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Maintenance 4.0 Systems Architecture

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Abstract: *The Maintenance 4.0 movement results from changes to processes and manufacturing systems due to the Industry 4.0 paradigm. By anticipating anomalies, foreseeing failures, and reducing asset downtime, maintenance 4.0 is a methodology that boosts productivity and efficiency. Additionally, it makes use of cutting-edge technologies like ML (Machine Learning), CPS (Cyber-Physical Systems), and IoT (Internet of Things). These innovations make it possible to regularly monitor assets in real-time and streamline the maintenance procedure by offering suggestions for when to take action. The four main parts of maintenance 4.0 systems are data collection, analysis of collected data, dynamic monitoring and visualization, and decision-making. Despite its many advantages, maintenance 4.0 has yet to be widely adopted in industries. This paper aims to investigate and discuss the maintenance 4.0 typical system architecture and the maintenance opportunities and adoption challenges it poses.*

Keywords: Maintenance 4.0, Predictive maintenance, IoT, sensors, big data, condition-based maintenance, data analysis.

1 Introduction

The industrial sphere has continuously developed and improved over time. Additionally, the term "Industry 4.0" was created due to the need for the world to transition to a "smart" industry due to technological advancement. Industry 4.0 is a revolution made possible by implementing cutting-edge technologies at the production level to offer customers and the organization new values and services [1]. The transition to Industry 4.0 occurs at all levels, including maintenance. [2] asserts that Industry 4.0 has altered relevant procedures, manufacturing systems, and maintenance tactics.

Maintenance management is considered one of the first aspects of an Industry 4.0 environment to have technical and economic advantages. The technological innovations we are witnessing, such as Artificial Intelligence (AI), the Internet of Things (IoT), and Cyber-Physical Systems (CPS), are radically changing the way industrial systems work, and as "Industry 4.0" emerged, so did "Maintenance 4.0" [3]. Maintenance 4.0 is the application of those technologies to enhance

maintenance activities. Maintenance 4.0 offers a range of technological solutions to optimize maintenance operations through digital technologies, primarily by exploiting data collected in real time. The central tenets of Maintenance 4.0 are to move from preventive to predictive models and transition from a preventive to a prognostic approach. One of its key concepts is "predictive maintenance," which aims to analyze the equipment data and compare it with the maintenance history to determine the failure's premise and predict failures in advance. In the scope of this article, the terms predictive maintenance and maintenance 4.0 are used interchangeably, as they both insinuate the application of Industry 4.0 principles to maintenance to anticipate anomalies and make accurate predictions about asset behaviors.

Predictive maintenance aims to go beyond monitoring the state of a plant's installations by foreseeing defects, making it more agile than preventive maintenance. It anticipates flaws or failures in a failing system. It is dependent on the technological advancements previously mentioned. A predictive maintenance system finds early warning signs of defects or failure and starts maintenance procedures appropriately. However, preventive maintenance is still very much a part of maintenance operations. Predictive maintenance is now being prioritized to decrease the time industrial equipment is offline and the frequency of failures and breakdowns. Industries can become more productive and efficient thanks to this evolution.

Additionally, the pressure that could result from an incident on a production method will be relieved, which will be helpful for maintenance technicians. Real-time machine data can now also be gathered and examined for preventative maintenance. Profitability and customer satisfaction can both rise as a result.

Despite its benefits, this new approach is only sometimes used. Companies still need more trust in predictive maintenance techniques and technologies to handle intelligent and predictive maintenance tasks [4]. In fact, "It is a complex undertaking for a company/organization to implement predictive maintenance (PdM) since it involves meticulous planning of hardware, software, personnel, and training requirements [5]. According to [6], "Despite advances in predictive maintenance technologies, time-based and hands-on equipment maintenance is still the norm in many industrial processes. Nowadays, nearly 30% of industrial equipment does not benefit from predictive maintenance technologies" [6]. Moreover, [7] states that ". However, PdM has become a promising approach to decreasing machines' downtime, improving systems' overall reliability, and reducing operating costs. However, the high complexity, automation, and flexibility bring new challenges". To the point of maturity where PdM can be applied widely, several issues still need to be resolved [8]. These problems and difficulties include the architecture complexity of PdM systems, the lack of historical failure data, and the high initial infrastructure costs. There are also difficulties in familiarizing staff with PdM systems and a need for more qualified staff, both of which are challenges. It is crucial to comprehend the maintenance 4.0 approach in light of its advantages and opportunities for various industries.

This paper will examine the components and interactions of the works describing the architectures of maintenance 4.0 systems. On the other hand, it will discuss the benefits and chances they can present the upkeep function and the challenges and obstacles that hinder the adoption of this kind of system.

Eight sections comprise this work. The maintenance 4.0 domain is briefly described in section two, and we will then examine the concepts and ideas essential to this kind of maintenance. The third section will concentrate on exploring maintenance 4.0 system architectures. Section four explains how Maintenance 4.0 is deployed. The difficulties and opportunities of Maintenance 4.0 are discussed in detail in sections five and six. In section seven, the paper's findings are discussed. Section eight concludes with a presentation of the paper's highlights and perspectives.

2 Overview of maintenance 4.0 domain

Maintenance was seen as a "necessary evil" [9]. It was whittled down to repairs. Fortunately, as time went on, maintenance's significance began to gain more attention, and businesses started working to establish efficient maintenance procedures to minimize downtime and maximize asset utilization.

Reactive and preventive maintenance are the two main types that come to mind when we think of maintenance; when a machine malfunctions, reactive maintenance is carried out to fix it. Preventive maintenance involves performing routine visual inspections at predetermined intervals to stop equipment failures before they start.

However, with Industry 4.0, a fresh approach to predictive maintenance arose. Its emphasis is on foreseeing failures, as its name suggests. Additionally, predictive maintenance refers to using cutting-edge tools like the Internet of Things (IoT), artificial intelligence (AI), and advanced data analytics to sift through vast amounts of data in search of patterns and generate fresh, valuable insights for boosting equipment availability. Therefore, understanding those key concepts is crucial to understanding predictive maintenance:

- Internet of Things (IoT): According to [10], IoT could be defined as "a dynamic network infrastructure with self-configuring capabilities based on standard interoperable communication protocols where physical and virtual things have identities, physical attributes, and virtual personalities and use intelligent interfaces and are seamlessly integrated into the information network." In other words, IoT is a network of connected devices that share data between them. These devices are physical objects –hence the term «things»- embedded with different systems, likes sensors and processors. Therefore, implementing IoT in industrial environments can yield incredible results, as it facilitates data sharing.

- Artificial intelligence: AI is a field concerned with developing machines that mimic human intelligence to perform their tasks. In the industrial world, AI allows machines to learn from collected data, which helps predict future failures in maintenance 4.0.
- Advanced data analytics is a data analysis method using machine learning (ML) algorithms to analyze said data. It differs from classic analytics because it deals with complex datasets (thanks to AI and automation algorithms) and produces deeper insights and predictions than traditional analytics.
- Machine learning (ML): Machine Learning can be defined as "the field of study that gives the computer the ability to learn without being explicitly programmed" [11].

Predictive maintenance uses the technologies mentioned above to present insights into the future. According to IoT sensors that convert physical actions from machines into digital signals, the AI system monitors the equipment and determines when maintenance is needed. Those signals are then processed and analyzed using advanced data analytics. According to [12], "considering artificial intelligence and new human-machine interfaces allows developing smart decision support systems that help technicians execute maintenance interventions, reducing the maintenance costs and the machines' downtime."

The cyber-physical system (CPS) [4, 5, 6] is a core technology of Industry 4.0. A CPS is "an integrated control system combining different sensors, actuator devices, and computing power" [13]. It can also be regarded as an intelligent system capable of independent thought, gathering information from the environment, mining and searching for relevant information, and operating objects that obey the system.

The following are the core components of CPS, as defined by the authors in [14]: 1) The improvement of physical entities through the use of cyber capabilities; 2) Networking at various and extreme scales; 3) Dynamic behavior (plug and unplug during operation); 4) High degrees of automation; control loops are typically closed; 5) High degree of autonomy and collaboration to achieve a higher goal; and 6) close integration between devices, processes, machines, humans, and other software applications.

Many other techniques and concepts are used to implement predictive maintenance, such as Condition-based Maintenance (CBM) and prognostic health management (PHM). CBM is using condition monitoring systems for maintenance. This entails closely monitoring the asset's health state in real time and only performing maintenance in response to fault detection or when the asset's health state deteriorates to a predetermined threshold. The primary focus of CBM, which has been around for a while, is an asset's past and present health. However, by including the equipment's past, present, and projected future health conditions in the CBM systems, maintenance 4.0 will

benefit from this information. This addition is what we call PHM, or Prognostic Health Maintenance. The development of CBM led to PHM. PHM is "an engineering process where algorithms are used to detect anomalies, diagnose faults, and predict Remaining Useful Lifetime (RUL)," according to [4]. PHM and CBM complement each other.

The steps of condition-based monitoring-related activities can be divided into three categories: data collection, preprocessing, and establishing maintenance choices. In the first step, data acquisition, data is recorded and gathered, for example, from sensors. The data collected in the first step is then adjusted and interpreted by data preprocessing, such as reducing noise, to make it exploitable. Thirdly, decisions about maintenance are made using the processed data, such as choosing which maintenance task should be carried out.

Many international standards of the CBM concept exist, including the Open System Architecture for Condition Based Maintenance (OSA-CBM). It is a standard architecture for moving information in a condition-based maintenance system. It is defined using the Unified Modeling Language (UML). OSA-CBM is comprised of these seven blocks [13]:

1. Data Acquisition: this block collects data from physical sensors. Once assembled, it is digitalized.
2. Data Manipulation: In this layer, signal processing techniques preprocess data and convert it to an acceptable format.
3. Condition monitoring: this block compares processed data with expected data to check for outliers. This layer generates an alert for the user if a threshold is reached.
4. Health Assessment: This determines whether the machinery is deteriorating by considering trends in the health history. If there is degradation, relevant fault conditions are computed.
5. Prognostics Assessment: processes collected and statistical and historical data to estimate the machine's remaining useful life (RUL).
6. Decision support makes recommendations regarding maintenance actions.
7. Human interface: shows the user all the information calculated by the lower layers

3 Maintenance 4.0 systems architecture

To design efficient, accurate, and universal maintenance systems, predictive maintenance systems should be compatible with various industrial standards, be easy to integrate with emerging or future techniques, and satisfy the basic requirements of PdM [7]. According to [4], proper system architecture should mainly include a data collection block, a data analysis block, and a monitoring function comprised of a visualization component and an early Detection of Failures. Figure 1 illustrates the architecture of maintenance 4.0 systems that include the fundamental elements and meet the basic requirements of PdM, using new technologies such as IoT, CPS, cloud computing, and ML.

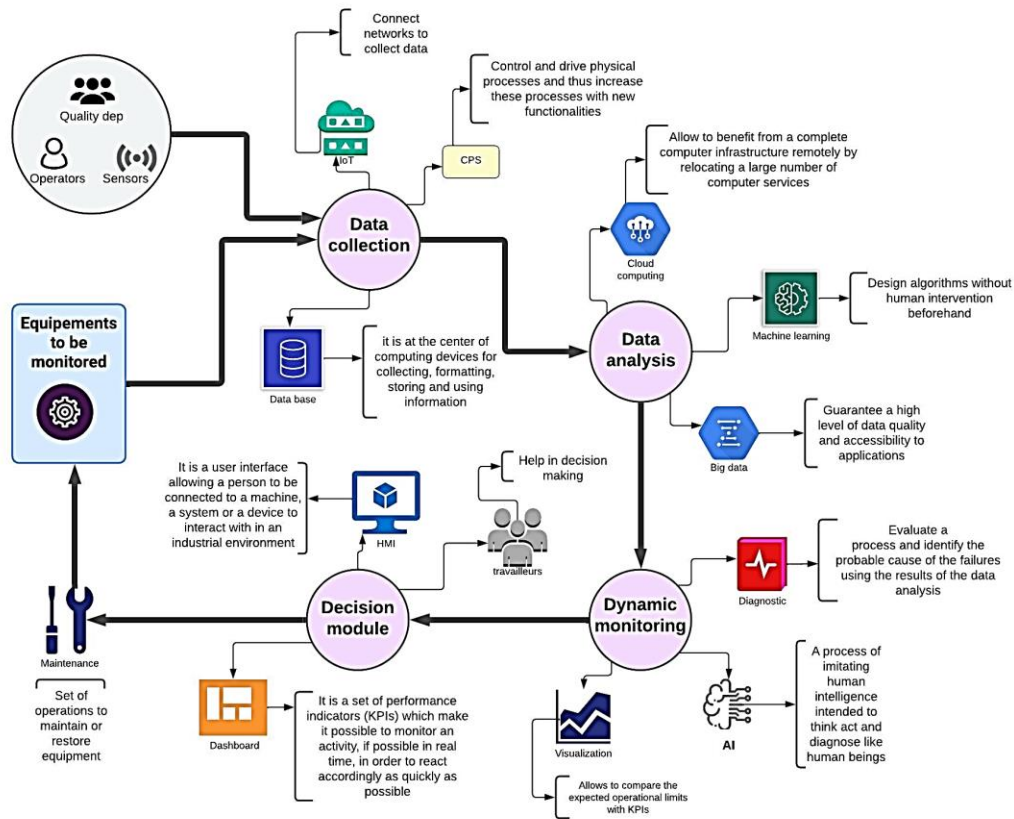


Figure 1: Maintenance 4.0 system architecture.

The data collection bloc is the first fundamental bloc of any predictive maintenance system. "After data has been captured, it must be saved in a database that creates a historical view of the equipment used" [15]. The collected data can either be the event or condition monitoring data [13]. Data collection can be semi-automatic or manual. The automatic data collection module uses sensors to gather several operational and environmental parameters. This data is collected automatically and then stored in a database. Semi-automatic data collection implies that information is automatically collected but manually stored in a database. Operators perform manual data acquisition. They collect it through interfaces and insert it into the database. Human-machine interfaces (HMIs) should be designed to involve users in defining the display and customization of the proper assistance by applying the User-Centered Design approach [16]. After data has been collected, it must be saved in a database that creates a historical view of the equipment used. Data collection is a crucial element of predictive maintenance. It is the basis of the following steps and needs to be done well to achieve accurate results.

Once data has been collected, the data analysis will take place. This module extracts knowledge from data collected in the previous module, using different technologies such as machine learning, cloud computing, and data analytics. It works using various machine learning algorithms with

supervised learning. Results provided by this module are used to assess the health of the equipment. "Health assessment tells whether the system's health is degrading or in a good state based on its behavioral history and prognosis, which will help predict its future health" [16].

The following module is dynamic monitoring. The acquired data is only helpful if it is analyzed, allowing for continuous monitoring of the machine's Condition, early prediction of failures, and triggering maintenance interventions to prevent machine performance decline [17], and that's where the dynamic monitoring module comes in. The active monitoring module uses real-time visualization to keep track of the data that has been gathered and examined. It consists of two crucial blocks: early failure detection and visualization. Visualization is used to predict the system's current state, and early failure detection is used to track the system's behavior over time. The visualization block thus contrasts Key Performance Indicators (KPIs) with the anticipated operational limits. The equipment's health is displayed in the Early Detection of Failures bloc, which alerts operators to defects. Furthermore, it "processes the facts and rules through an inference engine and triggers a maintenance warning when an anomaly is detected in an earlier stage" [5]. Machine learning and supervised learning can be used for the early prediction of failure [12].

The decision module makes the final contribution. It "selects the appropriate maintenance procedure and translates it into a language the human understands. The maintenance procedure is then given to the maintenance technician as they carry out the necessary maintenance tasks while utilizing cutting-edge Human-Machine Interfaces (HMI) [5]". Additionally, sophisticated tools, like big data, are used to systematically transform data into information and facilitate decision-making with more real-time information [10]. The intelligent decision support module consists of a human-machine visualization tool that enables the creation of maintenance procedures. It is a database linked to an inference engine that selects the appropriate maintenance procedure and converts it into a language humans can understand.

4 Deployment of maintenance 4.0

For businesses, deploying maintenance 4.0 systems can be complex. Few industrial implementations are mentioned in the literature [12] despite the substantial work implemented as lab prototypes. Furthermore, [18] claims that "implementing modular, flexible, reconfigurable, end-to-end solutions is still not easy."

We can investigate a digital platform called PROPHECY-PdM, created by [18], which offers end-to-end support for putting PdM applications into practice to better understand the deployment of predictive maintenance. Since the PdM systems described in the literature are made for specific datasets and are challenging to generalize, we decided to study this platform instead. However, this platform provides a simple method for facilitating data collection, data interoperability, and analytics while lowering the effort needed to implement predictive maintenance applications. Additionally, to support data collection, this platform uses IoT and machine learning technologies and the key features covered in the overall PdM system architecture.

The PROPHECY-PdM platform offers five fundamental functionalities:

- A data collection sub-system concerned with collecting maintenance data from different sources.
- A data interoperability sub-system ensures that all data sources follow the same data model.
- Configurable data analytics functionalities: facilitates various methodologies for obtaining predictive insights.
- A set of customizable dashboards to visualize predictive insights.
- Interfaces to automation: to close the loop to the field.

According to [18], the platform's architecture is as follows: It starts with a virtual folder synchronization component that gathers information from cloud service providers. Following that, the CPS is initialized in a sensing and acting component. A data bus infrastructure also circulates the information, and a machine learning (ML) toolkit supports the integration and application of ML algorithms. These two components make up the main parts of the toolkit. The first is a CPS processor engine (CPS-PE) that uses HF-ML (High-Frequency Machine Learning) Models gathered from the CPS to process low-level data streams. The second part, a PDM Processor-Engine (PDM-PE), processes data from different CPSs to provide complex analytics using LF-ML (Low-Frequency Machine Learning) Models gathered from different CPSs. ML toolkits also contain ML Models, which enable modularity in testing and deploying different ML algorithms. Another component is an end-user Predictive Maintenance Dashboard that enables the visualization of analytics results. A field actuator is also responsible for enabling user interaction with the field.

The authors describe in greater detail how ML algorithms use data models to extract data from CPS and IoT systems. These data models' main constituents are edge gateway, data source manifest, definition, and interface specification. The platform uses various algorithms to predict maintenance parameters like RUL (Remaining Useful Life). The platform has already demonstrated its modularity in several industrial deployments. Additionally, it provides a generalized solution that can be used by various plants, increasing the transparency of the implementation of PdM systems.

In addition to this platform, the work of [12] presented an industrial case study demonstrating the deployment of a smart and predictive maintenance system. This work provided a different viewpoint on deploying PdM systems because it offered a more specific implementation in a specific industry than the PROPHECY-PDM platform's more general approach. The system integrated IoT, ML, and augmented realities (AR) technologies and was implemented in an industrial case study comprising a metal stamping machine. The deployed system comprises a data collection module, an analysis and monitoring module, and an intelligent decision support (IDS) module. The data collection module was done automatically and manually. Automatic data collection relied on IoT. Several sensors were installed to pick up different parameters, such as pressure, temperature, and humidity. These sensing modules constitute IoT nodes capable of acquiring and transmitting these parameters over Wi-Fi, and this acquired data is stored in a database. A user interface (UI) was used for the manual data collection, which focused on defects and allowed operators to input the information. The following steps are visualization and dynamic

monitoring after the data has been acquired. An application that provides real-time visualization is then used to monitor the data the developed IoT nodes gathered. A dashboard was created to ensure monitoring, visualize data, and display alerts. A second dashboard was created to display statistical data on machine performance, product quality, and real-time events related to machine malfunctions and flaws.

Additionally, a machine learning approach with supervised learning was implemented for the early prediction of failure occurrences [12].

Finally, by accessing historical and current data on machine operations and demonstrating how to perform functions and execute procedures using text, images, video, and 3D animations, the IDS module helps operators perform maintenance interventions more quickly and effectively. Operators used the developed IDS applications in the industrial case study as part of routine tasks, allowing them to assess the user experience [12]. The system's implementation was successful because, according to a survey conducted to assess its dependability, it "obtained a score of 84.8 percentiles, corresponding to a qualitative evaluation of "Excellent," which indicates that, on the whole, users had a positive experience." The users mentioned they needed time to get used to the system before fully utilizing it.

An industrial plant's predictive maintenance system could be implemented and validated thanks to this work. It serves as evidence that PdM system deployment can produce fruitful outcomes. Additionally, it demonstrates that, despite operators' slow learning curves, implementing predictive maintenance systems in the manufacturing sector can have positive outcomes, such as the optimization of maintenance operations and an increase in productivity.

Based on the studied works, a typical deployment of PdM systems is illustrated in Figure 02.

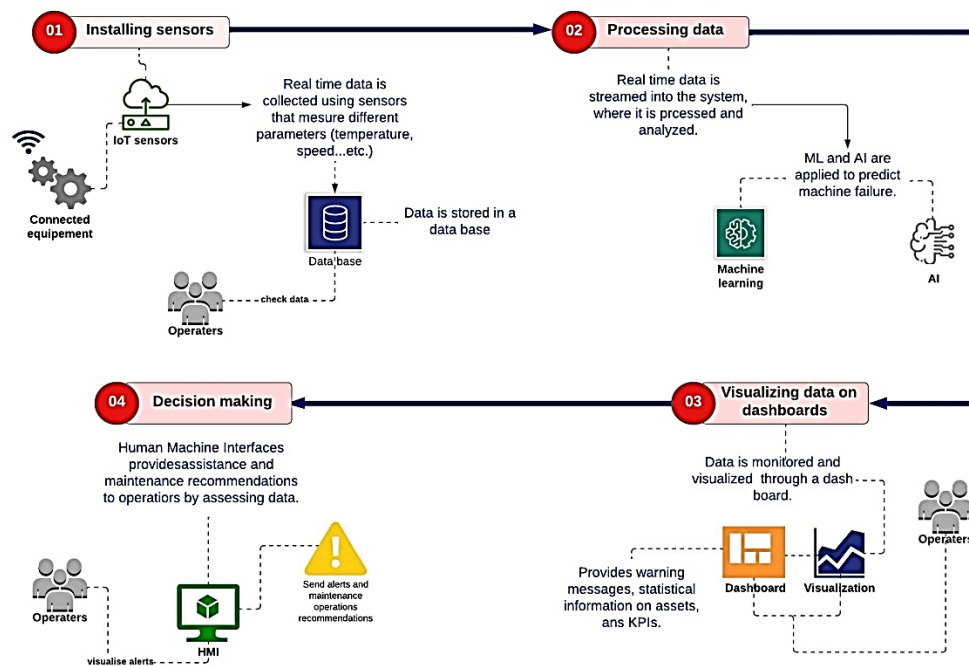


Figure 02: deployment of maintenance 4.0 systems.

5 Challenges of Implementing Maintenance 4.0

Industries 4.0's primary objectives today are to improve quality, decrease safety and environmental risks, decrease equipment downtime and costs, and boost efficiency. While Maintenance 4.0 works hard to achieve these objectives, many obstacles exist. Effective asset management from an organizational perspective requires a lifecycle and systemic view of assets [19], which must be reflected in data extraction and analysis techniques. The study's authors [20] found that the parameter selection and analysis methods analysis are poorly motivated, which is a challenge for the industry that has long been acknowledged as needing condition-based maintenance and predictive practices. Due to the lengthy and expensive implementation procedures, businesses must rely on trial and error.

Additionally, the quality of the analysis is not high enough to help with maintenance decision-making. Because of this, the technical capabilities of predictive systems are not well matched with the effects of maintenance on business. The technical challenge may come from in-depth data analysis.

Big Data analysis in maintenance has created new opportunities to support maintenance managers in decision-making. However, one limitation of the current literature on reading large data sets in maintenance is that it is difficult to filter what is needed from what is not [21]. Selecting suitable analysis techniques is a further issue with big data sets. Big data analytics must conduct extensive research using standardized methodologies to support knowledge discovery.

Another significant issue that must be considered is data accessibility. It is possible that there is not enough data to create predictive maintenance systems. Most predictive maintenance methods rely on machine learning algorithms, so a vast amount of data is required to create an accurate model. Typically, sensors installed on machines for preventive maintenance provide this data. Alternative methods must be found to gather enough data to create models if the sensor is new or the technique used to record the readings limits the available information.

Additionally, the availability of failure data is crucial for obtaining accurate results. Failure information is needed to train algorithms to recognize warning signs and start "just-in-time" maintenance procedures. If maintenance procedures are performed so frequently that no failures have occurred, or if it is impossible to let the system fail for security reasons, it might not exist.

It can be challenging to visualize large amounts of data. Utilize the best visualization tools and plot trends and predictions to maximize the use of large data sets. The best visualization tools and plot trends and predictions to maximize the use of large data sets. Traditional fact visualization techniques and tools, like tables, bar graphs, and line graphs, are ineffective due to the complexity of large data sets. The visualization of big data demands the use of cutting-edge methods. The primary goal of modern data representation techniques is to improve the shape of the chart to make it worthwhile for decision-makers while keeping in mind that human belief is limited.

Another problem is the inability to combine various maintenance modalities based on advanced analytics. Most maintenance tasks rely on just one method of maintenance issue detection, such as vibration analysis, oil analysis, or even thermal imaging. Recent developments in big data analytics (including machine learning, statistics, and deep learning) make the ability to utilize substantial amounts of data from various sources possible. However, these technologies are still only marginally well-controlled in maintenance solutions.

Another problem is the lack of qualified personnel. Therefore, ongoing staff development and training are required to ensure employees can operate the predictive maintenance system [22].

Data security is also a significant obstacle to delivering data security and integrity in interconnected and collaborative networks. Data must be secure throughout its life cycle, asset life, and ecosystem. For example, [23] discusses how data encryption cannot be easily enabled in the cloud for the entire exchange flow, and [24] discusses how data integrity issues in the Internet of Things relate to asset tracking using RFID tags.

Developing appropriate software is a challenge in itself when it comes to effectively utilizing big data and cloud computing. Last but not least, a more subdued but equally important challenge is the mindset shift required for strategic asset management and the new technology paradigm; businesses and organizations need to be aware of the business impact within Maintenance 4.0, both in terms of increased internal effectiveness and new business opportunities. In Service Management 4.0, the emphasis shifts from traditional business models that provide products to those that create value for the customer [13, 19].

6 Opportunities for Implementing Maintenance 4.0

Maintenance 4.0 is expected to expand quickly in the upcoming years due to the urgent need to extend the life of aging industrial machinery. This suggests that Maintenance 4.0 has an exciting future ahead of it.

Augmented reality (AR) applications can be helpful as maintenance processes become more intricate. The idea of augmented reality (AR), which combines real and virtual objects, is a common technique. It involves extending the physical world using digital images, sounds, or other sensory input made possible by technology. Maintenance technicians can make well-informed choices about maintenance and repair tasks by using an AR app on a smartphone or tablet, ensuring the work is done safely. According to the AR literature, the maintenance department is one of the expanding application areas. Applications (a multimodal maintenance skills training method) have been developed based on AR that may improve maintenance, repair, and assembly tasks.

The literature review in [21] provided a good summary of the opportunities for predictive maintenance in sustainability: "Maintenance processes can be improved on the economic, environmental, and social aspects of sustainability by utilizing data-driven maintenance approaches." The following opportunities were also emphasized:

In terms of the economy, adopting data-driven maintenance strategies can increase economic effectiveness, reduce maintenance time, and increase machine time. In terms of the environment, it can reduce the need for spare parts and lubricants, increase environmental safety, reduce end-of-

life waste, and optimize energy use. A new educational approach can be implemented, worker safety is increased, working conditions are improved, and worker satisfaction is increased.

Cloud computing represents an additional chance. According to several authors [16, 22, 25, 26], cloud computing can reduce the effort required to integrate disparate systems while enabling connections between existing systems. Furthermore, cloud services from SaaS (Software as a Service) to IaaS (Infrastructure as a Service) enable businesses to select the option that best supports their strategic asset management objectives and present technological setup.

Moreover, the current use of big data will open new avenues for combining various data types and analyzing asset performance and conditions at the aggregate and individual levels. This results in a better understanding of the operational asset phase and better documentation. Operations and maintenance must be considered during the design phase, necessitating effective feedback mechanisms from the functional to the design or redesign phases. IoT and AaaS (Asset as a Service) systems offer feedback mechanisms from design to operation and secure data throughout their life cycles. [25] Introduces an ontology-based exchange mechanism that would replace the time- and money-consuming paper-based alternative while enabling cooperation between various infrastructure partners [27].

In addition, [7,22,25] suggests that IoT and big data solutions will make it possible to create integrated and seamless data flows between physical assets and various stakeholders by ensuring asset life cycle approaches and system perspectives. These ontologies and standards facilitate parameter selection by ensuring a shared understanding and interpretation of pertinent data [8, 28].

Furthermore, network architectures such as CPS and IoT enable the integration of asset data with other corporate data sets [24]. Big data analytics sometimes changes the way decisions are made: instead of selecting appropriate methods for data analysis, BD analytics sifts through available data and discovers new patterns and correlations. This allows decision-making based on a shared understanding of the assets and previously unknown correlations between different parameters.

7 Discussion

Data collection, analysis, monitoring, reasoning, and decision-making are the main components of the predictive maintenance system architecture. However, the current industrial revolution has resulted in a massive amount of data (hence the term "Big Data"), which suggests that industries are moving increasingly toward a data-driven approach when dealing with data related to predictive maintenance.

CMMS (Computerized Maintenance Management System) software deployment should make managing things easier when implementing predictive maintenance. A CMMS system streamlines and automates every aspect of maintenance management. It is widely used in sectors, particularly manufacturing, where maintaining assets is essential. It is "a dedicated software that integrates and manages information related to maintenance activities, such as data collection, data processing, decision-making, order generation, maintenance scheduling, follow-up procedures, calibration scheduling, equipment history, spare part orders, reporting, and maintenance personnel database

management" [4]. Generally, every CMMS software has four essential components: asset management, inventory management, preventive maintenance planning (calendars), and maintenance documentation (histories, technical documents, work orders, and recipients of parts). All CMMS apps include preventive maintenance. However, predictive maintenance does not appear much, which is unfortunate for many reasons: It can be beneficial when the data is used later for reliability engineering analyses. It facilitates data acquisition and simplifies the process. In addition, as predictive maintenance comes with a substantial financial cost, most companies do not apply it to all their assets but rather to the most critical equipment. Therefore, CMMS can be convenient in narrowing down the selection of essential equipment. Implementing a predictive maintenance system is only possible when a CMMS is used. Predictive maintenance-ready CMMS software should be able to gather data from sensors, analyze it to identify useful information, and then translate it into signals to assess the system's maintenance requirements. As a result, the ML algorithms are fed information about equipment behaviors.

Nevertheless, implementing predictive maintenance effectively is a challenge, mainly due to the need for knowledge about deploying PdM systems. The following are steps that an organization should consider to successfully implement a predictive maintenance system: Step one is determining critical assets. They are often the ones equipped with high repair costs essential to production. CMMS software can be beneficial in determining whether an asset is suitable for predictive maintenance or not. The second step is creating a database. Providing enough information to provide actionable insights into machine behavior is crucial for successful predictive maintenance. This information can be used to help determine failure modes. Even the initial iteration of predictive algorithms can be made using it. The next step is to examine and categorize failure modes to identify which failures are most problematic. The last step is setting up sensors and other equipment to monitor the equipment's Condition and develop appropriate prediction algorithms. Data scientists should take this step. Now that everything is in place, all that is left to do is deploy the system.

Many problems, including the difficulty of big data visualization, the need for qualified personnel, and data security, may still exist even after these steps are completed. Along with these difficulties, deploying and developing a sustainable system for predictive maintenance is complex and could deter businesses. One of the main reasons is the upfront infrastructure cost of implementing predictive maintenance. Deploying a PdM system is expensive and requires many pricy technologies, like sensors. Additionally, seeing a positive return on investment takes a long time. Any new technology requires a monetary investment that must be justified, and in an ideal world, the amount of time it takes to recoup this investment should be as short as possible. Because the team needs time to learn these new skills, it can be challenging to predict how long it will take to recoup the investment in predictive maintenance systems.

Furthermore, the PdM technologies are considered risky because they are relatively new, uncommon, and untested. For instance, considering that ML is a relatively new technology, it is only logical to assume that any application that might be regarded as advanced is dangerous. However, it is possible to start using a predictive maintenance model immediately to reduce these risks.

In addition to these difficulties, there are numerous chances to improve the value of predictive maintenance. For instance, technological advancements and research in big data, signal processing, sensor technologies, and decision-making will significantly impact predictive maintenance. [4] lists some research areas supporting PdM work, including radio-frequency identification (RFID), management systems (RMMS), remote maintenance, and e-maintenance and remote maintenance. "A maintenance management concept wherein assets are monitored and managed over the Internet" is e-maintenance [4]. PdM can be used as an online maintenance system that offers forecasts and insights. IoT and ICT technologies make remote monitoring and maintenance systems (RMMS) and predictive maintenance possible. As they "serve the mere purposes of identification, localization, and tracking but also store maintenance data related to the past and future," radio-frequency identification can also be used in predictive maintenance systems [4].

The mind map shown in Figure 3 summarizes the key obstacles that Maintenance 4.0 must overcome and the promising opportunities.

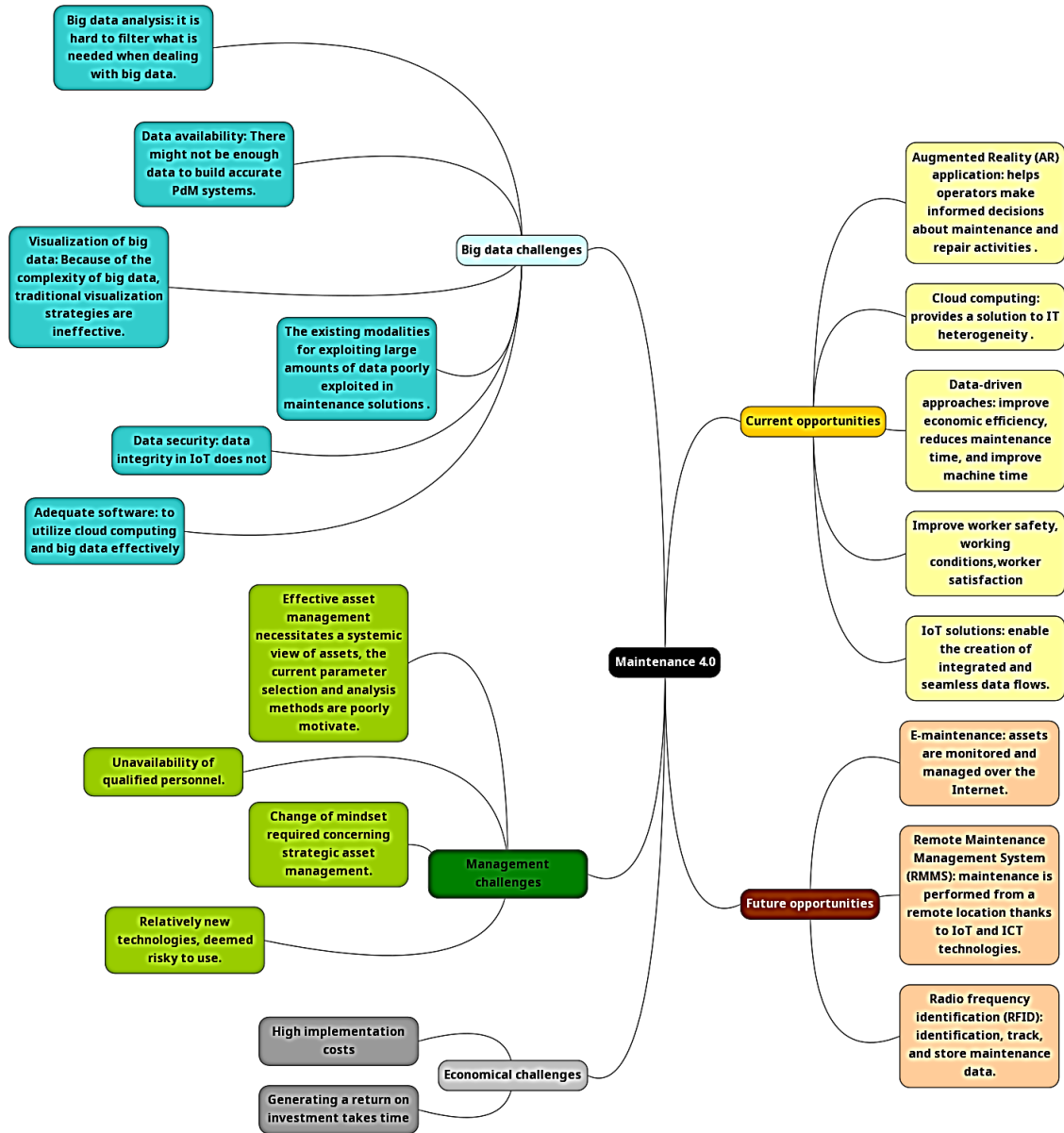


Figure 03: challenges and opportunities of maintenance 4.0 systems.

8 Conclusion

This paper aimed to clarify what maintenance 4.0 is, its essential elements, how it would be implemented, potential challenges it might encounter, and potential benefits. The primary characteristics include data gathering, analysis, preprocessing, dynamic monitoring, and a decision support system. The main obstacles that slow the implementation of predictive maintenance are the difficulty of analyzing and visualizing enormous amounts of data, the requirement for skilled personnel, and the scarcity of data. Future possibilities include cloud computing services like SaaS and IaaS and augmented reality applications that improve maintenance operations. The PdM work

will also be supported by research in e-maintenance and remote maintenance, management systems (RMMS), remote maintenance, and radio-frequency identification (RFID). IoT, ML, and CPS are considered when deploying PdM systems. Data collection, data interoperability, data analytics capabilities, customizable dashboards to visualize predictive insights, and interfaces for automation are some of its functionalities.

Even so, some gaps in the current research present opportunities for further study. For example, while we discussed how predictive maintenance systems are approached through CMMS applications, it would be interesting to study their integration into ERP (Enterprise Resource Planning) systems and discuss future scopes for their application. ERP systems provide a solution to manage all aspects of an enterprise in one connected system. Therefore, integrating predictive maintenance systems within an ERP may interest industries, as an added value might be produced if they are well incorporated.

Additionally, an industrial case study and a general case study (the PROPHECY-PDM platform) were used to study the application of predictive maintenance. Even though this was a beneficial insight into the deployment of predictive maintenance, more research on the more widespread application of predictive maintenance models is required.

The issue of significant data manipulation in maintenance 4.0 systems can be solved in various ways. An exciting solution to the need for failure data would be the development of new methodologies for producing accurate and realistic sample failure data. To simplify big data visualization, novel strategies and cutting-edge visualization tools must be created. New data reduction techniques can also be applied to reduce the volume of data and only keep the most valuable bits. Data integration is additionally crucial for the analysis of big data. Visualizing big data can be sped up using the right tools to integrate accurate data from various sources.

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References

- [1] Khan, A., & Turowski, K. (2016, April). A perspective on industry 4.0: From challenges to opportunities in production systems. In International Conference on Internet of Things and Big Data (Vol. 2, pp. 441-448). SCITEPRESS.

- [2] Di Bona, G., Cesarotti, V., Arcese, G., & Gallo, T. (2021). Implementation of Industry 4.0 technology: New opportunities and challenges for maintenance strategy. *Procedia Computer Science*, 180, 424-429.
- [3] Jantunen, E., Di Orio, G., Larrinaga, F., Becker, M., Albano, M., & Maló, P. (2018, June). A framework for maintenance 4.0. In 10th IMA International Conference on Modelling in Industrial Maintenance and Reliability.
- [4] Selcuk, S. (2017). Predictive maintenance, its implementation, and the latest trends. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 231(9), 1670-1679.
- [5] Cachada, A., Barbosa, J., Leitño, P., Grcaldcs, C. A., Deusdado, L., Costa, J., ... & Romero, L. (2018, September). Maintenance 4.0: Intelligent and predictive maintenance system architecture. In 2018 IEEE 23rd international conference on emerging technologies and factory automation (ETFA) (Vol. 1, pp. 139-146). IEEE.
- [6] Hashemian, H. M. (2010). State-of-the-art predictive maintenance techniques. *IEEE Transactions on Instrumentation and Measurement*, 60(1), 226-236.
- [7] X., Lin, Ran, Y., Zhou, P., Wen, Y., & Deng, R. (2019). A survey of predictive maintenance: Systems, purposes, and approaches. *arXiv preprint arXiv:1912.07383*.
- [8] Zio, E., Compare, M., & Baraldi, P. (2019). Challenges to IoT-enabled predictive maintenance for industry 4.0. *IEEE Internet of Things Journal*, 7(5), 4585-4597.
- [9] Al-Najjar, B. (2007). The lack of maintenance and not maintenance which costs: A model to describe and quantify the impact of vibration-based maintenance on a company's business. *International Journal of Production Economics*, 107(1), 260-273.
- [10] Kumar, U., & Galar, D. (2018). Maintenance in the era of Industry 4.0: issues and challenges. *Quality, IT and business operations*, 231-250.
- [11] Cardoso, D., & Ferreira, L. (2020). Application of predictive maintenance concepts using artificial intelligence tools. *Applied Sciences*, 11(1), 18.
- [12] Alves, F., Badikyan, H., Moreira, H. A., Azevedo, J., Moreira, P. M., Romero, L., & Leitão, P. (2020, June). Deployment of a smart and predictive maintenance system in an industrial case study. In 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE) (pp. 493-498). IEEE.
- [13] Campos, J., Sharma, P., Albano, M., Ferreira, L. L., & Larrañaga, M. (2020). An open-source framework approach to support condition monitoring and maintenance. *Applied Sciences*, 10(18), 6360.
- [14] Lin, H. Y., & Yang, F. N. (2020). Design and implementation of a CPS-based predictive maintenance and automated management platform. *IET Cyber-Physical Systems: Theory & Applications*, 5(1), 100-109.
- [15] Groba, C., Cech, S., Rosenthal, F., & Gosling, A. (2007, June). The architecture of a predictive maintenance framework. In 6th International Conference on Computer Information Systems and Industrial Management Applications (CISIM'07) (pp. 59-64). IEEE.
- [16] Motaghare, O., Pillai, A. S., & Ramachandran, K. I. (2018, December). Predictive maintenance architecture. In 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICIC) (pp. 1-4). IEEE.
- [17] A. Cakir (2011). *The handbook of human-machine interaction: a human-centered design approach*.
- [18] 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.
- [19] International Organization for Standardization. (2014). *Asset Management: Overview, Principles and Terminology*. Geneva: International Organization for Standardization.
- [20] Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2015). Adopting prognostic technologies in maintenance decision making: a multiple case study. *Procedia CIRP*, 38, 171-176.
- [21] Jasiulewicz-Kaczmarek, M., Legutko, S., & Kluk, P. (2020). Maintenance 4.0 technologies—new opportunities for sustainability-driven maintenance. *Management and Production Engineering Review*, 11.
- [22] Galar, D., & Kans, M. (2017). The impact of maintenance 4.0 and big data analytics within strategic asset management. In *Maintenance Performance and Measurement and Management 2016 (MPMM 2016)*. November 28, Luleå, Sweden (pp. 96-104). Luleå tekniska universitet.
- [23] Campos, J., Sharma, P., Jantunen, E., Baglee, D., & Fumagalli, L. (2016). The challenges of cybersecurity frameworks in protecting data are required to develop advanced maintenance. *Procedia Cirp*, 47, 222-227.
- [24] Whyte, J., Stasis, A., & Lindkvist, C. (2016). Managing change in the delivery of complex projects: Configuration management, asset information, and 'big data.' *International Journal of Project Management*, 34(2), 339-351.
- [25] Le, T., & Jeong, H. D. (2016). Interlinking lifecycle data spaces to support decision-making in highway asset management. *Automation in construction*, 64, 54-64. (141)
- [26] Kans, M., & Ingwald, A. (2016). Business model development towards service management 4.0. *Procedia Cirp*, 47, 489-494.
- [27] Olsson, N. O., & Bull-Berg, H. (2015). Use of big data in project evaluations. *International Journal of Managing Projects in Business*. (191)

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