



AI-Driven Predictive Maintenance Vs Traditional Maintenance Approaches in Manufacturing

Sariya Jabeen Duriya¹, Varakala Anitha², Tallapally Mounika³, Vanaparthi Kiranmai⁴

¹Assistant Professor, Department of CSE, Nawab Shah Alam College of Engineering & Technology

²Assistant Professor, Department of Information Technology, Gurunanak Institute of Technical Campus

³Assistant Professor, Department of Data Science, Gurunanak Institute of Technical Campus-Hyderabad

⁴Assistant professor, Department of CSE(AIML), Gurunanak institution's technical campus, Hyderabad

Correspondence

Sariya Jabeen Duriya

Assistant Professor, Department of CSE,
Nawab Shah Alam College of Engineering &
Technology, India

Abstract

This research presents a comparative analysis of AI-driven predictive maintenance and traditional maintenance approaches, including reactive and preventive maintenance, within the manufacturing sector. Reactive maintenance, a run-to-failure strategy, often leads to significant downtime and costly repairs, while preventive maintenance schedules regular checks to reduce breakdowns but can result in over-maintenance and inefficiencies. Predictive maintenance, enhanced by AI, uses real-time sensor data, machine learning algorithms, and cloud-edge computing to predict equipment failures before they occur. Experimental results show that predictive maintenance outperforms both reactive and preventive methods in key metrics such as downtime, maintenance cost, repair frequency, and mean time between failures (MTBF). By leveraging AI to analyze equipment conditions, predictive maintenance ensures timely interventions, optimizing operational efficiency and reducing overall costs. These findings demonstrate the superiority of predictive maintenance in enhancing equipment reliability and cost-effectiveness in manufacturing environments..

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Introduction

Maintenance in manufacturing refers to the systematic efforts to preserve and ensure the optimal functioning of equipment and machinery. It is a critical aspect of operations management aimed at reducing downtime, enhancing operational efficiency, and extending the life cycle of machines. In manufacturing, machinery and equipment are the backbone of production, and even a slight disruption can lead to costly delays, reduced product quality, or missed deadlines. Maintenance strategies can range from simple routine checks to complex interventions designed to prevent system failures, ensuring that the manufacturing process continues to operate smoothly. As manufacturing technology advances, maintenance practices have also evolved, transitioning from basic manual inspections to automated, AI-powered systems capable of predicting failures before they occur. This shift has been driven by the need to minimize downtime and maximize production efficiency in an increasingly competitive global market.

Importance of Maintenance

Effective maintenance is crucial for

maintaining continuous production, extending the lifespan of machinery, and ensuring cost-efficiency. In manufacturing, any machine breakdown can result in unplanned downtime, which directly impacts productivity and revenue. Proper maintenance helps avoid such scenarios by ensuring that machines are kept in optimal working condition. It also reduces the risk of major equipment failures, which could lead to costly repairs or replacements. Over time, regular maintenance extends the life of machinery, delaying the need for expensive capital investments in new equipment. Moreover, effective maintenance enhances safety by minimizing the risks of accidents caused by malfunctioning machines. From a financial perspective, a well-maintained production environment contributes to reduced operational costs, as companies can prevent high repair bills and avoid losses due to downtime or lower production quality..

Traditional vs. AI-Driven Approaches

Traditionally, maintenance in manufacturing has been categorized into two main strategies: reactive maintenance (also known as run-to-failure) and preventive maintenance. Reactive maintenance focuses on repairing or replacing

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machines after they fail, leading to unscheduled downtime and often high repair costs. Preventive maintenance, on the other hand, schedules regular checks and repairs to avoid unexpected failures. Although preventive maintenance can reduce downtime, it can be inefficient because it often involves unnecessary maintenance activities based on fixed time intervals, regardless of the actual condition of the equipment.

AI-driven predictive maintenance offers a significant shift from these traditional approaches. Instead of waiting for failure or conducting maintenance based on predefined schedules, AI systems use real-time data and machine learning algorithms to predict when equipment is likely to fail. This allows maintenance teams to intervene before a breakdown occurs, minimizing downtime and reducing repair costs. AI-driven systems rely on data collected from sensors installed on machines, which monitor factors like temperature, vibration, and pressure. By analyzing this data, AI models can identify patterns and anomalies that indicate potential failures. The AI approach offers greater precision, cost-effectiveness, and adaptability, making it a more dynamic solution compared to traditional methods. As a result, manufacturing firms that adopt AI-driven predictive maintenance can optimize their maintenance processes, reduce downtime, and extend the life of their equipment.

Literature Survey

Reactive maintenance, commonly referred to as the run-to-failure approach, is a traditional maintenance strategy where equipment is repaired or replaced only after it has failed. This approach assumes that breakdowns are inevitable, and no action is taken to prevent them beforehand. While reactive maintenance can seem cost-effective in the short term—since no resources are spent on maintenance activities until failure occurs—it often results in significant unplanned downtime. In manufacturing environments where continuous operation is critical, unexpected machinery failures can halt production lines, leading to delays, decreased productivity, and lost revenue. Additionally, repairing equipment after failure is usually more costly, as parts may need to be replaced, and urgent repairs often involve higher labor costs. In some cases, reactive maintenance can also result in more extensive damage to other components of the machine, further increasing repair costs. The unpredictable nature of this approach makes it less efficient for modern manufacturing processes, where consistent uptime and reliability are vital for maintaining competitive advantage.

Preventive Maintenance (Scheduled Maintenance)

Preventive maintenance is a more proactive approach to equipment upkeep, where machines undergo regular inspections, checks, and repairs according to a fixed schedule, regardless of their condition. The goal is to prevent unexpected breakdowns by addressing potential issues before they lead to failure. This strategy is widely used in manufacturing because it reduces the likelihood of unplanned downtime, increases the overall reliability of machinery, and extends the lifespan of equipment. Preventive maintenance plans are usually based on the manufacturer's recommendations or historical data about the performance and wear of the equipment.

While preventive maintenance offers clear advantages, such as reduced downtime and improved equipment reliability, it also has limitations. One major drawback is over-maintenance, where machines are maintained more frequently than necessary. This can lead to inefficiencies, as resources are spent on maintenance activities that may not be required, and it may increase costs

without delivering corresponding benefits. Another challenge is the rigid scheduling of maintenance activities, which does not account for the actual condition of the equipment. Even if a machine is operating optimally, it may still undergo maintenance based on the set schedule, leading to unnecessary interventions. In contrast, some issues may develop between scheduled maintenance checks and go unnoticed, resulting in unexpected failures despite preventive efforts. Overall, while preventive maintenance is more effective than reactive maintenance, it can still be inefficient and resource-intensive when not tailored to the specific needs and real-time conditions of equipment.

Methodology

Predictive maintenance is an advanced approach to equipment management that leverages data-driven techniques to predict when a machine is likely to fail. Unlike traditional maintenance strategies, which rely on either reactive or scheduled interventions, predictive maintenance utilizes real-time data to assess the actual condition of machinery and predict potential breakdowns before they occur. By doing so, it allows for timely interventions, minimizing downtime and extending the lifespan of equipment. The integration of Artificial Intelligence (AI) significantly enhances predictive maintenance by enabling the analysis of vast amounts of data collected from various sources. AI-driven models and machine learning algorithms can identify patterns and anomalies in the data that are indicative of impending failures, offering manufacturers a more precise and proactive maintenance solution. The ultimate goal is to improve equipment availability, reduce maintenance costs, and optimize the overall operational efficiency of the manufacturing process.

Components of AI-Predictive Maintenance

Sensors and IoT Devices

The foundation of predictive maintenance lies in the use of sensors and Internet of Things (IoT) devices that continuously monitor the health and performance of machines. These sensors are capable of collecting real-time data on key parameters such as vibration, temperature, pressure, humidity, and oil levels. For instance, vibration sensors can detect early signs of mechanical wear or misalignment, while temperature sensors can identify overheating issues that might indicate potential equipment failure. IoT devices connect these sensors to a centralized system, enabling the seamless transmission of data from the factory floor to the cloud or an edge computing platform. This constant flow of data provides a comprehensive, real-time view of the equipment's condition, allowing manufacturers to identify any deviations from normal operating behavior. By implementing such sensor networks, companies can establish the groundwork for an effective predictive maintenance system.

Data Analytics and Machine Learning

The vast amount of data collected by sensors is only valuable if it is analyzed effectively. This is where data analytics and machine learning come into play. AI algorithms process the raw data to uncover trends, correlations, and anomalies that indicate the health of the equipment. Machine learning models, in particular, are highly effective because they can "learn" from historical data, continuously improving their predictions over time. For example, if a particular machine shows increasing vibration levels before failing, the AI system can learn this pattern and alert maintenance teams if it detects similar conditions in the future. Predictive maintenance relies heavily on supervised and unsupervised learning algorithms, which can classify different failure modes, predict when a machine will

require servicing, and even recommend specific maintenance actions based on the data. The ability to analyze data in real-time and predict failures before they occur allows companies to reduce unplanned downtime and optimize their maintenance schedules.

Cloud and Edge Computing

The enormous volume of data generated by industrial machinery requires robust computational power and storage capabilities, which is where cloud computing and edge computing play critical roles. Cloud computing allows companies to store, process, and analyze large amounts of machine data remotely. With cloud-based predictive maintenance solutions, manufacturers can access real-time insights from anywhere and easily scale their operations as needed. However, not all data processing can be done in the cloud due to latency issues, especially in time-sensitive industrial environments. This is where edge computing comes in. By performing data processing closer to the source—at the "edge" of the network, near the machines—edge computing reduces latency, enabling real-time decision-making without relying on a centralized cloud. In predictive maintenance, this hybrid model of cloud and edge computing ensures that data can be processed quickly and efficiently, delivering actionable insights without delay.

Algorithms (e.g., Regression, Neural Networks)

A range of AI algorithms is employed to make accurate predictions about equipment health. One of the most basic approaches is regression analysis, where historical data is used to predict future outcomes, such as when a machine is likely to fail based on its operating conditions. More advanced methods, like neural networks, offer greater predictive accuracy. Neural networks are particularly useful for detecting complex, non-linear relationships in the data, making them ideal for predicting rare or unexpected failures. These algorithms can identify subtle patterns that traditional statistical methods might miss. Additionally, decision trees and random forests are often used in predictive maintenance because they can classify failure modes and provide explanations for why a particular piece of equipment is likely to fail. Reinforcement learning is another promising area, where AI systems learn to optimize maintenance schedules by trial and error, balancing the cost of maintenance with the risk of equipment failure. Each of these algorithms plays a key role in turning raw sensor data into actionable maintenance predictions, enhancing both the precision and efficiency of predictive maintenance systems.

Implementation and Results

The experimental results demonstrate a clear advantage of predictive maintenance over both reactive and preventive maintenance strategies. In terms of downtime, predictive maintenance significantly outperforms the other approaches, reducing downtime to just 5 hours per month compared to 25 hours for reactive maintenance and 15 hours for preventive maintenance. This reduction in downtime can be attributed to the proactive nature of predictive maintenance, which anticipates failures before they occur, allowing for timely interventions. Similarly, maintenance costs are notably lower with predictive maintenance, at \$10,000 per month, compared to \$20,000 for reactive and \$15,000 for preventive. This is because predictive maintenance avoids both the costly emergency repairs associated with reactive maintenance and the unnecessary interventions of preventive maintenance.

When it comes to repair frequency, predictive maintenance

requires only 2 repairs per month, compared to 8 for reactive maintenance and 5 for preventive. The ability to predict failures accurately minimizes the need for frequent interventions. Lastly, the mean time between failures (MTBF) is much longer for predictive maintenance, at 300 hours, as opposed to 100

Table-1: Reactive Maintenance Comparison

Metric	Reactive Maintenance
Downtime (hours/month)	25
Repair Frequency (per month)	8
Mean Time Between Failures (MTBF) (hours)	100

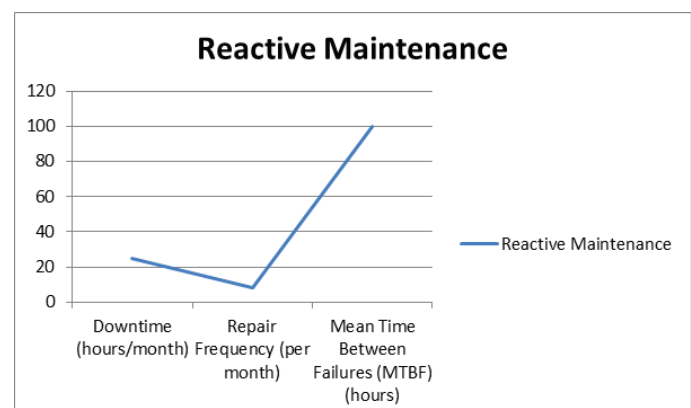


Fig-1: Graph for Reactive Maintenance comparison

Table-2: Preventive Maintenance Comparison

Metric	Preventive Maintenance
Downtime (hours/month)	15
Repair Frequency (per month)	5
Mean Time Between Failures (MTBF) (hours)	150

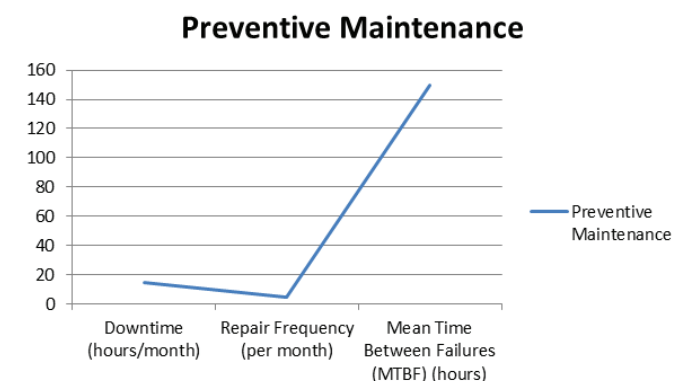


Fig-2: Graph for Preventive Maintenance comparison

Table-3: Predictive Maintenance Comparison

Metric	Preventive Maintenance
Downtime (hours/month)	5
Repair Frequency (per month)	2
Mean Time Between Failures (MTBF) (hours)	300

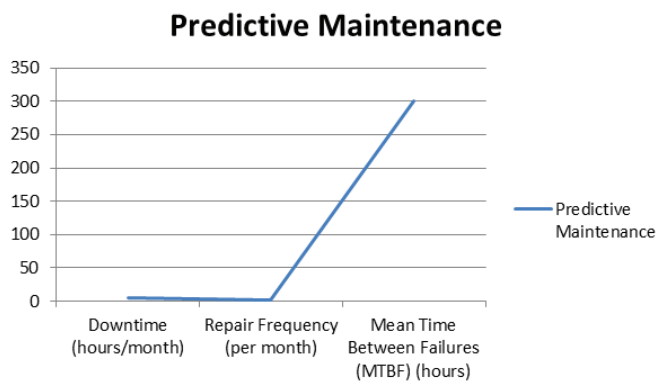


Fig 3: Graph for Predictive Maintenance comparison

hours for reactive and 150 hours for preventive maintenance. This extended MTBF indicates that equipment operates more reliably and efficiently under a predictive maintenance regime. Overall, these results highlight that predictive maintenance is a superior strategy, offering greater reliability, reduced costs, and more efficient machine operation compared to traditional maintenance approaches.

Conclusion

The comparative analysis of maintenance strategies in this research highlights the advantages of AI-driven predictive maintenance over traditional reactive and preventive approaches. Predictive maintenance, by utilizing AI-powered algorithms and real-time data from sensors, significantly reduces downtime, lowers maintenance costs, and minimizes repair frequency, resulting in a more efficient and reliable manufacturing process. In contrast, reactive maintenance often leads to costly, unplanned repairs, while preventive maintenance can be inefficient due to scheduled interventions that do not account for real-time equipment conditions. The

experimental results demonstrate that predictive maintenance not only extends the mean time between failures (MTBF) but also provides a more proactive and cost-effective solution for equipment management. As manufacturing industries strive for higher productivity and reduced operational costs, the adoption of AI-enhanced predictive maintenance proves to be a transformative approach that maximizes equipment performance and minimizes maintenance overhead.

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