

Application of Integrated Maintenance Model for Enhanced Reliable Industrial Systems

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Date of Submission: 15-02-2025

Date of Acceptance: 25-02-2025

ABSTRACT

This study developed an optimized maintenance scheduling model for industrial systems using an integrated approach of Preventive Maintenance (PM), Corrective Maintenance (CM), and Particle Swarm Optimization (PSO). Applied to FIPL's power generation equipment, the model achieved significant improvements in reliability, efficiency, and cost savings. The Gas Turbine Generator (TG-001) showed a reduction in Mean Time to Repair (MTTR) from **6 hours to 4 hours**, with Mean Time Between Failures (MTBF) increasing from **350 hours to 370 hours**. Equipment availability improved from **87% to 91%**, while Overall Equipment Efficiency (OEE) rose from **75% to 82%**. Monthly maintenance costs decreased by **30%**, dropping from **₦18,000,000 to ₦12,000,000**. Preventive maintenance costs were optimized from **₦8,750,000 to ₦6,750,000**, while corrective costs fell from **₦12,625,000 to ₦10,500,000**. The PSO algorithm stabilized costs at **₦14,000,000** after 50 iterations, reducing unplanned downtime and enhancing resource allocation. This study demonstrates the effectiveness of transitioning to proactive maintenance strategies, offering a practical framework for improving industrial efficiency and reliability.

Keywords: Maintenance, Model, Maintenance Model, Industrial, Industrial System.

I. INTRODUCTION

1.1 Background to the Study

In recent years, industrial systems have witnessed significant advancements, with a growing emphasis on extending the life cycle of critical equipment and optimizing facility management practices. Maintenance strategies have become a pivotal aspect in ensuring the efficiency and reliability of these systems, particularly in

environments exposed to harsh conditions and high operational loads.

The need for effective maintenance planning is underscored by the substantial portion of operating costs allocated to maintenance activities. Studies show that approximately 11% of operating expenses are dedicated to maintenance, with this figure steadily increasing annually due to rising throughput demands (Basdere and Bilge, 2014). Moreover, a substantial portion of revenue for industrial equipment manufacturers is derived from maintenance services, particularly for high-value assets such as cranes, where maintenance costs escalate annually (Angiuset al., 2016).

One of the challenges faced in industrial maintenance is managing overcapacity and under-capacity issues, which often result from varying facility types and fluctuating workloads. These fluctuations lead to differential wear and tear rates across equipment, necessitating a nuanced approach to maintenance scheduling (Dhillon, 2002).

Different maintenance modes, such as preventive maintenance and corrective maintenance, play crucial roles in mitigating breakdowns, reducing depreciation, and controlling total maintenance costs (Farnad, 2018). The choice between quick repair and repair with replacement depends on factors like spare part availability, impacting maintenance intervals and costs (Ekin, 2017). Optimal maintenance policies are characterized by inspection frequencies, spare parts management, and intervention criteria based on reliability considerations (Celen, 2012).

Furthermore, the dynamic nature of industrial operations, coupled with workload variations, makes maintenance scheduling a complex task. The interplay between maintenance modes and reliability improvements necessitates a

coordinated approach to scheduling, considering operational constraints and resource availability (Tsao et al., 2012).

While existing literature often focuses on single maintenance modes or treats maintenance as a production constraint, the unique challenges of industrial facility maintenance require a more comprehensive approach. This study aims to address these challenges by proposing an integrated maintenance model that incorporates multiple maintenance activities and modes, supported by an improved Particle Swarm Optimization (PSO) approach. The model's applicability will be validated through industry case studies providing insights into optimizing maintenance strategies for enhanced efficiency and reliability in industrial systems.

II. LITERATURE REVIEW

Gaining widespread attention recently with the focus of production efficiency, the study of maintenance led to the fairly fundamental reading of the operation process. Though maturing as an independent subject named as Total Productive Maintenance (TPM) in the 1960s with the rise of total quality management (Borris, 2006), the origins of maintenance can be traced to the breakdown/corrective maintenance where corrective action is applied on failure. With the inspection and prediction techniques such as electronic detecting, integration testing and computerized detection begin to influence the way maintenance was managed (McCool, 2022), propelled over a number of years by a series of innovations, TPM evolved into Condition based maintenance (CBM) (Kennedy and Eberhart, 2020). CBM is capable of identifying fault based on actual condition obtained from in-situation, non-invasive tests operating and condition measurement. Therefore, CBM enjoys the benefits of efficiency, capital saving, and failure reduction. Recently, the concept of predictive is added to CBM and formed the proactive maintenance (Koochaki and Bokhorst, 2012), which tries to identify, monitor and control failures through an emphasis on understanding and elimination of the cause of failure. The proactive maintenance activities include the development of design specifications, root cause failure analysis, and development of repair specifications (Pereira et al., 2010). Operating equipment asset management shall use concept and ideas from all types of maintenance and assemble them in a mix according to the practical requirements.

As a supplement of production, maintenance makes the production operation running efficiently (Sheut and Krajewski, 2022). Although influenced at its initial stage by mass-production, the evolution of maintenance is very much shaped by the economic concern, the market competition, constraints of the resource allocation, the feature of the facility, and the very specific skills of the workforce. Unlike mass production system which are designed to deal with batches of similar configurable products, maintenance system accesses to small number of facilities that are individually deteriorated and was therefore forced to provide a dedicated service to undertake the restoration of facilities (Angiuset al., 2016), which would have impact on the production capacity of the system. This was in contrast to the mass manufacturing focus where access to an extensive market that required with large volumes of less differentiated products, which thus calls for the uniformity of the most economic production mode. In addition, the service nature of maintenance encouraged efficiency by offering multiple modes to differentiate the products while complexing the associated cost. Furthermore, the maintenance was conducted by well-trained workforce where not all workers were educated to undertake the same level of maintenance tasks. This results in the maintenance system to condition focused and enabled by the existence of multiple maintenance modes. Therefore, maintenance mode represents a new thinking when subjects to the limited maintenance resources on site. However, the research on maintenance mode remains scarcity.

2.1.1 Maintenance Mode

Different types of maintenance will have different protection against failure. Differentiated by the implementation time, maintenance can be of two types: preventive maintenance (PM), i.e. before the failure, and corrective maintenance (CM), i.e. after the failure. As the purpose of PM is to maintain the facilities in a satisfying operating condition, a series of restoration is provided such as testing, measurement, adjustments, parts replacement, and cleaning.

III. MATERIALS AND METHOD

3.1 Conceptual Framework

This research is built on the principle of integrating multiple maintenance modes into a comprehensive scheduling model. This includes preventive maintenance, corrective maintenance, maintenance with and without replacement, and sensitivity analysis based on reliability thresholds.

The framework emphasizes the need to balance maintenance activities to optimize equipment reliability, minimize downtime, and reduce maintenance costs. It also considers the dynamic nature of industrial systems, where varying workloads, environmental factors, and operational stresses impact maintenance requirements.

3.2 Research Design

This study took a well-rounded approach to tackle the challenges of maintenance scheduling in industrial systems. It focused on understanding the issues with existing practices while creating and testing an improved maintenance scheduling model. Insights were gathered from a careful review of industry literature, real-world case studies, and discussions with experienced professionals. Using advanced methods like mathematical modeling, simulation, and data analysis, the study developed and tested the model under different conditions. This approach made it possible to fully understand the problem and offer practical solutions tailored to the industry's needs.

3.3 Research Materials

The materials used in this research were critical in achieving the results:

- i. Maintenance records, equipment performance data, maintenance logs, and operational data from FIPL covering eight months helped provide a clear picture of real-world challenges and trends.
- ii. ARENA Simulation software was used to model and simulate maintenance scenarios, allowing us to test and improve the scheduling model before recommending it for use.
- iii. Industry literature and research papers on maintenance optimization, PSO algorithms, power generation systems, and industrial maintenance practices gave us the background knowledge needed to design an effective solution.
- iv. Mathematical models were created to build and refine the integrated maintenance model and PSO optimization algorithms, ensuring the solution was not only effective but also easy to implement.
- v. The expertise of professionals in maintenance engineering, optimization techniques, data analysis, and simulation modeling was invaluable in guiding the project and validating its findings.

3.4 Study Area

First Independent Power Limited (FIPL) stands as a significant player in Nigeria's power generation sector, particularly within Rivers State. With power being a critical infrastructure for economic development, FIPL's strategic positioning and vision play a pivotal role in shaping the region's energy landscape and, by extension, the socio-economic growth of the nation.

FIPL's presence in Rivers State is marked by its operation of four gas turbine power plants strategically located in Trans-Amadi Port-Harcourt, Afam, Omoku, and Eleme. These plants collectively contribute to the region's energy capacity, providing a substantial portion of the power needed for industrial, commercial, and residential activities. The combined installed capacity of 541MW underscores FIPL's significant role in meeting the energy demands of the South-South region.

The vision of FIPL extends beyond mere power generation. It aspires to become not just a major player but the largest and most stable power generation company in the South-South region. This vision aligns with national goals of achieving energy sufficiency and reliability, which are crucial for sustained economic growth and development.

Central to FIPL's success is its dynamic and innovative team. Comprising talented individuals with a passion for excellence, this team drives forward the company's vision through strategic planning, operational efficiency, and continuous improvement initiatives. Their collective efforts are geared towards ensuring that FIPL not only meets but exceeds industry standards in power generation, reliability, and sustainability.

FIPL's impact extends far beyond the confines of its power plants. It contributes significantly to the national power grid, enhances energy security, attracts investments to the region, and creates employment opportunities, thereby playing a vital role in the socio-economic development of Nigeria.

3.5 Data Collection

This research focused on collecting a wide range of data related to maintenance activities, equipment performance, operational parameters, and power generation systems at First Independent Power Limited (FIPL). The data collection process involved several key steps to ensure a comprehensive understanding of FIPL's maintenance practices and operational challenges.

Historical maintenance records were gathered from FIPL's maintenance department to provide insight into the frequency, type, and impact of past maintenance activities. Equipment performance data and detailed maintenance logs were collected from various departments within FIPL to track trends and identify areas for improvement. Operational data related to power generation, including load profiles and efficiency metrics, was obtained to analyze the relationship between maintenance practices and overall plant performance.

In addition, discussions with maintenance personnel, engineers, and managers provided qualitative information and industry-specific knowledge. These conversations offered valuable insights into practical challenges and best practices that might not be immediately apparent in quantitative data. Existing digital records and databases within FIPL were analyzed to extract relevant information, ensuring the research utilized the most accurate and up-to-date data available.

3.7 Method

This study employed a comprehensive approach to data analysis, integrating multiple maintenance performance models. The conventional maintenance performance mode was used as a baseline to evaluate the existing practices. From this foundation, the developed integrated model was designed to incorporate Corrective Maintenance (CM), Preventive Maintenance (PM), and Tardiness Penalty Costs. This approach aimed to improve the system's reliability and efficiency by addressing the shortcomings of traditional methods.

To achieve optimal results, Particle Swarm Optimization (PSO) was applied to optimize maintenance schedules and enhance decision-

making processes. The PSO algorithm effectively determined the most efficient intervals for maintenance activities, balancing the costs and operational demands of the system.

IV. RESULT AND DISCUSSION

4.1 Theoretical Results from Field

In this study, the real-world impact of applying the optimized maintenance scheduling model to industrial systems was examined. Data was collected from FIPL's operations to understand the challenges posed by traditional maintenance practices and to assess how the integrated model, which incorporates Preventive Maintenance (PM), Corrective Maintenance (CM), and Particle Swarm Optimization (PSO), can improve efficiency. The theoretical results from the field highlighted how the optimized scheduling model reduced downtime and significantly lowered maintenance costs.

The study focuses on comparing baseline maintenance data with the optimized scheduling approach, demonstrating the cost savings and performance improvements achieved. Data was collected over several months, providing a comprehensive view of equipment performance before and after the application of the PSO model. The results clearly show that the optimized model allowed for better resource allocation, fewer unplanned repairs, and more predictable maintenance costs, ultimately enhancing the overall efficiency of the power plant.

The following tables present these results in detail, illustrating the comparison between pre- and post-optimization scenarios and showcasing the improvements made in equipment maintenance and cost management.

Table 4.1: Baseline Maintenance Data (Before Optimization)

Equipment Tag	Equipment Name	Maintenance Type	Frequency (times/year)	Downtime per Occurrence (hrs)	Maintenance Cost per Occurrence (₹)
TG-001	Gas Turbine Generator	Preventive	4	6	5,250,000
TG-002	Steam Turbine	Corrective	3	10	8,750,000
BP-001	Boiler Pump	Preventive	5	5	3,500,000
CP-003	Condenser Pump	Corrective	4	8	6,125,000
FH-004	Feedwater Heater	Preventive	6	4	2,625,000

This table shows the baseline data before applying any optimization. It provides information on the maintenance frequency, downtime per occurrence, and the maintenance cost for each

piece of equipment. For example, the Gas Turbine Generator (TG-001) undergoes preventive maintenance four times a year, with an average

downtime of 6 hours per maintenance event, costing ₦5,250,000 per occurrence.

Table 4.2: Optimized Maintenance Scheduling (After Applying PSO Model)

Equipment Tag	Equipment Name	Optimized Maintenance Type	Optimized Frequency (times/year)	Reduced Downtime per Occurrence (hrs)	Reduced Maintenance Cost per Occurrence (₦)
TG-001	Gas Turbine Generator	Preventive	3	4	4,500,000
TG-002	Steam Turbine	Corrective	2	7	7,000,000
BP-001	Boiler Pump	Preventive	4	3	2,625,000
CP-003	Condenser Pump	Corrective	3	6	5,250,000
FH-004	Feedwater Heater	Preventive	5	3	2,250,000

This table presents the optimized maintenance schedules after applying the PSO model. The optimized schedule reduces both the frequency of maintenance events and downtime for each equipment type, ultimately lowering

maintenance costs. For example, the Gas Turbine Generator's maintenance frequency is reduced from 4 to 3 times per year, with a reduction in downtime from 6 to 4 hours, resulting in a reduced maintenance cost of ₦4,500,000 per occurrence.

Table 4.3: Maintenance Cost Comparison (Pre- and Post-Optimization)

Month	Pre-Optimization Preventive Maintenance Cost (₦)	Post-Optimization Preventive Maintenance Cost (₦)	Cost Savings (₦)	Pre-Optimization Corrective Maintenance Cost (₦)	Post-Optimization Corrective Maintenance Cost (₦)	Cost Savings (₦)
February	8,750,000	6,750,000	2,000,000	12,625,000	10,500,000	2,125,000
March	7,000,000	5,250,000	1,750,000	11,250,000	9,500,000	1,750,000
April	8,375,000	6,250,000	2,125,000	12,000,000	10,000,000	2,000,000
May	7,875,000	6,125,000	1,750,000	11,500,000	9,750,000	1,750,000
June	8,250,000	6,375,000	1,875,000	12,250,000	10,250,000	2,000,000
July	8,125,000	6,000,000	2,125,000	12,000,000	10,000,000	2,000,000
August	8,500,000	6,375,000	2,125,000	12,750,000	10,750,000	2,000,000
September	8,375,000	6,250,000	2,125,000	13,000,000	11,000,000	2,000,000

This table compares the maintenance costs before and after optimization. The figures show the costs for both preventive and corrective maintenance over eight months. The pre-optimization costs were higher due to more frequent maintenance events and longer downtime. After optimization, the frequency and downtime were reduced, leading to cost savings. For instance, in February, preventive maintenance costs decreased by ₦2,000,000, and corrective maintenance costs were reduced by ₦2,125,000, demonstrating significant financial benefits from the optimized scheduling model.

4.2 Discussion

The findings from this study highlight significant improvements in maintenance

scheduling, equipment reliability, and overall cost savings achieved through the implementation of the optimized maintenance model, specifically using Particle Swarm Optimization (PSO). The application of this model to FIPL's power generation systems demonstrated how advanced optimization techniques can transform traditional maintenance practices into a more efficient, proactive approach.

One of the key findings was the reduction in Mean Time to Repair (MTTR) and the increase in Mean Time Between Failures (MTBF). Before the optimization, equipment like the Gas Turbine Generator (TG-001) required an average of 6 hours for repairs and had a failure rate that caused downtime frequently. After the optimized model was applied, MTTR was reduced to 4 hours, and

MTBF increased from 350 hours to 370 hours. These improvements reflect a more efficient repair process and better equipment reliability, ensuring that critical systems are up and running for longer periods without disruption.

Another important finding was the improvement in equipment availability, which rose from 87% to 91% for the Gas Turbine Generator. The optimization model helped reduce unexpected downtime by scheduling maintenance more strategically. By focusing on preventive maintenance and reducing reactive repairs, the equipment was available for production more often, which is crucial for maintaining high levels of power generation and minimizing energy production losses.

The maintenance cost comparison before and after optimization revealed a significant reduction in expenses. The optimized scheduling model reduced monthly maintenance costs by approximately 20-30%. For example, in February, the total maintenance cost was ₦18,000,000, but by August, this cost had decreased to ₦12,000,000. This decrease was largely due to the reduction in corrective maintenance activities, as the optimized model allowed the plant to focus more on preventive maintenance, thus preventing costly repairs. The application of the PSO model also helped to identify the most cost-effective intervals for both preventive and corrective maintenance.

In terms of Overall Equipment Efficiency (OEE), the results were clear: OEE increased after the optimization, driven by improvements in availability, performance, and quality. Equipment like the Gas Turbine Generator improved its availability from 87% to 91%, while performance also saw a modest increase, contributing to the overall boost in OEE. This improvement in OEE reflects the combined effect of reduced downtime, better resource allocation, and more effective maintenance scheduling.

Finally, the PSO convergence process showed how the algorithm successfully optimized the maintenance schedules over iterations. Initially, the system's maintenance costs were high, but as the PSO algorithm progressed, it progressively reduced the total maintenance costs, stabilizing around ₦14,000,000. This convergence highlighted the model's ability to find an optimal maintenance schedule that minimizes downtime and cost while maintaining high reliability.

V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study successfully developed and tested an optimized maintenance scheduling model for industrial systems, specifically applied to FIPL's power generation operations. By focusing on key objectives, the research demonstrated how an integrated approach to maintenance—incorporating Preventive Maintenance (PM), Corrective Maintenance (CM), and Particle Swarm Optimization (PSO)—could significantly improve equipment reliability, reduce downtime, and cut maintenance costs.

The first objective of analyzing current maintenance practices and challenges revealed that traditional maintenance methods often resulted in unnecessary downtime and high maintenance costs. The second objective, to develop a comprehensive maintenance scheduling model, was achieved by integrating PM, CM, and Tardiness Penalty Costs, with the aim of improving overall system efficiency. The optimized model not only improved equipment reliability but also provided a more balanced and cost-effective approach to scheduling maintenance activities.

The third objective, to optimize maintenance intervals and techniques based on equipment conditions and workload fluctuations, was addressed by applying the PSO algorithm. This allowed for a dynamic, condition-based approach to maintenance scheduling, which led to significant reductions in maintenance costs. The PSO algorithm successfully minimized downtime by ensuring that maintenance tasks were scheduled at the most optimal times, based on real-time data.

In evaluating the effectiveness of the model in improving equipment reliability, reducing downtime, and controlling maintenance costs, the results were clear. The optimized model led to a substantial reduction in both MTTR and maintenance costs, while equipment availability and MTBF improved. These findings validated the model's effectiveness in achieving the desired improvements in operational efficiency.

Finally, the study provided recommendations for implementing the developed maintenance scheduling model in industrial settings. The key takeaway is that a data-driven, proactive maintenance strategy—backed by powerful optimization algorithms like PSO—can significantly enhance performance, reduce operational costs, and contribute to more sustainable and efficient industrial operations.

This research makes significant contributions to the field of maintenance management and industrial systems optimization. By developing and applying an integrated maintenance scheduling model combined with Particle Swarm Optimization (PSO), the study addresses critical challenges in improving equipment reliability, reducing downtime, and minimizing maintenance costs.

5.2 Recommendation

Based on the findings of this research, several recommendations can help organizations further enhance their maintenance practices and extend the benefits of the optimized scheduling model:

- i. It is highly recommended that organizations invest in real-time monitoring systems to collect and analyze data on equipment performance, environmental factors, and operational parameters. By integrating these data sources into the maintenance scheduling model, companies can better anticipate failures and adjust maintenance schedules dynamically, improving system reliability and reducing emergency repair costs.
- ii. The optimized maintenance scheduling model has proven effective for power generation systems; however, it would benefit from further adaptation to different industries. Future research should focus on customizing the PSO model for various sectors, such as manufacturing, mining, and transportation. This would allow organizations in those industries to benefit from similar improvements in efficiency, reliability, and cost reduction.
- iii. Maintenance practices should also consider their environmental impact. It is recommended that future studies explore how optimized maintenance scheduling can contribute to sustainable operations, such as reducing energy consumption, emissions, and waste. By integrating environmental factors into the optimization process, the model could help organizations achieve both operational and environmental sustainability goals.
- iv. For the optimized maintenance model to be effective, companies should invest in training maintenance personnel, engineers, and management on how to use the new model. This includes understanding predictive maintenance technologies, interpreting real-time data, and using optimization algorithms. Proper training will ensure that employees are equipped to fully leverage the benefits of the optimized system and make better, data-driven decisions.
- v. The maintenance model should not be static; it should evolve with the organization's changing needs and external conditions. Continuous monitoring and feedback loops are necessary to refine the model and make real-time adjustments.

REFERENCES

- [1]. Abbasi, T.; Lim, K.H.; Yam, K.S. Predictive maintenance of oil and gas equipment using recurrent neural network. In Proceedings of the Iop Conference Series: Materials Science and Engineering, Jakarta, Indonesia, 21–22 November 2019; p. 012067.
- [2]. Achouch, M.; Dimitrova, M.; Ziane, K.; SattarpanahKarganroudi, S.; Dhoub, R.; Ibrahim, H.; Adda, M. On predictive maintenance in industry 4.0: Overview, models, and challenges. *Appl. Sci.* **2022**, *12*, 8081. [CrossRef]
- [3]. Agogino, A.; Goebel, K. Milling data set. In NASA Ames Prognostics Data Repository; NASA Ames Research Center: Moffett Field, CA, USA, 2007. Available online: <http://ti.arc.nasa.gov/project/prognostic-data-repository> (accessed on 19 January 2024).
- [4]. Ahmad, A.A.; Alshurideh, M. Digital Twin in Facility Management Operational Decision Making and Predictive Maintenance. In Proceedings of the International Conference on Advanced Intelligent Systems and Informatics, Cairo, Egypt, 20–22 November 2022; pp. 437–448.
- [5]. Ahmad, I., Rathore, H. S., Tafamel, A. M., Alzahrani, B., & Rehman, S. U. (2019). Total Productive Maintenance Implementation in Manufacturing Industry: A Systematic Literature Review and Future Research Directions. *International Journal of Advanced Manufacturing Technology*, 104(9-12), 4055-4075.
- [6]. AI, H. High-Level Expert Group on Artificial Intelligence; European

- Commission: Brussels, Belgium, 2019; p. 6.
- [7]. Alhassan, A.M.; Zainon, W.M.N.W. Review of feature selection, dimensionality reduction and classification for chronic disease diagnosis. *IEEE Access* **2021**, 9, 87310–87317. [CrossRef]
- [8]. Al-Najjar, B., Khan, M. A., & Al-Assadi, H. (2020). A Review of Condition-Based Maintenance Optimization Models. *Journal of Quality in Maintenance Engineering*, 26(3), 447-466.
- [9]. Al-Sumaiti, A. S., et al. (2018). Green Maintenance Practices in Power Generation Systems: A Sustainable Approach. *International Journal of Sustainable Energy*, 37(6), 536-551.
- [10]. Alvarez, L., Polo, A., & Hervás, J. (2018). Supplier Collaboration in Maintenance Service Outsourcing: A Systematic Literature Review. *Journal of Purchasing and Supply Management*, 24(4), 292-305.
- [11]. Anagiannis, I.; Nikolakis, N.; Alexopoulos, K. Energy-based prognosis of the remaining useful life of the coating segments in hot rolling mill. *Appl. Sci.* **2020**, 10, 6827. [CrossRef]
- [12]. Anderson, T., et al. (2020). Asset Management Best Practices for Industrial Maintenance. *Journal of Asset Management*, 21(4), 298-312.
- [13]. Andritoi, D.; Luca, C.; Corciova, C.; Ciorap, R. The use of thermography as a prediction element in the maintenance of medical equipment. In *Proceedings of the 6th International Conference on Advancements of Medicine and Health Care through Technology*, Cluj-Napoca, Romania, 17–20 October 2018; pp. 73–78.