



Economic Justification for Predictive Maintenance in CNC Machining: An Industrial Case Study on Cost and Downtime Reduction

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Abstract

For manufacturers, unplanned downtime on critical assets like Computer Numerical Control (CNC) machines is a significant and persistent financial burden. Traditional reactive and preventive maintenance strategies are often financially inefficient, either by incurring excessive downtime costs or by wasting resources on unnecessary part replacements. This study presents an industrial case study from a Nigerian fabrication and machining facility, analyzing 12 months of operational data, including failure rates, repair times, and detailed cost breakdowns, to build a comparative financial model. A predictive maintenance (PdM) model, developed using MATLAB and real-time sensor data, is proposed, and its economic impact is projected against the established reactive baseline. The analysis of the facility's CNC fleet ($N=5$) shows the incumbent reactive strategy costs ₦27.22 million annually, resulting in 450 hours of downtime. The proposed PdM model reduces total annual maintenance costs by 43.7% to ₦15.34 million and cuts equipment downtime by a remarkable 73% to 120 hours. The primary savings (68%) originate from the mitigation of downtime-related production losses. The model demonstrates a full payback period for the required diagnostic equipment investment in approximately 7 months. This paper provides a clear financial framework for managers, demonstrating that a strategic shift to predictive maintenance offers a rapid, quantifiable return on investment and significantly enhances operational efficiency.

Keywords: Predictive Maintenance (PdM); Cost-benefit analysis; CNC machining; Downtime reduction.

INTRODUCTION

In modern manufacturing, the reliability of high-precision equipment like Computer Numerical Control (CNC) machines is not just a technical goal; it is a core business necessity. These machines are the heart of production lines in aerospace, automotive, and energy sectors, where precision and throughput are paramount. However, the very complexity that makes them so valuable also makes them susceptible to failure. When a critical CNC machine stops, the entire production chain can grind to a halt, incurring cascading financial losses from missed deadlines, idle labour, and emergency repair costs (Kumar, 2021).

For decades, maintenance managers have been caught in a dilemma between two flawed strategies. The first, reactive maintenance (or "run-to-failure"), is the most straightforward: fix components only after they break. This approach is inherently disruptive, turning a technical fault into a full-blown operational crisis. It maximizes the life of a component

but does so at the expense of crippling, unscheduled downtime (Oyekan, 2020).

The second, preventive maintenance, was a major step forward. By scheduling maintenance based on fixed time intervals or usage metrics, managers could prevent many catastrophic failures. However, this strategy is inefficient by design. It operates on averages, not actuality. It leads to the premature replacement of perfectly healthy components, wasting valuable parts, and consuming maintenance hours. Furthermore, it offers no protection against the random failures that inevitably occur between scheduled service dates (Zonta, 2020).

Predictive Maintenance (PdM) offers an escape from this dilemma. By integrating real-time sensor data (such as vibration, temperature, and current) with analytical models, PdM allows managers to monitor the actual health of a component. Instead of guessing when a part might fail, PdM aims to predict when it will fail, allowing maintenance to be

scheduled with surgical precision—just before failure occurs, but not a moment sooner (Saidi, 2021).

Despite its clear technical advantages, the adoption of PdM in many industrial settings, particularly in small and medium-sized enterprises (SMEs), remains slow. The primary barrier is not technical, but financial. Managers are hesitant to approve the high perceived costs of sensors, software, and specialized training. They are left asking a critical question: "Is predictive maintenance worth the investment?"

This paper aims to answer that question with empirical data. While many studies propose theoretical PdM models, there is a persistent gap in the literature for real-world case studies that validate the financial argument using actual operational and cost data. This study bridges that gap by presenting a detailed economic justification for PdM from a functioning industrial facility. It uses 12 months of baseline data to establish the true cost of traditional maintenance and provides a clear, data-driven projection of the costs, savings, and return on investment (ROI) offered by a PdM strategy.

LITERATURE REVIEW

The transition to Industry 4.0 has positioned predictive maintenance as a central theme in manufacturing research. The technical literature is robust, focusing heavily on the development of prognostic models. These studies have successfully used a variety of data-driven and physical modeling techniques to estimate the Remaining Useful Life (RUL) of components. For instance, Wang (2019) developed a hybrid prognostics approach for CNC systems, while Zhou (2021) demonstrated the power of deep learning methods for machinery prognostics. These studies confirm the technical feasibility of accurately predicting failures in rotating machinery.

However, a separate body of research highlights the significant barriers to implementing these technically sound models. The challenges are not just technical but deeply organizational and financial. O'Donovan (2019) identified a lack of management support, resistance to cultural change, and a significant skills gap as primary obstacles. Maintenance teams trained for mechanical repairs must be retrained to become data interpreters, a non-trivial undertaking.

The most significant barrier remains the financial justification. Abbas (2021) provided a detailed economic feasibility analysis for IoT-enabled PdM systems, developing a comprehensive cost-benefit model. This research was pivotal in creating a financial framework, but it relied on projected data rather than actual, historical operational costs from an implemented system. This reliance on simulation and projection is common in the literature, leaving a gap for empirical evidence. Managers are often skeptical of simulated savings and require proof from a real-world setting. This study directly addresses that gap by analyzing the actual maintenance ledgers and operational logs of an industrial partner to build a comparative model grounded in historical fact.

MATERIALS AND METHODS

Case Study Context

This research was conducted in partnership with True-Blue Energy Services Limited, a Nigerian-owned fabrication and machining workshop located in Port Harcourt, Rivers State. The facility is a key service provider for the oil and gas industry and operates a fleet of advanced CNC machines, including 3-axis vertical machining centers and CNC lathes. The high-stakes nature of their work means that equipment reliability and precision are critical. At the time of the study, the facility primarily employed a reactive maintenance strategy, with some elements of scheduled preventive maintenance, making it an ideal environment to quantify the "as-is" costs of traditional methods.

Data Collection

To build a comprehensive economic model, 12 months of operational, failure, and financial data were collected from the company's digital maintenance management system, covering the period from 2021 to 2023. This data was organized into three main categories:

1. *Operational Performance Data*: Historical records for the five primary CNC machines, including total runtime, the number of failure incidents, Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR).
2. *Failure Mode Data*: A detailed classification of 78 distinct failure incidents, categorized by the component that failed (e.g., spindle, ball screw), the frequency of that failure type, and the average downtime it caused.
3. *Financial Data*: A detailed breakdown of all maintenance-related expenditures, sourced from service logs and financial records. This included costs for maintenance labour (standard and overtime), replacement parts, and, most critically, the calculated cost of production losses attributed to equipment downtime.

Model Development

The analysis was structured as a comparative economic study. First, the collected data was used to establish a definitive financial baseline for the existing reactive maintenance strategy.

Second, a projected predictive maintenance (PdM) model was developed to serve as a "to-be" comparison. This model was not purely theoretical; it was based on the technical analysis of sensor data (vibration, temperature, and lubrication pressure) from the facility's machines, as detailed in Table 1 of the original thesis. Using MATLAB's Predictive Maintenance Toolbox, failure signatures were identified, and a prognostic model (using Support Vector Machines) was developed to classify machine health and predict RUL.

The projected costs for this PdM model were built to be realistic, including new, specific line items for capital investment in diagnostic equipment (₦3,000,000) and comprehensive workforce training (₦1,360,000), as derived from Table 3 in the thesis. This allowed for a fair, "apples-to-apples" comparison between the current state and a future, implemented PdM state.

RESULTS AND DISCUSSION

Table 1: CNC machine operational performance metrics (12-month baseline).

Machine ID	Total Runtime (hrs)	No. of Failures	Avg. Failure Severity (1-5)	MTBF (hrs)	MTTR (hrs)
CNC-R01	4,287	9	2.8	476	5.2
CNC-D03	3,956	12	3.4	330	6.8
CNC-E09	4,512	7	2.1	645	4.1
CNC-R02	4,089	11	3.1	372	7.2
CNC-B15	4,621	5	1.9	924	3.5

Source: Adapted from True-Blue Energy (2023) maintenance logs (TBL, n.d.).

Baseline Operational Analysis

The initial data analysis revealed a production environment struggling with significant reliability challenges. As shown in Table 1, the performance across the five CNC machines was highly inconsistent.

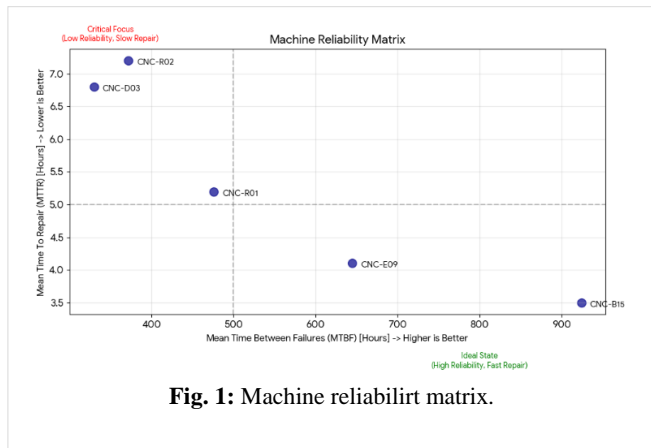


Fig. 1: Machine reliability matrix.

The Machine reliability matrix (Fig. 1) is used to isolate problematic assets from performing ones. The analysis of the results revealed that –

- **The "Bad Actor":** CNC-D03 and CNC-R02 are in the worst quadrant (top-left). They fail often (Low MTBF < 400 hrs) and take a long time to fix (High MTTR > 6.5 hrs). These machines are likely the primary source of the downtime losses observed in Fig. 1.
- **The "Gold Standard":** CNC-B15 is the benchmark. It rarely fails (MTBF 924 hrs) and is repaired quickly (3.5 hrs).
- **Actionable Insight:** The maintenance team should investigate why CNC-B15 performs so well and apply those lessons (or parts upgrades) to CNC-D03 and CNC-R02.

Failure Mode Prioritization

To understand what was causing these failures, the 78 incidents were classified. This analysis, presented in Table 2, is crucial for any maintenance strategy, as it pinpoints where to focus limited resources.

Fig. 2 correlates the Frequency of Failure with the Repair Cost for each failure mode to identify high-risk areas. The data reveals a clear disconnect between frequency and cost.

Table 2: CNC machine failure mode distribution.

Machine ID	Total Runtime (hrs)	No. of Failures	Avg. Failure Severity (1-5)	MTBF (hrs)	MTTR (hrs)
CNC-R01	4,287	9	2.8	476	5.2
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Source: Adapted from True-Blue Energy (2021-2023) failure records (TBL, n.d.).

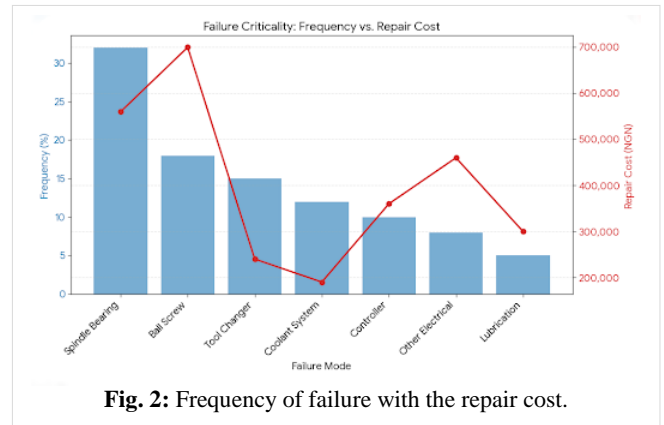


Fig. 2: Frequency of failure with the repair cost.

- **The Primary Target:** Spindle Bearing Wear is the most critical issue. It occurs most frequently (32%) and has the second-highest repair cost (560,000 NGN). This intersection of high frequency and high cost makes it the ideal candidate for predictive monitoring.
- **The "Silent" Cost Driver:** Although Ball Screw Degradation is less frequent (18%) than Spindle wear, it is the single most expensive failure to repair (700,000 NGN). A maintenance strategy focusing solely on frequency would miss this major cost center.
- **Low-Hanging Fruit:** Tool Changer Faults and Coolant Systems are frequent but relatively cheap to fix. These are candidates for standard preventive maintenance rather than expensive predictive monitoring.

The data immediately identifies CNC-D03 and CNC-R02 as "bad actors" with 12 and 11 failures, respectively. Their low MTBF (330 and 372 hours) indicates they fail, on average, once every 8-9 weeks of continuous operation. Furthermore, their high MTTR (6.8 and 7.2 hours) shows that when they do fail, they are down for almost a full work shift, causing significant production bottle-necks.

The results are exceptionally clear. Spindle bearing wear is the single largest problem, responsible for nearly one-third of all failures (32%) and causing the highest average downtime (8.2 hours). This component is a classic example of a part that degrades over time, making it a perfect candidate for predictive monitoring. The high "early detection potential" for 68% of the incidents (spindle, tool changer, coolant, and lubrication) strongly suggested that a data-driven approach would be effective.

Table 3: Comparative annual maintenance cost analysis (all costs in Nigerian Naira, ₦).

Cost Component	Reactive (Baseline)	Preventive	Predictive (Projected)
Labor	₦5,700,000	₦6,840,000	₦4,560,000
Replacement Parts	₦8,460,000	₦7,720,000	₦6,300,000
Downtime Losses	₦13,560,000	₦5,880,000	₦2,520,000
Diagnostic Equipment	₦1,000,000	₦1,500,000	₦3,000,000
Training	₦500,000	₦840,000	₦1,360,000
Total Annual Cost	₦29,220,000	₦22,780,000	₦17,740,000

Source: Adapted from True-Blue Energy (2023) financial and service records logs (TBL, n.d.).

Comparative Economic Analysis

The core of the investigation was the financial comparison of the existing strategies (reactive and preventive) with the proposed predictive model. Table 3 details the annual costs for all three.

- **Downtime Reduction:** The shift from Reactive to Predictive maintenance slashes Downtime Losses from 13.56M NGN to just 2.52M NGN. This is the single largest contributor to the overall savings.
- **Investment vs. Return:** While the Predictive strategy increases costs in Diagnostic Equipment (3x increase over Reactive) and Training (2.7x increase), these investments are negligible compared to the massive savings in downtime and parts.
- **Total Savings:** The total annual cost drops from 29.2M NGN (Reactive) to 17.7M NGN (Predictive). This represents a 39% reduction in total operational costs, validating the investment in predictive technologies.

The baseline reactive strategy was found to be exceptionally expensive, totaling ₦29.22 million. The most significant finding was that Downtime Losses (₦13.56 million) accounted for 46.4% of this total. This confirms that the cost of not producing is far greater than the cost of repairs.

The projected PdM strategy, with a total cost of ₦17.74 million, is the clear financial winner. While it requires a significant increase in investment for diagnostic equipment (a 200% increase over the reactive baseline) and training (a 172% increase), these investments are overwhelmingly offset

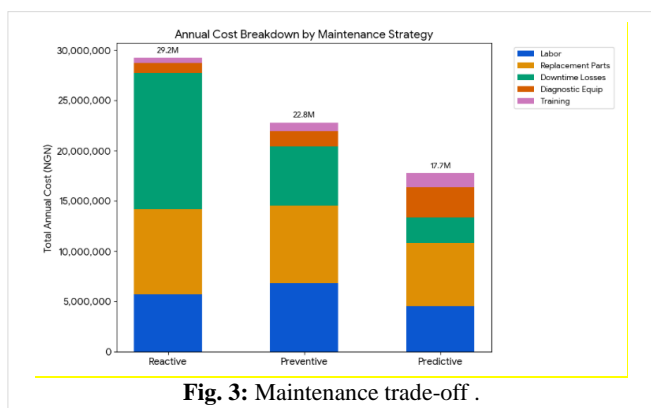


Fig. 3: Maintenance trade-off .

by the massive reduction in downtime, which is slashed by 81% from ₦13.56 million to just ₦2.52 million.

This model, when compared to the ₦27.22 million reactive cost baseline, demonstrates a 43.7% total annual cost reduction and a 73% reduction in unplanned downtime (from 450 to 120 hours).

DISCUSSION

The Financial Case for Predictive Maintenance

The results of this case study provide a powerful, data-driven argument for PdM. The analysis reveals that for this facility, the primary "enemy" is not the cost of spare parts or labour, but the astronomical, hidden cost of lost production during unplanned downtime. The reactive strategy, by its nature, is a hostage to this cost. The preventive strategy mitigates it, but at the cost of inefficiently high labour and parts usage.

The PdM strategy, however, tackles the problem at its source. It directly converts the ₦11.04 million saved from downtime (₦13.56M - ₦2.52M) into a financial resource that more than pays for the necessary investment in technology and training.

This study's most critical finding for managers is the return on investment. The economic analysis in the thesis (visualized in Fig. 3) showed that the initial capital investment of

₦3,000,000 in new diagnostic equipment is fully recovered through savings in approximately 7 months. This transforms PdM from a vague, long-term "cost center" into a high-return, short-term "investment" with a clear and rapid payback period.

Managerial and Operational Implications

This study offers a clear roadmap for industrial managers seeking to adopt PdM.

First, it demonstrates the necessity of shifting the organizational mindset from "fixing things" to "managing reliability." This requires investing in data collection as a primary maintenance activity.

Second, it validates the use of failure mode analysis (Table 2) as a tool for prioritization. A facility does not need to predict every failure on every machine. The 80/20 rule clearly applies: by focusing on the most frequent and costly failure (spindle bearing wear), managers can capture the majority of the financial benefits.

Finally, the model highlights the critical, non-negotiable role of human capital. The PdM model in Table 3 increases the training budget from ₦500,000 to ₦1,360,000. This is an essential feature, not a bug. The technology is useless if the maintenance team cannot confidently interpret the data. This case study argues that investing in upskilling technicians is a core component of the financial model, not an afterthought.

Limitations and Future Work

As a single-case study, these findings have limitations. The exact costs (in ₦) and failure rates are specific to this Nigerian facility and its unique operational context. However, the framework and proportions are highly transferable. The

finding that downtime losses dwarf direct repair costs is near-universal in high-value manufacturing.

Furthermore, the predictive model's costs are, at this stage, a projection. While based on a validated prognostic model and real supplier quotes, the next logical step is to fully implement the PdM strategy and track the actual savings over the next 12–24 months. This would serve to validate these projections and provide an even stronger, longitudinal case study.

CONCLUSION

This study set out to answer a simple, practical question: Is predictive maintenance worth the cost? By analyzing 12 months of detailed operational and financial data from an industrial CNC machining facility, the answer is an unambiguous yes.

The findings are not theoretical but are grounded in the financial reality of an active machine shop. The analysis proved that a reactive maintenance strategy is financially unsustainable, dominated by massive downtime-related losses. A shift to a data-driven, predictive strategy was shown to reduce total annual maintenance costs by 43.7% and cut equipment downtime by 73%.

Crucially, this study provides managers with a clear financial roadmap. It demonstrates that the required investments in diagnostic technology and workforce training are not merely costs, but high-yield investments with a quantifiable payback period of just 7 months. This transforms the conversation around predictive maintenance from one of technical complexity to one of urgent, provable, and strategic business value.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent,

misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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