Weather-Driven Flexibility Reserve Procurement

Zhirui Liang, Robert Mieth, Yury Dvorkin, and Miguel A. Ortega-Vazquez

Abstract—The growing penetration of variable renewable energy sources (VRES) requires additional flexibility reserve to cope with the uncertainty in power system operation. Current industrial practice typically assumes a certain fraction of the VRES production forecast power as flexibility reserve, even though the VRES variability and uncertainty is a function of weather conditions. Therefore, this paper focuses on weather-driven flexibility reserve sizing and allocation for large-scale wind power installations. First, we propose a method, which generates statistically credible wind power forecast errors based on forecasts of various weather features, thus stressing a given wind power forecast. Then, these errors are mapped into a risk-based reserve requirement, which is then compared with the current extent-based and probability-based requirements. Additionally, the risk-, extent-, and probability-based reserve requirements are allocated to compare their cost and deliverability performance. Throughout the paper, we use real-world data to compute weather-driven flexibility reserve requirements and evaluate their performance using numerical experiments on a 1819-bus NYISO system model with both on- and off-shore wind power installations.

I. INTRODUCTION

In current practice, flexibility reserve to compensate variability and uncertainty of variable renewable energy sources (VRES) is usually dimensioned and allocated in an ad hoc manner under stationary assumptions, which may recognize a probabilistic nature of the VRES [1], [2] but largely ignore current ambient conditions (e.g., weather) [3]. Coupled with lacking weatherization of generation resources, overlooking weather-driven impacts on the size and allocation of flexibility reserve may lead to high-impact power outages (e.g., 2021 Texas power crisis, [4]). Furthermore, the roll-out of large-scale wind power plants, e.g., 9 GW off-shore capacity in the NYISO service territory [5], has increased the demand for flexibility reserve, which may in turn become scarce due to the recent or planned phase-out of fossil-fired units, e.g., [6]. To address these shortcomings, this paper internalizes weather data into the computation of reserve requirements and enables risk-aware flexibility reserve sizing and allocation within a day-ahead unit commitment decision process.

Existing approaches to quantify flexibility reserve requirements can be classified in two groups: (i) implicit approaches using stochastic optimization models and (ii) explicit approaches using deterministic optimization models [7]. Implicit reserve sizing approaches internalize the VRES uncertainty into a scheduling model. Some approaches rely on scenario-based stochastic programming, which solve a unit commitment problem over a set of representative scenarios and derive the optimal reserve requirement and allocation based on the scenarios and their probabilities [8]–[10]. However, the accuracy of the implicit approaches depends on the number and quality of the chosen scenarios, [11], and requires extensive computational resources [12]. To avoid scenario-based computations, robust optimization approximates the scenarios by a predefined uncertainty set [13] and derives flexibility reserve requirements to accommodate the worst-case VRES forecast error within a given set, which may increase the operating cost. To reduce the cost increase, chance-constrained optimization relaxes the robust approach by discarding some low-probability VRES outcomes [14], which may not guarantee the reserve adequacy for low-probability extreme scenarios. However, implementing the implicit reserve approaches in practice is obstructed by their incompatibility with current market structures [15], which revolves around deterministic optimization.

Explicit reserve approaches, on the other hand, determine reserve requirements exogenously, relative to the scheduling optimization, and then enforce these requirements in the scheduling optimization. Most of the current reserve procurement methods are explicit and are extent-based, i.e., the flexibility reserve should cover a certain percentage of forecast VRES power injection (or net load) [16], thus ignoring that the output and the forecast errors of VRES are not necessarily proportional. In contrast, probability-based reserve methods account for a probability distribution of the VRES output and forecast deviations on the actual system conditions. Risk-based reserve requirements overcome this gap by assessing the risk impact of each scenario, e.g., the risk of an VRES output forecast error is equal to its probability times its cost impact [7]. However, computing risk-based reserve requirements is complicated by the inability to exactly estimate future system states, which requires computationally expensive and iterative risk exploration for different reserve allocations [19].

Given current market designs and US ISO practice, it is likely that explicit reserve sizing and allocation approaches will remain the state-of-the-art for the foreseeable future. Therefore, this paper focuses on this approach while enabling a risk-aware reserve procurement based on wind power statistics. This, and similar probability-based reserve as in [8]–[11], [13], [14], [17], [18], require knowing a probability distribution of the VRES forecast error, which may not be readily available because power system operations rely on point forecasts. Probabilistic forecasts [20] have been proposed but are still not widely adopted. For example, [8] formulates the conditional distribution of wind power forecast errors using copula theory. In [17], wind power forecast errors are modeled using a Lévy α-stable distribution. Motivated by the success of probabilistic reserve quantification, [21] converts probabilistic forecasts into discrete scenarios suitable for scenario-based reserve procurement. These methods all rely on historical forecast and actual wind power data.

While analyzing historical VRES power injections is suitable for already operational wind and solar plants, such anal-
yses are not possible for planned or newly installed systems. In this case, VRES power injections and their stochastic properties must be estimated from historical weather data. A straightforward way to transfer probabilistic forecasts of weather features (e.g., wind speed) to probabilistic forecasts of VRES power is by finding a functional relationship between weather and power output (e.g., power curve for wind turbines) and apply it to the former distribution. However, this functional relationship is complicated by various non-linearities. Moreover, modelling the compound influence of multiple weather features on VRES power (which is usually ignored in practice) requires their joint distribution, which could be prohibitive since granular historical weather data is limited.

To account for the effect of weather features on the VRES power output, this paper adopts data stressing, a data science technique, that generates statistically credible VRES forecast errors that can be used to determine risk-based flexibility reserve requirements. First, instead of generating a continuous probability distribution of the VRES power output, we generate statistically credible, stressed weather scenarios and map them into VRES power scenarios accordingly. The weather scenarios are stressed by adding statistically consistent errors to the original weather forecasts using principal component analysis (PCA). Second, instead of stressing all the weather features simultaneously, which may cause unnecessarily conservative forecast errors, one feature denoted as the key stressor is stressed based on its historical distribution and other features are stressed according to its statistical properties in the original data, i.e., the correlation between different features. After obtaining these scenarios, which collectively represent a range of potential VRES power with corresponding probabilities, we can calculate the risk of each scenario and derive risk-based reserve requirements. The main contributions of this paper are:

- In contrast with [8], [11], [13], [14], [17], [18], which directly model the uncertainty of wind power, this paper models weather uncertainty, which in turn affects wind power generation. This guarantees applicability for wind farms where no historical output power data is available.
- As in [8], [17], we use conditional distributions to model wind speed uncertainty in different wind speed intervals. However, we leverage the properties of the wind power turbine curve to reduce the number of required distributions via a suitably designed transition matrix.
- We propose a risk-based reserve sizing and allocation procedure that avoids complex probability computations as in [17] by leveraging the discrete nature of our scenarios.
- We demonstrate the effectiveness of our methods on a real-world 1819-bus, New York Independent System Operator (NYISO) transmission network model and weather data. We show the proposed reserve sizing and allocation approach is compatible with existing system-wide, zonal, and nodal reserve policies, as well as contingency reserve requirements. As a result, we consider the numerical conclusions obtained in this paper to be of interest to system operators and policymakers working towards future sustainable power systems.

## II. Weather-Driven Wind Uncertainty Model

Efficient procurement of flexibility reserve, e.g., in day-ahead planning and market-clearing procedures, requires quantifying potential differences between wind power forecasts and real-time injections. Weather-based wind power forecasts are derived from wind speed, wind direction, air temperature, and air density forecasts. These features and their potential forecast errors are correlated and their compound effect on the wind power output and its forecast error must be considered. Realizing that wind speed is the key driver and thus the key stressor for available wind power, Section II-B describes a method to generate wind speed forecast errors from historical distributions. Then, Section II-C describes a method to generate forecast errors of other weather features accordingly, while maintaining the correlation between different weather features. Finally, Section II-D translates these stressed multi-feature weather scenarios into stressed wind power scenarios, which informs the reserve sizing and allocation procedure in Section III.

The application of the proposed method is illustrated using data from the planned “Empire2” Offshore Wind Power Plant in New York, USA [24], with a total capacity of 1260 MW, the individual turbine capacity of 15 MW, and the turbine hub height of 100 m (as in the turbines from the supplier selected for this project [25]). Since this wind farm is still under construction and no output power data is available, we use day-ahead forecast wind speed (1-hour resolution) and real-time wind speed (5-min resolution) at the height of 100 m from the Wind Integration National Dataset (WIND) Toolkit of NREL [26]. The WIND Toolkit also provides real-time values (5-min resolution) for 32 additional weather features, including the air pressure, humidity, temperature, and wind speed/direction at different altitudes.

### A. Weather Data for Wind Power Calculations

The output power $P_{\text{wind}}$ of a wind turbine is related to its electromechanical properties and weather conditions, i.e.,

$$P_{\text{wind}} = \frac{1}{2} \rho A_{\text{rotor}} V_{\text{wind}}^3 C_p(\lambda, \beta),$$

where $P_{\text{wind}}$ is the wind power, $\rho$ is the air density, $A_{\text{rotor}}$ is the rotor swept area, $V_{\text{wind}}$ is the wind speed, and $C_p$ is the power coefficient, which ultimately depends on the wind speed. Power coefficient $C_p(\lambda, \beta)$ denotes a recoverable fraction of the wind kinetic power into electric power, where $\lambda$ is the tip-speed ratio and $\beta$ is the blade angle [27].

The relationship between wind speed and wind power can be modeled through turbine power curves. Fig. 1 shows the normalized power curve of the NREL reference offshore wind turbine [28]. However, this method only uses wind speed at the hub height and ignores other weather features. The wind power calculation method based on power curves can be modified to include multiple weather features to better reflect the relationship between wind power and other weather conditions [29], [30]. To fully use the available weather data, we introduce two modifications to the power-curve-based method. First, instead of using a constant air density (usually set to 1.225 kg/m$^3$ [29]), we calculate air density using air temperature, air pressure, and humidity from the available data based on Eqs. (2)–(3) from [31]. Second, instead of using the
For each time step in the available data set, we create a transition matrix for wind speed forecast errors for each region. To capture this behavior, we design a two-step approach to model the distribution of wind speed forecast errors by first calculating the wind power output and more/less forecast error as wind speed intervals. We use the Python package distfit [32] to increase modeling fidelity. The y-axis of Fig. 2 itemizes these intervals. Now, each of these tuples can be assigned a transition between a wind speed intervals and regions. Using the historical data, we compute transition probability $P_{mn} = P(V^A \in \text{Region } n | V^F \in \text{Interval } m)$, $m \in \mathcal{I}$, $n \in \{I, II, III, IV\}$ by dividing the number of transitions between each $mn$-pair by the total number of transitions. These transition probabilities are organized in a transition matrix, see Fig. 2, where the value of each cell is the transition probability and the row-wise sum of transition probabilities is one. For example, if the forecast wind speed is in the interval 0–4 m/s, then the likelihood that the actual wind speed is in Regions I and II is about 61% and 39%, respectively, and the likelihood of the actual wind speed to appear in Regions III and IV is negligible.

### 2) Conditional Distributions

Whenever the probability of the actual wind speed in Region II is non-zero, we model the specific distribution of the forecast errors. First, we compute the historical wind speed forecast error as $V^A - V^F$ and then fit suitable forecast error distributions conditioned by the forecast wind speed. The resulting conditional error distributions are shown in Fig. 3 for relevant wind speed intervals. We use the Python package distfit [32] to find the best-fit functions as reported in Fig. 3.

### 3) Error Sampling

Using the transition matrix and the conditional distributions, we sample forecast errors for a given wind speed forecast. For example, assume the forecast wind speed for a time interval is 9 m/s and we want to sample 1000 wind speed forecast errors. First, as per the fourth row in the transition matrix in Fig. 2, the 1000 samples should be distributed between Regions I, II, III, and IV as 29, 957, 13, and 1, respectively. Second, the 957 points in Region II should follow the distribution in Fig. 3(d), while the points in the other three regions can be set to constant values, which we choose as 1 m/s, 20 m/s, and 30 m/s without loss of generality.

For illustration purposes, we perform a numerical experiment using data from Jan. 30, 2013. The generated wind speed forecast errors are shown in Fig. 4(a). By adding these errors to the forecast 24h wind speed profile, we obtain statistically credible real-time wind speed scenarios, which we call stressed scenarios for wind speed, as shown in Fig. 4(b). It can be seen

---

**Fig. 1.** Normalized power curve of the NREL reference offshore wind turbine [28]. Wind speeds are divided to four regions by the cut-in speed (when the blades start to rotate and generate power), rated speed (when the turbine starts to generate power at its maximum capacity) and cut-out speed (when the turbine must be shut down to avoid damage to the equipment).

**Fig. 2.** Transition matrix between forecast wind speed itemized in intervals and actual wind speed itemized in regions of the power curve (see Fig. 1).

---

**TABLE I**

| No. | Weather Feature |
|-----|----------------|
| 1   | Surface air pressure (Pa) |
| 2   | Relative humidity at 2 m (%) |
| 3   | Air temperature at 10 m (°C) |
| 4–12| Wind direction at 40, 60, 80, ..., 200 m (°) |
| 13–21| Wind speed at 40, 60, 80, ..., 200 m (m/s) |

---

wind speed at the hub height only, we use the rotor equivalent wind speed calculated from a collection of wind speeds and directions at different altitudes using Eqs. (7)–(9) from [29].

---

In total, this paper uses 21 weather features, itemized in Table I, to calculate the wind power output and more/less features could be used in practice to meet actual data availability. For example, turbulence intensity could be added to the model based on the method introduced in [29] without modifying the proposed method in subsequent sections.

### B. Stressed Scenarios for Wind Speed

We analyze wind speed for four regions (or intervals) of the non-linear wind turbine power curve shown in Fig. 1. Within Regions I, III, and IV, the power output of the turbine is independent of the exact wind speed as it is either zero (when wind speed is below the cut-in or above cut-off speed) or at the rated level. Only wind speed values in Region II require wind power calculations. Therefore, forecast wind power in day-ahead and actual wind power in real-time differ only if (i) forecast and actual wind speeds are both in Region II, (ii) forecast and actual wind speeds are in different regions. In case of (i), a small forecast error in wind speed can lead to a large error in wind power due to the cubic relationship between wind speed and wind power. In case of (ii), the wind power forecast error could be even greater, e.g., if the actual wind speed exceeds the cut-out speed and moves from Region III to Region IV.

To capture this behavior, we design a two-step approach to model the distribution of wind speed forecast errors by first modeling transition probabilities between Regions I–IV and, second, by mining a set of conditional distributions on wind speed forecast errors for each region.

#### 1) Transition Matrix

For each time step in the available data set, we create a pair $(V^F, V^A)$ of forecast and actual wind speed $V^F$ and $V^A$. While each $V^A$ is assigned its respective region of the power curve, we assign $V^F$ to higher resolution intervals
4) Discussion
The procedure above assumes that the wind speed forecast errors are only related to the forecast wind speed, while the effect of other factors, e.g., inter-temporal correlations, are ignored. This effect can be taken into account by using rolling wind speed forecasting or by quantifying statistical parameters of scenarios spanning across multiple resolutions, [22], [33].

C. Stressed Scenarios for Other Weather Features.
To keep the statistical properties of multi-feature weather data, weather features other than wind speed must be modified to match the stressed wind speed. Fig. 5 shows the correlation matrix of 21 weather features for the data from Jan. 30, 2013. The wind speeds (or wind directions) at different altitudes are positively correlated, while the wind speed and wind direction are negatively correlated. However, it is hard to stress all the weather forecast data while maintaining the correlation between different weather features due to the high dimension of this correlation matrix. Therefore, we use PCA to reduce the correlation matrix to a lower-dimensional linear relationship between the 21 weather features. With this relationship, we can generate the forecast errors of weather features other than the key stressor (in this case, the wind speed at 100 m) based on the forecast errors of the key stressor.

PCA is a statistical procedure widely used for dimensionality reduction, increasing data interpretability, and at the same time, minimizing information loss, by creating new uncorrelated variables (so-called principal components – PCs). We refer the interested reader to [34], [35] for more details on PCA. The first PC is the eigenvector of maximum variance of the original data, while the second PC represents the direction of second highest variance, and so on.

PCA is applied to the data of weather features as follows:

Step 1: Construct standardized weather data matrix $X$ with dimension $h \times p$, where $h$ is the number of time steps (hours in a day, i.e., 24), and $p$ is the number of considered weather features (21 in this paper). We normalize wind direction using the sine function, which also removes the discontinuity between 359$^\circ$ and 0$^\circ$.

Step 2: Calculate the covariance matrix of $X$ as $C = X^T X$. Note that covariance matrix $C$ of standardized data $X$ is the correlation matrix of the original data. PCA on the standardized data is also known as correlation matrix PCA [34]. Correlation matrix PCs are invariant to linear changes in units of measurement and are therefore the appropriate choice for datasets where variables have different scales [34].

Step 3: Compute the eigenvectors of $C$ and sort them in descending order of eigenvalues. The eigenvectors are referred as the PC loadings, which are the coefficients for the linear combination used to calculate individual PCs. The variance of the original data that each PC accounts for is given by its corresponding eigenvalue [35].

Step 4: Keep the first $k$ eigenvectors of $C$ ($k \leq p$) and compute reconstruction $\hat{X} = \sum_{i=1}^{k} \lambda_i V_i$, where $\lambda_i$ is the $i^{th}$ eigenvalue and $V_i$ is the $i^{th}$ eigenvector.

Step 5: Restore $\hat{X}$ to the scale of the original data by performing the inverse operation of the standardization in Step 1.
Fig. 6. Eigenvalues and eigenvectors (loadings) of the correlation matrix. (a) The eigenvalues of each PC; (b), (c) The PC loadings of the first and second PC; (d) The weighted sum of the first and second PC loading.

| Feature | Coefficient | Feature | Coefficient | Feature | Coefficient |
|---------|-------------|---------|-------------|---------|-------------|
| 1       | -15.9445    | 8       | -0.0463     | 15      | 0.9853      |
| 2       | 0.7817      | 9       | -0.0457     | 16      | 0.9824      |
| 3       | 0.6567      | 10      | -0.0455     | 17      | 0.9894      |
| 4       | -0.0521     | 11      | -0.0462     | 18      | 1.0000      |
| 5       | -0.0490     | 12      | -0.0507     | 19      | 1.0321      |
| 6       | -0.0474     | 13      | 1.0087      | 20      | 1.0771      |
| 7       | -0.0468     | 14      | 0.9976      | 21      | 1.2195      |

After that, we obtain the coefficients of a linear relationship between different weather features.

Again, for illustration, we perform this five-step procedure for the data on Jan 30, 2013. Fig. 6(a) shows the resulting eigenvalues in a descending order. We focus on the first two PCs whose corresponding eigenvalues are greater than one as per Kaiser’s rule, a common, ad-hoc rule for selecting principal components [36]. The loadings of these PCs are shown in Fig. 6(b) and (c). We observe that in the first PC, the wind speed and the wind direction are negatively correlated, while in the second PC, they are positively correlated. The combination (weighted with the corresponding eigenvalues) of the first two PCs is shown in Fig. 6(d). In total, an increase in wind speed is correlated to a “decrease” in wind direction and air pressure, and an increase in humidity and temperature.

The coefficients obtained after Step 5 are shown in Table II, which represents the linear relationship between wind speed and other weather features. For example, when the wind speed at 100 m increases by 1 m/s, the air pressure is expected to decrease by 15.9445 pa and the relative humidity is expected to increase by 0.7817 %. We use these results to generate 1000 statistically consistent scenarios for the remaining 20 weather features based on the stressed wind speeds in Fig. 4(b). Fig. 7 shows the result for four representative weather features.

D. Stressed Scenarios for Wind Power
Using the proposed method in Sections II-B and II-C, we have generated 1000 stressed weather scenarios, based on which we can calculate 1000 stressed wind power scenarios for each time period. Fig. 8 shows the stressed wind power with its confidence intervals for Jan 30, 2013. We assume that the loss due to internal and external wake effects is 15%, so the maximum output of this wind farm is 1071 MW. Due to the existence of extreme data points (e.g., when the forecast wind speed is in Region III and the actual wind speed is in Region IV), the possible distribution of stressed wind power covers the entire range between 0 and the rated power. However, when, for example, the 0.5% extreme cases are ignored, the distribution pattern of the forecast errors becomes clearer. Before hour 10 of Jan 30, 2013, although the wind speeds could be relatively low, they are distributed mostly in the “sensitive” Region II, where the wind power is proportional to the cube of the wind speed. Therefore, both positive and negative forecast errors exist, while the absolute values of the errors generally do not exceed 50% of the rated power. After hour 10 of Jan 30, 2013, the forecast wind power reaches the rated power, but forecast errors still exist due to the occasional transitions of wind speed between Region II and Region III.

III. FLEXIBILITY RESERVE SIZING AND ALLOCATION
Flexibility reserve is procured to prevent frequency excursions, load-shedding, or excessive VRES curtailment [7]. We now integrate the developed weather-driven uncertainty model into day-ahead planning using a security-constrained unit commitment (SCUC) model, which is typical for day-ahead operations of US ISOs.

A. Reserve Sizing Using Scenarios of Stressed Wind Power
We follow [7] and show the application of the weather-driven uncertainty model in Section II and the wind power scenarios it produces for deriving extent-based, probability-based, and risk-based reserve requirements.
1) Extent-Based Reserve Requirements

Extent-based reserve requirements are computed as:
\[
R_t^+ = \varepsilon P_t^F \\
R_t^- = \min \left\{ P_t^R - P_t^F, \varepsilon P_t^F \right\},
\]
where \( R_t^+ \) and \( R_t^- \) are the system-wide upward and downward reserve requirements at time \( t \), \( P_t^F \) is the day-ahead point forecast of wind power at time \( t \), \( P_t^R \) is the rated power of the wind farm, and \( \varepsilon \) is the expected extent of deviation, which is predefined by the system operator or regulatory agency.

2) Probability-Based Reserve Requirements

Probability-based reserve requirements are computed such that the probability of reserve excess or shortfall does not exceed a predefined limit. For the scenarios of stressed wind power described in Section II-D which are assumed to be uniformly distributed, we can obtain the probability-based reserve requirements as follows:
\[
R_t^+ = \max \left\{ 0, P_t^F - \tilde{P}_{0.5N(1+CI),t}^S \right\},
\]
\[
R_t^- = \max \left\{ 0, \tilde{P}_{0.5N(1+CI),t}^S - P_t^F \right\},
\]
where \( \tilde{P}_{0.5N(1+CI),t}^S \) is the \( i^{th} \) stressed wind power scenario at time \( t \) sorted from the smallest to the largest. \( CI \) is a user-defined confidence level (i.e., probability of reserve sufficiency, \( CI \in [0, 1] \)), \( N \) is the number of scenarios (\( N = 1000 \) in this paper).

3) Risk-Based Reserve Requirements

Risk-based reserve requirements are computed such that the risk of reserve excess or shortfall does not exceed a predefined limit. Risk \( \rho \) of a scenario is given as the expected loss of load caused by insufficient reserve defined as \( \rho = P \times \xi \), where \( P \) is the probability of a wind power deviation (i.e., wind power forecast error) being greater than the reserve requirement, and \( \xi \) is the extent of this deviation [7]. As \( P \) is a conditional probability, this risk calculation is not straightforward and, as discussed in [7], requires integrating over the probability density function (PDF) of the wind power forecast errors. Using the scenarios of stressed wind power in Section II-D, risk calculation does not require integration but can be performed by a simpler counter procedure shown in Algorithm 1. Leveraging the uniform scenario distribution, Algorithm 1 computes risk, i.e., the expected reserve shortfall, by iteratively reducing the reserve requirement from the most extreme scenarios and counting the number of scenarios that are not covered by the reserve after the reduction. The relative number of these scenarios times the distance from the extreme cases is the risk and the algorithm finishes once the desired risk level is reached.

Fig. 9 shows the reserve requirements resulting from Algorithm 1 for the three methods with different extent levels, confidence intervals, and risk levels. The probability-based and the risk-based reserve requirements are obtained using the stressed wind power scenarios in Fig. 8 while the extent-based reserve requirements are calculated based on the forecast wind power (black line in Fig. 8). It can be seen that before hour 10 of Jan 30, 2013, the trends of the three methods of quantifying reserve requirements are similar, i.e., both upward reserve and downward reserve are required. After hour 10 of Jan 30, 2013, only upward reserve is required for most of the time. Meanwhile, the extent-based reserve requirements are always non-zero, which is overly robust and may lead to unnecessary cost increases. The probability- and risk-based approaches relax this conservatism.

B. Reserve Allocation in SCUC Model

1) Base SCUC Model

We use the SCUC formulation from [19] as the basis for our analysis. Note that [5] considers contingency reserve, i.e., operational reserve to respond to unplanned outages of generation or transmission equipment, but it does not consider flexibility reserve in the SCUC formulation.

\[
\min \sum_{g \in G} t_{g,t} C_g^0 + u_{g,t} C_g^{SU} + v_{g,t} C_g^{SD} \tag{5a}
\]
\[
\text{s.t. } \forall t \in T:
\]

Algorithm 1: Risk-Based Reserve Sizing

input : stressed wind power \( \{ P_{i,t}^F \}_{i \in S, t \in T} \); forecast wind power \( \{ P_t^F \}_{t \in T} \); upper limit of risk \( \rho \)
output: reserve requirements \( \{ R_t^+, R_t^- \}_{t \in T} \)
begin
\[
\text{for } t \in T, i \in 1 : N \text{ do}
\]
\[
de\varepsilon^+ = \tilde{P}_{i,t}^S - \tilde{P}_{i,t}^S;
\]
\[
devi^+ = devi^+ \times (i - 1) / N;
\]
\[
devi^- = devi^- \times (N - i) / N;
\]
\[
\text{if } \text{devi}^+ \leq \rho \text{ then}
\]
\[
R_t^+ = P_t^F - \tilde{P}_{i,t}^S;
\]
\[
\text{end}
\]
\[
\text{if } \text{devi}^- \leq \rho \text{ then}
\]
\[
R_t^- = P_t^F - \tilde{P}_{i,t}^S;
\]
\[
\text{end}
\]
\[
\text{if } (\text{devi}^+ > \rho) \& (\text{devi}^- > \rho) \text{ then}
\]
\[
\text{break}
\]
\[
\text{end}
\]
\[
\text{return } \{ R_t^+, R_t^- \}_{t \in T}
\]
end
Objective (5a) minimizes the system cost using no-load costs $C_0^g$, start-up costs $C_{SU}^g$, shut-down costs $C_{SD}^g$, and piece-wise linear generator cost functions defined in (5b), where $G$ is the set of conventional generators, $O$ is the set of linear cost curve segments for conventional generators, $p_g$ is the power output of generator $g$ at time $t$, $C_{O,g}$ and $C_{1,g}$ are the constant and linear cost coefficients of the operating cost for generator $g$ in cost segment $o$, respectively. Constraints (5c)–(5r) relate binary variables $u_{g,t}$, $v_{g,t}$, and $w_{g,t}$ that denote commitment, start-up and shut-down decisions. Commitment changes are restricted by the minimum up- and down-time limits enforced in (5c) and (5d), where $D_{Tg}$ and $U_{Tg}$ are the minimum downtime (off) and the minimum uptime (on) of generator $g$. Note that it is sufficient to explicitly define $u_{g,t}$ as binary in (5c), while $v_{g,t}$ and $w_{g,t}$ are continuous within interval $[0,1]$ as in (5d). Capacity limits of generators are enforced in (5s) and (5t), where $r_g^+ = P_{g,t}^\text{max}$ is the spinning reserve provided by generator $g$ at time $t$, and $P_{g,t}^\text{max}$ and $P_{g,t}^\text{min}$ are the maximum and minimum power output for generator $g$, respectively. Constraints (5u) and (5v) enforce generator ramping limits, where $R_{g,t}^+$ is the 60-min ramp rate for generator $g$. The DC power flow equations, reference bus definition and thermal power flow limits are modeled as in (5w)–(5z), where $L$ is the set of lines, $B_{ij,t}$ is the susceptance of line $ij$, $\theta_{ij,i}$ is the voltage angle at node $i$ at time $t$. Eq. (5aa) ensures the nodal power balance by accounting for the generation, demand, and power flows at all nodes in set $N$. Here, $W$ is the set of wind farms, $P_{DA}^w$ is the day-ahead forecast wind power of wind farm $w$, $D_{DA}^w$ is the day-ahead forecast load at node $i$. Finally, (5b)–(5p) enforce contingency reserve requirements. Specifically, the total contingency reserve must cover at least the power loss in case of the largest generator outage, $R_g^D$, or a fraction $R_g^{10}$ of system demand, $P_g^{SD}$, and are limited by the 10-min ramp rate of $R_{g,t}^D$.

2) System-Wide Flexibility Reserve

We first add system-wide flexibility reserve requirements to (5), which ignores network limits and therefore may not guarantee flexibility deployment in real time, as follows:

$$\min \sum_{g \in G} t_{g,t} + u_{g,t} C_0^g + v_{g,t} C_{SU}^g + w_{g,t} C_{SD}^g$$

s.t. $\forall t \in T : (5b) - (5e), (5f) - (5l)$,

$$r_g^+ \leq R_t^D, \forall g \in G$$

$$r_g^- \leq R_t^D, \forall g \in G$$

$$u_{g,t} F_g^\text{min} \leq p_{g,t} - r_g^t, \forall g \in G$$

$$u_{g,t} F_g^\text{max} \geq p_{g,t} + r_g^t, \forall g \in G$$

$$p_{g,t} + r_g^+ - p_{g,t-1} + r_g^- \leq R_t^D u_{g,t-1} + v_{g,t} P_{g,t}^\text{min}, \forall g \in G$$

$$p_{g,t} + r_g^- - p_{g,t-1} + r_g^+ \leq R_t^D u_{g,t-1} + v_{g,t} P_{g,t}^\text{min}, \forall g \in G$$

3) Zonal Flexibility Reserve

To increase flexibility deliverability and avoid network congestion, most power systems allocate reserve requirements among zones based on their specific needs and congestion patterns. For example, the NYISO system has 11 zones and reserve requirements for different zones are defined separately [37]. Therefore, instead of system-wide reserve requirements, in the following model we consider zonal reserve requirements, where $N^A$ is the set of zones, $D_a$ is the set of loads in zone $a$, $R_{a,t}^+$ and $R_{a,t}^-$ are the upward and downward flexibility reserve requirements for zone $a$, respectively.

$$\min \sum_{g \in G^a} t_{g,t} + u_{g,t} C_0^g + v_{g,t} C_{SU}^g + w_{g,t} C_{SD}^g$$

s.t. $\forall t \in T : (5b) - (5e), (5f) - (5l), (6b) - (6g)$,

$$\sum_{g \in G^a} r_g^+ - R_{a,t}^+ + \sum_{i \in D_a} c_{a,i} D_{D,i}^a, \forall a \in N^A$$

$$\sum_{g \in G^a} r_g^- - R_{a,t}^- + \sum_{i \in D_a} c_{a,i} D_{D,i}^a, \forall a \in N^A$$

4) Nodal Flexibility Reserve

While zonal reserve requirements can avoid some congestion effects, they are typically defined in a static and long-term manner and ignore changing system conditions and intra-zonal congestion. To address this shortcoming we formulate a nodal
We model the RT scheduling procedure as:

\[ \min \sum_{g \in G} t_{g,t} + u_{g,t} c_{t,g}^D + v_{g,t} c_{t,g}^{SU} + w_{g,t} c_{t,g}^{SD} \]  

(8a)

where we assume that every wind farm is connected to one node in the system. Variables \( f_{ij,t}^+ \) and \( f_{ij,t}^− \) are the additional flows and voltage angle changes due to reserve deployment. Since we use a linear DC power flow model, the power flow and additional power flow caused by reserve deployment can be superimposed such that \( f_{ij,t}^+ + f_{ij,t}^− \) is the cumulative flow between node \( i \) and \( j \) at time \( t \) when the upward reserve is deployed.

C. Reserve Deployment in Real-time Dispatch Model

If the real-time (RT) wind power is different from the day-ahead (DA) forecast wind power, then generators need to provide upward or downward flexibility during RT scheduling. The dispatched RT flexibility of generator \( g \) at time \( t \) can be calculated as \( R_{g,t} = f_{g,t}^+ - f_{g,t}^− \), where \( f_{g,t}^+ \) and \( f_{g,t}^− \) are the output power of generator \( g \) at time \( t \) during RT and DA scheduling, respectively. We evaluate the actual reserve dispatch, \( R_{g,t} \), in terms of the scheduled reserve, \( r_{g,t}^+ \) and \( r_{g,t}^− \), in the DA stage:

- **Range I:** If \( 0 \leq R_{g,t} \leq r_{g,t}^+ + 0 \geq R_{g,t} \geq -r_{g,t}^− \), the dispatched flexibility has been scheduled at the DA stage.
- **Range II:** If \( R_{g,t} > r_{g,t}^+ \) or \( -R_{g,t} \leq r_{g,t}^− \), then the excess flexibility, i.e., \( R_{g,t} - r_{g,t}^+ \) (if \( R_{g,t} > 0 \)) or \( -R_{g,t} - r_{g,t}^− \) (if \( R_{g,t} < 0 \)), is an impromptu emergency response and has not been scheduled at the DA stage.

The cost for flexibility in Range I is assumed to be smaller or equal to the cost for flexibility in Range II to account for higher cost of very-short term changes in production levels beyond a planned interval. If the system cannot be balanced from available reserve, load-shedding or wind-spillage occurs. We model the RT scheduling procedure as:

\[ \min \sum_{g \in G} \sum_{t \in T} M_{t,g}^{RG}, M_{t,g}^{LS}, M_{t,g}^{WS}, M_{t,g}^{RD} \]  

(9a)

Subject to:

\[ \forall t \in T : \quad (5b) - (5g), (5h) - (5l) \]

\[ M_{t,g}^{RG} = \sum_{g \in G} f_{g,t} + u_{g,t} c_{g,t}^{SU} + v_{g,t} c_{g,t}^{SD} \]  

(9b)

\[ M_{t,g}^{LS} = \sum_{i \in N} D_{i,t} \]  

(9c)

\[ M_{t,g}^{WS} = \sum_{w \in W} \tilde{w}_{w,t} \]  

(9d)

where \( M_{t,g}^{RG}, M_{t,g}^{LS}, M_{t,g}^{WS}, M_{t,g}^{RD} \) are the cost of power generation, load shedding, wind spillage and re-dispatching at time \( t \), \( C_{t,g}^{RD-I}, C_{t,g}^{RD-II} \) are the real-time load, \( C_{t,g}^{WS} \) are the penalties for load shedding and wind spillage, \( c_{t,g}^{RD-I} \) and \( c_{t,g}^{RD-II} \) are the unit cost of generator \( g \) providing flexibility in Ranges I and II, respectively, \( \tilde{w}_{w,t} \) is the curtailed wind power of wind farm \( w \). In (9a), the commitment status \( (u_{g,t}, v_{g,t}, w_{g,t}) \) is a fixed parameter given by the DA SCUC results.

IV. PERFORMANCE EVALUATION

A. Data Resource and Simulation Environment

We conduct numerical experiments using a synthetic NYISO system model with 11 zones, 1819 buses, 2207 lines, 362 generators and 38 wind farms (including 33 existing onshore wind farms and 5 planned offshore wind farms that are still under construction. For this case study we use data from February 2013. As in Section II-A, we use meteorological data from the NREL WIND Toolkit [26]. Additionally, we use load data from the NYISO data platform [38]. We generate the reserve requirements for each wind farm independently and then combine them into zonal (or system-wide) reserve requirements by adding the reserve requirements in each zone (or the whole system). The penalties for load shedding and wind spillage, \( c_{t,g}^{RD-I} \) and \( c_{t,g}^{RD-II} \) are set to 10,000 $/MW and 100 $/MW [39], respectively, and the unit cost for providing flexibility \( c_{t,g}^{RD-I} \) and \( c_{t,g}^{RD-II} \) are set to 2 $/MW and 5 $/MW, which captures average regulation market prices at NYISO [40] and prioritizes the utilization of reserve that have been scheduled in the DA phase as discussed in Section III-C below. If reserve requirements can not be met, they are relaxed with a penalty of 500 $/MW corresponding to the NYISO regulation demand curve [39].

All simulations were implemented in Python v3.8 using the Gurobi solver. All experiments were performed on a standard PC workstation with an Intel i9 processor and 16 GB RAM. The average computing time for the SCUC models with system-wide, zonal, and nodal reserve requirements were about 1 minute, 4 minutes and 6 minutes, while each RT model was solved in less than 6 minutes.

B. Comparing Different Levels of Reserve Requirements

We first compare five levels of reserve requirements as in Table III based on the SCUC model in [6] with the system-
risk-based reserve performs better considering the RT load power generation cost and RT wind spillage cost, while the reserve requirements is similar considering the SCUC and RT of the extent-based, probability-based, and risk-based reserve. Since the nodal reserve corresponds to the least RT cost, we D. Comparing Extent-, Probability-, and Risk-based Reserve for the wind farms in that zone. This is because sometimes the conventional generators in a system-wide reserve to wind power forecast errors. To analyze the redispatch cost, we define upward and downward reserve activation factors $RAF^+$ and $RAF^-$ as:

$$RAF^+ = (P_{g,t}^{RT} - P_{g,t}^{DA})/r_{g,t}^{+}$$

(10)

$$RAF^- = (P_{g,t}^{DA} - P_{g,t}^{RT})/r_{g,t}^{−}$$

(11)

Recall that $P_{g,t}^{DA}$ and $P_{g,t}^{RT}$ are the outputs of generator $g$ at time $t$ during DA and RT scheduling, and $r_{g,t}^{+}$ and $r_{g,t}^{−}$ are the scheduled upward and downward reserve. These reserve activation factors reflect how much DA scheduled reserve are deployed during RT scheduling, so the higher the reserve activation factors are, the more efficient are the reserve requirements. Table V shows the resulting reserve activation factors. Both $RAF^+$ and $RAF^−$ of the risk-based reserve are the highest compared to the other two reserve types, which explains the lower corresponding redispatch cost.

V. Conclusion

In this paper we proposed an effective method to sample wind power forecast errors from weather forecasts and its historical statistics. We have leveraged properties of the wind power curve to derive conditional probability distributions for wind speed forecast errors. Using principal component analysis (PCA) we then created statistically consistent weather scenarios that include not only wind speed but also other relevant features. Second, we demonstrated how the stressed

### Table III

| Levels | Extent-based | Probability-based | Risk-based |
|--------|--------------|-------------------|------------|
| ε = 5% | CI = 20%     | ρ < 0.1 Prate    |            |
| ε = 10%| CI = 40%     | ρ < 0.2 Prate    |            |
| ε = 15%| CI = 60%     | ρ < 0.3 Prate    |            |
| ε = 20%| CI = 80%     | ρ < 0.4 Prate    |            |
| ε = 25%| CI = 99.9%   | ρ < 0.5 Prate    |            |

### Table IV

| Cost                | Extent-based | Probability-based | Risk-based |
|---------------------|--------------|-------------------|------------|
| SCUC generation cost| 303.9554     | 303.9621          | 303.9670   |
| RT generation cost  | 3885.6175    | 3885.5296         | 3885.3490  |
| RT load shedding cost| 28.1184     | 27.6284           | 26.3516    |
| RT wind spillage cost| 65.2022     | 65.1760           | 65.1902    |
| RT redispatch cost | -4.0662      | 3.9678            | 3.5985     |
| RT total cost       | 3983.0042    | 3982.3017         | 3980.4894  |

### Table V

| RAF               | Extent-based | Probability-based | Risk-based |
|-------------------|--------------|-------------------|------------|
| Upward RAF        | 2.1431       | 2.3531            | 2.3800     |
| Downward RAF      | 6.7402       | 8.2036            | 8.8925     |
| Total RAF         | 8.8832       | 10.5567           | 11.2725    |
wind power scenarios can be used for sizing and allocation flexibility reserve. We compared different reserve polices and showed an efficient approach for a risk-based quantification of reserve requirements. We have applied these methods in a case study using real-world historical weather data and a realistic model of the New York ISO power system.

REFERENCES

[1] Y. Dvorkin, D. S. Kirschen, and M. A. Ortega-Vazquez, “Assessing flexibility requirements in power systems,” IET Generation, Transmission & Distribution, vol. 8, no. 11, pp. 1820–1830, 2014.

[2] E. Ela, M. Milligan, and B. Kirby, “Operating reserves and variable generation,” National Renewable Energy Lab. (NREL), Golden, CO (United States), Tech. Rep. NREL/TP-5500-51978, 2011.

[3] R. Khattam, M. Parvania, and A. Narayan, “Flexibility reserve in power systems: Definition and stochastic multi-fidelity optimization,” IEEE Trans. Smart Grid, vol. 11, no. 1, pp. 644–654, 2019.

[4] J. W. Busby et al., “Cascading risks: Understanding the 2021 winter blackout in texas,” Energy Research & Social Science, vol. 77, p. 102106, 2021.

[5] The Official Website of New York State, “Offshore Wind Projects.” [Online]. Available: https://www.nyserda.ny.gov/All-Programs/Offshore-Wind/Focus-Areas/ny-offshore-wind-projects

[6] New York Independent System Operator. Generator Deactivation Assessment. [Online]. Available: https://www.nyiso.com/documents/20142/1396324/Cayuga1and2-Generation-Deactivation-Assessment-vFinal.pdf/9328ed90-41aa-da58-354f-d02fa755f260

[7] M. A. Ortega-Vazquez et al., “Risk-based reserve procurement,” in 2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS). IEEE, 2020.

[8] N. Zhang et al., “Modeling conditional forecast error for wind power in generation scheduling,” IEEE Trans. Power Syst., vol. 29, no. 3, pp. 1316–1324, 2013.

[9] K. Bruninx and E. Delarue, “Endogenous probabilistic reserve sizing and allocation in unit commitment models,” IEEE Trans. Power Syst., vol. 32, no. 4, pp. 2593–2603, 2016.

[10] A. Papavasiliou, S. S. Oren, and R. P. O’Neill, “Reserve requirements for wind power integration: A scenario-based stochastic programming framework,” IEEE Trans. Power Syst., vol. 26, no. 4, pp. 2197–2206, 2011.

[11] J. Dupačová, N. Gröwe-Kuska, and W. Römisch, “Scenario reduction in stochastic programming,” Math. pr., vol. 95, no. 3, pp. 493–511, 2003.

[12] A. Papavasiliou, S. S. Oren, and B. Rountree, “Applying high performance computing to transmission-constrained stochastic unit commitment for renewable energy integration,” IEEE Trans. Power Syst., vol. 30, no. 3, pp. 1109–1120, 2015.

[13] C. Ning and F. You, “Data-driven adaptive robust unit commitment under wind power uncertainty,” IEEE Trans. Power Syst., vol. 34, no. 3, pp. 2409–2418, 2019.

[14] D. Bienstock, M. Chertkov, and S. Hannett, “Chance-constrained optimal power flow: Risk-aware network control under uncertainty,” SIAM Review, vol. 56, no. 3, pp. 461–495, 2014.

[15] M. Ortega-Vazquez, “Program on technology innovation: Contingency reserve dimensioning: Status and required attributes,” Electric Power Research Institute (EPRI), Tech. Rep. 3002018762, 2021.

[16] M. Ortega-Vazquez et al., “Reserve and flexibility products to facilitate the integration of variable energy resources: A survey of recent u.s. and international experiences,” Electric Power Research Institute (EPRI), Tech. Rep. 3002013679, 2018.

[17] K. Bruninx and E. Delarue, “A statistical description of the error on wind power forecasts for probabilistic reserve sizing,” IEEE Trans. Sustain. Energy, vol. 5, no. 3, pp. 995–1002, 2014.

[18] K. Parker and P. Barooah, “A probabilistic method for reserve sizing in power grids with high renewable penetration,” IEEE Trans. Power Syst., vol. 36, no. 3, pp. 2473–2480, 2020.

[19] R. Mieth, Y. Dvorkin, and M. A. Ortega-Vazquez, “Risk-aware dimensioning and procurement of contingency reserve,” IEEE Trans. Power Syst., 2022.

[20] A. Staid et al., “Generating short-term probabilistic wind power scenarios via nonparametric forecast error density estimators,” Wind Energy, vol. 20, no. 12, pp. 1911–1925, 2017.

[21] N. Costilla-Enriquez et al., “Operating dynamic reserve dimensioning using probabilistic forecasts,” IEEE Transactions on Power Systems, 2022.

[22] Y. Dvorkin et al., “Uncertainty sets for wind power generation,” IEEE Trans. Power Syst., vol. 31, no. 4, pp. 3326–3327, 2016.

[23] Z. Pu and E. Kalnay, “Numerical weather prediction basics: Models, numerical methods, and data assimilation,” in Handbook of hydrometeorological ensemble forecasting. Springer, 2019, pp. 67–97.

[24] Empire Wind, “Empire Wind Project.” [Online]. Available: www.empirewind.com/about/project/

[25] Equinor. (2021). [Online]. Available: https://nyiso.com/news/archive/20211108-empire-wind-turbine-supplier

[26] National Renewable Energy Laboratory (NREL), “NREL Wind Integration National Dataset (WIND) Toolkit.” [Online]. Available: https://www.nrel.gov/grid/wind-toolkit.html.

[27] Y.-M. Saint-Drenan et al., “A critical review on wind turbine power curve modelling techniques and their applications in wind based energy systems,” Journal of Energy, vol. 2016, 2016.

[28] National Renewable Energy Laboratory (NREL), “Normalized power curve of a reference wind turbine.” [Online]. Available: nrel.github.io/turbine-models/WTK/Validation_offshore_normalized.html

[29] M. A. Ortega-Vazquez, “Program on technology innovation: Contingency reserve dimensioning,” IEEE Trans. Power Syst., vol. 29, no. 3, pp. 1316–1324, 2014.

[30] M. Ortega-Vazquez, “Generation of multi-resolution scenarios of stochastic variables for operation planning studies,” in 2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS). IEEE, 2022, pp. 1–6.

[31] I. T. Jolliffe and J. Cadima, “Principal component analysis: a review and recent developments,” Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, vol. 374, no. 2065, p. 20150202, 2016.

[32] D. Astolfi, “Perspectives on scada data analysis methods for multivariate wind turbine power curve modeling,” Machines, vol. 9, no. 5, 2021.

[33] C. Jung, “The role of air density in wind energy assessment—a case study from germany,” Energy, vol. 171, pp. 385–392, 2019.

[34] C. Ning and F. You, “Data-driven adaptive robust unit commitment under wind power uncertainty,” IEEE Trans. Power Syst., vol. 34, no. 3, pp. 2409–2418, 2019.