

Effective Balancing of Preventive Maintenance Cost and Energy Loss to Improve Wind Turbine Performance

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ABSTRACT

Ensuring the reliability and efficiency of wind turbines is essential for the success of sustainable energy systems. Preventive maintenance plays a critical role in minimizing downtime, reducing energy losses, and controlling operational costs. This study presents an optimized maintenance planning approach using Monte Carlo simulation to determine optimal PM intervals for wind turbine components. The methodology balances maintenance costs and energy loss impacts by simulating various failure scenarios, incorporating Weibull-distributed failure rates. A comparative evaluation is conducted between individual and grouped PM strategies, based on a case study of a 2 MW wind turbine. The simulation results reveal that the grouped strategy significantly outperforms individualized maintenance, achieving a 3.20% increase in total energy production and reducing overall maintenance costs to USD 9997 compared to USD 11873 for the separate component-based approach.

These findings confirm the effectiveness of the proposed model in enhancing turbine reliability and operational efficiency, offering practical insights for sustainable asset management in renewable energy systems.

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التوازن الفعال بين تكلفة الصيانة الوقائية وفقدان الطاقة لتحسين أداء توربينات الرياح

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ملخص: تُعد موثوقية وكفاءة توربينات الرياح من الركائز الأساسية لنجاح أنظمة الطاقة المستدامة. وتُساهم الصيانة الوقائية بدور محوري في تقليص فترات التوقف والحد من خسائر الطاقة، والسيطرة على تكاليف التشغيل. يقترح هذا البحث منهجية محاكاة تعتمد على تقنية مونت كارلو لتحديد الفترات المثلى للصيانة الوقائية، من خلال تحقيق توازن فعال بين تكاليف الصيانة وخسائر الطاقة الناتجة عن الأعطال. وتعتمد الدراسة على توزيع ويبل في نمذجة احتمالية الأعطال، مع إجراء مقارنة بين استراتيجيات الصيانة الفردية والاستراتيجية المجمعّة. وقد تم تطبيق المنهجية على دراسة حالة لتوربين رياح بقدرة 2 ميغاواط. أظهرت نتائج المحاكاة أن الاستراتيجية المجمعّة تتفوق بشكل ملحوظ على الصيانة الفردية، حيث أسفرت عن زيادة بنسبة 3.20٪ في إنتاج الطاقة الكلي، وانخفاض في تكاليف الصيانة إلى 9997 دولاراً، مقارنة بـ 11873 دولاراً في الاستراتيجية التقليدية. وتؤكد هذه النتائج فعالية النموذج المقترح في تعزيز موثوقية التوربينات وكفاءتها التشغيلية، كما توفر حلولاً عملية لإدارة أصول الطاقة المتجددة بكفاءة واستدامة.

كلمات مفتاحية: الطاقة المتجددة، توربينات الرياح، الصيانة الوقائية، محاكاة مونت كارلو، فقدان الطاقة

1. INTRODUCTION:

Businesses continuously strive to improve internal operations, reduce costs, and optimize resources. In today's competitive environment, the effective management of human and financial resources remains a primary challenge in the pursuit of profitability. Resources form the backbone of strategic decision-making, driving competitive advantage and wealth creation. Efficient resource management is essential for business survival and growth in a global market characterized by intense competition and economic volatility. Concurrently, the global shift towards sustainable energy sources recognizes renewable energy as vital in addressing climate change [1]. Renewable energy technologies like wind turbines, solar photovoltaic systems, and hydroelectric power plants are gaining popularity as key components of the energy transition due to their advantages over fossil fuel-based counterparts [2]. Despite lower operational costs and reduced greenhouse gas emissions, these systems demand regular maintenance to sustain optimal performance and avert costly repairs. Preventive maintenance optimization is pivotal in enhancing renewable energy systems' reliability, increasing energy production, and curbing operational costs. This approach focuses on developing and analyzing mathematical models to improve and optimize maintenance strategies. Numerous studies have highlighted the importance of this field and its potential impact. [3] and [4] delve into mathematical models to optimize maintenance strategies. Wind turbines, vital in utilizing renewable energy, necessitate regular maintenance for reliable and efficient operation. Optimization of maintenance aims to reduce costs while maximizing equipment performance and availability [5]. Various research studies have examined optimizing preventive maintenance strategies for wind turbines, focusing on different aspects like cost minimization, challenges [6], component-specific maintenance, and condition monitoring integration. References [7] and [8] utilize optimization methods, such as genetic algorithms, to evaluate maintenance strategies, including time-based and condition-based approaches, while factoring in component failure rates and the specific challenges of offshore wind turbines. Additionally, models proposed by [9] and [10] incorporate condition monitoring and consider factors like wind speed impact and accelerating hazard rates, emphasizing the importance of optimizing maintenance for wind energy. Monte Carlo

simulation emerges as a promising method for optimizing preventive maintenance strategies. Studies like [9] and [11] employ Monte Carlo simulation to enhance maintenance strategies, considering weather conditions, maintenance correlations, and risk-based models for generators in distributed power systems. Furthermore, Monte Carlo simulation aids in evaluating reliability, **operational performance, and assessing faults' impact on power generation in wind turbines** [12], [13] and [14].

It helps optimize maintenance routing, evaluates fault impact, and determines optimal maintenance intervals for turbines [15], [16] and [17]. Nevertheless, there is a clear gap in combining cost assessment and energy loss analysis to enhance the optimization of preventive maintenance strategies for wind turbines using Monte Carlo simulation. This research aims to bridge this gap, offering a pioneering approach that provides comprehensive insights into this unexplored domain. The proposed methodology incorporates historical data, maintenance costs, and stochastic variables through Monte Carlo simulation to optimize maintenance schedules. This holistic method seeks to reduce costs and improve reliability by identifying the optimal maintenance intervals for individual components as well as for the turbine system as a whole. A numerical example validating the proposed approach is performed. This research contributes to advancing knowledge in optimizing preventive maintenance for wind turbines, offering tangible evidence of improved reliability and cost-efficiency through the Monte Carlo simulation approach. Notations are mentioned on Table 1.

Table 1 : notation

y_n	Random variable	CCCA	CM cost
β	Shape parameter	δ_j	Duration of PM
η	Scale parameter	T_i	Time interval
γ	Failure rate	r_i	Productive lost
F_i	Total number of failures	CT	Total cost
α_j	Number of CM	T_{ef}	Turbine efficiency
EL	Energy losses	CR	Rated capacity
FD	Failure duration and	E_p	Production energy
x_i	Number of turbines	T_i	Time interval
Γ	Gamma Function	C_j^{PR}	PM cost
MTBF	Mean Time Between Failures		

All cost values in this study are expressed in USD.

2. MATERIALS AND METHODS:

2.1. Optimized modeling methodology:

Adopting an optimization model for preventive maintenance in wind turbines is a strategic method to enhance reliability, reduce costs, and promote sustainable energy generation. By leveraging advanced analytics, predictive modeling, and optimization algorithms, this approach optimizes the performance and longevity of wind turbine assets. Monte Carlo simulation is a highly effective, it facilitates the evaluation of system performance, prediction of outcomes, and supports robust decision-making processes. In wind turbine maintenance, it simulates scenarios considering component failures, identifying optimal maintenance strategies. Equation 1 embodies its fundamental principle.

$$g = f(y_1, y_2, y_3, \dots, y_n) \tag{1}$$

The variables “ $y_1, y_2, y_3, \dots, y_n$ ” are random, while “ g ” serves as the dependent variable linked to the intricate function governing the system. “ $y_1, y_2, y_3, \dots, y_n$ ”. Monte Carlo simulation addresses this complexity by sampling “ y ” variables using random numbers, calculating “ g ” values accordingly to find the optimal solution. In addition to other parameters, which have to be modeled mathematically, such as distribution function. Where, several studies, demonstrate that wind turbine function distribution is modeled by Weibull distribution [18] and [19]. This research applies the two-parameter Weibull function, defined as shown below.

$$f(t) = \left(\frac{\beta}{\eta}\right) \cdot \left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^\beta} \tag{2}$$

Within, β the shape parameter and η represents scale parameter, are estimated using maximum likelihood estimation method. The modeling approach also relies on the others mathematical equations that will be used in the calculation, including failure Rate, downtime, cost, which includes preventive and corrective costs given, Energy losses and total energy production. The failure rate (y), which represents the frequency of turbine failures over a defined period, is calculated as the total number of observed failures. Expressed in Equation (3).

$$y = \frac{\sum_{i=1}^I F_i}{\sum_{i=1}^I x_i T_i} \tag{3}$$

F_i represents the total number of failures, x_i indicates the number of turbines, and T_i corresponds to the duration of the specified time interval. This gives the average number of failures per turbine per unit time. Hence each failure causes downtime of average duration. Equation (4) represents the downtime, indicating the period during which the turbine is non-operational due to failures. Within the time interval T_i , r_i is productive lost due to failures.

$$r = \frac{\sum_{i=1}^I r_i}{\sum_{i=1}^I x_i T_i} \tag{4}$$

Since each failure results in downtime of average failure duration FD , the total downtime can also be estimated as a function of the failure rate as:

$$r \approx y \cdot FD$$

This expression shows that the average downtime is directly proportional to the failure rate. As the failure rate increases, downtime increases proportionally, assuming a fixed mean repair time. To impact both productivity loss and the corrective maintenance cost.

Since each failure leads to one corrective maintenance action, α_j the number of corrective actions over an operational period T is:

$$\alpha_j = y \cdot T$$

Substituting this into the total maintenance cost equation (5), we obtain:

$$C_T = \sum_{k=1}^K \delta_j \cdot C_j^{PR} + y \cdot T \cdot C_{CCA} \tag{5}$$

Where, C_{CCA} is the corrective maintenance cost, δ_j , is the duration of preventive maintenance actions, and C^{PR} is the preventive maintenance cost. Providing a full mathematical correlation as part of the optimization framework.

Based on the previously introduced variables and functions, Equation (6) formulates the minimization objective function, aimed to minimize the total maintenance cost subject to

constraint on the allowable energy loss at identifying the optimal PM frequency.

$$\begin{cases} \min \{C_T = \sum_{k=1}^K \delta_j \cdot C_j^{PR} + \alpha_j \cdot C_{CCA}\} \\ E_L(f_{PM}) \leq \theta \end{cases} \quad (6)$$

Where, f_{PM} : PM frequency (decision variable) θ : Allowable energy loss (Constraint) E_L : total energy loss. Industry standards and empirical studies suggest that θ , the annual energy loss due to failures typically is 3% [20].

E_L quantifies the energy loss due to turbine downtime caused by failures, given by equation (7).

$$E_L = C_R \cdot F_D \cdot N_F \quad (7)$$

here, C_R is the rated capacity, F_D is failure duration and N_F is the total number of failures. the production energy for a specified period is given by (8), which represents the actual energy generated during the effective operating time.

$$E_p = \sum_{j=1}^n ((Period - T_D) * C_R * T_{ef}) \quad (8)$$

T_{ef} is turbine efficiency taken, and $(Period - T_D)$ is the effective operating time.

Equation (7) and (8) are used jointly to evaluate the impact of maintenance strategies on energy performance but do not serve as constraints to each other.

2.2. OPTIMIZATION ALGORITHM:

The main purpose of the developed algorithm is to optimize and determine the optimal PM frequency for wind turbine, by reducing total maintenance costs while keeping energy losses within permissible thresholds.

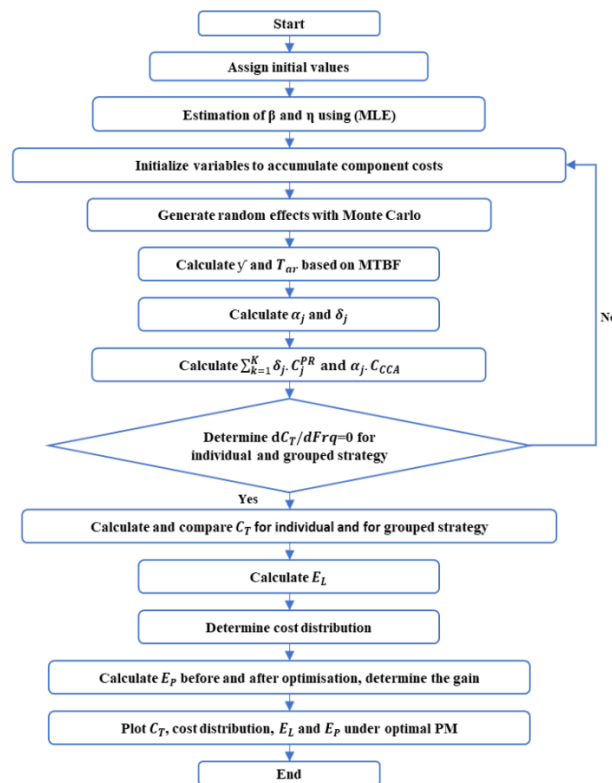


Figure 1. Optimization algorithm.

Using a Monte Carlo simulation in MATLAB, the algorithm considers different PM frequencies, simulating turbine operation and accounting for factors like failure rates and operating hours. The algorithm calculates energy loss and total maintenance costs for various frequencies to identify the optimal one, ensuring a balanced trade-off between cost reduction and controlled energy losses. Figure 1, shows the detailed simulation process, providing insights into efficient wind turbine system operation. The Weibull **shape (β) and scale (η) parameters are estimated using the Maximum Likelihood Estimation (MLE) method from component failure data found in references [18] and [21]. These values are used as inputs to the Monte Carlo simulation.**

3. CASE STUDY:

A case study of a 2 MW wind turbine is presented to demonstrate the practical application of the proposed model. Empirical data have been used from the studies of [21] and [18] providing a robust foundation for analysis. The pertinent details are summarized below, offering insights into key parameters and operational characteristics essential for the optimization process. This numerical application serves as a tangible demonstration of the model's efficacy in real-world scenarios, showcasing its potential to drive informed decision-making and enhance wind turbine performance. The operational characteristics and maintenance requirements of turbine components are summarized in table 2. All parameter values were taken or derived from reliable literature sources from [18] and [21].

Table 2: Data values.

Component	Pitch Bearings	Gearbox Bearings	Generator Bearings
β	1.2	1.9	1.7
η	16	17	19
MTBF (months)	30	52	34
Corrective Time (months)	7	15	20
Corrective Cost	4000	6100	5100
Preventive Time	2	5	8
Preventive Cost	1100	3000	2400

MTBF calculated using the equation (9).

Based on the component parameters defined earlier, the simulation was run over multiple PM frequency scenarios. Within $\theta = 3\%$ (MWh/year).

4. RESULTS AND DISCUSSION:

Utilizing the developed MATLAB code aimed at minimizing the turbine's expected maintenance cost per unit time. The optimization results provide insights into the optimal PM schedules and the corresponding minimal costs for each turbine component are presented in Table 3.

Table 3: Optimized PM for Individual Components.

Component	Optimal PM	Minimal costs (USD)
Pitch Bearings	92	3484
Gearbox Bearings	78	4637
Generator Bearings	77	3752

Figure 2 illustrates that the optimal frequency for performing grouped maintenance strategy, as determined by the simulation, is once every 93 months. This frequency is identified as the interval at which maintenance activities should occur to minimize the total maintenance cost within 9997 USD.

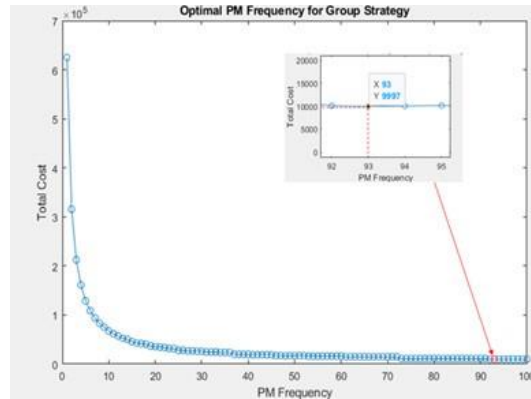


Figure 2: Optimized Group Maintenance Strategy.

This numerical finding holds significant operational implications. The 93-month frequency is strategically determined to achieve an optimal balance between cost reduction and the reliability of pitch bearings, gearbox bearings, and generator bearings. The grouped maintenance strategy proves cost-effective compared to individual maintenance. Wind turbine failures cause energy loss equivalent to **the turbine’s 2 MW capacity**. **Understanding the economic implications** of wind turbine operations is paramount for effective decision-making. To further explore this aspect, a maintenance cost distribution analysis is conducted to provide insights into the variability and probability of different maintenance cost scenarios. Figure 3 illustrates this distribution, exhibiting a pattern similar to a normal distribution. The graph visually represents the probability density, highlighting the likelihood of encountering various maintenance cost values.

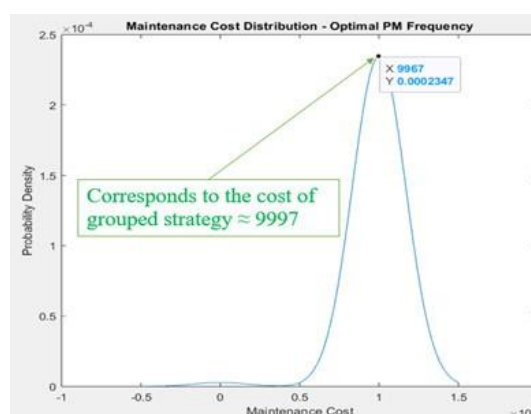


Figure 3: Maintenance cost distribution.

The curve shown in Figure 3 presents an interesting trend, where moderate maintenance costs are less frequent, while both lower and higher costs appear more common. Notably, a specific probability density value of 0.0002347 stands out, reflecting a higher likelihood of a particular maintenance cost. Interestingly, this probability density corresponds closely to the minimum cost achieved through a grouped strategy for the optimal PM frequency, as evidenced

by the closely aligned values of 9967 USD and 9997 USD cost per unit of time. This noteworthy correlation indicates that the maintenance cost corresponding to the 0.0002347 probability density value aligns closely with the minimum cost attained using the grouped strategy for the optimal PM frequency. This finding highlights the critical role of selecting the optimal PM frequency in reducing maintenance costs and enhancing the efficiency of wind turbine operations. Throughout its operational lifespan, a wind turbine experiences failures that cause downtime and result in energy loss. Each failure corresponds to an energy loss equivalent to the **turbine's rated capacity, which is 2 MW in this scenario. This energy loss accumulates over time** for each maintenance scenario, and to assess its impact, the total energy loss is divided by the number of scenarios to compute the average energy loss. Figure 4 serves as a crucial visual aid, offering invaluable insights into how different frequencies of preventive maintenance affect the energy losses experienced by the system throughout the defined period. At the core of our algorithm lies the critical task of balancing maintenance costs and energy losses. Each simulated scenario carefully evaluates both energy loss and total maintenance costs, providing a comprehensive perspective on the trade-offs involved in selecting the appropriate maintenance frequency. Through an iterative process, the algorithm determines the optimal PM frequency that achieves a balance between cost efficiency and system reliability. In this context, Figure 4 illustrates the frequency distribution of energy loss ranges observed across the maintenance scenarios.

Figure 4 presents a histogram that effectively illustrates the distribution and trends of energy losses over time. For example, an X-axis range of 30-31, combined with a Y-axis frequency of 1026, corresponds to an average energy loss of 30.88 MWh per month. This range, spanning 30 to 31 MWh, represents all energy loss values recorded during the simulation. The high frequency of 1026 on the Y-axis indicates that energy losses within this range occurred most frequently across the simulated scenarios. This highlights the significance of this range in evaluating energy loss patterns and refining maintenance strategies.

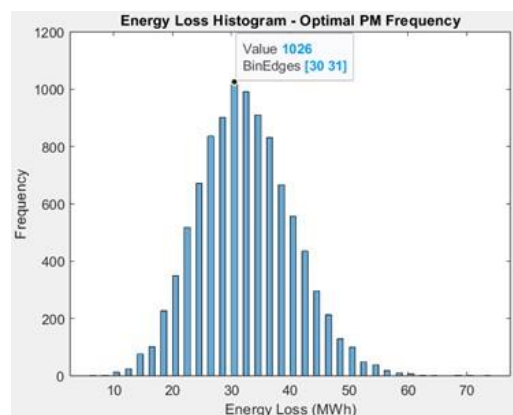


Figure 4: Optimal grouped strategy.

To demonstrate the effectiveness of the grouped maintenance strategy and highlight the critical role of wind turbine maintenance in optimizing energy production, a detailed analysis was carried out. This comprehensive evaluation compared energy output levels before and after

the implementation of the grouped maintenance optimization, offering valuable insights into its impact on operational efficiency and overall performance.

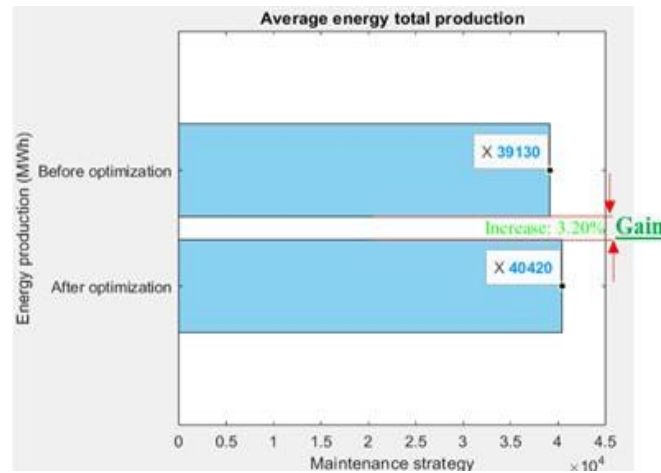


Figure 5: Total energy production.

Figure 5 illustrates energy production levels, offering a clear comparison between performance prior to optimization and the enhancements achieved afterward. This visual analysis underscores the tangible benefits of the grouped maintenance strategy, showcasing its contribution to improved energy production efficiency and overall system effectiveness. As a result of the optimization process, wind turbine energy production significantly increases, reaching a total of 1290 MWh. This notable improvement positions the grouped maintenance strategy as a highly effective solution, surpassing alternative approaches in its ability to enhance energy output. Specifically, this strategy achieves an impressive 3.20% increase in overall energy production. Figure 5 vividly illustrates these gains, showcasing the substantial benefits of implementing the grouped maintenance approach. By striking an optimal balance between increased energy generation and reduced maintenance costs, this strategy also demonstrates its efficiency in managing wind turbine energy losses effectively.

5. CONCLUSIONS:

This research leveraged Monte Carlo simulation to optimize the maintenance frequency for wind turbines, with a focus on minimizing total costs. The main findings and conclusions derived from the analysis are outlined as follows: •The grouped maintenance strategy is more cost-effective than individual maintenance approaches, allowing for the consolidation of maintenance activities and achieving significant cost savings through resource optimization. •An optimal preventive maintenance frequency not only reduces overall maintenance costs but also strikes a balance between preventive actions and the potential costs associated with unexpected failures. •The distribution of maintenance costs follows a normal distribution, reflecting the observed costs and their associated probabilities. •The minimum cost achieved through the optimal maintenance frequency confirms the validity of our optimization algorithm. Furthermore, the adoption of the grouped maintenance strategy led to a consistent 3.2% improvement in wind turbine production. Overall, Monte Carlo simulation proves to be an effective and reliable tool for evaluating and optimizing preventive maintenance strategies, contributing to both cost reduction and enhanced performance in wind turbine operations.

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Abdelmajid Daya and Rabie El Otmani: Supervision, validation, and critical review.

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REFERENCES

- [1] G. Luderer et al., "The role of renewable energy in climate stabilization: results from the EMF27 scenarios," *Climatic change*, vol. 123, no. 3, pp. 427-441, 2014.
- [2] O. A. Adelekan et al., "Energy transition policies: a global review of shifts towards renewable sources," *Engineering Science & Technology Journal*, vol. 5, no. 2, pp. 272-287, 2024.
- [3] S.-H. Ding and S. Kamaruddin, "Maintenance policy optimization—literature review and directions," *The International Journal of Advanced Manufacturing Technology*, vol. 76, no. 5, pp. 1263-1283, 2015.
- [4] E. Singh, S. S. Afshari, and X. Liang, "Wind turbine optimal preventive maintenance scheduling using fibonacci search and genetic algorithm," *Journal of Dynamics, Monitoring and Diagnostics*, vol. 2, no. 3, pp. 157-169, 2023.
- [5] Y. Eddouh, A. Daya, R. Elotmani, and A. Touache, "Age replacement and inspection models for estimating optimal maintenance cost: numerical performance comparisons with a case study from chemical industries," *International Journal of System Assurance Engineering and Management*, vol. 14, no. 4, pp. 1354-1369, 2023.
- [6] A. A. Eladl et al., "A comprehensive review on wind power spillage: Reasons, minimization techniques, real applications, challenges, and future trends," *Electric Power Systems Research*, vol. 226, p. 109915, 2024.
- [7] A. P. Gonzalo, T. Benmessaoud, M. Entezami, and F. P. G. Márquez, "Optimal maintenance management of offshore wind turbines by minimizing the costs," *Sustainable Energy Technologies and Assessments*, vol. 52, p. 102230, 2022.
- [8] T. N. Schouten, R. Dekker, M. Hekimoğlu, and A. S. Eruguz, "Maintenance optimization for a single wind turbine component under time-varying costs," *European Journal of operational research*, vol. 300, no. 3, pp. 979-991, 2022.
- [9] Q. Yu, P. Bangalore, S. Fogelström, and S. Sagitov, "Optimal preventive maintenance scheduling for wind turbines under condition monitoring," *Energies*, vol. 17, no. 2, p. 280, 2024.
- [10] R. Zheng, Y. Zhou, and Y. Zhang, "Optimal preventive maintenance for wind turbines considering the effects of wind speed," *Wind Energy*, vol. 23, no. 11, pp. 1987-2003, 2020.
- [11] Y. S. Duarte, J. Szpytko, and A. M. del Castillo Serpa, "Monte Carlo simulation model to coordinate the preventive maintenance scheduling of generating units in isolated distributed Power Systems," *Electric Power Systems Research*, vol. 182, p. 106237, 2020.
- [12] C. D. Dao, B. Kazemtabrizi, C. J. Crabtree, and P. J. Tavner, "Integrated condition-based maintenance modelling and optimisation for offshore wind turbines," *Wind Energy*, vol. 24, no. 11, pp. 1180-1198, 2021.

- [13] H. Su, X. Duan, and D. Wang, "Optimization of periodic maintenance for wind turbines based on stochastic degradation model," *Archives of Electrical Engineering*, vol. 70, no. 3, pp. 585-599, 2021.
- [14] S. Vittal and M. Teboul, "Performance and reliability analysis of wind turbines using Monte Carlo methods based on system transport theory," in *46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, 2005, p. 2218.
- [15] C. A. Irawan, M. Eskandarpour, D. Ouelhadj, and D. Jones, "Simulation-based optimisation for stochastic maintenance routing in an offshore wind farm," *European Journal of operational research*, vol. 289, no. 3, pp. 912-926, 2021.
- [16] D. Biazar, H. Khaloozadeh, and M. Siahi, "Evaluating the effect of wind turbine faults on power using the Monte Carlo method," *Wind Energy*, vol. 25, no. 5, pp. 935-951, 2022.
- [17] D. Wang, Y. Liu, X. Cao, Y. Jiang, and P. Ding, "A research on the Monte Carlo simulation based on-condition maintenance strategy for wind turbines," in *2020 Chinese Control And Decision Conference (CCDC), 2020: IEEE*, pp. 4016-4020.
- [18] M. Daoudi, A. A. S. Mou, and L. Ait Naceur, "Analysis of the first onshore wind farm installation near the Morocco-United Kingdom green energy export project," *Scientific African*, vol. 17, p. e01388, 2022.
- [19] S. Sheng and R. O'Connor, "Reliability of wind turbines," in *Wind energy engineering: Elsevier*, 2023, pp. 195-211.
- [20] N. Conroy, J. Deane, and B. P. Ó. Gallachóir, "Wind turbine availability: Should it be time or energy based?—A case study in Ireland," *Renewable Energy*, vol. 36, no. 11, pp. 2967-2971, 2011.
- [21] M. Shafiee and M. Finkelstein, "An optimal age-based group maintenance policy for multi-unit degrading systems," *Reliability engineering & system safety*, vol. 134, pp. 230-238, 2015.