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Maximizing Wind Turbine Efficiency: Monte Carlo Simulation Based on Cost and Energy Loss Analysis for Optimal Preventive Maintenance

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Abstract
In response to the urgent need for sustainable energy, this study addresses a critical challenge in wind turbine optimization. It focuses on developing a nuanced preventive maintenance strategy to minimize costs and mitigate energy losses. Within this framework, our paper introduces a novel approach employing a Monte Carlo simulation to identify the optimal preventive maintenance frequency, striking a balance between cost efficiency and energy loss mitigation. The results show, that grouped maintenance approach, pinpointing an optimal frequency of 93 months. This strategic configuration minimizes costs to $9997 while concurrently maintaining an average energy loss of 32.014 MWh, resulting in a notable 4.29% increase in total energy production. Variability analysis reveals that increasing maintenance frequency reduces cost fluctuations, while energy loss remains relatively stable. These findings elucidate the interplay among preventive maintenance strategies, cost, and reliability in the realm of wind turbine performance optimization.

Keywords
Wind turbine, Preventive maintenance, Optimization, Monte Carlo, Reliability, Production process.

Introduction

Enterprises are constantly searching for ways to improve the efficiency of their internal operations, reduce costs, and optimize their resources. In the present-day business environment, managing human and financial resources to maximize profitability is the most significant challenge faced by businesses. Resources form the fundamental basis of a strategic approach, and the distinctive amalgamation of resources generates competitive advantages that stimulate the creation of wealth. In a global market characterized by intense competition and a volatile economic climate, effective resource management is essential for survival and establishment. In this context, the world continues to move towards more sustainable energy sources and renewable energy is widely recognized as a crucial tool for addressing climate change mitigation (Luderer et al., 2013).

Renewable energy technologies such as wind turbines, solar photovoltaic systems, and hydroelectric power plants are experiencing a surge in popularity. These renewable energy systems provide several benefits compared to conventional fossil fuel-based power plants. They offer lower operational costs and contribute to a significant reduction in greenhouse gas emissions. However, they require regular maintenance to ensure optimal performance and avoid costly repairs. Preventive maintenance optimization is a critical component of renewable energy system maintenance and can help improve system reliability, increase energy production, and reduce operational costs. Maintenance optimization involves the creation and examination of mathematical models to enhance or optimize maintenance strategies. Numerous studies have delved into this area, recognizing its significance for instance the work of (Ding & Kamaruddin, 2015) and recently (De Jonge & Scarf, 2020). Wind turbines play a vital role in the utilization of renewable energy by converting wind

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power into electrical energy. However, the maintenance of wind turbines is essential to ensure their reliable and efficient operation, and maintenance optimization is of utmost importance in this context as it aims to reduce costs associated with maintenance activities while maximizing the performance and availability of wind turbines. In this context, a multitude of research endeavors has examined the efficacy of optimizing preventive maintenance strategies for wind turbines. Dui et al. (2023) provide an extensive review of the latest advancements in optimizing maintenance strategies for wind energy. Preventive maintenance optimization for wind turbines can be achieved through various methods. Gonzalo et al. (2022) present an optimal cost for the whole system of offshore wind turbines by considering 12 preventive maintenance tasks and one corrective maintenance task. The approach employs genetic algorithms and particle swarm optimization to achieve cost minimization. Hence, various factors, including time-based or condition-based maintenance, component failure rate, availability, costs, and the impact of wind speed when optimizing preventive maintenance strategies for wind turbines are considered. Schouten et al. (2022) discuss the optimization of maintenance for an individual component of a wind turbine, taking into account time-varying costs. Their study examines the age replacement policy, block replacement policy, and the unique considerations associated with offshore wind turbines. Yu et al., (2021) propose a mathematical model that calculates and continuously updates the preventive maintenance plan for a wind farm, incorporating condition monitoring as a vital component. Gonzalo et al. (2022) emphasize cost minimization and focus on the optimal maintenance management of offshore wind turbines. Their study employs genetic algorithms and particle swarm optimization techniques to optimize the maintenance process.

Zheng et al. (2020) present a preventive maintenance policy for wind turbines that considers the impact of wind speed, specifically addressing the accelerating hazard rate. Collectively, these studies highlight the importance of preventive maintenance optimization in the wind energy sector, considering various factors and employing diverse mathematical models and optimization techniques to improve maintenance practices.

Therefore, one promising approach to optimizing preventive maintenance strategies for wind turbines is through the utilization of Monte Carlo simulation. Several researchers have explored the utilization of Monte Carlo methods in optimizing preventive maintenance for wind energy systems. Lu et al. (2021), develops an optimized maintenance strategy for offshore wind farms, effectively addressing the challenges posed by weather conditions and limited accessibility.

By incorporating an improved Monte Carlo algorithm and considering maintenance correlations, the proposed model increases system availability and reduces maintenance costs for offshore wind turbines. Duarte et al. (2020), present a risk-based model that utilizes Monte Carlo simulation to coordinate the preventive maintenance of generators in an isolated distributed Power System with wind generation.

Wind turbines, as intricate machines, experience unpredictable environmental and mechanical loads that result in wear and damage to their components. This diminishes their availability, necessitating frequent shutdowns and inspections, which in turn incur costs and power losses. Hajej et al. (2020). presents a cost model that optimizes the sequence of production and maintenance activities for a wind farm. The primary objective of this strategy is to minimize the overall cost of production and maintenance, while simultaneously maximizing the operational capacity of the wind turbines. Hofmann & Sperstad (2013), use a Monte Carlo technique to simulate different maintenance and logistic approaches, considering weather uncertainty. The tool provides results such as availability, life cycle profit, and operation and maintenance costs. Therefore, Marmidis et al. (2008) propose a novel approach for optimizing wind turbine placement in a wind park. Where a Monte Carlo simulation method is used to determine the optimal arrangement based on maximum energy production and minimum installation cost criteria.

Monte Carlo is a widely used method for assessing wind turbine reliability and operational performance in the presence of uncertainties (Dao et al., 2020) and (Su et al., 2021). Its application extends to the analysis of wind turbine performance and reliability (Vittal & Teboul, 2005). In the context of wind turbine maintenance, Monte Carlo simulation offers several valuable applications. For instance, optimizing maintenance routing: Designing an optimal route for accessing turbines within a wind farm can significantly reduce maintenance costs. Monte Carlo simulation enables the simulation of various maintenance scenarios, facilitating the determination of the most efficient route for each selected vessel (Irawan et al., 2021). Evaluating the impact of faults on power generation using Monte Carlo simulation for the evaluation of how wind turbine faults affect power output. This analysis helps in identifying potential issues and making informed decisions regarding maintenance strategies (Biazar et al., 2022). In addition, Monte Carlo simulation aids in determining the most suitable and optimal maintenance interval for wind turbines by simulating different maintenance scenarios, it becomes possible to identify the optimal interval that minimizes maintenance costs

(Wang et al., 2020). Our work will contribute to this area. Hence, Monte Carlo simulation plays a crucial role in analyzing the reliability of wind energy systems. This assessment assists in identifying potential concerns and devising effective maintenance strategies (Abdusamad, 2018).

To summarize, the literature review reveals an increasing interest in the utilization of Monte Carlo simulation to optimize preventive maintenance strategies for wind turbines (Ali Elfarra & Kaya, 2021), Dao et al., 2021), Singh et al., 2023). Therefore, it is worth noting that our comprehensive literature review revealed a significant gap in existing research. To the best of the authors' knowledge, no prior work has specifically addressed the intricate interplay between cost analysis and energy loss assessment for optimizing preventive maintenance strategies in the context of wind turbines using Monte Carlo simulation. This underscores the pioneering nature of our research, as we bridge this critical knowledge gap and provide valuable insights into a hitherto unexplored domain. Our innovative approach not only contributes to the existing body of knowledge but also addresses a pressing need in the renewable energy industry for holistic, data-driven maintenance optimization strategies.

The primary research problem centers on the need for a nuanced preventive maintenance strategy that not only minimizes costs but also mitigates energy losses associated with turbine components. Framed within this context, our study formulates two key research questions:

1. How can preventive maintenance schedules be optimized for individual components and group strategies in wind turbines?
2. What is the optimal preventive maintenance frequency that strikes a balance between cost reduction and energy production enhancement?

A Monte Carlo simulation is employed to incorporate the probabilistic nature of various operational parameters, enabling a comprehensive analysis of maintenance strategies. To model the novel approach, an optimization algorithm is employed, which offers a powerful optimization technique capable of exploring a wide range of possible maintenance schedules and identifying the most cost-effective solutions. The model utilizes historical data and maintenance cost information to accurately represent the wind turbine system's behaviour and failure patterns, enabling realistic simulations and analysis.

By applying the proposed methodology, various performance metrics such as expected energy loss, and maintenance costs are obtained. These metrics serve as key indicators for assessing the effectiveness of different preventive maintenance strategies. The analysis aims to find the optimal preventive maintenance frequency that corresponds to the minimal maintenance cost for each wind turbine component, as well as for the overall wind turbine group strategy. In addition, a sensitivity study has been performed to assess which parameters affect the optimization result the most.

This paper proposes an innovative approach to optimizing preventive maintenance schedules for wind turbines, utilizing Monte Carlo simulation. The motivation behind this research is grounded in the pressing necessity to bolster both the cost-effectiveness and reliability of wind turbine operations, particularly within the overarching goal of advancing sustainable energy. As the world increasingly leans towards renewable energy sources, the efficiency and dependability of wind turbines become paramount. The imperative to optimize preventive maintenance schedules arises from the recognition that these maintenance practices directly impact the overall performance, longevity, and economic viability of wind energy systems. In the broader context of sustainable energy advancement, our research endeavors to make a meaningful contribution by introducing a novel approach to preventive maintenance optimization. This approach acknowledges the intricate interplay between various factors such as maintenance cost, system reliability, and downtime. By delving into the complexities of wind turbine operations, we seek to address the critical need for methodologies that go beyond traditional models and better account for the inherent uncertainties associated with these systems. The main contributions of this work are outlined below:

- Develop a model that seamlessly integrates historical data, maintenance costs, and stochastic variables. This model accurately represents the intricate behavior and failure patterns of wind turbines, providing a holistic foundation for maintenance optimization.
- Incorporation of Monte Carlo simulation is a key contribution, allowing for the systematic consideration of uncertainties inherent in wind turbine operations. By generating multiple random scenarios, our model captures the variability in performance, resulting in more robust and reliable preventive maintenance schedules.
- Determining the optimal preventive maintenance frequency, our study goes beyond conventional approaches by determining the optimal preventive maintenance frequency for individual components and overall group strategy. Through a detailed analysis of performance metrics, including expected energy loss and maintenance costs, we identify schedules that minimize costs while concurrently enhancing system reliability.

- Validation through a numerical example: To demonstrate the practical applicability of our approach, we apply the model to real wind turbine data, incorporating failure rates, maintenance costs, and historical performance records. The numerical example serves as tangible evidence, showcasing the effectiveness of the Monte Carlo simulation in optimizing preventive maintenance schedules and yielding improved system reliability and cost-efficiency.

This paper is structured as follows: Literature Overview in the following Section, where a comprehensive review of the relevant literature is provided. Monte Carlo Simulation in Section 3, introduces the Monte Carlo simulation technique and its application in our study. An optimization problem presented in Section 4, focuses on the optimization problem, including the necessary assumptions for cost-effective preventive maintenance. We also outline the algorithm employed in this study. Numerical Application in Section 5, we present a practical application of the methodology through numerical examples.

Monte Carlo simulation

Monte Carlo simulation is considered a powerful computational technique that employs random sampling to accurately analyze complex equipment. By iteratively running simulations using randomly generated inputs, it enables the examination of system behaviour and the estimation of diverse outcomes. By incorporating probability distributions and statistical analysis, Monte Carlo simulation provides a highly effective tool for evaluating and analyzing complex systems and optimizing decision-making in diverse fields.

The selection of the Monte Carlo method is driven by its unique ability to address the inherent uncertainties and variability present in wind turbine operations. Several factors contribute to the justification for employing Monte Carlo simulation:

- The Monte Carlo method excels in capturing this randomness by simulating multiple scenarios, allowing for a more comprehensive understanding of the system's behavior.
- Monte Carlo simulation provides a flexible framework to model intricate failure scenarios, enabling a more realistic representation of the system's reliability and susceptibility to unforeseen events.
- Monte Carlo simulation allows for the quantification of uncertainties associated with maintenance cost estimates, component failures, and energy production fluctuations. By generating a large number of random samples, the method provides a probabilistic view of the potential outcomes, aiding decision-makers in risk assessment and management.
- The iterative nature of the Monte Carlo method aligns well with the optimization process. Through repeated simulations, the model refines preventive maintenance schedules, converging towards solutions that balance cost-effectiveness and system reliability.

Taking into account, Monte Carlo simulation finds significant choice in maintenance optimization application, particularly in the context of wind turbine maintenance. By simulating various maintenance scenarios and considering uncertain factors, such as component failures and operational parameters. Monte Carlo simulation enables the identification of optimal maintenance strategies. It allows for the evaluation of different maintenance intervals, routing plans, and cost optimization techniques, leading to enhanced operational efficiency and cost-effectiveness. Monte Carlo simulation assists in assessing the reliability and performance of wind energy systems, facilitating the identification of potential issues and the development of effective maintenance strategies.

The basic principle of the Monte Carlo Simulation is given in Equation (1):

$$z = f(y_1, y_2, y_3, \ldots, y_n) \tag{1}$$

In practical scenarios, the variables $y_1, y_2, y_3, \ldots, y_n$ are random variables, and Z represents the dependent variable. The function formula $f(y_1, y_2, y_3, \ldots, y_n)$ associated with Z can be highly complex, and in many cases, it may even be completely unknown. Due to the complexity of "f" and the lack of an analytical method to calculate the probability distribution and mathematical characteristics of "Z", it becomes challenging. However, Monte Carlo simulation provides a solution. It involves the direct or indirect sampling of values for each set of variables $y_{1i}, y_{2i}, y_{3i}, \ldots, y_{ni}$ using a random number generator. Subsequently, the value of "Z_i" is calculated based on the equation. By repeatedly generating these random samples and evaluating the equation, Monte Carlo simulation allows for the estimation of the behaviour and characteristics of "Z". This approach circumvents the need for explicit analytical calculations and enables the exploration of a range of possible outcomes. It provides valuable insights into the system under study, even when the underlying function is complex or unknown.

By repeating the sampling process, we obtain a set of sampled data for the variable "Z_i". As the number of simulation iterations increases, the estimated probability distribution function of "Z_i" and its mathematical characteristics converge towards the true underlying distribution. The accuracy of the estimated value of "Z_i" can be quantified by the standard error, as mentioned in (Dubi, 1998).

Optimization model approach

The optimization model approach for wind turbine preventive maintenance presents notable advantages, marked by its comprehensive consideration of diverse factors. Through the integration of historical data, maintenance costs, and stochastic variables, the model provides a holistic representation of the intricate elements influencing wind turbine operations. This inclusive approach guards against oversimplification, ensuring that the optimization process yields robust and practical preventive maintenance schedules that accurately reflect the complex realities of wind energy systems.

Hence, thorough and accurate analysis is essential for wind turbines, and there are several methods available to evaluate wind resources. When there is a set of wind measurements at a specific site, the data can be represented as a histogram. In such cases, the Exponential or Gamma distribution may not always be the most suitable option. Hence, the Weibull distribution has now become the standard for representing wind climatology, (Daoudi et al., 2022). Thereby, the Weibull function is more flexible. To adhere to industry standards in the wind sector, this paper employs the two-parameter Weibull function, expressed as follows, (Dorvlo, 2002):

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

where ρ is the wind speed, η is the scale parameter, β is the shape parameter and the frequency of wind speed occurrence, denoted as $f(\rho)$.

Hence, the Reliability function is:

$$f(\rho) = e^{\left[-\left(\frac{\rho}{\eta}\right)^{\beta}\right]} \tag{3}$$

The cumulative distribution function is then expressed:

$$F = 1 - e^{\left[-\left(\frac{\rho}{\eta}\right)^{\beta}\right]} \tag{4}$$

Hence, the Reliability function is:

$$R(t) = e^{\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]} \tag{5}$$

We chose to utilize the maximum likelihood method for estimating the shape and scale parameters.

Cost model

The model approach for wind turbine maintenance is built upon the key parameters: failure rate (η), downtime (γ), and maintenance costs associated with corrective and preventive measures.

The measure of turbine failures over time, known as the failure rate (η), represents the frequency of these failures. The quantification of failure rate is expressed as the number of turbine failures per year, represented by equation (6).

$$\eta = \frac{\sum_{i=1}^{I} F_i}{\sum_{i}^{I} x_i T_i} \tag{6}$$

F_i denotes the count of failures that have occurred within a specific time interval. The variable xi corresponds to the number of turbines reported during the same time interval, while T_i denotes the duration of that time interval.

Equation (7) defines downtime (γ) as the average duration of hours lost as a result of failures. The downtime r provides a measure of the average time that the turbine remains non-operational due to failures.

$$\gamma = \frac{\sum_{i=1}^{I} \gamma_i}{\sum_{i}^{I} x_i T_i} \tag{7}$$

Within the time interval T_i, the variable γ_i represents the total number of productive hours lost due to failures. It quantifies the amount of time that the turbine is unable to operate effectively during that specific time period.

Hence, to model the total cost (C_T) and determine the optimization function. The calculation of the total cost takes into account various cost components, including the cost of preventive maintenance tasks (C_{PR}), the cost of corrective maintenance (C_{CC}). The cost of performing each preventive maintenance task is denoted as (C_{PR}), is calculated using equation (8).

$$C_{PR} = \sum_{k=1}^{K} \delta_j \cdot C_j^{PR} \tag{8}$$

Let δ_j represent the duration of the preventive maintenance task in hours, and C_j^{PR} denote the hourly cost for conducting preventive maintenance.

Therefore, cost resulting from carrying out corrective maintenance tasks can be expressed in equation (9).

$$C_{CC} = \alpha_j \cdot C_{CCA} \tag{9}$$

where α_j denote the number of corrective maintenance tasks, and C_{CCA} represent the average cost for conducting corrective maintenance.

The equation for the total cost is derived by adding the costs presented in equations (8) and (9). This resulting cost is expressed in equation (10).

$$C_T = \sum_{k=1}^{K} \delta_j \cdot C_j^{PR} + \alpha_j \cdot C_{CCA} \tag{10}$$

Given the previously mentioned variables and functions, the cost minimization described in equation (10) serves as the objective function to determine the optimal preventive maintenance PM frequency. Therefore, equation (11) represents the optimization objective.

$$\min \left\{ C_T = \sum_{k=1}^{K} \delta_j \cdot C_j^{PR} + \alpha_j \cdot C_{CCA} \right\} \tag{11}$$

which helps to compare the average total maintenance costs for each PM frequency being evaluated and select the frequency with the lowest cost.

Energy losses

Therefore, the energy losses E_L is given by equation (12)

$$E_L = R_C \cdot F_D \cdot N_F \tag{12}$$

where, R_C is the rated capacity, which represents the maximum/nominal power output it can generate under ideal conditions. F_D represents the Failure duration for which the turbine remains failed until it is repaired. This is the time during which the turbine cannot generate any power. N_F, denotes the total number of failures that occur during that time interval.

Production process

The production process of a wind turbine is influenced by various factors, including, wind turbine capacity, its efficiency and maintenance activities that have a direct impact on the reliability and availability of the turbine, thus affecting its energy output. Therefore, the energy produced E_P for a specified period is calculated using equation (13).

Let (Period $- T_D$) represent the effective operating time of the wind turbine during the specified period, to subtracts the total downtime from the total period to determine how much time the wind turbine was operational and able to produce energy. T_{ef} denote turbine efficiency.

$$E_p = \sum_{j=1}^{n} ((\text{Period} - T_D) \cdot R_C \cdot T_{ef}) \tag{13}$$

The application of the model approach and optimization function through a case study, along with a discussion of the results, will be treated in Section 3.

Optimization model

The optimization model used in this paper aims to determine the optimal frequency for preventive maintenance (PM) activities in a wind turbine system. The objective is to minimize the expected total maintenance cost while ensuring acceptable levels of energy loss.

To achieve this, the algorithm employs a Monte Carlo simulation approach. It considers different PM frequencies, representing the intervals at which the turbine undergoes inspection and maintenance. For each PM frequency, the algorithm simulates the operation of the wind turbine over a specified period (simulation years).

Various factors are taken into account, including the failure rate, operating hours, and the occurrence of maintenance activities based on the PM frequency.

The energy loss is estimated, and the total maintenance cost for each PM frequency. By averaging the performance metrics over multiple simulation scenarios, the algorithm provides insights into the average energy loss and total maintenance cost associated with each PM frequency. It then identifies the optimal PM frequency that yields the lowest expected total maintenance cost for the individual strategy and the grouped strategy. The optimization algorithm strikes a balance between maintenance costs and energy losses, ensuring efficient operation and maximizing the overall performance and reliability of the wind turbine system.

The optimization of the problem is accomplished by employing a simulation process in MATLAB, involving the following steps.

Step 1: Assign initial values for all parameters and variables in equation (1) to (12) by using the parameters in (Tab. 1).

Step 2: Define the maximum likelihood estimation function for the Weibull distribution.

Step 3: Perform a Monte Carlo simulation, for each PM frequency.

Step 4: Initialize variables to accumulate costs for each wind turbine component and the group strategy.

Step 5: Perform the specified number of simulations:

Simulate the failure time for each component using a Weibull distribution based on its MTBF.

Calculate the number of corrective maintenance actions based on whether the failure occurs within the simulation period.

Calculate the number of preventive maintenance actions based on the PM frequency and simulation period.

Accumulate the total corrective and preventive maintenance times and costs for each component.

Determine the maximum corrective and preventive maintenance times among all components for the group strategy.

Accumulate the total cost for the group strategy.

Calculate the average total costs for each component and the group strategy

Step 6: Determine the PM frequency that minimizes the total cost for each component and the group strategy.

Step 7: Generate random failure events based on the failure rate and calculate the energy loss.

Step 8: Determine the maintenance cost distribution.

Assumptions

The following assumptions are considered:

1. Failure rate: The failure rate is assumed to follow the Weibull distribution.
2. Maintenance activities: Performed only when the cumulative operating hours reach the threshold and the PM frequency condition is met. No other factors or criteria for performing maintenance are considered.
3. Maintenance cost: Assumed to be fixed for each maintenance activity and given as a parameter.
4. Energy loss: Assumes that when a failure occurs, the entire rated capacity of the Wind turbine is lost.
5. Simulation scenarios: A Monte Carlo simulation approach is used to evaluate different maintenance scenarios.
6. Simulation period: The turbine is assumed to operate continuously throughout the simulation period without any extended periods of downtime or shutdown.
7. Downtimes are based on both corrective maintenance and preventive maintenance.

The subsequent section showcases a numerical example that effectively demonstrates the proposed approach for optimizing preventive maintenance. We adopt the aforementioned algorithm and thoroughly discuss the achieved results.

Case study

Wind turbines operate by capturing the wind's kinetic energy using rotating blades. This rotational motion is then transmitted to a nacelle on top of the tower. Within the nacelle, a gearbox increases the rotational speed before transferring it to a generator, which converts the mechanical energy into electrical energy. The electricity is further converted to a higher voltage, adjusted for grid compatibility, and transmitted to the power grid through cables. The efficient and reliable functioning of wind turbines relies on several key components and processes, with bearings playing a crucial role. We specifically focus on four primary systems: pitch bearings, main bearings, gearbox bearings, and generator bearings shown in Figure 1. These bearings are selected based on their higher probabilities of failure and potentially severe consequences. The rationale behind selecting these four bearings stems from the similarity of their maintenance tasks. A brief description of this group is provided below.

- Pitch bearings: These are an integral component of wind turbine blades. Each blade features an individual pitching activator that includes a hydraulic cylinder, piston rod, and a bearing. These pitch bearings typically employ a four-point design, utilizing the hub as their housing.
- Main bearings play a critical role in the structural integrity of wind turbines, particularly in withstanding high loads during gusts and braking. Their primary function is to minimize frictional resistance between the blades, main shaft, and gearbox, facilitating smooth relative motion. However, main bearing failures are often attributed to wear, pitting, and deformation of the outer race and rolling elements, which are the main culprits behind these failures.
- Generator bearings are a primary source of failure in generators, making them a critical component to monitor. Consequently, the maintenance activities primarily focus on inspecting and ensuring the health of these bearings.
- Gearbox bearings support and facilitate the smooth operation of the gearbox. They distribute loads, enable power transmission, reduce noise and vibrations, provide axial and radial support, and protect against overloads. These bearings are crucial for the reliable and efficient functioning of wind turbines.

We gathered our data from a comprehensive field failure database, which includes operations and Maintenance reports. The database specifically focuses on a conventional onshore wind turbine system with $R_C = 2$ (Megawatts) and efficiency $= 35\%$. Addition-

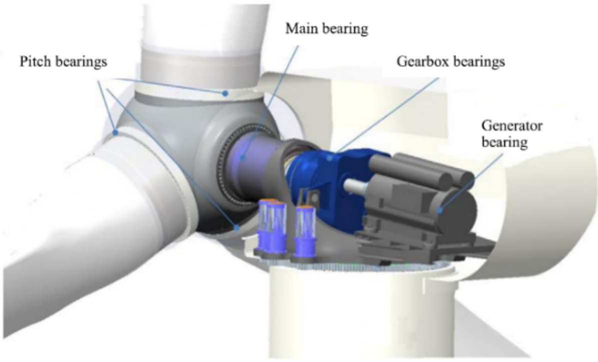

Fig. 1. Wind turbine bearings

ally, we have supplemented our data with information from relevant references (Shafiee & Finkelstein, 2015 and Daoudi et al., 2022).

The introduced parameters values of the Weibull parameters values, MTBF, preventive maintenance action time, corrective action time and maintenance cost of the bearings are depicted in (Tab. 1).

We have implemented a MATLAB program to minimize the expected maintenance cost per unit time of the system. Figure 2 illustrates the optimal preventive maintenance (PM) frequency, which corresponds to the minimum expected maintenance cost for each bearing in individual wind turbines. The optimal value is represented by the red dashed circle. The simulation results unveil a critical insight into the optimal (PM) frequency, with a focus on inspecting the Pitch Bearing every 92 months. This finding signifies that, according to the simulation, conducting maintenance activities at this specific interval proves optimal for minimizing the total maintenance cost to \$3484. The significance of this result extends beyond a mere numerical output. The 92-month interval is strategically determined to strike a delicate balance between two crucial considerations: mitigating maintenance costs and ensuring the reliability of the wind turbine system. By choosing this specific frequency, decision-makers can optimize resource allocation, scheduling maintenance activities at a frequency that minimizes costs while simultaneously maintaining the integrity and performance of the Pitch Bearing.

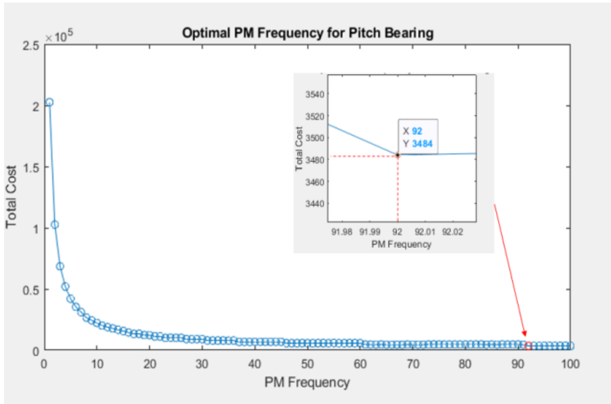

Fig. 2. Optimal PM frequency for Pitch Bearing

Figure 3 shows, the optimal (PM) frequency determined by the simulation is to inspect the Main Bearing every 74 Months. This means that maintenance activities should be performed at this interval to minimize the total maintenance cost within 1640. This numerical result carries substantial operational implications. The 74-month frequency emerges as a strategically determined interval that harmonizes the imperative of cost reduction with the imperative of sustaining the Main Bearing's reliability.

Figure 4 shows, the optimal preventive maintenance (PM) frequency determined by the simulation is to inspect the Gearbox every 78 Months. This means that maintenance activities should be performed at this interval to minimize the total maintenance cost within 4637.

Figure 5 shows, the optimal preventive maintenance (PM) frequency determined by the simulation is to inspect the Generator Bearing every 77 Months. This

Table 1
Parameters values

Wind Turbine components	Shape parameter	Scale parameter	MTBF (Months)	Corrective action time (Months)	PM action time (Months)	Corrective action cost (\$)	PM action cost (\$)
Pitch bearings	1.2	16	30	7	2	4000	1100
Main bearings	2.6	22	34	5	1	2000	1200
Gearbox bearings	1.9	17	52	15	5	6100	3000
Generator bearings	1.7	19	34	20	8	5100	2400

means that maintenance activities should be performed at this interval to minimize the total maintenance cost within 3752.

These interpretations underscores the practical utility of the simulation results, providing actionable guidance for real-world decision-making in wind turbine preventive maintenance. It showcases the power of the proposed methodology not only in offering specific numerical outputs but also in guiding stakeholders

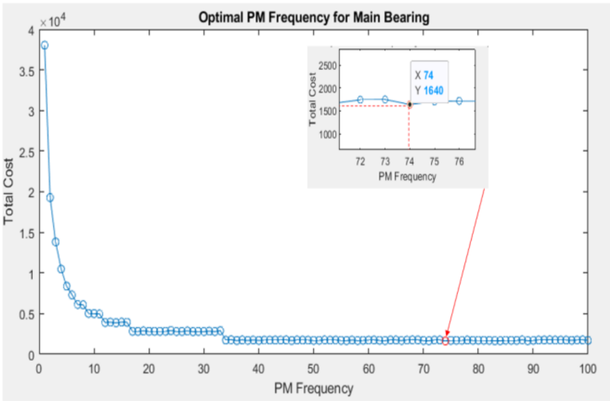

Fig. 3. Optimal PM frequency for Main Bearing

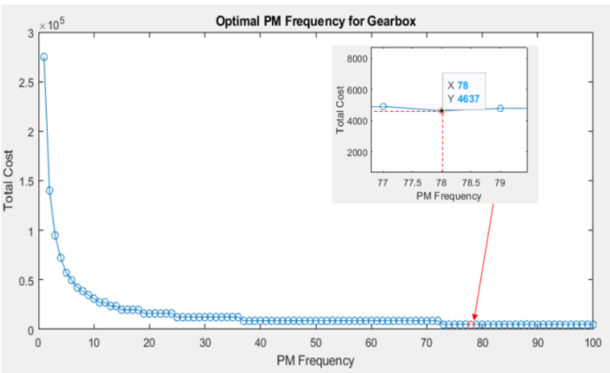

Fig. 4. Optimal PM frequency for Gearbox

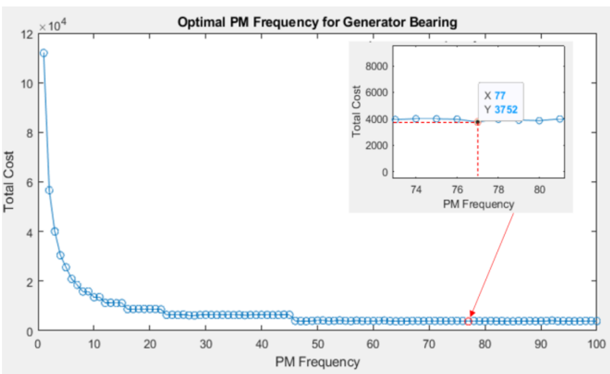

Fig. 5. Optimal PM frequency for Gearbox

towards strategically timed and cost-effective maintenance practices, thereby enhancing the overall efficiency and longevity of wind energy systems.

The optimal values obtained from the program are presented in (Tab. 2).

Table 2
Optimal individual strategy

Wind Turbine components	Optimal PM interval	Minimal expected cost
Pitch bearings	92 months	3484 ($)
Main bearings	74 months	1640 ($)
Gearbox bearings	78 months	4637 ($)
Generator bearings	77 months	3752 ($)
Total cost		13513 ($)

The findings indicate that both the main bearing and gearbox bearing share the same optimal preventive maintenance (PM) interval. Consequently, the pitch bearing also exhibits a PM interval that is very close to the optimal interval of the main bearing and gearbox bearing. Additionally, the PM interval for the generator bearings is also close to that of the pitch bearings. Taking these results into account, it is viable to investigate the optimal values of the expected total cost under a grouping strategy while considering clustered optimal PM interval.

While the wind turbine's maintenance is closely linked to its production. The optimal preventive maintenance strategy for a wind turbine must strike a balance between minimizing maintenance costs and minimizing production losses due to downtime. Maximizing the efficiency and profitability of the wind turbine requires careful consideration of the trade-off between maintenance activities and the impact of production loss. Therefore, production loss due to downtime is a critical factor in determining the optimal preventive maintenance strategy. When the turbine is under maintenance, it is unavailable for power generation, resulting in a loss of revenue. Hence, it is crucial to minimize the frequency and duration of maintenance activities while ensuring the turbine operates reliably and safely. For that, the MATLAB program can find the optimal PM frequency that minimizes the average total maintenance cost in a grouped preventive maintenance strategy, taking into account the associated production losses. The decision variable is the PM frequency, representing the number of years between preventive maintenance activities by striking the right balance between maintenance activities and minimizing production losses, the wind turbine can operate at its optimal level, ensuring reliable and efficient power generation.

Figure 6 illustrates the optimal PM frequency and the corresponding minimal expected cost under a grouped strategy, represented by the red dashed circle.

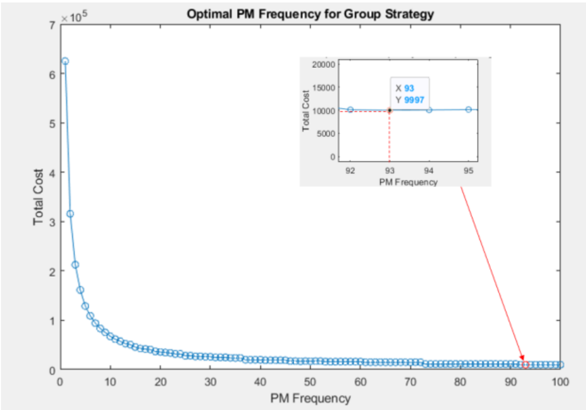

Fig. 6. Optimal grouping strategy of the wind turbine bearings

Based on (Tab. 3) and comparing it to the individual maintenance strategy, the results indicate that the grouped strategy is more economical, as it demonstrates the lowest minimal expected cost.

Table 3
Optimal grouped strategy

Wind Turbine	Optimal PM interval	Minimal expected cost
Grouped strategy	93 months	9997 ($)

During production, the wind turbine experiences failures that result in downtime and energy loss. Each time a failure occurs, the energy loss is equal to the rated capacity of the wind turbine, which is given as 2 MW. The energy loss is accumulated for each maintenance scenario. The total energy loss is divided by the number of scenarios to calculate the average energy loss.

Figure 7 provides valuable insights into the impact of different frequencies of preventive maintenance on the energy losses of the system over the defined period. By visually representing the observed frequencies of each energy loss range in the maintenance scenarios, the histogram allows for a clear understanding of the distribution and evolution of energy losses over time. For instance, where the histogram shows a value of 30-32 on the X-axis and 1050 on the Y-axis. This means that the average energy loss is 32.014 MWh per Months, and this range has been observed with a frequency of 1050. The X-axis value of 32 MWh indicates that the energy loss range considered in this histogram is from 30 to 32 MWh, and all the energy losses generated during the simulation fell within this range. The high frequency of 1050 on the Y-axis suggests that the energy loss range of 30 to 32 MWh occurred frequently.

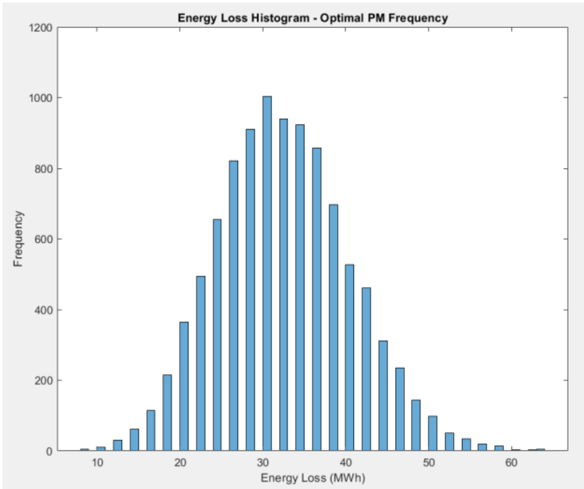

Fig. 7. Energy loss based on Monte Carlo simulation

This analysis aids in the identification of the most frequent energy loss ranges and their relationship with the chosen preventive maintenance frequency. With this information, informed decisions can be made to determine the optimal preventive maintenance frequency, leading to minimized energy losses and enhanced system performance.

Therefore, it is crucial in understanding the economic implications of wind turbine operations. For that, a maintenance cost distribution is determined to provide insights into the variability and likelihood of different maintenance cost scenarios.

Figure 8 shows the distribution of maintenance costs, which exhibits a shape similar to a normal distribution. This distribution represents the likelihood or probability density of different maintenance cost values.

The curve indicates that moderate maintenance costs occur less frequently, while higher and lower costs are more common. In particular, a specific probability density value of 0.0004639 stands out, indicating a relatively higher likelihood for a particular maintenance cost. Notably, this value is close to the minimum cost observed when using a grouped strategy for the optimal PM frequency. This suggests that the maintenance cost associated with the 0.0004639 probability density value aligns with the minimum cost achieved through the grouped strategy for the optimal PM frequency.

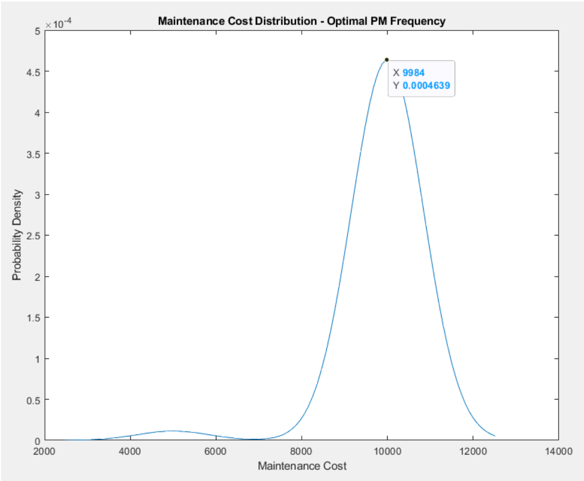

Fig. 8. Maintenance cost distribution

The results indicate that by optimizing the PM frequency and implementing the suggested maintenance strategy, the wind turbine can achieve an acceptable balance between minimizing costs and ensuring optimal performance. The estimated energy loss and maintenance costs provide valuable insights for decision-making regarding wind turbine maintenance strategy, and operational efficiency improvement. Hence, a variability analysis is performed to provide a deeper understanding of the reliability, predictability, with the Wind Turbine maintenance strategy. More specifically, variability analysis evaluates multiple (PM) frequencies to compare how the variability in key performance metrics (Energy loss and total cost) varies with different PM frequencies. This comparison helps in selecting the most robust and predictable frequency.

Figure 9 shows the variability of energy loss refers to the extent to which the energy loss in Wind Turbine, fluctuates or varies over time. A higher standard deviation indicates greater variability, meaning that in scenarios with a higher standard deviation, the energy loss tends to vary more widely from the average energy loss or maintenance cost. Conversely, a lower standard deviation indicates less variability, suggesting that the energy loss and maintenance cost values are closer to the mean and tend to cluster around a more predictable value. Understanding the variability is essential in risk assessment and decision-making for maintenance strategies.

In this study the variability of energy loss refers to how much the amount of energy lost due to failures and maintenance activities varies. It is quantified by calculating the standard deviation of energy loss for each preventive maintenance (PM) frequency being evaluated. A higher standard deviation indicates greater variability, meaning that in scenarios with a higher standard deviation, the energy loss tends to vary more widely from the average energy loss. Conversely, a lower standard deviation indicates less variability, suggesting that the energy loss values are closer to the mean and tend to cluster around a more predictable value. Understanding the variability of energy loss is essential in risk assessment and decision-making for maintenance strategies. Higher variability may indicate less predictability and more risk in terms of energy loss, while lower variability suggests greater consistency and reliability in the Wind turbine performance. In summary, the data provides valuable insights into how energy loss variability corresponds to different PM frequency. It can be useful for evaluating the stability and consistency of energy loss under different maintenance strategies.

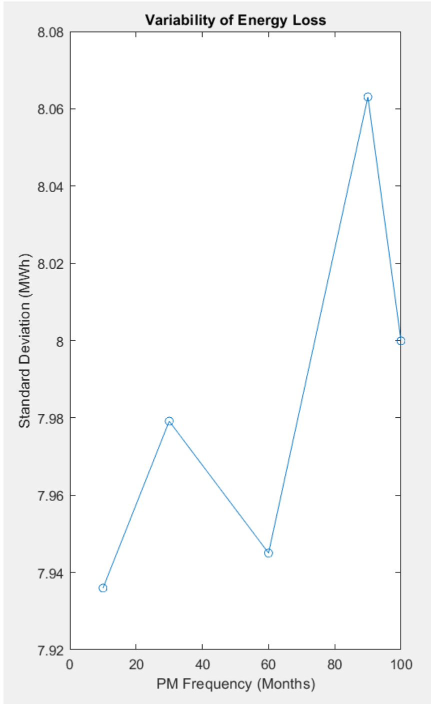

Fig. 9. Variability of energy loss

Based on the obtained data, we can draw several conclusions:

- Variability in Energy Loss: The standard deviation values for energy loss under various PM frequencies indicate the extent of variability in energy loss across different simulation scenarios.
- Consistency: When comparing the standard deviations, we can observe that they are relatively close in value for the different PM frequencies (ranging from approximately 7.936 to 8.063 MWh). This suggests that the variability in energy loss does not vary significantly with changes in the PM frequency.

- Lack of Strong Dependence: The results do not exhibit a strong pattern were increasing the PM frequency consistently leads to lower variability in energy loss. In some cases, higher PM frequencies may have slightly lower standard deviations, but the differences are not substantial.

Figure 10 illustrates the variability of total cost over time, pertaining to fluctuations in the overall maintenance costs for a wind turbine.. In this study the variability calculates the standard deviation of total maintenance costs across multiple simulation scenarios for each PM frequency.

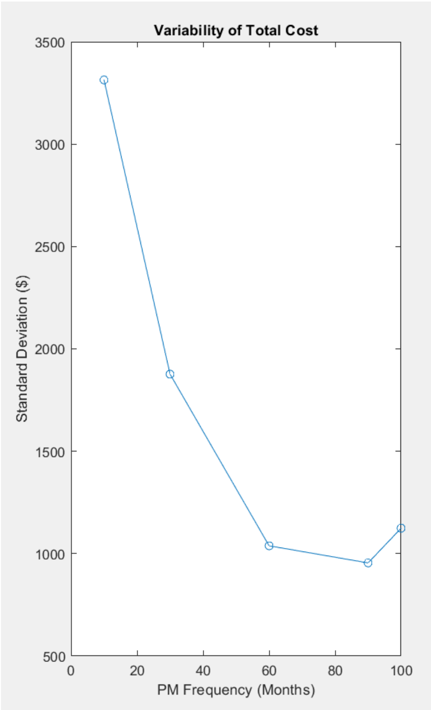

Fig. 10. Variability of energy loss

A higher standard deviation of total cost points to greater variability. In scenarios with a higher standard deviation, the total maintenance costs exhibit wider variations from the average total cost. Conversely, a lower standard deviation indicates less variability, signifying that the total maintenance cost figures tend to cluster closely around a more predictable average. Understanding the variability of total cost is pivotal for assessing the financial risk entailed by a maintenance strategy.

The data illustrates a clear trend: as the PM frequency decreases, the standard deviation of total maintenance cost decreases as well. In other words, costs become more stable and predictable with longer intervals between inspections. Longer inspection intervals can lead to more consistent maintenance costs, which can be advantageous for budgeting and financial planning.

Hence, the results demonstrate that:

- When maintenance is conducted every 11 months, the standard deviation of total maintenance cost is $3,313. This implies that the maintenance cost can fluctuate by approximately $3,313 from the average cost within this 11-month PM cycle.
- Extending the PM frequency to 30 months results in a reduced standard deviation of $1,877. This suggests that the maintenance cost variability decreases with less frequent inspections, leading to more predictable costs over the 30-month interval.
- With a 60 months PM frequency, the standard deviation drops further to $1,038. This indicates that maintenance costs are even more stable and consistent when inspections are performed every 5 years.
- With a 93 months PM frequency, the standard deviation stands at $954.8, indicating that maintenance cost variability remains minimal even with extended inspection intervals. This represents the optimal choice for achieving lower variability, aligning with the optimal value observed in the Grouped strategy, as illustrated in Fig. 6.
- 100 Months PM Frequency: When maintenance occurs every 100 months, the standard deviation increases slightly to $1,124. This suggests that the cost variability, while still relatively low, starts to show a slight uptick with even longer inspection intervals.

In order to emphasize the advantages of the grouped maintenance strategy and underscore the pivotal role of wind turbine maintenance in the production process, we conducted a thorough and comprehensive analysis of energy production. This analysis involved a detailed comparison of energy production levels both before and after the implementation of the grouped maintenance optimization.

The findings of our study regarding the energy production prior to optimization are represented in Figure 11. This illustration provides a baseline energy production, serving as a valuable reference point for understanding the subsequent improvements achieved through the grouped maintenance strategy.

Therefore, as depicted in Figure 12 the graphical representation provides a comprehensive view of the total energy produced subsequent to the optimization of the grouped maintenance strategy. The results light the profound impact of adopting the grouped maintenance approach on energy production.

Upon closer examination of the data, it becomes evident that the grouped maintenance strategy stands out as a pivotal factor influencing energy production positively. This outcome is particularly noteworthy, emphasizing the strategic advantage and consequential benefits of implementing a grouped maintenance strategy for wind turbines.

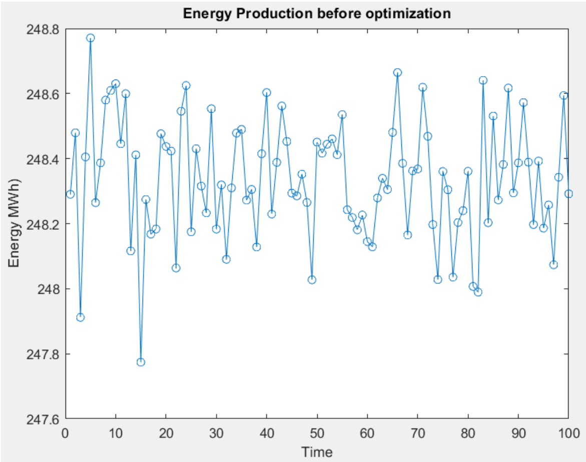

Fig. 11. Energy production before optimization

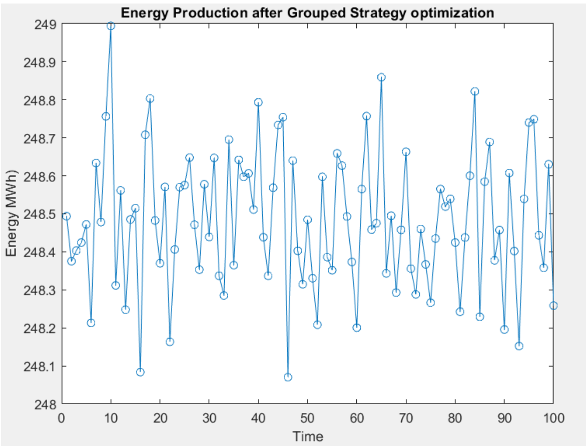

Fig. 12. Energy production after optimization

Hence, Figure 13 is a comparative analysis of total energy production between two scenarios: before and after the optimization of the grouped maintenance strategy.

Following the optimization, there is a substantial increase in wind turbine production, amounting to 1695.6142 MWh. This marked improvement positions the grouped maintenance strategy as a standout performer, surpassing other strategies in its impact on energy production. Emphasizing its effectiveness, this approach enables the turbine to achieve a noteworthy 4.29% increase in overall energy production. The significance of (Fig. 13) lies in its depiction of tangible improvements resulting from the implementation of the grouped maintenance strategy. This strategic optimization not only demonstrates a harmonious balance between increased energy production and minimized maintenance costs but also highlights a prudent management of wind turbine energy losses.

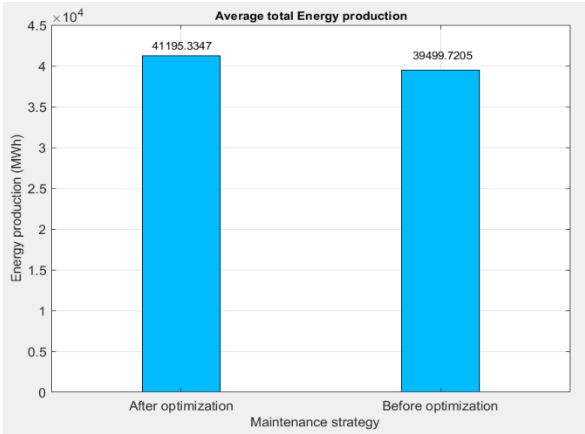

Fig. 13. Comparison of energy production

Comparative study

To determine the effect of the proposed maintenance strategy on the energy-cost tradeoff and gain in production, a comparative study is conducted, summarized on (Tab. 4), to compare our results with those of other studies, which have used different methods.

Table 4
Comparative studies

Study	Method	Finding
(Azizi & Jahangirian, 2020)	Genetic algorithm optimization	Gain in energy production by 4.45%
(Benmessaoud et al., 2013)	Stochastic degradation model	Gain in energy production of 4.22%

We can conclude that our findings indicate a close alignment with existing studies, suggesting that these various optimization methods operate within a comparable range of effectiveness.

Conclusion

The Monte Carlo simulation was conducted to identify the PM frequency that corresponds to the minimal cost for the wind turbine. The simulation involved generating multiple random scenarios to assess the impact of different PM frequencies on energy loss and maintenance costs. The following general results and discussions were obtained:

- The simulation results indicated that the grouped strategy is more economical compared to the individual strategy. This finding suggests that coordinating maintenance activities and performing them in a grouped manner can lead to cost savings.

- The simulation revealed that there is an optimal PM frequency that minimizes the total maintenance cost. By varying the PM frequency, it was possible to identify the specific frequency that achieved the lowest cost. This optimal frequency strikes a balance between the costs of preventive maintenance activities and the potential costs of unexpected failures.
- The simulation provided insights into the relationship between PM frequency and energy loss. It was observed that higher PM frequencies tended to reduce the occurrence of unexpected failures, resulting in lower energy loss. However, excessively high PM frequencies also incurred unnecessary maintenance costs, which impacted the overall cost-effectiveness.
- The analysis of maintenance costs revealed to tend a normal distribution. The distribution represented the range of observed maintenance costs and their associated likelihoods. This allowed for a comprehensive understanding of the variability in maintenance costs and helped in assessing the cost landscape.
- The minimal cost associated with the optimal PM frequency was analyzed within the context of the maintenance cost distribution. This provided a reference point to evaluate the achieved cost optimization outcome. The optimal cost was often aligned with the lowest cost values in the distribution, indicating successful cost reduction through the optimization process.
- Variability analysis indicates that as PM frequency increases, maintenance cost variability tends to decrease. Longer intervals between maintenance activities result in more stable and predictable outcomes. Hence, the findings do not reveal a robust trend where an increase in the PM frequency consistently results in reduced energy loss variability. While higher PM frequencies occasionally display slightly lower standard deviations, these variations are not significant.
- The implementation of a grouped maintenance strategy has demonstrated remarkable success, resulting in a substantial 4.29% increase in energy production. This outcome underscores the effectiveness of this strategy in optimizing energy generation and highlights its potential to contribute significantly to production process.
- A comparative study was conducted to validate the proposed maintenance strategy in comparison to alternative approaches.

Our future research will continue in investigating the application of Monte Carlo simulation in conjunction with artificial intelligence for a large wind park.

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