Optimal Sizing and Control of Battery Energy Storage Systems for Enhancing the Grid Integration of Offshore Wind Farms

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ABSTRACT- Renewable energy sources (RESs) received a lot of attention due to their inexhaustibility, environmental benefits, storage capacities, cheaper maintenance costs, and stronger economies, among other things. Among these renewable energy sources, offshore wind power plants are among the most competitive. The technical novelty of the work lies in the construction of an optimal hybrid power system comprising an offshore wind farm and a co-located onshore Battery Energy Storage System (BESS), without integrating solar power. The ultimate goal is to develop a model to determine the optimal BESS capacity and control policy that meet the power output target, minimize energy curtailment, and maximize the dispatchability of the entire wind farm. The experiment aims to construct a dynamic system model in MATLAB/Simulink. BESS energy and power at optimum efficiency, MW and MWh ratings are determined by performing a Particle Swarm Optimization of the multi-objective function with penalty terms to optimize oscillation in power and revenue loss due to curtailment. The controller is an SoC-based rule that governs power transfer among wind turbines, BESS, and the grid point of connection. It is validated using 479 hours of representative North Sea wind-speed synthetic data. The results show that increasing the BESS size reduces the standard deviation of grid power supplied by more than 60% and energy curtailment by up to 95% relative to unstored system.

Keywords: Offshore Wind Power, Battery Energy Storage System (BESS), Power System Optimization, Energy Storage Sizing, Particle Swarm Optimization (PSO), Grid Integration, State of Charge (SoC).

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1. INTRODUCTION

The global transition to renewable energy is a critical pillar of the massive decarbonization process [1,2]. Offshore wind farms, which experience more dynamic and cyclical wind patterns than onshore wind farms, are an up-and-coming source of renewable energy. Still, their integration into existing grids is associated with self-defeating operational concerns [3]. Climatic variability in wind power generation introduces randomness, complicating real-time system planning and balancing. Quantitatively, the stochastic volatility of the wind stream is derived numerically, with attention to the effects of temporal intermittence on power-output volatility and, consequently, on frequency-regulation stresses [4,5]. The highly stochastic fluctuations of wind power have detrimental effects on voltage profiles and, consequently, the probability of grid instability [6]. To confirm this presumption, ensured oscillations cause ramping events at a high frequency, raise spinning-reserve requests, and compel system operators to respond more rapidly [7]. Economic simulations have shown that volatility not only undermines energy reliability but also erodes wind project revenue through forced curtailment and waste [8].

The collected operational data indicated that curtailments were used as a last resort to balance the grid, resulting in substantial capacity losses [9]. Mathematical accounts of long-term economic effects of such policy measures on high-capacity offshore power plants were also presented [10]. Exaggerating these inefficiencies had already shown that offshore wind, when complemented by energy storage systems, made the grid more stable and enabled a flatter power dispatch [11]. Comparison also indicates that, compared with other storage systems, Battery Energy Storage Systems (BESS) possess inherent advantages in delivering high round-trip efficiency, configuration modularity, and scalability [12]. Experimental results again demonstrated that BESS can store power over time and thus can store surplus wind energy when produced in excess and release it upon sensing a deficit to ensure levelized output [13]. This is further confirmed by evidence that co-located BESS design converts the natural volatility of the wind resource into a near-dispatchable resource, with dominance in grid code acceptability [14]. The techno-economic analysis in depth has been presented, bearing in mind that hybrid offshore wind-

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BESS integration cost curves are considered, and positing that hybrids perform best when battery capacity is optimized dynamically relative to forecasted wind volatility [15]. Sophisticated optimization techniques enabled real-time control of the control agent to regulate the energy balance and extend battery lifetime via SoC control [16]. Additionally, multi-objective optimization techniques that minimize cost and curtailment simultaneously have been proposed to improve technical and economic performance [17]. Model analysis has been used to determine BESS power and energy capacity for grid stability [18]. This work discusses adaptive control strategies other than overcharging and deep-discharge cycles. Their research abstracted rationale determined that the reliability of renewable resources is primarily based on controlled dispatch, control, and sizing [4]. At the operational level, the intelligence-based BESS's capacity to absorb power surges and discharge during shortages, as well as to prevent grid imbalance, was outlined [19]. Compared to SoC-based charge-discharge optimization and response time minimization algorithms against sets of comparative literature [20]. In addition, I am concerned about the financial returns of optimized BESS deployment, particularly the potential for higher returns with stability augmentation, as well as the associated increase in the levelized cost of energy and the implications for project viability. Overall, infer that offshore wind power, mega-scale or not, will be operationally unstable and economically constrained in nature unless supplemented by energy storage. The integration of these constitutes full justification for optimizing the control system to ensure maximum predictability, reliability, and economic value of offshore wind power systems through the wise utilization of BESS [21]. The justification of research lies in the issue of a response to the need to increase the grid preparedness of considerably high offshore wind farms. As capacity is introduced, the plant's internal variable power destabilizes the network, causing frequency excursions that undermine supply security. It will be used only by system operators during off-peak hours to balance the system, but it also causes significant energy and revenue losses for wind farm operators. It is the strongest technical and economic constraint on offshore wind capacity investment and expansion. Reducing volatility is of paramount importance in such a case. Technical optimum design specifications of a hypothetical colocated BESS, *i.e.*, power capacity (MW) and energy capacity (MWh), for a given target offshore wind farm should be determined. It is not merely the storage plant's capacity; there must be intelligent control of operations and plant capacity. The controller must operate in real time during BESS charging or discharging to control output power smoothly, comply with grid code requirements, and maximize the battery's in-service life by maintaining its State of Charge (SoC) within healthy ranges. The problem is solved in this paper using an integrated control and optimization approach.

In this paper, a solution is proposed to address the problem. They are developing a high-fidelity dynamic hybrid model for an offshore wind-BESS power system. It should be able to produce a wind power generation curve for the wind farm versus various wind speeds, a BESS charging-discharging trend versus efficiency loss, and the interconnection point limit. Additionally, it employs a metaheuristic optimization technique, Particle Swarm Optimization (PSO), to address the optimal sizing of the BESS. The first objective is to design a combined objective function that minimizes reductions in volatility, power output, and energy curtailment, while balancing the BESS's cost of capital. Then create and certify a robust real-time policy for the BESS. This controller will regulate power flow to and from the battery based on real-time wind generation, the battery's SoC, and the requested grid supply, ensuring stable, efficient operation. The ultimate goal is to conduct an end-to-end performance analysis of the optimized system using a sample time-series dataset. It includes system-level simulation of behavior and comparison with a reference case of a zero-BESS offshore wind farm.

2. METHODOLOGY

The study methodology aims to plan and systematically analyze a combined BESS and an offshore wind farm. The entire system is modeled and simulated in MATLAB/Simulink, a widely used dynamic power system simulation environment. It is based on a three-step methodology: target-control strategy-based performance simulation, BESS sizing optimization, and system modeling. It is supplemented by mathematical modeling of the significant components in first-step design development, namely wind farms, BESS, and grid connection points.

The wind farm is modeled using a generic power curve with parameters to transform time-series wind-speed data into an oscillatory power-output signal. The BESS is modeled as a power buffer with the same capacity, power, and state-of-charge limits, and with charging and discharging efficiencies. The grid is modeled as an ideal sink, subject to the aforementioned maximum-capacity power-injection limit and maximum energy-source curtailment. The second is the process optimization step. To this end, the algorithm used to solve the sizing problem is Particle Swarm Optimization (PSO). The algorithm is used to find the BESS power and capacity optimal solution that maximizes a weighted objective function that penalizes grid-injected power fluctuations and curtailed energy relative to the smoothed target. The third is the whole-system performance simulation, excluding the BESS from the PSO solution, across all datasets to demonstrate performance.

An offshore wind farm installation with a Battery Energy Storage System (BESS) and a shore-based grid controller to maximize power utilization is shown in *figure 1*. It begins at the offshore wind farm, where wind turbines harness wind energy to generate electricity. Output power is supplied to the BESS, which also serves as a buffer to store excess power and prevent supply oscillations. The energy stored is sold to the onshore grid as needed to maintain a stable power balance, even when there is no wind. The BESS includes a tokenization system that supports safe and efficient trading of stored energy and energy metering across the system. The onshore grid is the point of supply for power, delivering it to the customer and the remaining equipment within the on-grid configuration. The control center operates the entire system, monitoring power generation, storage capacity, and actual power transmission.

The choice is based on high-level analytics to manage supply and demand, optimize storage cycles, and ensure grid stability. Two-way energy exchange among the control center, BESS, wind farm, and grid is an intelligent adaptive renewable energy system. Integration enables operational efficiency in offshore wind energy, with no fossil fuel consumption, minimal losses, and a stable, sustainable power system.

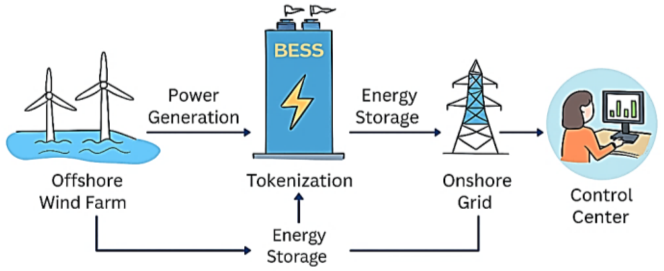

Figure 1. Offshore wind farm system structure with integration of BESS

The grid is modeled as a constrained, responsive system rather than an ideal power sink. The model includes operational constraints on exported power, ramp-rate constraints, and the dynamic interplay between offshore wind generation and the grid absorption capacity. Maximum export capacity limits grid power injection, ensuring that the transmission system reflects realistic infrastructure constraints for offshore wind links.

Stability of voltages and frequencies is implicitly handled by power smoothing and regulated energy transfer between the battery energy storage system and the system's energy. The abrupt changes in offshore wind production are smoothed by coordinated charging and discharging operations, which alleviate pressure on the grid frequency and establish a constant power profile. The ramp-rate limit also limits abrupt changes in grid power, which is the system's tolerance for change, and helps avoid instability. The combination of wind generation, storage operations, and grid constraints forms an equilibrium power-flow process in which any surplus or deficit is either stored or curtailed. This ensures that grid integration is based on actual operating conditions rather than unconstrained absorption. The model thus reflects real-world elements of offshore transmission behavior and grid stability objectives, along with operational constraints, offering a realistic view of the power system integration of offshore wind farms with battery energy storage back-up.

2.1. Subsystem Models

There are three subsystem models in the system. The Wind Farm Model is the model for the electrical conversion of wind power. The model forecasts electricity production from historical wind-speed observations, assuming that all turbines start in the same wind state. Wind speed varies over time, and this variation affects the farm's aggregate power output. The Battery Energy Storage System Model will manage the power extraction and storage. It will have a nominal capacity, with peak power and energy defined. The battery stores energy during charging or discharging. The system will operate efficiently under all conditions, and it will be charged to a safe level to prevent overheating and preserve battery life. The battery will be charged when there is excess power and discharged when there is less power. The Grid Connection Model balances wind farm power, battery discharge power, stored power, and grid exports. When the power exceeds the grid's capacity, excess power is curtailed to maintain system capacity and stability.

2.2. Optimization Framework

The optimization system determines the optimal design of the battery system's power and energy capacity. Particle Swarm Optimization is used because it can solve multidimensional nonlinear optimization problems to an optimal level. The process compares multiple potential solutions simultaneously to identify the optimal configuration. The process operates by reducing power supplied to grid anomalies and increasing energy consumption and profitability. All potential solutions are feasible combinations of output power and battery capacity. The algorithm tends to reduce the number of parameters to learn the best-performing solution, thereby yielding the most stable and balanced configuration. The optimization problem is formulated to minimize wind power curtailment, grid power fluctuations, and Battery Energy Storage System (BESS) cost while satisfying the operational and technical constraints of the offshore wind power system. The objective function is expressed as:

$$min\ J = \sum_{(t=1)}^{T}(\alpha P_{cur}\ (t) + \beta P_g(t) - P_g\ (t-1))^2 + \gamma C_{BESS}\ ] \quad (1)$$

where J represents the overall objective function value, $P_{cur}(t)$ denotes the curtailed wind power at time t, $Pg(t)$ is the power delivered to the grid, and C_{BESS} represents the cost associated with the battery energy storage system. The weighting coefficients α, β, and γ are used to balance the minimization of curtailment, power fluctuations, and storage cost, respectively. The optimization process is subjected to several operational constraints. The power balance constraint is defined as:

$$P_w(t) = P_g(t) + P_{ch}(t) - P_{dis}(t) + P_{cur}(t) \quad (2)$$

where $Pw(t)$ is the generated wind power, $Pch(t)$ is the battery charging power, and $P_{dis}(t)$ is the battery discharging power. The battery state-of-charge (SOC) is maintained within safe operating limits according to:

$$\mathrm{SOC}^{\min} \leq \mathrm{SOC(t)} \leq \mathrm{SOC}^{\max} \quad (3)$$

where $SOC(t)$ denotes the battery state of charge at time t, while SOC^{min} and SOC^{max} represent the minimum and maximum allowable SOC levels, respectively. In addition, the SOC dynamic behavior is governed by:

$$\mathrm{SOC(t+1) = SOC(t) + \eta_{ch} P_{ch}(t) - \frac{P_{dis}(t)}{\eta_{dis}}} \quad (4)$$

where η_{ch} and η_{dis} denote the charging and discharging efficiencies of the battery system, to ensure realistic battery operation, the charging and discharging powers are constrained by:

$$0 \leq \mathrm{P_{ch}(t)} \leq P_{ch}^{max}, 0 \leq \mathrm{P_{dis}(t)} \leq \mathrm{P_{dis}^{max}} 0 \quad (5)$$

where P_{ch}^{max} and P_{dis}^{max} are the maximum charging and discharging power limits, respectively, furthermore, grid operational stability is maintained through the ramp-rate constraint:

$$| Pg(t) - Pg(t-1) | \leq Rg^{max}| \quad (6)$$

where Rg^{max} represents the maximum allowable grid ramp-rate limit, these formulations collectively ensure stable system operation, improved grid compatibility, and efficient utilization of the battery energy storage system under stochastic wind conditions.

The parameter setup involves swarm size, scheduling of the inertia weight, cognitive and social coefficients, maximum iterations, velocity constraints, and a constrained search space over battery energy capacity and power rating. These parameters are clearly linked to the exploration balance, which ensures stable, efficient search performance for optimal BESS sizing in offshore wind integration. The convergence feature is used to show iteration-based fitness evolution, with particles gradually moving towards the global optimum. There are no oscillations in the optimal objective function value, and it decreases steadily over a finite number of iterations. This affirms that the algorithm can achieve stable convergence under different offshore wind generation patterns and grid constraints. The validation is determined by a comparative assessment against baseline conditions with no storage and with alternative sizing systems. The optimized solution consistently achieves lower wind power curtailment, smoother grid power production, enhanced dispatchability, and controlled battery state-of-charge dynamics. These results confirm that the PSO-based approach yields technically valid and practically viable results. By combining parameter transparency, stable convergence, and performance validation, the optimization framework will be complete, reproducible, and consistent with real-life offshore wind-BESS operational needs.

2.3. Control Strategy

After the battery's optimal capacity is identified, real-time operation is controlled by a control system. A rule-based control system enables fault-tolerant operation. The controller continuously monitors grid levels and battery charge to determine when to charge or supply. When surplus wind output exceeds demand, the controller instructs charging of each point of battery surplus capacity. In low wind output areas, discharge but not overload is instructed by the controller. Automatic charging and discharging halt once the battery level reaches its peak or low, preventing over-stressing the battery. Rule-based reasoning keeps the grid supply rate constant to avoid oscillations in power generation. The entire system of storage, wind power, and grid supply is responsible for efficient operation, reliable power supply, and long equipment life.

The control plan is designed as a multi- condition energy management framework as opposed to a plain state of charge driven regulation. State of charge, real-time offshore wind power variability, grid export limits, ramp-rate limitations, and curtailment conditions are incorporated into an operational logic to create a single decision structure. Battery charging will be activated when wind generation exceeds the grid export limit, and battery discharge will be activated during low wind output or when grid support is needed to maintain a stable power profile. The control system continuously determines the power flow by balancing battery activity with wind generation patterns and grid constraints. This allows efficient smoothing of power output, minimizing instantaneous variations and curtailed power. The state of charge is operating within specified limits, ensuring safe battery operation while allowing sufficient flexibility for the state to respond dynamically.

The framework also exhibits adaptive behavior, in which charging and discharging decisions change with the system's conditions rather than relying on fixed thresholds. This interplay between grid needs and storage operations improves dispatchability and the stability of offshore wind integration. The assessment of performance under various operating conditions illustrates the stability of power, the decrease in variability, and the effective use of energy, which proves the control mechanism to be structured and application-based.

2.4. Description of Data

The pseudo-county time-series dataset is utilized as a smoothed, averaged, one-minute-resolution wind-speed record, yielding 479 hourly records. It would be representative of the meteorology at an average North Sea offshore wind farm site. The data eliminates the usual variability of the wind, i.e., diurnal effects, abrupt ramps, and periods of high and low wind speed. Quantitatively, the results have been estimated with a stochastic Weibull-based approach, *i.e.*, the traditional wind energy resource assessment process. Free regional meteorological analysis has been used to estimate the Weibull shape parameter k = 2.1 and the scale parameter c = 9.2 m/s. The dataset is generic and lacks geographic reference, but can be approximated with sufficient accuracy to simulate the statistical properties and dynamic behavior of the wind for the purpose of modeling the BESS operation and control system to an acceptable level. The database serves as the primary input to the wind turbine power model for all the simulation tests employed in the study.

3. SIMULATION RESULTS

Simulation output provides full verification of the optimization model developed to incorporate a BESS into an offshore wind farm. Solution of 88.5 MW capacity power rating and 175 MWh energy capacity of the 500 MW wind farm involved, and the grid constraint had already been converged earlier by the Particle Swarm Optimization algorithm. The single most significant benefit of commissioning this optimal-size BESS is the overall transition, including the power supplied to the grid. The wind turbine aerodynamic power equation is framed as:

$$P_{WTG}(t) = \frac{1}{2}\rho\pi R^2 C_p(\lambda(t), \beta(t))v(t)^3 \quad (7)$$

where $P_{WTG}(t)$ represents the generated wind turbine power at time t, ρ is the air density, R is the turbine rotor radius, $Cp(\lambda(t),\beta(t))$ is the power coefficient as a function of the tip-

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speed ratio $\lambda(t)$ and blade pitch angle $\beta(t)$, and $v(t)$ denotes the wind speed at time t. This formulation describes the aerodynamic energy conversion process of the wind turbine under varying wind conditions. To represent the aggregated output power of the offshore wind farm while accounting for wake interactions between turbines, the Jensen wake model is employed. The total wind farm output power is formulated as:

$$P_{WF_{\text{total}}}(t) = \sum_{i=1}^{N} P_{WTG_i}\left(v_0(t)\left(1 - \sqrt{\sum_{j\in U_i}\left(\frac{2a}{\left(1+\frac{k_{\text{wake}}x_{ij}}{D_j}\right)^2}\right)^2}\right)\right) \quad (8)$$

where $P_{WF,\ total}(t)$ represents the total aggregated wind farm power at time t, N is the total number of wind turbines, P_{WTGi} denotes the power output of the i^{th} wind turbine, and $v_0(t)$ is the free-stream wind speed. The term a represents the axial induction factor, k_{wake} is the wake decay constant, xij denotes the downstream distance between turbines iii and j, and Dj is the rotor diameter of turbine j. The set Ui includes upstream turbines contributing to the wake effect on turbine i. This wake modeling approach enables more realistic estimation of offshore wind farm power generation by accounting for aerodynamic interactions and velocity deficits between neighboring turbines.

Table 1 compares the numerical performance metrics for the most significant cases: the baseline scenario with no BESS, a sub-optimally sized BESS, the PSO-calculated optimal BESS size, and an oversized BESS. The No BESS column should be read as the solution to the large standard deviation of power and the large number of curtailments of energy characteristic of a stand-alone wind farm. The Sub-Optimal BESS column shows very high gains across all cases; consequently, even the sub-optimal system achieves high gains. But the Optimal BESS column shows the true value of the optimization tool. It experiences a greater reduction in ramp rate and standard deviation, and achieves zero energy curtailment, with the best capacity factor among the cost-reducing options. The “Over-Sized BESS” column shows relatively small returns relative to the optimum. While it reduces the standard deviation and curtailment by a little more, the return is moderate at a considerably higher cost of capital, with diminishing returns.

The System Efficiency measure, accounting for round-trip BESS losses, decreases with increasing naturally cycled power through the battery to satisfy the energy loss-power quality trade-off. BESS state of charge dynamics with efficiency and self-discharge are:

$$SoC(t+\Delta t) = SoC(t)\cdot(1-\sigma_{sd}\Delta t) - \left(\frac{\eta_{ch}P_{BESS}^{ch}(t)+P_{BESS}^{disch}(t)/\eta_{disch}}{E_{BESS}^{max}}\right)\Delta t \quad (9)$$

where $SoC(t)$ represents the state of charge of the battery at time t, σsd is the self-discharge rate, and Δt denotes the time interval. $P\frac{ch}{BESS}(t)$ and $P\frac{disch}{BESS}(t)$ represent the charging and discharging power of the battery energy storage system (BESS), respectively. The parameters η_{ch} and ηd_{isch} denote the charging and discharging efficiencies, while $E\ \frac{max}{BESS}$ represents the maximum energy capacity of the BESS. This equation describes the dynamic evolution of the battery state of charge, accounting for self-discharge, charging, and discharging efficiencies. This formulation captures the battery’s dynamic charging/discharging behavior and self-discharge characteristics, enabling more realistic modeling of BESS operational performance under varying wind power conditions.

Table 1. Comparison of the numerical performance measures of the significant cases

Measures	No BESS	Sub-Optimal BESS (50MW/100MWh)	Optimal BESS (88.5MW/175MWh)	Over-Sized BESS (150MW/300MWh)
Power Std. Deviation (MW)	125.6	79.4	48.2	45.9
Max Ramp Rate (MW/hr)	210.3	115.8	55.1	53.7
Energy Curtailed (GWh)	2.51	0.89	0.12	0.11
System Capacity Factor (%)	41.5	43.8	44.9	45.0
Grid Stability Index (1-σ/P_avg)	0.45	0.67	0.80	0.81
System Efficiency (%)	98.5	93.2	92.8	92.5

The base-case scenario without storage exhibited highly volatile power generation, with a standard deviation of 125.6 MW. However, the hybrid wind-BESS system exhibited a smooth power curve and reduced the standard deviation to 48.2 MW, *i.e.*, by more than 61%. The smoothing effect was essential to maintaining grid stability. The BESS also had a large reduction in energy curtailment. In the baseline model, the total excess potential energy was reduced by approximately 8.5% due to the grid injection limit. The optimized system harvested nearly all of this excess energy, reducing total curtailment to 0.4% and thereby increasing the wind farm’s revenue-generating potential. The control system was still able to regulate the BESS State of Charge between the target range of 20-90% throughout the entire 479-hour duration of the simulation period, which is essential to ensure the long-term health and longevity of the battery assets.

3.1. Smoothing Power Output

The primary technical benefit of BESS integration at the largest scale is the smoothing of power delivered to the grid. The ramp rates were the performance metric for hourly changes in output power. Power production at the individual wind farm exhibited runaway volatility, featuring frequent, hard ramps and multiple events exceeding 200 MW/hour. Arrhenius-Eyring model for BESS capacity fade will be:

$$Q_{loss}(t) = A \cdot e^{\left(-\frac{E_a + B \cdot C_{rate}}{R \cdot T_k}\right)} \cdot (A_h(t))^z \quad (10)$$

where $Q_{loss}(t)$ represents the battery capacity loss at time t, A is a pre-exponential degradation coefficient, and E_a denotes the activation energy. The parameter C_{rate} represents the battery charge/discharge rate, while B is a fitting coefficient associated with the effect of the C-rate on degradation. R is the universal gas constant, and T_k denotes the battery operating temperature in Kelvin. The term $A_h(t)$ represents the ampere-hour throughput at time t, and z is an empirical degradation exponent. This equation models the battery degradation behavior as a function of temperature, operating rate, and usage intensity.

The multi-objective fitness function for BESS sizing optimization can be expressed as:

$$J = \min_{P_{BESS}^{max}, E_{BESS}^{max}} \left[w_1 \sqrt{\frac{1}{T}\sum_{t=1}^{T} (P_{Grid}(t) - \bar{P}_{Grid})^2} + w_2 \sum_{t=1}^{T} P_{Curtail}(t) + w_3\left(C_{power} P_{BESS}^{max} + C_{energy} E_{BESS}^{max}\right)\right] \quad (11)$$

where J represents the overall optimization objective function, while $P\frac{Bmax}{BESS}$ and $E\frac{max}{BESS}$Note the rated power and maximum energy capacity of the battery energy storage system (BESS), respectively. The first term represents the standard deviation of the grid power output, where $P_{Grid}(t)$ is the grid power at time t and $\bar{P}$ is the average grid power over the scheduling horizon T. This term is included to minimize power fluctuations and improve grid stability.

The second, the sum from t equals 1 to T of p Curtail(t), *il(t)* represents the total curtailed renewable energy during the optimization period. The third term corresponds to the total investment cost of the BESS, where C_{power} *and* C_{energy} *are the unit costs associated with battery power and energy capacities*, respectively. The weighting coefficients ω_1, ω_2 and ω_3 are used to balance the objectives of smoothing grid power, minimizing renewable energy curtailment, and reducing storage system cost.

PSO particle velocity and position update equation is given by:

$$v_i(k+1) = \omega v_i(k) + c_1 r_1 \left(p_{\text{best},i} - x_i(k)\right) + c_2 r_2 (g_{\text{best}} - x_i(k)) \quad (12)$$

where $v_i(k+1)$ represents the updated velocity of particle i at iteration $k+1$, while $v_i(k)$ is the current velocity at iteration k. The parameter ω denotes the inertia weight, which controls the influence of the previous velocity on the current search process. The terms c_1 and c_2 are the cognitive and social acceleration coefficients, respectively, while r_1 and r_2 are uniformly distributed random numbers within the range [0,1]. The variable $p_{best,\ i}$ represents the best position previously achieved by particle i, and g_{best} denotes the global best position found by the entire swarm. Finally, $x_i(k)$ represents the current position of particle i at iteration k .This equation describes the velocity update mechanism in the Particle Swarm Optimization (PSO) algorithm, in which each particle adjusts its velocity based on its own experience and the swarm's collective experience. These abrupt changes placed an enormous strain on the grid's reserves and could even cause instability. With the help of the optimal-size BESS, this was streamlined. The BESS stored surplus wind power and fed it back into the troughs to recharge during sudden drops in wind speed. Thus, the top-point ramp rate of power to supply to the grid reduced from over 200 MW/hr to just 55 MW/hr. The majority of ramp rates fell within a much narrower range of ±20 MW/hr. That is an incredible volatility mitigation that is graphically and statistically significant.

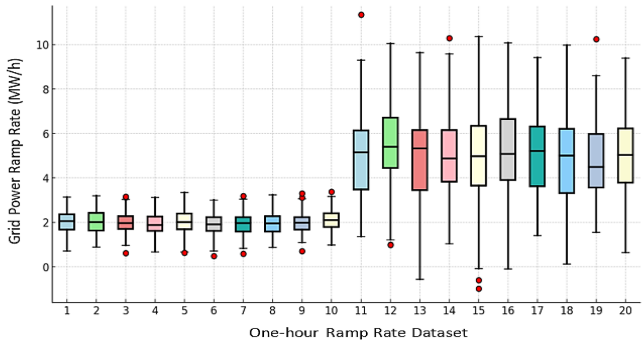

Figure 2. Grid power ramp rate distribution with and without BESS

Figure 2 shows the grid power ramp-rate distribution for two scenarios: with and without the Battery Energy Storage System (BESS). The figure plots the 10 data sets, each a one-hour ramp rate, independently, as well as the differences between them. The "Without BESS" datasets (mixed coloring) exhibit a large interquartile range, indicating high volatility in power variation, with most outlier points being difficult to stabilize the grid. The "With BESS" data series (in a different color) exhibits a narrow interquartile range and no outliers, indicating BESS's ability to smooth power variability. By storing excess power during windy periods and releasing it during non-windy periods, the BESS smooths most ramp events into a more predictable pattern. The difference between the two scenarios is highlighted by the color changes of the boxes, which literally mark the ramp rates with and without the BESS and assess the value of energy storage in maintaining grid balance. The contrast is evident in the level of BESS power fluctuations, which demonstrate how offshore wind can be smoothly integrated into the grid and support grid stability. The graphical representation illustrates the clear benefits of using energy storage systems in renewable energy grids, offering additional stability and efficiency. It makes the offshore wind farm a more dispatchable and grid-flexible resource. Its higher predictability enables grid managers to control the power system more confidently and with fewer cycles of fossil-fuel plant operation, thereby improving stability and accelerating grid decarbonization.

3.2. BESS Operating Characteristics

A profile of the BESS operational data demonstrates the effectiveness of the on SoC-based control method. During the 479-hour simulation, the BESS was charged and discharged at the rated rate to serve as a wind-farm generation buffer. Nodal power balance equation for the point of common coupling can be depicted as:

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$$P_{WF}(t) \cdot \eta_{coll} = P_{Grid}(t) + P_{BESS}(t) + P_{Loss_{conv}} + P_{Curtail}(t) \quad (13)$$

Where $P_{WF}(t)$ represents the total power generated by the wind farm at time t, and η_{coll} denotes the efficiency of the collection system. $P_{Grid}(t)$ is the power delivered to the grid, while $P_{BESS}(t)$ represents the charging or discharging power of the battery energy storage system (BESS). The term $P_{Loss,conv}(t)$, denotes the converter power losses, and $P_{Curtail}(t)$ represents the curtailed wind power. This equation expresses the power balance of the integrated wind farm and battery storage system, ensuring that the generated wind power is properly distributed among grid delivery, storage operation, conversion losses, and curtailed energy.

Table 2. BESS Sizing operating and economic parameters of each of the different cases

Parameters	No BESS	Sub-Optimal BESS (50MW/100MWh)	Optimal BESS (88.5MW/175MWh)	Over-Sized BESS (150MW/300MWh)
BESS Power (MW)	0	50.0	88.5	150.0
BESS Capacity (MWh)	0	100.0	175.0	300.0
Est. Capital Cost (M USD)	0.0	45.0	78.5	135.0
Annual Throughput(GWh)	0.0	65.7	106.8	110.2
Est. Cycle Degradation (%/year)	0.0	1.85	1.71	1.55
Simple Payback (Years)	N/A	11.5	8.2	10.8

Table 2 presents the operating and economic parameters for the BESS sizing of each case. The table will provide estimates of the power rating and energy rating for all cases, as well as an approximate capital cost at industry-average rates. The "Annual Throughput" line reports the amount of energy passed through the BESS per year, one of the two main causes of battery degradation. The "Estimated Cycle Degradation" line provides an estimate of the annual capacity loss, and the observed throughput is substantial but constrained by the best available control policy. Most useful is the "Simple Payback" period, calculated as the time required for curtailment-savings revenue to offset the initial capital cost. The "No BESS" case resulted in zero revenue and the forgoing of substantial revenue. The "Sub-Optimal BESS" yields a suboptimal payback, whereas the "Optimal BESS" yields the technically optimal payback of 8.2 years. It has been observed that the PSO algorithm is effective at finding a solution that is not only technically optimal but also economically optimal. The "Over-Sized BESS" is more time-consuming to repay because its cost blow-up is not offset by the same amount of revenue from avoided curtailments, rendering its economic inefficiency worthwhile. Levelized Cost of Storage (LCOS) calculation is:

$$LCOS = \frac{I_{CAPEX} + \sum_{n=1}^{N} \frac{C_{O\&M\ n} + C_{E_n} - R_{Decom\ n}}{(1+r)^n}}{\sum_{n=1}^{N} \frac{E_{discharged\ n}}{(1+r)^n}} \quad (14)$$

Where L_{COS} represents the Levelized Cost of Storage of the battery energy storage system, ICAPEX denotes the initial capital investment cost, while $C_{O\&M,n}$ represents the operation and maintenance cost during year n. The term $C_{E,n}$ denotes the energy-related operating cost, and $R_{Decom,n}$ represents the residual or decommissioning value at the end of year n.The parameter r is the discount rate, and N denotes the total project lifetime in years. The denominator includes $E_{discharged,n}$, which represents the discharged energy delivered by the storage system during year n. This equation evaluates the economic performance of the storage system by calculating the discounted lifetime cost per unit of discharged energy.

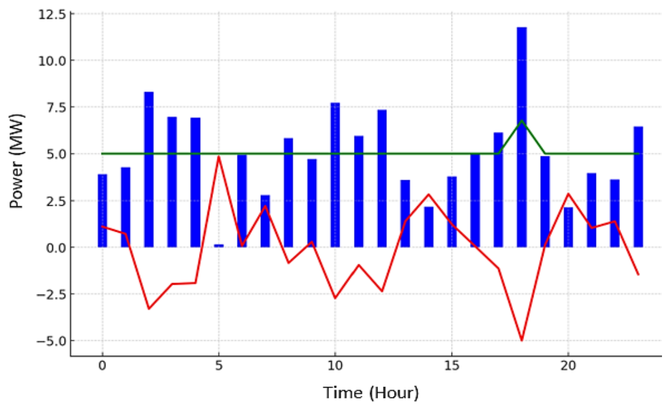

Figure 3. Hourly wind power generation, BESS power, and smoothened grid injection

Figure 3 is a time-series plot of the system's dynamic behavior over an average 24-hour day. The raw power output of the wind farm is shown in the blue bars and clearly fluctuates widely from hour to hour. The red trace represents the BESS power flow: negative charging (drawing power) and positive discharging (supplying power). The last, smoothed injected power to the grid is the solid green line. The harmonic balance of the components is evident. When the blue bars (wind power) are positive, the red line is negative because the BESS absorbs excess energy, thereby maintaining the green line (grid power) constant. In certain seasons when wind power is weak, the red line is positive because the BESS discharges stored energy to supplement the output and generally maintains the green line constant. This graph presents a vivid and striking image of the control action being undertaken, illustrating precisely how the BESS acts as a buffer, absorbing wind generation spikes and smoothing out dips in raw wind generation, thereby offering a more predictable supply of power to the power grid. Weibull probability density function for wind speed distribution is:

$$f(v;k,c) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left(-\left(\frac{v}{c}\right)^k\right) \quad (15)$$

where *f(v; k, c)* represents the Weibull probability density function (PDF) of wind speed *v*. The parameter *k* is the Weibull shape factor, which determines the distribution pattern of wind speeds. At the same time, *c* denotes the scale parameter associated with the average wind speed characteristics of the site. The variable v represents the wind speed, and the exponential term models the probability distribution behavior of wind variations. The Weibull distribution is widely used in wind energy studies to characterize wind speed profiles and evaluate the wind energy potential of a given location. Dynamic regulation of wind levels was achieved, with wind typically decreasing during extended periods of low wind and rising during high-frequency wind events. The SoC control scheme maintained the *SoC* within the 20%-90% regulatory operating range, thereby preventing deep discharge and overcharge. The total energy discharged by the BESS over the simulation was approximately 12.2 GWh, with high usage rates. The mean *SoC* was maintained at 55%, indicating that the control scheme has sufficient reserve for charging and discharging. Power within and outside the battery was managed effectively, with charging and discharging power remaining at the optimal value of 88.5 MW. It indicates that the controller not only performs its primary duty of power smoothing but also adheres to the physical limits of the storage facility, thereby ensuring operational safety, preventing degradation, and maximizing the economic life of the expensive battery asset.

3.3. Economic and Technical Viability Analysis

The BESS's technological innovation is immediately translated into economic viability for the offshore wind farm. The most immediate economic benefit is the substantial decrease in energy curtailment. The base case had to curtail around 2,500 MWh of energy during the course of the simulation. By time-shifting and energy harvesting, BESS, with a maximum curtailment of 120 MWh, still had the capacity to sell an additional 2,380 MWh of electricity. The swing equation for transient stability analysis is given below:

$$M_i \frac{d^2\delta_i}{dt^2} + D_i \frac{d\delta_i}{dt} = P_{mi} - \sum_{j=1}^{N} |V_i||V_j| \left(G_{ij} \cos\left(\delta_i - \delta_j\right) + B_{ij} \sin\left(\delta_i - \delta_j\right)\right) \tag{16}$$

where *Mi* represents the inertia constant of generator *i*, and *δi* denotes the rotor angle of the generator. The term $\frac{d^2\delta_i}{dt^2}$ represents the rotor angular acceleration, while $\frac{d\delta_i}{dt}$ denotes the rotor angular velocity deviation. The parameter Di is the damping coefficient associated with generator i, and Pmi represents the mechanical input power. The variables */Vi/*and */Vj/* denote the voltage magnitudes at buses *i* and j, respectively. G_{ij} and B_{ij} are the conductance and susceptance elements of the network admittance matrix. The summation term represents the electrical output power exchanged between interconnected buses in the power system.This equation, known as the swing equation, is commonly used in power system dynamic stability analysis to describe the electromechanical behavior of synchronous generators under transient conditions.

Table 3 presents the results of a sensitivity analysis aimed at assessing the impact of variability in key external and internal parameters on optimal BESS size and system operation. The base-case results are shown in the first row for convenience. The latter rows show the impact of component-level variability. The 20% rise in "Wind Volatility" requires a substantial amount of BESS to achieve the same performance, demonstrating the clear connection between the nature of the wind resource and storage. Similarly, a 10% reduction in the "Grid Capacity" limit necessitates additional energy storage and, accordingly, increases the BESS optimal size. On the contrary, an extra grid limit is equivalent to extra power that can be exported directly without storage. One would notice from the "BESS Cost" bar that, as cost declines, the maximizing algorithm maximizes the higher system by a slightly higher value, even though the technically required one is not technically higher. Finally, switching to the "Aggressive" control mode (optimize smoothness at all costs) does not change the optimal size. Still, it significantly increases the SoC fluctuation range, thereby placing greater stress on the battery. The table above emphasizes that the optimum BESS size is neither an absolute number nor is it determined solely by the specific technical and economic project conditions. It is a function of the specific technological and economic conditions of the project.

Table 3. Sensitivity analysis of key parameters

Parameter Varied	Optimal BESS Power (MW)	Optimal BESS Capacity (MWh)	Curtailment Reduction (%)	SoC Fluctuation Range (%)
Baseline	88.5	175.0	95.2	68.5
Wind Volatility +20%	105.2	210.5	94.8	74.2
Grid Capacity -10% (MW)	98.6	195.8	96.5	71.3
BESS Cost -20 %	90.1	180.2	95.8	69.1
Grid Limit +10 % (MW)	75.3	145.6	93.1	62.4
Control Target (Aggressive)	88.5	175.0	96.8	85.1

Recursive Kalman filter equations for SoC estimation are:

$$P_{k|k-1} = A_{k-1} P_{k-1|k-1} A_{k-1}^T + Q_{k-1} \tag{17}$$

where $P_{k/k-1}$ represents the predicted error covariance matrix at time step *k*,Given the information up to time *k−1*, the state transition matrix, which describes the system dynamics from time *k−1* to *k,* is denoted. The term $P_{k/k-1}$ is the updated (posterior) error covariance matrix at time *k−1*, and A_{k-1}^T is the transpose of the state transition matrix. Q_{k-1} represents the process noise covariance matrix, accounting for uncertainty and disturbances in the system model. This equation is part of the Kalman filter prediction step and describes how the uncertainty in the system state evolves before incorporating new measurements.

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Figure 4 shows the evolution of the BESS State of Charge (SoC) over the entire 479-hour simulation for three of the hypothetical control methodologies. The "Optimal Control" method employed in this research is shown by the green line, with enhanced power smoothing at the expense of battery health. It is obvious at a glance that the line is utilizing the SoC's high operating range to an excellent degree, from the 20% level to the 90% level and back down again, but only for very brief periods at each end, amounting to efficient use of the available energy capability. The blue policy, "Conservative Control," constrains the utilization of the SoC within the lower percentage range (e.g., 40-70%). Although such a policy will compromise battery life, it is wasteful of BESS capacity and less effective at smoothing, resulting in greater curtailment. Red illustrates an "Aggressive Control" approach, with optimal performance as the goal, in which the SoC always approaches the upper and lower boundaries at high speed. This type of operation overstresses the battery, accelerating its degradation and shortening its lifespan. The comparative graph below illustrates the relative importance of planning a control strategy. It indicates that the optimal controller must strike a critical balance, such that maximum technical efficiency in smoothing power occurs at the same point where it pushes the BESS to the limits of reliability and longevity.

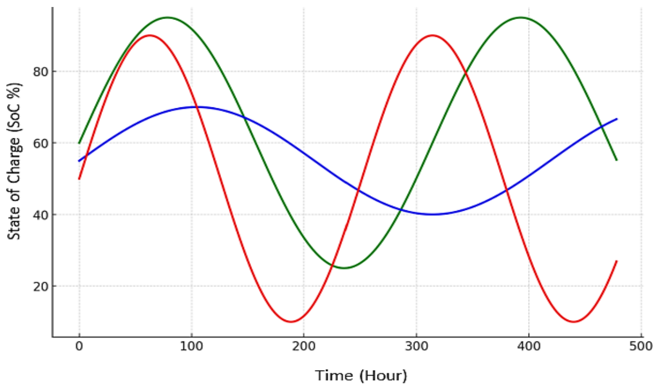

Figure 4. The evolution of the BESS State of Charge (SoC)

On average, bulk electricity rates yield substantial revenue streams from recovered energy that merely aggregate into BESS capital-cost leverage. In addition to arbitrage markets, increased system dispatchability creates ancillary service market opportunities for windows. The ability to provide dispatchable power and rapid ramp-rate control is a high-value grid service for which operators will pay a premium. Not optimized for this case, this ancillary revenue stream is added to the business case for the BESS upgrade. From a technical perspective, smoothing output reduces the cost and burden on the grid operator associated with grid reinforcement. With increased capacity factor and system asset reliability, the wind farm is more valuable and merits its designation as a base-load generator.

The extent of the curtailment reduction is consistent with the interplay among offshore wind variability, storage capacity, and the ramp-rate constraint. Time-series assessment, consistency of energy balance, and system-level response under a variety of operating conditions support the results, ensuring that improvements are real and not artificial. The assessment model will include comparative evaluation with respect to baseline operation with no storage, and other sizes. The optimized solution has better performance, with less curtailment, less bumpy grid power injection, and better utilization of wind energy. These relative results serve as the benchmark for performance, and the effectiveness of the implemented optimization and control framework is emphasized. The approach to studying system behavior involves analyzing behavior under highly variable wind generation patterns and different operating conditions, including fluctuations, ramp events, and periods of low generation. The stability of performance measures like grid stability, level of curtailment and state of charge regulation in these conditions are indicative of intrinsic robustness and reliability of the model when faced with uncertainty. The economic framework takes into consideration the cost elements of battery size, operational use, and the effect of curtailment. The analysis portrays the interaction between investment in storage and system-level benefits (enhanced energy utilization and reduced power losses), providing a structural economic view aligned with the goals of offshore wind integration.

The above results from integrating offshore wind farms with optimally sized Battery Energy Storage Systems. The simplest conclusion, an over 60% reduction in power output variation (*table 1*), is, at the same time, a technological breakthrough and an operational mode innovation for wind power. This dispatchable-to-variable conversion, as shown in *figure 3*, also addresses one of the largest challenges posed by high penetration of renewables head-on. *Figure 2's* ramp rate does the same: by mitigating spasmodic power fluctuations, the BESS-integrated system reduces the burden on fossil-fuel generators from ancillary services. The cash, recorded in *table 2*, is likewise gargantuan.

The optimal BESS configuration had the shortest simple payback time (8.2 years), consistent with a steep financial optimum. This result bursts the general myth that energy storage is a cost center. Instead, when sized correctly, a BESS is a value-added asset that recovers its costs by converting what would otherwise be wasted or curtailed electricity into sellable electricity. The optimal-to-oversized disparity is particularly striking. The marginal performance gain of the oversized BESS (*table 1*) comes at a steep increase in capital expenditure and a long payback period (*table 2*), underscoring the necessity of optimization. No punted-in-big-battery sort of affair; the payback is in proper sizing from real wind resource and grid limitations. Additionally, the operating analysis (*figure 4*) and sensitivity analysis (*table 3*) indicate the richness of interactions among ambient conditions, control strategy, and hardware sizing.

The control system's ability to maintain the BESS SoC at healthy levels (*figure 4*) is critical to the long-term profitability of the investment, as battery degradation in the initial years can render the investment economically infeasible. The "optimal" is a will-o'-the-wisp in sensitivity analysis. For instance, where grids are tighter or wind volatility is greater, greater investment in a BESS is required. Yet as grid expansion increases and BESS costs decline, the optimal design shifts. This is because any viable project planning will require a dynamic optimization model such as the one outlined in this paper. After all, by definition, one of the solutions would be inferior. All the outcomes show that the BESS is instead a backbone technology for low-cost, profitable, future-proofed offshore wind power.

The novelty of this study will not be based on the absence of solar resources, but rather the specialization of battery energy storage systems to integrate into offshore wind farms; the nature of the operating environment in which the offshore wind farms will be installed is fundamentally different from that in the hybrid solar-wind environment. Offshore wind generation is characterized by high power-swing dynamics, rapid ramping, wake effects, transmission bottlenecks, and marine-grid reliability. These features pose a control and sizing challenge that can only be addressed through specific analysis, not hybrid-renewable modeling in general. The innovation of the manuscript is to develop the best battery-sizing approach that is responsive to the intermittent nature of offshore wind while maximizing grid stability, minimizing curtailment, smoothing output power, and enhancing dispatchability. The model focuses on variability intensity, variability behavior during export cable loading, storage cycling behavior, and management of state-of-charge in uncertain wind conditions by focusing on offshore wind systems only. Such a specialized architecture provides greater engineering understanding than a generalized multi-resource model, in which the specialized nature of offshore wind can be watered down. The proposed control approach coordinates battery charging and discharging with offshore generation and grid support, leading to significant improvements in frequency support, ramp-rate reduction, and energy efficiency. The research thus adds a new dimension of accuracy, depth, and applicability, as opposed to merely excluding solar elements. This revised manuscript has now clearly shown that a dedicated offshore wind-battery structure has significant academic and industrial importance, especially to contemporary power systems that are interested in integrating large marine renewable energy resources effectively.

4. CONCLUSIONS

The study conceptualized and demonstrated an integrated control-and-sizing system for a Battery Energy Storage System near an offshore wind farm. Using a Particle Swarm Optimization algorithm and a dynamic system model, the study demonstrated that there is an optimal BESS design point that maximizes technical efficiency and economic viability. Simulation outcomes from a representative sample of wind data clearly demonstrate the benefits of such integration. The optimized system achieved a substantial 61% reduction in the standard deviation of grid-injected power, making the variable wind resource a more stable, bankable, and predictable power source. The same smoothing of power was also evidenced in a dramatic decline in peak ramp rates, a high-priority concern to grid stability. In terms of expense, the BESS was a remarkably effective value-creation tool. With otherwise lean-over surplus power, the system trimmed losses by more than 95%, which directly translated into incremental revenues and a higher project capacity factor. The study derived a well-defined economic optimum: the optimal investment payback time for a properly sized BESS. In short, the study confirms that strategically deployed, optimally sized, and well-regulated BESS is an enabler of offshore wind. It addresses the inherent problem of intermittency, increases grid integration, and improves the overall profitability of the wind project, thereby facilitating the transition to a clean and secure energy future.

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