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Article

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Enhancing industrial maintenance planning: Optimization of human error reduction and spare parts management

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ABSTRACT

Maintenance is pivotal in the industrial sector, influencing efficiency, reliability, safety, and profitability. An organized spare parts inventory supports maintenance efforts by minimizing downtime, ensuring safety, and optimizing maintenance budgets. Effective spare parts management enhances maintenance operations and improves cash flow. Conversely, human error can greatly diminish the effectiveness of maintenance efforts. This paper presents a mathematical model aimed at minimizing costs through optimized preventive maintenance (PM) planning, effective spare parts inventory control, and reduction of human error. The study provides decision-makers with crucial insights for strategically managing maintenance procedures while accounting for the effect of human error. The model is validated in real-world scenarios through sensitivity analysis, focusing on the shape parameter of the Weibull distribution, and the equipment's effective rate. Findings reveal that as the number of periods increases, maintenance operations follow a specific, predictable cycle. Moreover, the optimal human error probability (HEP) for cost minimization is identified as 0.02. These insights guide decision-makers in recognizing factors influencing human error and implementing proactive strategies to enhance maintenance performance.

1. Introduction

Maintenance operations are critical for improving organizational efficiency and ensuring reliable system performance, especially when substantial investments are made in production machinery [1–4]. Ineffective maintenance can lead to machine failures, downtime, and increased costs, including opportunity costs, reputational damage, and disruptions to production schedules [5,6]. Preventive maintenance (PM) is a widely adopted strategy to minimize unplanned breakdowns and downtime. However, poorly timed or inadequately executed PM can negatively impact efficiency and incur additional costs, such as resource allocation and temporary production halts. Effective planning and execution of maintenance are therefore essential to balance these trade-offs and optimize organizational performance [7–10].

Optimal planning of maintenance operations depends heavily on the effective management of spare parts inventory. Excessive spare parts inventory can lead to higher holding costs and unnecessary expenditures, while insufficient inventory can prolong downtime and result in greater losses due to machine inactivity [8–10]. To address these challenges, it is crucial to optimize the spare parts inventory control policy.

This presents a significant challenge in balancing costs through optimal inventory management while ensuring system reliability [11,12].

Both PM and corrective maintenance (CM) significantly influence the condition and virtual age of machinery. Effective maintenance planning must account for these factors to optimize the timing and frequency of PM operations, thereby enhancing machine reliability. However, even well-planned maintenance can fail due to human error, leading to improper implementation and increased system costs. Human Error Probability (HEP) is a quantitative measure used to estimate the likelihood of human errors occurring in specific tasks or systems [13,14]. It is commonly employed in human reliability analysis (HRA) to evaluate safety in industries such as aviation, nuclear power, healthcare, and manufacturing. HEP is typically expressed as a probability value ranging from 0 (no chance of error) to 1 (certainty of error) [10,15].

HEP during PM, CM, or inspections can undermine the effectiveness of maintenance and inflate costs. To mitigate this, maintenance plans must incorporate strategies to reduce human error, ensuring both cost efficiency and improved machine reliability [16–18]. Given the significant impact of human error on maintenance operation costs and the virtual age of machines, it is essential to consider human errors when

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optimizing maintenance plans.

In this study, data on human error, costs, and the virtual age of machines were collected from historical data in a case study. The cost of human error and the machine's virtual age functions were estimated using a regression method based on HEP. Thus, the proposed model quantitatively incorporates human error, highlighting its effects on costs and the virtual age of the machine. When estimating the cost function, two key challenges arise. First, the cost associated with human error in maintenance operations increases as the level of error rises. Second, improving contextual factors to mitigate human error also incurs additional costs. Contextual factors, which include environmental, organizational, and task-related elements, play a critical role in shaping HEP. By identifying, assessing, and optimizing these factors, industries can effectively reduce human errors, enhance safety measures, and improve overall system reliability.

Therefore, the cost function of human error related to maintenance operations is estimated by considering both aspects. Consequently, optimizing maintenance plans and minimizing human error are essential for reducing costs and achieving economic success across various industries. Although human error significantly affects maintenance operations, previous studies have largely overlooked this aspect, focusing instead on non-human factors. While spare parts have been examined in some studies, none have specifically investigated the repercussions of human error in maintenance operations. The model presented in this paper quantitatively considers the influence of human error, contributing to a more comprehensive analysis of the problem.

The research focuses on a case study of a cement company that operates continuously, utilizing heavy machinery with significant investment. Given the characteristics of the industry, proper and optimal maintenance operations are crucial for minimizing stochastic breakdowns and total costs. The model presented for this case study is multi-product, multi-machine, and multi-condition, providing a comprehensive approach to the problem. The objective of this research is to identify the optimal values for inventory management of spare parts, as well as for planning PM and CM operations, while considering the impact of associated human errors. Accordingly, in line with previous studies in this field, we emphasize five major contributions of this paper:

1. Impact of Human Errors on Equipment Utilization and Virtual Age:

The study investigates how human errors affect the effective rate of equipment utilization and the virtual age of equipment. By modeling these relationships, the research offers insights into how human errors accelerate equipment deterioration and provides strategies to minimize their impact on operational efficiency.

2. Development of an Integrated Optimization Model:

The study proposes a novel optimization model that integrates maintenance operations, spare parts inventory control, and human error management into a unified framework. This holistic approach addresses the interdependencies between these components, enabling more efficient and cost-effective decision-making.

3. Innovative Maintenance Planning Incorporating Equipment Lifespan:

The research pioneers a quantitative approach to maintenance planning by integrating equipment conditions and lifespan into the decision-making process. A novel constraint is introduced to account for equipment lifespan, allowing for the determination of threshold limits for maintenance activities in an innovative and systematic manner.

4. Consideration of Machine Setup Costs During Downtime:

The study incorporates machine setup costs during production line downtime caused by PM and CM operations. This inclusion allows for more accurate budgeting and resource allocation, optimizing production efficiency and minimizing financial disruptions during maintenance periods.

5. Simultaneous Implementation of Condition-Based Maintenance (CBM) and Time-Based Maintenance (TBM):

Unlike traditional PM models that rely solely on time- or usage-based scheduling, this study integrates both CBM and TBM to enhance maintenance decision-making.

6. Practical Application and Validation:

The model is applied to a real-world case study of a cement factory, utilizing data from maintenance logbooks to validate its effectiveness. This practical application demonstrates the model's ability to address real industrial challenges and improve maintenance practices in complex operational environments.

7. Quantitative Analysis of Human Error Costs in Maintenance:

The research introduces a novel mathematical model to quantify the costs associated with human error in maintenance tasks. Using regression methods, the study estimates the cost function linked to the probability of human error, addressing a critical gap in existing literature. This approach provides a systematic way to evaluate and mitigate the financial impact of human errors.

The remainder of this paper is organized as follows:

The second section offers a concise overview of prior research on this topic. The problem statement and case study are presented in [Section 3](#). [Section 4](#) details the methods employed in this study. The research findings are presented in [Section 5](#). [Section 6](#) examines the sensitivity analysis conducted to validate the proposed model. Lastly, [Section 7](#) presents managerial insights, while [Section 8](#) discusses notable conclusions and offers suggestions for future studies.

2. Literature review

Research conducted in this field focused on maintenance operations exclusively and ignored human error's impact on these operations. Liu et al. [19] introduced a model that takes into account buffer inventory and imperfect PM in production system. Zheng et al. [6] highlighted the cost-effectiveness of policies based on production quantity and condition-based maintenance for managing a deteriorating production system. Lynch, et al. [20] investigated the impact of an effective maintenance system on industrial performance. Bismut et al. [21] improved the maintenance and inspection strategies for the piping systems in nuclear fuel power plants. Emami-Mehrgani et al. [22] examined the effects of human errors on repairable production systems and proposed an optimal policy to reduce production costs.. Morato et al. [23] introduced optimal maintenance planning for deteriorating structural components using a Dynamic Bayesian Network (DBN) and Markov decision process.

Szpytko et al. [24] proposed a compatible and straightforward simulation approach based on a risk assessment model to optimize maintenance scheduling in different case studies. Liu et al. [25] proposed an integrated model that takes into account buffer stocks and imperfect PM in production systems. Sharifi and Taghipour [26] proposed an integrated model for production and maintenance planning. Kim et al. [27] presented a potential approach for optimizing inspection and maintenance planning. Zhang et al. [12] explored the simultaneous optimization of maintenance and spare parts inventory for a series-parallel system with dual failure modes.

Nasrfard et al. [28] introduced a Petri net model that considers the state of deterioration, inspection, age-dependent repair processes, and random repair. Briš and Thuy Tran [29] studied the problem of multi-objective maintenance optimization to minimize costs and maximize availability. Saleh et al. [30] introduced an intelligent Petri net algorithm to optimize maintenance operations for wind turbines. Fekri et al. [31] explored the workshop flow scheduling problem with limited multi-skilled human resources in PM. Zhu et al. [32] introduced an optimization model and algorithm for spare parts, taking into account trade-offs between cost and time as well as precedence constraints. Jiang et al. [33] optimized PM interval and the maximum inventory level,

with the ultimate goal of minimizing system downtime and inventory holding costs.

Cao et al. [34] examined an optimization model for decision-making aimed at the sustainable maintenance of intricate road networks. Their work introduced a bi-level programming approach that addresses the diverse characteristics of subnetworks, varying maintenance standards, and the allocation of maintenance funds. Levitin et al. [35] focused on the optimization of CM for multistate systems with storage, particularly production-storage systems in various industries. They addressed the impact of random external shocks on system performance and introduce a corrective maintenance policy (CMP). Liu et al. [36] provided an optimal condition-based maintenance policy for leased equipment, considering hybrid PM and periodic inspection. The authors addressed the complexity of leased equipment structures due to technological advancements, posing challenges for lessors in developing maintenance policies. Lee et al. [37] developed an optimized scheduling model for railway lines using a sophisticated deep reinforcement learning algorithm.

Liu et al. [38] introduced two innovative PM policies that account for substantial repair downtime. One policy is time-based, scheduling preventive replacements at one of two predetermined calendar intervals, contingent on the system's condition. Zhou and Zheng [39] introduced a multi-objective decision optimization model for prioritizing maintenance and repair of bus failures. Mikhail et al. [40] introduced a data-driven optimization method that considers contextual conditions. They combined machine learning and reinforcement learning techniques with a reliability-based remaining useful life methodology. Wang et al. [41] introduced a dynamic predictive maintenance strategy for predicting the remaining useful life (RUL) of systems. Zheng et al. [42] explored the joint optimization of maintenance and spare part ordering from multiple suppliers for systems with multiple components.

Zeng et al. [43] addressed a novel challenge in integrating PM with robot disassembly line balancing (DLB) to enhance the efficiency and stability of robotic disassembly systems. Their study focuses on optimizing both conventional disassembly scenarios and PM scenarios, while also improving the transition efficiency between these two contexts. O'Neil et al. [44] introduced a new resilience framework designed to optimize the performance of critical network infrastructures, such as power grids, telecommunications, and transportation systems. This framework tackles the challenges posed by disruptions caused by stress events and aims to enhance network resilience through efficient post-disruption restoration. Lima et al. [45] presented a novel model for managing imperfect maintenance in multi-component systems, specifically addressing the Selective Maintenance Problem (SMP) by incorporating both perfect PM and CM actions.

Tian et al. [46] introduced a heuristic algorithm that provides near-optimal solutions for this complex issue, focusing on efficient resource utilization and long-term system performance. They also developed a Selective Serial Maintenance Sequence Planning (SSMSP) model to optimize maintenance activities for mechanical equipment with multiple components. This model addresses inefficiencies, high costs, and resource wastage by integrating worker physical exertion and rest time into maintenance planning, thereby ensuring sustainable schedules. Additionally, it employs a multi-objective optimization approach to balance maintenance benefits, costs, and resource constraints.

Zhang et al. [47] focused on enhancing the reliability and maintenance efficiency of wind-photovoltaic (PV) hybrid power systems. They developed a reliability model and a maintenance optimization model that incorporates energy complementarity strategies. This study addresses the intermittency of renewable energy systems and aims to reduce maintenance costs across different failure modes and scenarios. The proposed maintenance optimization model integrates energy complementarity strategies to optimize system performance and minimize costs. Wei and Cheng [48] developed a maintenance policy optimization framework for self-service systems aimed at maximizing profit

by balancing service revenue and maintenance costs. Their model accounts for unique failure-induced demand-and-system interactions and employs a Tabu-search algorithm to optimize maintenance policies.

Leppinen et al. [49] tackled the challenge of optimizing maintenance schedules for multi-component systems by considering technical structural dependencies, which significantly impact the cost-efficiency of maintenance policies. Their study introduced directed graphs as a tool to represent the economic and structural dependencies of the system, including scenarios where maintaining one component necessitates disassembling or maintaining others. The maintenance scheduling problem is modeled as a Markov Decision Process (MDP) and solved using a modified policy-iteration algorithm to determine the most cost-efficient maintenance policy. Bafandegan Emroozi et al. [50] assessed HEP in maintenance tasks using the Cognitive Reliability and Error Analysis Method (CREAM) and System Dynamics (SD) modeling. Their study identifies and quantifies factors influencing HEP, explores their interactions, and estimates associated costs using machine learning techniques. Ultimately, the research determines the optimal HEP value to minimize costs and accidents, providing managers with scenarios for effective budget allocation and improved ergonomics. Table 1 provides an overview of previous studies on maintenance.

- TBM is scheduled at fixed intervals to ensure regular preventive actions and avoid unexpected failures.
- CBM is incorporated through real-time condition monitoring of the equipment, allowing early detection of potential failures and enabling adaptive maintenance interventions before scheduled TBM actions.

Previous studies have provided valuable insights into maintenance operations, as shown in Table 1. However, they did not consider the impact of human error on maintenance metrics. This oversight is significant because the human factor plays a critical role in maintenance operations, and neglecting it may lead to inaccurate results. Prior research has primarily focused on non-human factors, such as machine reliability and failure rates, while overlooking the effects of human error. To address this gap, our research aims to examine how HEP affects the total cost and the virtual age of machines resulting from maintenance operations. This paper conducts a quantitative analysis to determine the extent to which human error influences these costs and machine age. Additionally, we explore inventory control policies for spare parts to enhance maintenance planning.

Implementing an effective inventory control policy can help reduce downtime and maintenance costs by ensuring that spare parts are readily available when needed. It is important to note that previous studies have examined maintenance operations planning based on either condition-based or time-based maintenance. However, in our study, we investigate both condition-based and time-based maintenance simultaneously. This dual approach allows us to identify which maintenance strategy is more effective for different types of machines and maintenance tasks. Overall, our research aims to provide a comprehensive understanding of the impact of human error on maintenance operations and the importance of an effective inventory control policy.

3. Methodology

This section outlines a comprehensive and systematic methodology for optimizing maintenance operations, spare parts inventory control, and human error management within a cement factory. By integrating these critical components into a unified optimization model, the research aims to achieve cost-effective and efficient maintenance practices while rigorously adhering to operational constraints. The incorporation of real-world data from the cement factory not only enhances the model's accuracy but also ensures its practical applicability and relevance to industrial settings. This approach provides a robust framework for balancing cost reduction, operational efficiency, and

Table 1

Previous studies on maintenance.

| No | Reference | Maintenance Strategy | Subcategory | Distribution of failure function | Function estimation related to HEP | | Inventory management of spare parts | Solution approach |
|----|------------|----------------------|-------------|----------------------------------|------------------------------------|-----------------------|-------------------------------------|---|
| | | | | | Cost | Reduction coefficient | | |
| 1 | [20] | PM | TBM | – | ✗ | ✗ | ✓ | Genetic algorithm (GA) |
| 2 | [33] | PM, CM | TBM | Weibull | ✗ | ✗ | ✓ | Monte Carlo Simulation |
| 3 | [16] | PM, CM | TBM | Non-homogenous Markov processes | ✗ | ✗ | ✗ | Hamilton–Jacobi–Bellman (HJB) |
| 4 | [19] | PM, CM | TBM | Uniform | ✗ | ✗ | ✗ | Kushner and Dupuis' method and value iteration or policy iteration algorithms |
| 6 | [27] | PM, CM | TBM | Log-Normal | ✗ | ✗ | ✗ | SAW, TOPSIS, ELECTRE |
| 7 | [25] | PM, CM | TBM | Gamma | ✗ | ✗ | ✓ | A Lagrangian relaxation-based heuristic approach |
| 8 | [42] | PM, CM | CBM | Weibull | ✗ | ✗ | ✗ | The policy-iteration algorithm in the semi-Markov decision process (SMDP) |
| 9 | [26] | PM, CM | TBM | Weibull | ✗ | ✗ | ✗ | GA, simulated annealing (SA) algorithm, and a teaching–learning-based optimization (TLBO) |
| 10 | [24] | PM, CM | TBM | Weibull | ✗ | ✗ | ✗ | Petri net algorithm |
| 11 | [21] | PM, CM | TBM | Gamma | ✗ | ✗ | ✗ | Heuristic parameters optimization |
| 12 | [23] | PM, CM | CBM | Weibull | ✗ | ✗ | ✗ | the POMDP dynamics |
| 14 | [12] | PM, CM | CBM | Gamma | ✗ | ✗ | ✓ | Monte Carlo simulation |
| 15 | [32] | PM, CM | CBM | uniform | ✗ | ✗ | ✓ | Heuristic-based on a standard critical path method. |
| 16 | [28] | PM, CM | CBM | Weibull | ✗ | ✗ | ✗ | Petri net algorithm |
| 17 | [29] | PM, CM | TBM | Exponential | ✗ | ✗ | ✗ | Innovative and updated calculation methodology by MATLAB software |
| 19 | [31] | PM | TBM | – | ✗ | ✗ | ✗ | Metaheuristic method (GA) |
| 20 | [34] | PM, CM | CBM | Exponential | ✗ | ✗ | ✗ | Metaheuristic method (GA) |
| 21 | [35] | CM | CBM | – | ✗ | ✗ | ✗ | Metaheuristic method (GA) |
| 22 | [40] | PM, CM | CBM | Kaplan-Meier (KM) | ✗ | ✗ | ✗ | machine learning and reinforcement learning |
| 23 | [37] | PM, CM | CBM | Exponential | ✗ | ✗ | ✗ | Deep reinforcement learning |
| 24 | [36] | PM, CM | CBM | Gamma | ✗ | ✗ | ✗ | Metaheuristic method |
| 25 | [38] | PM, CM | CBM | Exponential | ✗ | ✗ | ✗ | Mathematical model |
| 26 | [41] | PM | CBM | – | ✗ | ✗ | ✓ | CNN |
| 27 | [42] | – | – | Exponential | ✗ | ✗ | ✓ | Hybrid deep reinforcement learning algorithm (HDRL) |
| 28 | [45] | PM, CM | SMP | – | ✗ | ✗ | ✗ | Heuristic algorithm |
| 29 | [46] | PM, CM | TBM | – | ✗ | ✗ | ✗ | Enhanced metaheuristic (brainstorming optimization + large neighborhood search) |
| 30 | [49] | PM, CM | TBM | Exponential | ✗ | ✗ | ✗ | MDP model, Modified policy-iteration algorithm |
| 31 | [50] | PM, CM | – | – | ✓ | ✓ | ✗ | SD modeling and machine learning |
| 32 | This study | PM, CM | TBM, CBM | Weibull | ✓ | ✓ | ✓ | Mathematical model (GAMS) |

Condition-Based Maintenance: CBM, Time-Based Maintenance: TBM, Selective Maintenance Problem (SMP).

equipment reliability in complex maintenance environments.

3.1. Notation

This section outlines the symbols and notations used in the paper. Table 2 presents the notations and definitions used throughout the mathematical model described in this paper.

3.2. Problem statement and case study

The primary purpose of this research is to identify the optimal values for decision variables related to maintenance operations ($Vo_{it}, Q_{it}, B_{it}, I_{it}, bB_{it}, bI_{it}$), spare parts inventory control ($z_{kjt}, a_{jt}, \psi_{cjt}, \xi_{cj}, \xi_{cj}^{[m]}, t_{kjt}^{[m]}, t_{jt}^{[p]}$), and human error (p, p_k), aiming to reduce costs while adhering to various constraints. It is important to note that carrying out PM and CM operations can lead to production line downtime and disrupt organizational processes. In this model, the timing and frequency of each level of PM operations are determined based on machine age, cost constraints, and other organizational limitations.

In this study, focusing on the case of a cement factory, maintenance operations are examined for two critical pieces of equipment: a rotary kiln and a clinker silo. The analysis includes four key spare parts associated with this equipment: bearings, a side motor, seals, and a pair of

brushes. Additionally, the study considers three different levels of PM operations and one feature to assess the condition of the equipment (i.e., noise). It is worth mentioning that the model is specifically designed for repairable mechanical equipment that undergoes a deterioration process and operates independently. The data used for the research comes from the maintenance logbooks of the plant and is presented in Tables 1A and 2A in the Appendix.

Simultaneously, the availability of spare parts is crucial for carrying out maintenance effectively and promptly, making spare parts inventory control a critical component of the process. This paper optimizes the order quantity of spare parts. Furthermore, the optimal level of human error is identified based on the conditions that influence human resource errors (i.e., Common Performance Conditions (CPCs)), as well as its impact on machine age and associated costs. The cost of human error in maintenance tasks and its effect on machine age are considered as a function of human error. Fig. 1 illustrates the structure and logic of the model through a detailed diagrammatic representation.

3.3. Assumption related to the presented model

The following assumptions underpin the model presented:

Constrained Time Horizon

The model operates within a finite time horizon, with all operations, costs, and activities analyzed over this duration. This ensures the model

Table 2

Notations.

| Sets | |
|--------------------|--|
| M | The set of periods represented by the index t ; |
| K | The set of different level types of PM represented by the index k ; |
| J | The set of equipment indexed by j ; |
| I | The set of spare parts indexed by i ; |
| C | The set of equipment conditions indexed by c ; |
| Decision variables | |
| $p^{[total]}$ | Human error probability. |
| p_k | Human error probability associated with conducting k^{th} level of PM operations. |
| z_{kjt} | The binary variable equals 1 if a PM operation is performed on the machine j at the k^{th} level in period t ; Otherwise, it equals 0. |
| a_{jt} | The virtual age of the machine j in period t . |
| $t_{jt}^{[p]}$ | The available time on machine j for carrying out production operations in period t . |
| $t_{kjt}^{[m]}$ | Preventive maintenance time on the machine j at the level k in period t . |
| ψ_{cjt} | The level of implementation of PM operations on machine j under condition c in period t . |
| VO_{it} | The binary variable for ordering or not ordering spare parts i in period t . |
| bI_{it} | The binary variable equals 1 if there is inventory available for i^{th} spare parts in period t ; Otherwise, it equals 0. |
| bB_{it} | The binary variable equals 1 if there is a shortage for i^{th} spare parts in period t . Otherwise, it equals 0. |
| B_{it} | The amount of shortage of i^{th} spare parts in period t . |
| I_{it} | The amount of holding of i^{th} spare part in period t . |
| Q_{it} | The order quantity of i^{th} spare part in period t . |
| Parameters | |
| Sh_{it} | The cost of shortage of i^{th} spare part in period t (each unit). |
| h_{it} | The cost of holding of i^{th} spare part in period t (each unit). |
| $Cset_{jt}$ | Setup cost after machine downtime resulting from PM and CM operations on j^{th} machine in period t . |
| dp_{ikjt} | The demand for i^{th} spare parts for the implementation of PM operations at k^{th} level on machine j in period t . |
| dc_{ijt} | The demand for i^{th} spare parts for implementation of CM operations on machine j in period t . |
| CO_{it} | The fixed ordering cost for i^{th} spare part in period t . |
| $LT_i^{[E]}$ | The lead time of emergency orders for i^{th} spare parts. |
| $MTTR_{jt}$ | CM time on j^{th} machine in period t . |
| War_{it} | The warehouse capacity for i^{th} spare parts in period t . |
| Nm_{kjt} | The number of technicians needed to perform PM operations on the j^{th} machine at k^{th} level in period t . |
| Nr_{jt} | The number of technicians needed to perform CM operations on j^{th} machine in period t . |
| Nsp_{ijt} | The number of i^{th} spare parts to carry out CM operation on j^{th} machine in period t . |
| Hm_{kjt} | The cost associated with human resources for PM operations on the j^{th} machine at k^{th} level in period t . |
| Hr_{jt} | The cost associated with human resources for CM operations on machine j in period t . |
| Cl_{jt} | The cost of the lost opportunity of production line downtime on machine j in period t . |
| Cl_{it} | Price of each unit of i^{th} spare part in period t . |
| AC_{jt} | The noise of j^{th} machine in period t . |
| CO_{it} | Ordering cost of i^{th} spare part in period t . |
| cd_{it} | purchasing cost of each unit of i^{th} spare part in period t . |
| $Q_{it}^{[max]}$ | The maximum quantity for ordering i^{th} spare parts in period t . |
| θ_{cjt} | The optimal level of PM operations on j^{th} machine under c^{th} condition in period t . |
| ξ_{cj}^u | The upper threshold for c^{th} condition on machine j . |
| ξ_{cj}^l | The lower threshold for c^{th} condition on machine j . |
| r | The learning coefficient of human resources in the implementation of PM operations on machine j . |
| μ | The number of levels of PM operations. |
| H | Length of the planning horizon. |
| β | Weibull distribution shape parameter. |
| η | Weibull distribution scale parameter. |
| α_k | The effective rate of virtual age through the execution k^{th} level of PM operation. |
| l | The interval length. |
| AE_j | The minimum accessibility* of j^{th} machine. |
| TB | The maximum allocated budget. |
| $p^{current}$ | The probability of human error in the current state. |

* In this paper, machine's accessibility is considered as the available and operational time of the equipment.

aligns with practical planning periods, such as financial years or project lifespans.

Spare Parts Shortage Costs

The cost implications of spare parts shortages are modeled based on the cumulative shortage over the planning horizon. This approach accounts for variations in demand and inventory levels while ensuring that downtime costs resulting from spare part unavailability are comprehensively captured.

Maintenance Cost Dependencies

Spare part costs for maintenance are influenced by dynamic inventory levels and service-level requirements, incorporating penalties

for stockouts and overstocking.

Cost of Corrective and Preventive Actions

The cost of replacing parts post-failure is explicitly higher than preventive replacement costs due to unplanned downtime and potential secondary damages. This difference is dynamically calculated based on severity and time-of-failure scenarios.

Failure Rate Distribution

The failure rate exhibits an increasing trend over time, modeled using a Weibull distribution with a shape parameter ($\beta > 1$). The initial parameter estimates were informed by expert judgment, ensuring alignment with domain knowledge, and subsequently refined and vali-

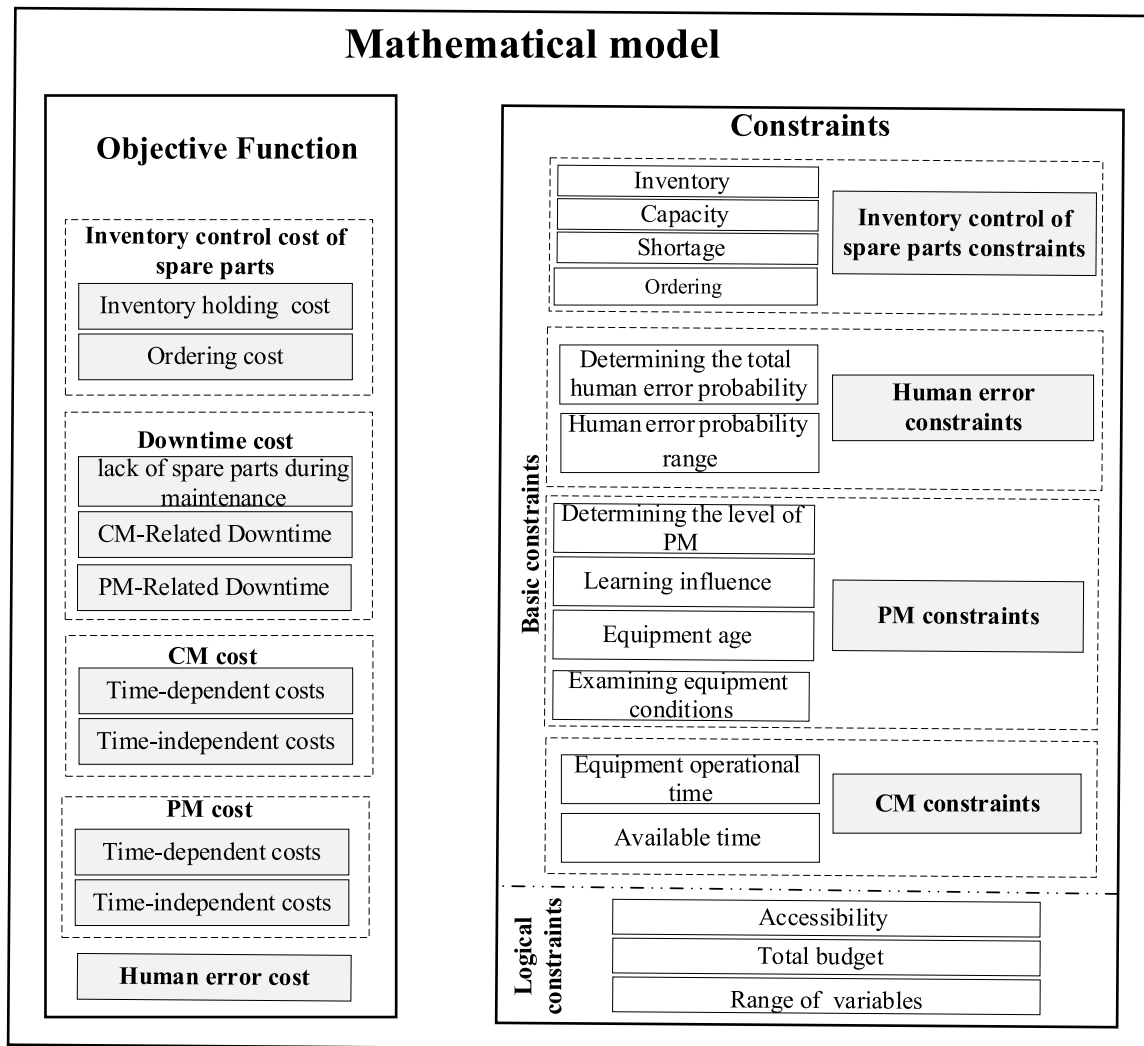


Fig. 1. Representation of the mathematical model's structure.

dated using Maximum Likelihood Estimation (MLE) for greater accuracy and reliability.

Learning Curve Effects on PM Times

Over time, personnel improve in performing PM, reducing the time required per task. This improvement follows a refined learning curve, incorporating plateau points where skill improvements diminish.

Corrective Maintenance (CM) Costs Stability

CM costs are assumed constant per unit task, but additional costs such as logistical delays, material surcharges, or overtime penalties are considered in sensitivity analyses.

Exclusion of Opportunistic Maintenance

Opportunistic maintenance actions are excluded; however, the model provides the flexibility to integrate them in future expansions.

Immediate CM Operations

CM operations are executed without delays upon fault detection. The fault detection system is assumed to be robust, with negligible lag between failure and response.

Preventive Maintenance Levels

PM is categorized into three levels—minimal, imperfect, and perfect. Each level's effectiveness is probabilistically modeled, incorporating both human error and equipment improvement factors. This provides realistic variations in outcomes based on effort and expertise.

Impact of CM on Failure Rate

CM is modeled as minimal, assuming it restores equipment functionality without altering its inherent failure characteristics, which remain Weibull-distributed with stable parameters.

Single Level of CM Operations

The study assumes a uniform CM approach. Future work may explore differentiated CM levels based on failure severity.

Inventory Control System

Spare parts for PM follow a fixed-order interval (FOI) system, with reorder points optimized for minimum total cost, considering order size, holding costs, and stockout penalties. Under this approach (FOI), orders are placed at predetermined, regular intervals, rather than being triggered by a reorder point. The order quantity is determined based on the inventory position at the review time to ensure sufficient stock until the next review period.

Alignment of Inspection and PM Periods

Inventory inspections coincide with PM periods, optimizing scheduling and resource utilization.

Dual Spare Parts Ordering System

Spare parts are procured through regular and emergency orders, with emergency orders incurring higher costs but ensuring service continuity during unexpected demand spikes.

The virtual age of a machine

The virtual age of a machine is defined as the measure of its effective age, based on factors such as operational history, maintenance, and usage, rather than its actual chronological age.

Homogeneous Weibull Parameters Across Equipment

This study assumes identical scale (η) and shape (β) parameters for the Weibull distribution across all equipment types, implying consistent failure characteristics under similar operational conditions.

3.4. Mathematical model

3.4.1. The objective function

The objective function of this research is so as to reduce inventory control costs associated with spare parts, downtime, human error, and CM and PM operation costs

Inventory control

The inventory control system ensures that spare parts are available when needed for maintenance operations. The model incorporates safety stock levels and reorder points to prevent stockouts. If the inventory level of spare parts falls below the safety stock level, an emergency order is triggered. Emergency orders are expedited to minimize downtime, but they incur higher costs compared to regular orders. This ensures that maintenance operations can proceed without significant delays, even in cases of unexpected spare parts shortages.

Inventory holding cost of spare parts

Holding costs are determined by the spare parts ordered in excess of the demand at the end of each time period. Since the demand for these spare parts is influenced by machine failures, its quantity is estimated using the demand function for machine failure, making it a random variable. In reality, the demand for spare parts derives from the overall demand for CM and PM operations that require spare parts replacement. Hence, the demand for spare parts is also a random variable, and the following equations are employed to calculate the average inventory and shortages.

$$I_{it} = Q_{it} + I_{i(t-1)} - dc_{it} - \sum_{k \in K} dp_{ikt} - B_{i(t-1)} \quad (1)$$

$$B_{it} = -Q_{it} - I_{i(t-1)} + dc_{it} + \sum_{k \in K} dp_{ikt} + B_{i(t-1)}$$

$$Q_{it} = Q_{it}^{[max]} - I_{i(t-1)} \quad (2)$$

Based on the stochastic behavior model proposed by Xiang et al., 2018 [51] inventory and shortage are formulated as a backorder with a loss function in Eq. (3).

$$l(\vartheta, w) = E[\max(\vartheta - w, 0)] \quad (3)$$

E represents the expected value of the random variable ω and the scalar variable ϑ . As previously mentioned, demand for spare parts is a random variable, and the order quantity for spare parts, inventory, and shortage are scalar variables. Therefore, Eqs. (4) and 5 can be presented for nonlinear estimation of inventory and shortage.

$$\begin{aligned} I_{it} &= l\left(Q_{it} + I_{i(t-1)} - \sum_{k \in K} dp_{ikt} - B_{i(t-1)}, dc_{it}\right) \\ &= E\left[\max\left(Q_{it} + I_{i(t-1)} - dc_{it} - \sum_{k \in K} dp_{ikt} - B_{i(t-1)}, 0\right)\right] \\ &= E\left(Q_{it} + I_{i(t-1)} - dc_{it} - \sum_{k \in K} dp_{ikt} - B_{i(t-1)}\right)^+ \end{aligned} \quad (4)$$

$$\begin{aligned} B_{it} &= l\left(-Q_{it} - I_{i(t-1)} + \sum_{k \in K} dp_{ikt} + B_{i(t-1)}, -dc_{it}\right) \\ &= E\left[\max\left(-Q_{it} - I_{i(t-1)} + dc_{it} + \sum_{k \in K} dp_{ikt} + B_{i(t-1)}, 0\right)\right] \\ &= E\left(-Q_{it} - I_{i(t-1)} + dc_{it} + \sum_{k \in K} dp_{ikt} + B_{i(t-1)}\right)^+ \end{aligned} \quad (5)$$

Consequently, Eqs. (6) and 7 can be formulated as follows:

$$\begin{aligned} E\left[Q_{it} + I_{i(t-1)} - B_{i(t-1)} - \sum_{k \in K} dp_{ikt} - dc_{it}\right] &\leq I_t \\ \Rightarrow Q_{it} + I_{i(t-1)} - B_{i(t-1)} - \sum_{k \in K} dp_{ikt} - E[dc_{it}] &\leq I_t \end{aligned} \quad (6)$$

$$\begin{aligned} E\left[\sum_{k \in K} dp_{ikt} - dc_{it} - Q_{it} - I_{i(t-1)} + B_{i(t-1)}\right] &\leq B_t \\ \Rightarrow \sum_{k \in K} dp_{ikt} - E[dc_{it}] - Q_{it} - I_{i(t-1)} + B_{i(t-1)} &\leq B_t \end{aligned} \quad (7)$$

where

$$E[dc_{it}] = \sum_{j \in J} Nsc_{ijt} \left[\frac{(a_{jt} + l)^\beta - a_{jt}^\beta}{\eta^\beta} \right]$$

Therefore, given the stochastic nature of spare parts demand, the inventory average in each period is multiplied by the holding cost per unit according to Eq. (8). If the random demand surpasses the number of spare parts ordered for that period, the cost of shortages is included in the total cost. In this model, the total shortage cost is calculated by multiplying the shortage by the cost of shortage in each unit, as specified in Eq. (9).

$$\begin{aligned} &\sum_{i \in I} \sum_{t \in M} h_{it} bI_{it} \left(Q_{it} + I_{i(t-1)} - B_{i(t-1)} - \sum_{k \in K} dp_{ikt} - E[dc_{it}] \right) \\ &+ \sum_{i \in I} \sum_{t \in M} sh_{it} bB_{it} \left(\sum_{k \in K} dp_{ikt} - E[dc_{it}] - Q_{it} - I_{i(t-1)} + B_{i(t-1)} \right) \end{aligned} \quad (8)$$

where

$$E[dc_{it}] = \sum_{j \in J} Nsc_{ijt} \left[\frac{(a_{jt} + l)^\beta - a_{jt}^\beta}{\eta^\beta} \right] \quad (9)$$

Eq. (4) represents the expected inventory average as the difference between the ordered amount of spare parts and their demand. This equation indicates that if the ordered quantity of spare parts exceeds the random demand, the expression will have a positive value, and if the demand for spare parts exceeds the ordered quantity of spare parts, the expected inventory will be zero. Similarly, Eq. (5) shows the expected shortage average. Eq. (10) is always non-negative. It is evident that these two equations cannot simultaneously assign values to themselves. In other words, if there is inventory in any period, there will be no shortage, and vice versa. Therefore, Eq. (9) represents this fact as follows:

$$bB_{it} + bI_{it} = 0 \Rightarrow bB_{it} + bI_{it} \leq 1 \quad (10)$$

Ordering cost of spare parts

The ordering costs in this study comprise of two different scenarios, and the decision regarding the type of ordering strategy depends on the inventory level. If the inventory level of spare parts is lower than the reorder point but higher than the safety stock level at the inspection point, the ordering timing will follow the usual procedure. Nevertheless, if the inventory level of spare parts falls below the safety stock level, the ordering will be done in an emergency state, leading to a reduction in ordering timing and an increase in costs compared to the usual situation.

Therefore, emergency orders are a critical component of the

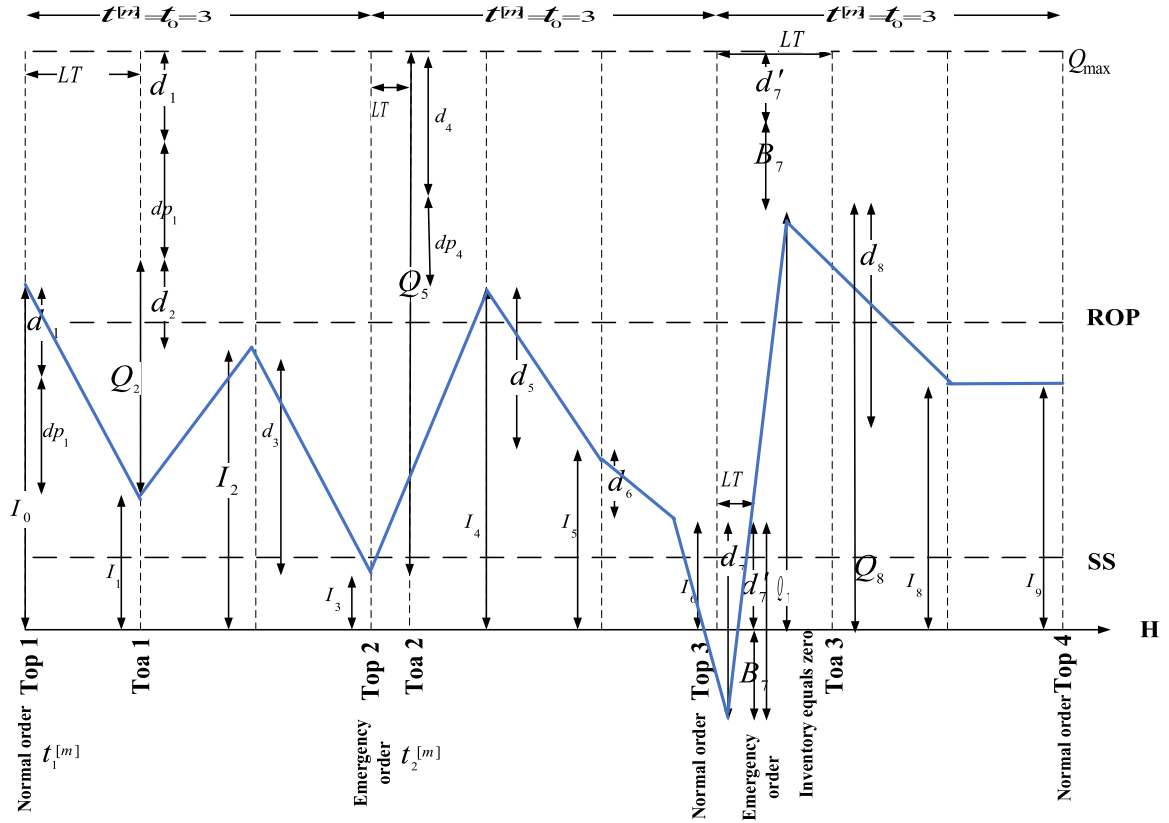


Fig. 2. The inventory control system of spare parts.

maintenance policy. When spare parts are unavailable in the inventory and fall below the safety stock level, the system initiates an emergency procurement process. This process reduces the lead time for spare parts delivery but increases the associated costs. The decision to place an emergency order is based on the urgency of the maintenance task and the criticality of the equipment. For example, CM tasks that require immediate attention are prioritized for emergency orders to minimize production downtime.

Fig. 2 clearly and comprehensively illustrates the process of ordering spare parts and its relationship with PM and CM operations. Thus, to calculate the ordering cost according to the type of ordering strategy, we can exploit Eq. (11) that:

$$CO_{it} = \begin{cases} 0 & \text{if } ROP_{it} < I_{it} \\ NO_{it} & \text{if } SS_{it} \leq I_{it} \leq ROP_{it} \\ EO_{it} & \text{if } I_{it} < SS_{it} \end{cases} \Rightarrow CO_{it}$$

$$= \begin{cases} 0 & \text{if } ROP_{it} + 1 \leq I_{it} \\ NO_{it} & \text{if } SS_{it} \leq I_{it} \leq ROP_{it} \\ EO_{it} & \text{if } I_{it} \leq SS_{it} - 1 \end{cases} \quad (11)$$

In order to calculate the ordering cost, it needs to be multiplied by the decision variable that is related to ordering or not ordering in each period. Consequently, the total cost for different periods can be calculated using Eq. (12), where the ordering cost is assumed to be a fixed cost in this study. Besides, the cost of purchasing spare parts is also dependent on the binary variable of ordering or not ordering. The cost of purchasing spare parts in each period is equal to the multiplication of the purchasing cost per unit of spare parts and the ordered quantity. If an order is placed in a specific period, this cost will be added to the model.

Otherwise, no cost will be included in the model for that period. The order quantity in each period is obtained through the difference between the inventory level and the maximum order quantity.

$$TO_{it} = \sum_{i \in I} \sum_{t \in M} VO_{it} \cdot CO_{it} + \sum_{i \in I} \sum_{t \in M} Cu_{it} Q_{it} VO_{it} \quad (12)$$

$$Q_{it} = Q_{it}^{[max]} - I_{i(t-1)} \quad (13)$$

Eq. (14) defines the constraint that is related to the demand for spare parts and its dependence on the binary variable of ordering or not ordering. This equation clarifies that if the binary variable VO_{it} equals zero, no order will be placed, and as a result, the value of Q_{it} will be zero. However, if VO_{it} equals one, the value of Q_{it} can vary from zero to its maximum value ($Q_{it}^{[max]}$), depending on the current inventory level.

$$Q_{it} \leq Q_{it}^{[max]} VO_{it} \quad (14)$$

Downtime cost

Machine downtime can occur due to several reasons, and this study focuses on three significant factors. First, it involves the unavailability of spare parts during maintenance operations. Second, it concerns the average time required to perform CM to restore the machine to production operations. Third, it pertains to the execution of PM operations at various levels, which necessitates temporary halts in the production line. Notably, the time required for these operations will decrease as employees gain experience from performing them more frequently.

To calculate the cost of machine downtime, we begin by determining the cost per unit of time for production line downtime and then multiply it by the duration of the machine downtime. The costs associated with machine downtime, specifically the second and third types, will be

discussed in later sections, as they depend on the time required for PM and CM operations. For now, our focus is solely on the cost of machine downtime caused by the unavailability of spare parts during machine repairs. In such cases, maintenance operations require spare parts to be available. However, when the inventory level for a specific spare part needing replacement is zero, the machine must be halted until the inventory is replenished and the required demand is met. Therefore, Eq. (15) defines the cost of machine downtime as the lost opportunity cost. This represents the cost of production line downtime caused by the shortage of required parts during CM and PM operations, respectively.

$$\begin{aligned} & \sum_{i \in I} \sum_{j \in J} \sum_{t \in M} (Cl_{jt} LT_i^{[E]} + EO_{it}) bB_{i(t-1)} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \\ & + \sum_{i \in I} \sum_{k' \in K} \sum_{j \in J} \sum_{t \in M} (Cl_{jt} LT_i^{[E]} + EO_{it}) bB_{i(t-1)} z_{k'jt} \end{aligned} \quad (15)$$

$K' < K$

k' represents the level of PM that requires spare parts. In this paper, since a lower level corresponds to a higher intensity of PM, a k' value less than k indicates a greater need for spare parts, whereas not all levels of PM require spare parts.

The CM cost

Since the machine breakdown is not predictable, it happens stochastically; as a result, the maintenance operation that occurs after the machine's breakdown is stochastic [52,53]. Taking into account the increase of machine age and during its lifetime, the components of the machine gradually deteriorate until eventually, failure occurs. In this research, the failure functions of various machines are represented using the Weibull distribution, with parameter values determined according to the degradation process and failure events. The Weibull distribution is used in research to estimate machine failures. This distribution has two parameters: shape and scale [54–57]. Eq. (16) illustrates the probability density function of the Weibull distribution. In this equation, β parameter is the shape parameter, and η is the scale parameter.

$$f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \exp \left[- \left(\frac{t}{\eta} \right)^\beta \right] \quad \beta > 1, \eta > 0, t > 0 \quad (16)$$

In Eqs. (16)–(19), the shape parameter (β) is defined as greater than one. In the Weibull distribution, a shape parameter greater than one indicates that the failure probability of the machine increases with its age. Conversely, a shape parameter equal to one implies a constant failure probability over time, while a value smaller than one signifies a decreasing failure probability over time. In this research, since the machine is deteriorating, the value of β is defined as greater than one. Eq. (17) shows the cumulative distribution function of the Weibull distribution as follows:

$$F(t) = 1 - \exp \left[- \left(\frac{t}{\eta} \right)^\beta \right] \quad \beta > 1, \eta > 0, t > 0 \quad (17)$$

Therefore, Eq. (18) shows the failure rate in the Weibull distribution that:

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{\frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \exp \left[- \left(\frac{t}{\eta} \right)^\beta \right]}{\exp \left[- \left(\frac{t}{\eta} \right)^\beta \right]} = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \quad (18)$$

As a result, the average number of failures in each period with length L is presented according to Eq. (19):

$$\int_{a_{jt}}^{a_{jt}+l} \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} dt = \left(\frac{1}{\eta} \right)^\beta \left[(a_{jt} + l)^\beta - (a_{jt})^\beta \right] \quad (19)$$

$$E(T) = MTTF = \eta \Gamma \left(1 + \frac{1}{\beta} \right) T \sim \text{Weibull}(\alpha, \beta)$$

In this research, it is assumed that CM is performed in a minimal form, meaning the virtual age of the machine remains unchanged after the CM operation, and the machine's condition stays "as bad as old." Consequently, no improvement in the machine's condition is considered. By adopting this proactive maintenance approach, referred to as minimal CM, the frequency of failures occurring in each time period can be effectively determined using the rate function $h(t)$, as defined in Eq. (18). The total cost of CM operations is then calculated by multiplying the number of machine failures by the associated costs. These costs per failure consist of both time-dependent and time-independent components.

Time-dependent costs include the opportunity cost, which represents the loss incurred from halting the production line, and labor costs, which vary depending on the hours required for equipment repair. Time-independent costs in CM activities include expenses such as procuring parts, purchasing spare components, and preparing equipment for resumed production. These costs are contingent on the frequency of CM operations. In this study, the duration of CM is assumed to be fixed, meaning it does not vary based on the number of CM instances or the system's failure time. Additionally, the study assumes a single level for CM operations. Eq. (20) outlines the total cost of the CM operation as follows:

$$\sum_{j \in J} \sum_{t \in M} ((Cl_{jt} + Hr_{jt} Nr_{jt}) MTTR_{jt} + Cset_{jt}) \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \quad (20)$$

$$MTTR_{jt} = \eta_{jt} \Gamma \left(1 + \frac{1}{\beta_{jt}} \right) \quad (21)$$

The PM cost

The system is inspected at regular intervals, which are determined based on equipment conditions such as machine age, production rate, and noise levels (monitored by sound sensors). These inspections are scheduled to proactively identify potential issues and plan maintenance

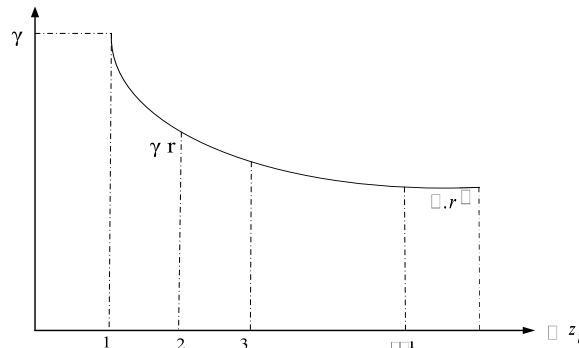


Fig. 3. The learning influence of PM operations.

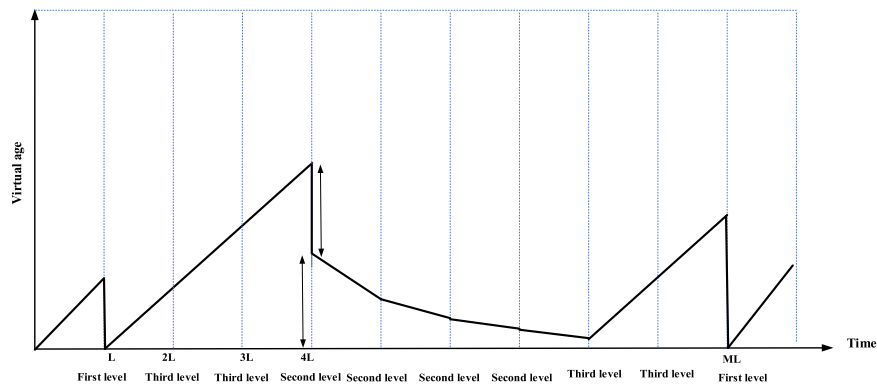


Fig. 4. The effect of various levels of PM operations and learning on the machine's age.

activities effectively. The frequency of inspections is optimized to balance the need for timely maintenance with cost constraints. For example, older machines or those operating under higher stress conditions may require more frequent inspections.

Similar to CM operations, PM operations also incur both time-independent and time-dependent costs. The duration of PM operations varies across different levels and depends on the frequency of PM executions and the surface type. This implies that, due to employees' experience and learning, the time required for PM operations fluctuates based on their frequency, with variations observed across different levels of PM operations. Eq. (22) serves as the time adjustment function for these operations. Here, γ represents the time needed for the initial PM operation, while r signifies the experience curve percentage. Fig. 3

depicts the learning curve, illustrating how operation time decreases with the repetition of the task. This curve visually demonstrates the efficiency gained through experience and practice in executing these operations..

$$t_{kjt}^{[m]} = \gamma_{kj} z_{kjt} \left(1 + \sum_{\substack{l \in M \\ l \leq M-1}} z_{kjl} \right)^{\frac{\ln r}{\ln 2}} \quad (22)$$

This study explores the effect of PM operations on minimizing the age of machines. Fig. 4 visually illustrates the impact of PM operations

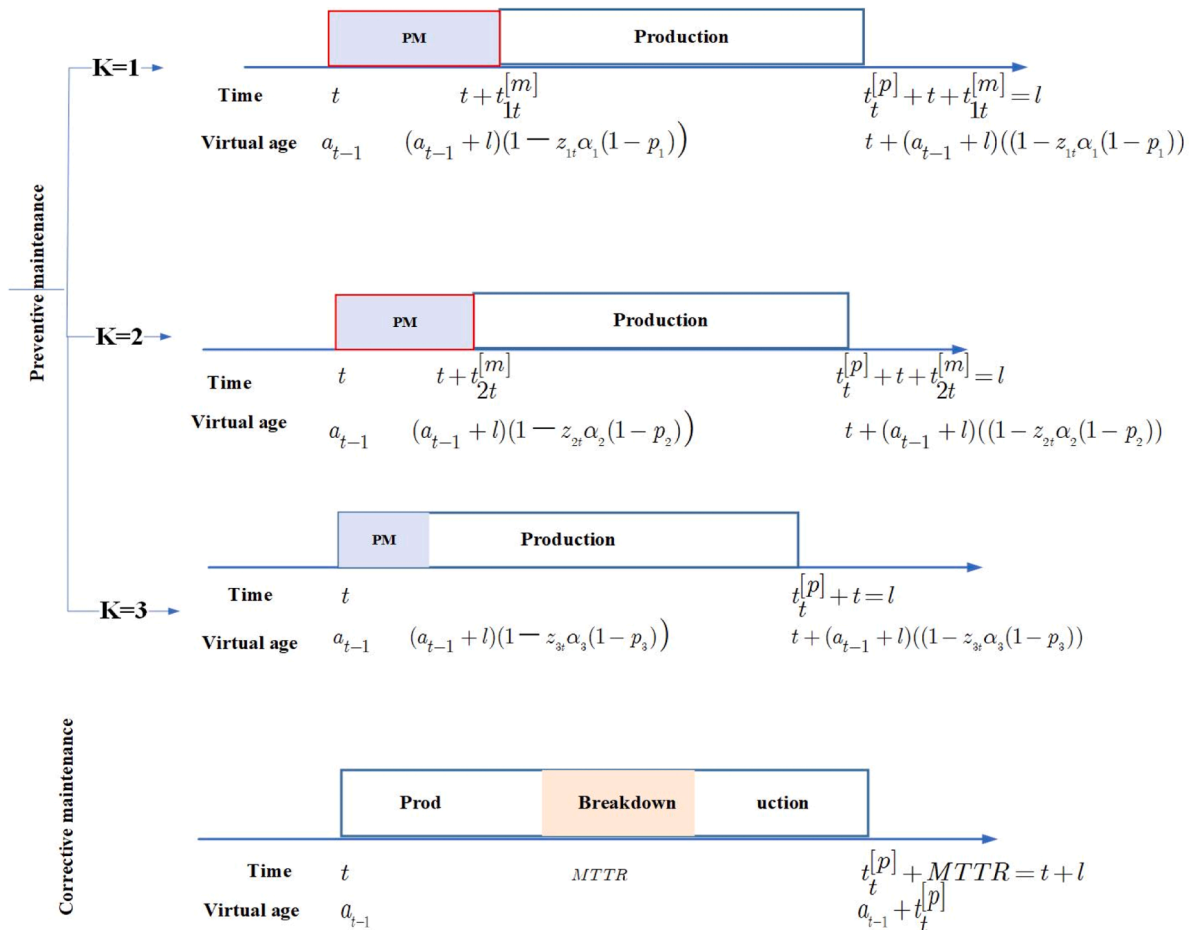


Fig. 5. Integrated approach of CM and PM for equipment performance enhancement.

on machine age. The coefficient α_k represents the effective rate, which specify the effectiveness of PM operations in reducing machine age. When each level of PM operation is executed, the effective lifespan of the machine decreases by a factor proportional to the α_k coefficient related to each level of PM operation. If PM operations are not performed at a specific level during a particular period, the coefficient $z_{kt}(\alpha_k)$ becomes zero, and there is no change in the machine's lifespan. In this scenario, the lifespan of the machine is calculated as the sum of the effective lifespan from the preceding period and the duration of the current period. Subsequently, the virtual age of the machine is computed using Eq. (23). Fig. 5 illustrates the disparity between actual time and virtual time resulting from the application of different levels of PM.

Overall, Fig. 4 illustrates the impact of a comprehensive maintenance strategy that integrates both CM and PM operations to maximize equipment performance, minimize downtime, and optimize operational efficiency. This study explores three distinct levels of PM operations: inspection and equipment servicing (third level), equipment servicing and repair (second level), and equipment servicing combined with parts replacement (first level). The effective rate's value varies across these levels in proportion to the impact of implementing PM operations on the machine's performance. Consequently, the effective rate (α_k) fluctuates accordingly. These levels cover the spectrum from "as good as new" to "as bad as old." For example, conducting PM operations at the third level results in a different outcome compared to the other levels. After implementing PM measures at this level, the equipment tends to degrade to an "as bad as old" state.

PM operations at the second level involve repairing worn-out parts and providing some degree of overall equipment servicing. However, this often results in incomplete maintenance, causing the machine's condition to fluctuate between "as bad as old" and "as good as new." In contrast, PM operations at the first level, which include servicing and replacing specific parts, fully restore the equipment to an "as good as new" condition. As a result, the equipment's lifespan is effectively reset, making it function like a new machine. Therefore, the effective rate (α_k) in this study varies depending on the level of PM operations conducted, ranging from zero to one.

Considering this study's focus on the impact of human errors on the effective rate and, consequently, on the virtual lifespan of the equipment, the execution of various levels of PM operations reduces the equipment's virtual lifespan (a_t). Therefore, the implementation of PM operations on the equipment proves effective, and its effectiveness on the virtual lifespan depends on the human error rate associated with these specific levels of maintenance activities (p_k). For instance, executing the first level (replacement and servicing of equipment) should ideally restore the equipment to a "good as new" state, resulting in a lifespan of zero. However, the effectiveness of this level's implementation is contingent upon human error, thereby diminishing its effect and preventing the equipment from attaining a "good as new" state.

In fact, human error hinders any significant improvement in the virtual lifespan of the equipment. This scenario only changes when the HEP is zero, and the effective rate remains constant, independent of the value of p . Therefore, while executing this level effectively extends the equipment's lifespan, its impact on the virtual lifespan relies on human error (p_k). Despite full execution at this level, the absence of human error ensures the operation's impact on the equipment's lifespan remains incomplete.

Therefore, considering the impact of human error, the implementation of different levels of PM operations can negatively affect the machine's age. While the different levels of PM operations influence the machine's age, the extent of their impact on the virtual age of the machine depends on the HEP ($\alpha_k(1 - p_k)$). As a result, these operations are carried out imperfectly, leading to only a partial impact on the machine's age. The presence of human error negatively affects the execution of various levels of maintenance operations, resulting in consistently imperfect impacts on the machine's age. Figs. 4 and 5 illustrate the effect of various levels of PM operations on the failure rate

and the virtual age of the equipment. The virtual age of the machine is calculated using Eq. (23).

$$a_{jt} = (a_{j(t-1)} + l) \left(1 - \sum_{k \in K} z_{kjt} \alpha_k (1 - p_k) \right) \quad (23)$$

The selection of PM operations to be performed in each period can be determined based on the machine's condition, which includes factors such as its lifetime, production rate, noise levels, and other machine-specific conditions. This study simultaneously focuses on time-based maintenance and condition-based maintenance. In this research, the symbols ξ and ξ' represent the upper and lower threshold values, respectively. These values enable the determination of suitable levels of PM operations based on the machine's age and other machine conditions, while also considering their associated costs and effects on other expenses. The symbol μ denotes the maximum number of levels, which is set to 3 in this study, while ψ represents the levels of PM operations. Eq. (24) represents the determination of the level of PM operation dependent on the machine's age.

$$\xi'_{1j} - \frac{\xi'_{1j} - \xi_{1j}}{\mu - 2} (\psi_{1jt} - 1) \leq a_{jt-1} + l \leq \xi'_{1j} - \frac{\xi'_{1j} - \xi_{1j}}{\mu - 2} (\psi_{1jt} - 2), \mu > 2 \quad (24)$$

Eq. (25) represents the method for determining the required level of PM based on a specific machine condition, namely noise. This condition is evaluated and monitored by a sound sensor installed on the equipment.

$$\xi'_{2j} - \frac{\xi'_{2j} - \xi_{2j}}{\mu - 2} (\psi_{2jt} - 1) \leq AC_{jt} \leq \xi'_{2j} - \frac{\xi'_{2j} - \xi_{2j}}{\mu - 2} (\psi_{2jt} - 2), \mu > 2 \quad (25)$$

If the level of PM operations depends on multiple machine conditions, it is essential to implement the level of PM that yields the most significant improvement in machine condition. For instance, if the level of PM is established based on the machine's age, and the level of PM operation is set to 2 in a specific period ($\psi_{1t} = 2$), and if the level of PM is determined on the basis of the machine's noise, and levels of PM operations is set to 1 in that same period ($\psi_{2t} = 1$), the first level of PM ($\psi = 1$) should be selected. This level creates a greater improvement in the machine conditions compared to the second level. Therefore, to create such conditions, Eq. (26) needs to be considered as a constraint.

$$\psi_{jt}^{[total]} = \min\{\psi_{1jt}, \psi_{2jt}, \dots, \psi_{cjt}\} \Rightarrow \psi_{cjt} \geq \psi_{jt}^{[total]} \quad (26)$$

So, the general form is defined as Eq. (27).

$$\xi'_{cj} - \frac{\xi'_{cj} - \xi_{cj}}{\mu - 2} (\psi_{cjt} - 1) \leq \vartheta_{cjt} \leq \xi'_{cj} - \frac{\xi'_{cj} - \xi_{cj}}{\mu - 2} (\psi_{cjt} - 2), \mu > 2 \quad (27)$$

Thus, Eq. (27) defines the general form, where ϑ_{cjt} denotes the critical parameter value of the machine based on condition c in period t . In order to establish a connection between Eqs. (23) and (27) and ensure logical PM levels, Eqs. (28) and (29) must also be taken into account. Eq. (28) indicates that only one level of PM operation is permitted at each inspection point. In other words, based on the machine conditions and costs, only one level of PM operation can be selected at each inspection point, which satisfies the logic of this problem. Eq. (29) establishes the relationship between Eqs. (26)–(28). Furthermore, Eq. (27) determines the appropriate level of PM operation based on the machine conditions. ψ_{cjt} represents the level of PM operation, and based on Eq. (28), it is possible to define the relationship between $\psi_{jt}^{[Total]}$ and k_{jt} as Eq. (29).

$$\sum_{k \in K} z_{kjt} = 1 \quad (28)$$

$$\psi_{jt}^{[total]} = \sum_{k \in K} k_{jt} z_{kjt} \quad (29)$$

The total costs associated with PM operations are addressed in Eq.

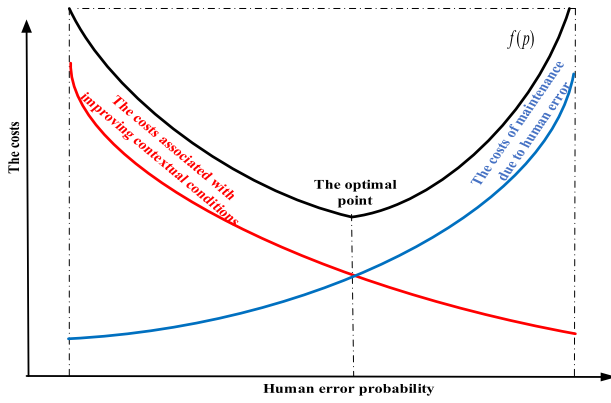


Fig. 6. The relationship between the HEP and the associated costs.

(30). The decision variable (z_{kt}), which is binary, represents the execution or non-execution of each level of PM operations on certain machines in each period. The time function for executing each level of PM operations is based on Eq. (31).

$$\sum_{k \in K} \sum_{j \in J} \sum_{t \in M} ((Cl_{jt} + Hm_{kjt} Nm_{kjt}) t_{kjt}^{[m]} + Cset_{jt}) z_{kjt} \quad (30)$$

$$t_{kjt}^{[m]} = \gamma_{kj} z_{kjt} \left(1 + \sum_{l \in M} z_{kjl} \right)^{\frac{\ln r}{\ln 2}} \quad (31)$$

The human error cost

Due to human involvement in inspection, PM, and CM operations, these processes are inherently susceptible to human error. Such errors can result in costly consequences, including incorrect maintenance procedures, misdiagnoses, unnecessary PM expenditures, and increased CM costs due to undetected failures. Therefore, minimizing human error is crucial to ensuring maintenance operations align with predefined targets and support cost-effective decision-making.

On one hand, if the HEP in CM, PM, and inspection activities exceeds acceptable levels—leading to excessive costs—organizations will seek to reduce these errors. This effort often involves investing in improved contextual conditions to lower the likelihood of human mistakes, such as enhanced training, clearer procedures, and better-designed human-machine interfaces (HMIs). HEP is influenced by various factors, including cognitive overload, fatigue, time constraints, ambiguous procedures, and suboptimal HMIs. Additionally, environmental, organizational, and task-specific elements can either exacerbate or mitigate human error risks. Real-world examples from different maintenance domains illustrate these challenges:

- **Aircraft Maintenance:** Time pressure and fatigue may lead to rushed inspections, increasing the risk of undetected failures.
- **Industrial Equipment Maintenance:** Poorly designed HMIs can cause misinterpretations, leading to incorrect troubleshooting and potential system malfunctions.
- **Nuclear Plant Maintenance:** Well-structured training programs and clear operational procedures enhance decision-making and situational awareness, significantly reducing human errors.

On the other hand, while reducing HEP improves system reliability and safety, it requires continuous investment in training, improved procedures, and better workplace conditions. Organizations must determine the optimal HEP level—a balance where error-related costs are minimized without incurring excessive expenses in error reduction efforts. Attempting to lower HEP beyond a certain threshold can lead to

Table 3
Evaluating different known functions.

| Distribution type | Maintenance cost function | |
|-------------------|---------------------------|-------|
| | Total | |
| | R-square | MSE |
| Exponential | 0.9988 | 1.365 |
| Gaussian | 0.9992 | 1.08 |
| Power | 0.9978 | 1.799 |
| Fourier | 0.9842 | 4.847 |
| Quadratic | 0.9953 | 2.636 |
| Cubic | 0.9943 | 2.919 |

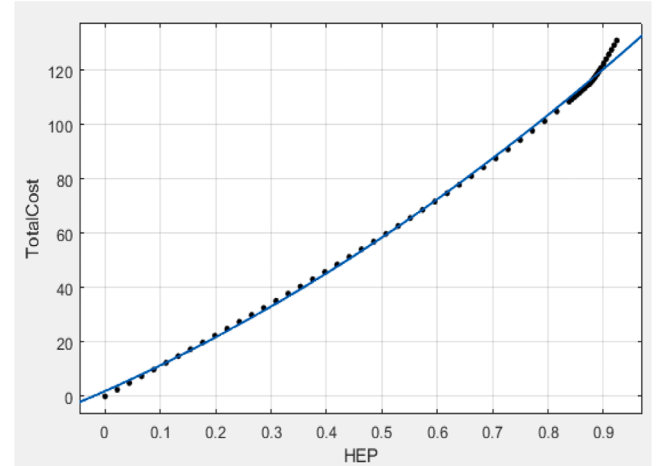


Fig. 7. The relationship between HEP and its cost (cubic function).

Table 4
The coefficients and intercept values for the fitted cubic function.

| Function | Coefficient value | | | |
|---------------|-------------------|---------|---------|-----------|
| | P_k^3 | P_k^2 | P_k^1 | intercept |
| Cost function | −1.022 | 128.9 | −55.41 | 69.83 |

diminishing returns, where additional investments in safety measures or training no longer justify the cost. Therefore, strategic error management is essential to identifying a cost-effective level of error probability.

Fig. 6 illustrates the relationship between HEP and its associated costs, emphasizing the need for an optimized approach to error management. The figure highlights how initial investments in error prevention significantly reduce overall costs, but beyond a certain point, further reductions in HEP become economically impractical. By carefully assessing the trade-offs between HEP reduction and cost feasibility, organizations can develop data-driven strategies to enhance maintenance efficiency without overextending resources.

To achieve this goal, maintenance costs associated with various types of human errors over a 12-month period were collected using historical data and expert opinions. Additionally, this study establishes a relationship between the effective rate of the equipment's virtual age and HEP. Consequently, the effective rate is influenced by human error. As a result, functions related to the costs associated with HEP and the coefficient of reduction in virtual age, both of which depend on HEP, were estimated using regression analysis. As shown in Table 3, among the known functions, the cubic function provides the most accurate estimation. This conclusion is based on the Root Mean Square Error (RMSE) values, which serve as a metric for evaluating the alignment of estimated values with actual values. Fig. 7 illustrates the relationship between HEP and its associated maintenance costs using the cubic function. Table 3 evaluates various known functions (e.g., quadratic, exponential,

Fourier) for estimating the maintenance cost function.

Table 4 provides the coefficients and intercept values for the cubic function.

Therefore, the function of the human error cost is estimated in Eqs. (32) as follows:

$$f(p) = (\pm \varphi_3 p^3 \pm \varphi_2 p^2 \pm \varphi_1 p \pm \varphi_0) \\ = -1.022p^3 + 128.9p^2 - 55.41p + 69.83 \quad (32)$$

Therefore, the objective function is presented in Eq. (33) as follows:

$$\begin{aligned} & \min \sum_{i \in I} \sum_{t \in M} h_{it} b_{it} \left(Q_{it} + I_{i(t-1)} - B_{i(t-1)} - \sum_{k \in K} dp_{ikt} - E[dc_{it}] \right) \\ & + \sum_{i \in I} \sum_{t \in M} Sh_{it} b_{it} \left(\sum_{k \in K} dp_{ikt} - E[dc_{it}] - Q_{it} - I_{i(t-1)} + B_{i(t-1)} \right) \\ & + \sum_{i \in I} \sum_{t \in M} VO_{it} CO_{it} + \sum_{i \in I} \sum_{t \in M} Cu_{it} Q_{it} VO_{it} + \sum_{i \in I} \sum_{j \in J} \sum_{t \in M} (Cl_{jt} LT_i^{[Etotal]} + EO_{it}) b_{B_{i(t-1)}} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \\ & + \sum_{i \in I} \sum_{k' < k} \sum_{j \in J} \sum_{t \in M} (Cl_{jt} LT_i^{[E]} + EO_{it}) b_{B_{i(t-1)}} z_{k'jt} + f(p) \\ & + \sum_{k \in K} \sum_{j \in J} \sum_{t \in M} ((Cl_{jt} + Hm_{kjt} Nm_{kjt}) t_{kjt}^{[m]} + Cset_{jt}) z_{kjt} \\ & + \sum_{j \in J} \sum_{t \in M} ((Cl_{jt} + Hr_{jt} Nr_{jt}) MTTR_{jt} + Cset_{jt}) \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \end{aligned} \quad (33)$$

3.4.2. Constraints

The initial constraint represents one of the capacity constraints within the model. Specifically, the inventory level for spare parts must not exceed the warehouse's storage capacity. Given that demand is random—due to the unpredictable rate of machine failures—the first constraint is expressed by the following equations, denoted as Eqs. (34) and (35):

$$E(Q_{it} + I_{i(t-1)} - B_{i(t-1)} - dc_{it} - dp_{ikt})^+ \leq War_{it} \quad (34)$$

$$Q_{it} + I_{i(t-1)} - B_{i(t-1)} - dp_{ikt} - E(dc_{it}) \leq War_{it} \quad (35)$$

where

$$E[dc_{it}] = \sum_{j \in J} Nsc_{ijt} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \quad (36)$$

Eq. (37) demonstrates that the sum of the inventory level from the previous period and the current period's order rate for spare parts must exceed the estimated demand level. This is implemented to minimize potential shortages within the organization. Shortages of spare parts lead to not only direct financial losses, such as increased machine downtime and opportunity costs, but also significant hidden costs for the company. These hidden costs include reduced company credibility, decreased customer satisfaction due to production downtime, disruptions in the production line, and more. Therefore, it is crucial to minimize the shortage level as much as possible to avoid these adverse consequences. The equation is expressed as:

$$Q_{it} + I_{i(t-1)} - B_{i(t-1)} \geq dp_{ikt} + E(dc_{it}), \forall t \quad (37)$$

Eq. (38) specifies the duration of production for each period tt . This is

calculated by subtracting the time intervals corresponding to production line stoppages—caused by system breakdowns, PM, and CM operations—from the total duration of each period l . The equation is expressed as:

$$t_{jt}^{[p]} = l - \sum_{k \in K} z_{kjt} t_{kjt}^{[m]} - MTTR_{jt} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \\ - LT_t^{[Etotal]} b_{B_{it}} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \quad (38)$$

where

$$\max \{ LT_t^{[E]} b_{B_{it}} \} = LT_t^{[Etotal]} \Rightarrow LT_t^{[E]} b_{B_{it}} \leq LT_t^{[Etotal]} \quad (39)$$

Eq. (40) stipulates that within each period, only a single level of PM operation can be performed on the machine. This is expressed mathematically as:

$$\sum_{k \in K} z_{kjt} = 1 \quad (40)$$

Eq. (41) specifies that if a particular level of PM operation is not conducted during the designated period, the required spare parts and components for that level of PM operation will be equal to zero. This condition is represented as:

$$-Q_{it}^{[max]} \sum_{j \in J} z_{kjt} \leq \sum_{k \in K} dp_{ikt} \leq -Q_{it}^{[max]} \sum_{j \in J} z_{kjt} \quad (41)$$

Eq. (42) describes the requisite condition for machine availability, stating that it must consistently exceed the minimum accessibility threshold required for servicing during each period. This is formulated as:

$$\sum_{t \in M} t_{jt}^{[p]} \geq AE_j \quad (42)$$

Eq. (43) emphasizes the critical requirement that the total organizational costs remain within the available budget. This is expressed as:

$$Total\ cost \leq TB \quad (43)$$

Eq. (44) defines the specific range of certain model variables. Based on their nature, these variables are constrained to a particular range of values. This is represented as:

Table 5
The values obtained from solving the model (the variables of PM operations).

| Period | $t_{kt}^{[m]}$ | | | z_{kt} | | | dp_{ikt} | | | | | | | | | | | |
|--------|----------------|-------|---|-------------|---|---|-------------|---|---|-------------|---|---|-------------|---|---|-------------|---|---|
| | Level of PM | | | Level of PM | | | Spare parts | | | | | | | | | | | |
| | | | | | | | 1 | | | 2 | | | 3 | | | 4 | | |
| | | | | | | | Level of PM | | | Level of PM | | | Level of PM | | | Level of PM | | |
| | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 | 3 | 2 | 1 |
| 1 | | 0.083 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 2 | 0.025 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 3 | 0.02 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 4 | | 0.066 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 5 | 0.018 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 6 | 0.016 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 7 | | 0.058 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 8 | 0.015 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 9 | 0.014 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 10 | | 0.053 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 11 | 0.013 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 12 | 0.013 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 13 | 0.012 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 14 | | 0.049 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 15 | 0.012 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 16 | 0.012 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 17 | 0.011 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 18 | | 0.047 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 19 | | 0.044 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 20 | | 0.042 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 21 | 0.011 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 22 | | 0.041 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 23 | | 0.04 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 24 | | 0.038 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 25 | | 0.037 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 26 | | 0.036 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 27 | | 0.035 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 28 | | 0.035 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 29 | | 0.034 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 30 | | 0.033 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 31 | 0.011 | | | 1 | 0 | 0 | 1 | | | 1 | | | | | | 1 | | |
| 32 | | 0.033 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 33 | | 0.032 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 34 | | 0.032 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 35 | | 0.031 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |
| 36 | | 0.031 | | 0 | 1 | 0 | | 1 | | | 1 | | | 1 | | | 2 | |

$$\begin{aligned} z_{kt}, VO_{it}, bI_{it}, bB_{it}, y_{it}^{[1]}, y_{it}^{[2]}, y_{it}^{[3]} &\in \{0, 1\} \\ 0.00005 \leq p_k, p^{CM}, p^{ins}, p^{[total]} &\leq p^{current} \\ \psi_t^{[total]}, \psi_{ct} &\in Int \end{aligned} \quad (44)$$

As a result, the research model is formulated as follows:

$$\begin{aligned} &\min \sum_{i \in I} \sum_{t \in M} h_{it} bI_{it} \left(Q_{it} + I_{i(t-1)} - B_{i(t-1)} - \sum_{k \in K} dp_{ikt} - E[dc_{it}] \right) \\ &+ \sum_{i \in I} \sum_{t \in M} Sh_{it} bB_{it} \left(\sum_{k \in K} dp_{ikt} - E[dc_{it}] - Q_{it} - I_{i(t-1)} + B_{i(t-1)} \right) \\ &+ \sum_{i \in I} \sum_{t \in M} VO_{it} \cdot CO_{it} + \sum_{i \in I} \sum_{t \in M} Cu_{it} Q_{it} VO_{it} + \sum_{i \in I} \sum_{j \in J} \sum_{t \in M} (Cl_{jt} LT_i^{[Etotal]} + EO_{it}) bB_{i(t-1)} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \\ &+ \sum_{i \in I} \sum_{k' < k} \sum_{j \in J} \sum_{t \in M} (Cl_{jt} LT_i^{[E]} + EO_{it}) bB_{i(t-1)} z_{k'jt} + f(p) \\ &+ \sum_{k \in K} \sum_{j \in J} \sum_{t \in M} ((CL_{jt} + Hm_{kjt} Nm_{kjt}) t_{kjt}^{[m]} + Cset_{jt}) z_{kjt} \\ &+ \sum_{j \in J} \sum_{t \in M} ((Cl_{jt} + Hr_{jt} Nr_{jt}) MTTR_{jt} + Cset_{jt}) \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \end{aligned} \quad (45)$$

subject to

$$Q_{it} + I_{i(t-1)} - B_{i(t-1)} - \sum_{k \in K} dp_{ikt} - E[dc_{it}] \leq I_{it} \quad \forall i, t \quad (46)$$

$$\sum_{k \in K} dp_{ikt} + E[dc_{it}] - Q_{it} - I_{i(t-1)} + B_{i(t-1)} \leq B_{it} \quad \forall i, t \quad (47)$$

$$bI_{it} + bB_{it} \leq 1 \quad \forall i, t \quad (48)$$

$$Q_{it} \leq Q_{it}^{[max]} VO_{it} \quad \forall i, t \quad (49)$$

$$Q_{it} = (Q_{it}^{[max]} - I_{i(t-1)}) VO_{it} \quad \forall i, t \quad (50)$$

$$t_{kjt}^{[m]} = \gamma_{kj} z_{kjt} \left(1 + \sum_{l \in M} z_{kjl} \right) \frac{\ln r}{\ln 2} \quad \forall k, j, t \quad (51)$$

$$a_{jt} = (a_{j(t-1)} + l) \left(1 - \sum_{k \in K} z_{kjt} \alpha_k (1 - p_k) \right) \quad \forall j, t \quad (52)$$

$$\xi'_{cj} - \frac{\xi'_{cj} - \xi_{cj}}{\mu - 2} (\psi_{cjt} - 1) \leq \vartheta_{cjt} \leq \xi'_{cj} - \frac{\xi'_{cj} - \xi_{cj}}{\mu - 2} (\psi_{cjt} - 2), \mu > 2 \quad \forall c, j, t \quad (53)$$

$$\sum_{k \in K} z_{kjt} = 1 \quad \forall j, t \quad (54)$$

$$\psi_{jt}^{[total]} = \sum_{k \in K} k_k z_{kjt} \quad \forall j, t \quad (55)$$

$$\psi_{jt}^{[total]} \leq \psi_{cjt} \quad \forall c, j, t \quad (56)$$

$$Q_{it} + I_{i(t-1)} - B_{i(t-1)} - dp_{ikt} - E[dc_{it}] \leq War_{it} \quad \forall i, t \quad (57)$$

$$Q_{it} + I_{i(t-1)} - B_{i(t-1)} \leq dp_{ikt} + E[dc_{it}] \quad \forall i, t \quad (58)$$

$$\begin{aligned} t_{jt}^{[p]} &= l - \sum_{k \in K} z_{kjt} t_{kjt}^{[m]} - MTTR_{jt} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \\ &- LT_t^{[Etotal]} bB_{i(t-1)} \left[\frac{((a_{jt} + l)^\beta - a_{jt}^\beta)}{\eta^\beta} \right] \quad \forall j, t \end{aligned} \quad (59)$$

$$LT_i^{[E]} bB_{it} \leq LT_t^{[Etotal]} \quad \forall i, t \quad (60)$$

$$\sum_{k \in K} dp_{ikt} = \sum_{k \in K} Nsp_{ikt} z_{kt} \quad \forall i, t \quad (61)$$

$$-Q_{it}^{[max]} \sum_{j \in J} z_{kjt} \leq \sum_{k \in K} dp_{ikt} \leq -Q_{it}^{[max]} \sum_{j \in J} z_{kjt} \quad \forall k, j, t \quad (62)$$

$$\sum_{t \in M} t_{jt}^{[p]} \geq AE_j \quad \forall j \quad (63)$$

$$VO_{it} \geq 1 - y_{it}^{[3]} \quad \forall i, t \quad (64)$$

$$(ROP_{it} + 1) - My_{it}^{[1]} \leq I_{it} \leq Q_i^{[max]} \quad \forall i, t \quad (65)$$

$$SS_{it} - My_{it}^{[2]} \leq I_{it} \leq ROP_{it} + My_{it}^{[2]} \quad \forall i, t \quad (66)$$

$$I_{it} \leq (SS_{it} - 1) + My_{it}^{[3]} \quad \forall i, t \quad (67)$$

$$y_{it}^{[1]} + y_{it}^{[2]} + y_{it}^{[3]} = 2 \quad \forall i, t \quad (68)$$

$$EO_{it} (1 - y_{it}^{[3]}) + NO_{it} (1 - y_{it}^{[2]}) = CO_{it} \quad \forall i, t \quad (69)$$

$$-Q_i^{[max]} (bB_{it}) \leq I_{it} \leq (1 - bB_{it}) Q_i^{[max]} \quad \forall i, t \quad (70)$$

$$-Q_i^{[max]} (bI_{it}) \leq B_{it} \leq (1 - bI_{it}) Q_i^{[max]} \quad \forall i, t \quad (71)$$

$$p^{[total]} = 1 - \left(\prod_{k \in K} (1 - p_k) \right) (1 - p^{corrective}) (1 - p^{ins}) \quad (72)$$

$$Total\ cost \leq TB \quad (73)$$

$$z_{kjt}, VO_{it}, bI_{it}, bB_{it}, y_{it}^{[1]}, y_{it}^{[2]}, y_{it}^{[3]} \in \{0, 1\} \quad (74)$$

$$0.00005 \leq p_k, p^{corrective}, p^{ins}, p^{[total]} \leq p^{current} \quad (75)$$

$$\psi_{jt}^{[total]}, \psi_{cjt} \in Int \quad (76)$$

$$Q_{it}, I_{it}, B_{it}, dp_{ikt}, dc_{it}, a_t, CO_{it}, t_{jt}^{[p]}, t_{kjt}^{[m]} \geq 0 \quad (77)$$

4. Findings

The model is formulated as a mixed-integer nonlinear programming (MINLP) problem and solved using GAMS software. The computations are carried out on a system equipped with an AMD Ryzen 32200U processor running at 2.5 GHz, 8 GB of RAM, and a 64-bit operating system. The results obtained from solving the model, which utilizes data from a case study involving multiple machines, spare parts, conditions, and three different levels of PM operations across various periods, are presented in Table 5. In this model, the PM approach is designed such that different levels of maintenance operations, each with varying effectiveness rates, influence the equipment's lifespan. Based on the overall results, the most effective level of PM operations is selected. Since one of the primary objectives of PM is to prevent system failures and unexpected production line shutdowns, the model incorporates costs related to production line disruptions that may occur due to the implementation of specific levels of PM and CM operations, as well as shortages of certain spare parts.

The results obtained from solving the model indicate the optimal levels of PM operations for different periods, taking into account both costs and the effective rate of the equipment. Implementing PM operations at the lowest level (Level 3) requires less cost, time, and resources, such as manpower and spare parts, compared to higher levels of PM operations. Conversely, executing PM operations at the highest level (Level 1) demands the most time, cost, and resources. Based on data from the case study company, performing Level 1 PM operations to restore equipment to an "as good as new" condition involves significant expenses. Therefore, as observed in the model results, Level 2 or Level 3 PM operations have been selected for various periods. As the number of periods increases, it becomes evident that maintenance operations begin to follow a specific and predictable cycle. This cyclic pattern allows for more efficient planning and allocation of resources, ultimately enhancing the overall maintenance strategy. The results of solving the

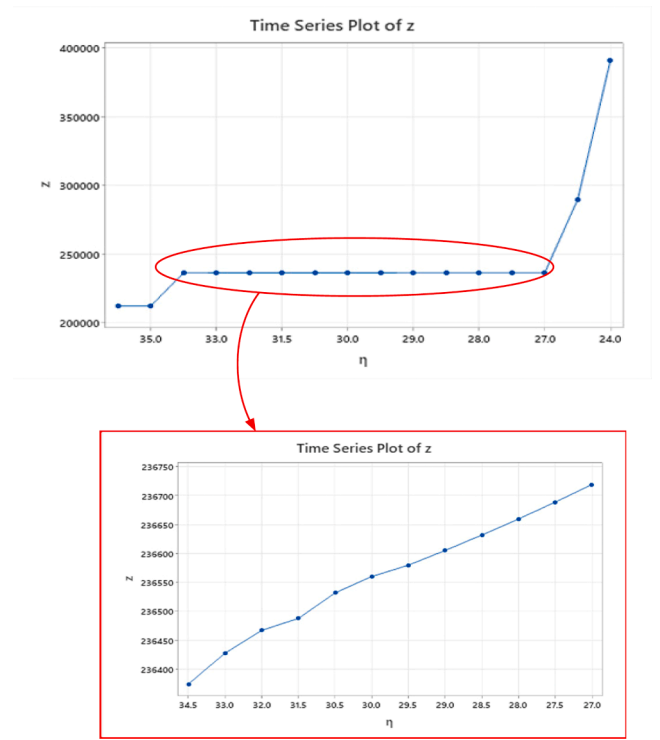


Fig. 8. The impact of changes in η parameters on the objective function.

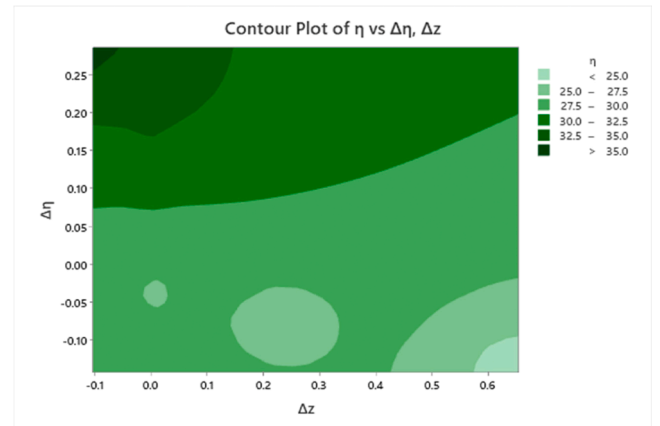


Fig. 9. The ratio of changes in total maintenance costs to changes in the scale parameter (η).

Table 6
The results of sensitivity analysis (η).

| No. | Δz_{cost} | η | $\Delta \eta$ |
|-----|-------------------|--------|---------------|
| 1 | -0.10285 | 36 | 0.285714 |
| 2 | -0.10296 | 35 | 0.25 |
| 3 | -0.001206 | 34 | 0.232143 |
| 4 | -0.000980 | 33 | 0.178571 |
| 5 | -0.000815 | 32 | 0.142857 |
| 6 | -0.000727 | 31.5 | 0.125 |
| 7 | -0.000540 | 30.5 | 0.089286 |
| 8 | -0.000421 | 30 | 0.071429 |
| 9 | -0.000338 | 29.5 | 0.053571 |
| 10 | -0.000230 | 29 | 0.035714 |
| 11 | -0.000118 | 28.5 | 0.017857 |
| 12 | 0 | 28 | 0 |
| 13 | 0.000123 | 27.5 | -0.01786 |
| 14 | 0.000252 | 27 | -0.03571 |
| 15 | 0.224561 | 26 | -0.07143 |
| 16 | 0.653825 | 24 | -0.14286 |

problem for the variables of PM operations are presented in Table 5.

Furthermore, the types of spare parts required for each level of PM operations are detailed in Table 5. As evident from the results, no spare parts are needed for unselected levels of PM operations. For the selected levels in each period, the appropriate spare parts are determined based on the chosen level of maintenance. The time required for executing PM operations is influenced by the learning curve effect, leading to a reduction in time for each subsequent execution of the same PM level. Consequently, as illustrated in Table 5, the duration for performing Level 2 and Level 3 PM operations decreases over time. Specifically, the time for Level 2 PM operations decreases from 0.083 h to 0.031 h, while the time for Level 3 PM operations decreases from 0.025 h to 0.011 h. This reduction reflects the efficiency gained through experience, improved techniques, and the cumulative impact of the learning curve. These findings highlight the importance of considering learning effects in maintenance planning to optimize resource utilization and enhance

Table 7

The changes in total maintenance operation costs for various effective rates of equipment.

| Effective rate | α_k | $\Delta\alpha_k$ | Δz_{cost} |
|----------------|-----------------|------------------|-------------------|
| $K = 1$ | (0.825, 0.5, 0) | -0.175 | 0.0721044 |
| | (0.85, 0.5, 0) | -0.150 | 0.0613767 |
| | (0.875, 0.5, 0) | -0.125 | 0.057943 |
| | (0.9, 0.5, 0) | -0.100 | 0.0403553 |
| | (0.925, 0.5, 0) | -0.075 | 0.0300581 |
| | (0.95, 0.5, 0) | -0.050 | 0.01999009 |
| | (0.975, 0.5, 0) | -0.025 | 0.009882 |
| $K = 2$ | (1, 0.5, 0) | 0 | 0 |
| | (1, 0.25, 0) | -0.500 | 0.033876 |
| | (1, 0.3, 0) | -0.400 | 0.027060 |
| | (1, 0.35, 0) | -0.300 | 0.020264 |
| | (1, 0.4, 0) | -0.200 | 0.013488 |
| | (1, 0.45, 0) | -0.100 | 0.006734 |
| | (1, 0.5, 0) | 0 | 0 |
| | (1, 0.55, 0) | 0.100 | -0.006713 |
| | (1, 0.6, 0) | 0.200 | -0.111557 |
| | (1, 0.65, 0) | 0.300 | -0.115236 |
| | (1, 0.7, 0) | 0.400 | -0.118907 |
| | (1, 0.75, 0) | 0.500 | -0.122570 |
| $K = 3$ | (1, 0.5, 0) | 0 | 0 |
| | (1, 0.5, 0.05) | 0.050 | -0.00427 |
| | (1, 0.5, 0.1) | 0.100 | -0.00852 |
| | (1, 0.5, 0.15) | 0.150 | -0.012777 |
| | (1, 0.5, 0.2) | 0.200 | -0.01701 |
| | (1, 0.5, 0.25) | 0.250 | -0.02125 |
| | (1, 0.5, 0.3) | 0.300 | -0.02547 |
| | (1, 0.5, 0.35) | 0.350 | -0.02969 |
| | (1, 0.5, 0.4) | 0.400 | -0.03389 |
| | (1, 0.5, 0.45) | 0.450 | -0.03809 |
| | (1, 0.5, 0.5) | 0.500 | -0.04228 |
| | (1, 0.5, 0.55) | 0.550 | -0.04647 |

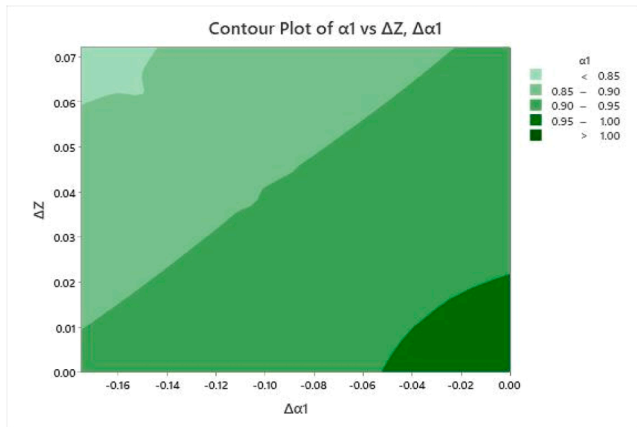


Fig. 10. The changes in costs relative to the effective equipment rate for Level 1 PM.

operational efficiency.

The results obtained from solving the first model for binary variables related to spare parts indicate that inventory is consistently available across all examined periods, with no shortages recorded. This outcome is logical, as the cost of maintaining spare parts is typically lower than the cost associated with shortages, which is notably higher in the context of the cement factory case study.

Although PM operations are pre-scheduled, and auxiliary lines and side motors are utilized to prevent production stoppages and kiln shutdowns, significant costs can still arise if spare parts are not available in the required quantities and the lead time for procurement exceeds the availability of these auxiliary resources. Furthermore, the total cost of maintenance operations over the 36-month period amounts to 3501,281,000 units of currency. Additionally, the optimal HEP for

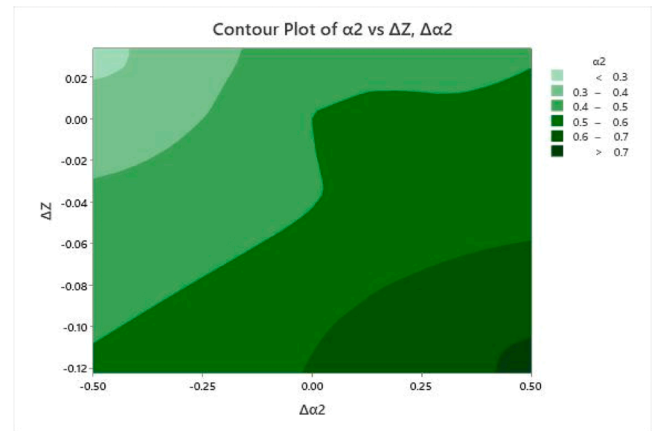


Fig. 11. The changes in costs relative to the effective equipment rate for Level 2 PM.

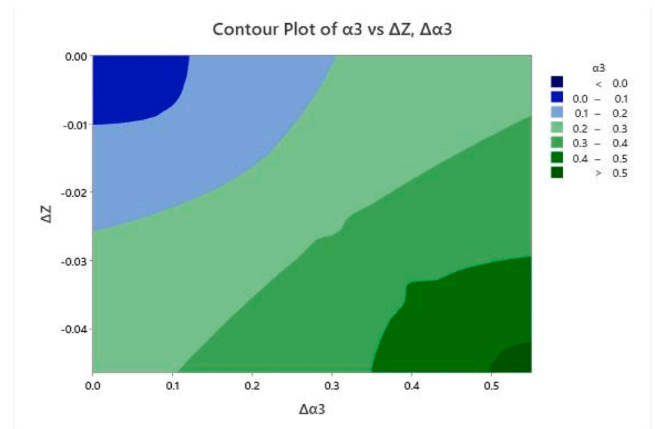


Fig. 12. The changes in costs relative to the effective equipment rate for Level 3 PM.

minimizing human error-related costs is determined to be 0.02. These findings underscore the importance of maintaining adequate spare parts inventory and optimizing maintenance strategies to mitigate costs and ensure operational efficiency.

5. Sensitive analysis

Sensitivity analysis is a widely used technique to evaluate the impact of variations in one or more input parameters on one or more desired outputs. It plays a crucial role in enhancing the understanding of a model's behavior and results, providing insights into its precision and effectiveness. In this section, a sensitivity analysis method is employed to assess the robustness of the designed model. This is accomplished by systematically varying key parameters to create a range of scenarios, including both reductions and increases in their values. Specifically, a comprehensive sensitivity analysis was conducted on two critical model parameters:

1. **The parameter η of the Weibull distribution:** The scale parameter (η) is often referred to as the characteristic life or lifetime characteristic of the equipment.
2. **The effective rate of equipment**

By analyzing these parameters under different scenarios, the sensitivity analysis provides valuable insights into how changes in these inputs affect the model's outputs, such as maintenance costs, optimal PM

levels, and inventory management strategies. This process helps validate the model's reliability and adaptability to varying operational conditions.

5.1. Sensitivity analysis with respect to the scale parameter (η)

The scale parameter η , often referred to as the lifetime characteristic, is directly associated with the mean time to failure (MTTF), which is calculated as $MTTF = \eta \Gamma(1 + 1/\beta)$. An increase in the scale parameter η leads to a longer MTTF, meaning the equipment can remain operational for a more extended period, thereby delaying the occurrence of failures. As a result, both CM and PM costs decrease with a higher η , as the need for maintenance interventions is reduced. Table 6 provides detailed information on the variations of the scale parameter η and its impact on maintenance costs. Additionally, Fig. 8 illustrates these variations and their influence on maintenance costs, offering a visual representation of how changes in η affect the overall maintenance strategy. This analysis highlights the importance of the scale parameter in determining equipment reliability and maintenance planning, demonstrating that higher values of η contribute to reduced maintenance frequency and costs.

Fig. 9 illustrates not only the inverse relationship between the scale parameter η and total maintenance costs but also emphasizes a more significant reduction in costs as the values of η increase. The figure clearly depicts cost variations within the range $27.5 < \eta < 32.5$, encompassing all observed cost values. Additionally, the figure reveals that cost changes are less pronounced for higher values of η compared to lower values, indicating a diminishing marginal effect as η increases.

The circles in Fig. 9 highlight shifts in the optimal solution for specific values of the scale parameter η . These shifts demonstrate how changes in η influence the model's outcomes, particularly in terms of cost optimization and maintenance strategy adjustments. This visualization underscores the importance of the scale parameter in determining maintenance costs and provides valuable insights into the sensitivity of the model to variations in η .

5.2. Sensitivity analysis with respect to the effective rate of equipment

As described, various levels of PM operations have varying effects on the lifespan of equipment. Specifically, each PM level impacts the virtual lifespan of the system differently, reflecting their distinct influences on equipment durability. This study investigates how the effectiveness of PM operations ranges from minimal to perfect. Each PM level affects the effective rate of the equipment in a unique way, thereby altering the system's virtual lifespan accordingly. The changes in total maintenance operation costs for various effective equipment rates are illustrated in Table 7.

Based on the results obtained from solving the model, as shown in Table 7, increasing the effective equipment rate leads to a reduction in costs. This outcome aligns with the assumptions of the problem and is entirely logical. An increase in the effective equipment rate typically results in a decrease in the equipment's virtual age, which in turn reduces the equipment's failure rate and, consequently, the associated maintenance costs. Figs. 10–12 illustrate this relationship: as the effective equipment rate increases, the virtual lifespan of the equipment decreases, and vice versa. In other words, a longer effective lifespan of the equipment shifts PM from a minimal to a more comprehensive level of implementation. This transition enhances the equipment's lifespan and reduces its failure rate, further contributing to lower maintenance costs. These findings highlight the importance of optimizing the

effective equipment rate to achieve cost-efficient and reliable maintenance strategies.

It is crucial to note that variations in the effective rate for any maintenance level can influence the optimal solution. For example, if the effective rate for Level 2 PM increases from 0.5 (imperfect) to 1 (perfect), the optimal solution may change. Instead of performing Level 2 maintenance in just one period, it might become optimal to apply this level of maintenance across multiple periods. This is because the cost-effectiveness of Level 2 maintenance, given its cost and effectiveness, could be more beneficial compared to other maintenance levels when extended over a greater number of periods.

As shown in contour Figs. 10–12, regions with uneven boundary curvature indicate where the optimal solution values change. Specifically, the optimal solutions for PM operations vary within the following effective equipment rate ranges:

- First level of PM: Changes occur when $\alpha 1 < 0.85$.
- Second level of PM: Adjustments are observed within $0.5 < \alpha 2 \leq 0.6$.
- Third level of PM: Variations are evident within $0.3 < \alpha 3 \leq 0.5$.

Even if the optimal solutions remain stable in other ranges, variations in the effective equipment rate can still impact the optimal value of the objective function (cost). This is because the equipment's lifespan affects the failure rate, which consequently influences the overall maintenance costs.

6. Managerial insights

The results of this study provide valuable insights into determining the most appropriate timing and intensity of PM operations, considering their impact on equipment lifespan, conditions, and associated expenditures. Overall, this paper presents a cost-reduction strategy for industries, aimed at improving equipment availability and reducing the HEP. The findings of this study assist managers in making informed decisions regarding the optimal level of HEP, taking into account the costs associated with human error, resource allocation for human error reduction, and the organization's overall budget. Managers can plan organizational and personnel conditions in a way that maintains the level of error at a desired and optimal threshold.

In other words, they can establish desirable thresholds for each of the Common Performance Conditions (CPCs) corresponding to human errors. Furthermore, the results of the proposed model significantly contribute to enhancing maintenance operations planning by incorporating human error into the decision-making process. This, in turn, leads to optimal decision-making regarding various levels of PM operations and improved management of spare part inventory. As a result, the costs associated with CM operations and overall organizational expenses can be managed in a cost-effective manner.

The presented model offers significant benefits to organizations where PM plays a crucial role, and the costs associated with human error and equipment failure are substantial. Additionally, this model provides considerable advantages for organizations that prefer to perform PM operations based on both equipment age and conditions. The simultaneous execution of PM operations based on both conditions and time can greatly enhance decision-making outcomes. This approach proves to be a reliable strategy for organizations that must conduct PM operations while considering time constraints and equipment conditions, ensuring a balance between cost efficiency and operational reliability.

7. Conclusions and suggestions

This paper is notable for its innovative approach in estimating the cost function related to human errors in maintenance tasks by leveraging regression analysis and historical data. The study highlights the significant effect of HEP on the efficiency and effectiveness of maintenance operations. For the first time, it demonstrates how human error can influence the effective rate of equipment lifespan, providing a novel perspective on the interplay between human factors and equipment reliability. In this study, a limited selection of spare parts has been analyzed based on the equipment under consideration. The research focuses exclusively on evaluating the spare parts typically utilized for both PM and CM operations for two specific machines. Establishing prioritized rankings and selecting the most essential spare parts—guided by factors such as required quantity, significance for operational objectives, lead time, supplier accessibility, repairability, pricing, and other relevant considerations—can significantly enhance the efficiency and effectiveness of spare parts inventory management.

Furthermore, future investigations could delve into exploring how personnel training impacts not only PM but also CM operations, as improved training may reduce human errors and enhance maintenance outcomes. Additionally, the study assumes a constant cost for CM and PM operations across all time periods. It is suggested that future research endeavors should account for real-world dynamics by incorporating factors such as inflation rates, fluctuations in spare parts inventory levels, and other economic variables to better reflect actual conditions. Such refinements would further improve the model's applicability and accuracy in real-world industrial settings. This study focuses primarily on determining the optimal value for HEP, without proposing specific strategies for enhancing and mitigating human errors across various CPCs. To address this limitation, it is advisable to develop a novel mathematical model that dynamically adjusts based on the optimal HEP. Such a model would provide a more comprehensive and impactful approach to reducing human errors and their associated costs.

In practical terms, this would involve implementing enhancements in the CPCs, taking into account the current organizational context, financial limitations, and the influence of these factors on human errors. This approach should facilitate the identification of optimal interventions for modifying each sub-condition and overall performance criteria, ensuring a more targeted and effective reduction in human errors. Furthermore, for future research endeavors, it is recommended to incorporate the consideration of variable variance in random factors during problem-solving processes. By establishing threshold limits for these variances, researchers can offer more practical and actionable insights for addressing human errors in real-world scenarios. This would not only enhance the robustness of the model but also provide decision-makers with clearer guidelines for implementing error-reduction strategies in dynamic and uncertain environments.

A valuable direction for future research would be to develop a more comprehensive model that integrates both learning and forgetting processes in the context of PM operations. This framework would quantify

the rate at which skills are acquired and lost over multiple maintenance cycles, considering factors such as task complexity, frequency of practice, and workforce experience. By exploring how learning-forgetting dynamics influence maintenance scheduling, HEP, and associated costs, this research could provide actionable insights into optimizing workforce training programs and operational efficiency.

To further advance the understanding of human error in maintenance operations and its economic implications, a future study could focus on developing a dynamic cost-benefit optimization model for HEP reduction across diverse maintenance domains. This model would integrate a detailed classification of human errors (e.g., slips, lapses, mistakes, violations) and evaluate the impact of specific contextual factors—such as training programs, procedural improvements, human-machine interface (HMI) design, and environmental conditions—on HEP and associated costs.

The study could also explore domain-specific HEP thresholds, identifying the point at which further investments in error reduction yield diminishing returns. By incorporating real-world case studies and simulation-based scenarios, the research would provide a decision-support framework to help organizations prioritize cost-effective strategies for minimizing human errors in inspection, PM, and CM activities.

Furthermore, the study could investigate the role of emerging technologies, such as AI-driven predictive maintenance systems and augmented reality (AR) tools, in reducing human errors and optimizing maintenance efficiency. These technologies could enhance decision-making, improve task execution, and reduce the cognitive load on maintenance personnel. By integrating these tools into the model, organizations could align their maintenance operations with predefined targets while balancing the trade-offs between error reduction costs and system reliability.

Such a framework would offer practical, data-driven insights for enhancing maintenance performance across industries, enabling organizations to achieve higher reliability, lower costs, and improved safety standards. By addressing the interplay between human factors, technological advancements, and economic considerations, this research would contribute significantly to the field of maintenance optimization and human error management.

CRediT authorship contribution statement

Vahideh Bafandegan Emroozi: Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Mostafa Kazemi:** Supervision, Data curation. **Mahdi Doostparast:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

The data related to this paper, derived from the case study, is presented in [Tables 1A to 2A](#).

Table 1
A. Data related to case study.

| Period | <i>Cu_{it}</i> | | | | <i>NO_{it}</i> | | | |
|--------|------------------------|------|-------|------|------------------------|------|------|------|
| | Spare Parts | | | | Spare Parts | | | |
| | 4 | 3 | 2 | 1 | 4 | 3 | 2 | 1 |
| 1 | 500 | 1500 | 10000 | 2000 | 500 | 500 | 500 | 500 |
| 2 | 500 | 1500 | 10000 | 2000 | 500 | 500 | 500 | 500 |
| 3 | 500 | 1500 | 10000 | 2000 | 500 | 500 | 500 | 500 |
| 4 | 500 | 1500 | 10000 | 2000 | 500 | 500 | 500 | 500 |
| 5 | 500 | 1500 | 10000 | 2000 | 500 | 500 | 500 | 500 |
| 6 | 500 | 1500 | 10000 | 2000 | 500 | 500 | 500 | 500 |
| 7 | 700 | 2000 | 13500 | 2700 | 700 | 700 | 700 | 700 |
| 8 | 700 | 2000 | 13500 | 2700 | 700 | 700 | 700 | 700 |
| 9 | 700 | 2000 | 13500 | 2700 | 700 | 700 | 700 | 700 |
| 10 | 700 | 2000 | 13500 | 2700 | 700 | 700 | 700 | 700 |
| 11 | 700 | 2000 | 13500 | 2700 | 700 | 700 | 700 | 700 |
| 12 | 700 | 2000 | 13500 | 2700 | 700 | 700 | 700 | 700 |
| 13 | 1000 | 3000 | 20000 | 4000 | 1000 | 1000 | 1000 | 1000 |
| 14 | 1000 | 3000 | 20000 | 4000 | 1000 | 1000 | 1000 | 1000 |
| 15 | 1000 | 3000 | 20000 | 4000 | 1000 | 1000 | 1000 | 1000 |
| 16 | 1000 | 3000 | 20000 | 4000 | 1000 | 1000 | 1000 | 1000 |

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Table 1 (continued)

| Period | Cu_{it} | | | | NO_{it} | | | |
|--------|-------------|------|-------|-------|-------------|------|------|------|
| | Spare Parts | | | | Spare Parts | | | |
| | 4 | 3 | 2 | 1 | 4 | 3 | 2 | 1 |
| 17 | 1000 | 3000 | 20000 | 4000 | 1000 | 1000 | 1000 | 1000 |
| 18 | 1000 | 3000 | 20000 | 4000 | 1000 | 1000 | 1000 | 1000 |
| 19 | 1400 | 4000 | 27000 | 5500 | 1400 | 1400 | 1400 | 1400 |
| 20 | 1400 | 4000 | 27000 | 5500 | 1400 | 1400 | 1400 | 1400 |
| 21 | 1400 | 4000 | 27000 | 5500 | 1400 | 1400 | 1400 | 1400 |
| 22 | 1400 | 4000 | 27000 | 5500 | 1400 | 1400 | 1400 | 1400 |
| 23 | 1400 | 4000 | 27000 | 5500 | 1400 | 1400 | 1400 | 1400 |
| 24 | 1400 | 4000 | 27000 | 5500 | 1400 | 1400 | 1400 | 1400 |
| 25 | 2000 | 6000 | 40000 | 8000 | 2000 | 2000 | 2000 | 2000 |
| 26 | 2000 | 6000 | 40000 | 8000 | 2000 | 2000 | 2000 | 2000 |
| 27 | 2000 | 6000 | 40000 | 8000 | 2000 | 2000 | 2000 | 2000 |
| 28 | 2000 | 6000 | 40000 | 8000 | 2000 | 2000 | 2000 | 2000 |
| 29 | 2000 | 6000 | 40000 | 8000 | 2000 | 2000 | 2000 | 2000 |
| 30 | 2000 | 6000 | 40000 | 8000 | 2000 | 2000 | 2000 | 2000 |
| 31 | 2800 | 8000 | 54000 | 11000 | 2800 | 2800 | 2800 | 2800 |
| 32 | 2800 | 8000 | 54000 | 11000 | 2800 | 2800 | 2800 | 2800 |
| 33 | 2800 | 8000 | 54000 | 11000 | 2800 | 2800 | 2800 | 2800 |
| 34 | 2800 | 8000 | 54000 | 11000 | 2800 | 2800 | 2800 | 2800 |
| 35 | 2800 | 8000 | 54000 | 11000 | 2800 | 2800 | 2800 | 2800 |
| 36 | 2800 | 8000 | 54000 | 11000 | 2800 | 2800 | 2800 | 2800 |

Table 2
A. Data related to case study.

| EO_{it} | | | | h_{it} | | | | war_{it} | | | |
|-------------|------|------|------|-------------|------|------|------|-------------|------|------|------|
| Spare Parts | | | | Spare Parts | | | | Spare Parts | | | |
| 4 | 3 | 2 | 1 | 4 | 3 | 2 | 1 | 4 | 3 | 2 | 1 |
| 500 | 500 | 500 | 500 | 1500 | 1500 | 1500 | 1500 | 3000 | 3000 | 1000 | 5000 |
| 500 | 500 | 500 | 500 | 1500 | 1500 | 1500 | 1500 | 3000 | 3000 | 1000 | 5000 |
| 500 | 500 | 500 | 500 | 1500 | 1500 | 1500 | 1500 | 3000 | 3000 | 1000 | 5000 |
| 500 | 500 | 500 | 500 | 1500 | 1500 | 1500 | 1500 | 3000 | 3000 | 1000 | 5000 |
| 500 | 500 | 500 | 500 | 1500 | 1500 | 1500 | 1500 | 3000 | 3000 | 1000 | 5000 |
| 500 | 500 | 500 | 500 | 1500 | 1500 | 1500 | 1500 | 3000 | 3000 | 1000 | 5000 |
| 700 | 700 | 700 | 700 | 2000 | 2000 | 2000 | 2000 | 3000 | 3000 | 1000 | 5000 |
| 700 | 700 | 700 | 700 | 2000 | 2000 | 2000 | 2000 | 3000 | 3000 | 1000 | 5000 |
| 700 | 700 | 700 | 700 | 2000 | 2000 | 2000 | 2000 | 3000 | 3000 | 1000 | 5000 |
| 700 | 700 | 700 | 700 | 2000 | 2000 | 2000 | 2000 | 3000 | 3000 | 1000 | 5000 |
| 700 | 700 | 700 | 700 | 2000 | 2000 | 2000 | 2000 | 3000 | 3000 | 1000 | 5000 |
| 700 | 700 | 700 | 700 | 2000 | 2000 | 2000 | 2000 | 3000 | 3000 | 1000 | 5000 |
| 1000 | 1000 | 1000 | 1000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 1000 | 5000 |
| 1000 | 1000 | 1000 | 1000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 1000 | 5000 |
| 1000 | 1000 | 1000 | 1000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 1000 | 5000 |
| 1000 | 1000 | 1000 | 1000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 1000 | 5000 |
| 1000 | 1000 | 1000 | 1000 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 | 1000 | 5000 |
| 1400 | 1400 | 1400 | 1400 | 4000 | 4000 | 4000 | 4000 | 3000 | 3000 | 1000 | 5000 |
| 1400 | 1400 | 1400 | 1400 | 4000 | 4000 | 4000 | 4000 | 3000 | 3000 | 1000 | 5000 |
| 1400 | 1400 | 1400 | 1400 | 4000 | 4000 | 4000 | 4000 | 3000 | 3000 | 1000 | 5000 |
| 1400 | 1400 | 1400 | 1400 | 4000 | 4000 | 4000 | 4000 | 3000 | 3000 | 1000 | 5000 |
| 1400 | 1400 | 1400 | 1400 | 4000 | 4000 | 4000 | 4000 | 3000 | 3000 | 1000 | 5000 |
| 1400 | 1400 | 1400 | 1400 | 4000 | 4000 | 4000 | 4000 | 3000 | 3000 | 1000 | 5000 |
| 2000 | 2000 | 2000 | 2000 | 6000 | 6000 | 6000 | 6000 | 3000 | 3000 | 1000 | 5000 |
| 2000 | 2000 | 2000 | 2000 | 6000 | 6000 | 6000 | 6000 | 3000 | 3000 | 1000 | 5000 |
| 2000 | 2000 | 2000 | 2000 | 6000 | 6000 | 6000 | 6000 | 3000 | 3000 | 1000 | 5000 |

(continued on next page)

Table 2 (continued)

| EO_{it} | | | | h_{it} | | | | war_{it} | | | |
|-------------|------|------|------|-------------|------|------|------|-------------|------|------|------|
| Spare Parts | | | | Spare Parts | | | | Spare Parts | | | |
| 4 | 3 | 2 | 1 | 4 | 3 | 2 | 1 | 4 | 3 | 2 | 1 |
| 2000 | 2000 | 2000 | 2000 | 6000 | 6000 | 6000 | 6000 | 3000 | 3000 | 1000 | 5000 |
| 2000 | 2000 | 2000 | 2000 | 6000 | 6000 | 6000 | 6000 | 3000 | 3000 | 1000 | 5000 |
| 2000 | 2000 | 2000 | 2000 | 6000 | 6000 | 6000 | 6000 | 3000 | 3000 | 1000 | 5000 |
| 2800 | 2800 | 2800 | 2800 | 8000 | 8000 | 8000 | 8000 | 3000 | 3000 | 1000 | 5000 |
| 2800 | 2800 | 2800 | 2800 | 8000 | 8000 | 8000 | 8000 | 3000 | 3000 | 1000 | 5000 |
| 2800 | 2800 | 2800 | 2800 | 8000 | 8000 | 8000 | 8000 | 3000 | 3000 | 1000 | 5000 |
| 2800 | 2800 | 2800 | 2800 | 8000 | 8000 | 8000 | 8000 | 3000 | 3000 | 1000 | 5000 |
| 2800 | 2800 | 2800 | 2800 | 8000 | 8000 | 8000 | 8000 | 3000 | 3000 | 1000 | 5000 |
| 2800 | 2800 | 2800 | 2800 | 8000 | 8000 | 8000 | 8000 | 3000 | 3000 | 1000 | 5000 |

Data availability

Data will be made available on request.

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