

Battery Energy Storage Optimization for Enabling Black Start in Offshore Wind Farms

D. Hari Krishna^{1,*}, Grandhi Sriram²

Abstract

The transition toward power systems dominated by renewable energy sources (RES) introduces significant challenges to the provision of black start services. Black start units are essential for restoring power following a system-wide outage; however, the gradual retirement of conventional generation reduces the availability of such resources, potentially compromising grid resilience. Offshore wind farms (OWFs) are increasingly considered as viable alternatives for black start support. Nevertheless, their inherent variability and intermittent power output make it difficult to satisfy technical requirements without external assistance. To address this issue, battery energy storage systems (BESSs) can be integrated with OWFs to enhance their black start capability. This paper proposes a probabilistic approach to determine the optimal BESS power rating required during black start operation. The methodology is based on technical requirements specified by the British Transmission System Operator (TSO). Wind generation is modelled using a Weibull distribution, and a worst-case scenario approach is employed to estimate the required BESS output. The results are validated through load-flow simulations, demonstrating that BESS sizing is primarily influenced by OWF capacity and TSO-defined availability requirements. Additionally, the suggested approach offers useful integration principles, lowers operational uncertainty, increases restoration reliability, and greatly increases overall system resilience during black start.

Keywords: Black start, offshore wind farm, BESS, Weibull distribution, probabilistic modeling

INTRODUCTION

In pursuit of the net-zero emission targets established under the Paris Agreement for 2050, conventional generation units are being progressively decommissioned and replaced by renewable energy sources (RES). This transition alters the dynamic characteristics of power systems, increasing operational uncertainty and, consequently, the risk of large-scale blackouts [1]. The restoration of an electrical power system following a blackout typically involves three key stages: black start, network reconfiguration, and load restoration [2]. A black start refers to the process of energizing portions of the grid and initiating power generation without relying on an external power supply. Currently, this function is predominantly performed by conventional generating units, such as thermal power plants.

However, the continued decline of such units in future RES-dominated systems is expected to limit the availability of reliable black-start providers, thereby weakening the overall system resilience.

Although renewable energy sources do not inherently possess black-start capability, offshore wind farms (OWFs) are emerging as promising alternatives owing to their large installed capacity and rapid startup characteristics [1, 3, 4]. Nevertheless, OWFs may require additional support to comply with the technical requirements specified by the transmission system operators (TSOs). In particular, the variability of wind speed

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leads to fluctuations in power output, raising concerns about the reliability and stability of OWF-based black start operations.

A practical solution to address this challenge is to integrate a battery energy storage system (BESS) with an OWF. In this context, determining the optimal BESS capacity is essential for enabling wind farms to function effectively as black-start sources, considering both technical feasibility and economic viability [2, 5, 6]. Several studies have examined BESS sizing for OWF-based black-start applications using probabilistic approaches, including combined and asymmetric probability distributions. For example, copula-based methods have been applied to model the dependency structure of wind generation and estimate the required energy storage capacity [6]. In such frameworks, a BESS is typically employed to maintain frequency stability during system energization and to smooth the power output during generator start-up. The associated optimization problem is often formulated using chance-constrained programming to minimize the capital costs. A comparable approach, with particular emphasis on sizing the energy storage system to mitigate power fluctuations during the final stage of the black start, namely, generator start-up. However, existing studies do not explicitly incorporate key technical requirements specified by TSOs, such as ensuring a minimum availability of 92% and the capability to supply a block load of at least 20 MW, as mandated by the British TSO [7].

The primary objective of this study is to determine the optimal inverter rating of a battery energy storage system (BESS) to enable an offshore wind farm (OWF) to operate in black-start mode while satisfying the availability and block load requirements specified by the National Grid Electricity System Operator (NGESO), the British transmission system operator. A probabilistic framework is proposed to achieve this. The stochastic nature of wind generation was modeled using a Weibull distribution, which was further employed to estimate the OWF power output under worst-case conditions. The remainder of this paper is organized as follows [8]: Section II presents a review of the state-of-the-art, outlines the technical requirements for black start service providers, and discusses the black start capability of OWFs supported by BESS, along with the commonly adopted sizing methodologies. Section III describes the proposed optimization framework and associated sizing procedure. Section IV provides the simulation results and discusses the key findings of this study. Finally, Section V summarizes the conclusions and highlights the directions for future research [9].

STATE OF THE ART REVIEW

Technical Requirements for Black Start

There is increasing global interest in enabling renewable energy sources (RES) to provide black-start services. However, offshore wind farms (OWFs) must satisfy stringent technical criteria to be considered viable black-start providers. Currently, these requirements are primarily defined for conventional generating units, with RES typically excluded. However, certain transmission system operators (TSOs), such as the British TSO National Grid Electricity System Operator (NGESO), have extended these requirements to include prospective RES-based solutions [5]. The key technical requirements are as follows:

- *Service availability*: TSOs specify the minimum duration for which a black-start provider must be capable of delivering the service. According to the NGESO, this availability must be at least 92% of the year [4, 9, 10]. For OWFs, whose generation is inherently dependent on wind conditions, maintaining a high level of availability is particularly challenging. The integration of a battery energy storage system (BESS) can help mitigate this limitation by providing supplementary power during periods of low-wind generation [11].
- *Block loading capability*: This requirement refers to the ability of the black start unit to supply a specified level of power demand, which is typically associated with the startup of generator units during system restoration. The NGESO mandates a minimum block load capability of 20 MW [10].
- *Resilience of supply*: Resilience Supply resilience denotes the ability of the black-start source to deliver sustained and reliable power output over a specified duration. The NGESO categorizes this requirement into two components [4]:

Table 1. Black start technical requirements specified by NGESO.

Category	Requirement
Self-start	Yes
Time to connect	≤ 2 h
Service availability	≥ 92 %
Voltage control	± 10 %
Frequency control	47.5 Hz – 52 Hz
Block load	20 MW
Black start service resiliency of supply	≥ 10 h
Black start auxiliary unit resiliency of supply	≥ 72 h
Reactive capability	≥ 100 MVar leading
Inertia value	≥ 800 MVAs
Sequential start-ups	≥ 3
Short-circuit level	240 MVA / 30 kA (<80 ms), and 10 MVA / 30 kA

1. The capability to continuously supply a defined block load for a minimum duration of 10 h represents the primary black-start resilience requirement.
2. The ability of auxiliary units to maintain or support the required output for at least 72 h ensures extended operational support during the restoration process [10].

The aforementioned requirements are of primary relevance to the present study. While the NGESO provides a comprehensive set of technical criteria for black start services, as shown in table 1 [12], this study focuses specifically on service availability, block loading capability, and supply resilience, as these factors critically influence the feasibility of OWF-based black start solutions [1].

Offshore Wind Farm Black Start Strategy with BESS

The black start process involving offshore wind farms (OWFs) supported by a battery energy storage system (BESS) can be described through four sequential stages [2, 6, 13].

1. Initialization of the wind farm,
2. Energization of transformers and transmission cables,
3. Start-up of large auxiliary equipment, and
4. Activation of the main generator unit.

During the energization of transformers and transmission lines, switching from no-load to full-load conditions may result in a significant overvoltage. To prevent turbine tripping and ensure stable operation, this stage requires appropriate reactive power compensation.

The problem of sizing the BESS to enable an OWF-based black start capability can be decomposed into three sub-problems, as follows [2]:

Sub-Problem 1

- *Wind farm start-up:* Wind turbines are not inherently self-starting and therefore require an external power source for their initialization. In this context, the BESS can act as a self-start unit by supplying the necessary active power to initiate the OWF operation.

Sub-Problem 2

- *Start-up of auxiliary systems:* This stage involves energizing large auxiliary equipment, which typically comprises double squirrel-cage induction machines in conventional power plants. The start-up of such machines can introduce voltage dips and frequency deviations in the grid. Reactive power compensation devices such as VAR compensators can be employed to mitigate voltage disturbances. Meanwhile, the BESS-supported OWF can rapidly restore the system frequency, thereby maintaining stability throughout the process.

Sub-Problem 3

- *Generator start-up:* The final stage concerns the start-up of the main generating unit, which requires a stable and continuous power supply to initiate the generator. In this phase, the BESS functions as an energy buffer, smoothing the fluctuating output of the OWF and ensuring a consistent power supply for successful generator synchronization.

The optimal sizing problem of the BESS can be formulated as follows:

$$P_{BESS} = \max \{P_1, P_2, P_3\}$$

$$E_{BESS} = E_1 + E_2 + E_3$$

where: The powers required for subproblems 1, 2, and 3 is P_1 , P_2 and P_3 . The capacities required for sub-problems 1, 2, and 3 are E_1 , E_2 and E_3 .

The required BESS power rating for sub-problems 1 and 2 is comparatively lower than that required for sub-problem 3 [2, 6]. Similarly, the energy capacities associated with sub-problems 1 and 2 are smaller than that required for sub-problem 3. Therefore, the power and energy requirements corresponding to sub-problem 3 can be considered as the governing criteria for determining the overall BESS size required to enable the OWF-based black-start capability.

In general, the formulation of the BESS sizing problem for black-start applications [2, 6] must account for the following key aspects:

1. The ability of the black-start source to deliver a stable and continuous power output over a specified duration to support block loading.
2. It can maintain the system frequency and voltage within acceptable limits during the restoration process.

To ensure a stable power supply during block loading, the fluctuating output of a wind farm must be smoothed adequately. Furthermore, issues such as frequency deviations and voltage dips typically arise during the start-up of wind turbines and large auxiliary equipment. Once sufficient power is generated and system stability is restored, additional non-black-start generating units can be gradually brought online to support the overall restoration process.

BESS Sizing Methods

Various approaches have been proposed in the literature to determine the optimal size of battery energy storage systems (BESS). The selection of an appropriate BESS size can be based on economic criteria aimed at minimizing total investment and operational costs or on technical criteria that ensure compliance with the required system performance standards, independent of cost considerations [14, 15]. The principal methodologies employed for BESS sizing are summarized below [14]:

- *Probabilistic methods:* Probabilistic techniques are widely adopted for BESS sizing in systems characterized by uncertainty, particularly those involving renewable energy sources (RES). These approaches typically model the stochastic behavior of RES using suitable probability distributions, such as the Weibull distribution for wind energy data. Based on this representation, multiple scenarios were generated to capture the variability of the underlying random processes. The use of a large number of scenarios offers two key advantages: it reduces the inaccuracies associated with deterministic forecasting and ensures a representative distribution of possible operating conditions. The resulting scenarios can be directly utilized to estimate the required BESS size or incorporated into stochastic optimization frameworks for a more refined analysis [15].
- *Analytical methods:* Analytical approaches have also been extensively applied in power system studies for BESS sizing. These methods rely on the iterative evaluation of system performance based on predefined input parameters and operating conditions. The sizing process is guided by performance indicators, which may include economic measures such as the net present value

(NPV) and technical metrics such as system frequency and voltage profiles. Analytical techniques have been employed in microgrid applications to determine the optimal BESS capacity required for frequency regulation by maintaining the balance between generation and demand [11].

- *Mathematical optimization methods*: These strategies are commonly used in electrical markets, including day-ahead and intraday markets, to improve system performance. The BESS size can be expressed as a linear problem (LP) or mixed-integer linear problem (MILP), with the objective function of minimizing battery cost or maximizing system profit within technological constraints. Professional software with optimization capabilities is required to determine the ideal solution based on the problem constraints [16].
- *Heuristic approaches*: These include nature-inspired methods such as Particle Swarm Optimization (PSO) and genetic algorithms (GA) [11]. Given the uncertain nature of the black start problem due to OWF production, a probabilistic technique is preferred.

BESS OPTIMIZATION METHODOLOGY

This section adopts a probabilistic framework to estimate the BESS power rating required for black-start support. The proposed approach relies on historical offshore wind generation data. In this study, the wind farm output is represented using the capacity factor of offshore wind generation in the United Kingdom, expressed in per unit (p.u.) [17]. The capacity factor is defined as the ratio of actual offshore wind energy production to the total installed offshore wind capacity in Great Britain [7]. The wind power output was calculated by multiplying the obtained capacity factor with the rated capacity of the considered OWF (in MW). The required BESS power rating is determined by evaluating the difference between the specified block-load demand and the corresponding wind power generation. To ensure a reliable black-start operation, the estimation must account for the worst-case wind generation conditions.

Cumulative Data Analysis

The wind generation profile was analyzed using statistical methods to capture its inherent variability. In this study, Weibull distribution was employed to model the fluctuations in wind generation. Based on this distribution, synthetic datasets were generated to represent a wide range of possible operating conditions. Subsequently, both historical and synthesized data were used to determine the 92% confidence level of wind power generation. This implies that there is a 92% probability that the available wind power will exceed the calculated threshold, whereas an 8% probability corresponds to lower generation levels, representing the worst-case scenario. This approach ensures that the required BESS capacity satisfies the availability criterion during block loading.

Figure 1 illustrates the variability in wind power output resulting from fluctuations in wind conditions. To accurately quantify the confidence level under worst-case scenarios, wind generation must be represented by an appropriate statistical distribution. The Weibull distribution is widely recognized for modeling wind characteristics and was selected in this study because of its strong fit with the historical wind generation data reported in [17, 18].

To estimate the parameters of the Weibull distribution, the probability density function (PDF), cumulative distribution function (CDF), and inverse cumulative distribution function (ICDF) were evaluated. The PDF of the Weibull distribution [9] is expressed as

$$W(x, a, b) = \left(\frac{b}{a}\right) * \left(\frac{x}{a}\right)^{b-1} * e^{-\left(\frac{x}{a}\right)^b}$$

where a denotes the scale parameter (0.415 p.u.), b represents the shape parameter (1.6), and x corresponds to the wind generation data expressed in the per unit.

Figure 2 illustrates the fitted PDF curve corresponding to the historical wind generation data set.

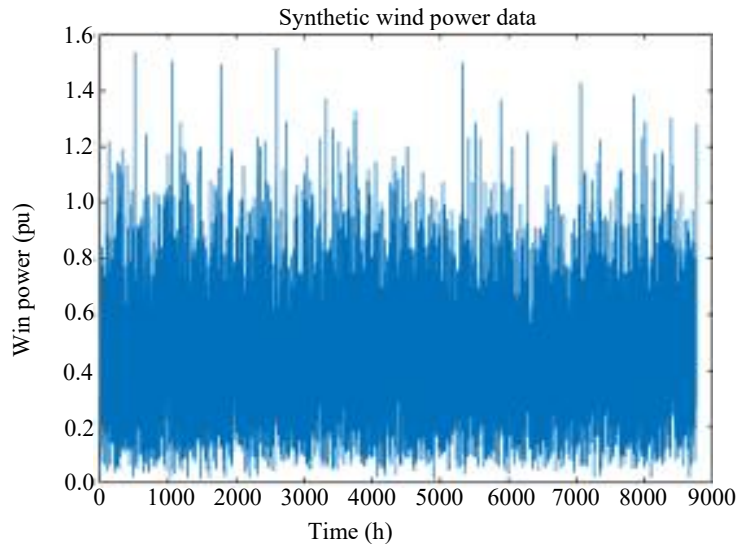


Figure 1. Historical offshore current wind generation.

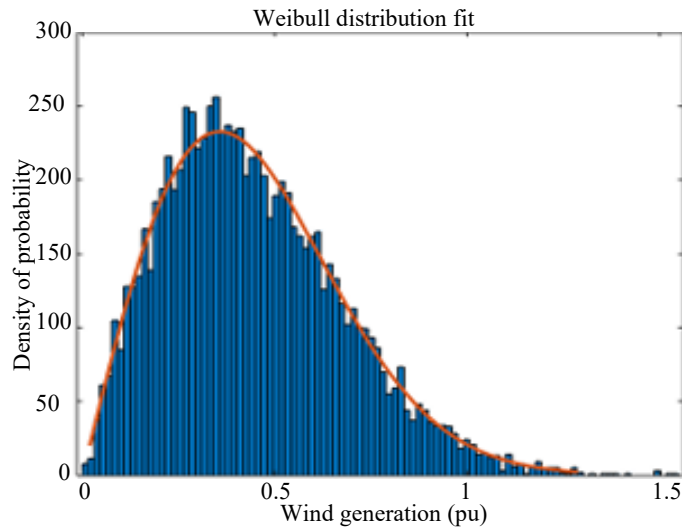


Figure 2. Data fitting by Weibull distribution.

The PDF describes the probability density associated with each value of x , thereby enabling an assessment of how well the Weibull distribution represents the observed wind generation behavior. The CDF and ICDF were subsequently employed to quantify wind generation probabilities. The CDF(x) for the Weibull distribution [9] is mathematically defined as

$$p(x, a, b) = 1 - e^{-\left(\frac{x}{b}\right)^a}$$

where $p(x, a, b)$ represents the probability that a random variable drawn from the Weibull distribution lies within the interval $[0, x]$.

Figure 3 compares the CDF obtained from the historical data with the corresponding Weibull-based CDF. The horizontal axis represents wind generation per unit, whereas the vertical axis indicates the cumulative probability ranging from 0 to 1. The CDF provides the likelihood that wind generation is less than or equal to a specified value. Accordingly, the confidence level associated with a given generation value can be expressed as:

$$\text{Confidence}(x) = 1 - p(x)$$

The ICDF of the Weibull distribution was used to estimate wind generation corresponding to a specified confidence level. The ICDF is given by

$$x = F^{-1}(p, a, b) = -a [\ln(1 - p)]^{1/b}$$

Figure 4 demonstrates the correspondence between the ICDF derived from the Weibull distribution and historical dataset. The ICDF enables the determination of wind generation values associated with specific probability levels, thereby facilitating the identification of worst-case generation conditions.

$$\text{ICDF}(p) = x$$

Synthesis Data Generation

Synthetic wind generation data were generated using the estimated Weibull parameters (a, b), which characterize the scale and shape of the distribution derived from historical data. In this study, synthetic data were produced using the MATLAB function random (Pd, S, N), where Pd represents the Weibull probability distribution object.

Parameter S denotes the number of scenarios, indicating the number of iterations performed, whereas N represents the number of generated wind power generation samples in each scenario. Thus, the function requires three inputs: the Weibull distribution parameters (a, b), number of samples N, and number of scenarios S.

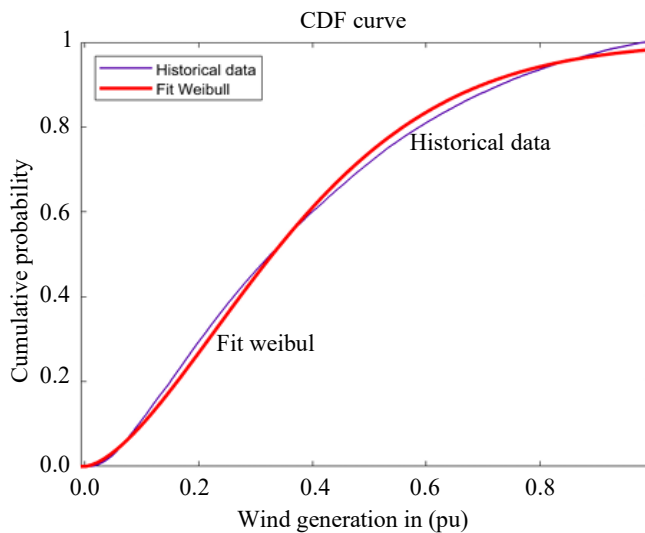


Figure 3. Cumulative distribution function curves: historical data versus Weibull distribution.

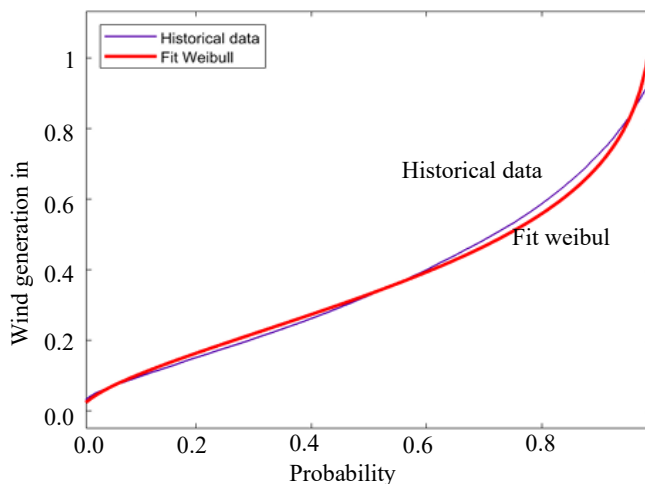


Figure 4. Inverse cumulative distribution function curves: historical data versus Weibull distribution.

Figure 5 illustrates the effect of varying the number of scenarios on the resulting probability distributions. Increasing the number of scenarios improves the representation of the wind generation profile and reduces inaccuracies in estimating the worst-case conditions. The distributions generated using 100 and 1000 scenarios closely approximate the Weibull distribution, whereas smaller scenario sets (e.g., 1 or 10) exhibit noticeable deviations. Because the distributions for 100 and 1000 scenarios are nearly identical, $N=100$ is selected for this study.

Figure 6 presents a comparison of the CDF and ICDF curves obtained from the synthesized data against the Weibull distribution. The results indicate that the use of synthetic data leads to reduced estimation errors compared to the reliance on historical data alone, thereby improving the accuracy of the probabilistic analysis.

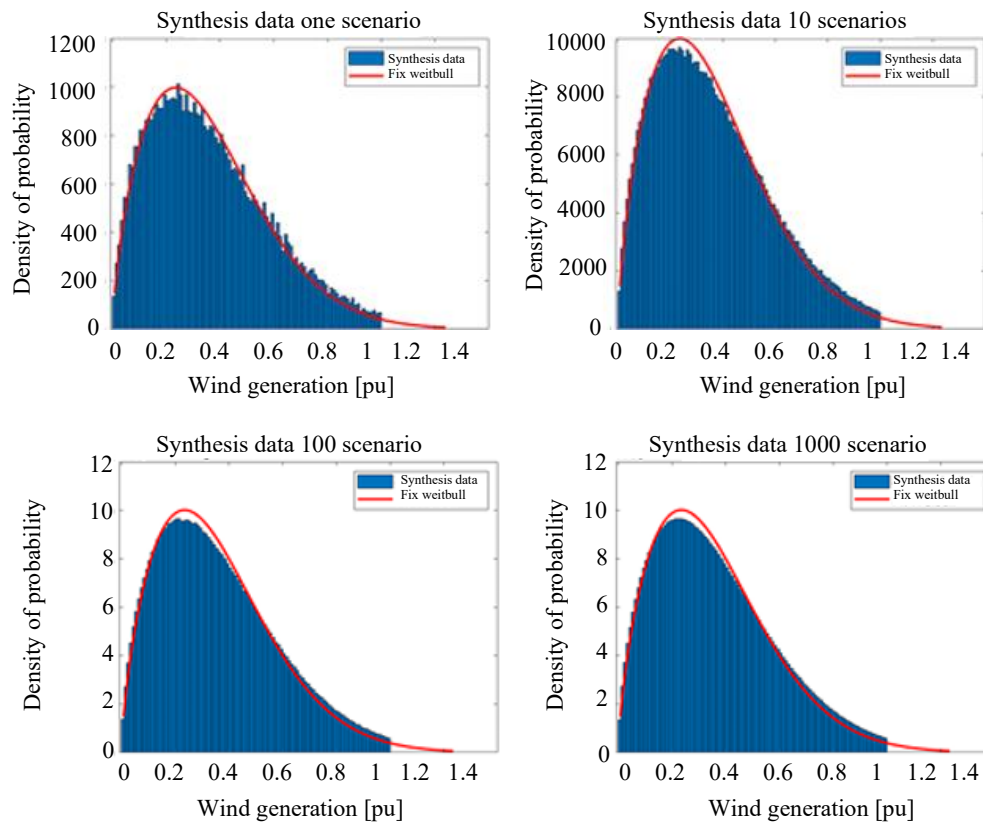


Figure 5. Synthesis data generation fit to Weibull distribution for different scenarios.

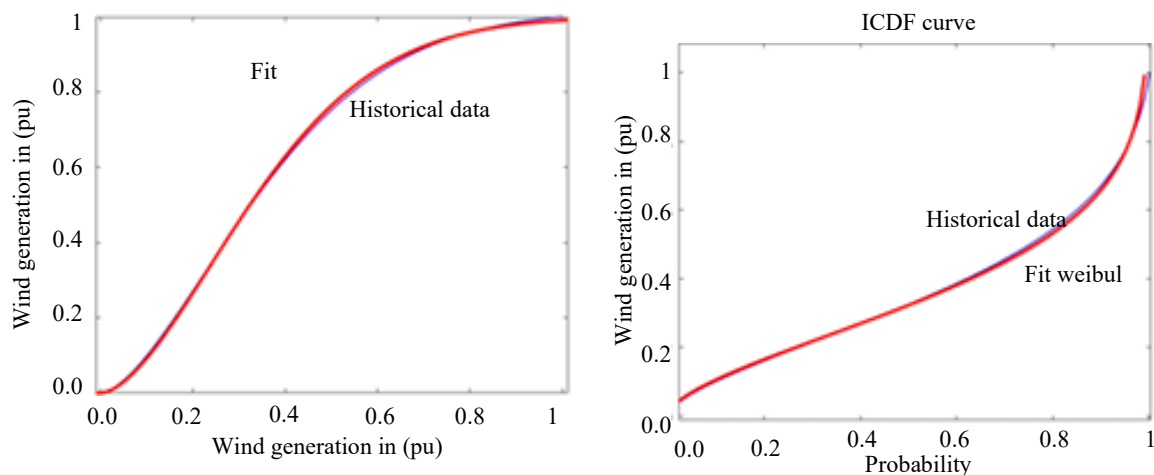


Figure 6. CDF and ICDF curves for synthesis data generation.

BESS Size Estimation Algorithm

Figure 7 illustrates the flowchart of the proposed methodology for estimating the wind farm power output and determining the required BESS size under worst-case operating conditions. The procedure begins with a statistical analysis of historical wind generation data using a Weibull distribution to characterize the most probable generation profile.

Subsequently, synthetic datasets were generated based on the estimated distribution parameters and validated against the Weibull model to improve accuracy and reduce estimation errors. Subsequently, a confidence level threshold of 92% was established to identify the minimum expected wind generation level. This threshold is then used to determine the corresponding worst-case BESS power requirement necessary to satisfy the black start constraints. Although the Weibull distribution was adopted in this study because of its suitability for wind data modeling, the proposed approach is sufficiently flexible to accommodate other statistical representations, such as kernel density or exponential distributions. The accuracy of the estimation ultimately depends on how well the selected distribution captures the temporal characteristics of the wind generation data over a specified time horizon.

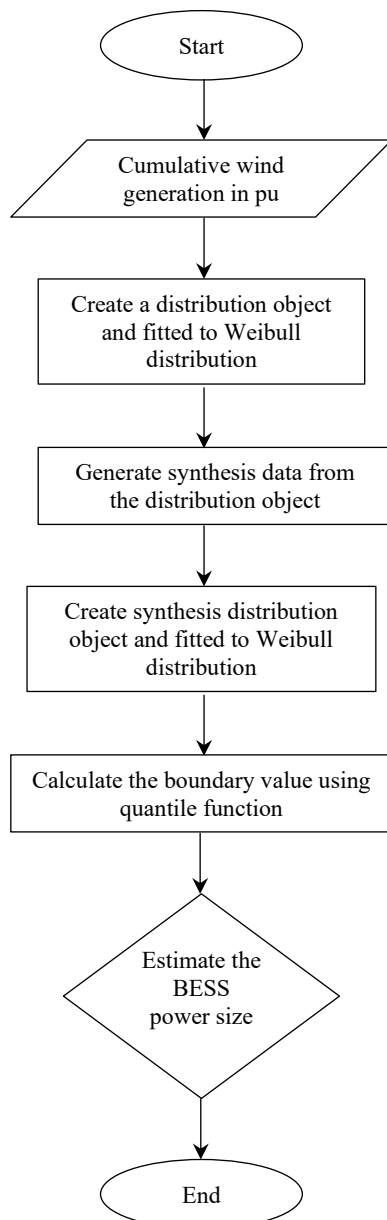


Figure 7. Flowchart to predict wind farm power rating and BESS Size.

BESS Power Rating Estimation

The BESS power rating was determined by evaluating the difference between the required block load demand and the estimated wind power generation under worst-case conditions. The corresponding expression for calculating the BESS power requirement is

$$P_{\text{BESS}} = P_{\text{block}} - P_{\text{Wind}}$$

where P_{BESS} denotes the required BESS power rating under worst-case conditions, P_{wind} represents the wind power output in the worst-case scenario, and P_{block} corresponds to the block load demand (with a minimum requirement of 20 MW).

If $P_{\text{BESS}} \leq 0$, the available wind power exceeds the block load demand, indicating that additional BESS support is not required for this stage of the black start operation. Conversely, if $P_{\text{BESS}} > 0$, the BESS must supply the deficit power to ensure that the block-load demand is satisfied. It should be noted that even when $P_{\text{BESS}} \leq 0$, the BESS may still be necessary during the earlier stages of the black start process, such as system energization and stabilization.

The procedure for estimating the optimal BESS size can be summarized as follows:

1. Analyze the historical wind generation time-series data.
2. Fit the data using an appropriate statistical model, such as the Weibull distribution.
3. Generate synthetic datasets to improve the representation of the underlying distribution.
4. Compute the PDF, CDF, and ICDF of the modeled data.
5. The worst-case wind generation value was determined by setting the ICDF probability threshold to 0.08 (corresponding to a 92% confidence level).
6. Calculate the required BESS power rating based on the worst-case scenario.

RESULTS AND SIMULATION

Probabilistic Optimization Results

Tables 2 and 3 present the estimated BESS sizing results required to support a 20 MW block load under the worst-case wind generation conditions, corresponding to a 92% confidence level. The analysis was conducted using both historical and synthesized wind generation data. The offshore wind farm (OWF) capacity considered in this study ranged from 8 MW (representing a single wind turbine) to 400 MW. Using the Weibull distribution, the worst-case wind generation derived from historical data corresponded to a per-unit value of 0.102 at the 92% confidence level, whereas the synthesized dataset yielded a slightly higher value of 0.105 p.u.

This variation indicates a marginal difference in the estimated minimum wind power outputs between the two datasets. In addition to the power requirements, the energy capacity of the BESS was determined based on the operational constraints specified by the British transmission system operator. In particular, the system must be capable of supplying continuous power to the block load for a minimum of 10 h. Accordingly, the calculated energy capacity reflects the minimum time requirement. The detailed results obtained from both historical and synthesized data, considering a 92% confidence level and a 20 MW block load, are summarized in Tables 2 and 3 for various OWF capacities.

Table 2. BESS sizing results using historical data at 92% confidence level for a 20 MW block load.

Base capacity in MW	Wind Generation (pu)	BESS power size in MW	BESS capacity in MWh
8	0.0377	19.698	196.98
50	0.0377	18.115	181.15
100	0.0377	16.230	162.30
400	0.0377	4.92	49.20

Table 3. BESS sizing results using synthetic data at 92% confidence level for a 20 MW block load.

Base capacity in MW	Wind Generation (pu)	BESS power size in MW	BESS capacity in MWh
8	0.040	19.68	196.8
50	0.040	18.00	180.0
100	0.040	16.00	160.0
400	0.040	4.00	40.0

Table 4. Results for a 400 MW OWF using synthetic data at 92% confidence.

Wind generation pu	Block load in MW	BESS power size in MW	BESS capacity in MWh
0.040	10	-6.00	0
0.040	20	4.00	40
0.040	30	14.00	140
0.040	40	24.00	240

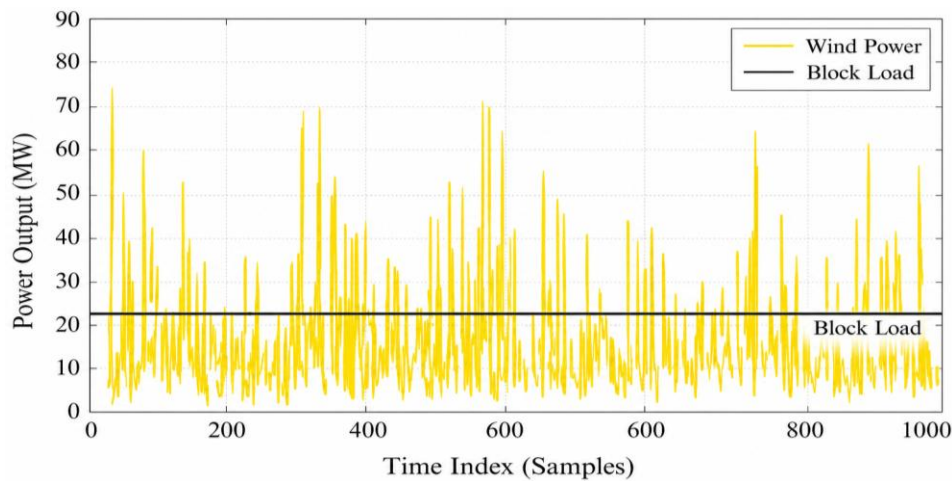


Figure 8. Wind generation versus block load.

To identify the operating conditions under which the BESS is required to discharge to support a 400 MW OWF during the block loading phase, a sensitivity analysis was conducted using synthesized wind generation data at a 92% confidence level. The results are presented in Table 4. The BESS discharge was initiated when the block load demand reached 50 MW. For BESS sizing, wind generation data [14] were analyzed using the Weibull distribution model. The distribution was fitted to the pre-processed wind data, and worst-case generation scenarios were determined at multiple confidence levels, namely, 8%, 50%, and 92%. Based on these scenarios, the required BESS power rating was calculated to ensure that the block load demand could be met during periods of reduced wind generation.

Figure 8 illustrates the variation in wind power generation compared with a constant block load demand of 20 MW. The results highlight the intermittent nature of wind energy, with generation levels fluctuating significantly between 0 and approximately 80 MW. Based on the probabilistic analysis conducted at a 92% confidence level, the minimum (worst-case) wind generation was estimated to be 0.0115 p.u., corresponding to 1.15 MW. Given that the block load demand remains fixed at 20 MW, a Battery Energy Storage System (BESS) is required to compensate for the power deficit during periods of low wind generation. Accordingly, the estimated BESS power rating required to ensure an uninterrupted supply was 18.85 MW. Furthermore, to sustain this support over the specified duration, the corresponding energy capacity was calculated to be 188.48 MWh.

Figure 9 presents the fitted Weibull model and the cumulative distribution function (CDF) of wind generation. The close agreement between the Weibull-based curve and empirical data confirms the suitability of the distribution in capturing the variability of wind power. Based on this probabilistic

representation, the worst-case wind generation at a 92% confidence level was estimated to be 0.0115 p.u., which was subsequently used to determine the required BESS capacity for reliable power support.

Figure 10 illustrates the probability density function (PDF) of wind generation, where the histogram represents the empirical data, and the fitted Weibull model is depicted by the continuous curve. The strong correspondence between the modeled distribution and observed data indicates that the Weibull distribution provides an accurate statistical representation of wind generation. This validation supports its application in probabilistic analysis and in determining BESS sizing requirements at the selected confidence level.

Figure 11 illustrates the inverse cumulative distribution function (ICDF) of the wind generation derived from historical data and the corresponding Weibull fit. The ICDF enables the estimation of wind power output at specified probabilities. In particular, for BESS sizing, the worst-case wind generation corresponding to a 92% confidence level was determined to be 0.0115 p.u.

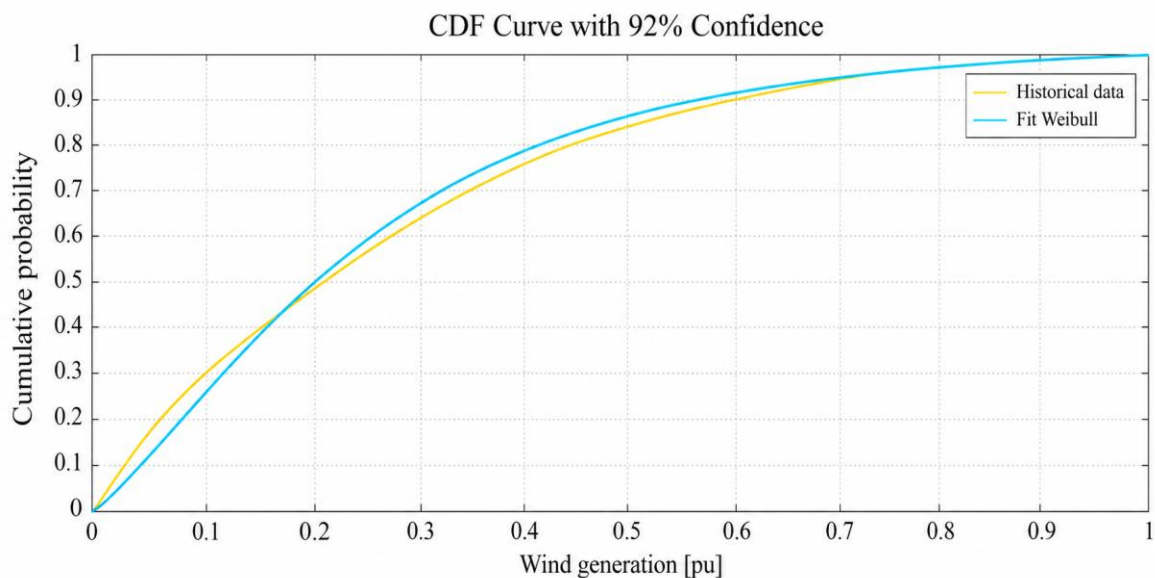


Figure 9. CDF curve with 92% confidence level.

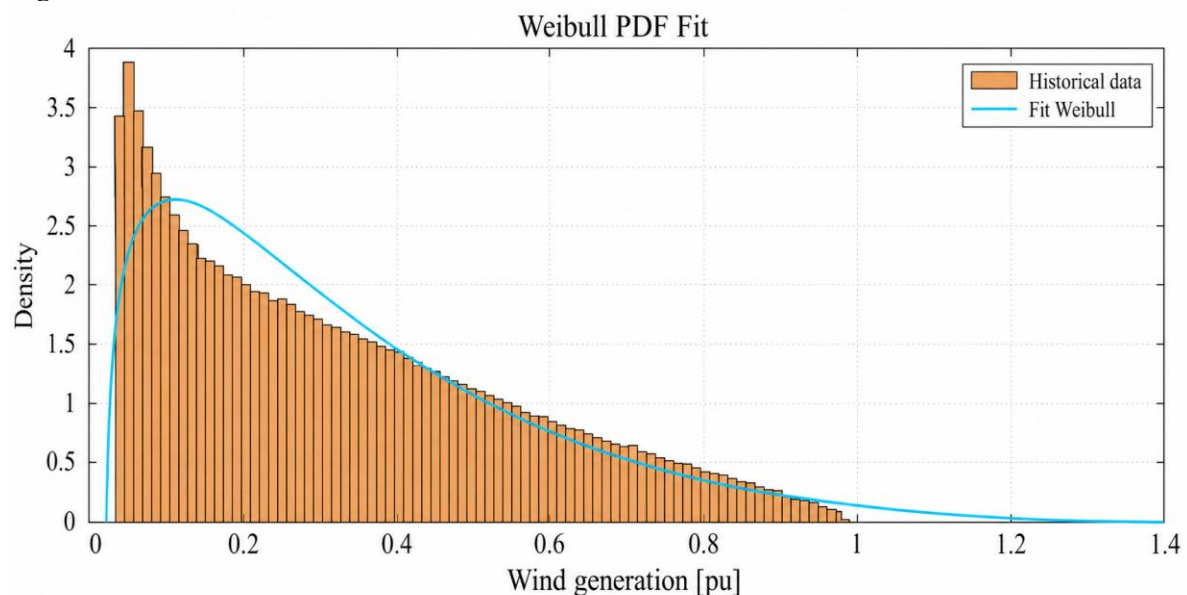


Figure 10. Weibull PDF fit.

Figure 12 illustrates the cumulative distribution function (CDF) of the wind generation based on the Weibull model. The vertical dashed line indicates the worst-case wind generation, corresponding to a 92% confidence level.

Figure 13 illustrates the variation in the BESS energy requirements with increasing confidence levels. As the desired level of reliability increases, the required energy storage capacity increases to compensate for the uncertainty in wind power generation. This relationship provides a useful basis for determining the optimal BESS capacity to ensure a reliable system operation.

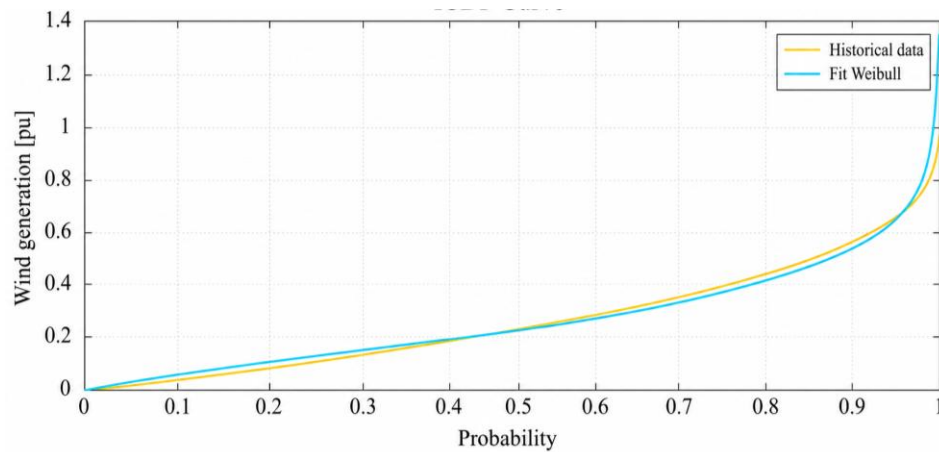


Figure 11. ICDF curve.

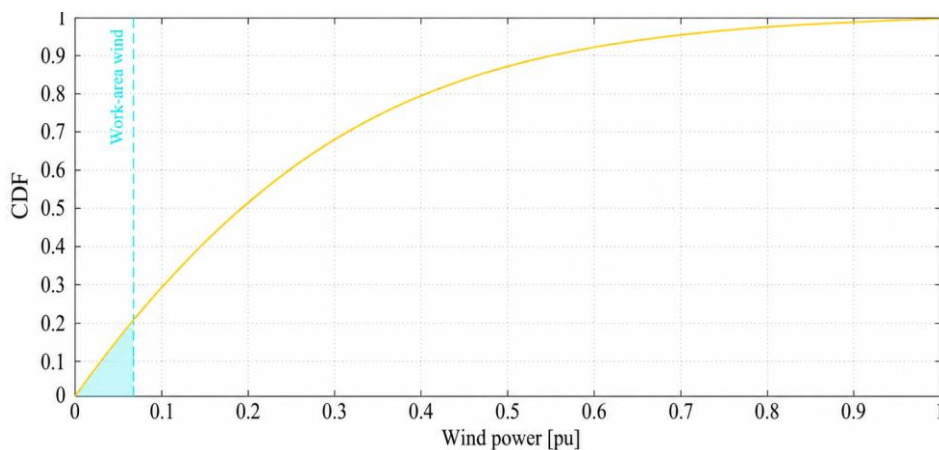


Figure 12. Weibull CDF confidence region 92%.

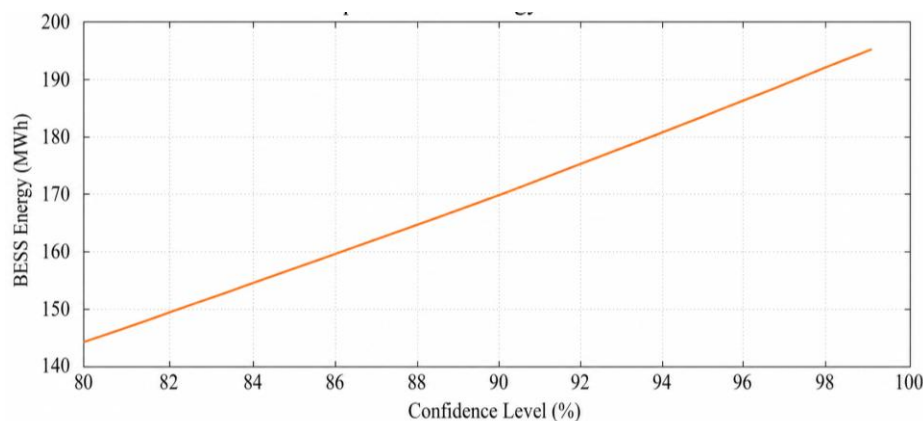


Figure 13. Required BESS energy at various confidence level.

CONCLUSION

This study employed a probabilistic framework based on the Weibull distribution to model wind generation characteristics and analyze the variability inherent in wind power output. The statistical behavior of wind generation was evaluated using probability density function (PDF), cumulative distribution function (CDF), and inverse cumulative distribution function (ICDF) analyses. A 92% confidence level was adopted to identify the worst-case wind generation scenario, which serves as a reliability benchmark for the system operation. Further analysis established the relationship between the required BESS energy capacity and selected confidence level. The results indicate that higher reliability requirements necessitate an increased energy storage capacity to effectively compensate for the variability in wind generation. Overall, the proposed probabilistic methodology provides a robust and systematic approach for determining the optimal BESS size in offshore wind-integrated power systems while ensuring compliance with reliability constraints.

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