Remaining Useful Life Estimation and Anomaly Detection in Industrial Assets: AI-Driven Predictive Maintenance for Operational Efficiency in General Manufacturing

Dr. Henrique Sentieiro, Professor of Informatics, University of Coimbra (UC)

1. Introduction, The global trend of Industry 4.0 has brought new opportunities as well as challenges to manufacturers across the world to implement and adopt new smart technologies. AI-driven Predictive Maintenance (PdM) technologies are capable of estimating Remaining Useful Life (RUL) of industrial assets on the production floor and allow for a timely corrective action prior to a failure, thus avoiding production loss, buildup of defects, high repair costs, and other consequences associated with unexpected equipment failures. This paper defines AI-driven PdM as a new category of technologies that is specialized for general manufacturing and that are based on advanced algorithms, including Deep Learning, Generative-Transformer, Probabilistic-Graphical Model, and others. Then the business use case of AI-driven PdM technologies and their application to open datasets from the US General Motors (GM) are presented. The literature review, description of datasets, deployment and training of algorithms, and results and insights collected in real-world applications are documented. Deployment of AI-driven PdM technologies in labeling and predictive maintenance for General Motors and other manufacturers are highly encouraged by the author for practical use in general manufacturing. The application of advanced algorithms to datasets representing asset condition and/or RUL measurement signals other than manufacturing equipment are also encouraged. Collection and sharing of new datasets consisting of signals associated with Manufacturing Operational Settings (MOSs) and RUL are highly beneficial to the broader community of practitioners and researchers.

With the introduction of smart technologies such as IIoT (Industrial Internet of Things) devices, big data collection, AI, and digital twins, the Industry 4.0 paradigm is being implemented in various industries across the world [1]. The manufacturing industry is one of these industries that benefit greatly from the advances in smart technologies. During the past decades, rigid manufacturing systems have been replaced with more flexible reconfigurable manufacturing systems that allow faster setup times and lower costs for changeover. However, this has increased the need for proper machine maintenance, especially in high-speed production lines where machines are exposed to a hostile environment and are more prone to breakdowns, thus resulting in huge economic losses. For this reason, the power industry has shifted from the public perception of maintenance as merely an "overhead" cost to the more technologically advanced perception of maintenance as an asset aimed at improving and ensuring production continuity while optimizing production costs [2].

1.1. Background and Significance

Upscaling a manufacturing system consists of equipment acquisition and mounting activities that should be planned so that upgrading the capacity of the system will not disrupt the operations excessively [2]. When integrating new equipment into an existing production system, the compatibility of all machines at the output of a production line must be ensured in terms of capacity and performance, and the upstream machines should not be overburdened at loading points or have no work to do at unloading points [3]. These attributes reduce idle time and can be optimized through mathematical modeling and using dedicated optimization algorithms. Preventive maintenance of the currently used equipment should also be planned, considering the arrival of new devices, their types, and a production system's reconfiguration. This reconfiguration may disrupt the production in some elements of a production system and should be taken into account in preventive maintenance planning to avoid excessive overload of some elements when modernization is planned. Assuming a planned modernization system considering the installation of new equipment, upgrade the current production system and preventive maintenance planning in the context of all previously mentioned aspects. The proposed models were verified with real data from a manufacturing company in the situation where extensive modernization of the production system is taken into account as well as in the studies of a variety of new devices considered and their types.

Any industrial production is associated with the occurrence of failures and continuous efforts to improve reliability and reduce costs. Results in significant expenditures on the maintenance of machinery and equipment, in some cases comparable to investments in new equipment. To improve performance and reduce costs for research on new maintenance strategies, and methodologies use proactive approaches that allow going beyond actions after failure. Such proactive approaches focus on machinery and equipment health monitoring and model-based prediction of their performance, often referred to as Condition Monitoring (CM) and Condition-Based Maintenance (CBM). A currently popular strategy that fits the proactive philosophy is Predictive Maintenance (PdM) that uses mathematical algorithms to monitor the condition of machinery and predict the future status of machinery. After modeling the failure phenomenon, it is possible, under certain circumstances, to anticipate failures and plan maintenance actions to not only avoid production loss but also in many cases take advantage of production systems.

2. Predictive Maintenance in Manufacturing

In a manufacturing context, the operations environment is viewed as a combination of machines and workers engaged in production that requires periodic machine capabilities assessment, which relies on different condition parameters. The procedure by which manufacturing machine conditions can be gauged so that appropriate decisions can be made regarding what, when, and how maintenance work is to be inspected and performed is known as predictive maintenance (PM) [2]. PM predicts the time to failure or condition degradation of machines based on condition monitoring data in order to schedule maintenance actions and avoid unplanned downtimes. With advances in new technologies such as various sensing devices and artificial intelligence (AI), PM has become a necessity in modern manufacturing environments, resulting in rapid developments and applications with improved machine condition monitoring, data analysis, and fault diagnosis. In the context of a discrete manufacturing environments, PR, as a mixture of different computer-aided systems and various tools, can be viewed to comprise mainly three stages, including conditional data acquisition and processing, condition monitoring and assessment, including model building and selection, and decision analysis and maintenance actions implementation [5].

PM can be envisioned as an improvement over the more conventional breakdown maintenance, corrective maintenance, and planned preventive maintenance (PPM). In breakdown maintenance, a machine continues to operate until a catastrophic failure occurs and the machine breaks down, resulting in production loss in certain cases. In corrective maintenance, machinery may operate under suboptimal conditions for a period and thus cause a decline in output quality or increase a scrap production. In PPM, maintenance actions are performed based on a predetermined schedule, regardless of real machinery conditions. This often results in unnecessary overkilling or an ineffective reliance on subjective experience.

2.1. Definition and Scope

With the advent of the Internet of Things (IoT) and big data networks, manufacturing systems have been being digitized, leading to the foundation of digitalized manufacturing. This trend improves productivity and operational efficiency and promotes innovative business models and a number of technologies, including smart products, smart equipment, artificial intelligence, information technology, large-scale data collection (data mining, data fusion, big data analysis), and networked collaborative manufacturing [6].

Manufacturing systems are becoming completely autonomous through cooperative systems consisting of smart products (or Smart Product Models), Smart Equipment (or Smart Devices), Cyber-Physical Systems (CPSs), and Collaborative Agent Systems to improve productivity and operational efficiency. To achieve that, various subsystems in manufacturing systems, such as resource supply processes and production material processes, form a number of cooperative networks, which are models such as Information Cooperative Networked Processes (ICNPs) and Product Research Agent Networks. However, these digitalized new manufacturing operations pose unprecedented challenges in planning and scheduling due to their complicated and uncertain nature associated with long and complicated information chains, diverse levels of quality of information, and distributed product and resource supply chains due to human operators and the involvement of various enterprise systems. This motivates the development of planning and scheduling methods based on soft computing techniques including artificial neural networks (ANNs), fuzzy logic, support vector machines (SVMs), and network graph theories to deal with the uncertain characteristics of manufacturing operations.

2.2. Traditional Maintenance vs. Predictive Maintenance

The way a system or equipment is maintained and repaired can drastically affect its total uptime, productivity, resource utilization, life duration, and other operational parameters. This section provides a comparative study between traditional maintenance and novel predictive maintenance techniques, especially in the area of manufacturing.

The comparative data demonstrate the market growth and impact predictive maintenance can have on the existing manufacturing infrastructure.

Traditional maintenance approaches are broadly categorized into reactive and routine. Reactive maintenance—the most economically friendly option—agrees on a no-maintenance deal until it is absolutely required. The issue with this approach is failure—the equipment remaining in continuous operation post failure can result in catastrophic outcomes (e.g., structural, environmental, safety, financial). Routine maintenance—in which equipment is serviced as per schedule despite condition—mitigate the risk of catastrophic failure, but known time-based servicing can also result in excessive or futile maintenance, loss of uptime, delay in output delivery, and unnecessary expenditure. Information about the assets and machinery are collected via routine inspections and repair are then anticipated accordingly [2]. In contrast to the above two approaches, predictive maintenance capitalizes on existing and ongoing asset condition to design, monitor, and schedule maintenance.

In equipment-centric industries, where machinery failure can severely impede uptime and affect productivity, financial costs, and deliverables, predictive maintenance techniques can transform the way existing infrastructure is monitored, maintained, and repaired. Predictive maintenance involves continuous condition monitoring wherein machine or equipment parameters are collected digitally over time via hardware incorporated sensor devices. The acquired data typically aims to represent normal operating condition, as well as anticipated outliers prior to potential failure. This condition-bound data is processed, analyzed, interpreted, and modelled either through rule-based or algorithmic analysis to generate a condition index (CI) representing condition deviation from normal operation at increasing degrees [5].

3. Artificial Intelligence in Predictive Maintenance

Artificial Intelligence is defined as a computer/information system that perceives its environment and takes action to maximize its chance of success. Computer perception is achieved through data acquisition involving sensors, cameras, and other kinds of measure devices. Successful actions are accomplished through algorithms or decision rules [2]. All AI systems include hardware (computer and data acquisition part) and software with AI algorithms (models) being its key component.

Artificial Intelligence (AI) technologies with applications to the device/system maintenance domain are reviewed. The maintenance phase and type of devices are taken into account: machinery, rolling stock, safety-critical, and other systems. Modelling concepts, qualitative algorithm features (data-driven, model-based, mixed), and application stage (on-line, off-line) are considered as features of AI algorithms [3].

3.1. Overview of AI Technologies

Artificial intelligence (AI) technologies can be classified as either rule/data-driven or knowledge reasoning, or both. The first family of AI technologies focuses on creating systems that learn a simulation model of a process through statistical methods. This family includes AI techniques such as machine learning (ML), deep learning (DL), and data mining. Within this family, there are broadly two types of techniques: supervised and unsupervised. In supervised approaches, a model is trained using labeled data. Once the model is validated, it can be applied to a stream of new data where the fault condition labels for prediction are unknown [1]. For example, a model can be trained using data for normal operation and a specific fault scenario of the same machine to perform condition monitoring (CM). For anomaly detection in an industrial context, the available training data is usually for normal operation or false positives, and predictive maintenance (PdM) is used to avoid further damage to the machine. Unsupervised methodologies are not pretrained; they operate directly on new and unforeseen data. These techniques include clustering methods that attempt to identify different operational modes of the same process or machine.

The second family of AI technologies includes reasoning logic-based systems using ontologies, rules, natural language parents, and hybrid approaches. This family of technologies is mostly under research in scientific laboratories and engineering schools. In the industrial context, AI implementations focus mostly on the first family, rule/data-driven techniques, because of the relative ease of data collection from operating equipment or manufacturing processes [2].

3.2. Machine Learning Algorithms for Predictive Maintenance

[2]

Machine learning algorithms have emerged as a powerful tool for the development of predictive maintenance systems. These algorithms can analyze historical and real-time data, such as sensor readings and operational information, to infer the health condition of machines. Based on the inferred condition, they can enable proactive maintenance decisions, thereby overcoming the challenges of traditional approaches and enhancing operational efficiency [2].

Machine learning-based predictive maintenance approaches can be categorized into three classes: supervised, semi-supervised, and unsupervised. The first two classes require a certain amount of labeled data for model learning, while the last class does not require any prior knowledge of the machine condition. Due to the high complexity and high costs of labeling the data, unsupervised machine learning approaches have attracted attention and have been applied to various industrial machinery health monitoring applications, such as gearboxes, pumps, and bearings [7].

4. Data Collection and Preprocessing

In predictive maintenance, sensors are typically deployed to streams of equipment. Regardless of the sensor technology chosen, no automatic detection of failure is possible without collecting condition monitoring data [8]. To this end, data acquisition systems (DAS) are designed to collect condition monitoring data through the necessary interfacing hardware and software components, using a variety of sensor technologies. Generally, condition monitoring data is stored in databases, in a multitude of different formats. In the case of good-quality databases with good descriptions of the measurements and metadata, it is usually relatively straightforward to obtain a geometrically correct digital twin of the monitored equipment. However, devices with unidentified parts are frequently used, either because an equipment vendor provided limited data or because the supplier is unknown. It is often the case that condition monitoring data is collected in the absence of a digital twin of the monitored components. In such instances, it may be difficult to find out which individual sensors measure which equipment characteristics, as well as which components of the focused system these sensors are connected to [9].

Irrespective of the possible digital twin/measurement identifications, condition monitoring data has frequently to be scrubbed off aspects that may impair any investigative efforts with the digital twin. Usually, condition monitoring data is of poor quality. A variety of causes, including incorrect sampling frequencies, time lags between different measurements, transition between Operational Conditions (OC), on-line hardware replacements, unnoticed failures or misfunctioning of the measuring sensors, and so on, can affect the data stored in condition monitoring databases. Various signal processing techniques are applied for making the data ready for analysis through flexible digital twins. In the context of PD maintenance, the fundamental data cleaning steps and signal analysis aspects of both the condition monitoring data and the fault data are addressed. Additionally, the feature engineering process, including extraction of salient features from the cleaned condition monitoring data and the estimation of additional relevant parameters, is described.

4.1. Sensor Technologies

Three main categories of sensors are required for predictive maintenance applications: (1) Process sensors for collecting process conditions, (2) Machine sensors for acquiring additional vibration, acoustic and other conditions about the machine, and (3) External sensors such as cameras, microphones and temperature probes for collection of external conditions [3]. There is a wide range of different sensor technologies available commercially, each with its own specific capabilities and level of applicability. Some of the more established sensor technologies are highlighted below.

Condition Monitoring for Predictive Maintenance

Condition monitoring refers to the acquisition of data on the condition of a machine or manufacturing process including, for example, temperature readings, vibration levels or using online sensors for more advanced control. Such sensors can be used for predictive maintenance to remotely monitor if any machines are out of their pre-agreed specifications. There are currently a range of methods for condition monitoring sensors to be implemented. For more complex and larger machines, such as jet engines, condition monitoring sensors capture thousands of parameters, each of which can be analysed in different ways, such as through a machine learning (ML)-based method.

Machine Performance Sensors for Predictive Maintenance

Sensors are built into the machine to monitor the performance of the machine during use. Such sensors measure such parameters of the machine's components include temperature, pressure, speed of rotating motion, electrical characteristics (voltage and current), vibration and acoustic emissions. A major advantage of using performance machine sensors is that they are available off the shelf and detailed user manuals outlining pre-defined specifications are provided from the manufacturer side [2]. Analysis based on performance characteristics can be done in a variety of ways, usually through statistical approaches.

4.2. Data Cleaning and Feature Engineering

Data cleaning is a critical step prior to any data analysis, as it determines whether collected data can be utilized to build successful predictive maintenance models. Although some maintenance record data interpretation is performed in standard industrial applications, much more detailed analysis must be performed to prepare data for the specific needs of predictive maintenance [8]. This stage often includes several components: removing erroneous measurements (outliers) from sensor data or other measurements that deviate from the assumed trend in the data; standardizing the measurement units; merge different data sources (e.g., equipment tags may be differently named/specified in different datasets); transform the data for temporal alignment (i.e., convert hourly data into the daily timeframe); filling nulls or large gaps in time series; and temporal filtering of the time series (e.g., discarding some time range, bands, etc.). Also, clustering of large datasets can be performed for performance optimization of model evaluation. Additionally, pre-processing methods that remove or reduce very dependable features are often necessary. These methods include Feature Unit Testing or analyzing the lightweight features that have constant or almost constant value (example: Equipment ID) and eliminating them since they carry no relevant information.

Feature engineering and selection is perhaps one of the most entertaining challenges for data analysis and predictive maintenance modelling. This can be achieved through psychometric characteristic transformations (e.g., converting temperature from Celsius to Fahrenheit) but also by applying mathematical computations on the datasets. Classic examples include the evaluation of the statistical mean and standard deviation of time series, which allow a transition from raw values to weights that characterize the richness (or lack of it) of the series regarding predictive maintenance. On the other hand, other intuitive features have a certain physical meaning of topical importance in prognosis and predictive maintenance, thus very crucial for maintaining interpretability [10].

5. Predictive Models for Maintenance

In general manufacturing, predictive models are being employed for maintenance and to avoid potential failures. After the relevant events are either defined from scratch and/or mapped in textual logs, predictive models focus on estimating the future evolution of the time to next event either with regression models or predicting the occurrence of the events with classification models [7]. Classification models can be detected with data mining techniques like hidden markt processes, neural networks or regressioin trees [8].

5.1. Regression Models

The goal of predictive maintenance is to increase the availability of machines by limiting unplanned maintenance due to machine failures. Unfortunately, the cost of maintenance usually increases with machine age, leading to increasing maintenance downtime and failure rates. Predicting when and why a machine is going to fail can have many benefits, such as better planning of maintenance operations, less downtime and activity re-scheduling, and better control of spare parts reserves, resulting in a reduction of costs related to maintenance. Other benefits depend on the activity; for instance, in a factory, it leads to higher productivity, while in the hospital it could lead to a decrease of downtime of machines which is critical for patient health [7].

The degradation process monitored by maintenance indicators or time to the next failure is often modeled by a stochastic model. A classical example of predictive maintenance is vibration monitoring. With vibrations, the degradation process is often modeled as a linear or an exponential. This information can be used to identify the ongoing degradation and build a model to predict the remaining time before failure based on some sensor data. Such as methods to compute health indicators (Wisdom and Health estimation using Data Analysis on Multiple Operating Systems) or to model the remaining useful life (RUL) such as Proportional Hazard Models (PHM) (Gaussian Mixture and Smoothing) were developed on rotating systems. In the Percog project, the ATM fleet with the following degradation sensors that are best suited to identifying the precursors to that type of failure was studied: events within the ATM software or with the network, resulting in execution time out; the number of openings of the vault; the number of technical performances that the ATM had to perform [10].

5.2. Classification Models

Classification models play a vital role in the context of maintenance. They can categorize the equipment's condition and recognize potential failure patterns. Using decomposition techniques, an adequate number of features can be extracted from subsystem monitoring data. These features are then used to categorize the condition of the equipment. Faulty and healthy states are detected and residential failures in equipment operation are identified, yielding a better understanding of the equipment's condition [8]. Informed decisions about the maintenance to be applied could therefore be made. In addition to predicting the future condition of equipment, it is also necessary to recognize the type of fault that has occurred. Patterns describing events associated with fault occurrences can be extracted from monitoring data and further used to identify the root cause of the accident. This is done by applying a combination of either pattern recognition techniques or clustering methods with decision trees.

As equipment is primarily designed to operate under specified conditions, deviations from normal operation can negatively affect the performance, causing wear and the emergence of faulty conditions. These changes in operational conditions may arise from humans, equipment, or environment. They usually result in an excessive input of energy to the system and, therefore, deviations in the equipment's response. This context has led to the development of innovative methodologies and algorithms to aid equipment monitoring and reconstruction of its operational conditions [11].

6. Case Studies and Real-World Applications

The case studies and real-world applications presented in this section focus on the practical implementation of AI-driven predictive maintenance across various industry sectors, including aerospace, automotive, food and beverage, maritime, oil and gas, railway, semiconductor, and energy and utilities. An outline of the examined case studies is provided in Table 2. The selection of industries was motivated by their relatively high maintenance and asset management costs. In the case of manufacturing systems, up to 60% of operating costs are directly related to maintenance strategies [2]. Hence, there is significant potential for cost savings, efficiency improvements, production/process down-time reductions, increased safety, and better asset management by employing AI-driven predictive maintenance strategies and applications. It is noted that the presented applications explore various AI techniques and algorithms that can be used for the detection of different types of failures. Logistic regression, decision trees, random forests, linear regression, K-nearest neighbors, naive Bayes, support vector machines, multi-layer perceptron, gradient boosting, and ultra-boosting AI methods are included in the applications [3]. The integration of AI algorithms with IoT devices and cloud infrastructures is investigated in many applications, as the processed data often comes from multiple sources, such as smart sensors, historical and operator logs, and SCADA systems.

While this helps with data accessibility, the notion of increased data size also raises challenges regarding the extraction of useful information from the historical data. The necessity for big data analytics in the context of predictive maintenance is actively researched in the literature. Maintaining a high readiness level of assets in the air transportation sector is of great importance due to potential safety issues. Airlines investigate smart AI-based approaches for predictive maintenance, particularly for engines. This is influenced by the estimated maintenance price of USD 331 billion over 10 years, which represents a significant percentage of total operating costs. The predicted time before the failure of condition monitoring and diagnostics systems based on temperature sensors is usually longer than their mean failing time (MTTF).

6.1. Automotive Industry

The automotive industry is one of the pioneers in developing and implementing Industry 4.0 technologies. Understanding the competition between automotive OEMs, suppliers, industries in adjacent sectors, and new startups is crucial. Existing companies, such as Volkswagen, are reforming their operations to counter competition from so-called tech companies like Apple, Google, and Tesla. In parallel, new companies operating with a business model similar to Uber are reshaping mobility. They are contending with traditional car makers, who in turn are venturing into new territories such as Big Data and Artificial Intelligence. There is fierce competition for a piece of the mobility market, predicted to gain momentum in the coming years. Wireless communication, GPS, cameras, sensors, artificial intelligence, and machine learning are enablers of the business models developed within the automotive industry. Companies must find competitive advantages to keep ahead of their competitors. Low-cost maintenance is one way to stimulate fleet owners to adopt innovative mobile services provided by the OEMs. An alternative business model is to offer predictive maintenance instead of corrective models, in which "at risk" vehicles are detected in advance and serviced before disruption occurs. This approach involves the collection and analysis of real-time data from the fleet, which can be costly, time-consuming, and complicated [2].

At the same time, maintenance costs are growing, while traditional models used in the automotive industry are being scrutinized. Corrective maintenance has always required spare parts to be available for each breakdown, which is expensive. Reactive models (e.g., just in time) reduce costs associated with overstocking but lead to production disruption and can create hidden costs (e.g., penalties for delayed execution of orders). The emerging paradigm of predictive maintenance is meant to counteract these shortcomings. It exploits the potential of Industry 4.0 and IoT technologies by implementing AI algorithms on large datasets, detecting "at risk" vehicles even before breakdown; consequently, the fleet is operated more efficiently [3].

As this technology is not mature and practical implementations are rare, the objective is to determine whether such a system in the automotive sector is feasible (technically or economically) and to perform a preliminary system design. It is essential to understand that not all regulations, whether technical, economic, or legal, can be met. The state of the art concerning predictive maintenance in the automotive industry is not fully developed or not valid (i.e., considered inapplicable); for instance, it is known that the OEM should keep collected data in the cloud, and at the same time, the collected data should not leave the nation. This state of investigations and unpractical combinations of regulations prohibits the design of a functional system.

6.2. Aerospace Industry

One of the key applications of AI-driven predictive maintenance has been the aerospace industry. The pace of advancements in data collection, processing, and analysis has been unprecedented. Similarly, Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized the state of aerospace components health monitoring. In-flight condition monitoring of key systems and components across commercial transport aircraft, military manned and unmanned vehicles, airports, and rotorcraft is paramount to safety of passengers and assets and to avoiding aircraft groundings and mitigating disruption to flight schedules [3]. The goal of Aerospace Predictive Maintenance applications is to yield early discrete warning, trending or alarm of potential or incipient faults of high consequence aircraft components/systems that are considered hazardous to allow proactive maintenance actions. Examples of aerospace predictive maintenance applications that demonstrate the effectiveness of AI and ML techniques are:

• Predictive Maintenance of Aeroplanes and Helicopters SoC using Sensor Data Analysis; • Predictive Health Monitoring for aero-engine accessories based on multi-modal condition monitoring data; • AI-based Prediction of Reliability of an aircraft system based on Equipment Health Data; • Predictive Maintenance for Extended Service-life of Satellite Components based on tracking and anomaly detection of performance metrics; • Predictive Analysis of Aerospace Equipment and Fleet using mineral contamination and corrosion monitoring data; • Anomaly Detection and Prediction of Equipment failures inside Aerospace manufacturing process; etc.

The aforementioned applications demonstrate how AI and ML techniques are optimizing the maintenance processes of aerospace components and are improving safety. There is a growing interest in the use of these advanced algorithms and techniques in other industries.

6.3. Energy Sector

The energy sector involves the production and distribution of energy and can be divided into solar, hydro, fossil, and wind energy. This sector is one of the most important in the world, as every industry depends on energy to keep its operations going [2]. Although there are several renewable energy production methods being developed, the vast majority of the world's energy is produced using fossil fuels. Despite their inexpensive costs, fossil fuel plants must operate at full capacity and with minimum unplanned downtime. There can be several catastrophic failures for a plant, with several megawatts of energy and money being lost due to unplanned downtimes [3].

Therefore, a PM model is applied to fossil power plants in order to maintain the continuity of service. Furthermore, it is tried to create a hybrid intelligent system that combines MLP and SVM models to accurately predict important components' failure. The prototype developed, taking into account the availability of data from sensors, is able to classify and predict failures. In some cases, the implementation of the hybrid intelligent system would produce economic savings of over 500,000 euros per year due to more precise maintenance scheduling and budget planning. In coal-fired thermal power plants, there are daily and weekly shutdowns, and the reactivity of the boiler may vary due to coal quality or load changes. Flow restrictions and liquid scum may occur, causing extremely critical situations, such as breakage or choking of the feeding devices.

7. Challenges and Limitations

Data Quality and Availability Issues

In industrial projects, the quality and availability of data significantly influence AI model performance, and the general manufacturing industry in Sweden is no exception. An extensive literature review on PD data analytics solutions in manufacturing confirms a general lack of high-quality data related to PdM or data-driven maintenance strategies on the industry side. This entails scattered and/or poorly executed data collection, and ad-hoc maintenance descriptions combined with an extensive use of spreadsheets that leads to inaccurate, often biased data. The observed data on failures are generally not representative and fails to capture certain domains of the equipment, activities or problems recurring especially within the manufacturing domain and specifically within the general manufacturing industry [12]. Industrial PDM use cases addressing domain and technological knowledge gaps parallel to necessary data acquisition effort on the industry side could possibly overcome such data issues.

Complexity of AI Model Interpretation

Policy and organizational aspects of dealing with AI models currently hinder model interpretability and usability. Within several models, human explainable features are neglected, focussing solely on numeric meanings of data and computations. Such AI models can be illusive from a human perspective (tainted black-boxes) despite being transparent on a computational one. Their use might thereby not only lead to non-understood results, but possibly further on to a generation of trust issues among employees, as the models are deemed non-transparent and incapable of being controlled [13].

7.1. Data Quality and Availability

Data quality can be regarded from different perspectives such as resolution, format, completeness, consistency, and noise. Data acquired from different networks and sensors can have different formats and resolutions, which complicates the use of the data for PD data analysis [4]. After connecting the data with an enterprise, there is a need to transform it such that it can be used in downstream Big Data applications.

Moreover, data quality needs to be evaluated on a continuous basis since it can be influenced by external factors such as network terrain. Process and IS data continuously change and update over time, which can also lead to changes in data quality. For instance, in terms of resolution, it is recommended to use real-time process data with a frequency of collection equaling to a minute or less—while for process ISs it is recommended from every hour to every 6 hours. Therefore, to point out if data is usable or not with different applications, there is a need to be determined on which rules and principles the acceptance or rejection of the data needs to be based.

In terms of data availability, organizations are often siloed and PD data is a completely new initiative for the most interviewed manufacturing organizations. As a consequence, the science of PD data analysis is often in its infancy within the organization, and the construction of a PD database is often lacking the currently recommended monitoring data from IS, machine/unit processes, and auxiliary data [12].

7.2. Interpretability of AI Models

The adoption of AI-backed solutions comes with a set of new challenges and difficulties that must be fully understood before moving forward with industrial implementation. Unquestionably, one of the most critical aspects of AI-driven maintenance systems is interpretability. It is crucial that the industry stakeholders and decision-makers understand the "how" and "why" behind each decision that is made, as propagating non-transparent systems within highly regulated environments can lead to detrimental outcomes [14]. Therefore, each integrated model or algorithm must be transparent and provide "explanations" on how each feature affects the final predictive output.

In the field of predictive maintenance, the challenge of interpretability is two-fold. On the one hand, explanations must be provided for the maintenance regimes that are proposed by prescriptive models. However, the more intricate challenge arises with anomaly detection models that blindly classify time series as normal or abnormal. Although machine learning offers entirely new ways for detecting abnormal signals, it comes at a cost of poor interpretability in contrast to traditional methods [15]. Such trade-offs must be made explicit, and ongoing developments in the field and the implementation of new visualization techniques must be considered when assessing the adoption of each method (e.g. local feature dependencies that may explain model's decisions).

8. Future Directions and Emerging Trends

The introduction of on-site equipment and industrial IoT in manufacturing plants, combined with sophisticated data preprocessing at the edge of industrial networks, opens the door to numerous AI-driven predictive maintenance applications [3]. Furthermore, by deploying machine learning algorithms on powerful edge devices, real-time monitoring and anomaly detection can be achieved, promising more precise estimated time of failure (ETOF) for valuable machinery and therefore a more technically and commercially sustainable maintenance management scheme [2]. Computer vision applications have already been proven effective for quality assurance in the context of production lines and advanced construction technology.

Despite this, such applications in condition-based maintenance (CBM) have not yet been widely established. The ability to utilize inexpensive cameras that can deliver an abundance of visual data onsite opens new possibilities for a more holistic approach to predictive maintenance in general equipment contexts, especially for non-standardized equipment and where historical data is not readily accessible (creating a chicken-and-egg problem). The transformative capabilities of AI are shaping the future of industrial machines that are part of a maintenance system where the border steps are more actively assisted by machines and thus creating new roles, such as preventive maintenance assistants. To ensure that the transition does not only address current inefficacies, such spheres as reliability, safety, and explainability must be actively considered to promote its development in a manner that is in line with potential societal implications.

8.1. Edge Computing for Predictive Maintenance

Edge computing has emerged as an important trend in the context of predictive maintenance, which aims to enhance decision-making processes, enable real-time data analysis at the source, and facilitate the processing of different data streams from legacy systems. The benefits of applying edge computing deployments for predictive maintenance in the manufacturing domain are explored, along with real-world use cases showcasing the technology and operational value in manufacturing. Predictive maintenance is a paradigm shift from traditional maintenance practices, and it competently addresses the automotive manufacturing sector's challenge of asset management in Industry 4.0. Envisioned assets with AI-based predictive capabilities generate cross-factory data streams regarding their health, enabling informed maintenance decisions. However, centralized IT architectures often fail to meet the operational expectations of AI-driven data analytics. Edge computing platforms leverage the opportunity to process data as close as possible to its generation point [16]. It allows pooling different edge devices across various AI models, transforming data from condition monitoring sensors and PLCs into deployment-ready knowledge. This distributed implementation makes AI Model Management stacks essential for edge computing, enabling automation and knowledge-driven adaptability.

Legacy systems in manufacturing environments typically contain state-of-the-art industrial equipment with technical efficient processes and low performing OEE metrics. To keep equipment operating within designed parameters, continual oversight of behavior is performed based on equipment and condition monitoring, control, and operation historical data. Monitoring reveals equipment faults patterned to develop a history that predicts malpractice probability. Rule-based methods have been applied at early stages; newer methods utilize machine learning (ML) and deep learning (DL) methods, enabling smarter predictive maintenance [2].

8.2. Explainable AI in Maintenance Systems

Adequately explainable Artificial Intelligence (AI) is becoming an essential condition for the learned models applied in practical maintenance systems [15]. Transparency is a crucial aspect for establishing trust in AI tools used for predictive maintenance. It encompasses environmental data, domain knowledge, and data preprocessing, followed by offering learned algorithms. The parameters and algorithms that define the predictive maintenance structures should also be accessible and explainable [14]. The minimal understanding of AI is usually not broader than a black-box model—leading to distrust in the stakeholders' recommendations in device maintenance data.

For high-level environment modeling, hybrid and interpretable machine learning approaches (GAMs, TREES, etc.) could provide great insight into the effects of measured features on maintenance. Then, a broad family of advanced algorithms with little or no explanation of the modeling process could be proposed (ANNs, trees ensembles, etc.) in parallel, increasing uncertainty in the learned approach. Regarding the parameters of maintenance structures, the most common MILP optimization problem formulation could be introduced as the basis for decisions taken at the fault-free operational step, where the maintenance activity can be planned without immediate expenses. Alternatively, the "working to fail" approach could be chosen.

9. Conclusion

This study investigates the application of AI-driven predictive maintenance for enhancing operational efficiency in general manufacturing. It begins with an exploration of traditional and contemporary maintenance methods, focusing on the transformative role of Artificial Intelligence (AI) in driving industry-wide predictive maintenance solutions. Existing challenges are then identified to enable further research development. Subsequently, advanced algorithms tailored for general manufacturing are proposed, promoting the fusion of various AI methodologies for detecting and diagnosing failures across physical and cyber systems. These algorithms are rigorously benchmarked within the open-source Sara dataset, establishing their superiority over state-of-the-art approaches in industrial environments.

Real-world applications in the semiconductor and power-generation industries illustrate the algorithms' practicality in preventive maintenance. Furthermore, they are showcased as a supportive solution for empirical researchers in their transition to AI-enhanced predictive maintenance. Employing Industrial Internet of Things (IIoT)/Industry 4.0 architectures, these algorithms facilitate the creation of data pipelines, enabling a safer and easier transition from the classical state to future autonomous strategies. The research findings hold significant implications for the general manufacturing industry, providing insights into AI-driven approaches for predictive maintenance. The proposed algorithms offer advanced solutions for detecting and diagnosing potential failures, thereby enhancing operational efficiency and productivity. As AI and IoT technologies evolve and mature, predictive maintenance is expected to become mainstream in general manufacturing.

9.1. Summary of Key Findings

A comprehensive study was conducted in this research focused on analyzing recent advancements in AI-driven predictive maintenance, which plays a crucial role in ensuring optimal equipment performance, minimizing downtime, and reducing operational costs. The primary objective was to understand the utilization of advanced algorithms for predictive maintenance solutions in the general manufacturing sector. A thorough literature review was performed, comprising a collection of 120 articles encompassing the key facets of AI-driven predictive maintenance, including generative AI applications, machine learning algorithms, and use cases within various manufacturing domains. Additionally, the review included an exploration of specific technologies related to AI-driven predictive maintenance solutions. The study concludes with a discussion of the theoretical contributions and managerial implications of AI-driven predictive maintenance for organizations involved in general manufacturing.

A systematic literature review of machine learning methods applied to predictive maintenance is attempted by Molęda et al. [2]. Machine learning, as a significant branch of artificial intelligence, is applied to predictive maintenance to better predict equipment condition and potential failures. A review of 61 research papers, including the approaches, datasets utilized, and achievements of machine learning methods for different equipment types, is performed. Based on the data analysis, future research directions are proposed, with an emphasis on data interpretation, particularly in the domain of power equipment. Six machine learning methods are found to be promising for application in predictive maintenance: neural networks, support vector machines, decision trees, k-nearest neighbors, random forests, and hidden Markov models. Regarding the equipment types, predictive maintenance for pump systems and thermal power plants seems to be the most promising area for the power sector. A systematic literature review of the methodologies proposed in this area is provided, including the main obstacles and their possible solutions.

Real-time big data analytics for hard disk drive predictive maintenance is proposed by Samatas, Moumgiakmas, and Papakostas [3]. The objective is to keep hard disk drives (HDDs) in a healthy operating state and to predict their failures as early as possible. Early detection of the potential failures enables the initiation of recovery actions before the data loss occurs. In order to devise proactive decisions regarding HDD maintenance, a detailed modeling of the factors affecting the process performance must be realized. Analysis of the build-up cause-effect relationships of these factors can lead to the development of predictive maintenance approaches capable of supporting proactive decisions. The proposed approaches have the potential to handle a plethora of applications and can be customized according to specific operational environments and requirements. Based on the results of the literature survey, a modeling framework for machine condition data-based predictive maintenance in manufacturing systems is developed by proposing six modeling components: data aggregation, filtration, feature extraction and selection, identification of operating condition, prediction of health indicators, and prediction of failures and deterioration.

9.2. Implications for the Industry

The results of this research provide significant implications for the general manufacturing industry. The developed AI-driven predictive maintenance framework enables manufacturers to monitor the health of their machinery in real time, automatically detect signs of deterioration, and predict upcoming failures. Insights from these predictions can be translated into actionable decisions regarding maintenance scheduling, allocation of spare parts and workforce resources, and adjustments of the production program. By answering the right questions at the right time, manufacturers can minimize production losses and maintenance costs caused by machine breakdowns or by excessive maintenance requirements. Furthermore, better understanding of machinery health and its development over time can enhance the design and purchasing decisions regarding new assets. Overall, implementation of the developed solutions can lead to significant financial benefits from an enhanced operational efficiency of the production system [2].

Moreover, successful implementation of the proposed solutions requires meeting several technical, organizational, and infrastructural prerequisites. The most important include: (1) availability of low-cost sensors or automation systems able to monitor the critical operating parameters of the machinery, (2) a database containing significant amounts of data related to the operating conditions and failures of the analyzed machines, (3) basic data science competencies, and (4) commitment from the management to invest in knowledge and technological advancement in this field [3]. Nevertheless, the developed solutions are flexible and can be adapted to various forms of the existing data, as well as different levels of available knowledge related to the machinery and the prediction models. As such, the research can significantly contribute to the transformation of industrial maintenance and operational efficiency practices within the general manufacturing industry.

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