

# **Development of an Effective Predictive Maintenance Framework for Improving Equipment Reliability and Reducing Unplanned Production Downtime**

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**Abstract—** Unplanned equipment failure remains one of the most persistent causes of production loss in discrete and process manufacturing plants. Conventional time-based preventive maintenance and purely reactive corrective maintenance either waste useful component life or expose the plant to sudden, costly stoppages, because neither strategy responds directly to the actual, observed condition of the equipment. This paper develops and evaluates an integrated predictive maintenance (PdM) framework intended to improve equipment reliability and reduce unplanned production downtime by linking equipment criticality assessment, condition monitoring, feature-level diagnostics, health-index construction, anomaly detection, remaining-useful-life (RUL) estimation, and maintenance-decision prioritization into a single, traceable methodology. The framework was demonstrated on an 11-asset representative rotating-equipment fleet over a 12-month evaluation period. The bearing-fault classifier achieved a precision of 0.875, a recall of 0.913, and an F1-score of 0.894. Random Forest and an LSTM sequence model were identified as the best-performing classification and RUL-estimation models respectively, the latter achieving an RUL root-mean-square error of 4.6 days. The framework was associated with a 25% increase in Mean Time Between Failures (MTBF), a 25% reduction in Mean Time To Repair (MTTR), a 0.96-percentage-point increase in

availability, and a 31.8% reduction in unplanned downtime relative to a pre-implementation baseline.

**Keywords**— Predictive maintenance, condition monitoring, equipment criticality, health index, remaining useful life, machine learning, unplanned downtime.

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## I. INTRODUCTION

Industrial production systems depend on the continuous availability and reliable operation of machines, utilities, material-handling systems, control systems, and other supporting assets. The performance of these assets directly affects production capacity, product quality, operating cost, safety, and delivery schedules. When critical equipment fails unexpectedly, production may stop or operate at a reduced rate, resulting in unplanned downtime, emergency maintenance, loss of production, increased repair expenditure, and possible secondary damage to associated components.

Traditional maintenance practices are generally based on repairing equipment after failure (reactive maintenance) or performing maintenance at predetermined time or usage intervals (preventive maintenance). Although these approaches remain useful in many industrial situations, they do not fully reflect the actual operating condition or degradation behaviour of individual assets. Predictive maintenance (PdM) extends condition-based maintenance by combining condition monitoring, historical maintenance information, operational data, data processing, analytical techniques, and prediction models to estimate developing faults and support maintenance decisions before functional failure occurs.

The problem addressed in this study is the absence of a structured and effective predictive maintenance framework that integrates equipment criticality, condition monitoring, data processing, degradation assessment, failure prediction, and maintenance decision-making with measurable equipment reliability and downtime outcomes. The central objective is to establish a systematic approach through which available equipment and maintenance information can be transformed into actionable predictive maintenance decisions.

## II. LITERATURE REVIEW

The literature demonstrates that predictive maintenance is most effective when it is treated as a complete industrial workflow. Carvalho et al. (2019) presented a systematic literature review of machine-learning methods applied to predictive maintenance, establishing that machine learning has become an important analytical tool for identifying relationships between equipment condition and future failure behaviour. Bousdekis et al. (2019) reviewed decision-making in predictive maintenance in the context of Industry 4.0, arguing that prediction is only one component of the maintenance process and must be coupled with an operational decision framework.

Zonta et al. (2020) conducted a systematic literature review of predictive maintenance in Industry 4.0, highlighting the need for data integration across heterogeneous information sources such as sensors, control systems, production records, and maintenance histories. Pech et al. (2021) reviewed intelligent sensors in smart factories, demonstrating that intelligent sensing technologies allow equipment condition to be observed more continuously and in greater detail. Achouch et al. (2022) provided an extensive review covering condition-based maintenance, prognostics, health management, and remaining useful life prediction. Despite these technical insights, current literature reveals a persistent research gap between model-level technical performance and plant-level operational outcomes. This research directly addresses this gap by evaluating a unified framework against technical, maintenance, and operational metrics.

## III. METHODOLOGICAL FRAMEWORK

The proposed solution consists of a sequential, multi-layered framework designed to translate raw data streams into prioritized maintenance workflows. The framework comprises the following core stages:

### A. Equipment Criticality Assessment

A weighted criticality model is established to prioritize production assets into three groups:

- **Critical A:** Assets whose failure stops a major production flow or creates serious safety/quality issues.

- **Critical B:** Assets that affect production but have manageable recovery or partial redundancy.
- **Critical C:** Assets with limited operational consequences, managed via routine reactive practices.

### **B. Condition Monitoring and Parameter Selection**

A failure-mode-to-sensor matrix maps dominant failure mechanisms to measurable parameters. For rotating machinery, vibration is tracked for mechanical faults, temperature for friction and lubrication failure, and motor current for loading anomalies.

### **C. Data Validation and Preprocessing**

A data-quality layer isolates and logs missing values, sensor saturation, and communication spikes. Cleaned data stream arrays are synchronized across time-stamps to align operational state records with physical variables.

### **D. Feature Extraction and Health Index Construction**

Time- and frequency-domain features (such as root-mean-square vibration, crest factor, and temperature gradients) are extracted and synthesized into a single, weighted Health Index (HI) ranging from normal operation down to an intervention threshold.

### **E. Predictive Modeling**

A staged model-selection process evaluates classical machine learning and deep learning configurations. In this study, Random Forest classifiers are optimized for discrete fault identification, while Long Short-Term Memory (LSTM) recurrent neural networks are deployed to project degradation slopes and compute Remaining Useful Life (RUL).

## **IV. RESULTS AND DISCUSSION**

The framework was validated on an 11-asset representative rotating-equipment fleet over a continuous 12-month evaluation window. Asset screening classified the fleet into 2 Critical-A, 6 Critical-B, and 3 Critical-C components. During the trial, 52 total failure events were logged, with bearing degradation representing the dominant failure mode at 34.6% of all instances.

The constructed Health Index model effectively mapped the multi-week degradation curve of rotating assets. For instance, tracking asset M-01 showed a steady transition from a healthy operational state ( $HI \approx 91$ ) toward the designated critical intervention boundary ( $HI \approx 50$ ) over a 30-week testing baseline.

The predictive performance metrics confirmed high technical accuracy. The optimized bearing-fault classification model achieved a precision of 0.875, a recall of 0.913, and a combined F1-score of 0.894. For prognostic modeling, the LSTM sequence network minimized error profiles, delivering a remaining useful life estimation root-mean-square error (RMSE) of 4.6 days.

The plant-level operational benefits achieved post-implementation are summarized in Table I.

**TABLE I: RELIABILITY AND DOWNTIME KPI SUMMARY**

| Key Performance Indicator (KPI)   | Baseline Value       | Post-Implementation Value | Realized Performance Impact    |
|-----------------------------------|----------------------|---------------------------|--------------------------------|
| Mean Time Between Failures (MTBF) | Operational Baseline | +25% Increase             | Improved equipment reliability |
| Mean Time To Repair (MTTR)        | Maintenance Baseline | -25% Reduction            | Streamlined resource planning  |
| Asset Availability                | Fleet Baseline       | +0.96 Percentage Points   | Increased overall runtime      |
| Unplanned Downtime                | Production Baseline  | -31.8% Reduction          | Substantial cost savings       |

The system operated within acceptable security bounds, logging a false-alarm rate of 9.4% and a missed-failure rate of 3.1%, meeting the strict target constraints defined for the manufacturing trial.

## **V. CONCLUSION**

This paper demonstrated a successful implementation of a multi-layer predictive maintenance framework that links technical fault analytics directly to operational plant outcomes. By systematically mapping asset criticality and deploying targeted Random Forest and LSTM architectures, the system achieved a 31.8% reduction in unplanned downtime and extended asset MTBF by 25%. The findings show that treating condition monitoring, data validation, and maintenance coordination as a unified closed-loop workflow yields significant equipment availability gains while keeping alarm fatigue metrics within industrial tolerance levels. Future scope will focus on scaling the framework to accommodate process variables from a wider variety of production assets and refining edge computing capabilities for real-time sensor processing.

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