The Industry of the Future: From Industry 4.0 to Industry 5.0 – Integration of Humans and Technology: New Technologies

Karabegović, Isak

2025

Akademija nauka i umjetnosti Bosne i Hercegovine

https://bastina.anubih.ba/handle/123456789/837

DOI: 10.5644/PI2025.220.03

Towards a Smart Maintenance Model

Vidosav Majstorovic[*1], Vladimir Simeunovic[2], Dragan Stosic[2], Sonja Dimitrijevic[2], Filip Todorovic[3]

Abstract: *Smart maintenanceis a model created on the concept of Industry 4.0, and uses its advanced technologies, the Internet of Things (IoT), artificial intelligence (AI) and predictive big data analytics (BDA), in order to reduce equipment failures and extend its life, thus reducing maintenance costs, and technological resources are used optimally. By monitoring data in real time, from sensors and IoT devices, the condition of the equipment is predicted, decisions are made automatically, and the operational performance of the equipment (OEE) is improved. Equipment failure prediction is done by analyzing the behavior patterns of equipment entities, which are obtained by machine learning (ML), generated by digital twins (DT) and supported by cloud computing.*

Today, we are witnessing the full maturity of Industry 4.0, and the emergence of its advanced or future version, Industry 5.0. However, we must state that the creators of the Industry 4.0 model (German Academy of Engineering Sciences) believe that the Industry 5.0 model today, as promoted by its creators, is not a NEW model, but only a somewhat improved version of Industry 4.0 in the areas of: greater human integration into this automation model (operator 4.0/5.0), greater environmental aspects of production (green production) and the application of artificial intelligence (AI), which we are witnessing today in the Industry model as well 4.0.

Starting from the above facts, this paper deals with the current level of development of the maintenance model in the context of Industry 4.0, which is the smart maintenance model (SM). System analysis of predictive maintenance model, smart maintenance framework model was performed. Some results of our research in this area are also given at the end of the paper.

Keyword: *Industry 4.0, Smart Maintenance, Deep Machine Learning, Proactive Maintenance.*

1. Introductory Notes

The evolution of the maintenance model in the new era moved through the following models [1-3] : (i) corrective maintenance ((the machine is repaired only when a failure occurs, low maintenance costs, minimal planning (if any), major production stoppages and consequently losses, this model was created in

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[*1]University of Belgrade, Faculty of Mechanical Engineering , Belgrade
E-mail: vidosav.majstorovic@gmail.com
[2] "Mihajlo Pupin" Institute, Belgrade
[3]TE-KO Kostolac, EPS, Kostolac

the first industrial revolution (IR), and was also used in the II IR)), (ii) preventive maintenance (represents the planned maintenance model, which was established in the II IR, and was used in the III IR, maintenance operations are performed regularly (planned), regardless of the state of the machine entity, sudden failures are reduced and the life of the machine is extended, but maintenance costs may be increased, (iii) condition-based maintenance is closely related to the development and application of computers in technological systems.

This model also had its variants - total productive maintenance, world-class maintenance and the like, and (iv) with the advent of Industry 4.0 and the application of its technologies, smart maintenance, based on the real state of the machine entity and guided by AI, is being developed and increasingly applied today. This model generates data using IoT sensors in real time, predicts failures with deep learning models (DML) and provides reliable information for maintenance operations, only when they need to be done. In this way, sudden stoppages are eliminated, costs are reduced and resources are optimized.

On the other hand, this model requires the application of advanced Industry 4.0 technologies, qualified workforce and additional investments in hardware/software infrastructure of the model. That is why it is applied on equipment of high technological value (turbines, aircraft engines, special machine tools, robots and others), or on systems where it is justified to do so due to safety, high downtime costs (mining, railways, etc.). An overview of the development of the maintenance model is shown in Table 1.

Table 1. Evolution of Maintenance models (adopted according to [4-6])

Industrial revolution	**Industry1.0 (1760 – 1880)**	**Industry2.0 (1890 – 1960)**	**Industry3.0 (1970 – 2000)**	**Industry4.0 (2010 –)**
Main characteristics	Mechanization, steam power (Traditional era)	Mass production, assembly lines (Industrial growth)	Automation, Maintenance information system (Digitalization)	IoT, AI, BDA, Cloud computing (Artificial intelligence)
Type of maintenance	Corrective maintenance	Preventive maintenance	Condition-based maintenance	Smart maintenance (SM)
Key maintenance operation	Visualinspection	Instrumental inspection	Sensormonitoring	Predictiveanalysis
OEE (*Overall Equipment Effectiveness*)	<50%	50 – 75%	75 – 90%	> 90%
Maintenanceteam reinforcement (Key person)	Trainedcraftsmen	Maintenance worker	Reliability engineers	Datescientists
Application of AI	-	-	Expert and knowledge based systems	Machine learning and deep machine learning

Smart Maintenance (SM) is defined by the elements of Industry 4.0, which is based on the digital transformation of the industry through advanced automation, real-time data analysis and interconnected entities (machines, processes, parts). Using CPS, IoT sensors and AI-driven analytics, SM enables industries to: (i) predict failures before they happen, with online entity condition monitoring and machine learning, (ii) automate maintenance decisions, with real-time diagnostics and cloud-based computing systems, (iii) improve interoperability by integrating smart factory (SF) entities and digital twins (DT) for maintenance operations.

The most important advantages of SM are: (i) cost reduction (through the elimination of unnecessary (planned) maintenance operations and timely prevention of sudden failures), (ii) improved efficiency and productivity (the overall effectiveness of the equipment (OEE) is maximized), because this is achieved with real-time data analytics, (iii) improved reliability and equipment life, because continuous monitoring enables early detection of failures, preventing major failures.

Also, continuous monitoring and application of the maintenance strategy according to the condition - predictive maintenance (PrM), extends the life of equipment, thus reducing capital costs, (iv) energy efficiency and sustainability (optimizes energy use, while reducing resource consumption and waste generation, thus supporting green industrial practices), (v) improving workplace safety and compliance with standards and industry regulations. To conclude, SM has revolutionized traditional maintenance models, making them more efficient, cost-effective and reliable, and in all this automation and digital transformation based on Industry 4.0 are the key framework.

1.1 Objectives of the Papers

The aim of this paper is to provide a comprehensive analysis of SM, including its technologies, applications, challenges as well as future development. The key objectives are: (i) research on SM models and technologies (the place and role of IoT, AI, machine learning, big data, cloud computing and digital twins in predictive and proactive maintenance) that enable real-time monitoring, failure detection and automatic decision-making, (ii) analysis of industrial case studies (application of SM in industries such as manufacturing, energy, transport and healthcare, as well as evaluations of the impact of smart maintenance on reducing maintenance costs and increasing equipment efficiency and reliability), (iii) case studies, through the analysis of rounded software products for SM and PdM, open source platforms and database (knowledge) models for the same purpose (SM, PdM), (iv) EXMAS model and (v) conclusions with future trends and possibilities of application of generative AI, and blockchain technology in SM and PdM models.

2. Literature Review

The basic framework for the development and application of the smart maintenance (SM) model is Industry 4.0, so this analysis refers to the period from 2011 to the present, and included only the most cited references in this field[3].
Reference [7] is part of the European SERENA Project, which involved a collaboration between fourteen partners, including academic institutions, technology companies and industrial plants, Table 2, and the model was developed for SMEs.

Table 2. Overview of smart maintenance model development

Purpose	Ref. / year	Method	Goal	Application
SM for SMEs	[7]2021	Deep learning models	Increasing model accuracy	Predictive maintenance (PdM)
Online analysis of big data	[8]2018	CNN, RNN	Optimization of computer resources	Cloud/fog computing
Anomaly detection	[9]2017	Seven different models	Selecting the appropriate model for a maintenance problem	PdM
The infrastructure of the Industry 4.0 model	[10]2015	5C architecture for CPS	Building a smart factory	Predictive maintenance of CPS
Detailed analysis of the SM model	[11]2020	Industry 4.0 technologies for PdM	Application of the Industry 4.0 model	Smart factories
Data mining for PdM	[12]2019	Collection, analysis and processing of signals and data	Creating reliable BDs	PdM
Classification of learning models	[13]2022	Determining the appropriate anomaly detection model	Online monitoring of possible cancellation status	PdM
Improve manufacturing process	[14]2023	Data mining to detect and predict potential anomalies	Knowledge representation in SM	Heterogeneous nature of industrial data
Improve manufacturing process	[15]2021	Financial implications of production downtimes	Define PdM model	Automotive industry

This approach means that such companies (SMEs) are limited in resources, especially in expertise in data analysis. And in this area, the biggest challenges are related to the heterogeneity and scalability of data, offering a model for the development of a robust data infrastructure. A critical analysis of various algorithms, such as Bayesian networks, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Term Memory (LSTM) networks, is performed, discussing their suitability and performance in the context of smart manufacturing (SM). Hybrid methods, which combine multiple algorithms, are also applied to improve the accuracy of PdM models. The potentials of integrating advanced technologies such as: digital twins (DT), autonomous systems and 5G network, in order to further improve SM capabilities, are analyzed. The authors suggest that embracing these innovations could lead to more proactive and autonomous SM strategies, thereby sustaining the growth of manufacturing intelligence.

Reference [8] gives an overview of the application of deep learning techniques in the online analysis of big data, from the aspects of quantity, speed, variety and variability. Convolutional neural networks (CNN), recurrent neural networks (RNN) and autoencoders proved to be the most suitable. As computer support, the following are suitable: cloud computing, for applications where real-time response is not required (equipment condition monitoring, to predict failures), but large data sets and complex DL models are involved, and fog computing, which provides decentralized computing resources, closer to IoT devices, facilitating real-time data processing and reducing latency.

Online monitoring of the state of entities of machines, processes and parts, in order to develop a model of predictive maintenance, requires the development of the concept of recognizing anomalies that arise from entity monitoring [9]. For these reasons, seven different methods have been developed: (i) distance - based anomaly detection approaches, uses the distance metric, defining application scenarios, (ii) clustering - based anomaly detection approaches, examines techniques that detect anomalies by identifying data points that do not belong to any cluster, addressing the nuances of points near the cluster boundaries, (iii) model - based anomaly detection approaches, covers strategies that rely on modeling the basic processes of data generation, enabling the identification of points data that deviate from expected patterns, (iv) distance and density based approach, considers methods that take into account both the distance between data points and the density of surrounding regions to detect anomalies, (v) rank based approach, uses techniques that rank data points based on their probability of being anomalies, offering an alternative perspective to distance and density methods, (vi) ensemble methods, describes the use of multiple algorithms in tandem to improve the performance of anomaly detection, taking advantage of different methods, and (vii) algorithms for time series data, addresses anomaly detection in sequential data, emphasizing the importance of temporal context. Each of the methods found has its advantages and disadvantages, for example, the last one is suitable for monitoring the state of vibration of control bearings, based on which the moment when the bearing should be replaced can be determined.

One example of the 5C architecture for CPS, adapted to the Industry 4.0 model, which provides the integration of physical and digital systems in production [10]. The key components of the 5C architecture are: (i) connection layer (defining sensor networks and IoT devices to collect real-time data, enabling their visibility into machine operations), (ii) conversion layer (transforms raw data into forms that can be generated by cloud/edge computing, creating a base for BDA analyses), (iii) cyber layer (generates DT, creating virtual replicas for simulation and monitoring, improving predictive capabilities), (iv) cognition layer (uses AI/ML models for diagnostic and prescriptive analytics, enabling autonomous decision-making, and (v) configuration level (facilitating feedback for system optimization, ensuring adaptability to dynamic environments).This model has the following characteristics: (i) structured framework, the 5C model provides a hierarchical approach to CPS, bridging the gap between physical infrastructure and digital tools, (ii) interoperability, emphasizing standardized communication protocols, although the specifics of existing standards (e.g. OPC UA) limited, and (iii) human-machine cooperation, interface for communication with users. This model is particularly interesting for predictive maintenance, as it enables real-time BDA to reduce downtime by predicting failures. Compared to other models, for example with IIRA (Industrial Internet Consortium), it focuses on broader IoT integration, while 5C emphasizes manufacturing-specific CPS layers, and RAMI 4.0 is aligned for digital twin use, but lacks 5C's explicit cognitive layer for AI-driven decisions. The advantages of this model are: holistic integration of data processing in real time and adaptable to management, as well as a clear roadmap for the application of the Industry 4.0 model, confirmed through case studies (eg smart factories), while the limitations are related to cyber security (can be improved by applying blockchain) and user training. The work became a fundamental reference, influencing subsequent DT and AI research in manufacturing (including maintenance) and remains key to understanding CPS in Industry 4.0, offering a balanced blend of theory and practical application.

In [11], a systematic literature review is given, which synthesizes research on PdM in Industry 4.0, providing insight into technologies, challenges and future research directions. Key technologies for PdM are: IoT and sensors, for collecting data from machines in real time, AI/ML models, especially deep learning models, cloud/edge computing, for storage/processing of BD data, DT as virtual models for condition monitoring and equipment behavior simulation. In this concept, there are special challenges related to data quality (noise, missing values), heterogeneity (multi-source integration) and scalability, then cybersecurity risks and high initial costs, and finally lack of knowledge and skills in implementing AI-driven solutions. Case studies in the automotive, energy and manufacturing industries show a 20 to 30% reduction in downtime due to sudden failures. Special aspects of the application of this model (PdM) are the standardization of its elements and interoperability. Therefore, future research will be directed towards: technology (edge AI for real-time decision-making, federated learning for privacy), modeling (hybrid approaches (physics-based + data-driven) and explainable AI (XAI)) and sustainability (PdM's role in reducing waste and energy consumption). Compared to previous review works in this area, this paper highlights the close interaction between PdM and the core technologies of Industry 4.0 (eg DT). The rapid evolution of Industry 4.0 technologies requires constant updates (sustainability metrics and the impact of 5G on the operation of PdM models in real time).

Research on the integration of Industry 4.0 elements such as CPS, IoT and data mining to improve the PdM model in SM is presented in [12]. The key components of this model are: (i) sensor and real-time data collection on various parameters, providing immediate detection of anomalies, (ii) signal and data processing, where noise filtering and extraction of significant information are performed, in the time and frequency domain. Techniques such as Wavelet Packet Decomposition (WPD) and Fast Fourier Transform (FFT) are utilized to transform time-domain signals into the frequency domain, aiding in accurate fault detection, (iii) and feature extraction (processed data is analyzed to identify specific features indicative of equipment health. This step is crucial for distinguishing between normal operational variations and potential faults), (iv) maintenance decision-making (leveraging AI and data mining, the system diagnoses current equipment conditions and predicts future failures. This proactive approach enables timely interventions, reducing unexpected downtimes), (v) maintenance scheduling optimization (based on diagnostic insights, maintenance activities are strategically scheduled to minimize disruptions and optimize resource allocation), and (vi) feedback control and compensation (the system incorporates feedback loops to adjust operational parameters in real-time, compensating for detected anomalies and maintaining optimal performance). The practical application of the PdM framework through a case study involving a pressure blower. Vibration sensors collected data, which was then decomposed using WPD and transformed via FFT. Features extracted from this analysis trained an Artificial Neural Network (ANN), enabling the system to diagnose faults and predict the Remaining Useful Life (RUL) of components. This approach demonstrated higher efficiency and effectiveness compared to traditional maintenance methods.

The paper [13]provides a comprehensive overview of PdM models in the context of Industry 4.0, focusing on technological developments, model frameworks and practical challenges. A particularly important aspect of this research is the analysis of machine learning models suitable for application in the PdM model, namely: (i) supervised learning (random forest, support vector machines (SVM), gradient boosting) - for failure classification and anomaly detection in machinery vibration data, (ii) unsupervised learning - clustering (eg, k-means) for identifying unknown failure patterns, (iii) deep learning (DL), used two models - CNNs for image-based fault detection (eg, thermal imaging of equipment) and recurrent neural network (RNN) and long short-term memory

(LSTM) for time-series sensor data (eg, predicting bearing wear), and (iv) hybrid and emerging models - physics-informed ML, combines domain knowledge (eg, mechanical wear equations) with data-driven models), and reinforcement learning (RL) for adaptive maintenance scheduling in dynamic environments.

In this study [14], the authors address the challenges posed by the heterogeneous nature of industrial data in achieving effective maintenance decision-making and interoperability among diverse manufacturing systems. They propose a hybrid approach that integrates ontologies, machine learning techniques, and data mining to detect and predict potential anomalies in manufacturing processes. The focus is on designing an intelligent system with standardized knowledge representation and predictive capabilities. By bridging the semantic gap and enhancing interoperability, ontologies facilitate the integration of various manufacturing systems, optimizing real-time maintenance decision-making. The experimental results demonstrate that this approach not only ensures system reliability but also promotes a seamless, integrated, and efficient production environment.

Reference [15]provides a comprehensive examination of PdM within the context of Industry 4.0. The authors highlight the significant financial implications of production downtimes, citing the 2016 Volkswagen incident where production issues led to losses of up to 400 million Euros per week. This underscores the critical importance of effective maintenance strategies in modern manufacturing environments. The authors propose a classification framework for PdM approaches. This framework categorizes existing methodologies, facilitating a clearer understanding of the diverse strategies employed in predictive maintenance within Industry 4.0. The paper delves into recent advancements in PdM, discussing how emerging technologies and data-driven approaches are being integrated into maintenance strategies. This includes the utilization of machine learning, IoT sensors, and data analytics to predict and prevent equipment failures. The transition from traditional maintenance schedules to more sophisticated, data-driven approaches that anticipate and prevent equipment failures. As industries continue to adopt Industry 4.0 principles, such comprehensive analyzes will be instrumental in guiding the development and implementation of effective PdM strategies.

3. Key Technologies in Smart Maintenance

Smart maintenance has evolved significantly, integrating advanced technologies to enhance equipment reliability, reduce downtime, and optimize maintenance processes. Key trends include using AI and IoT, because the convergence of AI and the IoT enables PdM by collecting real-time data from sensors embedded in machinery. AI algorithms analyze this data to predict equipment failures before they occur, allowing for proactive maintenance scheduling.

3.1. IoT and Sensor Networks

IoT and sensor networks play a crucial role in SM by enabling real-time monitoring, PdM, and automation in various industries [1,2,13]. SM leverages IoT devices and sensors to collect data, analyze performance, and optimize maintenance schedules to reduce downtime and improve efficiency.

Key aspects of IoT and sensor networks are: (i) real-time monitoring - IoT sensors continuously monitor machinery, infrastructure, and assets, tracking parameters like temperature, pressure, vibration, humidity, and energy consumption. This helps in detecting early signs of equipment failure, (ii) predictive maintenance (PdM), where sensors collect historical and real-time data, after that ML analyze patterns to predict failures before they occur, and maintenance is scheduled based on actual equipment conditions rather than a fixed schedule, reducing unnecessary maintenance costs, (iii) automated alerts and remote diagnostics, where IoT-enabled maintenance systems send automatic alerts to technicians when anomalies are detected, and remote monitoring allows experts to diagnose issues without physical inspections, reducing response time, (iv) energy efficiency and cost reduction, where sensors optimize energy usage by detecting inefficiencies in heating, ventilation, and air conditioning (HVAC) systems, motors, and lighting, and preventing unexpected breakdowns reduces downtime and repair costs, (v) DT and simulation, where a DT is a virtual model of physical assets that updates in real-time using IoT data, and it allows engineers to simulate scenarios, optimize maintenance schedules, and test solutions before implementing them, (vi) edge computing (processes sensor data closer to the source, reducing latency and network bandwidth usage) and cloud integration (cloud platforms store and analyze large datasets, providing insights into asset health and maintenance strategies). Today we have applications of those concepts in various industries, such as: (i) manufacturing for monitoring production lines for equipment (like CNC machine tools, robots, CMM), wear and tear, (ii) healthcare, where IoT-enabled medical devices ensuring operational efficiency, (iii) smart cities (infrastructure maintenance, including bridges, roads, and utilities, (iv) energy sector - wind turbines and power grids with predictive analytics, and (v) automotive and fleet management, where AI powered diagnostics for vehicle maintenance, etc. Challenges and future trends are related on: (i) cybersecurity risks - protecting IoT networks from hacking and data breaches, (ii) integration complexity - combining legacy systems with new IoT solutions, (iii) scalability, managing vast sensor networks efficiently, and (iv) AI / ML advancements, more accurate predictions and self-healing systems. At the end, IoT and sensor networks revolutionize smart maintenance by enabling proactive rather than reactive maintenance strategies. They enhance operational efficiency, reduce costs, and extend the lifespan of assets, making them indispensable for industries moving towards Industry 4.0.

3.2.Artificial Intelligence (AI) and Machine Learning (ML)

AI and ML are transforming smart maintenance by enabling predictive analytics and anomaly detection, where these technologies help organizations move from reactive or scheduled maintenance to a more proactive, predictive approach, reducing downtime and operational costs. AI and ML leverage sensor data, historical maintenance logs, and real-time operational data to optimize asset performance and improve reliability [1].

What are the main advantages of this maintenance model compared to others: (i) early fault detection, identifies potential failures before they occur, (ii) reduced downtime, prevents unexpected shutdowns and saving costs, (iii) optimized maintenance scheduling, means reduces unnecessary inspections and repairs, (iv) enhanced equipment lifespan is prolongs asset usability by ensuring timely intervention, and (v) automated decision-making, AI-driven systems can suggest or even initiate repairs.

Predictive analytics uses AI / ML models to analyze historical and real-time data to forecast when equipment might fail, based on the following steps: (i) data collection, by IoT sensors gather data (vibration, temperature, pressure, energy consumption, etc.), (ii) data processing, where AI cleans and preprocesses raw data to remove noise, (iii) feature engineering, identifies key parameters influencing failures, (iv) model training, using by ML models (eg, regression, neural networks, decision trees, etc) learn from past data, and (v) failure prediction, where AI predicts when maintenance should be performed.

Different AI techniques are used as learning models, which have different purposes in the PdM model: (i) time series analysis, for the forecasts future failures based on historical trends, (ii) regression models used to estimate the remaining useful life (RUL) of assets, (iii) neural networks and deep learning for recognizes complex patterns in equipment behavior, and (iv) bayesian networks, for estimates failure probability based on multiple factors.

By applying the aforementioned models, anomaly detection identifies unexpected deviations in operational data, signaling potential failures. The whole concept is realized as follows: (i) baseline learning, where AI learns normal operating behavior from historical data, (ii) continuous monitoring, sensors provide real-time data streams, (iii) deviation identification by AI detects abnormal variations (spikes, drifts, or sudden drops), (iv) root cause analysis, the system analyzes contributing factors and suggests corrective actions. The analysis of the learning model, according to the types of anomaly identification, was done in the previous point [13].

Future trends and challenges are : (i) integration of AI and IoT (AIoT), for real-time decision-making, (ii) use of digital twins to simulate maintenance scenarios, (iii) AI-powered for autonomous repair bots, and (iv) edge AI for faster anomaly detection at the device level.

On the other hand, possible difficulties, as challenges are: (i) data quality and availability, which means, inconsistent or incomplete sensor data can affect AI predictions, (ii) cybersecurity risks, where AI-driven maintenance systems are vulnerable to hacking, and (iii) high initial investment – AI implementation requires infrastructure and expertise. AI / ML are revolutionizing SM through predictive analytics and anomaly detection, ensuring efficiency, cost savings, and reliability. As AI continues to evolve, future maintenance systems will become even more automated, intelligent, and self-healing.

3.3. Big Data Analytics (BDA)

PdM leverages big data analytics to monitor equipment, predict failures, and optimize maintenance schedules [1,13]. Traditional maintenance methods—reactive (fixing after failure) and preventive (scheduled maintenance)—are inefficient, leading to unnecessary costs or unexpected downtimes. BDA in PdM transforms maintenance strategies by using sensor data, machine learning (ML), and real-time processing to anticipate failures before they occur.

Big data in PdM comes from multiple sources: (i) industrial IoT (IIoT) sensors, for following vibration, temperature, pressure, acoustic, etc., (ii) machine logs and operational data, where error logs, usage statistics, (iii) maintenance records, with history of past interventions, parts replaced, and (iv) environmental data, including humidity, external temperature affecting machinery. Data is collected in structured (databases), semi-structured (JSON, XML), and unstructured (video, images, audio) formats.

Data storage and management, handling vast amounts of data requires advanced storage solutions: (i) cloud storage (by platforms AWS, Azure, Google Cloud), scalable, distributed storage, (ii) edge computing, where localized data processing for real-time insights, and (iii) distributed file systems (using platforms such as HDFS, Apache Cassandra), efficient storage for high-velocity data. Data cleaning and preporocesing / processing and decision making with advanced analytics are performed, as already analyzed in point 2 [12].

Advanced PdM systems use real-time analytics to provide instant failure warnings by : (i) s treaming data processing (using platforms as apache kafka, apache spark streaming), (ii) processes continuous sensor data, using edge AI (processes data locally for faster decision-making), and DT for virtual models simulate and predict equipment behavior. The problems that arise in the application of the BDA model relate to: data quality issues (incomplete or noisy sensor data affects accuracy), computational complexity (high-dimensional data requires efficient processing), integration with legacy systems (many industries still use old equipment) and cybersecurity risks (vulnerability to cyberattacks on IIoT networks). Future trends in this area in the following research directions : (i) AI-driven prescriptive maintenance, which means recommends optimal actions after failure prediction, (ii) 5G-enabled PdM refers to ultra-low latency for real-time machine monitoring, (iii) explainable AI (XAI), which means improves interpretability of complex ML models, and (iv) federated learning, which means the use of decentralized training of ML models across multiple factories or machines. BDA is revolutionizing predictive maintenance by improving failure prediction accuracy, reducing operational costs, and optimizing asset performance using AI, IoT, and cloud computing evolve, predictive maintenance will become more intelligent, autonomous, and cost-effective.

3.4. Digital Twins

Digital Twins (DTs) are virtual representations of physical assets, systems, or processes that integrate real-time data, simulations, and analytics to optimize performance and predict failures. In PrM, DTs serve as a crucial technology by enabling proactive monitoring, fault detection, and operational efficiency improvements [1,13-15]. A DT is a dynamic, real-time digital counterpart of a physical entity. It is continuously updated with data from sensors, historical records, and operational parameters, providing a comprehensive model for analysis and decision-making.

The basic elements of DT are: (i) physical entity, which includes the real-world asset or system being monitored, (ii) data sensors and IoT connectivity (devices that capturereal-time data for analysis), (iii) virtual model - a software-based simulation representing the behavior and conditions of the asset, (iv) analytics and AI algorithms, including machine learning and AI-driven models that process data for predictions, and (v) feedback mechanism, meaning a bidirectional flow of information that allows for real-time optimization. PrM aims to reduce unplanned downtime, extend asset life, and optimize operational efficiency.

Digital twins enhance PrM by leveraging data-driven insights for better decision-making, and the whole concept provides the following: (i) real-time condition monitoring, where DTs provide continuous tracking of asset health, identifying anomalies early, (ii) failure prediction and risk assessment by analyzing historical and real-time data, DTs forecast potential failures, allowing timely intervention, (iii) scenario simulation and optimization, where DTs enable the testing of different maintenance strategies in a virtual environment, minimizing disruptions, (iv) prescriptive maintenance recommendations, where AI-driven DTs suggest optimal maintenance actions based on performance trends, and (v) reduced downtime and cost savings by proactive maintenance strategies lower repair costs and enhance system reliability.

Simulation and optimization are core functionalities of DTs in PrM, and depending on the field of application, they can be used for: (i) physics-based simulations, where models that replicate real-world behaviors using engineering principles, (ii) data-driven simulations, used AI and ML-based models that predict outcomes using historical data, and (iii) hybrid approaches is a combination of physics-based and data-driven models for accurate predictions.

Despite their benefits, several challenges hinder the widespread adoption of DTs: (i) data integration complexity, ensuring seamless data collection from heterogeneous sources, (ii) high implementation costs, because initial investment in hardware, software, and expertise, can sometimes be large, (iii) cybersecurity risks, where increased vulnerability due to connectivity and data exchange should be taken into account, (iv) scalability issues, meaning that difficulty in applying DTs across diverse assets and large-scale systems, and (v) model accuracy and maintenance, means ensuring that the digital twin remains an accurate representation of the physical asset over time.

Future trends in DT for PrM can be defined as: (i) AI and edge computing integration, which means enhancing real-time decision-making capabilities, (ii) Blockchain for secure data exchange, which means addressing cybersecurity concerns through decentralized data management, (iii) 5G connectivity, refers to enabling faster and more reliable data transmission, (iv) autonomous maintenance systems, is a trend that means combining robotics and AI-driven DTs for automated repair processes, and (v) cross-industry applications, means expanding DTs beyond manufacturing to healthcare, energy, and smart cities. As industries continue to embrace digital transformation, digital twins will play an increasingly vital role in achieving efficiency, cost reduction, and reliability in asset management.

3.5. Cloud/Edge Computing

A critical aspect of PdM is efficient data storage and processing, where Cloud and Edge Computing play pivotal roles. These architectures determine how data is collected, stored, and analyzed for actionable insights [13-15]. PdM systems rely on sensor data from industrial machinery, such as: vibration analysis, temperature monitoring, acoustic emissions, oil and fluid analysis, power consumption, wear of machine elements. These data streams generate vast amounts of information that must be processed efficiently to detect anomalies, predict failures, and recommend maintenance schedules.

Cloud computing provides scalable and cost-effective storage solutions, including: (i) object storage (for example used AWS S3, Azure Blob), for stores raw sensor data, logs, and images, (ii) time-series databases (eg, InfluxDB, AWS Timestream), for handles large-scale telemetry data, and (iii) relational databases (eg, MySQL, PostgreSQL, Snowflake), for stores structured historical maintenance records. Cloud processing and analytics hardware amd software support should solve the following tasks: (i) AI/ML model training, which includes the cloud enables large-scale training of PrM models using platforms like AWS SageMaker, Google Vertex AI, and Azure Machine Learning, (ii) BDA using platforms like Apache Spark, Hadoop, and Databricks process massive sensor datasets, (iii) building of DT, where cloud services help create real-time virtual models of equipment for continuous monitoring, and (iv) historical data analysis, which means storing years of operational data in the cloud supports trend identification and failure pattern recognition. Benefits of cloud computing in PdM refer to: scalable data storage and compute power, centralized model training and updates, integration with IoT platforms (AWS IoT, Azure IoT Hub), and global accessibility for maintenance teams. On the other hand, the challenges of cloud computing in PdM are: latency issues in real-time decision-making, high bandwidth consumption for transmitting large datasets, and data privacy and regulatory compliance concerns.

Instead of sending all data to the cloud, edge computing stores and processes data closer to the source using: local databases (SQLite, TimescaleDB), on-premise servers and industrial gateways, and embedded storage within IoT devices. Also, this model (edge computing) realizes the function of edge processing and analytics in the following way: (i) real-time anomaly detection - AI models run locally on edge devices (eg, NVIDIA Jetson, Raspberry Pi, Intel Movidius), (ii) edge AI/ML inference, which means - instead of cloud-based model execution, trained models are deployed at the edge using frameworks like TensorFlow Lite, ONNX Runtime, or AWS Greengrass, and (iii) event-driven alerts, where edge computing enables real-time response, such as stopping a machine upon detecting a failure risk.

When compared with cloud computing, this model (edge computing) has the following advantages: (i) low latency - faster decision-making and reduced downtime, (ii) reduced bandwidth costs - limits unnecessary cloud data transfers, (iii) enhanced security - local data processing minimizes cloud exposure, and (iv) offline functionality - systems can continue working even without cloud connectivity. On the other hand, the disadvantages of this model are: limited processing power compared to cloud platforms, requires frequent firmware and model updates, and higher initial infrastructure cost.

However, we must point out here that there is also a hybrid cloud-edge architecture in PrM, where many industries implement this concept for: (i) edge devices perform real-time anomaly detection and initial processing, (ii) cloud platforms handle long-term data storage, model training, and deep analytics, and (iii) IoT gateways serve as an intermediary between edge devices and cloud platforms. It is interesting to mention here an example hybrid workflow, in the PdM model, such as: (i) data collection, where sensors collect vibration and temperature data from industrial machines, (ii) edge processing, where edge AI models analyze real-time data and generate alerts if anomalies are detected, (iii) selective cloud upload, where only relevant or summarized data is sent to the

cloud for further analysis, (iv) model retraining in cloud - ML models are updated based on aggregated historical data, and (v) model deployment to edge - improved models are pushed back to edge devices for enhanced accuracy.
Concluding this analysis, we will also look at aspects of the application of these models in various industries: (i) manufacturing - edge-based vibration monitoring for CNC machines, and cloud-driven failure prediction for robotic arms, (ii) energy sector - wind turbine edge analytics for real-time fault detection, and cloud-based maintenance planning for power grids, (iii) transportation and automotive - edge AI for fleet vehicle predictive diagnostics, and cloud-enabled maintenance scheduling for airlines, and (iv) healthcare - edge-based failure prediction for MRI and CT scanners, and cloud AI for predictive hospital equipment maintenance.Concluding this analysis, we will also look at future trends in cloud/edge computing for PdM: (i) 5G integration, faster connectivity enables smoother cloud-edge coordination, (ii) federated learning, which means decentralized AI training improves edge-based model learning, (iii) quantum computing, enhances predictive accuracy with complex simulations, and (v) blockchain for security, means that it protects PdM data integrity in cloud and edge environments. PrM thrives on efficient data storage and processing, where cloud computing offers scalability and advanced analytics, while edge computing ensures real-time insights with lower latency. A hybrid cloud-edge approach is emerging as the optimal solution, balancing real-time processing and large-scale data analysis.

3.6. Robotics and Drones

The role of Robotics in PdM can be twofold: automated inspections, where robots equipped with sensors (vibration, thermal, acoustic) can patrol industrial environments (eg, factories, power plants) to monitor machinery health, and consistency and safety, where they perform repetitive or hazardous tasks (eg, inspecting high-temperature equipment) with precision, reducing human risk [7,14,15]. For example, in the refinery autonomous mobile robots (AMRs), or robotic arms with vision systems for detecting cracks in pipelines.
The role of drones can be threefold: accessibility, where drones excel in inspecting hard-to-reach infrastructure (wind turbines, bridges, transmission lines) using cameras, LiDAR, or thermal imaging, efficiency, where rapid aerial surveys replace manual inspections, cutting time and labor. For instance, drones detect blade erosion on wind turbines or corrosion in oil rigs, and data collection, by high-resolution imagery and multispectral sensors provide rich datasets for AI-driven anomaly detection. In order for these systems, robots and drones, to be adequately applied in the PdM model, they are supported by the elements of Industry 4.0, namely: sensors, for vibration analyzers, infrared thermography, ultrasonic detectors, and gas sniffers, then AI/ML models where algorithms

process sensor data to identify patterns (eg, bearing wear) and predict failures, and integration, where data from robots/drones feeds into centralized platforms (eg, CMMS) for actionable insights, requiring robust IT infrastructure. The application of this technology brings the following benefits: cost savings, because it reduces reactive maintenance costs and downtime, then increases safety, because it limits human exposure to dangerous environments, and scalability, because it is suitable for large or distributed assets (eg, solar farms, rail networks).

However, there are also challenges, which can be defined as: initial investment, which can be high upfront costs for robotics/drone systems and training, then, data accuracy, which means that sensor reliability and algorithm precision are critical to avoid false positives/negatives, and then, regulatory hurdles, which especially relates to drone operations face airspace restrictions and certification requirements, and finally, maintenance of tools, which means ensuring robots/drones remain operational adds complexity. Now it is important to list examples of the real application of these technologies, namely: energy, where drones inspect offshore wind farms; robots monitor nuclear facilities, then transportation, where drones assess bridge integrity; rail robots check tracks, and finally, manufacturing, where for example AGVs patrol factories, while collaborative robots (cobots) assist in real-time equipment monitoring. In this area, future trends are: AI advancements, which means improved predictive models using deep learning for earlier fault detection, then 5G/edge computing, which refers to enables real-time data processing and faster decision-making, and swarm robotics - coordinated drone/robot fleets for large-scale inspections. Robotics and drones are transformative for predictive maintenance, offering efficiency, safety, and scalability. While challenges like cost and integration persist, technological advancements and growing industry adoption signal a promising future. Companies should evaluate ROI, pilot projects, and invest in training to fully harness these tools.

4. Case Studies

In this part of the paper, four case studies are presented, one of which refers to the PdM model of a well-known software manufacturer, and the other three represent open source platforms to support the development of PdM models.

4.1. Siemens PdM Model

This study [16], defines DT as virtual replicas of physical systems, enabled by IoT, AI and real-time data analytics, to optimize performance and maintenance. Smart maintenance, especially predictive maintenance, uses these technologies to predict failures, minimize downtime and reduce costs. Siemens, a leader in industrial automation and digitization, emphasizes their role in the application of the Industry 4.0 model through these innovations. Siemens uses its MindSphere IoT platform for data collection and analytics, integrated with software NX (product design) and Teamcenter (product life cycle management), to create DT from design to customer use. The model uses AI and machine learning as enhanced predictive algorithms, which analyze historical data, along with real-time data, to predict sudden equipment failures. Siemens has developed AI models that are highly accurate in detecting anomalies. Special emphasis is placed on real-time data processing via 5G networks and edge computing, for low-latency decision-making in critical applications such as energy networks.

This Siemens model has a variety of applications today, to name just a few: in manufacturing - an automobile manufacturer reduced downtime by 30% using Siemens tools for PdM, energy - wind turbines monitored through DT achieved a 20% increase in operational efficiency through PdM, and healthcare - MRI machines modeled with DT enabled proactive replacement of parts, reducing service costs by 15%. Detailed research into the application of this concept in practice shows that by applying the PdM model, unplanned downtime is reduced by up to 50% in industrial plants. Also, this concept is used to optimize energy consumption in factories, reducing the carbon footprint by 25% in implemented projects. Also, modular DT solutions have enabled SMEs to use phased solutions to have a return on investment within 12 months. Problems can arise due to data security, so Siemens has developed and implemented encrypted data transmission with blockchain technology. Upgrading of existing Siemens solutions is possible, using middleware gradual digital transformation. The lack of knowledge is solved by training through certified Siemens training courses.

Further research is being done to develop autonomous AI DTs, which will define application parameters themselves, using ML models. As far as sustainability is concerned, future research will make even more use of circular economy and green agenda paradigms. Application areas will expand to smart cities, precision agriculture and other areas. Siemens defines DT and SM as key elements for the application of the Industry 4.0 model in maintenance. Although challenges remain, their holistic ecosystem and focus on AI and 5G networks will be the leading directions in shaping future industrial applications. The study also highlights the need for continued investment in education and digital security to accelerate implementation in various fields.

4.2. Azure IoT Hub and Azure Digital Twins

Microsof Azure IoT Hub and Azure Digital Twins are the base components of Industrial IoT (IIoT) and DT ecosystem [17]. Azure IoT Hub serves to manage the platform in the cloud, as well as for two-way communication between IoT devices and the cloud. Azure Digital Twins enables the creation of dynamic

digital models of physical models using graphs (eg factories, smart cities, smart grid). Together, they provide a scalable open-source framework for real-time tracking of real objects (machines), predictive analytics, and application of SM models. Open source integration is supported by software development kit (SDK), application programming interface (API) and tools (eg Azure IoT Edge, Raspberry Pi integration).
Interoperability is built on industry standards such as the OASIS standard messaging protocol for the IoT (MQTT), Advanced Message Queuing Protocol (AMQP) and HTTPS, ensuring compatibility with various IoT devices. The flexibility of the hybrid cloud is provided through integration with on-premises systems through Azure Arc, thus providing hybrid applications. Azure IoT Hub has the following features: (i) Device Provisioning Service (DPS) provides automatic secure device registration and authentication using X.509 certificates and Trusted Platform Module (TPM), (ii) data ingestion is performed by handling telemetry from millions of devices, with support for message routing to Azure services (eg, Blob Storage, Event Hubs), (iii) security is provided by end-to-end encryption, with Role-based access control access control (RBAC) and integration with Azure Active Directory, and (iv) using the edge computing model allows Azure IoT edge to work with AI/ML models locally on devices, reducing latency and bandwidth costs.
Azure Digital Twins has the following features: (i) uses the open-source Digital Twin Definition Language (DTDL) modeling language to create hierarchical, property-rich digital DT models (e.g., machines in a factory, assembly components), (ii) Twin Graph represents a database of graphs that map relationships between entities (e.g., "sensor X follows machine Y"), (iii) works in real-time, updates the model using IoT Hub telemetry and external data sources (e.g., APIs for machines in operation), and (iv) API and SDK modules enable integrations with Python, C#, Node.js models. And the integration itself is performed in several steps: (i) device connection is done by entering data from sensors, PLCs or other entities into the IoT Hub, (ii) model creation is done by using Azure Digital Twins and the use of DTDL to build a virtual representation of the physical system, and (iii) model enrichment is done by integrating Azure services such as: time series (analytics), Azure ML (predictive models) and power BI (visualization). Applications of this concept are best seen in the smart factory model for SM, where for example IoT Hub collects vibration/temperature data from CNC machines and then Azure Digital Twins models machine health by predicting bearing failures. Also, a well-known car manufacturer reduced downtime by 25% by using Azure IoT Edge to detect local anomalies. In the smart city model, traffic management is performed by digital twins simulating traffic flow based on real-time IoT data (eg congestion sensors), and energy optimization is performed by integrating data from the grid and renewable sources and dynamic load balancing. In healthcare, monitoring of

asset equipment (CT, MR) is carried out, with the IoT hub monitoring the location/status of medical equipment and digital twins monitoring its health.

Microsoft's Azure IoT Hub and Azure Digital Twins provide a robust open source platform for building scalable solutions for DT. Although challenges such as complexity and cost still exist, their interoperability, security and integration with the Azure AI/ML ecosystem make them a good choice for enterprises working to implement Industry 4.0 models. Future innovations in AI/ML, edge computing and sustainability analytics are likely to cement their place and role in the SM model and IoT-driven digital transformation.

4.3. Smart Factory Dataset (SFD)

This platform was designed to support the development of the PdM model, to detect anomalies and predict failures in the SM model [18]. It is used to collect multimodal data, namely: time series (vibration, temperature, pressure), equipment health status monitoring (normal, degraded, faulty), production log monitoring (batch ID, cycle time, quality metrics), contextual data generation (operator work, maintenance log), and synthetic data generation (digital failure scenario).

Data sources are: IoT sensors (high-frequency data from CNC machines, robotic arms, conveyor belts, and HVAC systems), process histories (logs from SCADA/MES systems that monitor production parameters), maintenance records (timescales for repairs, part replacements, and root cause analysis), and environmental data (ambient temperature, humidity, and energy consumption). All this data can be structured (Comma-separated values (CSV)/Parquet files with labeled sensor readings), unstructured (images/video (eg thermal image of machines)), and metadata (JavaScript Object Notation (JSON) files describing equipment specifications and factory layout). The temporal granularity of the data shows us that sensor data is generated at the millisecond level for real-time analysis, the rest on an hourly, daily or weekly basis, as an aggregated production metric. Digital Twin integration is performed by generating synthetic failure scenarios using physics-based simulations (eg Ansys, MATLAB).

This is how testing scenarios are realized, according to the "what - if" principle (eg equipment degradation under changing load). And the anomalies of the machine entity are linked to the underlying causes (eg bearing wear - lubrication failure) using sensor data. AI model validation (e.g. SHapley Additive exPlanations (SHAP)/LIME compatibility), is performed when cyber security incidents occur (logs of simulated cyber attacks (e.g. false sensor readings, PLC hacking) are kept to study resilience. Application of this model is done through several elements: PrM - train ML models (LSTM, Transformer) to predict equipment failures, following reference metrics: precision/accuracy, mean time time to failure (MTTF), anomaly detection, using unsupervised methods (autoencoders, isolation forests) to identify process deviations, process optimization, reinforcement learning (RL) agents to minimize energy use or maximize throughput, explainable AI (XAI) validation, is test if XAI methods (eg, Grad-CAM, counterfactuals) align with ground-truth root causes, and cyber security allows us to detect hostile attacks on sensor networks using anomaly detection.

Technical challenges and limitations in the application of this model are: data volume and complexity (petabyte-sized data require distributed computing (Spark, Dusk) for processing and high dimensionality complicates feature engineering), labeling accuracy (manual labeling of root causes is a source of error and wastes more resources), generalization (models trained on synthetic data may fail in real-world application (sim-to-real gap), and privacy and compliance (anonymization of proprietary factory data Future improvements of this model will move in the following directions: real-time streaming - integration with Kafka/Flink for live anomaly detection, federated learning - enable privacy-preserving model training across factories, sustainability metrics - include carbon footprint data to align with green manufacturing goals, Human-in-the-Loop - incorporate operator feedback to refine AI predictions. SFD represents a valuable contribution to the development of SM and PdM models in them, multi-modal data with ground-truth labels for failure diagnosis and XAI validation. Its integration of synthetic scenarios and cybersecurity logs makes it a versatile tool for research and industry. However, challenges like data complexity and sim-to-real gaps require ongoing innovation. Future iterations could focus on real-time streaming and sustainability to further align with Industry 5.0 goals.

5. EXMAS Model

In this part, an example of research in the field of development of an expert system model for maintenance, which was carried out at the Department of Technological Systems, Faculty of Mechanical Engineering in Belgrade [19], is cited. It is an Expert Maintenance System (EXMAS) model. It is a knowledge-based system for planning the maintenance of workstations in flexible technological systems (FMS), which include CNC machine tools, robots and CNC numerically controlled measuring machines, whose knowledge base uses IF-THEN rules, of which there were 264, Figure 1.

The knowledge base had two knowledge domains: facts and rules, and ES had three modules: (i) communication interface, (ii) shell ES (knowledge base and inference engine), (iii) processor (recognition of diagnosis and maintenance plans), and was developed in the Prolog language.

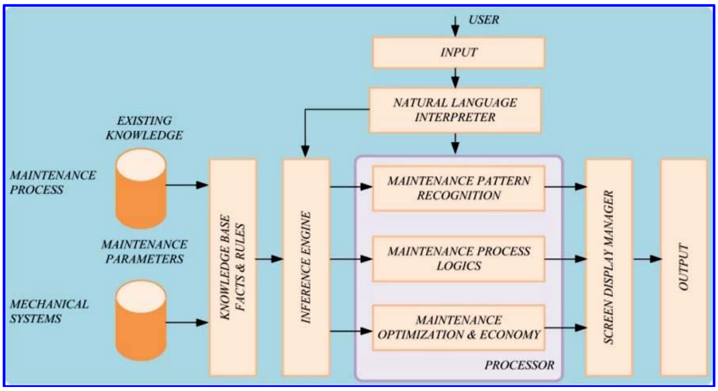

Fig. 1. EXMAS – Basic structure

The conclusion was made by searching the knowledge base backwards (backward searching), from symptoms to diagnosis. ES was developed and implemented as a laboratory prototype for FMS workstations. According to the classification from Table 1, it belonged to the models that were suitable for the concept of Industry 3.0 - KBS.

6. Conclusions and Future Research

Smart maintenance in the context of Industry 4.0, includes the integration of CPS, IoT, DT, AI/ML and cloud/edge, where these technologies are used to predict and prevent equipment failures, optimize maintenance schedules and reduce downtime. CPS is an entity where IoT devices collect real-time data, which DT then uses to model and simulate the state of the equipment. AI/ML analyze this data to predict maintenance needs and activities. But how exactly do these components integrate? IoT provides a data layer, continuously feeding information to DT, which processes this data, using simulations to predict future states or diagnose problems. ML models analyze historical data as well as real-time data to predict failures or maintenance needs. However, traditional ML models can be "black boxes", so using XAI would make these predictions understandable. For example, if AI predicts an engine failure, XAI could highlight that vibration levels have consistently exceeded a certain threshold over the past week, leading to the appropriate conclusion.

One of the most important future research directions is the application of generative AI (GAI) to synthetic data in maintenance. It has enormous potential and can revolutionize the way PrM systems will be developed and optimized[14]. Here's how, and why. Simulation of rare failures - in real industrial conditions, certain failures are very rare, which means that there is little real data to train the model. Generative AI can create synthetic data that simulates such events and thereby improve its ability to predict failures, reducing costs and time for data collection - traditional data collection requires sensors, time-consuming testing and expensive experiments, and GAI can reduce these costs of generating realistic data based on existing samples, increasing data diversity - ML often suffers from imbalanced datasets, but this is why generative models like GANs (Generative Adversarial Networks) and diffusion models can generate a variety of scenarios, including unusual or extreme ones system operating conditions, improving the accuracy of diagnostics and prognostics - by combining real and synthetic data, maintenance models can better adapt to unexpected situations, which increases their ability to detect and predict failures, and reliable testing and development of AI models - GAI enables the development and testing of models in a simulation environment before they are implemented in real industrial conditions, thus reducing the risk of costly errors. GAI is a powerful tool for improving maintenance through synthetic data, but it should be used carefully in combination with real industry data. Its true value lies in its ability to enhance and extend existing data sets, but not to replace them entirely.

Blockchain technology can bring significant benefits in the field of maintenance, especially when it comes to ensuring traceability, transparency and data security[15]. In an industry where data reliability and accuracy are key (aerospace, rail, energy sector), blockchain can provide an immutable and transparent record of all maintenance activities. The advantages of blockchain technology in the development and application of PrM are: immutability and data security - every generated data in the blockchain is cryptographically protected and cannot be changed or deleted. This means that maintenance data is authentic and protected from manipulation, which reduces the possibility of fraud and inaccurate reports, transparency and traceability - blockchain allows full tracking of the entire maintenance history of a particular equipment. All data (repair date, who performed the work, used parts) is visible and verified, which is useful for history, user and internal checks, automated smart contracts (Smart Contracts) - these contracts can automate certain maintenance processes, such as service activation after a certain number of working hours, automatic ordering of spare parts or verification that maintenance is carried out according to prescribed standards, resistance to data loss and cyber attacks - classic databases can be hacked or modified without authorization. Blockchain distributes data across the network, making it secure and available even in the event of a server failure, and simplified compliance with standards and regulations - industries with strict standards and regulatory requirements (e.g. aviation and pharmaceuticals) can use blockchain to securely store maintenance data, thus reducing red tape and speeding up the internal and supervisory review process. Its combination with IoT, AI/ML and smart contracts can create a fully automated, secure and reliable maintenance management ecosystem. Future trends in this area refer to: a combination with digital twins for accurate monitoring of the life cycle of equipment, private blockchain networks that offer a balance between security and speed, decentralized applications (dApps) for managing audits and data verification. It is believed that blockchain will become a key technology for the verification and security of PrM data in the future.

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