# Reserve Procurement in the New York Power Grid with Offshore Wind Farms

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*Abstract*— **The United States plans to incorporate 30 gigawatts (GW) of offshore wind (OSW) energy into its power grid by 2030. However, this expansion poses challenges to the economic and reliable grid operation due to the large power capacity and uncertainties in OSW generation as they are located within a close geographic proximity. Currently, there is a lack of research on the operating reserve requirements needed to mitigate these uncertainties for reliable grid operation. To address this gap, this study examines the operating reserve procurement needs for the New York power grid, which is expected to have 9 GW of offshore wind capacity by 2035. By using a dynamic probability of exceedance (POE) approach, this research aims to strategically procure the reserve resources to manage the forecasting uncertainties of the anticipated 9 GW OSW while minimizing the risk of loss of load in the New York power grid. The simulation results, based on real measurement data from NYSERDA Buoys, suggest that the dynamic POE configuration could potentially reduce operating reserve by nearly 12 percent overall.**

*Index Terms*—**Intermittent energy sources, renewable energy scheduling, operating reserve, quantile regression, wind-energy scheduling**

## I. INTRODUCTION

The United States is aiming to incorporate thirty gigawatts (GW) of offshore wind (OSW) resources into the power grid by Year 2030 [1], [2]. However, this rapid development of OSW is presenting difficulties for the economic and reliable operation of the grid. Each OSW project, such as Empire Wind 1 with a capacity of 800 MW, possesses a substantial amount of power, and multiple OSW farms may be situated in close geographic proximity. For instance, in New York State, it is anticipated that 9 GW OSW will be installed by 2035 and the nearby OSW farms exhibit strong, correlated generation uncertainties. To address the operational risks associated with these uncertainties in renewable energy sources, system operators are migrating from the static reserve procurement based on the largest generator contingency to the dynamic reserve concept [3].

Regional transmission organizations (RTO)/independent system operators (ISOs) in the United States have traditionally relied on static reserve modeling to procure operating reserve based on the largest generation resource in their service territory. However, this approach fails to account for real-time flow conditions of transmission lines that could potentially provide headroom for operating reserve services from the neighboring zones/systems, as well as the intermittent operation of solar and wind farms with large capacities and strong correlated uncertainties, which challenge the effectiveness of static reserve determination. In response to these challenges, the New York Independent System Operator (NYISO) has proposed the dynamic reserve concept, which is designed to procure the operating reserve based on three factors: 1) the potential loss of the largest generation resource; 2) the potential loss of transmission lines connected to the load zone of interest; and 3) the forecasting uncertainties of renewable energy sources. While the dynamic reserve concept represents a significant advancement in operating reserve procurement technology to mitigate the generation uncertainties associated with solar and wind farms, there are two understudied issues that need to be addressed. First, the POE of forecasted renewables should be strategically selected for scheduling generation resources when determining the operating reserve quantity to balance the grid operational cost and loss of load risk. Second, given the changing grid operation conditions and uncertainties associated with solar and wind farms, dynamically selecting POE may be more economical via the reduced quantity of reserved generation resources.

To examine the operating reserve requirement based on various POE curves, this study initially evaluates the reserve requirement based on scheduled or predicted intermittent generation. The probabilistic forecasting for the anticipated 9 GW OSW generation resources is based on the historical data from buoys deployed by the New York State Energy Research and Development Authority (NYSERDA) in the New York/New Jersey bight. The findings reveal that procuring the operating reserve based on a high confidence POE, such as POE 95, is extremely costly, and its cost can be up to four times that of the current practice, i.e., based on the largest contingency of losing the 1.3 GW nuclear power plants in New York [4]. To address this issue, the study proposes a recursive and anticipative model that dynamically updates the POE to account for probabilistic OSW uncertainties in determining operating reserve quantities. This approach reduces the risk of excessive unused reserve allotments and balances the system reliability need and grid operational economics when scheduling generation resources. By capturing real-time flexibility needs through dynamically modifying the operating reserve requirement, the proposed methodology is able to reduce the operating reserve quantity by up to 12% when compared against the static POE method and up to 80% when reserving for total generation during peak generation forecasts. It is worth noting that the forecasting practice for wind resources in NYISO's control room may be different from our study, we anticipate a similar level of benefit of dynamic POE for reserve procurement in New York State.

## II. PROBABILISTIC OSW GENERATION FORECASTING

First, based on actual meteorological buoy measurements, a probabilistic forecast of OSW generation is made in order to confirm the feasibility of the proposed dynamic POE selection with dynamic reserve. Based on the recent development of advanced methodologies, e.g., deep learning [5] and numerical partial differential equations [6], several approaches have been proposed for improved OSW forecasting. In this study, the quantile regression methodology is embraced due to its prevalent use in the industry for probabilistic forecasting.

### A. Offshore Wind Speed Data

The dataset under consideration in this study is derived from the Floating LiDAR Buoy Data, an initiative by NYSERDA [7]. The data specifically originates from the New York Bight region. This dataset encompasses wind speed and various meteorological factors over the course of years with varying time resolution measurements. This area is anticipated to be the site for future offshore wind energy farms, which are projected to contribute significantly to the power supply of the state of New York.

Table 1. NYSERDA LiDAR Buoy Variables Being Considered

| Variable | Units | Minimum-Maximum Value |
|---|---|---|
| Mean Horizontal Wind Speed | m/s | 0-50 |
| Mean Wind Direction | deg | 0-360 |
| Air Pressure | hPa | 600-1100 |
| Air Temperature | ℃ | (-52) - 60 |
| Relative Air Humidity | % | 0-100 |

All measurements of wind speed and direction used in this study were taken at an altitude of 158 meters above sea level. This was done to emulate the conditions at the hub height of the prospective wind turbines for the potential OSW farms [8]. Regarding the data from buoys E06 and E05, it was found that over 80 percent of the data was deemed valid. The invalid data had a negligible effect on the majority of the subsequent simulations. During the initial data collection phase, several outliers were identified as a result of the invalid data and were consequently excluded from this study.

### B. Wind Speed Forecast

To forecast future wind velocities, a multivariable quantile regression technique was employed, utilizing the sklearn quantile regression package for Python [9]. The predictive variables incorporated in this model were the historical average wind speed within the measurement interval, atmospheric pressure, temperature, and relative humidity, spanning several days. To find the optimal number of training days for accurate predictions, the model was assessed using training periods of 7, 14, 30, and 60 days. This assessment was conducted over representative days within each month present in each dataset by comparing the predicted wind speed at the 50th percentile with the actual wind speed represented in the data. The evaluation metrics used included the mean absolute error, standard deviation, variation, and correlation for both the error and the training day sets, as well as the predicted 24-hour wind speed against its actual measured values.

Table 2. Mean Absolute Error of Wind Forecast Day

| **Set #** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Training Days | 180 | 90 | 60 | 30 | 7 |
| Forecast MAE (m/s) | 20.5 | 18.4 | 6.2 | 1.4 | 3.5 |

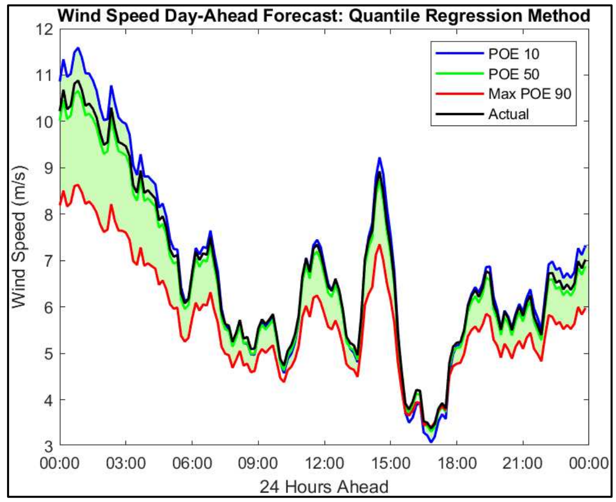


Figure 1. 24-hour Ahead Wind Speed Forecast.

The percentiles in this scenario represent the Probability of Exceedance (POE), a statistical construct that represents the probability of a process surpassing a specified value. In this context, it is defined in relation to wind speed exceeding the percentile prediction boundary which was determined through quantile regression that leverages the training data to find each instantaneous wind speed value and the data trends. For clarity, the POE 90 value indicates a 90 percent likelihood that power generation will surpass that set of values at any given time interval, just as POE 10 has a 10 percent probability that generation will exceed this value.

Based on the error analysis and the dispersion of prediction values, a standard training set duration of 30 days is utilized for each 24-hour forecast. The forecasted wind speed incorporates percentile trend lines and percent prediction intervals, which are employed to illustrate the probability of the realization of the predicted wind speed. The median of the prediction is identified as the 50th percentile, or POE 50. As depicted in Fig. 1, a 24-hour ahead-of-time average wind speed prediction in 10-minute intervals employs a 30-day training set. It can be observed in Fig. 1 that the actual average 10-minute horizontal wind speed (denoted by the black trace) aligns closely with the prediction median, POE 50, yielding a low mean error of 1.8 percent. In instances where the actual wind speed exhibits a higher error compared to POE 50, the correlation remains high, and the actual wind speed continues to fall within the 10 to 90 percent prediction interval region.

### C. Forecaasting and Probability of Exceedane

To convert from wind speed to OSW wind generation, the industry practice of the NYISO in Fig. 2 is adopted [10], in which the wind speed is converted to the percentage of nameplate power from the turbine specifications. Note that the predicted power generation in percentage of nameplate or in megawatts considers the wake effects while other factors, including electrical losses, the availability, and/or other losses due to turbine performance or environmental factors such as ice, are not incorporated.

Using the percentage of the nameplate power curve in conjunction with the forecasted wind speed, a generation prediction value is determined for each percentile, as previously discussed in the context of wind speed prediction. In Fig. 3, the three POE curves represent the predicted average 10-minute wind speed, POE 10, and POE 90 wind speed respectively which are derived through quantile regression note this is not using the wind speed from Fig. 1. All displayed values have been converted using the wind speed to percentage of nameplate power curve. The probability area for generation within a 24-hour period is represented by the shaded between the traces for POE 90, 10, and 50. The NYISO considers procuring operating reserves based on POE 95 which would lead to a large operating reserve procurement to support reliability scheduled in each dispatch interval [3], [10]. Given that the POE 50 from the wind speed prediction has the smallest mean average error, the power generation equivalent of POE 50 is utilized as the predicted scheduled power and is the currently accepted proposed variable for wind resource scheduling [10].

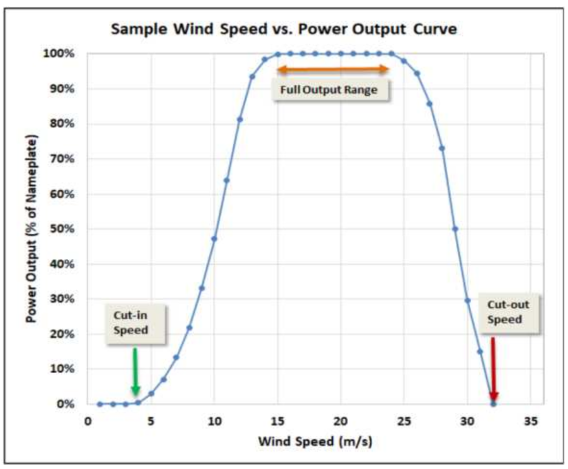


Figure 2. Sample Wind Speed vs. Power Output Curve. [8].

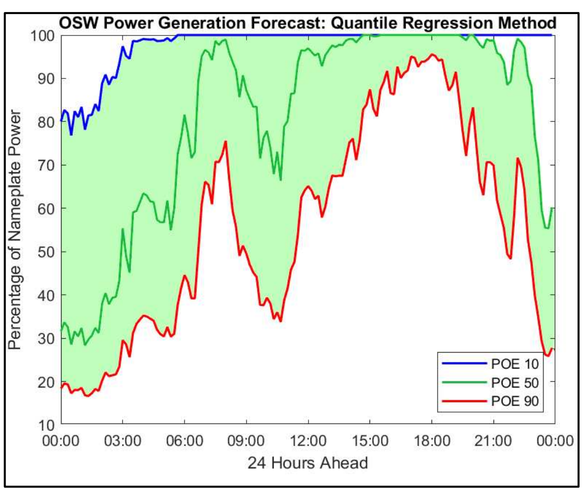


Figure 3. 24-hour Ahead Power Generation by Percentage of Nameplate Power Forecast.

## *D. Power Scheduling and Reserves*

The conversion of nameplate percentage into power units is based on the current objective of the New York State Climate Leadership and Community Protection Act (CLCPA) to achieve 9 GW of OSW generation resource by 2035 [11], and the Empire 1 and Empire 2 projects under development that aim to install Vestas 138 V236-15MW OSW turbines with a cumulative capacity of 2,610 MW [12]. This representation does not consider the impact of geographical location differences on wind speed-readings for the expected 9 GW OSW energy including the Empire 1 and Empire 2 projects. As observed in Fig. 3, the predicted generation at POE 50 can attain 100% of the nameplate rating. At a maximum power output of 2,610 MW, Empire Wind output when reserving for total generation could require the entirety of the 2.6 GW to be procured using existing reliability methods [12]. Previously proposed considerations [13] for scheduling generation and its reserves include transitioning the scheduled power to a static POE 95. In Fig. 4, using the same prediction day represented in Fig. 3, the mean predicted generation for both POE 50, POE 95, and actual wind speed are compared.

Our findings indicate that scheduling generation resources based on POE 95 of forecasted offshore wind, at its best during this prediction day, allows for just over 40 percent of nameplate capacity. This is less than half the capability presented by POE 50. If an energy schedule were to be based on the POE 95 forecast, more than half of the capability presented by the actual wind speed would be curtailed to maintain the schedule at its maximum point. An alternative method proposed for reserve procurement for OSW generation is to schedule at POE 50 and then reserve at either POE 95 (as shown in Fig. 4) or the lowest generation point of POE 95 (as depicted in Fig. 4). The average reserve requirement based on the expected generation at POE 50 is determined by comparing the difference between the reserve boundary with POE 50 at each time interval. The average reserve requirement with POE 50 scheduled, compared to the minimum point of generation at the POE 95 boundary in terms of percentage of nameplate generation capacity, exceeds 75 percent. The same measurement for only POE 95 is 63.2 percent. While there are advantages to having this level of reserves available for reliability, the scheduled reserves will result in an economic trade-off as the probability of an event is very low.

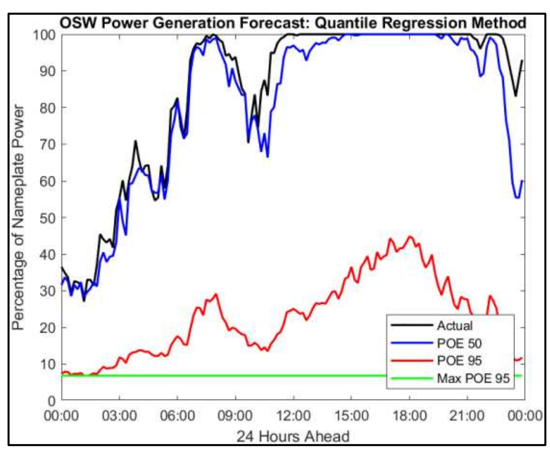


Figure 4. 24-hour Ahead Power Generation by Percentage of Nameplate Power Forecast P50, POE95, Actual, Max POE 95.

A more cost-effective approach, particularly during high-cost peak load periods, could ensure power availability using other POE reserve boundaries. Contrary to static reserves, which are procured in fixed quantities within each zone, dynamic reserves are calculated based on the most significant source contingency within a reserve region. This calculation considers the available transmission headroom, while also considering transmission contingencies. As the infrastructure for intermittent resources, such as OSW generation, continues to grow, it becomes imperative for optimization techniques for reserve scheduling to address emerging challenges. The NYISO proposes a scheduling of wind resources through POE,

$$Res_{RA_{ai}}^{30Total} \geq Mult_{RA_{ai}}^{30Total} * \left( \sum_{RA_{ai}} IPP_{Schedule_i} - \sum_{RA_{ai}} POEXX_{Forecast_i} \right) - RA_{aRes_{Capability_i}} \quad (1).$$

The POE 95 forecast is subtracted from the energy schedule of the resource to find the "at risk energy". For example, if the energy schedule were 100MW and POE 95 forecast were 50MW, then the at-risk energy would be 50MW. This is then multiplied by a reserve requirement multiplier for conservatism and then a transmission headroom is subtracted to find the resultant reserve requirement [13]. The current NYISO formulation uses a static POE which was covered previously, where having a high threshold of reliability at the proposed reserve procurement level of a static POE 95 may not be economically viable as the implementation of more OSW generation infrastructure increases, or the generation goal of 9 GW of generation comes to fruition [11]. A methodology for optimizing OSW generation reserves in terms of both grid reliability and economic efficiency is needed. This approach leverages multiple POE values over a 24-hour period to reduce reserve demand without compromising system reliability. This is achieved by utilizing the probability of OSW generation meeting or exceeding a specified distribution limit. Given that the distance between each POE megawatt value does not maintain a static distribution throughout the 24-hour period, a method is introduced that capitalizes on this variability. This method adjusts the reserve requirement POE threshold in one-to-three-hour time intervals or in each time interval based on the percentile distribution, thereby increasing available reserve resources. This dynamic POE reserve procurement process utilizes the predicted generation values at POE 50 and potential generation values at POE 80, POE 85, POE 90, and POE 95 to determine the expected reserve demand per interval. For instance, in a predicted 24-hour period, the reserve demand at each setting can be observed in Fig. 5. In Fig. 5, the 9 GW OSW generation is used to illustrate the power generation values that may need to be reserved by Year 2035. Each POE is associated with its own uncertainty factor, with the POE 80 setting having the highest level of uncertainty among the set of four values. The impact of the selected POE is contingent upon the numerical difference between the scheduled and reserved POE. The difference between POE 50 to POE 90 of Fig. 3 results in a lesser shift in reserve demands compared to a forecast with a tighter distribution. Employing POE 95 could supersede the use of POE 80 as the value of reliability found in an elevated reserve allocation and its economics outweigh the risk and economic benefit when using POE 80.

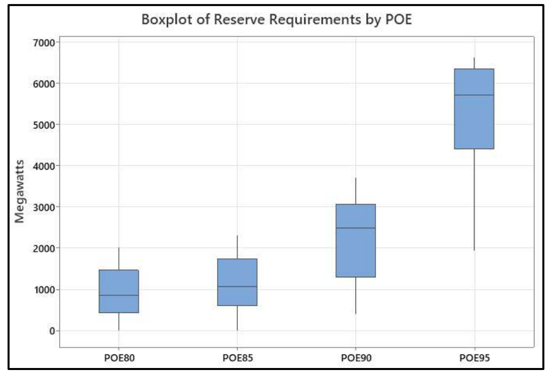


Figure 5. Boxplot of Predicted Reserve Requirements for 9 Gigawatts of offshore wind by POE with Schedule at POE 50.

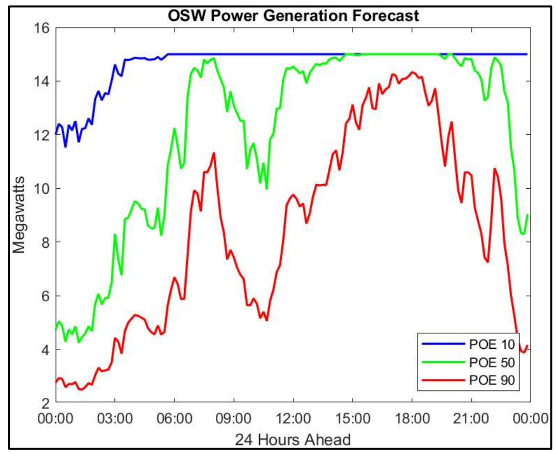


Figure 6. Power Generation Forecast of Single Vestas 138 V236-15MW.

This compares the risk assessed per POE as well as the economic viability of the necessary reserves. In scenarios where the POE distribution diverges excessively from the forecasted generation, resulting in a reserve demand that may exceed the system's capabilities despite modifying the POE boundary, the wind generation can be curtailed to a level that the system can manage. This adjustment ensures the system's behavior remains within manageable limits.

## III. PROJECTED DYNAMIC RESERVE REQUIREMENT

The adjustment of the POE reserve boundary is contingent upon the probability and its corresponding value, expressed in either MWs or as a percentage of the nameplate capacity. This process employs a base POE that modifies its position in response to the value discrepancy present within the model from adjacent POE traces. The value discrepancy serves as a set point, which can be altered based on economic factors and the associated reliability. This approach allows for dynamic adjustments to the POE reserve boundary, facilitating optimal system performance under varying conditions.

### A. Changing POE for Reserve Procurement

The difference between the set POE value and the adjacent POE values is the main deterministic factor that weighs the risk of changing the reserve procurement boundary as described in [13], [14]. $VD_{p,t}$ is a parameter for the value difference between the set base POE value, $POE_{p,t}^{BASE}$, and the $p^{\text{th}}$ adjacent POEs for the given time interval the POE above and below shown by {i-1,i+1}. Based on the value distribution in [9], POEShift is a variable derived on the sum of the distribution looking at a given set of time intervals ahead, i.e., three intervals in this study, which must be lower than the set point that is predetermined. When the value difference across the time specified is outside of the margin, the Reserve POE is set greater or lower than its current. If the value difference is still within the acceptable boundary, then the Reserve POE will remain unchanged for the coming reserve period. $Setpoint_{p,t}$ is a predetermined threshold parameter that is compared with the $VD_{p,t}$,and its outside the setting this creates the difference needed to move the reserve boundary. In the example in Fig. 7, the reserve boundary is chosen between POE 90 and POE 85 where it is seen that the boundary changes levels based on the distribution present in those time intervals.

$$VD_{p,t} = POE_{p,t}^{BASE} - POE_{p\epsilon\{i+1,i-1\},t}^{Adjacent} \tag{2}$$

$$POEShift_t = \begin{cases} 1, & Setpoint_{p,t} \geq \sum_{t_o=t+1}^{3} VD_{p,t_o} \\ -1, & -Setpoint_{p,t} \leq \sum_{t_o=t+1}^{3} VD_{p,t_o} \\ 0, & else \end{cases} \tag{3}$$

$$POE_{p,t}^{RESERVE} = POE_{p+POEShift_t,t-1}^{RESERVE} \tag{4}$$

In Fig. 7, the variable POE is depicted by the red trace. It dynamically adjusts its setting based on the difference between POE 90 and POE 85. This adjustment effectively reduces the overall reserve requirement throughout the forecasted day, a process that can be executed in real-time as the accuracy of the prediction improves. The proposed methodology is versatile and can be applied to a variety of POEs, contingent upon the degree of specificity required by the application. The threshold at which the POE will alter can also be fine-tuned based on the distribution of the forecasted days and/or factor in the reserve price or other constraints before shifting. As previously discussed, if the distribution from the scheduled POE50 to the lowest acceptable reserve POE (e.g., POE 80) is excessively large to reserve, then the schedule may be curtailed based on the distributions beneath it on the given day. This strategy facilitates the optimization of both schedule and reserve, predicated on the probability of generation realization. It encompasses both the method of reserve procurement and the potential necessity for generation curtailment.

### *B. POE Based Thereshold Procurement*

In the context of power system reliability, a threshold based on the POE is proposed. This approach emphasizes reliability by utilizing the minimum forecasted generation within a given POE reserve period as the procurement basis. As illustrated in Fig. 8, the reserve base is defined by POE 90, while the threshold is determined every three hours based on the lowest forecasted generation. This methodology can be integrated with a variable POE to mitigate risk at each POE level, thereby facilitating an adjustment to balance economic considerations. This approach provides a robust framework for maintaining system reliability while managing economic trade-offs. The proposed procurement strategy can function independently by adopting a POE of 90 or 95, as suggested in the referenced literature [13]. Alternatively, it can be integrated with the variable POE approach by selecting the minimum value from any given POE. This flexibility allows for a more comprehensive and adaptable procurement process, catering to varying system requirements and conditions.

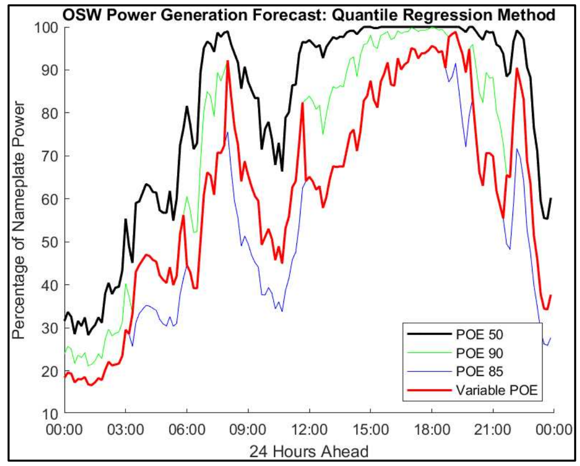

Figure 7. Variable POE Reserve Procurement Setting.

### *C. Effect of Reserve Procurement*

In the context of the Variable POE method and employing a variation difference set point below 5% of the nameplate capacity for any given time interval, it was observed that the reserve requirements were reduced on a month-to-month basis compared to a static POE setting of 90 or 95. Although this approach may compromise potential reliability, the test dates utilizing this model did not exhibit actual nameplate power generation falling below the determined POE setting, except for days that included invalid data during the training phase. The reliability faults could be resolved with the previously mentioned additional constraints and varying shift boundaries based on the predicted load profile. Table 3 illustrates the average savings in terms of percentage of nameplate capacity from three distinct time periods when using POE 90 as the set point.

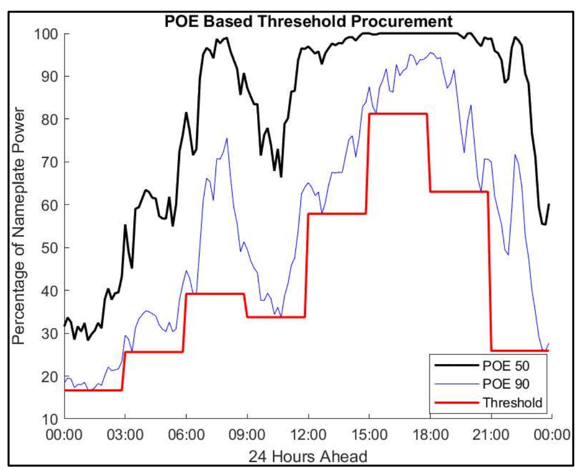

Figure 8. POE Threshold Reserve Procurement Setting.

Table 3. Mean Reserve Percentage of Nameplate Capacity POE 90 versus variable POE reserve setting.

| Test Day | Mean Reserve % at POE 90 | Mean Reserve % at Variable POE | Reserve Demand Reduction in % |
|---|---|---|---|
| 1 | 25.15 | 19.85 | 5.35 |
| 2 | 31.62 | 28.11 | 3.51 |
| 3 | 20.41 | 12.73 | 7.68 |

The decrease in reserve demand results in a reduction in economic costs and based on the actual wind speeds observed on the test periods, it provided equivalent scheduled reliability without breaching the reserve procurement boundary. Considering New York's policy goal of 9GW OSW, under the assumption of uniform performance irrespective of geographical location and efficiency differences, a variation as much as five percent translates to a potential reserve savings of 450MW. The adoption of this method may incur higher computational costs, contingent on the current prediction models in use, compared to the strategies of reserving for total generation or opting for a static POE. Reserving for total generation could lead to an exceedingly high reserve demand and economic cost, which is likely to escalate as the infrastructure expands. This could necessitate curtailing the generation based on the reserve limit or economic limit at the time, inherently forfeiting the full capability of available offshore wind generation. The advantage of a variable reserve POE, as opposed to the total generation reserve, is that a variable POE might be able to better exploit the OSW generation capability. It is not constrained by a reservation of total generation because it is predicated on the calculated probability that there will not be an unexpected total or partial generation loss within a reserve period. This provides a confident level of security while being able to supply more overall power to the grid. The concept of the static POE reserve is a straightforward method but fails to leverage the available generation prediction distributions. As can be observed, fluctuations in distribution across an hour or across 24 hours may incur a higher cost than that of a variable POE that accounts for this variability and optimizes based on it. The implementation of a variable POE introduces certain complexities, including the determination of the differential level to modify the POE, the decision-making process for curtailing, and potential impacts on system reliability that were not evident in the conducted simulations. However, the economic advantages of this approach could potentially surpass the drawbacks, particularly when juxtaposed with the reserve methodologies currently proposed within the industry.

## IV. Conclusion

The adjustment of the POE reserve limits, facilitated by monitoring the fluctuation in POE values over a 24-hour cycle, presents an opportunity to decrease reserve procurement requirement to manage OSW generation uncertainties without significantly compromising the power system's reliability. This strategy ensures that the generation probability consistently satisfies or surpasses the predetermined points, thereby improving the efficiency of wind energy production. The setpoints are determined based on the available data. The optimization of wind generation via its reserves could potentially enable increased market participation, thereby contributing to the system's sustainability and reliability as the shift away from fossil fuels persists. The outcomes of this research could have significant implications for the future of wind energy, providing more efficient and dependable wind power generation. Future enhancements of this methodology could encompass the optimization of the energy schedule, also referred to as POE 50 in preceding sections. The optimization of both the schedule curve and the reserve requirement could potentially provide additional economic benefits with reliability, while responding to the evolving load demands in both the day-ahead market forecasts and the real-time optimization horizon.

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