



AI for Predictive Maintenance in Engineering Systems

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Abstract:

This comprehensive article examines the transformative impact of artificial intelligence on predictive maintenance strategies across various engineering systems, highlighting the evolution from traditional, reactive, and scheduled maintenance approaches toward sophisticated, data-driven methodologies. The article explores core technologies, including vibration analysis, thermal imaging, and sensor fusion techniques, that enable machine learning algorithms to detect equipment anomalies and predict failures with unprecedented accuracy. Through detailed examination of applications spanning industrial manufacturing, aviation, power generation, and transportation infrastructure, this article demonstrates how AI-enabled predictive maintenance systems significantly enhance operational reliability while reducing costs and improving safety outcomes. The article identifies key implementation methodologies, including anomaly detection algorithms, neural networks for pattern recognition, and real-time analytics platforms that process streaming sensor data to enable proactive maintenance decisions. While acknowledging substantial benefits such as extended equipment lifespan, optimized maintenance resource allocation, and enhanced safety performance, the article also addresses critical implementation challenges, including data quality issues, organizational change management requirements, and technical integration complexities with existing systems. The article reveals emerging trends toward autonomous maintenance systems, digital twin integration, and blockchain applications for data integrity, while identifying significant research opportunities in human-AI collaboration and ethical AI implementation. The article concludes that AI-driven predictive maintenance represents a paradigm shift that fundamentally alters equipment management practices across engineering disciplines, establishing new standards for operational excellence while addressing evolving sustainability and regulatory requirements in modern industrial environments.

1. Introduction

The evolution of maintenance strategies in engineering systems has undergone a fundamental transformation over the past decade, driven by the convergence of artificial intelligence technologies and advanced sensor networks. Traditional maintenance approaches, characterized by reactive repairs following equipment failures or scheduled interventions based on predetermined timelines, have proven increasingly inadequate for modern industrial operations where unplanned downtime can cost manufacturers thousands of dollars per minute. The integration of machine learning algorithms with real-time monitoring systems has enabled a paradigmatic shift toward predictive

maintenance strategies that anticipate equipment failures before they occur.

This transformation represents more than a technological upgrade; it constitutes a comprehensive reimagining of how engineering systems maintain operational integrity. Industries ranging from aerospace to manufacturing have begun adopting AI-driven predictive maintenance solutions that leverage vast datasets generated by industrial Internet of Things sensors, thermal imaging systems, and vibration monitoring equipment. These technologies enable maintenance teams to move beyond educated guesswork and reactive problem-solving toward data-informed decision-making processes that optimize both equipment performance and operational costs.

The practical implications of this shift extend far beyond simple cost reduction. Predictive maintenance strategies powered by artificial intelligence algorithms demonstrate significant improvements in equipment reliability, worker safety, and overall operational efficiency. Advanced analytics platforms now process complex sensor data streams to identify subtle patterns indicative of impending mechanical failures, often detecting issues weeks or months before traditional diagnostic methods would recognize problems. This enhanced capability allows maintenance personnel to schedule interventions during planned downtime periods, minimizing disruption to production schedules while ensuring optimal equipment performance.

Contemporary research demonstrates that organizations implementing AI-based predictive maintenance systems achieve substantial improvements in key performance indicators across multiple operational domains [1]. These systems represent a critical evolution in engineering practice, where data-driven insights replace intuition-based maintenance decisions, ultimately establishing new standards for operational excellence in complex industrial environments.

2. Literature Review

A. Traditional Maintenance Strategies

Reactive maintenance represents the earliest approach to equipment servicing, where repairs occur only after complete system failure. This methodology, while requiring minimal upfront planning, often results in unexpected production interruptions and elevated repair costs due to secondary damage from cascading failures. Manufacturing facilities historically accepted this approach as unavoidable, despite its inherent inefficiencies and safety risks.

Preventive maintenance emerged as an improvement over reactive strategies, implementing scheduled interventions based on manufacturer recommendations or historical failure patterns. This time-based approach reduces unexpected breakdowns through regular component replacement and system inspections. However, preventive maintenance frequently leads to premature part replacement and excessive maintenance activities, as scheduling rarely aligns with actual equipment condition.

Condition-based maintenance introduced real-time monitoring capabilities that assess equipment health through continuous sensor feedback. This methodology represents a significant advancement

over previous approaches by enabling maintenance decisions based on actual system performance rather than arbitrary schedules. Condition-based strategies form the foundation for modern predictive maintenance systems by establishing the data collection infrastructure necessary for advanced analytics.

B. Artificial Intelligence in Industrial Applications

Machine learning algorithms have revolutionized fault detection processes by identifying complex patterns within operational data that human analysts cannot easily recognize. These algorithms process vast datasets from multiple sensor sources simultaneously, detecting anomalies that indicate potential equipment degradation before visible symptoms appear.

Deep learning approaches enable sophisticated pattern recognition capabilities that excel at analyzing complex, multi-dimensional industrial datasets. Neural networks trained on historical failure data can identify subtle correlations between operating conditions and equipment deterioration, providing maintenance teams with early warning systems for critical components.

Integration of IoT and AI in industrial environments creates comprehensive monitoring ecosystems where interconnected sensors continuously feed data to intelligent analytics platforms. This convergence enables real-time decision-making processes that optimize maintenance scheduling while minimizing operational disruptions.

C. Current State of Predictive Maintenance Research

Key performance indicators for predictive maintenance success include reduced unplanned downtime, extended equipment lifespan, and improved maintenance cost efficiency. Research consistently demonstrates that organizations implementing these systems achieve measurable improvements across multiple operational metrics.

Industry adoption rates vary significantly across sectors, with heavy manufacturing and aerospace industries leading implementation efforts due to high failure costs. Implementation barriers include data quality challenges, integration complexity with legacy systems, and workforce adaptation requirements.

Comparative studies across different sectors reveal that predictive maintenance effectiveness depends heavily on equipment complexity,

operational environment, and organizational commitment to data-driven decision-making processes [2]. These studies highlight the importance of tailored implementation strategies that account for sector-specific requirements and constraints.

3. Methodology and Core Technologies

A. Data Acquisition Systems

Vibration analysis techniques utilize accelerometers and velocity sensors to detect mechanical irregularities in rotating equipment. These systems monitor frequency spectrums and amplitude variations that indicate bearing deterioration, misalignment, or imbalance conditions. Modern vibration monitoring platforms integrate wireless connectivity for continuous data transmission to central analytics systems.

Thermal imaging applications employ infrared cameras and temperature sensors to identify hotspots and thermal anomalies in electrical and mechanical systems. These non-invasive diagnostic tools detect overheating components, insulation degradation, and energy losses that precede equipment failures. Automated thermal monitoring systems enable continuous surveillance of critical infrastructure components.

Sensor fusion methodologies combine multiple measurement parameters to create comprehensive equipment health profiles. This approach integrates vibration, temperature, pressure, and acoustic data streams to provide holistic condition assessments that surpass individual sensor capabilities. Multi-parameter monitoring reduces false alarms while improving diagnostic accuracy [3].

B. Machine Learning Approaches

Anomaly detection algorithms identify deviations from normal operating patterns using statistical methods and machine learning models. These algorithms establish baseline performance parameters and flag unusual behaviors that may indicate developing problems. Unsupervised learning techniques prove particularly effective for detecting previously unknown failure modes.

Neural networks excel at pattern classification tasks involving complex, multi-dimensional industrial datasets. Deep learning architectures can process raw sensor data directly, eliminating the need for manual feature engineering while identifying subtle correlations between operational parameters and equipment degradation.

Time-series analysis methods predict future equipment conditions by analyzing historical performance trends and identifying recurring failure patterns. These techniques incorporate seasonality, cyclical variations, and long-term degradation trends to forecast optimal maintenance timing.

C. Data Processing and Analytics

Signal processing techniques remove noise and artifacts from raw sensor data to improve analysis accuracy. Digital filtering, spectral analysis, and wavelet transforms enhance signal quality while preserving critical diagnostic information. These preprocessing steps ensure reliable input data for downstream analytics algorithms.

Feature extraction methodologies convert raw sensor measurements into meaningful indicators that correlate with equipment health. Domain expertise guides the selection of relevant features such as statistical moments, frequency domain characteristics, and trend indicators that optimize predictive model performance.

Real-time analytics platforms process streaming sensor data to enable immediate response to critical conditions. Edge computing solutions perform local analysis at sensor locations, reducing network bandwidth requirements while enabling rapid decision-making for time-sensitive maintenance interventions [4].

4. Applications Across Engineering Domains

A. Industrial Manufacturing Systems

Bearing wear prediction systems monitor conveyor belt operations through vibration analysis and temperature sensing to forecast bearing replacement timing. These applications prevent catastrophic failures that could damage extensive conveyor sections while optimizing maintenance scheduling during planned production breaks.

Motor malfunction detection in robotic automation employs current signature analysis and thermal monitoring to identify winding deterioration, bearing problems, and control system issues. Predictive algorithms enable proactive motor replacement before failures disrupt automated production processes.

Production line optimization integrates maintenance predictions with production scheduling to minimize disruptions while maximizing equipment availability. These systems coordinate maintenance activities across interconnected equipment to maintain overall line efficiency.

B. Aviation and Aerospace Engineering

Engine health monitoring systems analyze multiple parameters, including temperature, pressure, vibration, and oil analysis, to predict component degradation in aircraft engines. These critical applications ensure flight safety while optimizing maintenance intervals to reduce operational costs.

Structural health assessment monitors aircraft components for fatigue crack development, corrosion progression, and material degradation using strain gauges, acoustic emission sensors, and ultrasonic testing. Predictive models help maintain airworthiness while extending component service life.

Regulatory compliance requirements in aviation drive sophisticated prognostic systems that meet stringent safety standards while demonstrating equipment reliability. These applications must satisfy certification requirements while providing actionable maintenance guidance [5].

C. Other Engineering Applications

Power generation systems employ predictive maintenance for turbines, generators, and transmission equipment to ensure a reliable electricity supply. Condition monitoring prevents cascading failures that could affect entire power grids while optimizing maintenance costs.

Transportation infrastructure applications monitor bridges, railways, and highway systems for structural deterioration and component wear. These systems enable proactive repairs that maintain safety while extending infrastructure service life.

Process industries utilize predictive maintenance for pumps, compressors, heat exchangers, and pressure vessels in chemical and petrochemical facilities. These applications prevent hazardous material releases while maintaining production continuity in complex process environments.

5. Performance Analysis and Benefits Assessment

A. Operational Improvements

Downtime reduction metrics demonstrate significant improvements in equipment availability through predictive maintenance implementations. Organizations typically observe substantial decreases in unplanned outages as maintenance activities shift from reactive responses to proactive interventions. Cost savings analysis reveals that prevented failures generate substantially higher returns than reactive repair expenses, particularly

when considering secondary damage and production losses.

Equipment lifespan extension occurs through optimized operating conditions and timely maintenance interventions that prevent accelerated wear patterns. Predictive systems enable maintenance teams to address minor issues before they escalate into major component failures, preserving capital investments while maximizing asset utilization throughout extended operational lifecycles.

Maintenance resource optimization improves workforce efficiency by eliminating unnecessary inspections and focusing technician efforts on equipment requiring attention. Predictive algorithms enable maintenance scheduling that aligns with operational requirements while ensuring optimal resource allocation across multiple facilities and equipment types.

B. Safety and Risk Management

Risk mitigation in high-consequence environments becomes critical where equipment failures could endanger personnel or cause environmental damage. Predictive maintenance systems provide early warnings that enable safe shutdown procedures and hazard prevention measures before dangerous conditions develop.

Safety performance indicators show marked improvements in workplace incident rates following predictive maintenance implementation. Early detection of equipment deterioration prevents catastrophic failures that historically resulted in injuries, environmental releases, or facility damage [6].

Regulatory compliance requirements drive sophisticated monitoring systems that ensure adherence to industry safety standards. Predictive maintenance documentation provides audit trails that demonstrate proactive equipment management while meeting regulatory oversight requirements for high-risk industries.

C. Economic Impact Analysis

Return on investment calculations for predictive maintenance systems typically demonstrate positive outcomes within two to three years of implementation. Payback periods vary across industries but consistently show favorable economics when considering prevented failures, extended equipment life, and optimized maintenance costs.

Comparative cost analysis reveals that predictive approaches generate lower total maintenance expenses than reactive or preventive strategies over extended operational periods. These systems eliminate unnecessary maintenance activities while preventing costly emergency repairs and production interruptions.

Long-term financial benefits include reduced insurance premiums, improved asset values, and enhanced operational reliability that creates competitive advantages in demanding market conditions. Organizations with mature predictive maintenance programs demonstrate superior operational performance compared to competitors using traditional maintenance approaches.

6. Implementation Challenges and Limitations

A. Technical Challenges

Data quality issues pose significant obstacles to successful predictive maintenance implementation. Sensor calibration, data completeness, and measurement accuracy directly impact algorithm performance. Organizations must establish robust data governance processes to ensure reliable analytics inputs [7].

Algorithm accuracy varies significantly across different equipment types and operating environments. False positive rates can undermine maintenance team confidence, while false negatives may result in unexpected failures. Continuous model refinement and validation remain essential for maintaining system effectiveness.

Integration challenges with existing maintenance management systems require substantial technical coordination. Legacy system compatibility, data format standardization, and workflow integration demand significant information technology resources and careful change management.

B. Organizational Factors

Change management processes must address cultural resistance to data-driven maintenance approaches. Workforce adaptation requires comprehensive training programs that develop new skills while addressing concerns about technology displacing traditional maintenance practices.

Initial investment requirements can strain organizational budgets, particularly for comprehensive sensor networks and analytics platforms. Budget constraints often limit implementation scope, potentially reducing system effectiveness in early deployment phases.

Skills gap challenges require organizations to develop technical capabilities in data analytics, machine learning, and advanced diagnostic techniques. Training needs span multiple organizational levels, from technicians to management teams responsible for maintenance strategy decisions.

C. Industry-Specific Constraints

Regulatory requirements in highly regulated industries impose strict certification processes for new maintenance technologies. Compliance documentation, validation testing, and approval procedures can significantly extend implementation timelines while increasing project costs [8].

Legacy system compatibility presents particular challenges in mature industries with extensive installed equipment bases. Modernization costs and retrofit complexity may limit predictive maintenance adoption for older facilities or specialized equipment types.

Scalability issues arise when organizations attempt to expand successful pilot programs across diverse operational environments. Standardization challenges, varying equipment types, and different operational conditions require customized approaches that complicate large-scale deployments.

7. Future Directions and Emerging Trends

A. Technological Advancements

Advanced AI algorithms are evolving toward autonomous maintenance systems that can execute repair decisions without human intervention. These systems integrate robotics with predictive analytics to perform routine maintenance tasks, component replacements, and system adjustments based on real-time condition assessments. Autonomous capabilities promise to revolutionize maintenance operations in hazardous or remote environments where human access remains challenging.

Digital twin integration creates virtual replicas of physical systems that enable sophisticated simulation-based predictions. These models combine real-time sensor data with physics-based simulations to forecast equipment behavior under various operating scenarios. Digital twins allow maintenance teams to test different intervention strategies virtually before implementing physical changes, optimizing maintenance decisions while minimizing operational risks.

Blockchain applications address maintenance data integrity concerns by creating immutable records of

equipment history, maintenance activities, and performance data. This technology ensures audit trail authenticity while enabling secure data sharing across organizational boundaries. Blockchain integration particularly benefits industries requiring strict compliance documentation and multi-party maintenance collaborations.

B. Industry Evolution

Standardization efforts focus on developing common frameworks for predictive maintenance implementation across different sectors. Industry organizations work to establish best practices that reduce deployment complexity while ensuring consistent performance metrics and interoperability between systems from different vendors.

Cross-industry knowledge transfer accelerates predictive maintenance adoption by sharing successful methodologies between sectors facing similar equipment challenges. Manufacturing insights inform aerospace applications, while energy sector innovations benefit transportation infrastructure. This collaborative approach reduces development costs while accelerating technology maturation [9].

Sustainable maintenance practices integrate environmental considerations into predictive maintenance strategies. These approaches optimize equipment efficiency to reduce energy consumption, minimize waste generation, and extend asset lifecycles. Environmental impact assessments become standard components of

maintenance decision-making processes, aligning operational improvements with sustainability objectives.

C. Research Opportunities

Unexplored application domains offer significant potential for predictive maintenance expansion into emerging technology areas. Smart city infrastructure, renewable energy systems, and advanced manufacturing processes present unique challenges that require novel analytical approaches and specialized sensor technologies.

Human-AI collaboration research focuses on optimizing the interaction between maintenance professionals and intelligent systems. These studies examine how artificial intelligence can augment human expertise rather than replace it, developing interfaces and decision support tools that enhance maintenance team capabilities while preserving critical human judgment.

Ethical considerations surrounding responsible AI implementation gain increasing attention as predictive maintenance systems become more autonomous. Research addresses algorithmic transparency, bias prevention, and accountability frameworks that ensure fair and reliable maintenance decisions. Privacy protection and data governance remain critical concerns as organizations share sensitive operational information across predictive maintenance networks [10].

Table 1: Comparison of Maintenance Strategies [2]

Strategy Type	Implementation Approach	Cost Structure	Downtime Pattern	Predictive Capability
Reactive	Post-failure repairs	High emergency costs	Unplanned, extensive	None
Preventive	Time-based scheduling	Moderate, scheduled	Planned, frequent	Limited
Condition-based	Real-time monitoring	Variable, targeted	Planned, optimized	Basic
AI Predictive	Data-driven analytics	Lower long-term	Minimal, strategic	Advanced

Table 2: Core AI Technologies in Predictive Maintenance [4]

Technology Category	Primary Function	Data Input Types	Processing Location	Application Examples
Vibration Analysis	Mechanical fault detection	Accelerometer signals	Edge/Cloud	Bearing wear, misalignment
Thermal Imaging	Temperature anomaly detection	Infrared data	Local/Remote	Electrical hotspots, insulation
Machine Learning	Pattern recognition	Multi-sensor fusion	Cloud/Edge	Failure prediction, optimization
Neural Networks	Complex pattern classification	Time-series data	Cloud computing	Motor diagnostics, trend analysis

Table 3: Implementation Benefits by Industry Sector [5]

Industry Sector	Primary Applications	Key Performance Improvements	Safety Enhancements	Regulatory Compliance
Manufacturing	Conveyor systems,	Production continuity	Worker protection	ISO standards

	robotics			
Aviation	Engine monitoring, structures	Flight safety, reliability	Passenger safety	FAA regulations
Power Generation	Turbines, transmission	Grid stability	Environmental safety	NERC standards
Process Industries	Pumps, pressure vessels	Product quality	Hazard prevention	EPA compliance

Table 4: Implementation Challenges and Solutions Framework [8]

Challenge Category	Specific Issues	Impact Level	Recommended Solutions	Success Factors
Technical	Data quality, integration	High	Robust validation, standards	Technical expertise
Organizational	Change resistance, training	Medium	Leadership support, education	Management commitment
Financial	Initial investment, ROI	Medium	Phased implementation	Business case development
Regulatory	Compliance, certification	High	Early engagement, documentation	Industry collaboration

8. Conclusions

The integration of artificial intelligence into predictive maintenance represents a transformative evolution in engineering practice that fundamentally reshapes how organizations approach equipment reliability and operational efficiency. This comprehensive article demonstrates that AI-driven predictive maintenance systems deliver measurable improvements across multiple performance dimensions, from substantial reductions in unplanned downtime to enhanced safety outcomes in high-risk operational environments. The convergence of advanced sensor technologies, machine learning algorithms, and real-time analytics platforms has created unprecedented capabilities for anticipating equipment failures before they occur, enabling maintenance teams to transition from reactive problem-solving to proactive system optimization. While implementation challenges, including data quality concerns, organizational change management, and technical integration complexities, remain significant barriers, the documented benefits consistently justify the investment required for successful deployment. The future trajectory of this field points toward increasingly autonomous maintenance systems, enhanced human-AI collaboration, and expanded applications across emerging technology domains. Organizations that embrace these predictive maintenance technologies position themselves to achieve superior operational performance while establishing competitive advantages in industries where equipment reliability directly impacts profitability and safety. As standardization efforts mature and cross-industry knowledge transfer accelerates, predictive maintenance will likely become an essential capability rather than a competitive differentiator, fundamentally altering

expectations for equipment management across all engineering disciplines. The continued evolution of these systems promises to deliver even greater operational improvements while addressing sustainability objectives and regulatory requirements that define modern industrial operations. Machine learning is applied to different fields and reported in the literature [11-22].

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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