} \le P_g^{max} I_{gt} \quad \forall g, t \ge 2 \tag{6}$$

$$P_g^{min} I_{gt} \le -SR_{gt}^{D} + P_{gt} \quad \forall g, t \ge 2 \tag{7}$$

$$0 \le P_{bt,s}^{FLC} \le P_{bt}^{D} \quad \forall g, t \tag{8}$$

$$0 \le P_{wt,s}^{WC} \le P_{wt,s}^{W} \quad \forall w, t, s \tag{9}$$

$$P_{gt} - P_{g(t-1)} \le 5RU_g \quad \forall g, t, s \ge 2 \tag{10}$$

$$P_{g(t-1)} - P_{gt} \le 5RD_g \quad \forall g, t, s \ge 2 \tag{11}$$

$$0 \le SR_{gt}^{U} \le 5RU_g \quad \forall g, t \tag{12}$$

$$0 \le SR_{gt}^{D} \le 5RD_g \quad \forall g, t \tag{13}$$

$$0 \le sr_{gt,s}^{U} \le SR_{gt}^{U} \quad \forall g, t, s \tag{14}$$

$$0 \le sr_{gt,s}^{D} \le SR_{gt}^{D} \quad \forall g, t, s \tag{15}$$

$$\theta_{1,t,s} = 0 \quad \forall g, t, s \tag{16}$$

B. WIND POWER GENERATION UNCERTAINTY MODELING

In the stochastic FR scheduling model, the uncertainty is modeled through renewable power generation scenarios. In this study, we use wind power as an example. In order to generate the scenarios, first, the mean and standard deviation of the wind speed for each time interval is calculated based on historical wind data. Historical wind data can be obtained through different sources, and one of them is the NREL Wind Prospector [22]. Then, a desired number of wind speed scenarios can be generated through commonly used wind speed distributions, such as Gamma, Weibull, and Rayleigh. Finally, wind power generation is calculated based on the wind speed in each time interval in each scenario.

Different spatiotemporal characteristics need to be considered when selecting an appropriate PDF that properly models the region's wind speed characteristics. The most commonly used PDF in wind speed modeling is the Weibull distribution [23], [24], [25], [26], [27]. It has been used in the estimation of some wind power generation systems [28] and wind turbine failure analysis [29]. Nevertheless, Weibull is not suitable for locations with very low or very high wind speeds [26]. Meanwhile, the Gamma distribution, another widely used distribution to model wind speed [30], is suitable for very low or very high wind speeds, and regions with different underlying surfaces and climatic conditions [26]. The Rayleigh distribution is a special form of the Weibull distribution. Because it is easy to estimate the parameters of the Rayleigh distribution [26], it is also commonly used to model wind speed and evaluate the performance of wind turbines [31], [32].

The Gamma distribution is shown in Equation (17), followed by the respective Gamma shape and scale parameters, which are calculated by Equations (18) and (19), respectively [33].

$$f(v) = \frac{v^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} exp(-\frac{v}{\beta}) \tag{17}$$

$$\beta = \frac{\sigma^2}{\mu} \tag{18}$$

$$a = \frac{\mu^2}{\sigma^2} \tag{19}$$

The Weibull distribution is presented in (20). Similar to the Gamma distribution, the shape and scale parameters are calculated using the mean and standard deviation of the wind speed in Equations (21) and (22), respectively. One of the main limitations of the Weibull probability density function (PDF), as criticized by [34], is the lack of accuracy when representing probabilities of observing low wind speed values or zero wind cases.

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left(-\left(\frac{v}{c}\right)\right)^{k} \tag{20}$$

$$k = \left(\frac{\sigma}{\mu}\right)^{-1.086} \tag{21}$$

$$c = \frac{\mu}{\Gamma\left(1+k^{-1}\right)} \tag{22}$$

Lastly, the Rayleigh distribution is a special formulation of the Weibull distribution, following the same PDF as (20). Rayleigh distribution has a constant scale parameter of $k = 2$, with the only variable being the shape parameter, as Equation (23) shows. Rayleigh distribution has been widely implemented due to its easy implementation by being a single-parameter PDF [34].

$$c = \frac{2}{\sqrt{\pi}}\mu \tag{23}$$

To calculate the wind power generation according to the wind speed, Equation (24) is used [35]. The wind power generation model considers three important values: the cut-in speed, a wind speed below which will result in a zero-power output from the wind power generator, the cut-out speed, a wind speed above which will result in a zero-power output from the wind power generator, and the rated wind speed of the turbine. When the wind speed is between the rated and cut-out speeds, the wind power generator produces the rated power output.

$$P_{r,s} = \begin{cases} P_{rate}, & if\, v_{rate} \le v \le v_{co} \\ P_{rate}\dfrac{v^3 - v_{ci}^3}{v_{rate}^3 - v_{ci}^3}, & if\, v_{ci} \le v \le v_{rate} \\ 0, & otherwise \end{cases} \tag{24}$$

C. THE WIND POWER UNCERTAINTY PRICE CALCULATION

To accommodate the uncertainty of wind power, FR will be scheduled, and generation dispatch will be affected. Also, the uncertainty of wind power increases the likelihood of wind power and load curtailment. In this paper, we propose a method to evaluate the uncertainty of wind power uncertainty by comparing the dispatch costs, compensation for wind energy curtailment, and cost for load curtailment between the cases with and without uncertainty.

After the wind power generation without uncertainty and the wind power generation scenarios with uncertainty are obtained, two cases of optimal FR scheduling can be implemented using the model presented in Section III-A: (1) FR scheduling with only one scenario, the case without uncertainty, and (2) FR scheduling with a large number of wind power generation scenarios, the case with uncertainty.

First, the generation dispatch cost can be calculated as

$$C_{t,\phi}^{d} = \sum_{seg=1}^{N} \mu_g^{seg} P_{g,t}^{seg} \tag{25}$$

Then, the difference in the dispatch costs between the deterministic and uncertainty cases can be calculated as

$$\Delta C_{t,\phi}^{d} = C_{t,\phi}^{d,Case(2)} - C_{t,\phi}^{d,Case(1)} \tag{26}$$

In the end, the total uncertainty cost can be calculated by adding up the differences in generation dispatch cost, compensation of wind power curtailment, and penalty of load curtailment in the cases with and without uncertainty, as shown in Equation (27).

$$\mu_{t,\phi}^{UNC} = \Delta C_{t,\phi}^{d} + \mu_w^{WC}\left(P_{t,\phi}^{WC} - P_t^{WC}\right) + \mu_b^{FLC}\left(P_{t,\phi}^{FLC} - P_t^{FLC}\right) \quad \forall t, \phi \tag{27}$$

III. MODEL SETUP AND SPECIFICATIONS

A. TEST SYSTEM

The simulations were performed on a modified RTS-96 test system, similar to [36], with minor modifications. In this study, the original peak load values of the system were used. The system includes two 200-MW wind farms at bus 3 and 24, respectively.

B. WIND SPEED SCENARIOS

To study the impact of wind power uncertainty, 200 wind speed scenarios on a five-minute resolution were created for the duration of a day using the three wind speed distributions, Gamma, Rayleigh, and Weibull, as described in Section III-B. To generate these scenarios, the wind speed data of Taylor, TX, for the year 2012 was obtained [29], [35], [36], and the mean and standard deviation of the wind speed at each five-minute time point in January were computed. The mean and standard deviation of the wind speed at each time point was used to create 288 shape parameters c and scale parameters p (i.e., twelve 5-minute intervals each hour for 24 hours) that yielded 288 different PDFs. Using these PDFs, 200 random wind speed values were generated at each time point using the *gamrnd*, *wblrnd*, *raylrnd* functions for Gamma, Weibull, and Rayleigh PDFs, respectively, in MATLAB (version 2020a). The 200 scenarios allowed the optimization problem to cover a representative number of uncertainty cases of the wind speed.

C. WIND POWER GENERATION FOR EACH SCENARIO

With the wind speed scenarios generated in Section IV-B, the wind power output at each wind speed was calculated using Equation (24). The cut-in speed used for the model was 4 m/s, and the cut-out speed was 25 m/s. The rated wind speed was 14m/s, and the rated power output of each wind farm was 200MW. Using the 200 wind speed values for each 5-minute interval, 200 wind power output scenarios were created for every interval of the day for each PDF.

D. CONDITIONS FOR THE CASE STUDIES

In this study, case studies were carried out under five conditions:

1) Only one scenario was considered in the stochastic optimal FR scheduling problem, and wind power generation was assumed to be always zero in this scenario.
2) Only one scenario was considered, and the mean wind speed at each time point was used to generate the wind power output scenario.
3) 200 scenarios generated from the Gamma distribution were considered.
4) 200 scenarios generated from the Rayleigh distribution were considered.
5) 200 scenarios generated from the Weibull distribution were considered.

In the stochastic optimal FR scheduling model, wind power curtailment and flexible load curtailment were allowed but penalized in the objective function. The penalties for wind power curtailment and flexible load curtailment were \$30/MW and \$10,000/MW, respectively. In Conditions (i) and (ii), FR was not allowed because there was no uncertainty in the two cases.

IV. SIMULATION RESULTS

A. UNCERTAINTY ANALYSIS

To evaluate the impact of wind speed uncertainty, the deviations of wind speed from its average value were evaluated. The deviations were calculated using the wind speed of each five-minute interval during the day in Condition (iii)-(v), respectively, minus the wind speed in Condition (ii). The process was repeated for each of the 200 scenarios, creating a total of 57600 deviation entries for each of the three distributions.

The histograms in FIGURE 2 - FIGURE 4 show the normalized errors of the deviations. The normalization process was realized by dividing each individual error by the maximum absolute error of each distribution. In order to evaluate

TABLE 1. Error distribution parameters.

	μ	σ	κ	γ
Gamma	-0.0002	0.1620	3.879	0.7457
Weibull	0.0007	0.2394	2.787	0.1874
Rayleigh	-0.0886	0.1594	3.624	0.7209

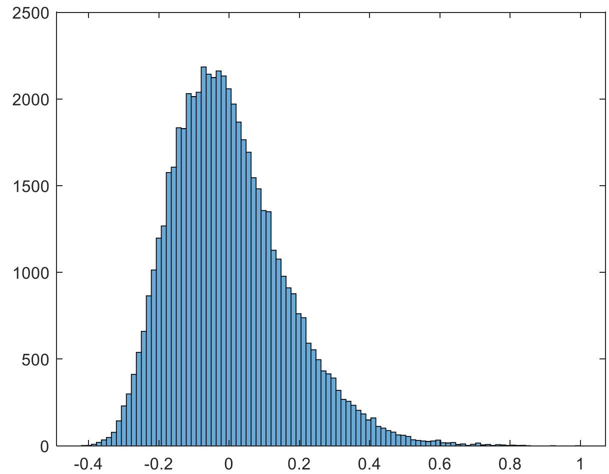

FIGURE 2. Normalized histogram of forecasted Gamma errors.

these deviations, four statistical parameters were obtained from the 57600 deviation entries from each distribution, as presented in Table 1. The four parameters are mean (μ), standard deviation (σ), kurtosis (κ), and skewness (γ).

From the results, it can be seen that the Gamma and Rayleigh distributions tend to underestimate the wind speed, while the Weibull distribution tends to overestimate the wind speed, and the standard deviations indicate that the deviations from the Gamma and Rayleigh distributions have a smaller spread and higher concentration of mass near the mean than those from the Weibull distribution. The kurtosis values indicate that the distributions of the deviations from the Gamma and Rayleigh distributions tend to have a higher peak and fatter tail than those from the Weibull distribution. The skewness of the deviations from the three distributions shows that those from the Gamma and Rayleigh distributions tend to lean toward the farther left side than those from the Weibull distribution.

B. FR CAPACITY SCHEDULING

To analyze the FR scheduling with uncertainty generated by different distributions, we calculated the averages of scheduled FR for each hour of the day considering the results from simulations carried out using load profiles in the month of January. The averages in MW are presented in FIGURE 5. The valley at hour 4 corresponds to small deviations from the average values, which could be addressed by using only a relatively small amount of FR. The spike from Hours 11-16 in the FR down curve shows that there was excessive wind energy generated during these hours from both the Gamma and Weibull distributions, which required conventional, dis-

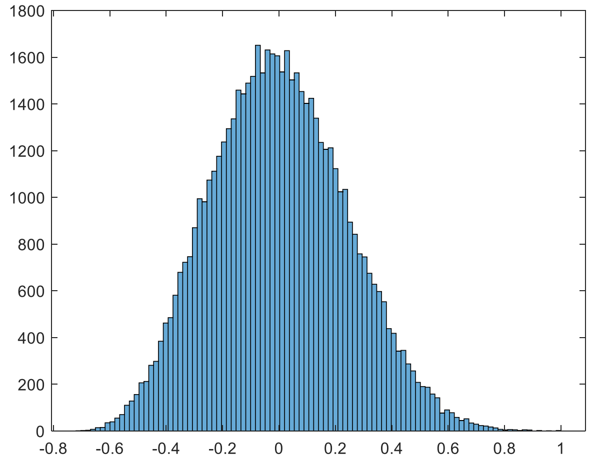

FIGURE 3. Normalized histogram of forecasted Weibull errors.

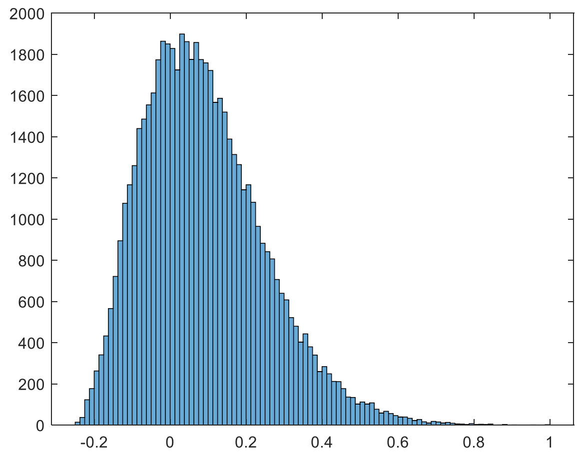

FIGURE 4. Normalized histogram of forecasted Rayleigh errors.

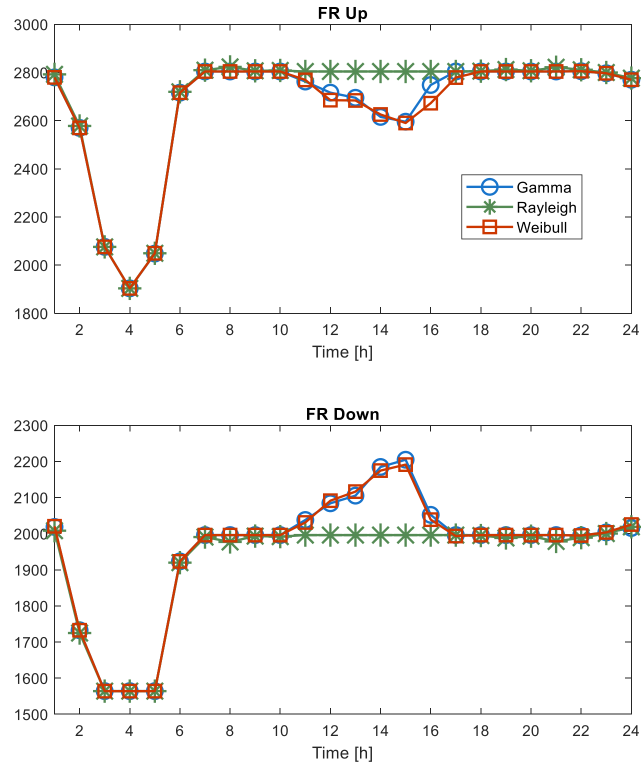

FIGURE 5. Gamma, weibull, and rayleigh FR up / FR down capacity scheduling.

patchable resources to ramp down to facilitate the integration of wind energy.

C. FR DEPLOYMENT

While FR capacity was scheduled to meet the worst-case scenario in Conditions (iii), (iv), and (v), the deployment of FR varies in each scenario. To analyze FR deployment, we calculated the average percentage of FR deployed for each hour in the day considering the 200 scenarios in an overall length of 31 days. The results are shown in FIGURE 6. Since FR deployment was co-optimized with generation dispatch, the deployment of FR is determined by several factors, such as the availability of wind energy, load profile, and generation dispatch. During night hours, with a low load level and high wind speed, downward FR was more frequently used than upward FR to address the deviations in wind speed. During the day, with a high load level and low wind speed, upward FR was more frequently used than downward FR to address the deviations in the wind speed.

D. DISPATCH COST

Since producing wind energy does not incur a fuel cost, integrating wind energy in a power system can reduce its generation dispatch cost. FIGURE 7 shows that regardless of uncertainty being present or not, the generation dispatch cost in the case with RES is lower than that without RES. By excluding the cost of FR capacity and FR deployment, the dispatch cost is slightly higher overall in cases with uncertainty. The difference in dispatch cost in the cases with and without uncertainty is calculated as a percentage of the dispatch cost without uncertainty and is shown in FIGURE 8. Positive percentages indicate that the cases with uncertainty have a higher generation cost than the case without uncertainty. As the figure shows, the average generation dispatch cost is higher in the cases with uncertainty in most hours of the day.

E. WIND POWER CURTAILMENT

The wind power that could not be integrated into the system even with the deployment of FR was curtailed in the model. The average wind power curtailment for each hour of the day is presented in FIGURE 9. The wind power curtailment in the figure was obtained from the stochastic optimization model with uncertain scenarios generated by Gamma, Rayleigh, and Weibull distributions, respectively. It can be seen from the plot that wind energy curtailment occurred at night when the wind speed was high. For the cases with uncertainty, the case with scenarios from the Rayleigh distribution had the most curtailment among the three cases, this is because the Rayleigh distribution tends to underestimate wind speed values, as Table 1 shows.

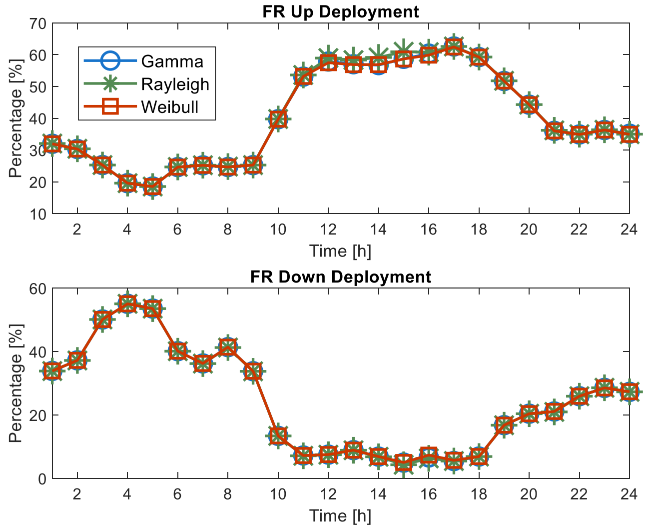

FIGURE 6. Gamma, weibull, rayleigh FR up/down deployment.

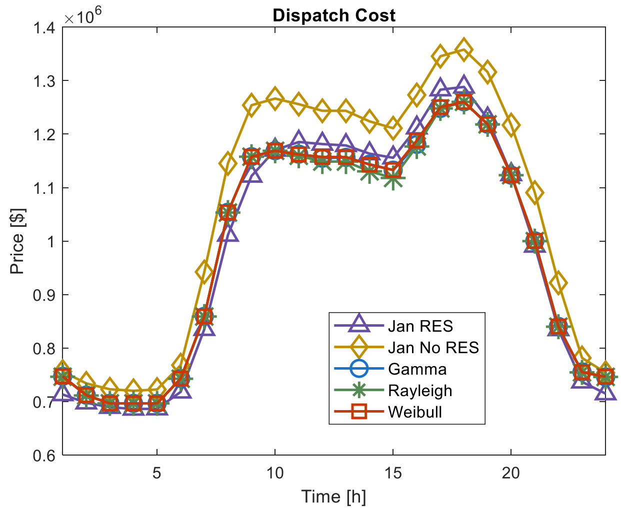

FIGURE 7. Generation dispatch cost.

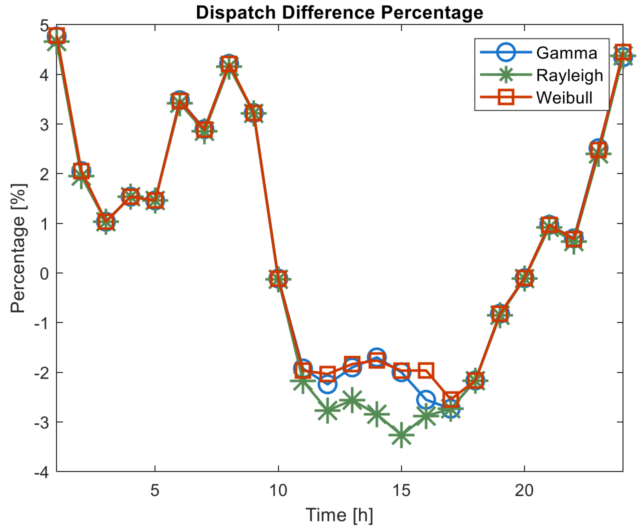

FIGURE 8. Generation dispatch percentage difference.

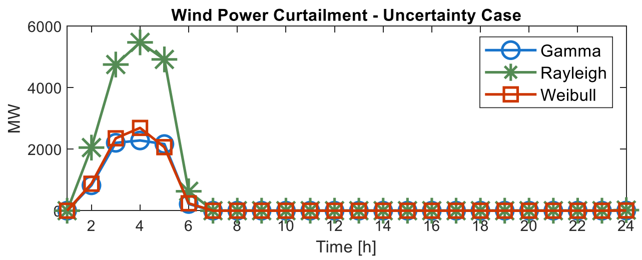

FIGURE 9. Wind power curtailment.

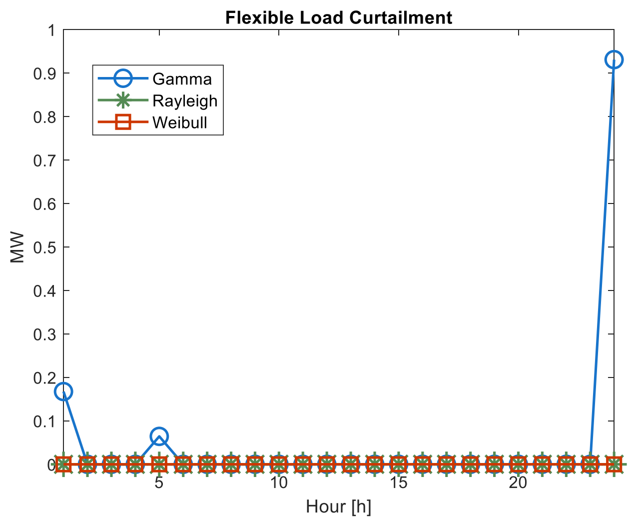

FIGURE 10. Gamma, rayleigh, and Weibull flexible load curtailment.

F. FLEXIBLE LOAD CURTAILMENT

Flexible load represents the load that could be curtailed during emergencies, such as customers who possess emergency generators and have a contract in place with the utility that allows the utility to disconnect them from the grid for a short period of time during emergencies. In the simulations implemented in this study, load curtailment is a very rare condition. The average flexible load curtailment for each hour of the day is presented in FIGURE 10. As the figure shows, load curtailment only occurred when the Gamma distribution was used to generate the scenarios and the maximum load curtailment was less than 1 MW. The load curtailment was caused by a combination of low actual wind speed and a high expectancy for the availability of wind energy.

G. UNCERTAINTY PRICE EVALUATION

As Section IV-D indicates, uncertainty increases the overall dispatch cost. In addition, the uncertainty also causes wind power curtailment and flexible load curtailment in some situations. In this study, uncertainty prices were calculated in Conditions (iii), (iv), and (v) using Equation (27) considering generation dispatch cost, compensation of wind power curtailment, and penalty of flexible load curtailment. The uncertainty prices of wind power evaluated under each distribution in each hour of the day are shown in FIGURE 11. In a further uncertainty price comparison, a daily average uncertainty price was computed for each distribution and displayed in Table 2. Results show that Rayleigh distribution

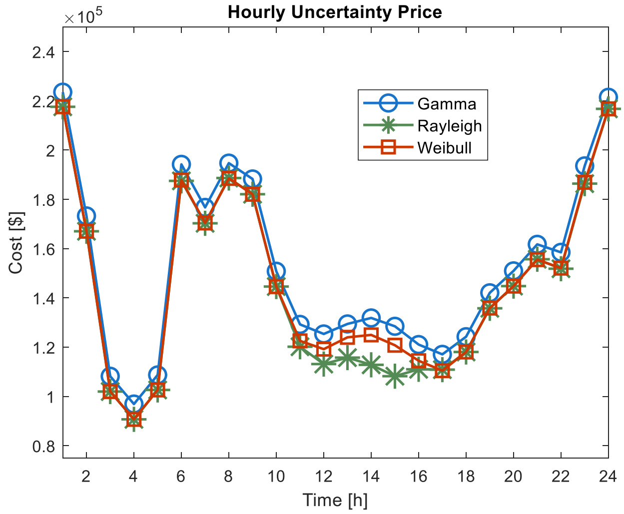

FIGURE 11. Gamma, rayleigh, and weibull hourly uncertainty price.

TABLE 2. Average daily uncertainty Price.

	$/Day
Gamma	152,098.96
Rayleigh	143,927.70
Weibull	145,825.20

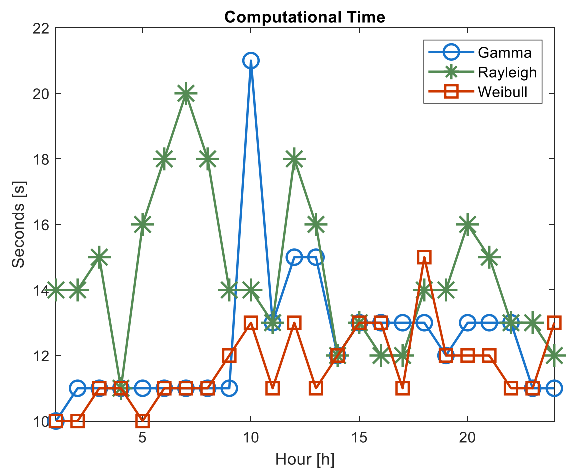

FIGURE 12. Gamma, weibull, and rayleigh computer efficiency.

induced the lowest uncertainty cost, followed by Weibull, and lastly Gamma by presenting the highest uncertainty cost.

H. COMPUTATIONAL EFFICIENCY

FIGURE 12 shows the average computational time of the FR scheduling optimization model with predetermined dispatch and reserve for each hour of the day for the whole month of January. The model was implemented using the Gurobi C++ API in the Linux Environment on a computer with an Intel Core i7-8550U processor and 16 GB of RAM. Fig. 9 shows that every FR optimization model can be solved within 21 seconds (s), with a whole average of 12.45s for Gamma, 11.67s for Weibull, and 14.46s for Rayleigh.

V. CONCLUSION AND FUTURE WORK

This paper proposes a method to evaluate the uncertainty price of wind power based on a stochastic optimization model. The model was implemented using wind speed scenarios generated from the Gamma, Weibull, and Rayleigh distributions. Results show that the model can schedule FR products to effectively address the uncertainty of wind power. Also, the uncertainty of wind power increases the generation dispatch cost, wind power curtailment, and load curtailment. Thus, the price of wind power uncertainty can be defined as the sum of the increase in generation dispatch cost, the compensation for wind power curtailment, and the penalty of load curtailment. The uncertainty prices differ by up to 5% depending on the probability distribution function used to represent the uncertainty. Thus, selecting the right method to represent the uncertainty is important for system operators. Although the uncertainty prices in the case studies were obtained for a specific test system, the proposed method can be used by any power system operators to guide policymakers and electricity market designers to incentivize the builders to reduce the uncertainty from RES. Also, the uncertainty pricing model could be solved within 15 seconds, which shows the computational efficiency of the proposed model.

For future work, we plan to further improve the computational efficiency of the method and use it for large-scale, real-world power systems. A sensitivity study on how the number of scenarios affects computational efficiency and the representativeness of the distributions will be done, and a trade-off between the computational efficiency and the representativeness of the distributions will be studied.

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