PREDICTIVE MAINTENANCE: UTILIZING AI-DRIVEN TECHNOLOGIES TO PREDICT EQUIPMENT FAILURES ON INDUSTRIAL FACILITIES

Lappeenranta–Lahti University of Technology LUT

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ABSTRACT

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Keywords: AI, Artificial Intelligence, Predictive Maintenance, Industrial Maintenance, Technologies.

This study aims to provide a comprehensive evaluation of the AI-driven predictive maintenance approach, covering four key aspects of the topic through a systematic literature review: the motivators for adopting the approach, the key technologies that accompany AI-driven PdM, the models and methods with which AI-driven PdM predicts failures, and the operational and managerial impacts of its implementation in an industrial facility. From the research conducted, it was found that the adoption of PdM is mainly provoked not only by the pursuit of improvement, but also by the problems that the company or industrial facility either already has or will face in the future. There are various technologies that are implemented to enable and facilitate the PdM strategy, which are sensors, IoT solutions and digital twins. Machine learning algorithms are provided, which are usually used to classify data and its anomalies, if any, and these algorithms are used in modern AI PdM. Last but not least, there is an impact of the PdM implementation on the operational performance and management of a plant. All four research aspects contribute to a comprehensive understanding of the modern PdM approach, which may become even more widespread in the near future due to its long-term benefits.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CBM	Condition-based maintenance
DL	Deep learing
IoT	Internet of things
ML	Machine learning
PdM	Predictive maintenance
PvM	Preventive maintenance
R2F	Run-to-failure

1 INTRODUCTION

In recent years, companies and their stakeholders have become increasingly interested in the topic of AI - artificial intelligence (Hessenkämper et al. 2018). Technology provides undeniable advantages, for example, in the prompt analysis of big chunks of data, simultaneous control of multiple equipment, and interpretation of data for effective management of the company (Zhang & Lu, 2021). Previous studies describe the numerous contemporary applications of AI-driven technologies in different industrial domains (Malik, Muhammad & Waheed, 2024). Notably, given the complexity of the existing systems, structures and established frameworks in any organization, it becomes more evident AI will advance even further simplifying control over complex systems and operations. Additionally, AI application would help avoid the unwanted consequences for the facility. Therefore, AI gradually becomes widespread and is applied already in a whole variety of ways on industrial facilities of any size.

The thesis addresses the topic of equipment maintenance, in which AI plays an increasingly important role every year. The brightest example of such approaches is predictive maintenance (PdM), which alongside its predecessor methods aims to conducting maintenance in time for the equipment to prevent its failure. This method has become a widespread practice as it provides long-term advantages due to its reliance on the powers of AI. The most researched and notable benefit is the reduction of costs, especially considering the costly downtimes, which are extremely preferable to be avoided.

Despite PdM's functional importance and presence in various domains, there is a lack of attention to the evaluation of the AI-driven approach. This is due to majority of research papers focusing either on single real-world cases or advantages the AI approach provides. Overall, the limited scope and the scarcity of knowledge across scientific studies in this domain create an observable gap in comprehensive evaluation of AI-driven PdM approach. Thus, there is a need for a synthesis that examines the AI-driven approach from multiple dimensions to provide a holistic understanding of drivers for its adoption, implications of its implementation, the current PdM technologies and the ways AI PdM systems predict equipment failures.

This study addresses the discovered gap by focusing on the four key dimensions to compile a holistic understanding of the AI-driven predictive maintenance approach in industrial facility context that is the main objective of the study:

- drivers/motivators for AI-driven PdM adoption
- existing PdM technologies
- prediction mechanism
- effects of AI-driven PdM on industrial facilities.

This paper is divided into three main sections: the theoretical background, which frames the terms used throughout the research; the research method, which includes the literature review conducted to understand the trends and extract the related knowledge on the topic; and the findings section, which presents the results of the research. In addition, the findings are further divided into parts that cover the respective dimensions of the evaluation of AI-driven predictive maintenance.

In this study, the motivators for the adoption of the AI-based PdM were identified, which are not only driven by the goal of achieving a competitive advantage, but also by solving the existing problems that facilities might already have or will have in the near future. The AI-driven technologies in PdM are extremely specific to each industrial facility and do not prompt a common technology or standard that stands behind their development. However, each of the technologies enabling PdM has the common characteristics of working with data and further AI training on large amounts of data by applying the Internet of Things (IoT) concept, sensors, and digital twins. As for the working mechanism, AI PdM technologies serve the same purpose as this maintenance approach predecessors of preventing equipment failures but additionally attempt on anticipating failures via using various machine learning and deep learning algorithms before failures occur and indicate the need for equipment maintenance. Finally, the effects of its implementation usually include but are not limited to three subcategories of cost savings, operational and managerial performance.

2 THEORETICAL BACKGROUND

This chapter is concerned with two main topics discussed throughout the research work and represent the basis for findings discussion: Artificial Intelligence (AI) and Predictive Maintenance (PdM). It will cover the definitions of AI, the types of AI by the algorithms applied and used in predictive maintenance, and the predictive maintenance approach itself covering PdM and other maintenance strategies that stand alongside it.

2.1 Artificial Intelligence

The emergence of AI technologies has had a significant impact on a number of industries. Even today there are numerous chatbots, a variety of large language models competing for quality output, and ongoing implementation of different advanced AI solutions on phones, tablets, and personal computers. Initial contribution to understanding of AI could be referred to Turing (1950) with the work on measuring the machine "intelligence". Since then, the concept of AI has been evolving with new approaches, mechanisms, and frameworks being created. The capabilities of AI now may include learning, analysing, processing natural language input (Lee et al., 2018). There are several AI technologies which are applied to build artificial intelligence: machine learning and deep learning, that are inevitably often referenced together with the term of AI (Stryker & Kavlakoglu, 2024).

Machine learning (ML) considers the algorithm of computers imitating the human learning process enabling computers to analyse raw data and get insights from it. This is done by providing guidelines for processing the input, then comparing the output with similar examples to exclude potential and obvious errors and lastly processing the error and "understanding" why the error occurred to optimize the process and exclude other similar mistakes. (UC Berkeley, 2020). The whole concept of ML indeed corresponds to the same approach human intelligence would apply to learn analysing specific data.

Deep learning (DL) is a part of ML algorithm and is more advanced in terms of various input and output layers which thrive to simulate the human decision-making process. Basically, it is more advanced since it enables the machine to conduct learning without human intervention potentially allowing for large scale and continuous machine learning process

(Stryker & Kavlakoglu, 2024). It is also used in training AIs for processing the natural language input, and is closely associated with large language models (LLM), which are also able to generate somewhat natural output, for example, ChatGPT, DeepSeek, Claude, etc. (Stryker & Holdsworth, 2024).

Nevertheless, the development of AI is not only about the personal use in the form of LLMs and chatbots. It is also a substantial consideration for implementation in different companies and their industrial facilities. Considering all the potential benefits companies can get with the application of AI companies in various industries already have or in the process of implementation of AI-driven equipment and systems (Kejriwal, 2023).

2.2 AI in Predictive Maintenance

Industrial facilities are perceived as units that maintain continuous workflow, sometimes even without any pause because the cost of getting the work back on track may be enormous for some facilities that require significant power consumption. Constantly running equipment requires close attention as it gradually wears out and may lead to failure. Companies reach out for maintenance strategies that provide a relatively consistent way of managing equipment health.

There are four main types of maintenance strategies that industrial facilities usually consider. Even though one approach could be more efficient than the other it is a matter of prioritization and what maintenance industrial facility/company sees appropriate for specific systems and equipment. Nevertheless, those four types of maintenance strategies are: Run-to-failure (R2F); Preventive maintenance (PvM); Condition-based maintenance (CBM); Predictive maintenance (PdM) (Susto et al., 2015; Susto, Beghi & De Luca, 2012).

R2F is probably the most basic maintenance strategy as it is concerned specifically with the event of equipment failure. Only when some failure occurred with the equipment or system the respective maintenance actions are taken. (Editorial Team, 2024).

PvM is the maintenance which aims to prevent such failures with consistent check-ins on the equipment and providing maintenance according to the schedule. (IBM, n.d.). This is a step forward considering the previous R2F approach, however, it requires more allocated resources respectively.

Next is the CBM approach which employs sensors and sometimes may even be empowered with machine learning and AI. This strategy is concerned with collecting the real-time data, interpreting the results and indicating when maintenance is required for the equipment's stable work. Basically, when an issue is clearly identified then the maintenance takes place before equipment fails. (IBM, 2023).

And lastly the PdM strategy that is similar to the CBM and might apply the same sensors, machine learning and AI. However, predictive maintenance implies making predictions. This is done through the analysis of the historical data linked to the equipment (IBM, 2023). This way AI PdM may be able to estimate the possible failure or when it might occur, which in turn is used to indicate when maintenance is needed before the predicted failure. In other words, it is possible to state that AI in PdM applies deep learning algorithms in addition to machine learning.

3 METHOD

In this chapter the research methodology used to explore the topic is presented. This research is undertaken as a systematic literature review related to the use of AI-driven technologies in predictive maintenance on industrial facilities. The aim of the literature review is to identify the current trends and gain the respective knowledge in the research of drivers of AI-driven technologies adoption for predictive maintenance, the current technologies in the field, how those technologies facilitate the prediction of equipment failures, and, lastly, the impacts of use of those technologies on the facilities operations and management.

3.1 Search Strategy

The search was conducted on Scopus using the following keywords and their combinations connected with the four subquestions defined for the research problem: “AI”, “Artificial intelligence”, “Predictive maintenance”. The other databases and sources which are Google scholars, Google search, LUT Primo chosen to be supplementary to find specific information regarding the topic.

The main objective of the literature review is to extract the knowledge on what drives the facilitates’ or companies’ decision about the adoption of AI-driven technologies for predictive maintenance, what the latest technologies are in AI-driven predictive maintenance field, how the technology of AI driven predictive maintenance works, and pros and cons that AI-driven predictive maintenance brings to the facility.

Another objective of the literature review is to get the latest trends in the domain of AI predictive maintenance. For that purpose, the literature database “Scopus” is chosen. Thus, to understand the current trends it is decided to focus on the articles published from 2015 to 2025 with occasional exclusions to result in a comprehensive evaluation and accuracy of findings.

Table 1. Scopus database search based of relevant keywords

Keywords	***Number of results***	***Keywords***	***Number of results***
Predictive, Maintenance, Artificial, Intelligence	1946	Predictive, Maintenance, Machine, Learning	4327
Predictive, Maintenance, AI	1306	Predictive, Maintenance, AI, Machine, Learning	660
Predictive, Maintenance, Industry 4.0	1470	Predictive, Maintenance, Technologies	3376
Predictive, Maintenance, AI, Industry 4.0	245	Predictive, Maintenance, Machine, Learning, Technologies	1072
Predictive, Maintenance, Drivers	258	Predictive, Maintenance, Machine, Learning, Solutions	790
Predictive, Maintenance, Machine, Learning, Motivation	21	Predictive, Maintenance, AI, Technologies	601
Predictive, Maintenance, AI, Motivation	3	Predictive, Maintenance, AI, IoT	312
Predictive, Maintenance, Machine, Learning, Impacts	469	Predictive, Maintenance, Machine, Learning, Benefits	397
Predictive, Maintenance, AI, Impacts	312	Predictive, Maintenance, AI, Benefits	187

Considering the research problem of the thesis is divided into four subquestions concerned with different parts of the topic, search queries that focus on specific subquestions are indicated with the specific colour: **red** – general knowledge about the topic; **yellow** – the drivers for the adoptions of AI-driven predictive maintenance methodology or technologies; **blue** – the AI and regular technologies in predictive maintenance; **green** – the impacts of the adoption of AI-driven predictive maintenance technologies.

3.1.1 Literature selection

The results achieved from the Scopus database are scattered across various domains. The core of these search results remains the predictive maintenance and the application of AI. However, some papers are expected to be not relevant for the research topic because of the limited research scope. Hence, the results were screened based on their title, abstract, and findings consecutively.

The screening resulted in the following numbers of output research papers fitting the topic of the thesis:

Table 2. Screening stages for literature used in the thesis

Screening stage	***Number of screening results (Approx.)***
Keyword & keyword combinations	2000
Title	260
Abstract	100
Findings	40

Even though the retrieved literature may provide an insightful overview over a specific domain concerning the predictive maintenance and the use of AI, there are some other sources from Google Scholars, Google search, and LUT Primo that are referenced in the work. Nevertheless, the screening process was used for each of the sources to ensure credibility where applicable. For the internet pages where the above-mentioned screening process is of little use, clarification sources were used to understand the quality of the source.

3.2 Considerations

Given the relative trend boom in application of AI in the industrial processes and equipment, specifically with the predictive maintenance approach, most of the studies provide real-world case studies and a fraction provides a theoretical basis about the research topic. Most of the research papers were focused on the framework or solution proposition increasing efficiency and performance or solving an issue specific to a certain industrial market. Such broad perspectives over the topic of AI predictive maintenance implied in the substantial decrease in the number of articles relevant for the topic during the screening.

Even though most Scopus results consist of case studies, the screening process gave an insight into the current trends in the thesis's research domain. Contemporary research papers are focused on the creation of frameworks and propositions of solutions across various industries, starting from the agricultural industry and ending with improvement of plane predictive maintenance. Given the nature of the results obtained, it hints on the relative novelty of the topic and there are few established and consistent frameworks in the domain of AI predictive maintenance.

4 FINDINGS

This chapter presents the findings on the subquestions of the main research problem concerning the AI-driven predictive maintenance. There are four main subsections, which are: 1) the motivators or drivers for the adoption AI predictive maintenance; 2) impacts on industrial facilities with its adoption; 3) the general way of work of the AI PdM to facilitate the timely maintenance of the industrial equipment; 4) current technologies in the field of AI-driven PdM.

4.1 Key Drivers of AI Predictive Maintenance Adoption

The description of findings in this part presents the motivators for the adoption of AI-driven technologies for the equipment predictive maintenance. The causes of the transition towards AI-driven technologies in general are usually led by a need to address some specific issues which might hinder the competitive advantage in the form of operational efficiency, managerial challenges, equipment wearing out, the need for prompt decision-making, etc. The timely decision-making possibly is the most important factor, since any industrial facility is a complex system of interconnected nodes and if any event occurs it would require immediate attention followed by prompt response.

4.1.1 Timely Decision-Making

Equipment failure in an industrial facility can occur at any time, as it depends on many factors, which implies large amounts of data that should be processed in order to make an accurate and timely prediction. The causes of the failure are, but not limited to, the equipment operating time, employee error in setting up the equipment, and the inability to monitor the equipment's current state, and that in turn results in the need for prompt decision-making processes (Brightly, 2023). Due to the adoption of AI-driven technologies it becomes possible to predict those failures whether they are going to become in the near or distant future.

However, for the adoption of AI-driven technologies there is a premise that the respective maintenance technique out of four other strategies is chosen (Susto, Beghi & C. De Luca, 2012; Susto et al., 2015):

One of the four main approaches to maintenance is predictive maintenance, relies on prediction tools and implies less maintenance, since the respective maintenance procedures are performed only when predictive maintenance systems indicate the need to.

This transition to an appropriate and more effective approach to maintenance requires specific tools that support the analysis of big chunks of data continuously (Carvalho et al., 2019) and provide accurate predictions to facilitate the prompt or even real-time decision-making (Davis et al., 2012) regarding the equipment in general, and maintenance, specifically.

4.1.2 Costly Downtimes

Performance concerns are of great importance on manufacturing facilities, since downtimes appear to be a costly event especially as a result of schedule mismatch after equipment failure and the following adjustments to bring the schedule back in order (Kaźmierczak, Żywicki & Rewers, 2025). Due to the nature of industrial facilities continuous uptime, any unexpected changes in the schedule will inevitably imply challenges either in the cost of handling the situation or the cost of undelivered products because of downtime.

Therefore, to address the issue of costly downtimes due to equipment that gradually becomes worn out provoking stutters in production or processing, there is a need in systems capable of analysis the state of the equipment and indicate the need for repair or diagnostics – maintenance.

Senseye (2022) conducted a survey regarding how much money in total downtimes cost to industrial facilities for the years 2021 to 2022 across four organizations in the automative industry. Additionally, by applying the method of extrapolation to the retrieved data Senseye estimated the total downtime losses in $2 million per hour across the whole automative industry in 2022 year. While this number is an estimation, it can still point out the motivation for the adoption of technologies to decrease costs of downtime substantially, in the case of this study – the AI predictive maintenance solutions.

4.1.3 Need For Automation

The trends toward automation and digitalization across various industries facilitated by rapid technological innovations and increasing market demand have significantly influenced industrial operations, products, services etc. Additionally, these advancements have an influence on the maintenance approaches. Since traditional human-driven maintenance is relatively inefficient and costly in contemporary complex industrial environments, companies shift toward more intelligent maintenance solutions, which in most cases nowadays are AI-driven in order to meet the production demands (Bousdekis et. al., 2020).

The need for changes in maintenance dimension is the increasing complexity of industrial machinery. Modern equipment conducts the same work faster, more precisely, and itself consists of even more subsystems and components inside a single unit of equipment. This transition to more advanced and intelligent solutions relevant for the industry 4.0 requires real-time monitoring and prompt fault detection to make timely equipment failure predictions (Johnson, 2024).

Growing volumes of production in industrial facilities lead to rising equipment wear rates eventually. The ability to watch over the increasing number of complex equipment becomes essential for the consistent work of the facility (Ucar, Karakose & Kırımça, 2024). Therefore, the adoption of AI-driven predictive maintenance methods alongside the already automated processes appears to be the necessary step for most facilities to maintain work and continue growth and technological development.

That is why the overall need for automation increases the need for maintenance strategies as well. Otherwise, facilities would confront the costly and longer equipment maintenance, which is economically inefficient in bigger scale.

4.1.4 Volumes Of Data For Analysis

Modern industrial facilities maintain massive amounts of data generated from the machinery, various sensors, and IoT systems. The data flow becomes difficult to manage with as it comprises the enormous real-time statistical data regarding the equipment performance and production statistics (Tao et al., 2018). Basically, it is a challenge to process this data efficiently, especially on big facilities. Workforce responsible for data processing uses the data processing tools to generate an insightful output. However, it is necessary to address this challenge as it might hamper the timely decision-making. One way to mitigate the growing data challenge nowadays through the application of AI-based solutions. This issue also covers the dimension of maintenance as it is also concerned with the data that is generated by equipment and IoT sensors.

Considering data is unstructured and uninterpreted material to process into understandable information, there is a need to interpret it into perceivable information that could be used for decision-making, specifically in determining whether the maintenance is needed. Artificial intelligence that leverages machine learning and deep learning algorithms continuously processes the input data flows (Naren & Subhashini, 2020). It empowers predictive maintenance systems with the ability to interpret and indicate the need to provide maintenance to industrial equipment in time.

Since lots of factors contribute to the equipment wear rates and this number of factors is only increasing over time, the need for the adoption of AI-driven predictive maintenance likely will become even more relevant not only to solve current issues of unstructured and complex data flows, but also to enable more flexible and smooth scaling capabilities to facilities in the future.

4.1.5 High-quality Input For Quality Assurance

Another concern that is relevant to modern industrial facilities is quality assurance. Industrial facilities are required to produce high-quality products or process materials properly, which in turn will be put into use to produce other products. Quality assurance could be conducted by humans, but there are also various systems which are usually employed for this purpose. Those could include mechanical systems or computer systems which filter out products by specific characteristics. (Coleman, 2016). However, as AI spreads in different industries, it is also used in quality assurance more often as it is required to have products that meet the quality standards (Wang & Gao, 2021).

Even though maintenance is somewhat separate from quality assurance, the products produced by the equipment represent an input for quality assurance. Therefore, maintenance strategy indirectly plays one of the key roles in the process of quality assurance. With the ongoing wear of the equipment the products processes could be affected by the health of the machinery and various product defects may occur (Bhatta & Chang, 2023).

AI-driven predictive maintenance improves the input for quality assurance by ensuring that equipment operates optimally, preventing most potential failures or performance degradation before they occur or have a significant impact on performance (Choudhary, n.d.). By leveraging AI to analyze data, it is possible to increase the likelihood that the output will be of high-quality, which will likely pass quality checks. Overall, the more advanced maintenance systems are in place, the better and timely maintenance is provided for the equipment, the better input there will be for the quality assurance process.

4.1.6 Security And Safety Concerns

The security of the equipment and its safety for employees is an extremely important factor to consider in any industrial facility. The poorer the condition of the equipment, the less safe it is to operate with it or even to be around it. If the inappropriate attention is paid to the equipment's health, the more likely it is that downtime will occur or, however, in the worst case, employees could be injured by the faulty machinery. Therefore, safety in industrial facilities is one of the major concerns as it is not only important for the following regulatory purposes but also for the matter of employees' safety (Jittawiriyanukoon & Srisarkun, 2022)

Due to different kinds of failures that may occur during the work of the equipment, which also include safety-related failures, there is a need to constantly monitor the equipment's health (FSSC Prognostics Working Group, 2024). This is usually done by the implementation of the appropriate maintenance strategy and predictive maintenance stands out of the other four mentioned in this thesis. PdM enables the timely prediction of the equipment's failure, therefore, taking the required actions before failure, especially safety-critical failure, occurs.

Another concern is the security of the industrial facility. This is a bit controversial because it is two-sided. On the one hand, if the system is centralized and predictive maintenance systems are connected, it would be dangerous because the digital threat can easily spread if it finds its way into the system. It would require an additional layer of security to defend the entire system. On the other hand, if the system is designed to be decentralized, it may be safer because the threat can be isolated and the overall threat to the maintenance system is generally less dangerous. In addition, predictive maintenance can be safe because the analysis and prediction part of the maintenance is conducted digitally by AI, potentially eliminating the human factor in this case. The question of the safety of the equipment being maintained by an employee and the reliability of the AI is a separate question.

4.2 Technologies In Predictive Maintenance

Since predictive maintenance is only a strategy or approach to the maintenance of equipment/machinery, it cannot simply be adopted without the tools to enable the strategy to operate on its own. It is possible to consider these technologies as prerequisites for the efficient application of PdM. Therefore, this section provides an overview of the technologies used to facilitate and employ the PdM approach. These include data collection technologies (sensors, digital twins) and data analysis technologies (machine learning and deep learning algorithms).

The first step in enabling the implementation of predictive maintenance is to establish the required infrastructure. The system employed for the chosen approach requires an input that it can analyze and from which it can get valuable insights into equipment's health. Thus, data collecting/generating sensors need to be implemented as a compulsory prerequisite. These sensors could already be in place in established equipment, therefore, the decision on implementation of sensors or purchasing new equipment is solely a question of feasibility and rationality. Sensors used on industrial facilities are usually referred to as part of Internet of Things (IoT), which is most important in enabling effective predictive maintenance strategy (Elkateb et al., 2024; Liu, Li & Yan, 2024; Passlick et al., 2021). Either legacy equipment modified to modern standards or brand-new equipment is connected to the industrial IoT system, which makes it much easier for information to be transferred from one place to another (Alexopoulos et al., 2021). Once installed, sensors generate output data – datasets that comprise operational data and equipment conditions for later use.

Additionally, for the matter of simplification and digitalization of data gathering the concept of digital twin could be incorporated into industrial processes. This concept enabled by IoT brings a digital representation of physical machinery. Moreover, by creating digital twins it is possible to test the equipment under different circumstances isolated from the physical replica. It contributes to the prediction capabilities of the entire system. (Schleich et al., 2017). For example, it is possible to generate datasets of the equipment's health over time, or the impact of specific characteristic deviation on other characteristics or on the machine.

Once the data is collected from sensors, it must be processed, otherwise the data would likely be of little use. This requires the analytical tools to enable continuous analysis. In fact, the infrastructure for this step may already be in place at an industrial facility if a condition-based maintenance strategy is in place. This is because the analytical tools used for condition-based and predictive maintenance techniques are quite similar, but the latter one suggests a deeper analysis using more advanced algorithms (IBM, 2023). These are the deep learning algorithms that AI can use to make accurate predictions, since machine learning not only helps processing real-time data, but also uses statistical/historical data in the analysis to make accurate failure estimates.

Another aspect is AI training. It is possible to collect data from the systems built specifically for AI training by running simulations of the equipment, that can be referenced as an isolated digital twin. However, if the facility has already implemented digital twins, then it is possible to generate sample datasets from systems already in use. Despite the variety of data source types, the data is then used to train AI algorithms in different circumstances and environments to achieve high-definition predictions (van Dinter, Tekinerdogan & Catal, 2022). Later, AI can continue its training with or without supervision on an ongoing basis, especially if it uses deep learning algorithms to further supplement AI-driven decision making (Alexopoulos et al., 2021).

Overall, predictive maintenance requires specific infrastructure and technologies. These are various sensors, digital twins of physical machinery, AI applying machine and deep learning algorithms that technologically enable the effective application of the predictive maintenance strategy on industrial facilities - interconnected components of the IoT system.

4.3 The Approach To Facilitating The Prevention Of Equipment Failures

This chapter focuses on the AI PdM approach to predicting equipment failures. The found common algorithms used in classifying data are presented, which are also applied in AI machine learning and deep learning failure prediction.

The approach and implementation of the required technologies is a good start in maintaining a high level of reliability of the production or processing line. However, the maintenance system cannot rely on the implemented technologies alone, as they only provide some functions for a more comprehensive interaction of technologies. Considering that the main goal of equipment maintenance is to prevent any failures with machinery and modern maintenance systems employ machine learning algorithms, there should be an actual failure prediction methodology such as predictive maintenance to enable effective decision-making and failure prediction.

Currently, there are several machine learning algorithms which enable AI to decide on whether the failure would likely occur or not. It is a common sense that to predict something in the given input one needs to define what the normal values are – it is the very basic concept of the algorithms and what they try to achieve. Discovering anomalies in the given input could be done initially by classifying data using one or multiple approaches: k-nearest neighbors (k-NN) (GfG, 2025d); naïve Bayes classifiers (GfG, 2025c); support vector machines (SVMs) (Abe, 2010); (deep) artificial neural networks (LeCun, Bengio & Hinton, 2015); decision trees (GfG, 2025b); random forests (Breiman, 2001, GfG, 2025a) and XGBoost (Theissler et al., 2021).

The k-nearest neighbours is a simple yet effective way to analyse data. Given there is a datapoint in the dataset, the algorithm "looks" at the number of nearby datapoints – therefore assigning it specific classification on whether it is an anomaly or not. It is almost similar to the way humans recognize that an apple has a round shape: imagining the round shape and deciding how many similar characteristics a round apple has with round shapes and why it is not a square. (GfG, 2025d). Nevertheless, this method is not free of faults just as any other approach, since if anomalies would be considered as a normal equipment's condition, then the system would likely incorrectly classify the input as normal while it is not.

The next approach is naïve Bayes classifiers. It is based on features and responses in dataset. Each independent feature equally contributes to the end response. It enables the calculation of probability of what the response would likely be by answering whether a specific feature exists or not. The GfG (2025c) presents an analogy for it: finding an answer to a question on whether to play golf. There is a matrix of features which contributes to the ultimate answer on playing golf in good weather conditions or not if there are inappropriate conditions. It is similarly possible to apply this approach to not only condition-based maintenance, but also to predictive maintenance AI systems since AI is capable of processing multiple equipment's condition parameters and make respective calculations for the failure prediction.

Theissler et al. (2021) mention artificial neural networks separately, however, it refers to deep learning algorithms that are becoming gradually more and more widespread. As it was mentioned in the thesis's theoretical background deep learning is almost similar to machine learning, but it additionally conducts statistical or historical analysis for more accurate calculations, probability calculations in this case. Deep learning is concerned with increasing the system's "understanding" of the given input by having an accurate abstract level input, which could be referred as "knowledge" or "experience" from previous inputs and analyzing the current input against the comprehensive "knowledge" (LeCun, Bengio & Hinton, 2015).

There are also decision trees which represent a simple decision-making process based on answers to a sequence of questions. While the concept is quite simple and solely is not enough for building an automated predictive maintenance system, it is beneficial as a supplement to other failure prediction methods to streamline the classification, for example, whether a datapoint characteristic is an anomaly or not (GfG, 2025b).

Another approach comprises a random forest which represents multiple decision trees contributing to the output answer. Each tree goes through the dataset and achieves a specific result. Considering the predictive maintenance, it is possible to say that all the predictions from each tree are considered to understand whether the failure is going to happen on the basis which prediction has the most "votes" from each tree. If there are lots of these trees this algorithm might handle large datasets much better (Breiman, 2001; GfG, 2025a). Therefore, if this machine learning algorithm of random forests is applied alongside the deep learning algorithms it might achieve more accurate results.

The last approach is concerned with XGBoost. It helps with finding more hidden correlations between different data points. It could be perceived as the previous approach with random forests where trees output a vote, however, with this method each tree tries to correct the residual mistakes from previous trees' votes (Chen & Guestrin, 2016; GfG, 2025e). Therefore, with each run the process will output less errors and will be more accurate.

Overall, each mentioned algorithm in classifying data points could be applied in the field of predictive maintenance, since AI which is used most probably uses one or multiple machine learning algorithms, otherwise it would be of little use to industrial facility. The question of which method to apply mostly depends on how critical the system is to be maintained, or how accurate the prediction is allowed to be, or any other matrix industrial facility prioritizes in achieving.

4.4 The Implementation Impacts

This chapter provides the general impacts of the adoption of AI predictive maintenance on an industrial facility. As mentioned in the motivators or drivers chapter, the employment of this maintenance strategy is driven by the need to mitigate the issues of contemporary facilities in a complex environment. Nevertheless, the AI PdM adoption itself impacts the operational and managerial performance of the facility.

The study by Er-Ratby et al. (2025) on predictive maintenance impacts on industrial enterprises mentions four impacts: resource and operation cost reduction, minimization of downtime, resource optimization, maintenance cost reduction. These are surely the features following the implementation of AI-driven PdM, since the strategy emphasizes more proactive approach in a range of linked processes strategy comprises.

One of the most apparent impacts that affects the facility and the company's budget in the beginning is the cost to be spent on the appropriate implementation of AI predictive maintenance. Such system would either require an already established infrastructure, e.g. IoT systems, sensors, servers, etc., or it would require the installation of the infrastructure before the PdM implementation itself, therefore leading to a substantial share of allocated resources (Benhanifia et al., 2025). Although the costs may differ, in general it would normally be perceived as a substantial investment, which will pay off in the long run saving more and more money during the facility's work.

The next impacted domain is the facility's performance. Considering various parts of the facility are interconnected and one influences the performance of another, via the implementation of predictive maintenance, which indirectly increases the uptime of the equipment and its condition, the production/processing line performance should be increased. Major maintenance actions are no longer needed that frequently. Even though an aggressive maintenance approach might be more beneficial to the production/processing line's performance, which is described in the research by Swanson (2001), it would also cost more, and it would severely hinder the ability to keep industrial equipment in operational state longer. Also, the efficiency of each maintenance action undertaken would be substantially smaller compared to a proactive approach, which monitors and analyses the potential failure causes much more efficiently.

As was mentioned in the motivators chapter, the quality of products would be increased. If equipment and strategy are used appropriately then there would be a positive effect on the quality of the output. Products would meet the employed standards and specifications more frequently, manufacturing even fewer defective products (Er-Ratby et al., 2025). It is possible to perceive this impact as an impact on performance due to a potential benefit in the high-quality output products. Additionally, PdM adoption is relevant to the facilities' overall productivity which essentially represents a performance matric.

In terms of managerial implications, they might not be so obvious, however, Bousdekis et al. (2020) list some of them in the research on opportunities, benefits and managerial implications of predictive maintenance: digital, governance and organizational strategies, change management, reliability engineering skills, and project management. Since any company has a vision and the internal structure, PdM should be aligned with or within this structure, or the established system should be adapted to employ the new strategy. The same affects the vision as it also needs to accept new technologies and practices.

Another impact on management is change management, which is concerned with employees' readiness to change. The implementation of the unknown or new technology or strategy requires understanding from all the stakeholders that the new practice is beneficial and would increase safety, or simplify employee's work, or any other advantage brought with PdM to the facility's structure.

The above managerial impacts are not only brought by the existence and implementation of predictive maintenance strategies and respective systems, but those are the impacts of most digital solutions nowadays. However, maintenance domain is a somewhat critical topic to consider on industrial facilities, especially those that cannot afford frequent downtimes. The implementation of such complex systems would likely require knowledgeable engineers to verify PdM systems' results and validate them. Hance, implementation of predictive maintenance brings also human resource considerations.

Additionally, taking into account the diverse machinery in industrial facilities it is irrational to employ such a strategy to each and every equipment of different sizes and purposes. Therefore, the question of prioritization for the implementation of AI PdM systems covering specific equipment is important to process. Likewise, if the PdM is installed partially, the prioritization of which equipment to augment is also of high importance (ProCom, 2024).

Overall, the impacts on the facility that AI PdM implementation implies are not limited to pure benefits. It also influences the budget of the company and the industrial facility management. Aside from the pros, this strategy brings relatively similar cons as a company would deal with if implementing any complex technology in its operations. Same effects influence the managerial part.

5 CONCLUSION

While maintenance is not only the prerogative of industrial enterprises, but also the important dimension to consider in numerous other industries, it is still a high priority area to consider in any organization. One such maintenance approach evaluated in this thesis is AI predictive maintenance.

First of all, the research findings provide an overview of the motivators and drivers for the adoption of a PdM strategy. Given today's trends, some companies may indeed thrive for pure improvement of their operations and performance, ultimately influencing the decision to adopt PdM. However, this is not the only reason for adopting PdM in an industrial facility. There are also the issues that may already affected operations of the plant. Therefore, those problems would contribute significantly to the decision to adopt modern maintenance methods. For example, one of the issues is the increasing cost of downtime, which might be difficult to mitigate or even economically inefficient in the future, or it might be the need for timely decision making, which becomes essential for prompt response to any problems that might arise in the modern environment. In addition, one type of driver that could influence the adoption of PdM is the need to be flexible in order to position the organization efficiently in the market, and modern maintenance methods can bring some flexibility.

As for the current technologies, considering that predictive maintenance is only a strategy and does not represent a specific system, it requires technologies to be implemented. Key technologies include: the sensors that provide a real time data on some specific characteristic of the equipment; Internet of Things system that allows the interconnectedness and real time flow of data essential for the efficient and timely maintenance of the equipment; and finally, digital twins that sometimes could be implemented to simplify the information collection and to some extent centralize the information flow serving the same purpose as IoT to provide timely and relevant information of the equipment in real time.

Due to the fact that Predictive maintenance utilizes AI machine learning (ML) and deep learning algorithms, it has been found that a series of different ML algorithms are used to classify the anomalies in the gathered datasets. While the provided models differ in accuracy and level of complexity, each can be applied to various equipment depending on how critical the failure on that machinery would be. The choice over the models is mainly influenced by the rationality and feasibility, as one would not expect immediate and complete implementation of the latest models in every equipment PdM system – it would be at least irrational.

Finally, the impact of AI predictive maintenance implementation in general includes the impact on the company's budget, operational and managerial performance. The first and the most apparent impact, however, is the company's budget to be allocated for the purpose of PdM adoption, which is a somewhat costly decision. As it was found, PdM is a strategy, therefore it would require the appropriate technologies or infrastructure to facilitate predictive maintenance. However, in the long run, PdM should save money for the organization.

Then equipment performance will also benefit from a predictive maintenance strategy. Most importantly, such a maintenance approach increases equipment uptime, keeping the entire production line running longer. Constant monitoring of the machine's health helps detect anomalies in real-time characteristics and take appropriate maintenance actions. Overall, the equipment lasts longer.

Another less obvious effect is the higher quality of the products. This is, of course, due to the good condition of the equipment. Predictive maintenance provides timely recommendations in this regard, and keeping equipment healthy and running has an impact on product quality by reducing the likelihood of failure.

In terms of management implications, predictive maintenance, like any new strategy involving high-end technology, creates relatively similar management changes and challenges. The organization's vision must be well aligned with the direction of using new approaches and technologies, the need for effective change management, and a feasibility check on which equipment to apply PdM first and which to apply later (prioritization challenge). However, like any other automated technology, it requires regular validation and verification of its work, so the need for knowledgeable experts increases significantly.

Table 3. Findings summary

Dimension	*Key findings*
Motivators for AI-PdM adoption	• Costly downtimes • Need for automation • Timely decision-making • Safety concerns • Growing data volumes • Quality assurance
Enabling technologies	• IoT sensors • Digital twins • Machine learning & deep learning algorithms
Prediction mechanisms	• Algorithms: k-NN, SVM, Naïve Bayes, Decision Trees, Random Forest, XGBoost • Data classification & anomaly detection
Implementation Impacts	• Cost-intensive setup with long-term savings • Improved uptime & performance • Better product quality • Managerial changes and prioritization needs

Overall, given the findings summarized in the table above (Table 3) AI-driven predictive maintenance is a promising and state-of-art approach to addressing the challenge of timely equipment maintenance. AI capabilities can save manpower and time – the most valuable assets facilities have when problems arise. With the gradually increasing complexity of various processes and manual work becoming inefficient, facilities are likely to move towards its implementation. In addition, the cost of downtime is an issue that modern facilities would like to mitigate beforehand through AI solutions, and AI-driven predictive maintenance is no exception.

5.1 Limitations

This research provides a comprehensive evaluation of the AI-driven strategy in maintenance, namely predictive maintenance on industrial facilities. However, there are limitations that affect the universality of the work. Knowledge on the topic is relatively scarce across different domains and applications. The research articles regarding the topic mainly focus on solving a specific problem on a specific facility, so some research articles may have overlooked some theoretical knowledge about the research problem. Therefore, the reliance on the research databases Scopus, Google Scholar, and LUTPrimo may have an impact on finding relevant research articles. Also, there could be more issues or problems industrial facilities have, so it can imply more motivators or drivers for the adoption of AI PdM other than mentioned in the thesis. Another limitation relates to the technologies used with AI PdM, as there may be more specific technologies related to strategy, but the ones listed are the most common. Finally, there may be a wider range of impacts that affect specific areas of an industrial facility.

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