



REVIEW ARTICLE



Artificial Intelligence-Supported Predictive Maintenance in Industrial Systems: Methods Applications and Limitations

Yapay Zekâ Destekli Kestirimci Bakımın Endüstriyel Sistemlerde Kullanımı: Yöntemler, Uygulamalar ve Sınırlılıklar

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ABSTRACT

Maintaining equipment reliability, reducing unplanned downtime, and controlling maintenance costs are essential for production continuity in industrial systems. Predictive maintenance uses equipment condition data to identify maintenance requirements before failures occur. Advances in sensor technologies, the Internet of Things, and industrial data acquisition systems have enabled continuous monitoring and the application of machine learning and deep learning methods. This review examines artificial intelligence-supported predictive maintenance in terms of methods, industrial applications, and limitations. Support vector machines, Random Forest, decision trees, k-nearest neighbors, XGBoost, and artificial neural networks are widely used for fault detection, condition classification, and remaining useful life estimation. CNN and LSTM models are prominent in analyzing high-dimensional and time-dependent sensor data. Applications in manufacturing, automotive, mining, and facility management have reported favorable outcomes. Major limitations include data quality, insufficient labeled failure data, explainability, computational requirements, model generalizability, and system integration. Long-term industrial validation and adaptable models remain research priorities.

ÖZET

Endüstriyel sistemlerde ekipman güvenilirliğinin korunması, plansız duruşların azaltılması ve bakım maliyetlerinin kontrol edilmesi üretim sürekliliği açısından önem taşımaktadır. Kestirimci bakım ekipmanının mevcut durumuna ilişkin verileri kullanarak arıza oluşmadan önce bakım gereksiniminin belirlenmesini amaçlamaktadır. Sensör teknolojileri, Nesnelerin İnterneti ve endüstriyel veri toplama sistemlerindeki gelişmeler, ekipmanlardan sürekli veri alınmasını sağlamış, makine öğrenmesi ve derin öğrenme yöntemleri bu verilerin analizinde kullanılmaya başlanmıştır. Bu derlemede yapay zekâ destekli kestirimci bakım sistemleri kullanılan yöntemler, endüstriyel uygulamalar ve uygulamada karşılaşılan sınırlılıklar açısından incelenmiştir. Literatürde destek vektör makineleri, Random Forest, karar ağaçları, k-en yakın komşu, XGBoost ve yapay sinir ağlarının arıza tespiti, durum sınıflandırması ve kalan yararlı ömür tahmininde kullanıldığı görülmektedir. CNN ve LSTM gibi derin öğrenme modelleri yüksek boyutlu ve zamana bağlı sensör verilerinin analizinde öne çıkmaktadır. Üretim, otomotiv, madencilik ve tesis yönetimi uygulamalarında bakım planlaması, ekipman kullanılabilirliği ve maliyetler açısından olumlu sonuçlar bildirilmiştir. Veri kalitesi, etiketli arıza verisinin yetersizliği, açıklanabilirlik, hesaplama gereksinimi, model genellenebilirliği ve mevcut sistemlerle entegrasyon başlıca sınırlılıklardır. Gerçek endüstriyel koşullarda uzun süreli doğrulama ve değişen çalışma koşullarına uyarlanabilir modeller alanın başlıca araştırma gereksinimleridir.

Anahtar Sözcükler: Kestirimci bakım, yapay zekâ, endüstriyel sistemler

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1. Introduction

Maintenance activities have a direct impact on the availability of industrial systems, continuity of production, and operating costs (Görgülü et al., 2024). An unplanned failure of a machine or piece of equipment does not merely create a need for repair; it may also result in production losses, delivery delays, quality problems, and additional labor costs (Ersöz et al., 2025). Calayır and Kabak (2021) noted that maintenance is not only a technical function in manufacturing organizations but also an activity that affects organizational revenues and expenditures. In their application in the defense industry, they addressed the costs associated with component losses and delivery delays resulting from unplanned maintenance.

The concept of industrial maintenance has evolved from corrective maintenance, in which intervention occurs after a failure, to preventive maintenance performed at predetermined intervals, and subsequently to predictive maintenance, which takes the actual operating condition of the equipment into account (Gürsey, 2026). In predictive maintenance, maintenance timing is determined not according to a fixed schedule but on the basis of measurements related to equipment condition and historical operating data (Dündar, Sarıçiçek, Çınar, & Yazıcı, 2021). Gürsoy, Büyükbaş, and Çakıroğlu (2019) similarly describe predictive maintenance in terms of monitoring equipment condition before failure, evaluating the resulting data through analytical methods, and estimating failure probability and equipment life.

Industry 4.0 has expanded the data infrastructure through which this approach can be implemented. Sensors, the Internet of Things (IoT), big data, and cloud computing technologies enable the continuous collection, storage, and analysis of machine data (Ceyhan and Kasapbaşı, 2022). Cardoso and Ferreira (2021) reported that the increasing volume of data obtained from industrial systems through sensors and IoT infrastructure supports predictive maintenance applications and that machine learning can be used to process these large datasets. Gürsoy et al. (2019) likewise identified the analytical processing of big data generated through IoT as one of the principal technological components of predictive maintenance.

The primary function of artificial intelligence in predictive maintenance is to identify patterns associated with failure and degradation in equipment operating data (Özel, 2026). Machine learning methods are used for problems such as fault detection, fault classification, condition monitoring, and remaining useful life (RUL) estimation. In their review of 83 studies published in 45 journals, Dündar et al. (2021) identified Random Forest, decision trees, artificial neural networks, support vector machines, k-nearest neighbors, linear regression, and deep learning algorithms as methods used in predictive maintenance applications. Similarly, the 123 studies reviewed by Arez, Navas, and Gaspar (2026) showed that Random Forest, support vector machines, decision trees, and k-nearest neighbors are frequently used for failure prediction, fault detection, and RUL estimation.

Recent developments in predictive maintenance are not limited to new prediction algorithms. Ucar, Karakose, and Kırımça (2024) conceptualize AI-supported predictive maintenance systems as integrated structures comprising sensors, data preprocessing, artificial intelligence algorithms, decision modules, communication and integration components, and user interfaces. Their study identifies IoT, digital twins, edge and cloud computing, and explainable artificial intelligence as emerging components of predictive maintenance. Bitam et al. (2025), in turn, reported that the AIoT approach, which integrates artificial intelligence with the Industrial Internet of Things, combines real-time monitoring, failure prediction, RUL estimation, and maintenance decisions within a single architecture.

The aim of this study is to examine the use of AI-supported predictive maintenance in industrial systems in terms of the methods employed, application areas, and technical limitations. Machine learning and deep learning methods, sensor and IoT infrastructures, outcomes of industrial applications, explainability, data-related problems, and next-generation maintenance architectures are evaluated in light of the existing literature.

2. AI-Supported Predictive Maintenance Methods

The first stage of AI-supported predictive maintenance is the acquisition of data representing the operating condition of the equipment. Parameters such as temperature, vibration, pressure, current, power consumption, oil condition, and wear provide information about the physical condition of equipment. Ucar et al. (2024) identified sensors as the primary data source in predictive maintenance systems and stated that raw sensor data should undergo cleaning, normalization, and missing-data processing before modeling. According to Bitam et al. (2025), operational variables such as temperature, vibration, and pressure obtained from distributed sensors in AIoT-based systems can be transmitted to artificial intelligence models in real time.

Data preprocessing is a stage that directly affects model performance. Sensor data may contain noise, missing observations, and variability arising from different operating conditions. Menteşe and Özkahraman (2026)

compared logistic regression, Random Forest, XGBoost, support vector machines, and multilayer perceptron models after preprocessing current, power, and operational signals obtained from a CNC milling machine. Model outputs were subsequently used in a risk-based threshold system designed to support maintenance decisions.

Supervised learning is one of the most widely used approaches in predictive maintenance. In this approach, historical observations are provided to the model together with known outputs such as normal operating conditions, failure type, or time to failure. Calayır and Kabak (2021) used linear regression, polynomial regression, and support vector machines to plan maintenance for a critical chemical painting machine in the defense industry and compared the models using root mean square error. The literature review by Dündar et al. (2021) likewise shows that support vector machines, Random Forest, artificial neural networks, linear regression, and k-NN are among the principal methods used in predictive maintenance studies.

The selection of conventional machine learning methods depends on the structure of the data and the prediction problem. Support vector machines can be used for complex classification problems, whereas Random Forest can be applied to both classification and regression tasks. Dündar et al. (2021) stated that Random Forest can be used particularly with datasets containing numerous variables, although model interpretation may become more difficult. The systematic review by Arez et al. (2026) also indicates that no single algorithm is superior across all predictive maintenance problems and that different algorithms are used for different tasks, including failure prediction, fault detection, and RUL estimation.

Unsupervised learning methods are used when labeled failure data are unavailable. Azeta et al. (2026) reported that methods such as K-Means, DBSCAN, and autoencoders can be used for anomaly detection without requiring labels. Although unsupervised methods reduce dependence on labeled failure data, false-positive results remain an important limitation. The same study showed that SVM, Random Forest, and artificial neural networks are used for fault classification and RUL estimation with labeled data, whereas CNN and LSTM models are used for sensor fusion and time-series analysis.

Deep learning methods are prominent in the analysis of high-dimensional sensor data and temporal patterns. CNN models are used to extract discriminative features from sensor signals, whereas LSTM models are used to model relationships among sequential measurements. Azeta et al. (2026) highlighted the use of CNN and LSTM models for processing complex sensor data and time series. Dündar et al. (2021) also reported an increase in the use of deep learning over time, with deep learning algorithms being employed in 68% of the studies they examined from 2020.

One of the principal outputs of predictive maintenance is RUL estimation. RUL refers to the estimated period during which equipment can continue to operate under acceptable operating conditions. Dündar et al. (2021) found that condition monitoring, fault diagnosis, and RUL estimation have been studied extensively in the literature, particularly for bearings, motors, and wind turbines. In the 94 automotive studies reviewed by Mahale, Kolhar, and More (2025), RUL estimation, health-condition monitoring, fault diagnosis, and maintenance scheduling were also among the primary application areas of AI-supported vehicle maintenance.

Translating model output into a maintenance decision constitutes the final stage of a predictive maintenance system. Menteşe and Özkahraman (2026) evaluated the probability of tool wear obtained through XGBoost within a threshold model that considered maintenance costs and the risk of production loss. Maintenance was recommended when the specified threshold was exceeded, whereas production was continued when the estimated probability remained below the threshold. This structure illustrates the use of an artificial intelligence model not merely as a failure-prediction tool but as a component of a decision system that supports maintenance planning.

AIoT architectures integrate sensor, communication, and artificial intelligence layers within a single system. Bitam et al. (2025) stated that condition-based maintenance, Prognostics and Health Management, and prescriptive maintenance approaches are considered together in AIoT-based predictive maintenance. Edge-cloud collaboration, federated learning, self-adaptive learning, and digital twins have been identified as core architectures of next-generation systems.

Edge computing reduces latency in real-time applications by enabling data to be processed close to the point at which they are generated. Cloud computing is used for greater computational capacity and long-term data storage. Ucar et al. (2024) stated that edge computing can be used for real-time analysis, whereas cloud computing can support big-data storage and the analysis of historical data. In the applications reviewed by Bitam et al. (2025), lightweight models were deployed at the edge while more complex predictive models were used in the cloud layer; improvements in latency, energy consumption, and bandwidth utilization were reported.

Digital twins constitute virtual representations of physical equipment that are updated with real-time data. Ucar et al. (2024) identified digital twins as a next-generation predictive maintenance technology for real-time equipment monitoring and the evaluation of alternative maintenance scenarios. In the applications reviewed by Bitam et al. (2025), Random Forest and XGBoost were used in CNC systems, autoencoder-LSTM architectures were used in winding machines, and edge-cloud-based digital twin architectures were applied to wind turbines.

3. Industrial Applications and Limitations

Manufacturing is the largest application area for AI-supported predictive maintenance. Arez et al. (2026) found that the manufacturing sector predominated in 123 studies covering the 2014-2024 period. The same review determined that a substantial proportion of the studies relied on standard datasets rather than real manufacturing environments. The review by Ucar et al. (2024) also indicates that AI-supported predictive maintenance is used not only in manufacturing but also in the automotive, energy, aerospace, and transportation sectors.

CNC machine tools constitute one of the concrete applications in manufacturing. Menteşe and Özkahraman (2026) analyzed sensor data obtained from a CMX 1100 V CNC milling machine using the XGBoost algorithm and developed a system that classified machining conditions and generated probability-based maintenance decisions. Current, power, and operational signals served as the data sources for maintenance decisions. Cardoso and Ferreira (2021) likewise demonstrated that machine learning can be applied to industrial data to improve equipment availability, reduce maintenance costs, and support operational decision-making.

The application in the defense industry demonstrates the relationship between maintenance planning and the production process. Calayır and Kabak (2021) focused on predicting maintenance timing for a critical chemical painting machine using supervised machine learning. The study was motivated by costly components becoming unusable and delivery delays resulting from unplanned maintenance. In this application, predictive maintenance was used primarily to determine maintenance timing in advance so as to reduce production losses rather than to diagnose faults.

In the automotive field, sensor data, maintenance history, and operational data obtained from vehicles constitute the primary inputs for artificial intelligence models. Mahale et al. (2025) reviewed 94 studies addressing applications of machine learning, deep learning, explainable artificial intelligence, and generative artificial intelligence. Fault diagnosis, RUL estimation, health-condition monitoring, and maintenance scheduling were identified as the principal application areas. Data quality, scalability, and the integration of artificial intelligence systems with existing vehicle infrastructure were identified among the main challenges in automotive applications.

Mining is another application area in which equipment operates under demanding conditions. Chambi et al. (2025) monitored temperature, pressure, oil-analysis, and wear data from underground mining equipment using IoT sensors and evaluated these data with machine learning models. In the application based on actual operational data, an 8% reduction in maintenance costs and a 10% increase in equipment availability were reported. Because these results relate to a specific field application, they should not be directly generalized to other industrial systems.

Facility management is another area in which AI-supported predictive maintenance is applied. Scaife (2024) reviewed the literature on artificial intelligence and predictive maintenance in facility operations and found that artificial intelligence contributes to data-driven maintenance and investment decisions. Insufficient data were identified as one of the most prominent barriers to the implementation of artificial intelligence in the reviewed literature. The same review included applications in building systems in which digital twins and machine learning were used to monitor equipment condition and support maintenance scheduling.

The impact of predictive maintenance is not limited to technical performance. Nagy, Figura, Valaskova, and Lăzăroiu (2025) examined the relationship between predictive maintenance and economic performance using data from 1,094 manufacturing firms. In the regression analysis, predictive maintenance remained a significant predictor of economic performance after firm size, legal form, and geographical scope were taken into account. This finding indicates that investments in predictive maintenance should be evaluated not only in terms of algorithmic accuracy but also in relation to organizational performance and cost structure.

One of the principal limitations of AI-supported predictive maintenance is data quality. A model requires a sufficient quantity of reliable data for learning. Because failures occur less frequently than normal operating

conditions, the number of labeled failure examples is often limited. Scaife (2024) identified insufficient data as a major barrier to the full implementation of artificial intelligence in the facility management literature. Ucar et al. (2024) likewise regarded data quality and quantity as fundamental requirements for model training and validation.

The limited availability of real-world field data also affects model generalizability. Arez et al. (2026) reported that a substantial proportion of the reviewed studies used standard datasets and that long-term real-world validation remained limited. Ucar et al. (2024) emphasized that AI-supported predictive maintenance systems should be tested across different equipment types, operating conditions, and levels of data quality. High accuracy on a controlled dataset does not imply that the same level of performance will be maintained under different load and environmental conditions.

Explainability represents another important challenge. Particularly for critical equipment, maintenance decisions produced by complex machine learning and deep learning models must be understandable to technical personnel. Ucar et al. (2024) identified methods such as SHAP and LIME as tools used to explain predictions generated by predictive maintenance models. Arez et al. (2026) found that the use of explainable artificial intelligence (XAI) remains limited in the existing predictive maintenance literature. Mahale et al. (2025) described explainable artificial intelligence as an emerging area of automotive predictive maintenance with respect to improving the interpretability of model outputs.

The computational requirements of deep learning models constitute an additional limitation in field applications. Azeta et al. (2026) reported that models such as CNN and LSTM can provide strong results with high-dimensional data, while high computational requirements and limited interpretability constrain their application. When edge devices have limited processor, memory, and energy capacity, model size becomes a direct consideration in system design.

Integration with existing industrial infrastructure also increases implementation costs. Ucar et al. (2024) stated that differences in data formats, communication methods, and protocols make the integration of artificial intelligence into existing systems more difficult. Modular designs, standard protocols, APIs, and edge/fog computing are among the approaches used to address this problem. Bitam et al. (2025) also identified infrastructure complexity, cybersecurity, data heterogeneity, and resource constraints as major implementation challenges in next-generation AIoT systems.

Federated learning and digital twin technologies are current research areas addressing some of these challenges. Federated learning allows data located at different facilities or machines to be used for joint model training without being transferred to a centralized data repository. In the federated-learning applications reviewed by Bitam et al. (2025), high classification performance was reported, while model orchestration, local computational load, and dependence on network quality were identified as limitations. Digital twins, in turn, enable condition monitoring, failure prediction, and maintenance planning to be conducted within the same system through continuous data exchange between physical equipment and its virtual model.

One emerging direction in AI-supported predictive maintenance is the transition from prediction to prescriptive maintenance. In prescriptive maintenance, the system does not merely estimate the probability or timing of failure; it also generates recommendations regarding the maintenance action to be implemented. Ucar et al. (2024) stated that prescriptive maintenance translates prediction results into specific maintenance actions. Bitam et al. (2025) likewise identified this approach as an emerging area of AIoT-supported maintenance systems.

The human operator remains an important component of the decision-making process in these systems. Azeta et al. (2026) described an AI-based maintenance architecture in which operators and engineers interpret model outputs, approve maintenance actions, and feed the results back into the system. Bitam et al. (2025) also identified human-centeredness, explainable artificial intelligence, and human involvement in the decision loop as components of next-generation maintenance systems within the context of Industry 5.0.

4. Conclusions and Recommendations

AI-supported predictive maintenance is based on the use of data obtained under actual equipment operating conditions for fault detection, condition monitoring, and remaining useful life estimation. Sensors and IoT infrastructure constitute the data-acquisition layer, machine learning and deep learning methods form the analytical layer, and decision-support systems translate predictions into maintenance applications. Whereas

intervention timing is predetermined in conventional periodic maintenance, predictive maintenance is based on the measured condition and degradation trend of the equipment.

The reviewed studies show that conventional machine learning and deep learning methods are used for different predictive maintenance problems. Random Forest, support vector machines, decision trees, and k-NN are particularly common in classification and fault-detection tasks. CNN and LSTM models are used with high-dimensional sensor data and time series. RUL estimation, fault diagnosis, and condition monitoring are among the most frequently addressed problems in the literature. While the review by Dündar et al. (2021), which also covered the Turkish literature, indicates a growing shift toward deep learning, the more recent systematic review by Arez et al. (2026) shows that conventional machine learning algorithms continue to retain their importance in predictive maintenance applications.

Industrial applications demonstrate that AI-supported predictive maintenance is not limited to experimental datasets. Applications include classification of machining conditions and maintenance decision-making in CNC machine tools, prediction of maintenance timing in the defense industry, vehicle health monitoring in the automotive sector, and real-time failure prediction in mining equipment. The field study by Chambi et al. (2025) reported an 8% reduction in maintenance costs and a 10% increase in equipment availability. The study by Nagy et al. (2025), which included 1,094 manufacturing firms, also showed that the use of predictive maintenance was associated with economic performance.

The principal challenges in implementation extend beyond algorithm selection. The availability of sufficient and reliable data, labeling of failure examples, maintenance of model performance under different operating conditions, adequacy of computational resources, and integration with existing production systems must be considered together. Limited real-world field data and dependence on standard datasets make it difficult to evaluate model generalizability. Explainability is particularly important for safety- and cost-critical equipment because maintenance personnel must be able to assess and trust AI-generated outputs.

AIoT, edge-cloud computing, federated learning, and digital twins represent current directions in predictive maintenance. These technologies are moving data acquisition, analysis, and decision-making toward distributed and real-time architectures. Bitam et al. (2025) identified explainability, data quality, resource constraints, cybersecurity, and human-AI collaboration as key issues that remain to be addressed in next-generation predictive maintenance research. Ucar et al. (2024) likewise identified real-world validation, trustworthy artificial intelligence, digital twins, and human-machine interaction as major areas for future research.

Future studies should not focus solely on developing models with higher predictive accuracy. Models should be tested over extended periods in real production environments, their transferability across different equipment and operating conditions should be established, computational costs should be reported, and predictions should be understandable to maintenance personnel. The industrial value of predictive maintenance depends less on the isolated performance of an artificial intelligence model than on the coordinated operation of the sensor infrastructure, data quality, model, decision mechanism, and maintenance process. When this integration is achieved, AI-supported predictive maintenance provides a viable engineering approach for reducing unplanned downtime and managing maintenance resources according to the actual condition of equipment.

Declarations

Ethics Approval. Ethics committee approval was not required for this study because it is a review article based exclusively on previously published literature and did not involve human participants, animals, or the collection of primary data.

Informed Consent. Not applicable.

Conflict of Interest. The author declares no conflict of interest.

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