OVERVIEW OF THE USE OF ARTIFICIAL INTELLIGENCE IN PREDICTIVE MAINTENANCE AND STATE MANAGEMENT OF TECHNICAL SYSTEMS

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Article

In recent years, enterprises have been increasingly implementing artificial intelligence technologies to optimize the maintenance processes of machines and equipment in order to increase the efficiency of their functioning. Predictive maintenance, based on data analytics and machine learning algorithms, allows you to predict possible equipment failures, reduce unplanned downtime, and optimize repair costs. The review combines the results of the analysis of both commercial reviews presented in the materials (1, 3, 4) and scientific studies (2, 5, 7), and also confirms the relevance and wide interest in this issue. Additional studies (9-13) introduce new methodological recommendations for determining the optimal service life, forming diagnostic tool sets, and organizing automated equipment condition management, which emphasizes the versatility and interdisciplinary nature of the issue.

Numerous studies show that the basis for successful predictive maintenance is the collection and analysis of large amounts of data coming from IoT sensors and other equipment. In this area, classical machine learning algorithms such as regression analysis, classification and clustering algorithms are used to detect anomalies and predict potential failures (1, 2). Deep learning methods, including neural networks, namely convolutional and recurrent models, are successfully used to analyze time series and recognize complex patterns in data (5, 7). Combined methods that combine traditional algorithms with deep learning approaches can improve the accuracy of forecasting by taking into account the multi-factor nature of data [4]. The latest trends also include the use of multi-modal pre-trained large language models, which can be used for system diagnostics and recognition of information received from video or audio channels, providing automatic audio-visual control, as well as the use of large language models as AI assistants in combination with speech recognition (ASR) and speech synthesis (TTS) models for speech processing. dispatching of production processes. In addition, studies on the modification of damage accumulation models, for example, the refinement of the Lemaitre model taking into account the local multi-axis loading under nonlinear deformation, demonstrate the potential for integrating mechanistic models into analytical predictive maintenance systems, which allows taking into account complex equipment operation modes [8].

The practical cases presented in the Deloitte review highlight the importance of integrating AI-based analytical solutions with existing enterprise information systems, which allows real-time monitoring of equipment status, data analysis, and operational maintenance decisions [3, 4]. Additional methodological recommendations for organizing automated equipment condition management [12] and the formation of sets of metrological support tools for diagnostics (10) contribute to improving the compatibility and adaptability of such systems. The developed methodology for determining the optimal service life of machines (9) demonstrates that the integration of AI technologies with automated control systems allows for more accurate maintenance planning.

The introduction of AI into predictive maintenance and technical system state management systems leads to a number of positive results. Timely fault detection and failure prediction can significantly reduce repair costs and unplanned downtime (1). Trend analysis and optimization of maintenance schedules contribute to planning repairs during periods of minimal load, which is confirmed by the results of a number of studies (2, 4, 9). Constant monitoring and prompt intervention can increase the service life of equipment, preventing accidents This is confirmed by engineering approaches to ensuring the durability of machines (11). At the same time, the combination of engineering methods presented in monographs and recommendations [11, 12] with AI technologies and traditional engineering approaches provides comprehensive management of the state of technical systems.

Despite the obvious benefits, implementing AI in predictive services faces a number of challenges. The quality and integration of data remain critical for making accurate forecasts, since a variety of sources requires standardization and unification of measurement methods, which is confirmed by studies on the formation of metrological support kits [10]. An additional problem is the complexity of models and their interpretability: modern deep learning models are highly accurate, but their "black box" makes it difficult to interpret the results for managerial decision-making, and the adaptation of state control structures described in studies on structural adaptation of security control programs (13) can help increase the transparency and reliability of systems. In addition, the implementation and adaptation of AI systems requires significant investments in IT infrastructure and staff training (4).

The future of predictive maintenance is linked to further development of algorithms, increased computing power, and improved big data analysis tools. Promising areas are the development of hybrid machine learning models or multimodal large language models that can combine the advantages of various analysis methods and take into account complex equipment operation modes, taking into account improvements in mechanistic models [8]; the creation of standards for interpreting forecasts and integrating automated control systems, confirmed by methodological recommendations [12]; and the use of engineering methods for predictive modeling. ensuring the durability and reliability of equipment, which is reflected in monographic studies [11] and adaptation of safety control programs [13].

Thus, the analysis of the presented materials demonstrates that the use of artificial intelligence in predictive maintenance and condition management systems of technical systems is an effective tool for improving the reliability and optimizing the operation of equipment. Integration of modern machine and deep learning algorithms with industrial information systems can significantly reduce costs and minimize the risk of failures, and additional methodological studies (8-13) emphasize the need for an integrated approach that includes improving data quality, improving the interpretability of models, and optimizing maintenance planning processes. Despite the existing challenges, further research and development in this area contributes to the creation of more adaptive and reliable technical condition management systems.

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How AI is Used in Predictive Maintenance – a Review

Whether dealing with conveyor belts in a manufacturing or mining plant or a leaking pipe in an oil pipeline, things wear down or break and must be fixed or replaced. Unfortunately, failure is often no fatality; there is a lack of proactive identification. This article will focus on the contribution of Artificial Intelligence to proactive or predictive maintenance to reduce the risk of catastrophic or costly problems before they occur.

From the fundamentals of predictive maintenance to recent machine learning algorithms, one would use artificial intelligence and machine learning to reshape best practices as a powerful tool, giving actionable insights and empowering organizations to "stay ahead of failure." Ideally, one will be equipped to overcome challenges for a more sustainable future with increased productivity and better product quality.

Machine learning in predictive maintenance can offer benefits such as cost savings, increased reliability, extended equipment life, and customer satisfaction.

Predictive maintenance is a proactive approach to predicting and preventing failure.

Predictive maintenance relies on real-time data and advanced analytics to predict when equipment will likely fail. Predictive maintenance algorithms can identify patterns and anomalies indicative of impending failure by continuously monitoring machine performance indicators such as temperature, vibration, and fluid levels.

A technique used in predictive maintenance is condition-based monitoring, where sensors collect data on equipment health and performance. Machine learning analyses this data to detect early warning signs of potential issues for maintenance teams.

The advantage of predictive maintenance is its ability to maximize productivity: organizations can avoid costly unplanned equipment downtime and reduce unnecessary maintenance activities. Predictive maintenance can extend asset lifespan by preventing premature failures and optimizing maintenance schedules.

Predictive maintenance requires a predictive model to support it, and machine learning is an AI branch that offers various data analysis approaches to prediction.

Supervised learning involves training a model on "labelled" data. Here, the artificial intelligence neural network algorithms learn to map input features to corresponding output labels. This approach is commonly used to predict failure probabilities based on historical data.

An **unsupervised** machine learning model deals with unlabelled data to identify hidden patterns or clusters within the dataset. Unsupervised learning algorithms can uncover anomalies or detect deviations from normal equipment behaviour in predictive maintenance, signalling potential failures.

Reinforcement learning involves training an agent to interact with an environment and learn optimal actions through trial and error. It can be used to optimize maintenance schedules or resource allocation strategies to minimize unplanned downtime and maximize reliability.

Data collection in predictive maintenance comes from various sources, such as sensors, monitoring systems, and historical records. Records include equipment health metrics, operating conditions, and environmental factors.

Once datasets are collected, they undergo thorough analysis using statistical techniques, machine learning algorithms, and data visualization tools. Analysis helps identify patterns and trends and spot anomalies indicative of potential equipment failures or maintenance needs. Predictive models are delivered as easily deployable tools, giving meaningful insights to anticipate failures in manufacturing operations and other operations, such as logistics, without requiring data science skills.

Thus, maintenance professionals in the manufacturing industry can anticipate and proactively address issues using embedded or canned software solutions through advanced analytics and predictive modelling before they escalate into costly breakdowns. Data elaboration enables continuous machine performance monitoring, facilitating condition-based interventions and optimizing maintenance schedules.

AI-powered predictive maintenance offers numerous advantages that revolutionize practices across industries.

First, it significantly lowers maintenance costs by enabling proactive measures to address potential equipment failures before they occur. By analysing data from sensors and monitoring systems, AI algorithms can detect early warning signs of malfunctions. This allows timely interventions to prevent equipment failures and reduces the need for costly emergency repairs.

Furthermore, AI-powered predictive maintenance contributes to extending the product's lifecycle. By addressing issues promptly and preventing unnecessary strain on equipment, predictive maintenance reduces the frequency of replacements, machine downtime, and capital expenditures, maximizing organizations' return on investment.

AI-driven predictive maintenance improves operational efficiency by optimizing maintenance schedules and resource allocation. Analysing real-time data and predictive analytics allows AI algorithms to prioritize tasks and allocate resources more effectively. Maintenance teams achieve more with fewer resources: labour costs are reduced, and service technicians' productivity increases!

Courtesy: https://www.neuralconcept.com/post/how-ai-is-used-in-predictive-maintenance