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Contact to corresponding author: Tomas Kliestik, tomas.kliestik@uniza.sk

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Tomas Kliestik
University of Zilina, Slovakia
orcid.org/0000-0002-3815-5409

Elvira Nica
The Bucharest University of Economic Studies, Romania
orcid.org/0000-0002-7383-2161

Pavol Durana
University of Zilina, Slovakia
orcid.org/0000-0001-5975-1958

Gheorghe H. Popescu
Dimitrie Cantemir Christian University, Romania
orcid.org/0000-0002-3281-6042

Artificial intelligence-based predictive maintenance, time-sensitive networking, and big data-driven algorithmic decision-making in the economics of Industrial Internet of Things

JEL Classification: *I15; O14; O32*

Keywords: *artificial intelligence (AI); predictive maintenance (PM); Industrial Internet of Things (IIoT); big data; algorithmic decision-making; time-sensitive networking (TSN)*

Abstract

Research background: The article explores the integration of Artificial Intelligence (AI) in predictive maintenance (PM) within Industrial Internet of Things (IIoT) context. It addresses the increasing importance of leveraging advanced technologies to enhance maintenance practices in industrial settings.
Purpose of the article: The primary objective of the article is to investigate and demonstrate the application of AI-driven PM in the IIoT. The authors aim to shed light on the potential benefits and implications of incorporating AI into maintenance strategies within industrial environments.
Methods: The article employs a research methodology focused on the practical implementation of AI algorithms for PM. It involves the analysis of data from sensors and other sources within the IIoT ecosystem to present predictive models. The methods used in the study contribute to understanding the feasibility and effectiveness of AI-driven PM solutions.
Findings & value added: The article presents significant findings regarding the impact of AI-driven PM on industrial operations. It discusses how the implementation of AI technologies contributes to increased efficiency. The added value of the research lies in providing insights into the transformative potential of AI within the IIoT for optimizing maintenance practices and improving overall industrial performance.

Introduction

The industry is no longer seen as a one-sided production chain that seeks to produce without thinking about the process, physical and logical constraints which surround the industrial environment. With the arrival of Industry 4.0, the manufacturing process has become more intelligent (Chahed *et al*., 2023; Kumar & Kumar, 2019) and it integrates data of different nature and format coming from a set of data sources. In such a context, the manager faces several challenges in order to make effective decisions within the required time frame.

We focus on the maintenance of the means of production, namely production machines. In this regard, maintenance is no longer considered a reactive or preventive operation (Christou *et al*., 2020). We are in the digital age, where predictive maintenance (PM) is based on monitoring performance in the active state. According to Hurtado *et al*. (2023), PM is an approach to identify the best time to maintain it before it breaks down. PM has become a necessity for intervention in order to make the production process efficient and more flexible.

According to Usman *et al*. (2022), this new trend in maintenance process control requires very sophisticated means in order to deploy more robust solutions. At this time, edge control infrastructures and applications have been introduced. This new infrastructure ensures flexibility, scalability and cost control. This aspect of scalability of industrial processes must be taken into account when developing machine learning (ML) software by integrating an adaptation mechanism that predicts anticipated changes (Li *et al*., 2022).

The importance of artificial intelligence (AI)-based PM in the field of Industrial Internet of Things (IIoT) is highlighted by its profound impact on economic efficiency and sustainability. This article delves deeper into the central role played by PM in the optimization of industrial processes, with particular emphasis on its economic implications. By harnessing the power of AI to predict equipment failures and streamline maintenance procedures, organizations can realize substantial savings, improve productivity, and extend asset lifecycles. This exploration not only highlights the technological intricacies of AI-based PM, but also elucidates its central role in shaping a more economically resilient and competitive industrial landscape.

The methodology employed in the study involves the application of advanced techniques within the realm of AI for PM. The approach centers on harnessing the power of AI in the context of IIoT. The research employs sophisticated algorithms and data analytics to proactively predict and address potential issues in industrial equipment before they escalate into significant failures. This method aims to enhance the efficiency and reliability of maintenance practices, leveraging AI-driven insights to optimize industrial processes within the framework of IIoT.

This study comprises several sections that collectively explore the intersection of AI and PM within the IIoT landscape. The first part provided direct research gap diagnosis and presents an introduction to the architecture of IIoT. The second part highlights the growing importance of PM in the optimization of industrial operations. Following this, the background section delves into the evolution of PM and the role of AI in revolutionizing traditional approaches. The methodology section outlines the various AI-driven techniques employed in PM, providing an overview of relevant ML algorithms. The results and case studies section offers real-world examples, illustrating the tangible benefits of implementing AI-driven PM strategies. Finally, the conclusion synthesizes the key findings, emphasizes the transformative potential of AI in PM within IIoT, and suggests future directions for research and implementation in this rapidly evolving field.

Through these sections, the article provides a thorough exploration of the synergy between AI and PM, offering valuable insights for researchers, practitioners, and decision-makers in the industrial domain.

Conceptual review

Research gap diagnosis

This research fills an important gap, being the only paper configuring the economics of IIoT in terms of digital twin simulation and movement and behavior tracking tools, haptic and biometric sensor technologies, and geospatial big data management algorithms. Multisensory customer experiences, blockchain and image recognition technologies, socially interconnected virtual services, and smart contracts require mobile location analytics, remote sensing data fusion techniques, event modeling and forecasting tools, and spatial cognition algorithms.

This paper shows how visual imagery and ambient scene detection tools, neural network-based recognition and visual cognitive algorithms, and distributed sensing and dynamic routing technologies enable big data-driven governance of cyber-physical system-based manufacturing across product decision-making information and neuromorphic computing systems. Data-driven sustainable smart manufacturing integrates machine learning-based object recognition and deep learning-based sensing technologies, haptic augmented reality and interactive 3D geo-visualization systems, predictive modeling techniques, and virtual simulation algorithms. Industrial big data and real-time sensor networks are pivotal for advanced robotics and automated production systems by harnessing simulation modeling tools, tactile sensing, multisensor fusion, and cognitive modeling technologies, and image processing computational algorithms.

The value added to the literature is that AI-based PM, time-sensitive networking (TSN), and big data-driven algorithmic decision-making in the economics of IIoT shape Industry 4.0-based large-scale value chains through digital readiness, personnel expertise, and lean workplaces by deploying environment mapping and computer vision algorithms, geospatial simulation tools, and Industry 4.0 wireless and IoT sensing networks to enable deep learning-assisted smart process management.

The rationale underlying our hypotheses is that spectrum sensing and computing technologies, big data management clustering and visual perception algorithms, and mapping and navigation tools optimize cyber-physical smart manufacturing systems throughout big data-driven smart urban economy by use of the Internet of Robotic Things.

Architecture of IIoT

The emergence of a new era of industrialization requires adequate ideas and resources that meet new environmental requirements. Industrial systems must be flexible, modular, and interoperable to manage small batch orders. Faced with the increased complexity surrounding manufacturers, automation has been complemented by self-optimization (Dubey *et al*., 2023; Jurczuk & Florea, 2022). According to Khan *et al.* (2020), the latter notion relies on a variety of resources, such as decentralization typical of industries, borderless competitiveness, autonomy and execution time, vertical integration, connectivity and mobile, cloud computing, and advanced analytics.

In order to fully understand the conceptual framework of the study, knowing how to determine the key concepts of the study is a major orientation in current research. Table 1 shows the main abbreviations of the key words and their descriptions.

In this context, the concept of smart factory comes into force in particular with the arrival of networks of robotic devices, sensors, and interconnected software to monitor and optimize the production process. In this context, smart factories can be used to monitor the manufacturing process, from raw materials to finished products (Soori *et al*., 2023). This will bring out a variety of data in different forms from various sources. In this regard, according to Chahed *et al*. (2023), data can be classified into two forms: application data and monitoring and telemetry data from edge infrastructure and network devices. Application data are the incoming streams from IoT sensors that are required for everyday industrial applications, while monitoring and telemetry data represent real-time monitoring information from edge compute nodes and network infrastructure.

The data collected is categorized in different databases. The nature of data stored in flow databases is related to ordinary industrial operations such as transfer of raw materials, logistics, standardization of industrial procedures, standardization of results, the operational characteristics of each piece of equipment, and the industrial control software involved. Additionally, configuration bases seek to identify all the data that reshape how an industrial operation functions, such as reformulating the production equation, introducing quality standards into the process, and the integration of methods that regulate the industrial process. Finally, event databases make it possible to identify exceptional industrial cases, such as predicting failures, reducing machine downtime or material waste, forecasting spare parts not conforming to the production system, and even the malfunctions recorded in the industrial chain.

The intelligent operation of factories is subject to several sensitive constraints which constantly interact. For this purpose, according to Gugueoth *et al*. (2023) and Christou *et al.* (2020), a multilevel platform composed of three layers is needed, illustrated in table 2.

Here are more details on how the IIoT infrastructure can serve decision-makers in operational processes. In a first layer, data should be captured using wireless captures which have more batch transfer power between nodes than traditional wired sensors. In this context, data extraction is a process that requires very sophisticated support. According to Gupta *et al.* (2023), three modes of extracting relevant data are required: i) temporal side, ii) frequency side, and iii) frequency-time side. Table 3 presents the different dimension of relevant data extraction.

The extraction of lots (data) based on the temporal dimension is an action based on statistical parameters such as the root mean square, which can be used as a measure of the quality of an estimator, the kurtosis, which estimates whether distribution is sharp or spread, the mean, which estimates the center of gravity of lots, the variance which estimates the degree of dispersion of lots, and the asymmetry, which estimates the distribution of lots. In addition, the extraction can be based on a frequency approach which transforms batches of data via the accelerometer which plays a key role in activity recognition, movement analysis, fall detection, and so on. Additionally, data transfer can combine both modes at the same time, which gives more regularity and completeness to the transferred data.

The proper functioning of the first layer depends on the other following layers. In this regard, the network layer plays an important role in strengthening the interconnected data transfer process. Connected objects must interact with each other via protocols that serve the decision-maker during its mission. Indexed data are primarily related to the entities that control the flow of data transfers between them. The entity can be a source, node, root, etc.

The source data is considered a key reference in order to identify the configurations that formulate the datasets. For this reason, a digital model called Data Source Definition (DSD) defines the properties of a data source coming from a sensor or automation device. Each DSD is subject to a Data Identifier (DI) which facilitates access to data, including details such as network protocol, port, network address, etc. In order to identify the nature of the source, a Data Kind (DK) digital model is integrated at the level of each identifier in order to determine the semantics of the data source. It allows the identification of the type of data, whether there are event data such as planned failures on machines or simply configuration data linked to an update of management rules. Finally, the selected data will be displayed via a Data Source Manifest (DSM), which will be used to represent the data sources available in the factory in order to place them under future processing.

The third layer is dedicated to data processing and purification. In this regard, the application layer serves decision makers in analyzing data, data cleaning, feature engineering, and application of various ML algorithms to understand and visualize the massive amount of data (Bagheri & Dijkstra, 2023). In this regard, data coming from IoT edges differ from other types of data due to the large amount of input generated by various systems and business units. While traditional data is generated following a user-driven query, IoT data are delivered via a data push approach (Devi *et al*., 2020).

According to García and García (2019), for the proper functioning of the different layers of the IoT system, various technologies must be part of the system as a whole (see table 4).

Each technology works in relation to the others. In this context, the cyber-physical system (CPS) is considered as a regulator which controls the progress of batch flows. The flow is divided into several distinct levels. The acquisition flow makes it possible to monitor the industrial state whether in the development, maturity or decline phase. This input is converted via auto-conversion of data into information. This is achieved through analysis techniques capable of understanding the semantics and context of the operation.

CPS, via its technical potential, can play an important role in the phase of extracting additional information for specific problems while relying on advanced self-comparison models. Each technology is used to explore and analyze the meaning of information via a set of techniques such as augmented reality, simulators, ML or even AI systems which are essential for the most advanced data processing. Batches of data cannot be moved or visualized without the support of mobile, location and sensing, and data storage technologies.

Operational PM

Faced with the development of means of capturing, calculating and storing information, intervention mechanisms within industries have configured a complex ecosystem which is evolving towards multi-objective optimization in which several application criteria are considered jointly (Pinciroli *et al*., 2023). This is why producers want to minimize the costs of transforming their equipment, while maximizing the availability of machines and the efficiency of their production line. Another criterion that has recently emerged for critical systems and infrastructures with high data volume is resilience. According to Alrumaih *et al.* (2023), resilience is defined as the ability of a system to withstand potential high-impact disruptions, mitigating impacts and quickly restoring normal conditions. Resilience is considered a cornerstone in the context of Industry 4.0, as systems can be affected by several potentially disruptive events, such as natural events, pandemics, or cyberattacks.

In this context, competition has become more robust, especially with the entry of the multi-faceted system known as "product-service systems" (Nguyen *et al*., 2022), comprising a complete set of services with a major benefit to the customer by ensuring "choice" and "flexibility". This new production system is attached to several services which are associated with several maintenance models depending on several factors ensuring the reliability, availability, and safety of the system, and regulating the degradation processes and the state of health of the components of the system (Table 5).

In order to fully understand the different approaches to maintenance in the IoT era, we propose the increased evolution of maintenance from corrective maintenance to PM (Figure 1).

From passive maintenance towards anticipatory maintenance, operations rely on prior planning via models and approaches which seek to identify the economic advantage provided by the maintenance strategy (Pinciroli *et al*., 2021; Ferreira *et al*., 2021), such as maintenance cost, profit, production loss, and unmet demand. Likewise, security, reliability, availability, resilience, environmental impact, and sustainability are typical quantitative measures that should be considered.

Research method

A conceptual approach was presented based on the 2020–2023 literature indexed in WoS and Scopus. We focused on a semantic search by words and phrases such as: IIoT applications; PM; ML-based industrial decision-making strategies; and PM challenges. These keywords are combined using the 'AND' command to get the most relevant and narrowly defined articles. Selected documentation from a set of reputable peer-reviewed journals was retained for analysis. This research draws on Emerald, IEEE Xplore and ScienceDirect platforms as well as NCBI to create a narrower search. Additional sources were then inspected and, if relevant, added. Table 6 illustrates the various methodological aspects of the study.

Related work

In order to clearly identify the constraints of PM in the booming digital industry, we propose two conceptual frameworks.

Prognostics & health management (PHM)

The data stored and generated by machines, tools, and spare parts are mainly dispersed in different systems which makes analysis and reconfiguration operations very complicated. This operation requires a more flexible integrated system that ensures good proactive maintenance at the right time. In this context, Ciancio *et al.* (2022) proposed a methodology for PM presented in the table 7. The PM approach is a very sensitive interconnected process, and is divided into two parts: "Better understand machines and processes" and "Better analyses objects and processes". The first part is divided into three phases. The first step begins with the identification of the machine or unit of the production system that will be studied. In this regard, knowing how to identify the point of failure is considered a very complicated step to carry out. Indeed, equipment containing different objects gives off a variety of signs that make it difficult to understand failure modes.

In order to clearly identify the cases of failure, an approach was proposed to determine the most sensitive cases. First of all, a Computerized Maintenance Management System (CMMS) must be integrated in order to properly manage the different interventions and keep past data on the production system, to classify the different failures observed according to their costs and their occurrences. The CMMS system is often connected to applications, advanced software and even integrated applications such as ERP (Enterprise Resource Planning) in order to access thousands of data stored in clusters in a very short time.

The second important element of this architecture to know how to analyze failure modes and their effects is FMEA (Failure Modes and Effects Analysis). This system is widely integrated in the industry to understand potential breakdowns that may occur and better understand them by analyzing their causes and effects on the equipment concerned. This system takes two different forms: the first is used to analyze the process (PFMEA) and the second is used to assign a criticality score to the failure modes (FMECA). The PFMEA can provide us with a list of failure modes that can be studied by the PM system. On the one hand, the FMECA offers us the a priori knowledge of causes and effects that can help us to choose a first set of data to be collected by the PM system. Furthermore, expert knowledge is also important in order to choose the most appropriate failure mode. For this purpose, some knowledge can be found at FEMA. In parallel, other experts relate to several groups of people within companies with increased importance to expand the range of theoretical and practical knowledge on the breakdowns expected to appear on equipment.

In the next phase, it is important to set the amount of data that will be collected and stored for further processing. Data circulate between equipment and applications via different communication protocols such as OPC UA, Modbus, MQTT, and also directly to the Programmable Logic Controller (PLC) of the machine through its proprietary protocol: Siemens S7 protocol. The data will be stored in variables. Most of the data collected from the production system are subject to time series techniques, being strongly associated with a timestamp of the data. The data transferred are strongly associated with a fixed time interval, that is to say the operation of sending data is calculated by estimated measurements suggested by experts, e.g.:

$$Y = X_1 \cdot a + X_2 \cdot b + X_3 \cdot c + X_4 \cdot d + \cdots + X_n \cdot n \qquad (1)$$

where:

Y	Quantity of failure data expected for subsequent processing.
X_1	The seasonality of breakdowns.
X_2	The unexpected in terms of breakdowns.
X_3	The most frequent breakdowns.
X_4	Costs.
a, b, c, d and n	The regression weight of each predictor.

After a data collection phase, users are asked to research the type of monitoring that will be performed and the event thresholds in order to be considered a failed resource. For this reason, everyone seeks to identify the failure zone. The threshold can be known a priori from simulation tests and applications based on augmented reality which are generally exploited to deal with the uncertainty inherent in stochastic processes such as degradation or evolution of operating conditions and environment. Furthermore, the expectation of an optimization threshold is calculated using ML algorithms (see Table 6).

In this context, the optimization of maintenance processes has become stricter and seeks to target a specific objective such as the maintenance period or the age threshold for triggering a maintenance process, the degradation threshold to trigger a maintenance operation or the type of action planned (e.g., repair or replacement).

The second part focuses on the analysis of objects and processes. The ultimate goal in this phase is to be able to create correlations between the selected data in order to effectively predict the occurrence of the failure. In this regard, the PHM system must understand what is happening in other areas of the industrial process. For this purpose, the data management system must integrate modules based on ML to perform these actions. Most of these analyses are multivariate, because the state of several data must be studied and taken into account in relation to other aspects of the industrial process.

The PM process is supported by a range of ML-based technologies divided into three parts; the first was mainly used to optimize the parameters of a predefined maintenance strategy, the second integrates reinforcement learning to select the optimal maintenance actions to carry out and the third part presents how the actions are selected for better optimization of the MP. All this is summarized in Table 8.

A holistic AI-driven networking and processing (AIDA)

The industrial environment has experienced a new generation of manufacturing methods, control methods, and treatment of anomalies. This new generation of resources is integrated into lightweight virtualization technologies with a large quantity of data stored in several media (machine, capture, mobile, mental map, etc.). In this context, permanent monitoring of its resources is a very complicated task that requires an evolving configuration of the company's system linked to the environment. In order to address this issue, we clearly explore the different components of the AIDA system proposed by Chahed *et al*. (2023). In this context, AIDA is a highly time-sensitive control system. It provides real-time capabilities with high compute capacity via an edge-to-cloud continuum that automates monitoring in a proactive manner. Table 9 presents the AIDA system architecture.

The operation of the AIDA system has brought new meaning to the data generated by IoT devices. All actions taken are generated in a systemic manner based on ML systems. In this context, the first step of Data-Driven Maintenance (DDM) is to collect relevant data from various sources, including sensors, IoT devices, maintenance records, and other sources. According to Wolfartsberger *et al.* (2020), each execution phase until failure (K) is presented in a model that controls the data transfer until reaching the level of deterioration. For example, we have three levels of deterioration observed in ascending order and denote them x1, x2, ..., xn. In addition, the binary variables y1, y2, . . ., yn ∈ {0, 1} seek to identify whether an observation of deterioration led to a failure at the next time step (1) or not (0).

In order to properly support the operation of network system, we explore how software-defined networking helps users control data flow through a centralized network configuration (CNC). In fact, according to Al-Saedi *et al.* (2017), there are different types of control systems that monitor various machines in all types of manufacturing industries. According to Chahed *et al.* (2023), the CNC is composed of two subsystems:

1. An operational system with triple roles presented in the points below:
   a) Seeks to build a synchronization tree responsible for applying the synchronization policy decided by the time-based control subsystem. This can be done via a Precision Time Protocol (PTP), which aims to identify the entire time synchronization path of all entities.
   b) Aims to manage configuration features and network devices (sending verification messages, cancellation, etc.). Additionally, it re-

trieves monitoring information from time-sensitive devices, collects statistics, derives metrics from real-time system status information, and analyzes network events.

2. TSN subsystem: based on three main entities presented in the points below:
   a) The entity responsible for clearing the data flow path and maintaining the routing paths within the network.
   b) The resource allocation entity, which is responsible for allocating resources (data) on the network.
   c) The main entity, responsible for coordinating all operations inside the CNC and all communications through the different interfaces.

TSN's mission is to ensure that high priority and urgent information is transmitted without interference (Zezulka *et al*., 2019). There are several time synchronization mechanisms via industrial protocols such as PTP which seek to attach a large quantity of links, entities, data, conditions, distances, and heterogeneity of components on the same predefined failure point before launch, but how does the synchronization task actually work?

According to Adame *et al*. (2021), PTP allows for the distribution of a single reference clock integrated on network devices in the form of a master/slave base. According to Gundall *et al.* (2021), this would enable successful scheduling of multi-user uplink and downlink transmissions, as well as establishing coordination mechanisms between access points. In this regard, time propagates in frames between a master and a port of call. This is to clearly regulate the flow of data, thus being able to calculate the offset of a clock and adjust its own time accordingly.

For the purpose of good circulation of data flows, the IEEE 802.1Q standard, according to Gerhard *et al.* (2019), specifies up to eight different traffic classes for better data transmission based on the priority code point (PCP). This makes it possible to index and differentiate traffic that is less time-sensitive. The IEEE 802.11 standard provides an option to support traffic flow differentiation via two means, namely Traffic Specification (TSPEC) and Traffic Classification (TCLAS) via Traffic ID (TID), which allows the type of traffic to be classified into several categories. For example, the failure flow of safety-critical equipment requires immediate attention to prevent accidents and hazards. In contrast, routine maintenance is a lower-level but important routine task, such as cleaning, lubrication, and inspection, which helps extend the life of equipment and prevent unexpected breakdowns.

The operation of the CNC is no longer efficient except after the deployment of a centralized user configuration (CUC) infrastructure linked to the CNC system. The CUC plays the role of receiver of endpoint configuration requests in terms of time-related resource frequency, range of resources sent, etc. The CNC controls the configuration of the end point via calculations based on a set of parameters such as the life cycle of the resource. Likewise, the CUC receives the response in the form of the regels executed indicating the actual configuration of the network interfaces which allows the network to operate efficiently in terms of speed and reliability.

From Figure 2 results, according to Trifonov and Heffernan (2023), it follows that the data flowing in the network are strictly controlled via a TSN subsystem which makes all control decisions like inspecting the data load, finding the most optimized circuit via highly optimized and sophisticated algorithms, and even minimizing the latency rate. Additionally, the TSN subsystem communicates with the operational subsystem via storage. The CNC keeps all generated, received, and collected information in a central storage which includes the topologically classified databases such as: metrics database, flow database, configuration database, and event database.

In this context, reaching the point of failure is the ultimate objective towards better maintenance threshold prediction. According to Nazemi Absard and Javidan (2023) monitoring via edge computing is a critical point towards better end-to-end execution performance. The following points show the different services of edge computing involved in an IoT industry based on the AIDA processing system:

1. Measurement and delivery services: Such operations have mastered the different metrics coming from various sources (application, machine, mobile, report, etc.). According to Usman *et al.* (2019), the selection of measurements is calculated via appropriate measurement intervals to obtain the desired failure zone. To this end, a double data quality assessment is carried out in two phases. The first is done at the level of peripheral nodes and the second is the most complete and is carried out in the cloud.
2. Merging and storage services: The data storage and fusion operation constitutes a major challenge for the company. According to Turnbull (2018), the AIDA system relies on supervised techniques such as time series which seek to subdivide the operation of storing and merging metric data according to a set of parameters such as failure seasonality

related to actual operating times, failure times, and previous downtimes. In contrast, log storage through Loki is primarily used to collect, store, and query logs, making it ideal for monitoring and debugging computer systems (Bautista *et al*., 2022). This task is subdivided in Table 10.
3. Viewing and notification services: Visualizations are important to facilitate immediate data retrieval, visually detect patterns, and take action against unwanted operational behaviors. Grafana is an open source data monitoring and visualization platform designed to help users analyze and display data in real time (Chakraborty & Kundan, 2021). It is widely used for monitoring IT infrastructure, applications, cloud services, databases, and other systems. How Grafana works can be described in several steps (Table 11).
4. Provisioning and orchestration service: According to Gokhale *et al*., 2021, the provisioning and orchestration service plays a dual role, on the one hand determining the components responsible for installation and execution, and on the other hand determining the configuration of a specified number of services required on the nodes and peripheral devices. Table 12 illustrates the different installation and configuration services.

Industrial process control is regulated through an ML system that serves to address manufacturing challenges (Drakaki *et al*., 2021), consistently, making operations more predictive and scalable. According to Çınar *et al*. (2020), ML algorithms can be used to solve several problems related to highly available data generated by industries. The diversity of methods constitutes one of the possible areas at this stage of deduction. Table 13 presents a detailed description of each method and how it actually works.

Results, discussion, and managerial implications

From the two models presented we retain certain valuable information. With technological advances for the benefit of the object-oriented industry, the process of collecting, indexing, analyzing, storing, and reusing data has become a careful operation both in terms of choice of the methodology followed and of the machine learning technique employed. In this context, managers are called upon to change their approaches in order to regulate their production chains within data-generating industries. In this regard, a new air of pretreatment of equipment (machines, parts, gateway, etc.) comes into play. The manager seeks to predict the object of the equipment in active state before it is broken.

PM is a new equipment control regulation based on AI. The maintenance process is associated with a set of technical, organizational, and even professional constraints. Technical constraints are evident in how data flow is circulated within the industry, how we can develop a maintenance plan that takes into account the time factor and how we can predict the point of failure before it arrives.

For this purpose, the flow of data between the nodes is controlled in a constant manner. The node (partial database, spare part) plays the role of an intermediate data storage point. Multi-form data require different recognition protocols such as thermal data which are processed using two protocols: Low Energy (BLE), LoRaWAN, spatial data via LoRa (Long Range) protocols, MQTT (Message Queuing Telemetry Transport), CoAP (Constrained Application Protocol) and more. The data flow is only active after self-authorization from the user network center which gives access to circulation and consultation, and calculates the failure threshold in order to set the highest priority data flow.

At this stage, the prediction of a breakdown will be operational with the support of ML algorithms that are trained on historical data to recognize patterns that precede an outage. To this end, continuously monitoring data in real time can lead to identification of deviations from normal operating conditions and predict potential failures. This is achieved through TSN technology, which allows different types of traffic to coexist on the same network, ensuring that critical data is delivered on time while avoiding congestion and minimizing delays for other non-network sensitive data factor time. This task is ensured via a set of components presented in the following points:

1. Time scheduling: TSN ensures that time-critical data are transmitted on priority.
2. Precise synchronization: TSN synchronizes the clocks of all devices on the network to a common master clock. This ensures precise coordination of actions between the different nodes of the network and therefore reduces the variance rate during data dissemination.
3. Flow control: TSN uses flow control mechanisms to avoid network congestion and ensures stable performance even under high load conditions.

4. Quality of Service (QoS): TSN supports multiple classes of services with different quality of service (QoS) guarantees to meet the varied needs of industrial applications, such as real-time and non-real-time data transmission.
5. Scalability: TSN enables the extension and scaling of industrial networks without compromising performance. It is designed to be compatible with standard Ethernet technologies, making it easy to integrate into existing infrastructures.

The organizational aspect is also present to clearly predict the failure rate of equipment. To this end, a range of important organizational resources will perhaps be exploited for the effective use of PM in the IoT industry. We present certain organizational aspects that should not be neglected:

1. Systems Integration: For successful implementation of PM, it is essential to integrate existing IoT systems within current maintenance processes. This often requires close coordination between IT, maintenance, and production teams.
2. Data Security: Since PM involves collecting and analyzing large amounts of data in real time, it is crucial to have robust security measures in place to protect sensitive information from cyberattacks and data breaches.
3. Cross-Functional Collaboration: Encouraging collaboration between different departments, such as production, maintenance, and engineering, can facilitate a holistic approach to equipment management. Cross-functional teams can leverage their diverse expertise to identify potential failure points, develop comprehensive maintenance strategies, and implement timely interventions to minimize equipment downtime and failures.

Finally, PM in an industrial IoT environment can be heavily influenced by business context, as needs, challenges, and priorities vary depending on industry, company size, specific processes, equipment used, etc. Here's how the business context can affect PM:

1. Types of Equipment: Industries can use a wide variety of equipment, ranging from heavy machinery to high-tech equipment. The sensors and IoT data relevant to PM will vary depending on this equipment, and monitoring systems may need to be adapted accordingly. For example, in the automotive industry, we find many types of equipment, such as engines, brakes, suspension systems, on-board electronics, etc.

2. Asset Criticality: Some assets in the industry are more critical than others. In the aviation industry, for example, predictive maintenance must be extremely accurate to ensure safety. In other industries, predictive maintenance may be more focused on reducing downtime and costs.
3. Process complexity: Industrial production processes can be complex, with many interdependent steps. PM should be coordinated with these processes to minimize disruption. Different constraints linked to complexity include a high number of components, interdependence of systems, heterogeneous data, variety of conditions of use, and type of production followed such as mass production.

Conclusions

The integration of AI-based PM in the field of IIoT has brought about transformative changes, revolutionizing the landscape of maintenance practices in the industry. Through the use of advanced algorithms and data analytics, AI has demonstrated the ability to predict potential equipment failures and avoid costly downtime, thereby optimizing overall operational efficiency. Real-time data collection and analysis enable proactive decision-making, facilitating timely interventions and implementation of preventive measures, thereby ensuring that machines are operating at their optimal performance levels.

Furthermore, the deployment of AI-based PM systems has not only led to improved asset reliability, but also facilitated cost reduction through efficient resource utilization and minimized unscheduled maintenance. This shift towards a proactive maintenance approach has established a culture of forethought and preparation, enabling businesses to allocate resources efficiently and focus on long-term productivity and sustainability. While there are significant benefits to implementing AI in PM, challenges persist in terms of data security, algorithmic bias, and the need for skilled professionals who can manage and interpret complex data sets. Striking a balance between technological advancement and ensuring data integrity remains crucial to fostering trust and reliability within the IIoT ecosystem.

In conclusion, this study provides significant contributions to both theoretical and practical domains, making it a valuable resource for scholars and industry practitioners.

The direct long-term value of this study for theory lies in its thorough exploration of the integration of AI in PM within the IIoT framework. Theoretically, the study enhances our understanding of the symbiotic relationship between AI and IIoT, shedding light on novel approaches to optimize machinery performance and prevent unforeseen breakdowns. This theoretical foundation not only enriches academic discussions on AI and IIoT, but also lays the groundwork for future research directions in the broader field of technology-driven industrial systems.

From a practical standpoint, the article's significance is evident in its actionable insights for industry professionals. By delving into real-world applications of AI-driven PM, the article equips practitioners with innovative strategies to enhance operational efficiency, reduce downtime, and cut maintenance costs. The practical implications of the study make it a valuable resource for decision-makers in industrial settings, providing them with tangible solutions to improve overall equipment effectiveness and ensure the reliability of their systems.

The article is crucial for research and the scientific community as it advances the state of the art in the intersection of AI, IIoT, and PM. Scholars seeking to stay at the forefront of technological advancements should inspect this article for its insights and its potential to inspire further investigations in the rapidly evolving landscape of industrial technologies. By referencing this work, the scientific community can acknowledge and build upon the methodologies and findings presented, fostering a collective effort towards pushing the boundaries of knowledge in this interdisciplinary field.

However, it is important to acknowledge potential limitations in the study. One such limitation may be the generalizability of the findings across diverse industrial sectors, as the effectiveness of AI-driven PM could vary based on the nature of the equipment and operational conditions. Additionally, the article might not fully address the ethical considerations and potential biases associated with AI algorithms, which could impact decision-making in critical industrial processes.

Looking ahead, the perspectives offered by this study suggest a trajectory towards further refinement of AI models for PM. Future research could focus on addressing the identified limitations, exploring hybrid approaches that combine AI with other emerging technologies, and adapting the proposed methodologies to suit the evolving landscape of industrial practices. Embracing a holistic perspective, the article encourages ongoing discourse on the responsible and effective integration of AI in industrial settings, paving the way for a more resilient and intelligent industrial future.

References

Adame, T., Carrascosa-Zamacois, M., & Bellalta, B. (2021). Time-sensitive networking in IEEE 802.11 be: On the way to low-latency WiFi 7. *Sensors*, *21*(15), 4954. doi: 10.3390/s21154954.

Ali, Z. A., Abduljabbar, Z. H., Taher, H. A., Sallow, A. B., & Almufti, S. M. (2023). Exploring the power of eXtreme gradient boosting algorithm in machine learning: A review. *Academic Journal of Nawroz University*, *12*(2), 320–334. doi: 10.25007/ajnu.v12n2a1612.

Alrumaih, T. N., Alenazi, M. J., AlSowaygh, N. A., Humayed, A. A., & Alablani, I. A. (2023). Cyber resilience in industrial networks: A state of the art, challenges, and future directions. *Journal of King Saud University-Computer and Information Sciences*, *35*(9), 101781. doi: 10.1016/j.jksuci.2023.101781.

Al-Saedi, I. R., Mohammed, F. M., & Obayes, S. S. (2017). CNC machine based on embedded wireless and Internet of Things for workshop development. In *2017 International conference on control, automation and diagnosis (ICCAD)* (pp. 439–444). IEEE. doi: 10.1109/CADIAG.2017.8075699.

Ammar, M., Haleem, A., Javaid, M., Bahl, S., Garg, S. B., Shamoon, A., & Garg, J. (2022). Significant applications of smart materials and Internet of Things (IoT) in the automotive industry. *Materials Today: Proceedings*, *68*, 1542–1549. doi: 10.1016/j.matpr.2022.07.180.

Aslam Zainudeen, N., & Labib, A. (2011). Practical application of the decision making grid (DMG). *Journal of Quality in Maintenance Engineering*, *17*(2), 138–149. doi: 10.1108/13552511111134574.

Bagheri, S., & Dijkstra, J (2023). Capabilities for data analytics in Industrial Internet of Things (IIOT). *ECIS 2023 Research Papers*, *416*. Retrieved from https://aisel.aisnet.org/ecis2023_rp/416.

Bautista, E., Sukhija, N., & Deng, S. (2022, September). Shasta log aggregation, monitoring and alerting in HPC environments with Grafana Loki and ServiceNow. In *2022 IEEE international conference on cluster computing (CLUSTER)* (pp. 602–610). IEEE. doi: 10.1109/CLUSTER51413.2022.00079.

Boulesteix, A. L., Janitza, S., Kruppa, J., & König, I. R. (2012). Overview of random forest methodology and practical guidance with emphasis on computational biology and bioinformatics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *2*(6), 493–507. doi: 10.1002/widm.1072.

Chahed, H., Usman, M., Chatterjee, A., Bayram, F., Chaudhary, R., Brunstrom, A., Taheri, J., Bestoun, S. A., & Kassler, A. (2023). AIDA – A holistic AI-driven networking and processing framework for industrial IoT applications. *Internet of Things*, *22*, 100805. doi: 10.1016/j.iot.2023.100805.

Chakraborty, M., & Kundan, A. P. (2021). Grafana. In *Monitoring cloud-native applications: Lead agile operations confidently using open source software* (pp. 187–240). Berkeley, CA: Apress. doi: 10.1007/978-1-4842-6888-9.

Christou, I. T., Kefalakis, N., Zalonis, A., Soldatos, J., & Bröchler, R. (2020). End-to-end industrial IoT platform for actionable predictive maintenance. *IFAC-PapersOnLine*, *53*(3), 173–178. doi: 10.1016/j.ifacol.2020.11.028.

Ciancio, V., Homri, L., Dantan, J. Y., Siadat, A., & Convain, P. (2022). Development of a flexible predictive maintenance system in the context of Industry 4.0. *IFAC-PapersOnLine*, *55*(10), 1576–1581. doi: 10.1016/j.ifacol.2022.09.615.

Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in Industry 4.0. *Sustainability*, *12*(19), 8211. doi: 10.3390/su 12198211.

Click, C., Malohlava, M., Candel, A., Roark, H., & Parmar, V. (2017). *Gradient boosting machine with H2O*. Mountain View: H2O.ai.

Devi, M., Dhaya, R., Kanthavel, R., Algarni, F., & Dixikha, P. (2020). Data science for Internet of Things (IoT). In *Second international conference on computer networks and communication technologies: ICCNCT 2019* (pp. 60–70). Springer International Publishing. doi: 10.1007/978-3-030-37051-0_7.

Drakaki, M., Karnavas, Y. L., Tziafettas, I. A., Linardos, V., & Tzionas, P. (2022). Machine learning and deep learning based methods toward Industry 4.0 predictive maintenance in induction motors: State of the art survey. *Journal of Industrial Engineering and Management (JIEM)*, *15*(1), 31–57. doi: 10.3926/jiem.3597.

Dubey, G. P., Stalin, S., Alqahtani, O., Alasiry, A., Sharma, M., Aleryani, A., Shukla, P. K., & Alouane, M. T. H. (2023). Optimal path selection using reinforcement learning based ant colony optimization algorithm in IoT-based wireless sensor networks with 5G technology. *Computer Communications, 212,* 377–389. doi: 10.1016/j. comcom.2023.09.015

Fecarotti, C., Andrews, J., & Pesenti, R. (2021). A mathematical programming model to select maintenance strategies in railway networks. *Reliability Engineering & System Safety*, *216*, 107940. doi: 10.1016/j.ress.2021.107940.

Ferreira, W., Cavalcante, C., & Do Van, P. (2021). Deep reinforcement learning-based maintenance decision-making for a steel production line. In B. Castanier, M. Cepin, D. Bigaud & C. Berenguer (Eds.). *Proceedings of the 31st European safety and reliability conference, ESREL 2021*. Singapore: Research Publishing. doi: 10.3850/ 978-981-18-2016-8_600-cd.

García, S. G., & García, M. G. (2019). Industry 4.0 implications in production and maintenance management: An overview. *Procedia Manufacturing*, *41*, 415–422. doi: 10.1016/j.promfg.2019.09.027.

Gerhard, T., Kobzan, T., Blöcher, I., & Hendel, M. (2019). Software-defined flow reservation: Configuring IEEE 802.1 Q time-sensitive networks by the use of software-defined networking. In *2019 24th IEEE international conference on emerging technologies and factory automation (ETFA)* (pp. 216–223). IEEE. doi: 10.1109/ETFA.2019.8869040.

Gerum, P. C. L., Altay, A., & Baykal-Gürsoy, M. (2019). Data-driven predictive maintenance scheduling policies for railways. *Transportation Research Part C: Emerging Technologies*, *107*, 137–154. doi: 10.1016/j.trc.2019.07.020.

Gokhale, S., Poosarla, R., Tikar, S., Gunjawate, S., Hajare, A., Deshpande, S., Gupta, S., & Karve, K. (2021). Creating Helm Charts to ease deployment of enterprise application and its related services in Kubernetes. In *2021 international conference on computing, communication and green engineering (CCGE)* (pp. 1–5). IEEE. doi: 10.1109/CCGE50943.2021.9776450.

Gugueoth, V., Safavat, S., & Shetty, S. (2023). Security of Internet of Things (IoT) using federated learning and deep learning-Recent advancements, issues and prospects. *ICT Express*, *9*, 941–960. doi: 10.1016/j.icte.2023.03.006.

Gundall, M., Huber, C., & Melnyk, S. (2021). Integration of IEEE 802.1 AS-based time synchronization in IEEE 802.11 as an enabler for novel industrial use cases. arXiv preprint arXiv:2101.02434. doi: 10.48550/arXiv.2101.02434.

Gupta, V., Mitra, R., Koenig, F., Kumar, M., & Tiwari, M. K. (2023). Predictive maintenance of baggage handling conveyors using IoT. *Computers & Industrial Engineering*, *177*, 109033. doi: 10.1016/j.cie.2023.109033.

Hien, N. N., Lasa, G., Iriarte, I., & Unamuno, G. (2022). An overview of Industry 4.0 applications for advanced maintenance services. *Procedia Computer Science*, *200*, 803–810. doi: 10.1016/j.procs.2022.01.277.

Hurtado, J., Salvati, D., Semola, R., Bosio, M., & Lomonaco, V. (2023). Continual learning for predictive maintenance: Overview and challenges. *Intelligent Systems with Applications*, *19*, 200251. doi: 10.1016/j.iswa.2023.200251.

Jurczuk, A., & Florea, A. (2022). Future-oriented digital skills for process design and automation. *Human Technology*, *18*(2), 122–142. doi: 10.14254/1795-6889.2022.18-2.3.

Khan, W. Z., Rehman, M. H., Zangoti, H. M., Afzal, M. K., Armi, N., & Salah, K. (2020). Industrial internet of things: Recent advances, enabling technologies and open challenges. *Computers & Electrical Engineering*, *81*, 106522. doi: 10.1016/j.compeleceng.2019.106522.

Kotsiantis, S. B. (2013). Decision trees: A recent overview. *Artificial Intelligence Review*, *39*, 261–283. doi: 10.1007/s10462-011-9272-4.

Kumar, N., & Kumar, J. (2019). Efficiency 4.0 for Industry 4.0. *Human Technology*, *15*(1), 55–78. doi: 10.17011/ht/urn.201902201608.

Li, C., Chen, Y., & Shang, Y. (2022). A review of industrial big data for decision making in intelligent manufacturing. *Engineering Science and Technology, an International Journal*, *29*, 101021. doi: 10.1016/j.jestch.2021.06.001.

Maalouf, M. (2011). Logistic regression in data analysis: An overview. *International Journal of Data Analysis Techniques and Strategies*, *3*(3), 281–299. doi: 10.1504/IJD ATS.2011.041335.

Miranda Filho, R., Lacerda, A., & Pappa, G. L. (2020). Explaining symbolic regression predictions. In *2020 IEEE congress on evolutionary computation (CEC)* (pp. 1-8). IEEE. doi: 10.1109/CEC48606.2020.9185683.

Nazemi Absardi, Z., & Javidan, R. (2023). A QoE-driven SDN traffic management for IoT-enabled surveillance systems using deep learning based on edge cloud computing. *Journal of Supercomputing*, *79*, 19168–19193. doi: 10.1007/s11227-023-05412-y.

Nguyen Ngoc, H., Lasa, G., & Iriarte, I. (2022). An overview of Industry 4.0 applications for advanced maintenance services. *Procedia Computer Science*, *200*(10), 803–810. doi: 10.1016/j.procs.2022.01.277

Patil, S., & Patil, S. (2021). Linear with polynomial regression: Overview. *International Journal of Applied Research*, *7*, 273–275. doi: 10.22271/allresearch.2021 .v7.i8d.8876.

Pinciroli, L., Baraldi, P., & Zio, E. (2023). Maintenance optimization in Industry 4.0. *Reliability Engineering & System Safety*, *234*, 109204. doi: 10.1016/j.ress.2023. 109204.

Pinciroli, L., Baraldi, P., Ballabio, G., Compare, M., & Zio, E. (2021). Deep reinforcement learning based on proximal policy optimization for the maintenance of a wind farm with multiple crews. *Energies*, *14*(20), 6743. doi: 10.3390/en142 06743.

Roy, A., & Chakraborty, S. (2023). Support vector machine in structural reliability analysis: A review. *Reliability Engineering & System Safety*, *233*, 109126. doi: 10.10 16/j.ress.2023.109126.

Shvets, Y., & Hanák, T. (2023). Use of the Internet of Things in the construction industry and facility management: Usage examples overview. *Procedia Computer Science*, *219*, 1670–1677. doi: 10.1016/j.procs.2023.01.460.

Siraskar, R., Kumar, S., Patil, S., Bongale, A., & Kotecha, K. (2023). Reinforcement learning for predictive maintenance: A systematic technical review. *Artificial Intelligence Review*, *56*, 12885–12947. doi: 10.1007/s10462-023-10468-6.

Soori, M., Arezoo, B., & Dastres, R. (2023). Internet of Things for smart factories in Industry 4.0, a review. *Internet of Things and Cyber-Physical Systems*, *3*, 192–204. doi: 10.1016/j.iotcps.2023.04.006.

Trifonov, H., & Heffernan, D. (2023). OPC UA TSN: A next-generation network for Industry 4.0 and IIoT. *International Journal of Pervasive Computing and Communications*, *19*(3), 386–411. doi: 10.1108/IJPCC-07-2021-0160

Turnbull, J. (2018). *Monitoring with Prometheus*. Turnbull Press.

Usman, M., Ferlin, S., Brunstrom, A., & Taheri, J. (2022). A survey on observability of distributed edge & container-based microservices. *IEEE Access*, *10*, 86904–86919. doi: 10.1109/ACCESS.2022.3193102.

Usman, M., Risdianto, A. C., Han, J., & Kim, J. (2019). Interactive visualization of SDN-enabled multisite cloud playgrounds leveraging smartx multiview visibility framework. *Computer Journal*, *62*(6), 838–854. doi: 10.1093/comjnl/bxy103.
Viera-Martin, E., Gómez-Aguilar, J. F., Solís-Pérez, J. E., Hernández-Pérez, J. A., & Escobar-Jiménez, R. F. (2022). Artificial neural networks: A practical review of applications involving fractional calculus. *European Physical Journal Special Topics*, *231*(10), 2059–2095. doi: 10.1140/epjs/s11734-022-00455-3.
Wolfartsberger, J., Zenisek, J., & Wild, N. (2020). Data-driven maintenance: Combining predictive maintenance and mixed reality-supported remote assistance. *Procedia Manufacturing*, *45*, 307–312. doi: 10.1016/j.promfg.2020.04.022.
Zezulka, F., Marcon, P., Bradac, Z., Arm, J., & Benesl, T. (2019). Time-sensitive networking as the communication future of industry 4.0. *IFAC-PapersOnLine*, *52*(27), 133–138. doi: 10.1016/j.ifacol.2019.12.745.
Zhang, J., Liu, C., Li, X., Zhen, H. L., Yuan, M., Li, Y., & Yan, J. (2023). A survey for solving mixed integer programming via machine learning. *Neurocomputing*, *519*, 205–217. doi: 10.1016/j.neucom.2022.11.024.

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Annex

Table 1. Terminology related to IoT technology

Concept	Abbreviation	Description	References
Internet of Things	IoT	Interested in analysing the software architecture of industrial models.	Shvets and Hanák (2023)
Industrial IoT	IIoT	A new technology and includes many innovations. IoT describes the network of physical objects and even human interface to exchange processed data with other devices and systems over the Internet.	Ammar *et al*. (2022)
Smart Industry or Industry 4.0	SI	Industry 4.0 sees itself as an industrial ecosystem where all manufacturing industries must be managed without human interaction.	Hien *et al*. (2022)
Smart Factory	SF	Facilities that use digital technologies to improve operational efficiency and productivity	Soori *et al*. (2023)

Table 2. The structure of Industry 4.0

Components	Physical Layer	Network Layer	Application layer
Support	This layer consists of physical resources such as sensors and actuators to obtain real-time information using various communication devices.	In this layer, various network protocols will be incorporated in order to establish secure communication between network devices.	This layer provides application specific services such as smart cities, smart factory, smart health services, etc. based on learning machine algorithms.
Tool	High frequency RFID; Light Emitting Diode (LED); Spectrometer; Accelerometer	MQTT protocol; Constrained application protocol; Mutual authentication and key agreement; Long Range Wide Area Network (LoRaWAN); Bluetooth Low Energy (BLE); Advanced Encryption Standard (AES); digital model : Data Source Definition (DSD) ; Data Identifier (DI); Data Kind (DK); Data Source Manifest (DSM)	Group method of data processing (GMDH) neural network (NN); Pareto multi-objective optimization; Monte Carlo simulation; Unscented Kalman filter (UKF); Fuzzy logic (FL), technical
Benefit	It plays the role of a data receiver.	Create gateways between objects (node)	It plays a role in the world of data analysis.

Source: Gugueoth *et al*. (2023); Christou *et al*. (2020).

Table 3. The structure of Industry 4.0

	Definition	Benefits
Temporal side	The "temporal side" in the context of the Physical Layer refers to aspects related to time in the transmission of data.	Timing and Synchronization; Data Rate; Temporal Patterns in Signal; Error Detection and Correction;
Frequency side	The "frequency side" of extracting relevant data from the Physical Layer refers to considerations related to the frequency domain in the context of data transmission. In communication systems, signals are often analyzed in terms of their frequency components and characteristics	Frequency Selectivity; Frequency Planning; Frequency Diversity; Frequency Stability
Frequency-time side	The frequency-time side of extracting relevant data from the Physical Layer involves considerations related to both frequency and time domains in the transmission and reception of signals	Frequency Spectrum; Frequency Selectivity; Time-Frequency Analysis;

Source: Gupta *et al*. (2023).

Table 4. The most popular IT component in IoT

IT component	Advantage	Outcomes
Adaptive robotics	Learn from human activities, thus improving their autonomy and flexibility towards appropriate action.	Repetitive action
Embedded systems (Cyber-Physical Systems, CPS)	Plays a multivariate role especially in state monitoring, self-awareness, self-comparison, self-cognition and self-adaptive.	Regulate data flow in an intelligent way
Cloud technologies	Plays multi-role such as collaborative design; data storage; calculates data; virtualization.	Ubiquitous and integrated data access
Virtualization technologies	Reproduce reality in a more developed way with the aim of ensuring the scalability of inductive action.	Improved production models
Simulation	Emulate reality through an experimental model capable of acquiring knowledge transferable to reality.	Building digital twin models
Data analytics and artificial intelligence	Discover latent industrial associations.	Delete unnecessary data; clean data
Mobile Technologies	Increased ability to interact between supports (machine-machine or machine-human).	Receiving large amounts of information

Table 4. Continued

IT component	Advantage	Outcomes
RFID & RTLS	Batch location detection.	Extraction of Lots (data)
Communication & Networking	Connectivity between agents.	Application performance enhancement

Source: García and García (2019).

Table 5. Product-service systems foundations

System of production					
Product 1 Service 2 Model maintenance 1	Product 2 Service 2 Model maintenance 2	Product 3 Service 3 Model maintenance 3	Product 4 Service 4 Model maintenance 4	Product 5 Service 5 Model maintenance 5	Product 6 Service 6 Model maintenance 6

Table 6. The different aspects of the methodology

Define Research Objectives	We focus on scientific articles that clearly define the process of data circulation between the different captures of the LoT database in order to properly analyse and define the most likely failure zone.
Inclusion and Exclusion Criteria	Clearly define inclusion criteria for articles to be considered in the study: *Inclusion Criteria*: – Articles published in reputable journals and conferences. – Studies focusing on AI-driven PM in IIoT. – Real-world case studies or implementations. Define exclusion criteria to filter out irrelevant or low-quality studies. *Exclusion Criteria*: – Articles lacking transparency in methodology. – Studies without a clear connection to real-world implementations.
Selection of Qualitative Tools	– Content Analysis: To systematically analyze and categorize textual data from articles. – Thematic Analysis: To identify and analyze recurring themes across different studies.

Table 6. Continued

Search Strategy	Develop a comprehensive search strategy using a combination of keywords, Boolean operators, and controlled vocabulary specific to the subject.
Initial Article Selection	– Screen titles and abstracts of retrieved articles against the inclusion and exclusion criteria. – Eliminate articles that do not meet the criteria.
Full-Text Review	– Retrieve and thoroughly review the full text of selected articles. – Apply qualitative tools (content analysis, thematic analysis) to extract relevant information related to AI-driven PM in IIoT.
Data Synthesis	– Synthesize qualitative data to identify patterns, themes, and key insights across the selected articles. – Relate findings to the real-world implementation of AI-driven PM in IIoT.
Reporting and Documentation	– Present findings in a transparent manner, using quotes or excerpts from selected articles to support the analysis.

Table 7. System of prognostics & health management

	Prognostics & Health Management					
	Better understand machines and processes				Better analyses objects and processes	
	Identify the fault	Objectives	Data kind (DK)	The thresholds of failure	IA support	Prognosis and visualization
Failure selection	**CMMS** Computerized Maintenance Management System	Its main objective is to organize maintenance activities, monitor the various interventions and keep a history of all this data.	Time-related data; images: (3D), Televisual inspections, Thermal images, X-rays images; buffer or spare parts inventory levels.	Thresholds or limits are often the first type of monitoring that will be performed on new failure mode studies such as: loss of costs expect 5% of production costs; Downtime more than hour per equipment.	The main objective at this stage of the methodology is to be able to create correlations between the selected data to predict the appearance of the mode failure. This is done via a set of techniques such as: Mathematical Approaches (MAs); Mixed integer programming (MIP); Dynamic Programming (DP); Metaheuristic Search algorithms (MSAs); Reinforcement Learning (RL) (see the next session)	Visually detect patterns and take action against unwanted operational behaviors. Graphical visualization such as box plots, scatterplots, or other graphs. A set of techniques can serve the user such as natural network, Bayesian network
Repairs costs; non-production cost; repair time; occurrence; ERP Data, Equipment Data: machine, tools & application, procedure,	**FMEA** Failure Modes and Effects Analysis	Its main objective is to understand the potential breakdowns that may occur and to better understand them by analyzing their causes and their effects on the equipment concerned.				
	Experts knowledge	Its aims to choose the right failure modes for the operation of the system. There is an expanded team including process engineers, automation engineers, machine design departments, maintenance technicians and operators.				

Table 8. Optimization approaches

Approaches	Technique	Algorithms	Natures	Benefits	Outcomes	References
Identification of the best maintenance strategy among a predefined set of alternatives.	Multiple Criteria Decision Making (MCDM)	The optimization is based on an analytical hierarchy process (AHP), which hierarchically structures the decision process into a series of pairwise comparisons.	Combines both qualitative and quantitative aspects.	Create clusters of homogeneous failure based on distance	Clearly define the failure zone based on a maintenance strategy criterion, such as: a maintenance refinement strategy based on the availability of spare parts; intervention time per month and per day, per schedule; by product costs, etc.	Taherdoost and Madanchian (2023)
		Analytic Network Process (ANP) : the decision-making process is structured as a network rather than a hierarchy.	Combines between quantitative aspects.	Create clusters homogeneous failure based on distance.		Aslam Zainudeen and Labib (2011)
		Similarity to Ideal Solution (TOPSIS): Finds the best option based on distance calculation. It aims to minimize the Euclidean distance from the ideal optimal option and maximizes the Euclidean distance from the worst possible option.			Identify aspects of the most effective strategy in the form of a multivariate graph.	
	Decision making grid (DMG)	Is a graphical support tool used to help the decision makers in selecting the most effective maintenance strategy by considering multiple criteria.	Graphical object.	Improved Equipment Reliability. Extended Equipment Lifespan.		

Table 8. Continued

Approaches	Technique	Algorithms	Natures	Benefits	Outcomes	References
	Mathematical Approaches (Mas)	-MA includes all approaches in which the optimization problem is formulated by means of mathematical equations, which are then solved by means of calculus to identify the optimal parameters of the maintenance strategy	Based on metric measurements	MA was proposed to optimize the inventory management and the scheduled maintenance strategy of a single unit.	Define the optimal PM plan.	Fecarotti, *et al.* (2021).
	Mixed integer programming (MIP)	MIP seeks to identify optimization of the maintenance schedule. There are two types: linear (MILP) and non-linear.	Based on continuous and integer variables.	Continuous Improvement. Long-Term Strategic Planning. Optimal Resource Allocation.	- Optimize decisions related to equipment replacement, refurbishment or upgrades.	Zhang et al. (2023)
Approaches to optimize the parameters of a maintenance strategy selected a priori.	Dynamic Programming (DP)	DP is a method for solving multistage decision problems. It is based on the concept of breaking down complex problems into simpler sub-problems, for example: Introduce a system that determines the optimal maintenance strategy for a road network based on budgetary constraints.	Numeric Data: For example, It can be used to find the shortest failure path in a graph, or solve optimization problems with numerical constraints. Sequences: For example, it can be used to find the longest common subsequence of two failure chains, solve the edit distance problem, or optimize a sequence of choices.	Overlapping Subproblems. Optimal Substructure.	Optimal Substructure. Overlapping Subproblems	Gerum *et al.* (2019)

Table 8. Continued

Approaches	Technique	Algorithms	Natures	Benefits	Outcomes	References
			Matrices: For example, the matrix chain multiplication problem consists of optimally finding the most critical failure chain in terms of time and space. Text Data: DP is used for text processing problems, including text alignment, text segmentation, and natural language processing tasks.			
	Metaheuristic Search algorithms (MSAs)	Metaheuristics are computational procedures used to approximate the solution of an optimization problem by iteratively improving the candidate solutions Genetic algorithms (Gas) are one of the most popular MSAs. The Gas was applied to define the degradation threshold to trigger the maintenance process. Grid search: was used to set the optimal scheduled maintenance interval in the power distribution industry.	Failure Data: his data can include the dates and types of past failures, which are used to model and predict future failures. Hyperparameter Space based on Scoring Metric. Real-Valued Data: These variables are often represented as vectors of real numbers in a multidimensional search space such as : Position Data, Personal Best (pBest) Data, Global Best (gBest) Data PM	Feature Selection. Model Parameter Tuning.. Handling Multimodal Solutions. Feature Selection and Engineering, Handling Non-linearity, Continuous Improvement. Reduced Overfitting, Model Robustness, Reproducibility.	Multiple Solutions, Runtime and Efficiency. Cross-Validation Results, visualization: Grid search results can be visualized using tools like heatmaps or plots. Optimal Maintenance Scheduling, Real-time Adaptation, Anomaly Detection	Pinciroli *et al.* (2023)

Table 8. Continued

Approaches	Technique	Algorithms	Natures	Benefits	Outcomes	References
		Particle Swarm Optimization was applied to optimize the PM interval of a manufacturing system.		Real-time Monitoring; Parallelization, No Gradient Information, Multi-objective Optimization.		
Approaches for the selection of the optimal maintenance actions	Deep learning	Reinforcement Learning (RL): is a type of ML paradigm that deals with how agents or decision-makers should take actions in an environment in order to maximize a cumulative reward. It is useful for the selection of failure cases.	Observation Data, Action Data, Reward Data, Policy Data, Experience Data.	Autonomous Decision-Making, Optimal Control and Improved Predictive Accuracy	Scalability, Continuous Learning model ,	Siraskar *et al.* (2023).

Table 9. The architecture of the AIDA platform

Data source	Network configuration	Edge compute monitoring architecture	Outcome
– Quantitative Data such as: data related to network performance, latency, throughput, error rates, power consumption, and more. – Qualitative Data such as non-numerical data like textual information from interviews, surveys, or textual analysis of documents and reports. – Time-Series Data. – Network Data. – Sensor Data.	– CNC (Centralized Network Configuration). – CUC (Centralized user configuration).	– Measurement and delivery services. – Fusion and storage services. – Visualization and notification service. – Provisioning and orchestration service.	– Network reconfiguration. – Fault detection/recovery and monitoring overhead at edge nodes.

Table 10. Loki process

1) Log Collection	2) Log Labeling	3) Compact Storage	4) Queries and search	5) Scalability
Loki can collect logs from multiple sources, including containers, applications, servers, services, and system components. It uses an agent called Promtail to retrieve logs from different sources and send them to Loki.	Loki supports the concept of labels to organize and index logs. You can add tags to logs to categorize them based on different information, such as application, environment, severity level, etc. These labels make it easier to search and filter logs.	Loki uses a compact storage method called "chunking" to reduce the storage space required. Logs are grouped into "chunks" based on their tags and timestamps, reducing duplication and storing data efficiently.	You can query logs stored in Loki using the Prometheus Query Language (PromQL) query syntax. This allows you to search for specific logs, aggregate data, create dashboards, and view trends.	Loki is designed to be highly scalable and can be configured to adapt to your log storage needs, adding or removing nodes depending on the workload.

Table 11. Grafana process

1) Data Collection	2) Configuring dashboards	3) Creating queries	4) Creating visualizations	5) Setting up alerts	Task planning:
Data Collection: Grafana does not collect data directly, but it integrates with a variety of data sources, such as databases, monitoring systems, APIs, text files, etc.	Dashboards are workspaces where you can organize and view graphs, gauges, charts, tables, alerts, and other visualizations. The data deployed relates to a set of parameters which are the status of the equipment ("Running," "Stopped," "Under maintenance," "Breaked," etc.); maintenance alerts; Maintenance key performance indicators (KPIs) (mean time between failures (MTBF), mean time to repair (MTTR), uptime rate, failure rate, etc.)	To display data on a dashboard, you can create queries to extract data from the data source. Grafana supports different query languages, such as SQL, PromQL (for Prometheus), InfluxQL (for InfluxDB), etc.	Once the data is extracted, you can create visualizations to display it. Grafana offers a variety of visualization types, including line charts, gauges, bar charts, geographic maps, tables, Failure Probability Curves, Heatmaps and more.	You can also configure alerts in Grafana to be notified when certain conditions are met. For example, you can set alerts to monitor server performance, service availability, or other important metrics.	You can also schedule automated data collection and reporting tasks using Grafana such as : Sensor Data Analysis Reports; Failure Prediction Reports; Performance and Cost Reports, Trending and Analysis Reports and more.

Table 12. Installation and configuration services

Installation and execution services	Objectives	Configuration services	Objectives
– Security: Intrusion detection, data encryption and security update to protect data and systems against potential threats. – Device Management: To effectively manage edge nodes, it may be necessary to have device management services, including remote monitoring, configuration management, firmware updates, and license management. – Communication: Edge nodes may require communication services, such as supporting specific communication protocols (Bluetooth, Zigbee, LoRa, etc.), managing network connectivity (Wi-Fi, cellular), and setting up communication gateways to centralized systems. – Sensors and data acquisition: If edge nodes are equipped with sensors to collect data, they will need services to manage these sensors, collect the data, store it locally or transmit it to a central system. – - Local processing: Some edge nodes may require local processing services to perform computing or data processing tasks on-site, before transmitting information to remote servers such as algorithms for statistical analysis, classification, anomaly detection, data filtering, image and video processing, embedded artificial intelligence, data aggregation, local security and more.	– Application deployment. – Resource management – Orchestration. – Security. -	– DHCP (Dynamic Host Configuration Protocol): The DHCP service allows edge nodes to automatically receive network configuration, including an IP address, subnet mask, default gateway, and DNS servers. This simplifies the management of IP addresses on devices. – SNMP (Simple Network Management Protocol): SNMP is used to monitor and manage network devices. Edge nodes can be configured to report information about their status and performance to a central management server. – TFTP (Trivial File Transfer Protocol): TFTP is often used for updating firmware on network devices, such as routers and switches. – SSH (Secure Shell): SSH is a secure connection protocol widely used for remote management of edge nodes. It allows encrypted and authenticated connections to configure, monitor and administer devices. – - NTP (Network Time Protocol): NTP is used to synchronize the clock of edge nodes with an accurate time source, which is essential to ensure time consistency across a network.	– Managing system settings. – Configuration automation. – Managing updates and patches. – Security policy management. – Error and incident management

Table 13. ML techniques in PM

	Objectives	Settings	Device Used for Data	PdM Data Description	Outcomes	References
Artificial Neural Network (ANN)	Classification; regression; pattern recognition; natural language processing (NLP); prediction and recommendation and more.	Number of layers (Depth); number of neurons per layer; activation function; connectivity; cost function (loss function); weight initialization and more.	Graphics processing units (GPUs); Tensor Processing Units (TPU); CPU processors; High performance computing (HPC) systems; RAM and more.	Sensor Data; Time-Series Data; Maintenance History; Environmental Conditions; Equipment Specifications; Failure Records; Maintenance Logs; Data Preprocessing; Event Logs; Failure Labels and more.	Early Fault Detection; Improved Equipment Reliability; Reduced Downtime; Cost Savings; Increased Asset Lifespan; Enhanced Safety; Improved Maintenance Efficiency; Data-Driven Insights; Customized Maintenance Strategies and more.	Viera-Martin *et al.* (2022)
Support Vector Machine (SVM)	Classification; Maximize margin; Find the support vectors; Nonlinear data management; Regression; Complexity control and more.	Kernel; Regularization coefficient (C); Gamma (for nonlinear kernels); Kernel degree (for polynomial kernels); Weighted class; Tolerance (tol); Kernel coefficient (coef0); Cache size (cache_size) and more.	Cloud Platforms; High-Performance Computing (HPC) Clusters; Tensor Processing Units (TPUs); Mobile Devices; IoT Devices and more.	Vibration data; Temperature data; Pressure data; Electric current data; Acoustic data; Energy consumption data; Flow data and more.	Precision; Sensitivity (recall); Specificity; ROC (Receiver Operating Characteristic) curve; AUC (Area Under the Curve)	Roy and Chakraborty (2023)
Decision Tree (DT)	Automation of decisions; Feature selection; Interpretability; Classification and more.	Splitting criterion ; max dept; min_samples_leaf; max_features and more.	Workstations; Servers; Cloud Services; Mobile Devices and more.		Predictive Accuracy; Interpretability; Feature Importance; Early Warning; Cost Savings; Improved Resource Allocation; Reducing Downtime; Customization and more.	Kotsiantis (2013)

Table 13. Continued

	Objectives	Settings	Device Used for Data	PdM Data Description	Outcomes	References
Random Forest (RF)	High Predictive Accuracy; Reduced Variance; Feature Importance; Handling Missing Values; Outlier Detection; Robustness to Noise and more	Number of Trees (n_estimators); Tree Depth (max_depth); Minimum Samples for Split (min_samples_split); Maximum Features for Split (max_fseatures); Out-of-Bag (OOB) Error Estimation and more.	Cloud Computing Platforms; Distributed Computing Clusters; GPUs (Graphics Processing Units) and more.	Sensor Data; Operational Data; Failure History; Maintenance Records; Historical Data and more.	Data-driven decision-making; Continuous improvement; Reduced downtime; Cost savings; Anomaly detection and more.	Boulesteix *et al.* (2012)
Logistic Regression (LR)	Predict Probability (success) or (failure); Classification; Relationship Modeling; Goodness of Fit; Feature Selection and more.	Regularization; Learning Rate; Number of Iterations (Epochs); Batch Size; Threshold; Feature Scaling and more.	Statistical software	Target Variable (Binary Outcome): Failure Indicator (e.g., 1 for failure, 0 for no failure). Predictor Variables (Features): Sensor Data; Time-Based Features; Maintenance History; Equipment Information; Environmental Conditions; Operational Parameters; Alarm Logs; Fault Codes and more.	Probability of Failure; Classification; Feature Importance; Model Validation; Early Warning System; Improved Asset Reliability	(Maalouf, 2011)
Extreme Gradient Boosted Trees (XGBoost)	Gradient Boosting; Regularization; Gradient Optimization; Customizable Objective Functions; Parallel Processing; Handling Missing Data and more.	n_estimators (or num_boost_round); learning_rate (or eta); max_depth; min_child_weight; subsample and more.	Servers and Cloud Services; Distributed Computing Clusters; GPU (Graphics Processing Unit) and TPU (Tensor Processing Unit); Mobile Devices and more.	Sensor data; Maintenance history data; Operational data; Environmental data; Preventative maintenance data; Alarm and event data and more.	Improved Predictive Accuracy; Real-time Predictions; Reduced Maintenance Costs; Root Cause Analysis and more.	Ali *et al.* (2023)

Table 13. Continued

	Objectives	Settings	Device Used for Data	PdM Data Description	Outcomes	References
Gradient Boosting Machines (GBM)	Minimize Loss Function; Sequential Learning; Model Generalization; Flexibility and Robustness	Number of Trees (n_estimators); Learning Rate (or Shrinkage, or Step Size); Maximum Tree Depth (max_depth); Minimum Samples per Leaf (min_samples_leaf); Maximum Features (max_features); Early Stopping and more	XGBoost; LightGBM; CatBoost; Scikit-Learn; H2O; Apache Spark MLlib and more.	Information about how the equipment is being used, such as load, speed, and throughput. Data related to the operating conditions, including start-stop cycles, runtime, and power consumption. Historical records of maintenance activities, including details about repairs, part replacements, and maintenance schedules. Information on past failures, their causes, and actions taken to resolve them and more.	Anomaly Detection; Failure Prediction; Remaining Useful Life (RUL) Estimation; Early Warning Alerts; Trend Analysis and more.	Click *et al*. (2017)
Linear Regression Multiples	Predictive Modeling; Relationship Estimation; Model Interpretability; Error Minimization; Hypothesis Testing; Evaluate the trend of an event and more.	Dependent Variable (Response Variable); Independent Variables (Predictors or Features); Assumptions; Coefficient Estimation; Model Assessment: R-squared (R^2), mean squared error (MSE), or mean absolute error (MAE) and more.	Statistics software	Dependent Variable (Target Variable): Independent Variables (Features or Predictors):	Relationship Strength; Predictive Model; R-squared (R2); Residual Analysis; Feature Importance; Multicollinearity; Outliers and Anomalies and more.	Patil and Patil (2021)

Table 13. Continued

	Objectives	Settings	Device Used for Data	PdM Data Description	Outcomes	References
Symbolic Regression (SR)	Function Discovery; Modeling Complex Phenomena; Modeling and Prediction; Feature Engineering; Data-Driven Optimization	Population Size; Generations; Function Set; Terminal Set; Fitness Function; Crossover and Mutation; Stopping Criteria and more.	SymPy; Eureqa; Genetic Programming and more.	Maintenance history: Historical maintenance records, including details about the type of maintenance performed, dates, and duration, can provide insights into the maintenance needs of equipment. Operating parameters: Data related to the operating conditions of machines, such as load, speed, and environmental factors, can impact their performance and wear and tear.	Feature Discovery; Predictive Models; Improved Understanding; Model Interpretability; Model Comparison; Model Validation; Anomaly Detection; Continuous Monitoring and more.	Miranda Filho *et al.* (2020)

Figure 1. Evolution of the maintenance context in industry

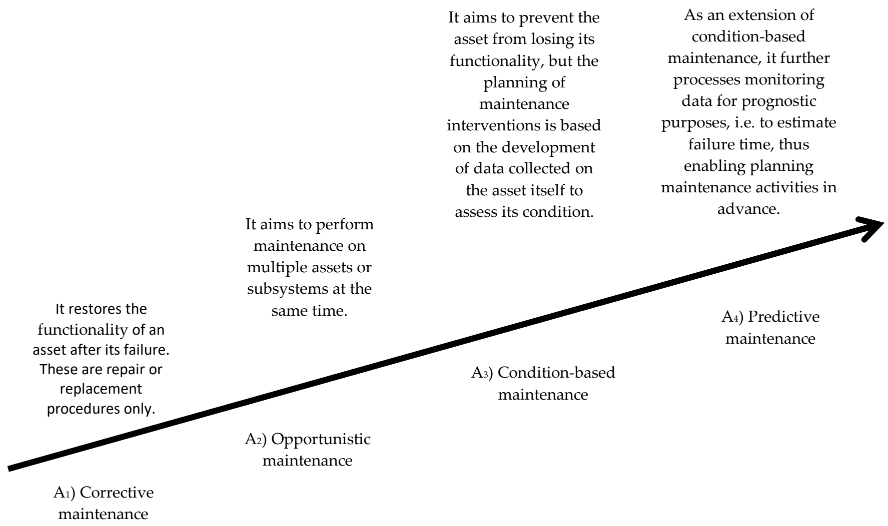
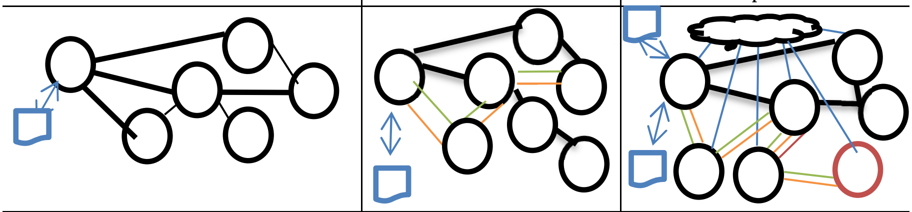


Figure 2. The AI-based maintenance data circuit diagram

Production system			
Phase 1 (Standard circuit)		Phase 2 (Middle circuit)	Phase 3 (Optimal circuit)



Level 1	CNC	Node (resource); Application; Load Balancing; Failure node (Fault); Standard flow; Data flow from node to Cloud	Optimized Routing; Minimizing Latency; Cloud
Level 2	CUCs	Uniform User Experience. Efficient User Onboarding.	Centralized Security Policies.
Level 3	Edge Compute Monitoring	Measurement and delivery services Merging and storage services	Viewing and notification services Provisioning and orchestration service
Level 4	Machine Learning (ML)		