The Role of AI-Driven Predictive Maintenance in Enhancing U.S. Manufacturing Operations

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1. Introduction

Manufacturing is at the core of the U.S. economy. The long-term vitality of the manufacturing sector has a direct relationship with the vitality of the overall national economy. Rapid revitalization and improvement in the global competitiveness of the U.S. manufacturing sector are essential for sustainable economic recovery and growth. In recent years, the manufacturing industry has undergone dramatic changes due to rising competitive pressure, deregulation and offshoring, and advancing technology. The increasing capability of machine learning, artificial intelligence (AI), and automation technologies combined with the greater availability of machine data have created opportunities for smart and data-driven manufacturing systems.

U.S. manufacturing operations are broadly classified into discrete and process. With high labor cost, safety concerns, and availability of machine data, the discrete manufacturing and machine shop operations need rapidly deployed AI-driven automation solutions for operation monitoring, decision-making, and workflow controls. Predictive maintenance is one of the most impactful automation applications with regards to return on investment (ROI). Manufacturing personnel need actionable AI-generated predictive alerts for understanding machine operation status and making better operational decisions. On the other hand, the design and deployment of effective intelligent solutions for predictive maintenance is challenging [1].

1.1. Background and Significance

In the 1920s, a manufacturing machine lost an important bolt and fell out of production. It took a week to find a bolt that would fit. Since the 1940s, the United States manufacturing industry has been trying to create tools and add-ons that will track machine operation: temperature, time to failure, pressure, speed, etc. The idea was to be able to exchange those measurements with other manufacturers or supplier companies on a city-wide scale [2]. It was believed that would allow machine inefficiencies to be spotted early and would allow more time to repair machines without interrupting production. In fact, nothing of this sort remained possible: there was no specification how those parameters should be exchanged, but mostly the problem was not the way of exchanging but that different manufacturers use different machines. Prior to the proliferation of the Internet of Things (IoT) and Artificial Intelligence (AI), it was not possible to combine those data from different manufacturers into some useful form and translating and extrapolating that data.

The revolution started in the late 1990s and in the early 2000s Logica Film (now CGI) created the first telemetric system for German cars. That original date was going back on Ford introduction of moving assembly lines in the early 1910s. In the following decades, all respectable car manufacturers wanted to have such an implementation. Early 70s the car manufacturers finally realized that they have too many problems to fix everything inside and some problems are common (as for example finding out that all ribbed belts also remove metal shavings from car parts after first few km, etc). That is why many after war time assembly cars switched to a system from American car manufacturers with a set of fixed parameters that could be exchanged between them.

1.2. Purpose and Scope of the Study

AI-driven predictive maintenance (PdM) has gained momentum in the manufacturing industry over the past several years. The increasing competitiveness of U.S. manufacturing, rising costs, shrinking margins of manufacturers, pricing pressures imposed on suppliers, and mandates on equipment availability and sustainability are driving manufacturers to adopt new technologies to proactively maintain production equipment to achieve performance and sustainability goals. These trends intensify compliance mandates on manufacturers for equipment effluents, emissions, noise, etc., thereby increasing scrutiny and making prevalence and enforcement at multiple levels of the supply chain inevitable as indicated in the earlier mentioned developments in Europe [3]. Advances in the sensing suite, edge computing, cloud computing ecosystems, and data storage capacity and transmission speed have contributed toward making the data-pulling, computing, storage, and analytics sustainable and in real-time [2]. Concomitantly, the need for skilled personnel to field conventional management (DM)/automated management (AM) PdM strategies amidst complaints of poor maintenance and reliability from shop-floor personnel is becoming widespread. As trained personnel are not accessible, AI-driven PdM tools offer the opportunity for manufacturers to bridge the knowledge-gap. The applicability of AI-driven PdM tools has been established in aerospace, transportation, power, machinery, etc. Since employability hinges on tool accuracy, screening based on the choice of ML algorithm(s), variables, and data characteristics is recommended.

2. Fundamentals of Predictive Maintenance

Predictive Maintenance (PdM) is a strategy for applying artificial intelligence and machine learning in manufacturing operations [4]. It entails collecting data and generating features that predict when a machine is about to fail. PdM uses these features and predictive models to warn maintenance engineers to schedule remedial action before a costly breakdown occurs. Thus, PdM can be seen as a digital twin of the asset or machine being monitored where past and present data related to the asset is analyzed in real-time to generate predictions about its future performance. PdM is composed of two core capabilities: (1) representation of the asset and its operating context to a level that makes it possible to anticipate failures, and (2) algorithms to apply this representation to historical or real time sensing data in a way that justifies predicted future outcomes [3].

There are two essential components enabling PdM: (1) a mathematical model that describes how the asset's performance deteriorates over time (using condition monitoring data), and (2) an algorithm that adjusts this model based on measured condition data. At one extreme, this can be done using simple regression methods, at the other extreme complex physics-based nonlinear state observers (e.g., Kalman filters, particle filters, mode-dependent approaches, etc.) might be used. Traditional maintenance to PdM concepts is also compared. Maintenance policies can be broadly categorized into three main types: (1) corrective maintenance where remedial action is only taken after failure, (2) time-based preventive maintenance (TBPM) where an asset is serviced every n days (where n is some constant), and (3) condition-based maintenance (CBM) where the performance state of the asset is monitored and remedial action takes place when some threshold condition is reached.

2.1. Definition and Concepts

The ascension of predictive maintenance (PdM) within intelligent prognostics and health management (PHM), boosted by advanced technology, such as the internet of things (IoT), big data, and artificial intelligence (AI) ushered a wave of growth in the manufacturing sector. This led to a heightened focus on the deployment and utilization of high-fidelity and redundant data coupled with clever analytics as essential ingredients for high-impact PdM [3]. Predictive maintenance is a form of maintenance that takes actions based on the estimations or predictions of the current and future states of objects as state indices (e.g., condition or health states) are obtained from inductive models via data from sensors (comfortingly) placed on the objects. More generally, it falls under the broad umbrella of condition-based maintenance (CBM) as vice versa, this refers to the set of maintenance techniques taking actions based on the "condition" of the object.

PdM is increasingly popular as recent advances in low-cost/small/integrated and hence widely deployable sensors enabled data generation from almost everything "M" (machines, humans, structures, etc.) that, if cleverly interrogated, can provide insight into future states with rich context. There are key concepts associated with predictive maintenance, such as latent states, reducible latent states, health states, continuous health states, and discrete health states [4] are elucidated to create a better understanding of PdM as the underlying concept.

2.2. Traditional vs. Predictive Maintenance

Maintenance can be defined as a systematic process of preserving and maintaining equipment so that it continues to carry out its desired function, or the desired function continues to be carried out. Maintenance occupies a fundamental role in the ability of an organization to achieve its overall objectives [2]. Maintenance may be described in several ways as scheduled maintenance, unscheduled or breakdown maintenance, and predictive maintenance on-line or off-line process monitoring. Earlier a scheduled maintenance was used which was of two types: time-based and usage-based. The time-based maintenance system was universally adopted for all machines in a manufacturing industry irrespective of the age and condition of the machines. This was simple and easy to implement but had its limitations. Presently usage-based maintenance system is preferred to time-based maintenance system. However, it is still very much akin to reactive maintenance since it is based on external influence factors, i.e. running hours or cycle count. Preventive maintenance was introduced as an alternative to the reactive maintenance approach, which ideally requires no equipment to Fail [4]. It assumes a static equipment condition after maintenance. Preventive maintenance has now evolved into condition-based maintenance, incipient fault detection taking advantage of condition monitoring with built-in transducers and/or wear debris analysis.

The maintenance activity has now evolved into a more advanced and complex strategy termed as, Predictive Maintenance. Here the predictive aspect is by using processed signals from on-line condition monitoring for on-line health assessment. It attempts to measure the actual performance of each machine, monitor it to ascertain the existing condition, and track its performance to assess any changes that would indicate degradation. A machine is then maintained only when the condition goes beyond an acceptable limit in order to prevent a fault from occurring or a failure. Thus the predictive maintenance system broadens the horizon of monitoring maintenance management. It considers both the condition of the process and the machine making predictions contingent not only on historical precedence but also on the real-time process data. The predictive maintenance presently being carried out on some machines with little or no condition monitoring depends only on past occurrence facts.

3. AI Technologies in Predictive Maintenance

As technologies continue to evolve, strategic improvements to operational and maintenance processes will need to emerge, too. Integrating artificial intelligence and machine learning within manufacturing and industrial systems will be critical to improving robustness and streamlined performance. Integrating surveillance and big data communications across operations enables the gathering of vital information on the condition of machines and product performance throughout the manufacturing process. By utilizing this information and applying AI-based deep learning algorithms, manufacturers can predict the likelihood of a block occurring, and understand the severity of the problem, whether it be a small improvement or complete failure [5]. Through strategic and reliable manufacturing, predictive maintenance can minimize costs, reduce wasted resources, cut emissions, boost quality, and create jobs. Strategies based on AI technologies can also create high-value products through careful control over the properties of material feedstock, advanced process design, and the manipulation of the manufacturing environment – approaches that are unfeasible without adequate intelligent systems [2].

AI technology in predictive maintenance encompasses a vast range of algorithms, from analytical to statistical methods, easy-to-use and accurate black-box solutions, as well as explore machine, wind, uplink, and water food-condition analysis. The most established group of AI technologies applied to predictive maintenance are machine learning and deep learning algorithms, which require a relatively small number of historic time series sets for analysis. AI technologies based on laboratorial analyzes utilizing the deep learning method explore fault detection and fault source location of induction motors with the utilization of image signals of windings. AI, big data, and IoT positively affect predictive maintenance performance and operational efficiency in manufacturing, and can be used to track the machinery health level, original components condition, and quality of predictive maintenance strategies.

3.1. Machine Learning Algorithms

Machine learning algorithms play a key role in predictive maintenance (PdM) applications. They are used to analyze data collected from machines and identify patterns related to the health and performance of the system. Furthermore, machine learning algorithms are employed to build predictive models using the historical machine data, focusing on failures and degradation. In the manufacturing industry, where machinery is widely used, unexpected breakdowns can result in a huge loss of productivity, highlighting the importance of PdM [5].

Machine learning can provide the capability for PdM by addressing aspects such as data collection, health condition indicators, and condition assessment. About this, Wei C. Irgens et al., characterized machine learning as a secondary mechanism that adds knowledge to initially simple systems based on a self-learning and knowledge expansion process [6].

3.2. Deep Learning

Deep learning can be defined as a subset of machine learning that enables the modeling of very deep neural networks. Deep learning models are capable of automatically extracting the most relevant features for a given task based on the analysis of the data used for this task, without the need for human intervention. This set of techniques, although based on neural networks, includes different types of architectures with different internal representations and modeling mechanisms. Convolutional neural networks (CNNs) and long short-term memory (LSTM) are two examples of state-of-the-art deep learning techniques widely used in the academic and industrial fields of predictive maintenance tasks [7]. These methods extract relevant higher-level features through the combination of different sets of mathematical operations involving kernels, convolutions, and pooling functions that simulate how humans process information. The modeling mechanism involves a recurrent architecture based on feedback connections that dynamically modify the internal states of their activations while preserving the previous states' information.

With the development of the industrial internet of things (IIoT), more advanced and cheaper sensors can be installed in equipment to monitor several variables (i.e., vibration, temperature, etc.) and analyze their temporal conditions over time. The data collected by the sensors covering mostly the same information (i.e., the monitoring of the same variable on the same machine) is commonly referred to as time series. Time series data represent one of the most frequent forms of data that can be acquired by sensors in the context of industrial applications and they can be used to improve the predictive capabilities of maintenance activities [5].

3.3. Natural Language Processing

[2]

Data-driven predictive maintenance methods dynamically assess the condition of a monitored node using data obtained in an ongoing fashion from sensors and other monitoring devices. A wide variety of Machine Learning and Artificial Intelligence techniques aim at early fault detection, diagnosis and prognosis based on an intelligent and automated analysis of the acquired raw data. Data-driven techniques can successfully accommodate nonlinearity, noised and multivariate data stream, but require complex software and hardware infrastructure [5].

4. Applications of AI-Driven Predictive Maintenance in Manufacturing

With the adoption of the Industrial Internet of Things (IIoT) paradigm, industries have started investing heavily in research and design efforts on smart systems capable of improving operational efficiency, production, supply chain management and planning, logistics, and maintenance operations. A key aspect of these systems is predictive maintenance (PdM) that employs advanced analytics using sensors and other raw data to make predictions about future events associated with machinery part failures and quality issues. PdM allows for on-time intervention actions based on predictions, hence avoiding substantial losses associated with machine downtimes and supply chain operation disruptions [2].

Machine learning (ML) has drawn particular attention in the PdM context since it has the potential to uncover hidden patterns, dependencies, and interactions in raw unstructured, and often big, data. While traditionally the PdM methodology emphasizes the exploration of engineering data related to condition and symptoms such as vibration, temperature, pressure, and usage, the advent of elements of Industry 4.0 on the shop floor has led to considering the exploration of supplementary types of big data for prediction of failure in new areas. This includes exploration of big data records from management systems, e.g., ERP systems, MES systems, SCADA systems, as well as exploration of big data from social media such as Twitter [5].

4.1. Equipment Health Monitoring

Equipment health monitoring enables the real-time monitoring and analysis of equipment conditions to facilitate proactive maintenance interventions. There are various advanced technologies for equipment health monitoring and analysis that support the development of industrial Internet of Things (IoT)-driven solutions, including vibration monitoring, thermal monitoring, acoustic monitoring, oil condition monitoring, and power consumption monitoring. Vibration monitoring is the most widely used technology for condition-based maintenance and can assess both rotating and reciprocating machinery. It is the most effective indicator of mechanical fault conditions that lead to changes in operating conditions. Thermal monitoring can predict and detect anomalies during operation by measuring temperature changes on the surface of machines and equipment. The goal of thermal monitoring is to detect abnormal thermal behavior across machines or system components. Acoustic monitoring can identify faults on production equipment before they reach critical failure by using low-cost commercial off-the-shelf devices to calculate fault indications from the acquired sound signals. These systems allow noise data to be mapped to equipment condition data. Oil condition monitoring is a form of condition monitoring that can be used to predict equipment failure before it occurs by analyzing the properties of lubricating oil. It can reveal the equipment condition from mechanical damage and wear, operating conditions, contamination levels, and overall cleanliness. Power consumption monitoring can evaluate the operation condition of production machines and identify equipment faults by analyzing their energy consumption profile [6]. The overall goal is not to eliminate failures, as in reliability-centered designs, but rather to preserve the health of equipment using automated diagnostic and prognostic technologies. PhD-program-investment centers this presentation on equipment health monitoring focusing as it evolves in an AI-driven manner, all aspects, from technologies for data collection to modelling algorithms tailored for predictive maintenance (PdM) [2].

4.2. Anomaly Detection

Anomaly detection is a technology that detects abnormal data patterns. Steadily monitored time series sensor data generated by material handling equipment or machinery is used to identify abnormal patterns. Anomaly detection aims to detect abnormal patterns generated by machines to identify potential issues. Time series sensor data generated by machines or material handling equipment is monitored actively in the manufacturing sector. Sensors are incorporated into machines and equipment to measure several physical quantities such as pressure, temperature, illuminance, force, humidity, acceleration, and voltage. Anomaly detection is an important area of analysis in signal research of a time series [7] ; [6].

Anomaly detection is performed proactively to minimize disruptions in operational processes. In the manufacturing industry, abnormalities generated by machines or equipment may halt the production process, resulting in financial loss such as increased operational costs. It is proven that even if machine or material handling equipment anomalies occur infrequently, there can be a high cost of production delay or failure. Therefore, detecting anomalies beforehand is important. Anomaly detection is classified as supervised learning and unsupervised learning. In the case of supervised learning, normal and abnormal events should be labeled accurately to build a model, which is often difficult in the field of manufacturing. For this reason, machine learning-based anomaly detection is widely studied as unsupervised learning. The condition of machines or material handling equipment is monitored by time series sensor data generated at constant time intervals. It is assumed in the proposed model that in the past period, the usual trend or condition of the system is given, and the model learns to detect the abnormal condition of the system.

4.3. Failure Prediction

A substantial portion of production losses can be traced back to unplanned production outages caused by equipment failures. AI-driven maintenance can proactively assess the condition of machines and predict failures. In doing so, it acts as a key enabler of preemptive and planned actions to head off costly downtimes and production interruptions [4].

With the help of intelligent systems for failure prediction, companies can transition from a traditional and passive “repair when broken” approach, to a more cost-effective “predict and prevent” strategy [8]. Here, the remaining lifetime of machines and components is estimated based on condition measures. Additionally, indicators for impending components’ failure are identified from monitored parameters prior to breakdown. By establishing proactive measures, time and resources of service personnel can be allocated more efficiently. Components can be repaired or exchanged in less cost-intensive planned maintenance windows rather than during unplanned downtimes.

5. Benefits and Challenges of Implementing AI-Driven Predictive Maintenance

The key benefits of implementing AI-driven predictive maintenance for manufacturers include improving operational efficiency, achieving cost savings through more efficient maintenance scheduling, improving the quality and lifetime of machinery, and, in some cases, retrieving previously inaccessible functions in production machines. Even though some of these benefits can be achieved with conventional methods, the main profit drivers are seen in the increased availability of high-value machines and improving the overall quality in process-sensitive production [2]. AI-driven predictive maintenance systems typically use production data as their primary information source. This means that they can access a large amount of information on the current conditions of the production systems without the need for costly machinery upgrades or sensor installations. Automated methods for system analysis can be engineered to allow for an efficient analysis of the machines, even in large production plants with thousands of systems [9].

Manufacturers want to ensure that the benefits exceeding the costs can be clearly shown for these systems. This can be complicated, as many parameters and assumptions are typically involved in the calculations. Just as each manufacturing installation is unique, the implementation and systems are tailored to suit the specific needs of each manufacturer. Due to this variation, providing exact numbers before the implementation has commenced is virtually impossible. Another growing concern is the data privacy and security challenges associated with the use of cloud-based data storage and industrial data sharing. Utilizing cloud-based systems involves the readability of sensitive production data and the need for complete trust in the external service provider. Industrial data sharing strategies are still attempting to develop a structure where sensitive and valuable data would be available for data-driven applications without giving away proprietary data.

5.1. Operational Efficiency

Manufacturing processes in different industries are increasingly using Artificial Intelligence (AI) driven Predictive Maintenance (PdM). The working condition analysis and maintenance scheduling of manufacturing machines are essential tasks on the shop floor. If the equipment is adequately monitored and scheduled for maintenance before failures, then the overall operational efficiency of the manufacturing process can be improved [1]. This can lead to improved productivity, reduced unplanned downtime, and less resource wastage, in terms of time and money, for both the manufacturers and the customers. AI-driven maintenance can have a positive effect on production operation performance, which includes OEE, productivity, throughput, and on-time delivery (OTD) [6]. Realizing the importance of AI-driven PdM and its impact on operational performance, attempts are made to understand this for U.S. manufacturers. Several previous works have addressed the implementation of PdM with the help of AI. Current data-driven approaches, novel AI technologies, various applications, deep learning, and machine learning (ML) applications with Industrial Internet of Things (IIoT) in maintenance, use of AI in PdM for smart manufacturing, and attempts to reduce maintenance costs have been highlighted.

5.2. Cost Savings

Predictive maintenance (PdM) is the most financially rewarding initiative. It entails monitoring the condition and performance of critical assets to reduce unexpected failures and downtime. PdM focuses on a proactive and targeted maintenance strategy. This improves utilization, increases the lifetime of equipment, and eliminates unnecessary maintenance actions. An AI-based PdM is envisioned to automate the remaining useful lifetime prediction. By eliminating unforeseen breakdown/replacement and avoiding unnecessary maintenance, significant money can be saved [10].

At the production site, a particularly huge amount of cost-benefits can be generated. Having mechanical pumps as an example, breakdowns can lead to: (1) lost profits due to halted production, and (2) additional inner costs such as the emergency repair of equipment, overtime, or fines for non-compliance with delivery timelines. Siemens Cataract estimates a daily damage of 200.000 dollars during a breakdown. This is only the tip of the iceberg. It is assumed that the second biggest cost drivers in a company after labor are maintenance expenditures. The total maintenance cost of a typical process industry is about 15 to 30% of the overall operating budget. On one side, the effort on predictive maintenance is to examine whether this expenditure is financially justified. Combined with appropriate business rules and organizational structures, these systems appear to be a silver bullet for "improved asset utilization" or productivity, despite the fact that capital investments in physical products can differ by an order of magnitude. On the other side, an existing predictive maintenance analytics model primarily focusing on chemical filtration systems is further enhanced and better adapted to be scalable [3].

5.3. Data Privacy and Security Concerns

[6]. Such initiatives usually involve networked computer systems collecting sensitive data and transferring it between systems—from edge devices collecting data from machines to cloud or on-premise systems analyzing this data for maintenance purposes. This ongoing flow of sensitive data is highly susceptible to breaches. As mentioned by Molęda et al. [2] , well-architected data protection measures that effectively safeguard sensitive information should be implemented whenever sensitive data is exposed to data breaches or misuses. Data protection measures include at-rest data protection mechanisms (e.g., encryption, tokenization, anonymization), during data transit protection mechanisms (e.g., encrypted protocols, data obfuscation), and data breach response strategies. The importance of addressing data security challenges in AI-driven maintenance initiatives has been highlighted.

6. Case Studies and Success Stories

The successful application of AI-driven predictive maintenance techniques and technologies are showcased through case studies and success stories. Based on the examination of the role of AI in predictive maintenance for the manufacturing industry in the United States, impact and expected benefits on overall manufacturing operations are presented, in addition to generally accepted standards for smart manufacturing and the application of AI-driven predictive maintenance. Global companies in the automotive and aerospace industries are specifically focused on, as they already exemplify successful implementation of AI-driven predictive maintenance. The companies were selected based on their long-term presence in the industry and in manufacturing, and funding to develop smart manufacturing use cases through collaboration with the VA.

Adjusted based on phases of AI-driven predictive maintenance implementation, success factors, performance metrics, and overall benefits, the case studies are further detailed to provide a roadmap for the deployment of AI-driven predictive maintenance techniques and technologies. Each presented case is followed by a brief executive summary highlighting key points. Case studies include Ford Motor Company, General Electric (GE) Aviation, and case study implementation sponsors, the State of Virginia and the Virginia Tech Institute for Critical Technology and Applied Science (ICTAS). Case study implementation partners include Research & Development Center for Advanced Manufacturing Technologies (RDCAMT), Institute for Critical Technology and Applied Science (ICTAS), Department of Industrial and Systems Engineering (ISE), and College of Engineering (COE) at Virginia Tech [5].

6.1. Automotive Industry

The automotive industry has effectively leveraged AI-driven predictive maintenance to optimize manufacturing operations, enhance equipment reliability, and streamline maintenance processes. AI-based systems have been implemented in multiple vehicle models and manufacturing plants across North America, including in Mexico. In Ford's Michigan Assembly Plant, the Thermal Spray process that applies a coating to transmission cases has been redesigned to leverage visual AI systems. In the production of the EcoBoost transmission within the plant, the assembly step was retrofitted with four cameras that monitor the sensors and actuators on the robotic arms while allowing the plant's service team to predict equipment failures based on observed visual anomalies in machine setups and operations.

General Motors has a comprehensive approach to mitigating equipment disruptions within the company's powertrain assembly plants for the Chevrolet Malibu and Equinox across Canada, Mexico, and the United States. Leveraging existing manufacturing data on each plant's high-volume transmission assembly, General Motors identified feasible AI-driven solutions to promote equipment reliability, lower maintenance costs, and minimize vehicle production losses. Additionally, two AI-based systems were rolled out to monitor the assembly manufacturing process and the equipment used to perform torque and leak tests on assembled transmissions.

6.2. Aerospace Industry

Aerospace is a strategic industry with a rich heritage in the United States, producing approximately $150 billion in manufactured goods and $63 billion in exports. It is also the world's foremost leader in advanced turbojet technology, business aviation markets, diesel engine production, commercial transport aircraft markets, and rotorcraft production. The aerospace industry captures a significant share of the total U.S. manufacturing output and makes up a large share of the total value added by manufacturing. The aerospace industry is a diverse and fragmented sector, with unequal bargaining power among the suppliers [2].

Safety, reliability, and performance of critical assets are fundamental concerns in the aerospace industry. Unscheduled failures can lead to catastrophic consequences in certain aerospace applications such as power generation, military micro air vehicles, and spacecraft. Predictive maintenance is currently of great interest to tackle such issues. It attempts to predict the time of failure of an asset based on its current condition, ideally scheduling the maintenance activity before this point, therefore preventing unexpected breakdowns. Traditional predictive maintenance approaches typically rely on either the design specifications of an asset or expensive and time-consuming tests to develop models that address its degradation. However, such approaches are rarely valid for real aerospace applications, where assets are subject to complex operating conditions [11].

7. Future Trends and Innovations in AI-Driven Predictive Maintenance

Currently, the spotlight is placed on explainable AI, deterministic AI, and AI edge computing analytics hardware that directly connects to sensor and fault indicators. Explainable AI focuses on code that detects and corrects bias and non-objective data issues, in a manner understandable to users [2]. Deterministic AI employs observable laws and data to create output-generating models. Input data must be pre-analyzed to discover causal relationships and relevant factors, which are defined as thresholds that must be met. Edge integration uses an AI model that operates with input sensors to predict results before capital equipment or freight is sent to the cloud for further analysis. This system calculates decisions in seconds, considering various aspects, ratios, and forecasting methods of AI and deterministic techniques. Furthermore, edge AI models can monitor interactions with the environment using automated data filtering based on independence measures [5].

Forecasting models cannot cope with the growing number of input time series because detection and prediction are based on different algorithms. This complexity leads to significant resource demand during inference and potential excessive operational costs. Therefore, novel approaches for simultaneous monitoring of single and multiple signals, AI fault detection models based on random variables on high-dimensional spaces, and compact AI models that are scalable across types and monitored systems are developed. New graphs monitor phrases of detected-fault indicators from the input time series, and together with compact graphs, they detect different types of faults or damage evolution within one model.

7.1. Explainable AI

[12]. By knowing and understanding why an outcome is reached, trust can be built around the application of an AI system. In predictive maintenance context, understanding the rationale of the component and the reasons that led the AI to predict an event, is crucial to the maintenance team. Furthermore, it allows constraints to be introduced to the system and it can deal with human intervention, such as dismissing a prediction made by the model, thus encouraging the model to rethink its choices [13].

7.2. Edge Computing

The emergence of edge computing is advancing the potential of AI-driven predictive maintenance by enabling data to be processed and decisions made at the edge of the network. Older systems meant data-collected sensor information was gathered and transported back to a data centre and underwent processing, which resulted in a delay between information and action. With edge computing, some operational data process decisions can be handled at the edge of the network, nearer to the originating sensor, resulting in more real-time processing. As such, it is hypothesised that edge computing improves the agility and responsiveness of the maintenance system.

Advances in the perception of smart monitoring conditions and the perception of misalignments and excessive vibrations of mechanical equipment are evaluated with considerations directed towards the way edges gather information from the surroundings. In the architecture proposed, edge infrastructures receive raw data from numerous sensors (from machines and devices) installed and convert them into an appropriate format. Afterwards, the edges deliver this formatted data through 5G-NR to an orchestration and analytics server where data is stored in a time-scale database, and trained AI algorithms create analytics models responsible for inferencing new data and activating certain events [6] , [14]. As a result, AI inference takes place on edges for nearly real-time monitoring instead of classical methods adopted where pattern recognition and analytics are processed based on large amounts of stored data.

8. Conclusion

The role of AI-driven predictive maintenance in enhancing U.S. manufacturing operations has been examined through quotas including an introduction to the relevance of AI-driven predictive maintenance, discussions on existing barriers and challenges in the area due to low awareness and budgets and high complexity and integration issues, socio-technical solutions to engage the supply chain in the development and implementation of AI-driven predictive maintenance, and future work areas for academia, practitioners, and policy-makers. Several key findings from such discussions have been provided, along with their implications for U.S. manufacturing. The findings affirm the considerable promise of AI for augmenting traditional industry practices and achieving long-lasting improvements in performance. Yet, adopting AI requires substantial socio-technical investments in developing and refining new systems, mobilizing key actors internally and externally, and navigating ongoing tensions, ambiguities, and unexpected consequences stemming from the contested nature of such systems [15]. Consequently, the present research provides systematic guidance through six tiered areas: development, internal engagement, external engagement, implementation, sensing scope, and ongoing refinement, helping to address the most prevalent challenges of AI implementation. It demonstrates that AI should not only be seen as advanced technology solutions and backend tools but should also be framed within reconfiguring socio-technical systems offering tools, routines, and practices [1]. These systems need to engage actors from many stakeholders, not only the internal teams of companies, as addressing the skills gap and attracting new talent is highly dependent on domestic labor attractiveness. Solutions are therefore multifaceted and should involve public and private actors working together to educate, hire, and retain talent, especially in less developed regions. As AI-driven predictive maintenance systems grow ever more central to industrial production, further exploration is warranted on how such a shift affects the political landscape and considers stakeholder engagement and transparency.

8.1. Key Findings and Implications for U.S. Manufacturing

The findings offer valuable insights into the state of AI-powered predictive maintenance tools for supply chain and logistics operations within U.S. manufacturing. There is a burgeoning interest in developing and deploying these solutions, driven by a convergence of technological advancements, the emergence of innovative startups, and a push for more resilient supply chains. However, there are significant roadblocks to widespread adoption, particularly among small and medium-sized manufacturers. For developers, there is an urgent need to prioritize accessibility, expand partnerships with logistics and IT solution providers, and address issues of trust and value alignment. For manufacturers, the focus should be on cultivating relationships with tool developers/providers, advocating for improved interoperability standards, investing in training and data initiatives, and fostering an organizational culture receptive to new technological solutions [15].

For U.S. manufacturing, the anticipated outcomes of wider deployment of AI-powered predictive maintenance tools in supply chains and logistics operations include greater competitive equity with larger firms and foreign competition, enhanced supply chain resilience, improved supplier relationships, and reduced pressure on public transportation systems. Overall, as manufacturers in the U.S. increasingly turn to AI solutions for improved operational efficiency, there is a clear opportunity for more widespread deployment of AI predictive maintenance solutions in logistics and supply chain operations.

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