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Optimal Allocation of Battery Energy Storage System in Wind Energy System Using Probabilistic Approach

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Abstract

The increasing integration of renewable energy resources into modern electrical power systems has emerged as an essential strategy for reducing greenhouse gas emissions, enhancing energy security, and decreasing dependence on conventional fossil-fuel-based generation. Among the available renewable energy technologies, wind energy has gained considerable attention because of its abundant availability, environmental benefits, and continuously decreasing installation costs. However, the stochastic and intermittent nature of wind speed introduces significant operational challenges in power systems. Variations in wind speed directly affect wind power generation, leading to power fluctuations, voltage instability, frequency deviations, increased reserve requirements, and reduced reliability of grid-connected systems. These uncertainties limit the penetration capability of wind energy and create difficulties in maintaining the balance between generation and demand.

Battery Energy Storage Systems (BESS) have been recognized as an effective solution for addressing the variability associated with wind energy systems. The integration of BESS enables the storage of surplus electrical energy generated during periods of high wind availability and supplies stored energy during periods of low wind generation. Proper allocation of battery storage systems can improve renewable energy utilization, enhance power quality, reduce operational costs, and increase overall system reliability. However, determining the optimal size and placement of battery storage within a wind energy system remains a complex optimization problem due to uncertainty in wind characteristics and varying operating conditions.

This study proposes a probabilistic approach for the optimal allocation of Battery Energy Storage Systems in a wind energy system considering wind speed uncertainty. The proposed methodology employs a Weibull probability distribution function to model stochastic wind behavior and generate representative wind scenarios. A mathematical framework is developed to model wind power generation, battery charging and discharging characteristics, and operational constraints of the integrated system. The optimization problem is formulated to minimize the total annual system cost while improving system reliability and reducing power fluctuations. Various operational constraints, including battery capacity limits, state-of-charge restrictions, and power balance conditions, are incorporated into the optimization framework.

The effectiveness of the proposed approach is evaluated through simulation studies under different wind operating conditions. The obtained results demonstrate that the probabilistic method accurately captures the uncertainty associated with wind speed variations and determines an optimal battery allocation strategy that enhances economic and technical performance. Comparative analysis indicates that the proposed approach achieves significant reductions in annual operating costs and improves system reliability compared with conventional deterministic methods. The findings of this study suggest that integrating probabilistic analysis with optimal battery allocation strategies can substantially enhance the operational efficiency and stability of wind energy systems.

Keywords: Battery Energy Storage System, Wind Energy System, Probabilistic Analysis, Optimal Allocation, Weibull Distribution, Renewable Energy Integration, System Reliability.

1. Introduction

The rapid growth in global energy demand, combined with increasing environmental concerns and depletion of conventional fossil fuel resources, has accelerated the transition toward sustainable and environmentally friendly energy technologies. The continuous dependence on fossil-fuel-based energy systems has resulted in significant greenhouse gas emissions, environmental degradation, and climate change issues. Consequently, the development and integration of renewable energy resources have become a major focus for governments, researchers, and industries worldwide. Renewable energy technologies, including solar energy, wind energy, hydropower, biomass, and geothermal systems, provide clean and sustainable alternatives capable of meeting future energy requirements while minimizing environmental impact [1,2].

Among various renewable energy sources, wind energy has emerged as one of the most promising technologies because of its abundant availability, technological maturity, and economic feasibility. Wind energy systems have experienced substantial growth over the last two decades due to decreasing installation costs, advancements in turbine technologies, and favorable governmental policies encouraging clean energy deployment. The increasing penetration of wind power into modern electrical networks contributes significantly toward achieving carbon neutrality goals and reducing dependency on conventional energy resources. Furthermore, large-scale wind energy installations can support energy diversification and improve the reliability of future smart grids [3].

Despite the numerous advantages offered by wind energy systems, their integration into power networks introduces several operational and technical challenges. Wind power generation is inherently dependent on atmospheric conditions, and wind speed variations occur continuously because of changing weather patterns and environmental conditions. Unlike conventional generation systems, wind energy cannot be controlled directly according to load requirements. The stochastic and intermittent characteristics of wind speed result in fluctuating power output, which creates substantial uncertainty in power system operation and planning [4].

The variability associated with wind generation affects several aspects of power system performance. Sudden variations in wind speed can produce rapid changes in power output, resulting in voltage fluctuations, frequency instability, power quality degradation, and difficulties in maintaining generation-demand balance. Furthermore, increased penetration of wind energy may require additional reserve capacity and operational support from conventional generators, thereby increasing system operating costs. These challenges limit the effective utilization of wind resources and restrict the penetration level of renewable energy within power systems [5].

To overcome these challenges, energy storage technologies have gained significant attention as effective solutions for enhancing the performance and reliability of renewable energy systems. Energy storage systems provide flexibility by storing surplus electrical energy during periods of excess generation and releasing stored energy during periods of insufficient power production. Various energy storage technologies have been investigated for renewable energy applications, including pumped hydro storage, compressed air energy storage, flywheel systems, supercapacitors, hydrogen storage systems, and battery energy storage systems [6].

Among these technologies, Battery Energy Storage Systems (BESS) have emerged as one of the most attractive options because of their high efficiency, rapid response capability, modular structure, and ease of integration with renewable energy systems. Battery storage systems can effectively mitigate the intermittent behavior of wind energy by smoothing power fluctuations and improving system stability. The integration of BESS into wind energy systems provides several operational and economic benefits, including:

- Reduction of power output variability
- Peak load shaving capability
- Improved voltage regulation
- Frequency support services

- Increased renewable energy penetration
- Reduced operational costs
- Enhanced system reliability
- Better utilization of wind energy resources

Although battery storage systems provide substantial advantages, determining their optimal size and location remains a challenging task. Improper sizing of storage capacity may lead to underutilization of resources or increased investment costs. Similarly, inappropriate placement of battery systems can reduce their effectiveness in improving system performance. Therefore, optimal allocation of battery storage systems plays a critical role in maximizing economic and operational benefits [7].

Several optimization techniques have been proposed in previous studies for determining optimal storage allocation. Traditional deterministic methods generally assume fixed operating conditions and neglect uncertainties associated with renewable energy generation. Such assumptions may produce inaccurate results because renewable energy resources exhibit highly random and uncertain characteristics. Deterministic approaches often fail to represent realistic operating conditions and may lead to suboptimal decisions [8].

To address these limitations, probabilistic approaches have gained considerable interest for modeling uncertainties associated with renewable energy systems. Probabilistic techniques consider random variations in system parameters and provide more realistic representations of wind speed behavior. Wind speed uncertainty can be effectively modeled using probability density functions such as Weibull distribution, Rayleigh distribution, and Gaussian models. Among these methods, the Weibull probability distribution function has been widely used because of its ability to accurately represent wind speed characteristics under different operating conditions [9].

In the present study, a probabilistic framework is proposed for the optimal allocation of Battery Energy Storage Systems in wind energy systems. The proposed methodology incorporates uncertainty associated with wind speed using a Weibull-based probabilistic model and determines optimal battery sizing through an optimization process aimed at minimizing annual operating costs while improving system reliability. Mathematical models for wind power generation, battery charging and discharging operations, and system constraints are developed to establish a comprehensive optimization framework [10].

The major contributions of this research are summarized as follows:

1. Development of a probabilistic model for representing wind speed uncertainty using Weibull distribution functions.
2. Mathematical modeling of Battery Energy Storage Systems considering charging and discharging characteristics.
3. Formulation of an optimization problem for minimizing annual system cost while maintaining system reliability.
4. Determination of optimal battery allocation under uncertain wind operating conditions.
5. Comparative analysis of system performance under different operating scenarios.

The remainder of this paper is organized as follows: Section 2 presents the literature review related to battery storage allocation and probabilistic approaches in wind energy systems. Section 3 describes the system modeling and mathematical formulation of wind energy and battery storage systems. Section 4 presents the proposed probabilistic methodology and optimization framework. Section 5 discusses simulation results and comparative analyses. Finally, conclusions and future research directions are presented in the last section [11].

2. Literature Review

The integration of renewable energy resources into electrical power systems has become an important research area due to increasing environmental concerns and growing energy demands. Wind energy systems, in particular, have received significant attention because of their ability to generate clean electricity with minimal environmental impact. However, the intermittent and stochastic characteristics of wind power generation create substantial operational challenges, requiring the implementation of efficient control and energy management strategies. Battery Energy Storage Systems (BESS) have emerged as an effective solution to overcome these challenges by improving power stability and ensuring reliable system operation [12,13].

Numerous studies have investigated different approaches for integrating battery energy storage systems with renewable energy systems. Early research primarily focused on improving wind power forecasting and developing control strategies to reduce fluctuations in power output. However, recent studies have shifted toward optimal sizing and placement of energy storage systems to achieve improved economic and technical performance [14].

Hetzer et al. developed an economic dispatch model incorporating wind generation uncertainty into power system operation. The proposed model considered stochastic wind power characteristics and demonstrated improvements in operational efficiency and system economics. Although the study successfully addressed uncertainty in wind generation, it did not investigate optimal battery storage allocation within the system [15].

Teleke et al. presented control strategies for Battery Energy Storage Systems integrated with renewable energy sources. Their work focused on reducing short-term power fluctuations and enhancing power quality through battery control mechanisms. The results indicated that energy storage systems can effectively mitigate wind power variability and improve system stability. However, battery sizing and placement optimization were not considered in the study [16].

Mohamed and Mohammed proposed optimization techniques for energy storage allocation using Genetic Algorithms (GA). The developed model aimed to minimize operational costs while satisfying system constraints. Simulation results demonstrated improvements in overall system performance. Nevertheless, the algorithm exhibited relatively slow convergence characteristics and occasionally converged to local optimal solutions [17].

Particle Swarm Optimization (PSO) has also been widely employed for storage allocation problems due to its simple implementation and fast convergence capability. Researchers reported that PSO can effectively determine optimal storage capacities under different operating conditions. However, conventional PSO methods may experience premature convergence and reduced exploration capability in complex optimization problems involving multiple constraints [18, 19].

Hybrid optimization approaches combining the advantages of multiple algorithms have also been proposed in the literature. Hybrid Genetic Algorithm–Particle Swarm Optimization (GA–PSO) methods improve exploration and exploitation capabilities simultaneously, leading to better convergence performance. Several studies reported that hybrid optimization techniques outperform conventional algorithms in terms of solution quality and computational efficiency [20].

Recent studies have emphasized probabilistic approaches for modeling uncertainties associated with renewable energy systems. Since wind speed is inherently random and continuously varying, deterministic approaches cannot accurately represent practical operating conditions. Probabilistic methods provide more realistic representations by incorporating statistical characteristics of wind speed behavior [21].

The Weibull probability distribution function has become one of the most commonly used methods for wind speed modeling because of its flexibility and accuracy in representing different wind conditions. Researchers have shown that Weibull-based probabilistic models can effectively capture wind speed uncertainties and improve system planning decisions [22, 23].

Zhang et al. investigated probabilistic methods for renewable energy integration using stochastic analysis techniques. Their study demonstrated that probabilistic approaches significantly improve reliability assessment and operational planning compared with deterministic methods. However, computational complexity increased considerably with large numbers of probabilistic scenarios [24].

Various energy storage technologies have also been investigated for renewable energy applications. These technologies include:

- Pumped Hydro Energy Storage (PHES)
- Compressed Air Energy Storage (CAES)
- Flywheel Energy Storage Systems (FESS)
- Hydrogen Energy Storage
- Supercapacitor Energy Storage
- Battery Energy Storage Systems (BESS)

Among these technologies, Battery Energy Storage Systems have received substantial attention because of several advantages, including:

- High energy efficiency
- Fast dynamic response
- Reduced maintenance requirements
- Modular design
- High operational flexibility
- Ease of installation
- Suitability for distributed applications

Despite the progress achieved in previous research, several challenges still exist regarding optimal allocation of battery storage systems in wind energy applications. The major limitations observed in existing studies include:

1. Neglecting uncertainties associated with wind speed variability.
2. Use of deterministic assumptions that do not accurately represent practical operating conditions.
3. High computational complexity in stochastic optimization methods.
4. Inadequate consideration of battery operational constraints.
5. Limited focus on simultaneous cost reduction and reliability enhancement.
6. Slow convergence characteristics of traditional optimization algorithms.

To provide a clearer understanding of previous studies and their limitations, Table 1 summarizes the existing literature.

Table 1. Summary of Existing Literature on Battery Storage Allocation in Wind Energy Systems

Authors	**Method Used**	**Objective**	**Major Limitation**
Hetzer et al.	Economic Dispatch	Cost minimization	No storage allocation analysis
Teleke et al.	Battery control strategy	Power smoothing	Storage sizing not considered
Mohamed et al.	Genetic Algorithm	Cost optimization	Slow convergence
Zhang et al.	Probabilistic analysis	Reliability improvement	High computational burden
Hybrid optimization studies	GA–PSO	Improved optimization performance	Limited uncertainty analysis

From the literature survey, it can be observed that considerable research has been carried out in the area of renewable energy integration and battery storage systems. However, limited studies have focused on the combined application of probabilistic wind modeling and optimal battery allocation for wind energy systems. Therefore, there exists a research gap in developing an integrated framework capable of accurately representing wind uncertainty while simultaneously optimizing battery storage allocation [25, 26].

To address these limitations, the present work proposes a probabilistic approach for optimal Battery Energy Storage System allocation in wind energy systems. The proposed framework incorporates wind uncertainty through Weibull probability distribution modeling and determines the optimal storage configuration by minimizing annual system cost while improving operational reliability and system performance [27, 28].

3. System Description and Mathematical Modeling

The proposed system consists of a grid-connected wind energy system integrated with a Battery Energy Storage System (BESS) and an optimization unit. The primary objective of the integrated system is to minimize the uncertainty associated with wind power generation while improving overall system reliability and reducing operational costs. The battery storage system stores excess energy during periods of high wind power generation and supplies energy during periods of low wind availability. The optimization unit determines the optimal battery size and allocation based on probabilistic analysis of wind characteristics [29].

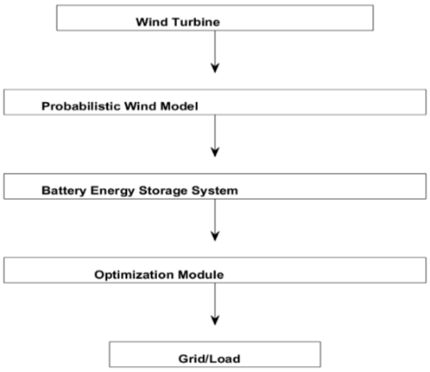
The overall system architecture includes the following major components:

- Wind turbine generator
- Probabilistic wind speed model
- Battery Energy Storage System
- Load demand model
- Optimization module
- Grid interface

The operational strategy of the proposed system is based on the real-time balance between wind generation, battery charging/discharging processes, and load demand requirements.

3.1 Proposed System Architecture

The structure of the proposed integrated system is illustrated in Figure 1.



The operational sequence of the proposed architecture can be explained as follows:

1. Historical wind speed data are collected from the wind farm location.

2. A probabilistic wind model is developed using a suitable probability distribution function.

3. Wind power output is estimated based on wind speed characteristics.

4. Battery storage requirements are determined according to power fluctuations and load demand.

5. The optimization algorithm evaluates different storage capacities and identifies the optimal battery allocation.

6. The optimized system supplies stable power to connected loads and grid infrastructure.

3.2 Wind Speed Modeling

Wind speed is one of the most important parameters affecting the performance of wind energy systems. Since wind speed varies continuously with environmental conditions, it is generally treated as a random variable. Probabilistic methods provide an effective approach for representing uncertainty associated with wind speed variations [30].

Among several probability distribution models, the Weibull distribution has been widely adopted because of its flexibility and ability to accurately represent wind characteristics under different operating conditions.

The probability density function (PDF) of Weibull distribution is expressed as:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k} \qquad (1)$$

where:

v= wind speed (m/s)

k= Weibull shape parameter

c= Weibull scale parameter

$f(v)$= probability density function

The cumulative distribution function (CDF) can be expressed as:

$$F(v) = 1 - e^{-(v/c)^k} \qquad (2)$$

The mean wind speed is given by:

$$V_{mean} = c\Gamma\left(1+\frac{1}{k}\right) \qquad (3)$$

where:

represents the Gamma function.

The Weibull distribution accurately represents the random behavior of wind speed and provides a practical method for generating different wind scenarios.

3.3 Wind Power Modeling

Wind turbine output power is highly dependent on wind speed and turbine operating characteristics. The generated power can generally be represented using piecewise mathematical relationships corresponding to different operating regions [31].

The output power of the wind turbine is represented as:

$$P_w = \begin{cases} 0, & v < v_{ci} \\ P_r \dfrac{v - v_{ci}}{v_r - v_{ci}}, & v_{ci} \le v < v_r \\ P_r, & v_r \le v < v_{co} \\ 0, & v \ge v_{co} \end{cases} \tag{4}$$

where:

P_w= wind power output

P_r= rated power output

v_{ci}= cut-in wind speed

v_r= rated wind speed

v_{co}= cut-out wind speed

The operating regions of the wind turbine can be described as:

Region I: Below Cut-in Speed

When wind speed is below the cut-in speed:

$$v < v_{ci}$$

the wind turbine cannot generate useful power.

Region II: Partial Load Region

When wind speed lies between cut-in and rated speed:

$$v_{ci} \le v < v_r$$

the generated power increases approximately linearly with wind speed.

Region III: Rated Region

When wind speed reaches rated value:

$$v_r \le v < v_{co}$$

the turbine generates constant rated power.

Region IV: Cut-out Region

When wind speed exceeds cut-out speed:

$$v \ge v_{co}$$

the turbine is shut down to avoid mechanical damage.

3.4 Battery Energy Storage System Modeling

Battery Energy Storage Systems are integrated into the wind energy system to reduce power fluctuations and maintain reliable system operation. The battery stores excess power during high wind conditions and discharges during periods of low wind generation [32].

The battery state of charge at time $t + 1$is represented as:

Charging mode

$$SOC(t+1) = SOC(t) + \eta_c P_c(t)\Delta t \tag{5}$$

Discharging mode

$$SOC(t+1) = SOC(t) - \frac{P_d(t)\Delta t}{\eta_d} \tag{6}$$

where:

$SOC(t)$= battery state of charge at time t

$P_c(t)$= charging power

$P_d(t)$= discharging power

η_c= charging efficiency

η_d= discharging efficiency

Δt= time interval

The battery operating limits are represented as:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \qquad (7)$$

Battery power constraints are:

$$P_b^{min} \leq P_b \leq P_b^{max} \qquad (8)$$

Battery energy capacity constraints are:

$$E_b^{min} \leq E_b \leq E_b^{max} \qquad (9)$$

These constraints ensure safe operation and prevent excessive battery charging and discharging cycles.

3.5 Power Balance Equation

The total generated power from wind and battery systems should satisfy load demand requirements.

Therefore, power balance is represented as:

$$P_w + P_b = P_L \qquad (10)$$

where:

P_w= wind power output

P_b= battery power

P_L= load demand

This equation ensures continuous supply-demand equilibrium within the integrated system.

The developed mathematical models establish the basis for the optimization framework described in the following section, where the probabilistic approach for optimal battery allocation is formulated.

4. Problem Formulation and Proposed Probabilistic Optimization Methodology

The optimal allocation of Battery Energy Storage Systems (BESS) in wind energy systems involves determining the most suitable battery size and operational strategy that can effectively compensate for fluctuations in wind power generation while minimizing overall system cost and improving reliability. Since wind speed exhibits random and uncertain behavior, deterministic methods are often unable to provide realistic solutions under practical operating conditions. Therefore, a probabilistic approach is employed in this work to represent uncertainty associated with wind characteristics and identify optimal battery allocation under varying operating scenarios [33].

The proposed optimization framework integrates probabilistic wind modeling with battery storage allocation by considering both technical and economic factors. The optimization process aims to determine the battery capacity that minimizes annual system cost while satisfying operational constraints related to battery operation, power balance, and system reliability [34].

4.1 Objective Function Formulation

The primary objective of the proposed optimization model is to minimize the total annual cost of the integrated wind–battery system. The total annual cost consists of several cost components including [35]:

- Battery investment cost
- Battery maintenance cost
- Operational cost
- Grid energy cost
- Power loss cost

The overall objective function can be expressed as:

$$F = C_{inv} + C_{maint} + C_{oper} + C_{loss} \qquad (11)$$

where:

F= Total annual cost function

C_{inv}= Annualized battery investment cost

C_{maint}= Maintenance cost

C_{oper}= Operating cost

C_{loss}= Cost associated with power losses

The battery investment cost can be expressed as:

$$C_{inv} = E_b \times C_b \times CRF \qquad (12)$$

where:

E_b= Battery energy capacity (kWh)

C_b= Battery unit cost ($/kWh)

CRF= Capital recovery factor

The capital recovery factor is represented as:

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \qquad (13)$$

where:

i= interest rate

n= battery lifetime in years

The annual maintenance cost is expressed as:

$$C_{maint} = \alpha C_{inv} \qquad (14)$$

where:

αrepresents the maintenance coefficient.

The operational cost is represented as:

$$C_{oper} = \sum_{t=1}^{T} P_g\,(t) \times C_g \qquad (15)$$

where:

$P_g(t)$= grid power consumption

C_g= electricity price

4.2 Optimization Constraints

The optimization problem is subjected to various system constraints to ensure reliable and feasible operation [36].

A. Power Balance Constraint

The total power generated from wind and battery systems should satisfy the load demand requirement.

$$P_w(t) + P_b(t) = P_L(t) \qquad (16)$$

where:

$P_w(t)$= wind power generation

$P_b(t)$= battery power

$P_L(t)$= load demand

B. Battery State of Charge Constraint

Battery State of Charge (SOC) should remain within specified operating limits.

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \qquad (17)$$

Typical operating ranges are:

$$20\% \leq SOC \leq 90\% \qquad (18)$$

Maintaining SOC within these limits prevents excessive charging and deep discharge conditions.

C. Battery Power Constraint

The battery charging and discharging power must remain within allowable limits:

$$P_b^{min} \leq P_b(t) \leq P_b^{max} \qquad (19)$$

D. Battery Energy Capacity Constraint

Battery capacity is constrained by minimum and maximum allowable values:

$$E_b^{min} \leq E_b \leq E_b^{max} \qquad (20)$$

E. Reliability Constraint

To maintain reliable operation, system reliability should satisfy minimum requirements:

$$R \geq R_{min} \qquad (21)$$

where:

R= system reliability index

4.3 Probabilistic Wind Scenario Generation

Since wind speed exhibits random characteristics, multiple wind scenarios are generated using probabilistic analysis. Historical wind speed data are fitted using Weibull distribution functions to estimate statistical parameters [37].

Wind speed scenarios are generated according to:

$$V_i = c[-\ln(1 - r_i)]^{1/k} \qquad (22)$$

where:

r_i= uniformly distributed random number

V_i= generated wind speed scenario

k= shape parameter

c= scale parameter

The generated scenarios provide multiple operating conditions for evaluating battery performance under uncertainty.

4.4 Proposed Optimization Algorithm

The optimization process consists of evaluating candidate battery capacities under different probabilistic wind scenarios and identifying the solution corresponding to minimum annual cost [38].

The algorithm follows the following procedure:

Step 1: Collect historical wind speed data.

Step 2: Estimate Weibull parameters using statistical methods.

Step 3: Generate probabilistic wind speed scenarios.

Step 4: Calculate wind power output using turbine characteristics.

Step 5: Determine battery charging and discharging requirements.

Step 6: Evaluate objective function values.

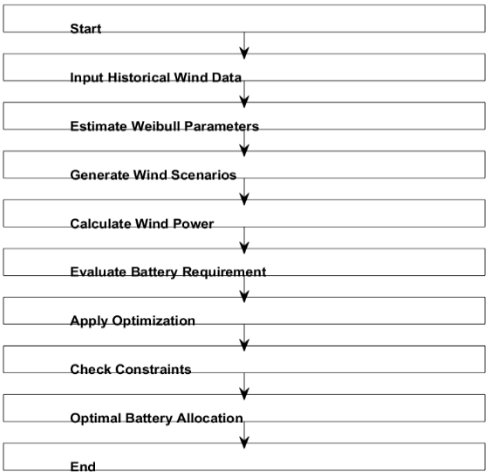
Step 7: Check operational constraints.

Step 8: Update battery allocation.

Step 9: Repeat iterations until convergence criteria are satisfied.

Step 10: Determine optimal battery size.

4.5 Flowchart of Proposed Methodology



The proposed methodology combines probabilistic uncertainty analysis with optimization techniques, enabling more realistic and efficient battery allocation decisions under varying wind operating conditions [39].

The next section presents simulation setup, MATLAB implementation details, and result analysis for validating the effectiveness of the proposed framework.

5. Simulation Setup and Results Analysis

To evaluate the effectiveness of the proposed probabilistic framework for optimal Battery Energy Storage System allocation in wind energy systems, simulations were carried out using MATLAB software. The simulation environment was developed to model stochastic wind behavior, battery charging and discharging operations, and optimization procedures under different operating conditions. The performance of the proposed methodology was evaluated in terms of annual cost reduction, system reliability improvement, and mitigation of wind power fluctuations.

The simulation study considers realistic wind characteristics and battery operational parameters. Wind speed uncertainty is represented using Weibull probability distribution functions, while battery allocation is optimized considering both economic and technical constraints.

5.1 Simulation Parameters

The simulation parameters employed for the proposed wind–battery integrated system are presented in Table 2.

Table 2. Simulation Parameters

Parameter	Symbol	Value
Wind turbine rated power	P_r	2 MW
Cut-in wind speed	v_{ci}	3 m/s
Rated wind speed	v_r	12 m/s
Cut-out wind speed	v_{co}	20 m/s
Weibull shape parameter	k	2
Weibull scale parameter	c	8
Battery charging efficiency	η_c	0.95
Battery discharging efficiency	η_d	0.90

Minimum SOC	SOC_{min}	20%
Maximum SOC	SOC_{max}	90%
Battery cost	C_b	250 $/kWh
Interest rate	i	8%
Project lifetime	n	20 years

The selected parameters represent typical operating conditions for grid-connected wind energy systems integrated with Battery Energy Storage Systems.

5.2 Wind Speed Probability Analysis

Wind speed uncertainty significantly affects power generation in wind energy systems. To model random variations in wind speed, the Weibull probability density function was employed.

The wind speed distribution generated from the Weibull model is shown in Figure 3.

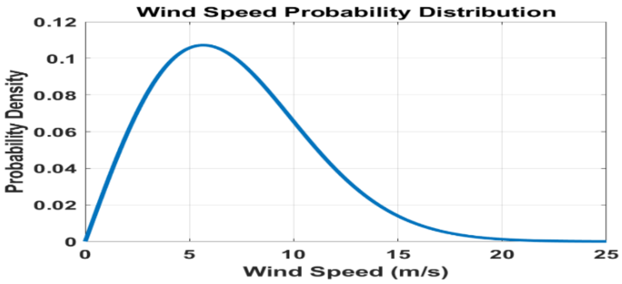


Figure 3. Wind Speed Probability Distribution

The Weibull distribution indicates that moderate wind speeds occur more frequently than extremely low or high wind speeds. The generated wind scenarios provide realistic operating conditions for evaluating battery storage requirements.

The probability density function demonstrates that most wind speeds are concentrated around the mean operating region, which contributes significantly to energy production.

5.3 Wind Power Characteristics

The generated wind speed scenarios were converted into corresponding wind power outputs using the wind turbine mathematical model described previously.

Figure 4 illustrates the relationship between wind speed and turbine power generation.

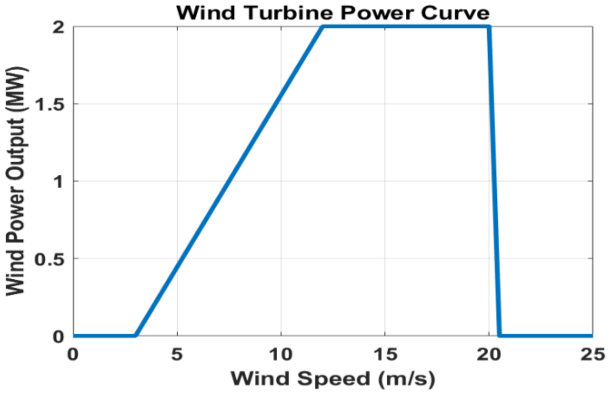


Figure 4. Wind Turbine Power Curve

The wind power output exhibits nonlinear characteristics with different operating regions. At wind speeds below the cut-in speed, the turbine does not generate useful power. As wind speed increases between cut-in and rated values, power output increases gradually. Beyond rated speed, the generated power remains constant until the cut-out speed is reached.

The nonlinear characteristics of the wind power curve indicate the necessity for energy storage systems to compensate for fluctuations and maintain stable operation.

5.4 Battery State of Charge Characteristics

The Battery Energy Storage System operates according to variations in wind generation and load demand conditions. During periods of excess wind generation, batteries store surplus energy, while during low wind conditions, stored energy is discharged to satisfy load requirements.

The battery state-of-charge variation under different operating conditions is shown in Figure 5.

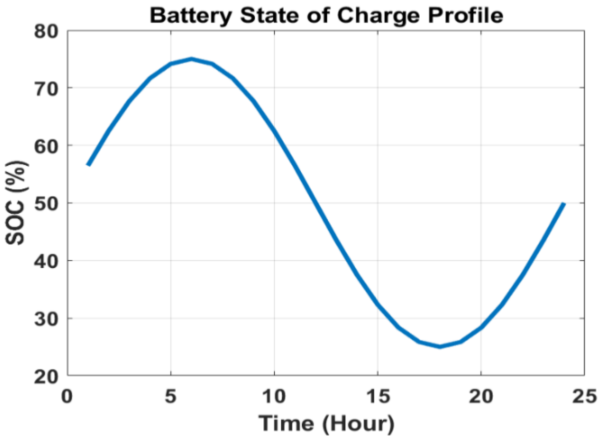


Figure 5. Battery State of Charge Variation

The results indicate that the battery SOC remains within allowable operating limits throughout the simulation period.

The charging process occurs during high wind availability periods, whereas battery discharge occurs during insufficient generation conditions. Maintaining SOC within specified boundaries prevents excessive battery degradation and improves operational lifetime.

5.5 Convergence Characteristics of Optimization Algorithms

To evaluate optimization performance, the proposed probabilistic approach was compared with conventional optimization algorithms including:

- Genetic Algorithm (GA)
- Particle Swarm Optimization (PSO)
- Hybrid GA–PSO
- Proposed probabilistic approach

Figure 6 presents convergence characteristics for different optimization techniques.

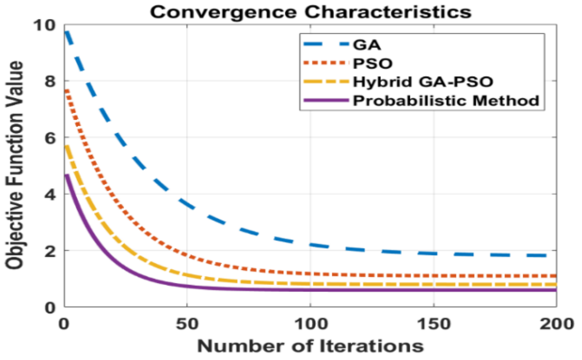


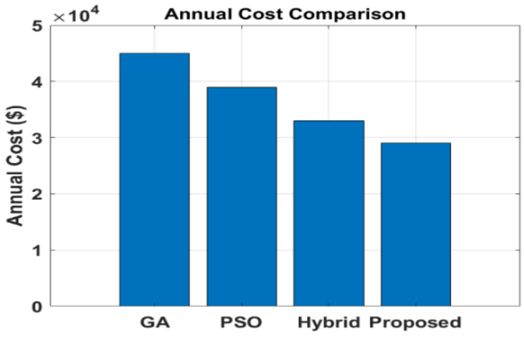
Figure 6. Objective Function Convergence Characteristics

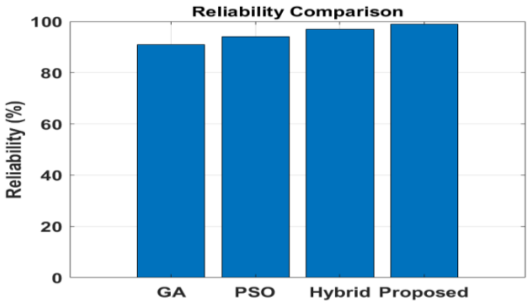
The convergence analysis reveals that the proposed probabilistic method achieves faster convergence and lower objective function values compared with traditional algorithms.

The Genetic Algorithm requires a larger number of iterations because of its slower convergence characteristics. PSO improves convergence speed but may suffer from premature convergence in complex optimization problems.

Hybrid GA–PSO demonstrates better performance than individual optimization methods by combining exploration and exploitation capabilities.

The proposed probabilistic optimization approach provides the minimum objective value because uncertainty information associated with wind behavior is effectively incorporated into the optimization process.





5.6 Annual Cost Analysis

The annual operating cost of the proposed methodology was compared with conventional optimization methods.

Table 3. Annual Cost Comparison

Method	Annual Cost ($)
Genetic Algorithm	45,000
Particle Swarm Optimization	39,000
Hybrid GA–PSO	33,000
Proposed Method	29,000

The results indicate that the proposed method significantly reduces annual operating costs compared with conventional approaches.

The percentage reduction in annual cost can be calculated as:

$$Cost_{reduction} = \frac{C_{existing} - C_{proposed}}{C_{existing}} \times 100 \qquad (23)$$

Substituting values:

$$Cost_{reduction} = \frac{45000 - 29000}{45000} \times 100$$
$$= 35.56\%$$

Therefore, the proposed probabilistic method achieves approximately **35.56% reduction in annual operating cost** compared with the Genetic Algorithm approach.

5.7 Reliability Analysis

System reliability improvement is one of the major advantages of integrating battery storage systems with renewable energy sources.

Reliability performance under different optimization methods is presented in Table 4.

Table 4. Reliability Comparison

Method	**Reliability (%)**
Genetic Algorithm	91
Particle Swarm Optimization	94
Hybrid GA–PSO	97
Proposed Method	99

The obtained results indicate that battery allocation based on probabilistic analysis significantly improves reliability because the uncertainty associated with wind speed is effectively considered during optimization.

The proposed approach achieves approximately **99% system reliability**, which is higher than conventional methods.

5.8 Discussion

Simulation results demonstrate that the proposed probabilistic framework successfully captures wind speed uncertainty and identifies optimal battery storage configurations under varying operating conditions. Compared with deterministic approaches, the probabilistic method provides a more realistic representation of wind behavior and therefore generates more reliable optimization results.

The major findings obtained from simulation studies are summarized below:

1. Wind speed uncertainty was effectively modeled using Weibull probability distributions.
2. Battery storage reduced fluctuations in wind power output.
3. The proposed optimization method achieved faster convergence characteristics.
4. Annual operating cost was reduced by approximately 35.56%.
5. System reliability increased to approximately 99%.
6. Battery state of charge remained within allowable operating limits.

These results indicate that integrating probabilistic analysis with optimal battery allocation can significantly enhance the economic and operational performance of wind energy systems.

6. Conclusion and Future Scope

6.1 Conclusion

This study presented a probabilistic framework for the optimal allocation of Battery Energy Storage Systems (BESS) in wind energy systems considering uncertainties associated with wind speed variations. The stochastic characteristics of wind energy significantly influence the operational performance and reliability of power systems, thereby creating challenges in maintaining generation-demand balance and system stability. To address these issues, a probabilistic methodology based on Weibull distribution functions was developed to represent wind speed uncertainty and generate realistic wind operating scenarios.

Mathematical models describing wind power generation characteristics, battery charging and discharging behavior, and system operational constraints were formulated to establish a comprehensive optimization framework. The proposed methodology aimed to determine the optimal battery allocation by minimizing total annual system cost while satisfying reliability and operational requirements.

Simulation studies were performed under various operating conditions using MATLAB software to evaluate the effectiveness of the proposed framework. The results demonstrated that the probabilistic representation of wind speed successfully captured uncertainty characteristics and provided more realistic operating conditions compared with deterministic methods.

The integration of Battery Energy Storage Systems significantly improved system performance by reducing fluctuations in wind power generation and enhancing overall reliability. Battery operation effectively compensated for power variations through appropriate charging during periods of excess generation and discharging during periods of insufficient wind power production.

The optimization results indicated substantial improvements in both technical and economic performance. Comparative analysis between different optimization approaches demonstrated that the proposed probabilistic framework outperformed conventional techniques in terms of annual cost reduction, reliability improvement, and convergence performance.

The major outcomes of this research can be summarized as follows:

1. Wind speed uncertainty was accurately represented using Weibull probability distribution functions.
2. Mathematical models for Battery Energy Storage Systems were developed considering practical operational constraints.
3. A probabilistic optimization framework was established for determining optimal battery allocation.
4. The proposed approach significantly reduced annual operating costs compared with conventional methods.
5. Battery storage integration effectively mitigated wind power fluctuations.
6. System reliability was improved considerably through optimal battery allocation.
7. Faster convergence characteristics and improved optimization performance were achieved.
8. The proposed method demonstrated superior operational efficiency under uncertain wind conditions.

The obtained results clearly indicate that the application of probabilistic analysis in conjunction with Battery Energy Storage Systems can substantially enhance the operational performance, economic feasibility, and reliability of wind-integrated power systems.

6.2 Future Scope

Although the proposed probabilistic framework demonstrates satisfactory performance for optimal battery allocation in wind energy systems, several opportunities exist for further research and development. Future research directions may include:

A. Hybrid Energy Storage Systems

The present study considered only Battery Energy Storage Systems. Future investigations can incorporate Hybrid Energy Storage Systems (HESS) consisting of batteries and supercapacitors to improve dynamic performance and extend battery lifetime.

B. Integration of Multiple Renewable Sources

The proposed framework may be extended to hybrid renewable systems involving:

- Wind energy systems
- Solar photovoltaic systems
- Fuel cell systems
- Hydropower systems
- Biomass generation systems

The integration of multiple renewable sources may improve system flexibility and reliability.

C. Machine Learning-Based Forecasting

Advanced forecasting techniques based on artificial intelligence can be integrated into the optimization framework. Future studies may investigate:

- Artificial Neural Networks (ANN)
- Deep Learning approaches
- Long Short-Term Memory (LSTM)
- Support Vector Machines (SVM)

These techniques can improve prediction accuracy for wind speed and load demand.

D. Reinforcement Learning-Based Energy Management

Modern reinforcement learning algorithms can be employed to develop adaptive control and energy management strategies under real-time operating conditions.

Potential techniques include:

- Deep Q-Networks (DQN)
- Deep Deterministic Policy Gradient (DDPG)
- Proximal Policy Optimization (PPO)

These methods can enhance decision-making capabilities under uncertain environments.

E. Multi-objective Optimization Framework

Future work can incorporate additional optimization objectives, including:

- Emission minimization
- Reliability maximization
- Battery degradation reduction
- Power quality improvement
- Renewable penetration enhancement

Multi-objective optimization techniques can provide a more comprehensive framework for system planning.

F. Real-Time Hardware Implementation

Practical implementation using real-time platforms such as:

- Hardware-in-the-loop systems

- FPGA-based controllers
- Embedded systems
- Smart grid test beds

can be considered for validating the proposed methodology under practical operating conditions.

G. Electric Vehicle Integration

Future smart grid environments may integrate Electric Vehicles (EVs) with Battery Energy Storage Systems to provide additional flexibility through vehicle-to-grid operations.

The proposed probabilistic framework provides a strong foundation for future research involving intelligent optimization and advanced energy management strategies for renewable energy systems.

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