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Methodological Framework for Optimizing Inspection Frequency in a Preventive Maintenance Policy

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Determining the optimal inspection frequency is a significant challenge, as it requires balancing frequent inspections, which increase operational costs, with infrequent inspections, which can lead to unexpected failures. This paper presents a stochastic simulation model that captures the uncertainty in equipment behavior by defining probabilistic parameters such as maintenance costs and the probability of equipment deterioration. The model uses the Weibull distribution to represent the time to failure and Monte Carlo simulations to evaluate different inspection intervals and their associated costs. The optimal inspection frequency is determined by minimizing the total expected cost, which includes inspection, maintenance, and failure costs. Through the expected cost analysis, a global optimum within the discrete interval is identified, revealing that both excessive inspections and too few inspections lead to increased costs. The sensitivity analysis shows that repair time is the most influential variable, and the CVaR analysis highlights the importance of accurately defining parameters and controlling their fluctuations to manage risk effectively. These results provide valuable insights for decision-making in high-risk and uncertain industrial environments, offering an effective tool for preventive maintenance planning.

Keywords: Stochastic Simulation, Preventive Maintenance Policy, Inspection Frequency Optimization, Maintenance Costs, Risk Assessment.

1. Introduction

Maintenance in industrial environments is an essential practice to ensure the continuous and efficient operation of equipment and systems (deJonge, 2020). This set of activities not only aims to prevent failures and extend the equipment's lifespan but also optimize its performance and reduce long-term costs. Within maintenance strategies, preventive maintenance stands out for its proactive approach, intervening before failures occur, which is crucial to avoid production interruptions and ensure the availability of equipment (Shafiee, 2013) (Zhang, 2024).

Preventive maintenance includes a series of scheduled tasks, such as inspections, adjustments, repairs, and component replacements, carried out at predetermined intervals. The frequency with which these inspections are performed is a determining factor in the effectiveness of preventive maintenance, as an appropriate inspection frequency allows the detection and correction of potential issues before they become major failures. However, establishing this frequency is not a simple task, as various factors must be considered, such as the type of equipment, operating conditions, maintenance costs, and the potential consequences of unexpected failures.

Determining the optimal inspection frequency is a significant challenge because it involves finding a balance between frequent inspections, which can increase operational costs and reduce productivity, and sporadic inspections, which may result in unexpected failures and unplanned downtime (Nasrfard, 2022). In contexts where failure costs are not high, a fixed-interval approach may be sufficient and more cost-effective. However, in environments where equipment reliability and availability are critical, a more sophisticated approach is needed.

In this context, a stochastic approach is particularly useful because, unlike deterministic methods that assume fixed failure and repair times, stochastic models consider the inherent variability in these times (Escobar, 2007). This allows for the development of more realistic and adaptive maintenance strategies that can dynamically adjust to operational conditions and the evolving state of equipment. Stochastic models allow for modeling and managing uncertainty, offering a robust and flexible solution that can adapt to various operational conditions and achieve an optimal balance between costs and equipment.

2. Problem Statement

The analyzed problem can be formalized by considering a critical component in operation, whose deterioration process, resulting from its operation, is classified into L levels. In this case, the index $l = \{1, 2, \ldots, |L|\}$ represents the deterioration level, where $|L|$ is the total number of possible levels. Level 1 corresponds to the optimal state of the component, while level $|L|$ indicates a total failure.

Depending on the detected deterioration level, M types of maintenance can be performed, where $m = \{1, 2, \ldots, |M|\}$. The M types of maintenance considered in this study differ in the level of intervention required and the associated resource consumption. While all maintenance actions fully restore the component to its optimal state, their cost and complexity increase with the deterioration level at the time of intervention. Lower deterioration levels allow for simpler and less costly interventions, whereas advanced deterioration requires more extensive repairs, longer downtime, and higher resource allocation. This classification captures the trade-off between performing maintenance early to reduce costs and delaying intervention at the risk of incurring higher corrective expenses.

This component will be subject to a preventive maintenance policy that uses periodic inspections as a strategy to prevent unexpected failures. For this purpose, the component will be inspected periodically over a time horizon T, measured in time units $(t.u.)$. During each inspection, three possible scenarios may arise (See Fig. 1):

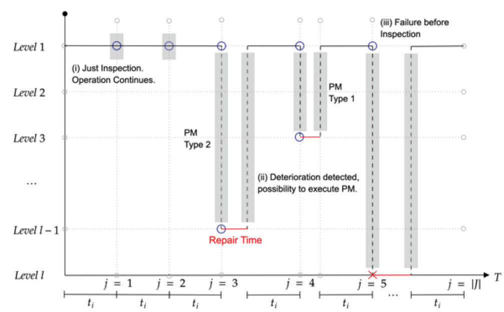

Fig. 1. Diagram illustrating the possible conditions of the equipment at the time of inspection and an example of the trajectory of equipment deterioration over time.

i. **Optimal state:** The component shows no significant signs of deterioration, allowing it to continue operating without intervention until the next scheduled inspection or until an unexpected failure occurs.
ii. **Deterioration detected:** Significant signs of wear are observed, requiring a preventive intervention to avoid a potential future failure.
iii. **Failure before inspection:** The component fails before the scheduled inspection can be performed. This is the most critical scenario, as it requires an

urgent corrective intervention, resulting in additional costs associated with repairs and system downtime.

The objective is to determine the optimal inspection frequency so that the total expected costs during the planning horizon are minimized. These costs include both those associated with conducting the inspections, covering labor and resources, as well as costs resulting from preventive and corrective interventions that may be necessary during the component's operational life.

3. Simulation Model Design and Methodology

3.1.*Methodology*

The methodology adopted to model the maintenance process of a critical component integrates stochastic simulation and optimization to evaluate inspection frequencies and associated costs. This methodological approach is structured in four main stages, which are described below:

i. **Data and Parameter Definition:** In this stage, the critical system variables are identified, such as maintenance costs, inspection times, and failure rates. Additionally, the necessary information is gathered to build the input matrix that allows modeling the behavior of the equipment under different preventive maintenance policies based on periodic inspections. The defined parameters are validated using historical data, technical literature, and consultations with experts, ensuring that they adequately represent the industrial environment.

ii. **Execution of Stochastic Simulation:** The simulation model is implemented by configuring the necessary experimental conditions to evaluate different scenarios. From a discrete range of inspection frequencies titi, simulations are executed using Monte Carlo techniques (Li, 2019) (Dąbrowska, 2020). This allows modeling the inherent uncertainty in the system and capturing the variability of results, both in terms of costs and operational performance.

iii. **Results and Sensitivity Analysis:** The data generated during the simulations is processed to extract key information about the system's performance. Metrics such as total expected cost and CVaR (Xu, 2021) (Sadeghian, 2021), which acts as a risk indicator, are calculated. A sensitivity analysis is also conducted to identify the variables with the greatest impact on the results, providing relevant insights into how different factors affect the system's metrics.

iv. **Optimization and Conclusions Generation:** The obtained results are used to optimize decisions related to inspection frequency, selecting the one that best meets the system's objectives, such as minimizing costs and operational risks. The final conclusions highlight the practical implications of the model, the potential benefits of its implementation, and possible future research directions.

3.2.*Model Formulation*

The simulation model is developed to represent the operating environment of a critical component subject to periodic inspections and maintenance interventions. The model incorporates probabilistic parameters and cost assessments to capture system variability and inform decision-making.

3.2.1.Model Parameters

To represent the operating environment, the model defines parameters that serve as essential inputs for the simulation. These parameters include costs, maintenance durations, inspection intervals, and probability distributions that model the component's deterioration. These key parameters are provided in Table 1.

Table 1. Parameters of the proposed model and their associated descriptions.

Notation	Description
α	Scale parameter.
β	Shape parameter.
T	Annual operational time.
$RT_{m,k}$	Repair time por type m.

RT_j	Inspection duration.
$CM_{m,k}$	Maintenance cost for type m.
CR_k	Spare parts cost.
CI_j	Inspection cost.
CD_k	Downtime cost per hour
t_i	Inspection interval
n	Number of simulations
$State_{l,i}$	Deterioration probability matrix

Source: Prepared by the author.

The parameters α and β are central to characterizing the behavior of the component using the Weibull distribution, commonly applied in reliability analysis (De Assis, 2020) (Zhang, 2021) (Meeker, 2022). The parameter α indicates the characteristic lifetime, while β defines the shape of the distribution (Cohen, 2020).

The analysis horizon is defined by T, which represents the total operational time, typically one year. This is essential for calculating cumulative metrics such as total expected costs and system availability. On the other hand, the maintenance and inspection durations are represented by $RT_{m,k}$ and RT_j, which capture the time required for maintenance type m during intervention k and for inspection j, respectively. These values affect system availability and costs.

3.2.2. *Stochastic Parameters*

Uncertainty in maintenance systems requires the inclusion of stochastic parameters. The costs and durations associated with inspection and maintenance activities are treated as random variables due to external factors such as equipment condition, spare parts availability, and workforce efficiency. These factors cause fluctuations in the value of these parameters due to the inherent variability in maintenance processes.

Table 2. Stochastic parameters of the proposed model and the distributions that model them.

Parameter	Distribution
$RT_{m,k}$	$\sim\mathcal{N}(\mu_{RT}, \sigma_{RT})$
$CM_{m,k}$	$\sim\mathcal{N}(\mu_{CM}, \sigma_{CM})$
CR_k	$\sim\mathcal{N}(\mu_{CR}, \sigma_{CR})$
CD_k	$\sim\mathcal{N}(\mu_{CD}, \sigma_{CD})$
CI_j	$\sim\mathcal{N}(\mu_{CI}, \sigma_{CI})$

Source: Prepared by the author.

The values of these parameters are derived from historical records or expert opinions, ensuring that the model realistically captures the variability of costs and times. The normal distribution is considered appropriate due to its flexibility and ability to model a wide range of variables. Table 2 shows the stochastic parameters modeled with normal distributions.

3.2.3. *Optimization Criterion*

The optimization criterion focuses on minimizing the total expected maintenance cost (CT), including inspection costs, preventive maintenance costs, and costs for unexpected failures. Eq. (1) presents the formulation:

$$E(CT) = \sum_{j\in J} CI_j \cdot RT_j + \sum_{k\in K} CR_K + \sum_{k\in K}\sum_{j\in J} CM_{m,k}\cdot RT_{m,k} + \sum_{k\in K}\sum_{m\in M} CD_k \cdot RT_{m,k} \quad (1)$$

Where:

- J: Set of inspections.
- K: Set of maintenance interventions.
- M: Set of types of maintenance.

3.2.4. *State Probability*

The proposed model is fed with probabilistic information to estimate the behavior of equipment under different inspection and maintenance scenarios. An input is the matrix $State_{l,i}$, which captures the probability of the equipment being at each deterioration level l at a given time t_i, based on the evaluated inspection frequency. This matrix serves as a tool to model the probabilistic evolution of equipment deterioration over time without relying on classical degradation models. In this article, the matrix is presented as a foundational input, with its development and refinement planned for future research.

The deterioration levels are defined qualitatively, ranging from an optimal state (Level 1) to the maximum deterioration level, which represents total equipment failure. These levels are determined based on expert observations, physical inspections, and operational characteristics such as operating time, workload, and environmental conditions. The probabilities $P(l,i)$ of the equipment being at a specific deterioration level l at time t_i could be derived using approaches such as historical data analysis, machine learning (ML) techniques, and statistical methods. Historical data, including records of past failures and operational conditions, could serve as a basis for estimating these probabilities. ML models could be employed to identify patterns in the data, improving the accuracy of deterioration probability predictions by incorporating operational variable and, similarly, statistical methods could be used to estimate probabilities based on operational characteristics.

The general structure of this matrix is shown in Eq. (2):

$$State_{l,i} = \begin{pmatrix} \mathbb{P}_{1,1} & \cdots & \mathbb{P}_{1,i} \\ \vdots & \ddots & \vdots \\ \mathbb{P}_{l,1} & \cdots & \mathbb{P}_{l,i} \end{pmatrix} \quad (2)$$

Where $\mathbb{P}_{l,i}$ represents the probability of the equipment being at deterioration level l at time t_i, t_i are discrete time intervals at which the equipment's condition is evaluated, determined by the inspection frequency and deterioration levels range from Lvl 1 (optimal state) to $Lvl\ l$ (total failure). In future work, the methodology for determining deterioration probabilities will be further refined.

3.2.5. *Times to Failure*

To model the time to failure, the Weibull distribution is used, which is widely employed in reliability analysis and in the study of the time-to-failure behavior of components and systems The calculation of these times uses the inverse of the cumulative distribution function (CDF). This function allows the calculation of the time to failure based on a randomly generated probability, denoted as P_f uniformly distributed in the interval (0,1). The inverse of the Weibull function is given by the following expression:

$$Time\ to\ failure = \alpha\left(-\ln\left(1-\mathbb{P}_f\right)\right)^{1/\beta} \quad (3)$$

Where α is the scale parameter and β is the shape parameter.

To simulate the time to failure, random values can be generated from the Weibull distribution using the parameters α and β. This process allows for the creation of a data set that represents the behavior of the equipment over time and facilitates reliability analysis and the development of preventive and predictive maintenance strategies. Together with Monte Carlo simulation, the defined stochastic parameters, and the evaluation of different inspection intervals, this provides a powerful tool for decision-making in maintenance management.

4. Numerical Experiments

4.1. *Case of Study*

This section details the configurations of the numerical example used to demonstrate the operation of the developed stochastic simulation model. The goal is to analyze how different parameter combinations affect maintenance decisions and the total system cost, providing insights into the model's behavior.

The model considers the following key features:

- **Levels of Deterioration:** There will be l levels of deterioration, with $l = \{1,\ldots,4\}$. Where $l = 1$ indicates that the equipment is in an optimal state and $l = 4$ implies a failure of the equipment.
- **Types of Maintenance:** There are mm types of maintenance, with $m = \{1,\ldots,3\}$. Where $m = 1$ corresponds to preventive maintenance Type 1, $m = 2$ to preventive maintenance Type 2, and $m = 3$ to corrective maintenance.
- **Time to Failure:** The time to failure follows a Weibull distribution with α and β representative of the equipment, allowing for the estimation

of event occurrence and maintenance planning.

The analysis is carried out considering a time horizon of $T = 8760$ hours. On the other hand, the evaluated inspection frequencies correspond to a discrete interval defined by $t_i = [20, 450]$, with increments of 10 hours, which makes it easier to analyze the impact of different inspection frequencies on the equipment's performance.
The times to failure are randomly generated in each simulation using the Weibull distribution with parameters $\alpha = 250$ and $\beta = 2.5$, values that will characterize the studied equipment, aiming to ensure that the failure times represent the component in its operational context.
Finally, to ensure the robustness of the results, $n = 10000$ simulations are conducted per inspection frequency to obtain statistically sound results.

Table 3. Value of the time parameter of the proposed model.

Parameter	Value
$RT_{1,k}$	$0.25 \cdot \mu_{3,k}$
$RT_{2,k}$	$0.50 \cdot \mu_{3,k}$
$RT_{3,k}$	$\sim\mathcal{N}(\mu_{3,k} = 9,\ \sigma_{3,k} = 2)$
CI_j	1

Source: Prepared by the author.

Table 4. Value of the cost parameter of the proposed model.

Parameter	Value
CM_k	$\sim\mathcal{N}(\mu_{CM} = 40,\ \sigma_{CM} = 5)$
CR_k	$\sim\mathcal{N}(\mu_{3,k} = 9,\ \sigma_{3,k} = 2)$
CD_k	$\sim 1000\ \mathcal{N}(\mu_{3,k} = 9,\ \sigma_{3,k} = 2)$

Source: Prepared by the author.

The stochastic parameters presented in Tables 3 and 4 provide the key variables to model the uncertainty and dynamics of the system in the numerical example. These variables encompass both repair times and associated costs, which are fundamental for the simulation and analysis of the model.

In Table 3, the repair times used in the model are presented. The preventive repair time Type 1 and Type 2 are proportional to the average corrective repair time, reflecting their planned and predictable nature. In contrast, corrective maintenance time is modeled as a stochastic variable due to the uncertainty associated with unplanned failures, which depend on factors like failure severity and resource availability. Inspection time is deterministic, as inspections do not induce downtime that impacts system inefficiency or costs.

In Table 4, cost parameters include repair and spare parts costs are modeled as random variables with normal distributions, and inefficiency cost, set at 1000 times the repair cost to reflect its relationship with operational and maintenance expenses.

In addition to the above, the matrix, the behavior of the matrix $State_{l,i}$ shows how the probability of the system being in a particular deterioration level varies with time between inspections. At the lower deterioration levels, the probability of staying in a low-deterioration state decreases over time, while at higher levels, the probability progressively increases, reflecting more severe deterioration of the system.

4.2. *Results and Analysis*

The following presents the results obtained from the stochastic simulation model. First, the results based on the expected value are shown, which help identify the optimal inspection frequency to minimize the total cost. Then, an analysis using CVaR is conducted, along with a sensitivity analysis, offering a more comprehensive perspective for decision-making that accounts for the inherent uncertainty of the process.

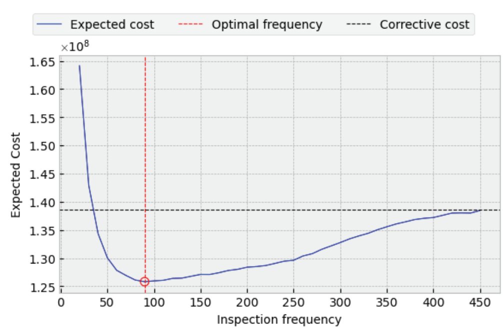

Fig. 2. Relationship between expected cost and inspection frequency, showing how costs vary with different inspection frequencies.

Fig. 2 illustrates how total maintenance costs vary with inspection frequency, highlighting the optimal frequency where costs are effectively balanced. As the inspection frequency increases, inspection costs rise, but the costs of undetected failures decrease, emphasizing the importance of finding the right point to minimize total costs.

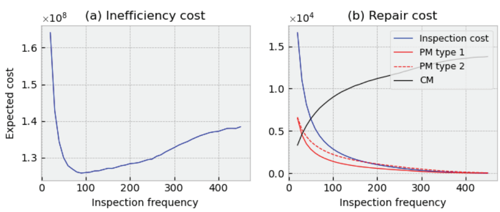

Fig. 3. Behavior of inefficiency, maintenance, and inspection costs, illustrating the distribution of these costs as inspection frequency changes.

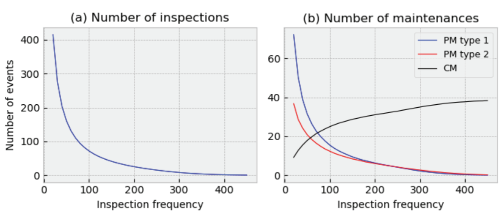

Fig. 4. Behavior of intervention frequency, highlighting how it changes with inspection frequency.

Fig. 3 and 4 complement this analysis: Fig. 3 shows how different costs (inspection, preventive maintenance, and undetected failures) respond to changes in inspection frequency, while Fig. 4 analyzes maintenance interventions, highlighting the differences between preventive and corrective maintenance in terms of costs and times. Both figures help to better understand the impact of inspection frequency on costs and system efficiency.

3.2.5. *Risk and Sensitivity Analysis*

Fig. 5 analyzes the relationship between inspection frequency and risk-related costs, represented by the CVaR (Conditional Value at Risk) calculated for the system's risk tail. This analysis highlights that, in the most extreme scenarios, expected costs exceed corrective costs. This underscores the importance of not only determining an optimal inspection frequency to minimize the CVaR but also carefully defining the parameters that influence the system. A detailed analysis of these parameters can help reduce variability in outcomes and, consequently, associated risks, enabling more robust and predictable management.

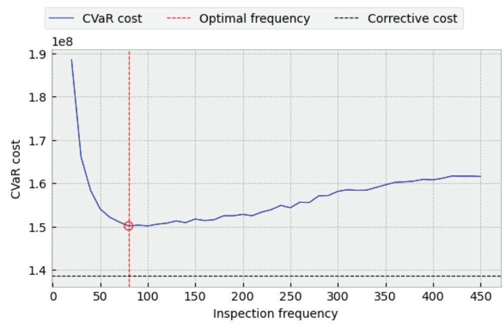

Fig. 5. Behavior of CVaR with respect to inspection frequency, showing how inspection frequency impacts risk exposure.

On the other hand, the tornado chart of Fig. 6 complements this analysis by illustrating the sensitivity of key metrics to changes in inspection frequency. Repair time emerges as the most critical factor, which is logical given its direct impact on labor costs and inefficiency-related expenses. This analysis helps prioritize efforts on the most influential variables, optimizing resource allocation, reducing uncertainty, and minimizing the system's economic risks.

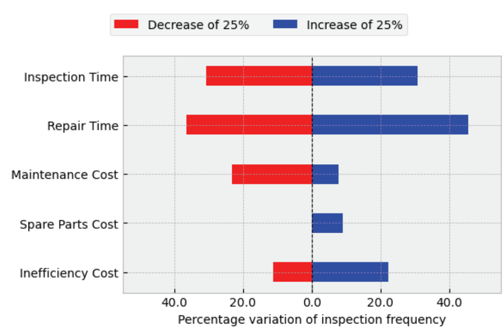

Fig. 6. Tornado diagram for sensitivity analysis, highlighting the variables that most influence the determination of the optimal inspection frequency.

These analytical tools represent some of the proposed elements for alternative result visualization, aimed at facilitating decision-making. Further development of these tools will be included in an extended version of this study, which is intended for publication in a peer-reviewed journal in the field.

5. Conclusions and Future Work

This study proposed a stochastic simulation-based methodology to determine the optimal inspection frequency in maintenance policies relying on periodic inspections. The results identified repair time as the most influential factor in total expected costs, as longer durations significantly increase maintenance and inefficiency costs. Strategies such as staff training, process optimization, and the adoption of advanced technologies are key to mitigating these costs.

The analysis revealed an optimal inspection frequency that balances the costs of frequent inspections with those of undetected failures. Extremely low frequencies lead to high corrective maintenance costs, while excessively high frequencies increase operational expenses. This balance underscores the importance of sustainable and efficient inspection strategies.

The inclusion of Conditional Value at Risk (CVaR) complemented the expected value analysis by evaluating risks in extreme scenarios. This metric showed that the optimal frequency not only minimizes average costs but also reduces the financial impact of extreme events, offering a robust solution from a risk perspective.

The contribution of this work lies in its stochastic approach, which optimizes inspection frequency without relying on complex degradation models, making it more adaptable to practical industrial settings. While this article presents a simplified version of the problem, future work will extend the methodology to address more complex, multi-component systems and refine the state probability matrix. Additionally, advanced sensitivity analysis techniques, such as the Sobol method and semi-deviation-based approaches, will be explored to provide deeper insights into model behavior and risk interactions. These extensions will further enhance the methodology's versatility and applicability across diverse industrial contexts.

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