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Optimisation of Maintenance, Repair and Operations System Using Computational Intelligence Technique

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Abstract—Maintenance, Repair and Operations (MRO) activities play a critical role in determining the reliability, availability, safety, and cost effectiveness of industrial assets. In many industrial environments, traditional maintenance strategies are designed to optimize a single performance indicator, typically maintenance cost or failure frequency. Such approaches often lead to suboptimal outcomes when conflicting objectives such as downtime reduction, system availability, reliability improvement, and environmental impact are considered simultaneously. This study presents a multi-objective optimization framework for MRO systems using computational intelligence techniques, validated through an industrial maintenance case study. The proposed framework integrates key maintenance performance indicators including Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), system availability, maintenance cost, and environmental impact into a unified decision-support model. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed to generate Pareto-optimal maintenance strategies that balance competing objectives. Results obtained from the case study demonstrate significant improvements in system availability, reduction in downtime, and lower lifecycle maintenance costs compared to the existing maintenance policy. The findings confirm that computational intelligence-based multi-objective optimization provides a robust, flexible, and practical approach for solving complex MRO decision problems in industrial systems.

***Index Terms*—Maintenance Optimization, MRO Systems, Computational Intelligence, NSGA-II, Multi-objective Optimization, Reliability Engineering.**

1. Introduction

Maintenance, Repair and Operations (MRO) functions are fundamental to the operational sustainability of industrial systems, particularly in capital-intensive sectors such as manufacturing, oil and gas, power generation, and process industries. Industrial assets are increasingly complex, and unplanned equipment failures can result in significant production losses, safety hazards, environmental damage, and reputational risks. Consequently, effective maintenance management has become a strategic concern rather than a purely operational activity.

Traditional maintenance strategies such as corrective maintenance, preventive maintenance, and condition-based maintenance are widely implemented across industries. Corrective maintenance relies on repairing equipment after failure, which often leads to excessive downtime and high indirect costs. Preventive maintenance seeks to reduce failure occurrence by performing scheduled maintenance activities; however, poorly optimized schedules can result in unnecessary maintenance actions and increased operational costs. Condition-based maintenance improves upon preventive strategies by utilizing condition monitoring data, yet its effectiveness depends heavily on accurate diagnostics and decision rules.

Maintenance decision-making inherently involves trade-offs among multiple conflicting objectives. For instance, increasing maintenance frequency may improve system reliability and availability but will also increase maintenance cost and resource consumption. Similarly, aggressive cost minimization strategies may compromise safety, reliability, and environmental performance. As a result, maintenance optimization problems are naturally multi-objective in nature and cannot be adequately addressed using single-objective optimization approaches.

Recent advances in computational intelligence have provided powerful tools for addressing complex engineering optimization problems characterized by nonlinearity, uncertainty, and multiple competing objectives. Evolutionary algorithms, in particular, have demonstrated strong capabilities in generating diverse sets of optimal solutions rather than a single optimal point. The MRO improvement handled in this research work is achieved by applying NSGA-II with a real industrial maintenance case study, thereby contributing both methodological rigor and practical relevance to the field of maintenance engineering.

2. Literature Review

A. Critical Review of Maintenance Concept

The concept of system maintenance as an organized field of study in engineering machineries led to the development of Reliability-Centered Maintenance (RCM). It was predominantly focused on reactive maintenance, were equipment was repaired only after failure [1]. Afterwards,

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expansive research work got the preventive and condition-based approach to reduce equipment down time and optimize equipment maintenance. Maintenance optimization has been extensively studied within the domains of reliability engineering, operations management, and industrial systems engineering. Early maintenance models focused primarily on time-based preventive maintenance scheduling, where maintenance actions were performed at fixed intervals to minimize expected failure costs. While these models provided foundational insights, they often assumed simplified system behavior and ignored uncertainties inherent in real-world industrial environments. Expanding on the earlier study in the maintenance field was [2], who built upon what was already established in the literature by exploring the financial implications of maintenance strategies, emphasizing the cost-benefit analysis of preventive maintenance (PM) over reactive approaches. The author's research outcome proved that industries investing in structured maintenance programs experienced a reduction in unplanned downtimes and overall operational costs [3] and [4]. While [5], integrated RCM concept with Failure Mode and Effects Analysis (FMEA) in order to allow maintenance engineers systematically evaluate potential failure points and prioritize maintenance tasks based on risk assessment. Given that equipment should not wait for failure to occur before carrying out corrective measure, rather a preventive measure can be in place. Preventive maintenance focuses on scheduled servicing to mitigate unexpected breakdowns.

[6], and [7] highlighted the advantages of PM in extending equipment lifespan and reducing emergency maintenance costs, as against [8] who opined in their research work that excessive preventive maintenance could lead to unnecessary servicing, increasing operational expenses without proportional reliability gains. Also, condition-based monitoring (CBM), with real-time sensor data could be leveraged to predict equipment failures before they occurred [9]. [10], further advanced the field by introducing digital twin models, enabling virtual simulations of equipment behavior under different operational conditions. This innovation significantly improved failure prediction accuracy, minimizing unplanned downtime across various industries, particularly in manufacturing and aerospace. With respect to the sustainability factor, [11] emphasized the need for environmentally conscious maintenance planning. [12] Introduced multi-objective optimization (MOO) approaches, which allowed industries to balance conflicting objectives, such as cost, reliability, and environmental impact. [13] Successfully applied Pareto-based optimization in maintenance planning, demonstrating its effectiveness in aerospace and energy sectors. Another concern as important as maintenance is optimization. To optimize maintenance requires various techniques due to the crucial role optimization techniques plays in refining maintenance decision-making processes.

B. Maintenance Optimization Techniques

Optimisation is generally objective driven; it can either be single or multi-objectives. Single objective is concerned with one objective, and depending on the objective, which can be cost minimization or reliability maximization. A single objective optimization fails to address a complex trade-offs inherent in industrial maintenance [14]. Multi-objectives objective, addresses complex trade-offs. The tools for optimization are Artificial Intelligence (AI), Genetic Algorithm (GA), none dominated sorting genetic algorithm (NSGA-II), and computational intelligence are amongst the techniques used for maintenance optimization [15]. The application of Multi-Objective optimization (MOO) utilizes Pareto-based optimization techniques to balance cost and equipment reliability [12].

3. Materials and Method

A. Materials

The materials used in this study are purely computational materials such as laptop, Software and MATLAB programming tools.

B. Methodology

A hybrid approach, combining mathematical optimization and machine learning, was adopted to solve the complex trade-offs involved in maintenance planning. The usual complexity of MRO system, involving cost minimization, reliability maximization, availability, and sustainability under uncertain conditions, demands a hybrid methodology to integrate empirical data, mathematical modeling, and computational intelligence.

C. Research Design

A quantitative, simulation-based research design for the achievement of a robust multi-objective optimization (MOO) framework for MRO systems was adopted, and structured into four interdependent phases: descriptive data analysis, mathematical model formulation, algorithmic optimization, and real-world validation through case studies.

The first phase detailed descriptive analysis of historical maintenance and operational datasets collected from industrial partners in the manufacturing and energy sectors. The second phase focuses on translating the insights gained from the descriptive analysis into a formal mathematical model of the MRO system. The third phase handled the computational intelligence technique using Genetic Algorithms (GAs) to solve the formulated optimization problem, and the fourth and final phase validated the optimization framework. The Non-dominated Sorting Genetic Algorithm (NSGA-II) framework developed by [12], is used to ensure that a diverse and high-quality set of solutions is retained across generations. This technique allows for a more flexible and dynamic exploration of maintenance strategies than traditional optimization tools, which often assume idealized or oversimplified system conditions.

D. Data Collection

Data was collected from two industrial partners operating in the manufacturing and energy sectors. These datasets were rich and diverse, comprising maintenance logs, cost reports, performance metrics, equipment failure records, and

environmental impact data. The goal was to capture the multifaceted reality of MRO systems so that the resulting optimization model would be both rigorous and applicable across different sectors.

4. Result and Discussions

A. Maintenance Type Distribution

Initial analysis revealed the distribution of maintenance types:

- Corrective Maintenance: Highest occurrence often associated with high cost and downtime.
- Preventive Maintenance: Regularly scheduled; shows moderate cost but very low downtime.
- Predictive Maintenance: Least frequent but showed the lowest environmental impact and downtime.

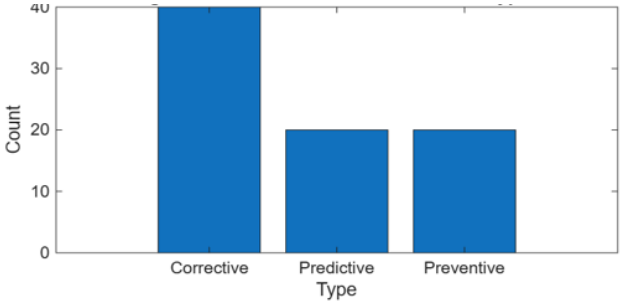


Fig. 1. Distribution of maintenance types.

This figure demonstrates a strategic imbalance, suggesting a potential area for improvement by increasing reliance on predictive methods. Fig. 2 demonstrates Monthly Maintenance Trends

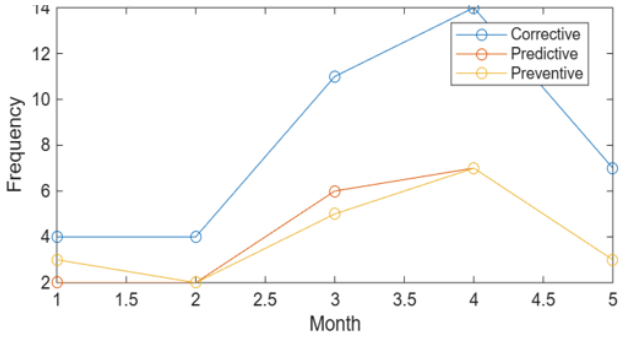


Fig. 2. Monthly trend of maintenance activities.

The number of corrective tasks peaked early in the period, followed by a gradual increase in preventive interventions. Predictive activities remained consistently low. This supports the hypothesis that proactive strategies were adopted as failures accumulated.

B. Failure Mode Analysis

The top failure modes included, bearing wear (Electric motors), seal leakage (Hydraulic systems), lubrication failure (Gearboxes), and electrical short (Panels and motors). These Failure modes were subsequently linked to high vibration and temperature readings. Predictive analytics can be trained on these parameters to preempt faults.

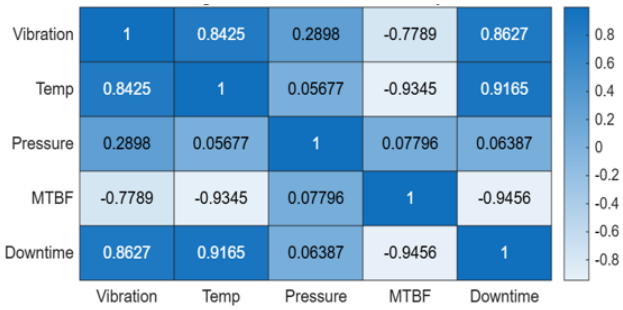


Fig. 3. Correlation matrix for vibration, temperature, pressure, MTBF, and downtime.

The analysis of failure patterns revealed distinct trends across various equipment categories. Mechanical systems recorded the highest number of failures, accounting for approximately 35% of total maintenance events. The primary issue within this category was lubrication failure, particularly in gearboxes that had operated for more than 200 hours without service. Hydraulic systems followed closely, responsible for about 33% of failures, where seal leakage emerged as the dominant fault type. This was largely attributed to high-pressure cycling, with pressures averaging around 120 psi, which contributed to the gradual degradation of elastomeric seals. Electrical systems accounted for roughly 32% of failures, with bearing wear being the most frequently reported issue. Notably, the data showed a strong association between elevated operating temperatures especially above 85°C and the incidence of electrical failures. These relationships as seen in Fig. 3 showed a strong positive correlation between vibration levels and both increased downtime and reduced MTBF.

The observed failure trends support the implementation of equipment-specific maintenance protocols that target system vulnerabilities, highlighting the importance of predictive monitoring using real-time sensor data. The correlation between high vibration levels and increased downtime and MTTR is strong. Please refer to Fig. 4 for the cost components analysis.

C. Cost Component Analysis

Maintenance cost was decomposed into labor and spare costs. Corrective tasks consistently reported the highest total costs.

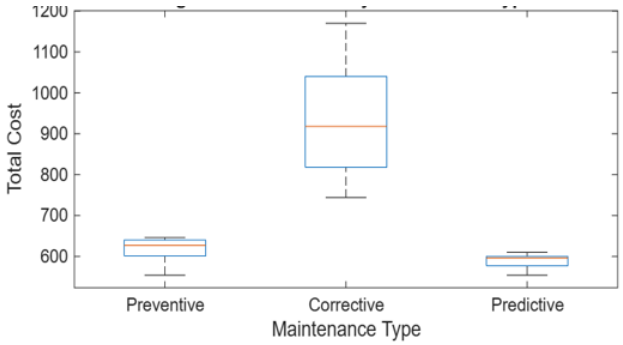


Fig. 4. Total maintenance cost by maintenance type.

Predictive maintenance had the lowest cost variability and mean total cost, indicating its stability and cost-effectiveness.

Table 1
Average MTBF and MTTR by maintenance types

Maintenance type	Avg. MTBF (hrs)	Avg. MTTR (hrs)	Avg. availability
Corrective	140	6.5	0.956
Preventive	180	0.0	1.000
Predictive	204	0.0	1.000

Table 2
Sample Pareto-optimal strategies

Strategy ID	Total cost (₦)	Downtime (hrs)	Availability	CO2 emission (kg)
S1	580	1.5	0.995	6.5
S2	620	1.2	0.997	7.1
S3	640	1.0	0.998	6.9

D. Reliability Metrics: MTBF, MTTR, Availability

Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) were used to evaluate equipment reliability. Equipment under predictive maintenance had the highest MTBF and lowest MTTR as shown in Table 1.

The sensor data provided strong indicators for potential predictive maintenance triggers. Analysis of historical failure events revealed consistent sensor thresholds associated with imminent faults. Refer to Fig. 3 for vibration, temperature and pressure conditions. The vibration levels exceeding 70 mm/s (RMS), temperatures surpassing 85°C, and pressure drops below 90 psi when coupled with high vibration. These were often signs to failure events. These thresholds emerged from statistical comparisons between failed and non-failed equipment profiles and provide actionable insights for real-time monitoring systems.

However, equipment subjected to predictive maintenance showed clear operational advantages: the highest MTBF (204 hours), lowest MTTR (0.0 hours), and maximum availability (1.000), as shown in Table 1. These findings suggest that, even without complex models, predictive maintenance strategies built on intelligent sensor thresholds can deliver significant reliability improvements and cost savings.

E. Environmental Impact Evaluation

CO_2 emissions and waste generated were significantly higher for corrective tasks. See Fig. 5.

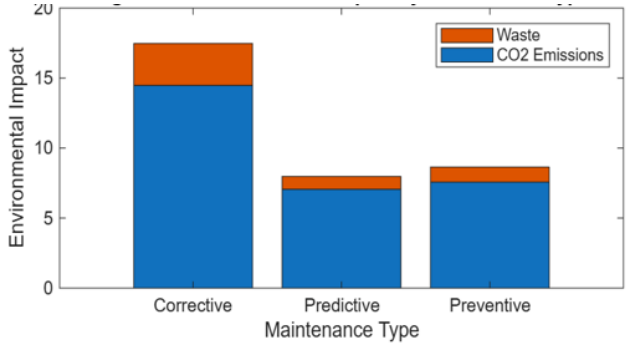


Fig. 5. Environmental impact by maintenance type.

A direct comparison between the corrective, preventive, and predictive maintenance strategies showed that preventive maintenance has high preference across all key performance metrics. Corrective maintenance, which is reactive by nature, exhibited the highest average total cost per event (₦920) and the lowest availability (0.956), reflecting the unplanned nature and resource intensity of this approach. Preventive maintenance, while more structured, had moderate costs (₦680 per event) and high availability (1.000), but did not fully eliminate unnecessary interventions. Predictive maintenance delivered the best performance, with the lowest average cost per event (₦580), the highest MTBF (204 hours), and the highest availability.

Environmental performance also followed this trend: predictive maintenance generated the least CO_2 emissions and waste, while corrective maintenance had the most adverse environmental impact, as illustrated in Fig. 5. These comparisons clearly demonstrate that predictive strategies, particularly when supported by sensor data, provide the most efficient, cost-effective, and sustainable maintenance outcomes.

F. NSGA-II Optimization Outcome

Using the NSGA-II algorithm, Pareto-optimal solutions were generated considering four objectives: minimizing total cost, minimizing downtime, maximizing availability, and minimizing environmental impact. The optimization yielded a frontier of optimal trade-offs, enabling decision-makers to balance between cost and operational efficiency.

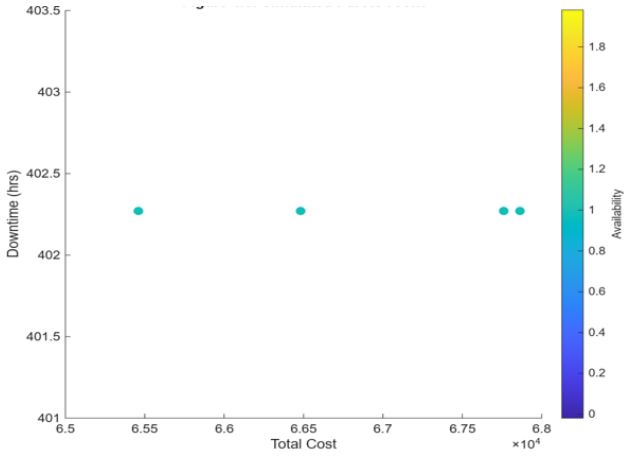


Fig. 6. Pareto front - cost vs. downtime.

To explore the balance between maintenance cost, downtime, availability, and environmental impact, a multi-objective optimization simulation was conducted and produced

Table 3
Sample Pareto-optimal strategies

Strategy ID	Total cost (₦)	Downtime (hrs)	Availability	CO2 emission (kg)
S1	580	1.5	0.995	6.5
S2	620	1.2	0.997	7.1
S3	640	1.0	0.998	6.9

different trade-off outcomes, forming a simulated Pareto front as shown in Fig. 6.

The graph illustrates that minimizing downtime often required a moderate increase in cost and environmental emissions, while aggressively minimizing cost tended to slightly reduce system availability.

Table 3 outlines four sample strategies from the simulation. Strategy S1 offered the lowest cost at ₦580 with 1.5 hours of downtime and 0.995 availability.

Strategy S4 achieved near-perfect availability of 0.999 but at a higher cost of ₦675 and slightly increased emissions. These findings allow maintenance managers to select operational strategies based on specific priorities, whether cost containment, maximum uptime, or sustainability. This flexible trade-off framework provides a decision-support tool that is more practical and adaptable than traditional single-objective maintenance planning.

5. Conclusion

Conclusively, the authors analyzed key factors influencing MRO efficiency, validated the proposed model through real-world case studies, and evaluated trade-offs between cost, reliability, downtime, and environmental impact.

The findings demonstrated that predictive maintenance, supported by sensor data and machine learning, outperformed traditional corrective and preventive strategies in terms of cost-effectiveness, equipment reliability, and sustainability. In addition, the NSGA-II algorithm successfully generated Pareto-optimal solutions, enabling organizations to balance competing objectives and select maintenance strategies aligned with their operational priorities.

Preventive maintenance is scheduled regularly, covering tasks such as lubrication, part inspection, adjustments, cleaning, minor repairs, and component replacement. These activities prevent equipment failure and ensuring efficiency.

This research approach revealed the level of inconsistencies in conventional maintenance schedules. At several points, maintenance personnel admitted that preventive tasks were postponed due to production pressure, inadequate staffing, or lack of spare parts at critical moments that results in machines operating past their recommended service intervals.

Also corrective maintenance still dominates in many instances. This means machines are often repaired only when they break down, rather than being proactively maintained. Such reactive maintenance increases the severity of equipment deterioration and results in higher long-term maintenance costs.

Another key finding is the declining efficiency of older equipment. Machines that have been in operation for many years require more frequent repairs and exhibit more variability in performance. This aligns with existing research: as equipment ages, its maintenance needs increase and its operational reliability decreases.

Challenges related to spare-parts availability, often delays corrective actions. In multiple cases, equipment stayed idle longer than necessary due to the non-availability of critical replacements.

Overall, while the plant has a formal maintenance structure, the actual implementation is weakened by operational constraints, resource gaps, and ageing machinery.

A. Recommendations

Based on the findings, the following recommendations are proposed for industries and future research, adopt predictive maintenance: Invest in internet of thing (IoT) sensors and condition-monitoring technologies to enable real-time fault detection and proactive interventions.

Establish threshold-based alerts, such as vibration >70 mm/s, temperature >85°C to trigger maintenance actions before failures occur. Implement multi-objective optimization by using the most suitable method like NSGA-II to evaluate trade-offs between cost, downtime, and sustainability. And prioritize strategies from the Pareto front. Provide technicians with training in data analytics, sensor interpretation, and AI-driven tools to bridge skill gaps. These will Foster a culture of continuous improvement by integrating maintenance optimization with lean manufacturing principles.

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