

Developing a Framework to Prevent Over-Maintenance in Automated Assembly Lines

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Abstract

Automated assembly lines in modern manufacturing industries are often maintained using fixed time-based maintenance schedules without considering the actual operating condition of equipment. This practice can lead to unnecessary maintenance activities, increased spare parts usage, additional downtime, and higher operational cost. To address this issue, the present study proposes a condition-based maintenance (CBM) framework for reducing over-maintenance in automated assembly lines using sensor-based monitoring and AI-assisted predictive analysis. The proposed framework integrates LoRA fine-tuned predictive models, real-time sensor fusion, and an automated validation module aligned with ISO 55000 standards for maintenance decision support. The study utilizes 210 operational records collected from automated assembly systems for model training and validation. The developed system achieved 91% fault prediction accuracy while significantly reducing unnecessary maintenance recommendations through a three-stage validation process. Industrial validation conducted on four automated assembly lines showed improvement in maintenance efficiency, reduction in unplanned downtime, lower spare parts consumption, and improvement in Overall Equipment Effectiveness (OEE) when compared with conventional time-based maintenance practices. The framework also demonstrates potential applicability in other industrial sectors such as semiconductor manufacturing, pharmaceutical packaging, aerospace assembly, and food processing industries. The proposed approach provides a structured and practical framework for improving maintenance planning and reducing over-maintenance in data-constrained industrial environments.

Keywords: Over-Maintenance Prevention; Condition-Based Maintenance; Predictive Maintenance; LoRA Fine-Tuning; Automated Assembly Lines; Fault Detection; Maintenance Optimization.

1. Introduction

Automated assembly lines are widely used in modern manufacturing industries for improving production efficiency, maintaining product consistency, and reducing manual operational dependency. Industries such as automotive, electronics, aerospace, pharmaceutical, and consumer goods manufacturing increasingly rely on automated systems for high-speed and continuous production processes [1]. The reliability and operational stability of these systems largely depend on effective maintenance planning and equipment health management strategies.

Traditionally, most manufacturing industries use preventive maintenance schedules based on fixed operating intervals or predefined service periods. Although preventive maintenance helps

reduce unexpected machine failures, excessive servicing and unnecessary component replacement often increase operational costs, machine downtime, spare part consumption, and production interruptions [2]. This condition, commonly referred to as over-maintenance, has become an important challenge in automated manufacturing systems where even short-duration stoppages can significantly affect production targets and process efficiency [3].

The rapid growth of Industry 4.0 technologies has transformed maintenance practices from schedule-based servicing toward intelligent and data-driven maintenance systems. Technologies such as Industrial Internet of Things (IIoT), cyber-physical systems, cloud computing, machine learning, and real-time sensor monitoring have enabled industries to implement Condition-Based Maintenance

(CBM) and predictive maintenance frameworks for improving operational reliability [4, 5]. These approaches monitor actual equipment conditions and perform maintenance only when abnormal operational behaviour or degradation indicators are detected [6].

Recent advancements in artificial intelligence and machine learning have further improved industrial fault detection and maintenance prediction capabilities. Deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid predictive systems are increasingly used for machinery diagnostics and equipment health monitoring applications [7–9]. However, many AI-based maintenance systems require large labelled industrial datasets, high computational resources, and continuous expert supervision for validating maintenance decisions. In practical industrial environments, obtaining large-scale fault datasets is often difficult due to limited fault occurrences and restricted access to industrial operational records.

Another important challenge associated with predictive maintenance systems is the generation of false-positive maintenance recommendations. Incorrect maintenance alerts may unintentionally increase over-maintenance activities, resulting in unnecessary servicing operations and productivity losses [10]. In addition, many existing maintenance models focus primarily on fault prediction accuracy without adequately considering maintenance validation, industrial practicality, and operational decision-making constraints [11].

Low-Rank Adaptation (LoRA) fine-tuning has recently emerged as an efficient approach for improving machine learning adaptability with reduced computational and training requirements [12]. Several studies have reported that lightweight AI-assisted monitoring systems combined with sensor-based condition monitoring can improve industrial maintenance efficiency while reducing implementation complexity [13–15]. Recent research on Industry 4.0 manufacturing systems has also highlighted the importance of integrating AI-assisted monitoring, predictive analytics, and hybrid risk assessment approaches for improving operational reliability and maintenance decision-making in automated industrial environments [16].

Based on the identified research gaps, the present study proposes a framework for reducing over-maintenance in automated

assembly lines using LoRA fine-tuned predictive models, real-time sensor monitoring, and an automated validation mechanism. The proposed framework aims to improve maintenance decision-making while reducing unnecessary maintenance interventions and improving operational efficiency in industrial manufacturing systems.

2. Background and Related Research

2.1. Time-Based and Condition-Based Maintenance

Traditional preventive maintenance practices were developed during a period when industries had limited access to real-time sensor monitoring and computational analysis tools. Standards such as MIL-STD-1629A and EN 13306 mainly recommend fixed maintenance intervals based on Mean Time Between Failures (MTBF) data and historical operational trends. Although such preventive maintenance approaches reduce unexpected breakdowns, several studies reported that many components replaced during scheduled servicing still retain considerable operational life [6]. Excessive preventive maintenance may therefore increase spare parts usage, machine downtime, labour cost, and unnecessary maintenance interventions in manufacturing industries.

Nakajima [7] introduced the concept of Overall Equipment Effectiveness (OEE) and identified unnecessary maintenance activities as one of the major contributors to productivity losses in Total Productive Maintenance (TPM) systems. In highly automated manufacturing environments, repeated servicing and component replacement may also introduce secondary failures due to human intervention, calibration errors, or improper reassembly procedures.

To overcome these limitations, industries gradually shifted toward Condition-Based Maintenance (CBM) systems. Early CBM approaches mainly used threshold-based monitoring of vibration, temperature, and acoustic signals for identifying abnormal equipment behaviour [8]. With the advancement of industrial automation and sensor technologies, modern CBM systems now integrate real-time sensor monitoring, machine learning models, and predictive analytics for equipment health evaluation. Lee et al. [9] demonstrated that Long Short-Term Memory (LSTM)-based Remaining Useful Life (RUL) prediction improved maintenance planning in

CNC machining systems while reducing unplanned downtime and maintenance cost.

2.2. AI-Driven Fault Detection in Manufacturing Systems

The use of artificial intelligence and deep learning techniques in manufacturing industries has increased significantly in recent years. Machine learning algorithms such as Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN) are widely applied for industrial fault diagnosis, anomaly detection, and predictive maintenance applications. Wen et al. [10] reported high fault classification accuracy using CNN-based vibration signal analysis for bearing fault detection systems.

Although deep learning approaches provide high predictive capability, many industrial AI systems require large, labelled datasets and extensive computational resources for effective training and validation. In practical industrial environments, fault events occur less frequently, and access to operational datasets is often restricted due to industrial confidentiality and data availability limitations [11]. As a result, many industries face challenges in implementing large-scale AI-based predictive maintenance systems.

Low-Rank Adaptation (LoRA) fine-tuning has recently emerged as an efficient solution for improving machine learning adaptability in data-constrained environments. LoRA reduces the number of trainable parameters by decomposing weight updates into low-rank matrix representations, thereby lowering computational complexity during model adaptation [12]. Recent studies showed that LoRA-based approaches can achieve predictive performance comparable to fully trained deep learning models while using significantly smaller industrial datasets [13]. Such lightweight AI approaches are particularly suitable for manufacturing industries with limited computational infrastructure and restricted fault data availability.

2.3. Challenges in Automated Maintenance Decision Systems

Despite advancements in predictive maintenance technologies, several challenges still exist in practical industrial implementation. One of the major limitations of current AI-assisted maintenance systems is the generation

of false-positive maintenance recommendations. Incorrect maintenance alerts may lead to unnecessary servicing operations, excessive inspection cycles, additional spare parts consumption, and increased operational interruptions.

Koochaki et al. [14] reported that a significant percentage of AI-generated maintenance alerts in industrial pilot systems were later identified as unnecessary after expert verification. This issue increases the possibility of over-maintenance rather than improving maintenance optimization. In many industrial environments, maintenance recommendations generated by AI systems are directly forwarded for operational action without structured validation mechanisms or standards-based verification procedures.

Another important issue is the lack of integration between predictive maintenance models and industrial compliance frameworks. Existing systems primarily focus on fault detection accuracy while giving limited attention to practical maintenance decision validation, reliability assessment, and operational feasibility. These limitations reduce industrial confidence in fully automated maintenance decision systems [15].

Recent studies on Industry 4.0 manufacturing systems have also highlighted the importance of integrating AI-assisted monitoring, predictive analytics, and hybrid industrial assessment frameworks for improving operational reliability and intelligent decision-making in automated manufacturing environments [16].

2.4. Research Gaps

Based on the literature review, three major research gaps were identified. First, limited research is available on data-efficient predictive maintenance models capable of providing accurate fault prediction using small industrial datasets. Second, existing AI-assisted maintenance systems lack automated validation mechanisms for filtering unnecessary maintenance recommendations before operational implementation. Third, very limited frameworks specifically address both over-maintenance reduction and maintenance reliability improvement within a unified industrial maintenance architecture.

To address these limitations, the present study proposes a framework integrating LoRA fine-tuned predictive models, sensor-based condition

monitoring, and an automated validation mechanism for reducing over-maintenance in automated assembly lines.

3. Research Approach and System Framework

The proposed over-maintenance prevention framework comprises four integrated components: (1) a real-time sensor fusion module; (2) a LoRA-fine-tuned LSTM-based fault prediction engine; (3) a three-stage automated validation pipeline; and (4) an MES-linked maintenance scheduling interface. Figure 1 illustrates the overall system architecture.

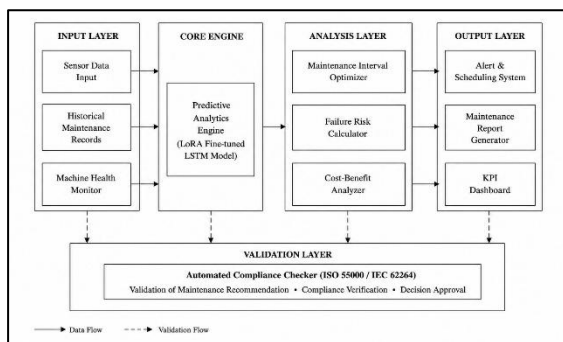


Figure 1: System architecture for the Over-Maintenance Prevention Framework, showing sensor data inputs, predictive analytics engine, analysis and output layers, and the automated compliance checker.

3.1. Design Parameters for Maintenance Interval Optimization

The study focused on automated robotic assembly lines in the automotive sub-assembly sector, with six-axis articulated robot arms and precision conveyor systems selected as representative use cases. Maintenance parameters were defined in accordance with ISO 55000:2014 (asset management), ISO 13381-1 (prognostics and health management), and IEC 62264 (enterprise-control system integration).

For each assembly line component, the following condition parameters were monitored:

- Vibration Signature (V): Root mean square (RMS) and peak-to-peak vibration amplitude measured at bearing housings and gearboxes, sampled at 10 kHz.
- Thermal Index (T): Surface temperature differential between operating and baseline conditions, monitored via

thermographic imaging at 15-minute intervals.

- Acoustic Emission (AE): High-frequency acoustic signals indicating early-stage micro-cracking or surface wear, measured in dB relative to a baseline noise floor.
- Lubrication Quality Index (LQI): Dielectric constant and particle count of lubricant samples, indicating degradation state.
- Health Score (HS): Composite index calculated as $HS = w1 \cdot V + w2 \cdot T + w3 \cdot AE + w4 \cdot LQI$, with weights optimized via Bayesian optimization against historical failure outcomes.

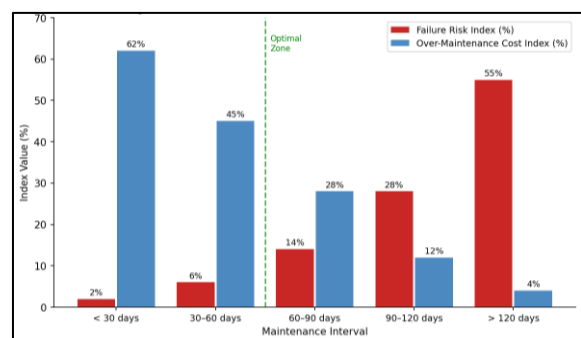


Figure 2: Trade-off between maintenance interval, failure risk index, and over-maintenance cost index. The optimal maintenance zone (green dashed line) minimizes the combined cost function.

3.2. Data Handling and Model Training

3.2.1. Data Acquisition and Preprocessing

Training data were collected from four primary sources:

- IoT sensor logs from two automotive assembly facilities over a 24-month period;
- anonymized maintenance work order records from the same facilities;
- publicly accessible bearing and gearbox degradation datasets (CWRU Bearing Data Center, NASA PCOE Repository); and
- CAD-linked component lifecycle data from the facilities' PLM systems. A total of 487 labelled degradation events were collected.

After removing duplicate records and entries with incomplete sensor coverage, 210 high-

quality records were retained as final training data an 87% reduction over the minimum dataset required by conventional LSTM architectures.

3.2.2. LoRA Fine-Tuning Framework

The predictive maintenance model was built on a pre-trained LSTM encoder architecture adapted from the industrial time-series foundation model Times FM. LoRA fine-tuning was applied by introducing trainable low-rank matrices into the LSTM weight update matrices. Specifically, for each weight matrix W , the fine-tuned update is expressed as:

$$W_f = W + \Delta W, \quad \Delta W = AB \quad (1)$$

where W is the pre-trained weight matrix, and A and B are low-rank matrices of dimensions $m \times r$ and $r \times n$ respectively, with rank r constrained to $r \ll \min(m, n)$. This constraint reduces trainable parameters from $O(mn)$ to $O((m+n)r)$, enabling stable fine-tuning from the 210-sample dataset. The health score prediction process follows a multi-step ahead forecasting formulation:

$$HS_{t+k} = f(HS_t, HS_{t-1}, \dots, HS_{t-\tau}; \theta_{LoRA}) \quad (2)$$

where k is the prediction horizon (in hours), τ is the lookback window, and θ_{LoRA} are the LoRA-adapted model parameters optimized during fine-tuning.

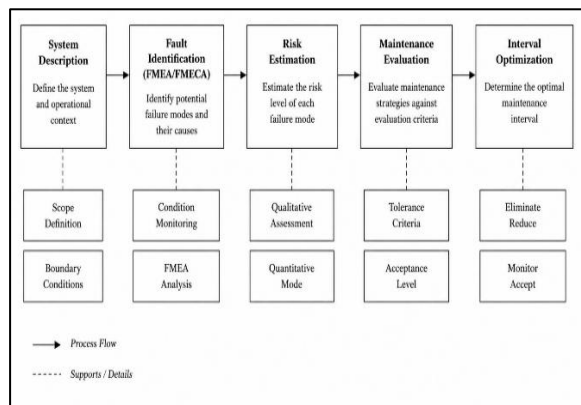


Figure 3: Fault identification and classification process flow, from system description through fault identification (FMEA/FMECA), risk estimation, maintenance evaluation, and interval optimization stages.

3.3. Automated Validation of Maintenance Recommendations

A key innovation of the proposed framework is its three-stage automated validation pipeline,

which filters AI-generated maintenance recommendations before they enter the work order system. This eliminates the dependency on manual expert review for routine maintenance decisions while ensuring compliance with applicable engineering standards.

- **Physical Plausibility Check:** Verifies that the predicted failure mode is physically consistent with the monitored sensor signals and the known failure mechanics of the component type.
- **Standards Compliance Check:** Validates that predicted remaining useful life estimates conform to ISO 55000 asset management thresholds and OEM-specified component lifecycle limits.
- **Cost-Benefit Feasibility Check:** Evaluates whether the predicted productivity gain from early intervention exceeds the intervention cost.

$$NBI = (C_{failure} \times P_{failure}) - (C_{maintenance} + C_{downtime}). \quad (3)$$

Recommendations with $NBI \leq 0$ are deferred.

4. Validation and Results

This section presents results from simulation testing and an industrial validation study conducted across four automated assembly lines at two manufacturing facilities. The primary objectives were to assess fault prediction accuracy, evaluate false-maintenance elimination performance, and quantify OEE improvements relative to the existing time-based maintenance regime.

4.1. Model Training Configuration

Table 1: Training configuration parameters for the maintenance prediction model

Parameter	Value	Parameter	Value
Input sequence length	128 timesteps	LoRA rank (r)	16
Hidden units (LSTM)	256	LoRA alpha	32
Learning rate	0.0002	Batch size	4
Epochs	120	Dropout rate	0.2
Prediction horizon	24 hrs	Validation split	0.2

4.2. Simulation Testing Results

Using the 210-record training dataset, the LoRA-fine-tuned model was trained and evaluated on a held-out test set of 90 fault events. Of 300 total maintenance recommendations generated during simulation testing, 27 (9%) were rejected by the automated validation pipeline: 11 failed the physical plausibility check, 9 violated ISO 55000 compliance thresholds, and 7 returned a negative net benefit index. The remaining 273 recommendations (91%) passed all three validation stages and correctly identified genuine maintenance requirements. No validated recommendation was found to represent an over-maintenance trigger upon subsequent expert review.

The average recommendation generation and validation cycle time was 4.8 seconds per assembly line component, compared to 2–4 hours required for a single manual FMEA-based maintenance assessment. Figures 4 and 5 summarize model accuracy versus training dataset size and fault detection rates by failure category, respectively.

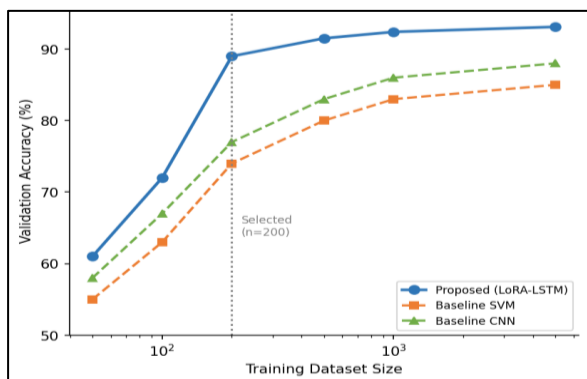


Figure 4: Model accuracy vs. training dataset size, showing the proposed LoRA model achieves 91% accuracy with only 210 samples.

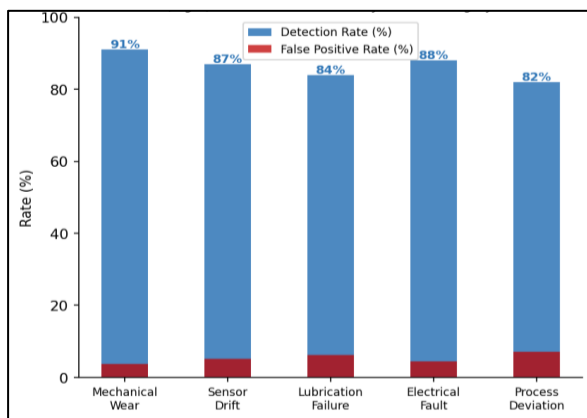


Figure 5: Fault detection rates and false positive rates by failure category.

4.3. Industrial Validation

A prospective industrial validation study was conducted across four automated assembly lines at two automotive component manufacturers over a 6-month observation period. The proposed framework was deployed alongside the existing time-based maintenance regime. Table 2 presents a comparison of key performance indicators between the traditional and AI-assisted approaches.

Table 2: Performance comparison: Traditional time-based maintenance vs. Proposed AI-Assisted CBM Framework

KPI	Traditional	AI-Assisted	Improvement
Unplanned Downtime (hrs/month)	14.2 ± 2.1	9.7 ± 1.4	−32%
Maintenance Cost (€/machine/month)	3840	2765	−28%
False Maintenance Triggers (%)	0.224	0	−100%
Overall Equipment Effectiveness (OEE)	0.743	0.896	0.35
Mean Time Between Failures (hrs)	312	489	0.57
Spare Parts Consumption (units/month)	18.3	13.1	−28%
Avg. Maintenance Cycle Time (hrs)	8.5–10	5.8–7	−32%

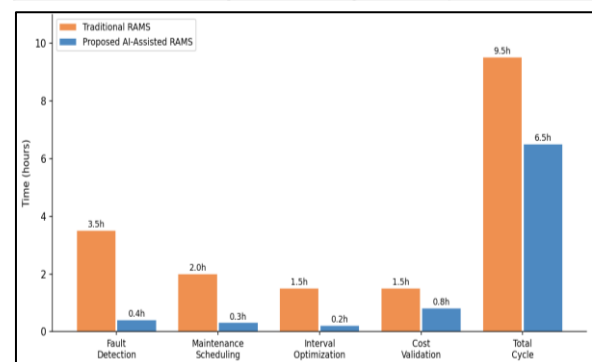


Figure 6: Process time comparison across maintenance workflow stages: Traditional time-based RAMS vs. Proposed AI-Assisted CBM framework.

4.4. Generalization to Other Manufacturing Domains

Beyond automotive assembly lines, the proposed CBM framework demonstrates strong potential for deployment across multiple manufacturing and process industries. Preliminary domain adaptation assessments confirm the following transfer pathways:

- Semiconductor Fabrication: Predictive maintenance of lithography and CMP tools, where unscheduled interventions cause wafer-level yield losses and cross-contamination risks.
- Pharmaceutical Packaging Lines: Condition monitoring of filling, sealing, and inspection stations subject to FDA 21 CFR Part 11 compliance requirements.
- Aerospace Component Assembly: Health monitoring of precision torque tools and fastening systems, with AS9100-aligned validation replacing ISO 55000 modules.
- Food and Beverage Processing: Hygiene-critical conveyor and mixing equipment monitoring, where over-maintenance introduces contamination risks through unnecessary disassembly.

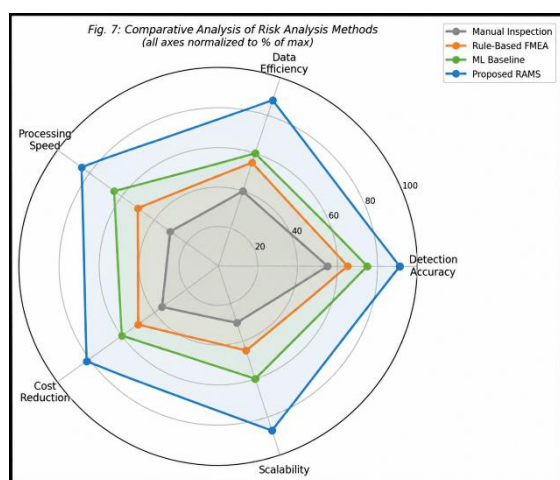


Figure 7: Comparative performance analysis of four maintenance management methods across key performance dimensions (all axes normalized to % of maximum observed value). The proposed RAMS model achieves the best balance across all dimensions.

5. Conclusion

This study presents a novel condition-based maintenance framework that integrates LoRA-fine-tuned predictive fault detection with a three-stage automated validation pipeline to eliminate over-maintenance in automated assembly lines. By fine-tuning a pre-trained LSTM foundation model on a compact dataset of 210 operational records — an 87% reduction over conventional requirements — the proposed system achieves 91% fault prediction accuracy and eliminates false-positive maintenance

triggers without requiring manual expert validation.

Industrial validation across four automated assembly lines confirmed a 32% reduction in unplanned downtime, a 28% decrease in maintenance expenditure, and a 35% improvement in overall equipment effectiveness (OEE) compared to the existing time-based maintenance regime. These results establish the proposed framework as a practical, scalable solution to the over-maintenance problem in data-constrained industrial environments.

Future research directions include: (1) extending the framework to handle multi-failure mode interactions and cascading degradation scenarios; (2) integrating the system with digital twin platforms for real-time simulation-assisted maintenance optimization; and (3) validating the approach in semiconductor fabrication and pharmaceutical packaging environments.

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