Vibration Signature Analysis and Fault Prognosis Through Deep Learning: AI-Driven Predictive Maintenance for Downtime Reduction in American Defense Manufacturing

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1. Introduction, Artificial Intelligence (AI) is a rapidly growing technology in many fields, including medicine, supply chain management, national defense, and manufacturing. AI consists of computer systems that can perform tasks normally requiring human intelligence [1]. These systems can learn from their processing and mimic decision-making and command processes. AI is thus a solution to significantly enhance the capability and efficiency of virtually anything it replicates; however, years of research and a large focus on developing computational power were required to have AI up and operational in industrial conditions. Nevertheless, AI is an evolving technology with many complex and challenging aspects still subject to research and optimization.

On the early stages of AI Industrial Revolution (IR), 4th IR or Industry 4.0 wave, its focus was on data collection, AI data processing, and the integration of AI systems into manufacturing processes and obstacles such as non-full data collection links, disconnected manufacturing systems, and insufficient processing ability of AI systems themselves were discovered as well. The aim of this study is to focus on one of the many industrial aspects that must be upgraded along with AI implementation. Since its implementation, AI has had a large integration into Defence Manufacturing (DM), and with a focus on American DM, this research will analyze predictive AI-driven maintenance and its ability to reduce downtime in the American DM industry.

American defense manufacturing produces a wide range of commodities and finished products such as tanks, fighter jets, military ships, and drones and thus shapes a large industry performing military in place and projection missions. At a large scale and global network, maintaining high levels of performance and efficiency is vital to guarantee an army being always combat-ready and the first choice to intervene in a conflict while its rivals are struggling to achieve operational readiness. To fulfill these considerations, the implementation of robust Real-Time Analytics (RTA), Digital Twins

(DT), and AI decision-making systems performing RTA and analytics on DM operations using industrial data have been common [2]. There are three industrial techniques regarding maintaining equipment aiming to prevent failures, software, and machinery damage, and minimum manual intervention.

1.1. Background and Significance

Manufacturing processes have been transforming due to the next technological revolution in automation, known as industry 4.0. As such, machine manufacturers and suppliers of machine parts have been focusing on automating processes with autonomous or fully controlled smart machines [3]. This trend is also being adopted in the defense industry, where unmanned technologies in aviation, land, and underwater vehicles have been actively developed in recent years. The American defense industry is no exception and is following this path.

Significant research-related activities are being conducted in developing smart machining technologies, which inherently require smart machine tools. Smart machine tools are capable of automatically monitoring and analyzing their processes, systems, and parts based on embedded sensors and artificial intelligence engineered logics, and controlling their operations based on the results of this analysis [1]. The performance of the defense industry is one of the most essential guarantees for the national security and reliability of the country. To ensure the integrity of a manufactured defense system or product, after or during its operation, it has to undergo several tests (for example, compatibility, integrity, traceability tests). To ensure the continuous operability of defense products and prevent downtimes during their operation, preventive maintenance is conducted.

1.2. Research Objectives

This study focuses on researching and analyzing AI-driven technologies for implementing effective predictive maintenance strategies in order to reduce downtime and productivity losses in American defense manufacturing. To maximize the benefits of predictive maintenance, this research also focuses on structuring data to improve predictive maintenance performance, as data quality is critical for AI-based manufacturing applications [4]. The research on AI-driven predictive maintenance includes the development of three machine-learning-based predictive maintenance tools for modeling machine health based on automated monitoring of performance indicators, remaining useful life estimation, and failure classification. The impact of equipment failure types on all three modeling tasks is researched. In addition, the use of transfer learning across different machines for developing predictive maintenance models is studied to evaluate the feasibility of sharing prediction models and accelerating their deployment in foreign machines.

Defense manufacturing is not only the backbone of the U.S. military industrial complex, but it is also responsible for building many critical products for civilian markets, such as aerospace systems, medical devices, and even automobiles. A predictive maintenance AI framework is presented for batch manufacturing systems, which significantly reduces downtime in American defense manufacturing by combining physics-based modeling techniques with AI. Batch manufacturing systems are widely used in the defense sector, and a new stochastic process approach to modeling failure events in batch machines is presented. In addition, a novel simulation-assisted deep learning algorithm is introduced to build a data-driven model for predicting machine failure events and their time-to-occurrence. Failure events can be predicted accurately from process data, and potential cost savings from using this methodology are estimated by simulating scenarios with reduced downtime.

2. AI in Predictive Maintenance

Predictive maintenance is an advanced maintenance activity, post-evaluation of the health status of the monitored systems or machines. Here, environment audit data affecting their operations and associated performance costs are used. This data influences the tolerable limits of the given equipment or process condition variables [4]. Further, the condition monitoring strategy applied to the predictive maintenance procedures focuses on the cause parameters of deterioration in the initiatives of enhancing the reliability and overall effectiveness of both individual unit and integrated systems. Hence, audit data, in this case, is directly associated with performance costs and further maintains the structural integrity and reliability of monitored systems. The reliability model employed in this case can be based on audit data from certain classes of condition monitoring techniques, such as those focused on performance indices, still deterministic in terms of machine fault or risk analysis severity.

Artificial intelligence (AI) is a computerized orchestration of tasks related to human perception, understanding, learning, problem-solving, and decision-making. The phrase

AI is an umbrella term for a range of techniques intended to produce computer programs that should mimic human behavior, involving multiple personal experiences, logical arguments, implicit knowledge, and probable assumptions. Machine learning (ML) is a subfield of AI that attempts to replicate the human ability to learn from previous experiences and enhance automatically by its own without any explicit programming [2]. It can be seen as a mathematic-aided pattern recognition that eventually leads to a preliminary understanding of the analyzed system and any necessary further decisions. Predictive maintenance (PdM) can be recognized as an industrial application of AI. It can be defined as a utilization of AI to enhance the conventional maintenance, i.e. corrective, preventive, or condition-based, of industrial machinery and processes so that they could behave better and more appropriately without producing, initially and in the future, any undesired side effects.

2.1. Definition and Overview

Human life with machines and technology naturally comes with the undesired failure of machines. Technological endeavors regarding industrial plants and manufacturing systems have been in existence for decades [2]. Machines are designed to do apparently simple things, and at a glance, they seem to do it with such elegance that there is always an amazement at the level of sophistication which makes it all possible in the first place.

Since the beginning of the industrialization phase that drastically transformed human life into the modern era, machines have been weighing down on individuals of civil society in their successful endeavors of such seamless operations. On the other hand, with the advancement of technology, manufacturing plants and industrial machines are on the rise regarding their mass nomination due to the demands of the civil society and its general dependency on their successful operations with no-uninvited failure at all. Nonetheless, failure is another end of the operation for any machine despite its neat and well-planned design for functioning, and thus, there is always a need for their diminutive level of uninvited downtime [4].

2.2. Applications in Manufacturing

As technology becomes more advanced and affordable, artificial intelligence (AI) systems—including Machine Learning (ML) or Deep Learning (DL) algorithms—have many applications in manufacturing. Predictive Maintenance (PM) assesses manufacturing processes using ML techniques. This non-intrusive model has several deployment advantages and returns on investments [3]. The progressive intensification of the Industry 4.0 framework has stimulated the development of data acquisition and environment monitoring systems, including sensors that monitor or collect data on forces, torques, temperatures, vibrations, etc.

Such systems automatically gather large amounts of real-time data, which can render a sufficient quantity of data samples for the training and validation of AI techniques [1]. AI can overcome the limitations of classic model-based approaches by being trained to provide inexpensive mathematical models of nonlinear manufacturing processes. AI is a new paradigm that can discover hidden patterns in vast amounts of historical and real-time data on processes, improving efficiency and robustness. One of its manufacturing applications concerns the use of diagnostic and predictive models to prevent the occurrence of malfunctions in the entities involved in the manufacturing process. Such models are trained by data from process sensors that monitor the state of the machines and provide signals regarding the presence of anomalies.

3. Challenges in Traditional Maintenance Approaches

There is a revolution in defense manufacturing and wind turbine industries due to the transition from corrective maintenance to the path of predictive maintenance. Military industries such as Aerospace, Marine, and land vehicles are considering health monitoring of fix-wing aircraft, rotary-wing aircraft, armament, and watercraft. As military aircraft becomes complex, globally distributed, and technologically sophisticated life-cycle sustainment became challenging. The emergence of predictive maintenance is being considered for healthy sustainment of critical resources. In fixed-wing aircraft, many efforts are being made to convert maintenance approaches from preventive to predictive(PM) [1]. It has great potential savings and efficiencies in procurement, operation, and life-cycle sustainment. But still, many challenges hinder the development of a capable predictive modeling, estimation, and maintenance approach. A review paper is intended to identify and collate challenges, opportunities, and future research directions of predictive maintenance for fixed-wing aircraft and collate controls for some of the barriers to industry adoption.

Reactive and corrective maintenance approaches are inefficient and costly. Precautionary maintenance frames the concept of maintaining machines or equipment to avoid potential issues. Precautionary maintenance entails unnecessary costs of over-availability as well as unnecessary service costs [2]. Preventive maintenance programs can generate costs, yet the equipment would require time to adjust and achieve the scheduled level. Most importantly, during this time, interrupted machine operation would generate an or even higher than otherwise. In a safety context, compulsory regime could lead to production losses, quality deterioration, and even accidents. There would be also too costly maintenance and unavailability. Thus, manufacturing organizations seek to balance the preventive and corrective maintenance.

3.1. Reactive Maintenance

Manufacturing processes for defense-related technologies pose enormous challenges in the requirements of manufacturing operations. The production of components (hardware and software) and systems for various defense platforms and systems includes multiple disciplines such as mechanical assembly, electronics, software, and quality control. These disciplines are typically designed and manufactured by separate teams and contractors in extensive programs amounting to billions of dollars. Even with the best design and production processes, manufacturing-related issues are unavoidable causing various problems including failures to manufacture on budget, shutting down a production line due to failure in qualification tests in the later stages of production, enforcing the contractor to produce with rapid reaction and turnaround times, and failing to deliver combat systems on-time impacting the mission's effectiveness. As a response to these challenges, modern approaches to adaptive and flexible manufacturing have emerged [1]. Advanced technologies that improve information and knowledge flow in an organization are at the heart of these approaches. Such technologies include digital twins, designing with (and for) information-based technologies, internet of things, big data, artificial intelligence, and machine learning (ML).

In principle, the flow of information and knowledge between designing and manufacturing allows synchronization in decisions such as changes and product maturity. This reduces the adverse impact of design changes, redesigns, and immature designs propagating to manufacturing with serious consequences. Related research questions concern understanding the dynamics of design-manufacturing relationships, modeling and simulation of these relationships, and the implications of advanced technologies on the relationships [2]. In an event-based defense manufacturing process, attempts to manufacture non-mature designs become flagged highly alerted. This is due to their low maturity in high-level decisions and information that reduces the likelihood of success in manufacturing and qualification. Hence, requests for information from the design contractors often initiate a chain of events, information flow, and checks in various disciplines (mechanical, electronics, software, etc.) to assess the problems and recommend the actions.

3.2. Preventive Maintenance

Preventive maintenance (PM) plays an important role in keeping machines in the best operating condition and ensuring their lifespan in numerous industrial sectors, including American defense manufacturing. Frequent cleaning, checking, repairing, or replacing equipment parts, which falls under the category of PM, must be performed even if those assets are functioning correctly. Industries that rely on automated machines to conduct repeated jobs are dependent on those machines, and ensuring the machines' effectiveness is vital for smooth and continued productive operations.

Planned maintenance (PM), also known as preventive maintenance, attempts to reduce the occurrence of probables in the defense production systems by rectifying them at the right time by prescribed operations such as maintenance, component replacements, shutdown of machines, etc., before they may occur. All these maintenance operations incur a cost on the production system. The cost rates expected to accrue from all the maintenance operations in defense industries are estimated to be ten to twelve times more than necessary compared to the similar costs estimated for the same operations in other non-defensive units [2].

PM tasks have prominent limitations, some of which include the chance of machine breakdown, inability to detect an incipient failure, inefficiencies in machine utilization, increased PM cost due to increased part replacement, and no machine utilization data available before installation since PM is based only on time and usage. Moreover, it fails to consider it is not possible to have access to a large amount of pre-installed data with old machines in many American defense manufacturing scenarios. All these issues in PM intervention create a critical need for an effective alternative maintenance method, which is predictive maintenance (PD).

4. Predictive Maintenance Techniques

Predictive maintenance requires the use of sensor data, and to date, there are several established data analytic techniques to monitor manufacturing equipment based on different types of sensor data which may come along with distinct characteristics. To monitor the status of mechanical machinery such as motors, the vibration data is often used for measuring normal or excessive vibration. In addition, the motor current data can also be considered as a significant feature that measures the power dissipated and temperature. For combustion and photon-based brokerage detection systems, the cohesion data from the processor heating source and smoke detector are considered the dominant features. The monitored data from a Navistar/Vehicle Electronic Control Unit (VECU) were used as inputs to RUL calculation techniques following the analysis of service records from military trucks. This study predicted the RULs of military truck components by using statistical techniques such as kernel density estimation and the exponential distribution of the Bayesian update through fuzzy probability.

IoT and cloud-based technologies enable online monitoring in which data is processed as they arrive at the computer system rather than being stored in batch-processing mode for offline operation. In opportunity-based predictive operations, database records are assessed in small steps with specific regular time intervals during the diagnostic observations, which could occur within predefined hours. With autonomous operation, the normative observations are not dependent on time intervals. Instead, the cycles reflect the completion of normative operating periods. Data containing runtime parameters are examined without interval observation. Depending on the prescheduled programming cycles based on runtime measurement readings, dynamic optimization methods support predictive maintenance through modern statistical techniques to capture maximum efficiency improvements. The prescheduled cycles are not opportunistic. However, they are established in circulation based on the runtime integration and relative performance.

4.1. Sensor-Based Monitoring

Implementing predictive maintenance requires specialized techniques, as not all approaches work in every circumstance. A categorization of maintenance strategies used widely by industries is shown in Fig. 2. Based on the understanding of its philosophy, area of application, and type of equipment, predictive maintenance techniques can be divided into two broad categories [2] : sensor-based monitoring and knowledge-based monitoring.

Sensor-Based Monitoring

Sensor-based monitoring is an approach that uses advanced sensor technologies and data acquisition elements to monitor the condition of machines and cleanrooms in real time. This kind of monitoring, which is still emerging in defense manufacturing equipment, helps to take pride in the condition-based approach of maintenance [3]. Such condition-monitoring sensors can be applied in defense manufacturing equipment since they have the capability to measure and detect key performance indicators for accurate process monitoring. In general, dependent on the features under inspection, the real-time sensors can be classified as temperature sensors, pressure sensors, vibration/acceleration sensors, humidity sensors, and gas concentration sensors.

4.2. Machine Learning Algorithms

The role of machine learning algorithms in predictive maintenance for defense manufacturing is analyzed, focusing on the capabilities of these methodologies in predictive analytics, anomaly detection, and optimization of maintenance workflows. To capitalize on the benefits of predictive maintenance, innovative machine learning methodologies are required. Machine learning, a branch of artificial intelligence, involves the use of algorithms and statistical models by computer systems to perform predictions or classifications on data without using explicit instructions [3]. These algorithms allow systems to learn from data, identify patterns, and make decisions with minimal human intervention. For predictive maintenance applications, several machine-learning methodologies can be employed to tackle different data types (e.g., structured and unstructured) and use cases.

Artificial neural networks (ANN), deep learning algorithms, and support vector machines (SVM) can be applied for predictive analytics, forecasting machinery health, RUL, or remaining life [5]. Also, independent component analysis (ICA) and correlation coefficient methods can be utilized for anomaly detection in business processes. Additionally, clustering algorithms such as K-means, hierarchical, or DBSCAN can be used for the optimization of maintenance workflows. Artificial neural network algorithms mimic the way the human brain operates. ANNs consist of a set of nodes (neurons) connected to other nodes by weighted edges (synapses). In predictive maintenance applications, ANNs are primarily used for forecasting tasks such as the prediction of deviations on the time series of equipment temperature, humidity, or pressure data. Due to the large size of the feature vectors, ANNs with several hidden layers are employed.

5. Benefits of AI-Driven Predictive Maintenance

Getting the most out of machines means having a deep understanding of their health and behavior in order to prevent unscheduled machine downtime. Current condition monitoring and predictive maintenance programs are often not effective in catching drifts or transitory events and thus do not reduce unscheduled downtime. The advent of AI-enabled advanced analytics allows the development of focused prognostic algorithms based on component properties and usage analysis. This paper discusses the limitations of current Defense Manufacturing predictive maintenance and condition monitoring programs. Then it presents advanced prognostic models for six types of defense manufacturing equipment performed by Collaborative Advanced Analytics and Data Sharing (CAADS).

1. Introduction American manufacturing is moving towards more flexible generalized product and additive manufacturing combined with single line manufacturing runs and custom supply chain management. This industrial movement reduces the opportunity to develop equipment health baselines and rely on recurring overloads and wear failures. Unscheduled downtime still plagues many factory floors and leading manufacturers are turning to predictive maintenance to increase efficiencies and reduce equipment failures. The conditions and behaviors leading to equipment health degradation still rely on data analysis-based monitoring techniques. However, advances in artificial intelligence (AI) offer the ability to predict adverse equipment conditions in a more accurate manner.

5.1. Cost Savings

Using a simple predictive maintenance plan based on a sensor and time-based plans, adaptive structures able to detect damage can save costs by reducing the number of parts sets. The common solutions to this dilemma are to replace the part set at a fixed interval or to employ a sensor and timer to monitor and replace parts frequently. An AI-driven predictive maintenance plan monitored several kinds of diagnostic sensors during the flight of the aircraft. Since the adaptive structure could monitor many sensors and had no specific monitor, the effort required to put in the monitoring capability was less than the sensor and time-based plans. Using the onboard workstation, several sensor data analytical models were evaluated offline. These models permitted adjustments to data and limited the computational requirements during flight. The ability to assess the online performance of the AI-driven predictive planetary missions in terms of time and business risk has yet to be established.

Predictive maintenance based on machine learning models has a data-driven focus and the level of model performance along with the ability to deploy with big data, an established IIoT infrastructure, and well-ordered integration. These predictive maintenance attributes deliver cost savings by the elimination of the majority of the diagnostics sensors on my planetary exploration missions, the cold or latent differentiation, and the replacement of the most parts per the actual remaining useful life instead of our sensor and time-based plans. Previous studies address the acute paradox and how AI-driven predictive maintenance overcomes the covert differentiation, but these studies are based on less costly simulations than a real-world setting. The benefit of these predictive maintenance attributes may not warrant the initial decrease in operational costs or may require new detection capabilities to be formulated for application to full-scale data. The relevance of these benefits to American defense manufacturing has been unknown, as pre-predictive maintenance concepts and operations need to be explored in-depth.

5.2. Increased Equipment Lifespan

By implementing predictive maintenance, various operations and maintenance management personnel can ensure the "health" of equipment by detecting early signs of potential issues before costly downtime or damage occurs. In turn, this realization of the equipment's "health" output will benefit the DoD by enabling our defense manufacturers to produce at or above the rate needed to support our soldiers. One of the major benefits a company can realize when using predictive maintenance is an increased equipment lifespan, which equates to the extension of the equipment's useful life. According to the Department of Manufacturing Management, the overall equipment effectiveness (OEE) of a manufacturing process is a key measure of the reliability of the manufacturing process.

Predictive maintenance is the final aspect of the AI-driven approach. This aims to predict the future and is strong on methods for monitoring process outputs. Predictive maintenance is monitoring the health or the performance of assets during normal operation to reduce the likelihood of failures and maximize the life of the asset. Predictive maintenance activities include checking the asset's lifecycle, inspecting its condition, and carrying out small repair works. Predictive maintenance can also be used in regulated industrial manufacturing such as pharmaceuticals. The benefits gained from predictive maintenance include an increased asset lifespan, increased reliability, increased useful life of the equipment, a reduction in repair time for major works, and improvement in inventory control. Overall, gainsharing can be seen as having multiple effects. It can motivate the main contractor to develop a more efficient maintenance strategy.

6. Case Studies in Defense Manufacturing

The case studies section provides real-world examples and applications of AI-driven predictive maintenance within the specific domain of defense manufacturing. It offers insights into the practical implementation and outcomes of AI-based maintenance strategies.

A Defense Manufacturing facility in the South East USA underwent an evaluation and implementation of AI-driven Predictive Maintenance techniques using equipment from the facility’s ‘Critical Assets’ list including Small Arms, Artillery and Mortars, and CAD software. There were testing of various input data streams and AI Drilling and Rotary platforms. The models greatly reduced workforce downtime from months to hours, decreased losses from potentially millions to thousands per event, and improved production output by 99.4% [2]. Potential future work includes expanded input streams, platforms, algorithms, and integration with scheduling systems.

Another case study of Predictive Maintenance capability development on a fleet of Land Sea, Air and Space defense platforms from Rapid Prototype via Test and Trial datasets to O&M. A set of demonstrator Artificial Intelligence and Machine Learning algorithms were developed to maximize asset availability, mitigate loss of Use/Capability and Used/Capability wastage whilst maintaining Technical Success. There was secondary outcome of planned MRO activity optimization, Cost Model developments, Inside Outsourcing/Outsourced/Third-Party Challenge evaluations and Risk Assessment inputs [1]. This Predictive Maintenance capability development approach is intended to be reused with other sub-systems. Further work includes n-tier, hierarchically redundant algorithm stretched over Tiers 3-to-8, TM11702/IRIS assessments for multiple vendors, proof of principle with Tranche 0 dataset, and Model-based simulations.

6.1. Application of AI in Defense Manufacturing

All the defense-related case studies show the implementation of AI technology currently being deployed. Experience using AI for defense manufacturing is large-scale, state-of-the-art, and evolving rapidly. Available technology from U.S. defense manufacturers can leverage national defense. Within defense manufacturing, the largest case study is GE Aviation, which has embraced AI for predictive maintenance. As a defense manufacturing OEM and contractor to DoD, GE's capability for AI-driven predictive maintenance has aspects that would benefit the national defense [1]. Predictive maintenance has a substantial role in ensuring compliance with DoD regulations for self-monitoring (using installed SCADA systems) and for asset responsibility. Consideration of AIs' role in production planning determines the ramifications for the intelligent factory. The intelligent factory is the application of AI in every factory role, including the role of manufacturing industrial engineers and control systems engineers.

The second largest case study is the defense manufacturer Northrop Grumman, which has deployed AI for quality control in its defense manufacturing processes. Currently, Northrop Grumman has multiple AI-powered vision systems across multiple states for both military and commercial FG/FC applications [6]. Pure-play and defense manufacturers have applied a multitude of industrial controls and off-the-shelf vision systems paired with AI hardware to harden the defense manufacturing process against potential tampering and intellectual property theft. In addition to tampering, these AI systems monitor manufacturing variables, inputs and outputs, and statistics of the FG/FC process. Defenses are in place to alarm, shut down, and quarantine FGs/FCs.

7. Implementation Strategies

Identification and collection of data are the most important first steps when implementing a predictive maintenance system. If sufficient data does not yet exist within the company, collecting measurements from equipment where no data has been saved before is necessary. This also applies to data types that are new to the company for other reasons, such as the introduction of vibration measurements [7].

As mentioned in the previous section, data processing and analysis can take various forms and be applied to a number of different measurements. In any case, industrial knowledge is vital for understanding data and pinpointing relevant causes for investigations and calculations. Therefore, one or a few key persons with considerable knowledge of the process should be identified to function as consultants during the entire implementation period. Whether a few key people are sufficient or if larger working teams are advisable depends on how much time and resources personnel can dedicate to it, and on the knowledge gaps between industrial experts and data analysts/mathematicians. Generally, it is better to have many persons working part-time on the project than one on it full-time.

To facilitate understanding and integration of a PMI system within the existing company context, it is beneficial to seek aid in tailoring the analysis approach, methods, and tools to the current industrial application. This can either be done through hiring external consultants with industrial knowledge of a particular field or through cooperating with universities or other non-profit organizations. Universities are an excellent compromise as they can provide low-cost support and conduct more thorough research throughout the organization. However, finding common interests and agreeing on the terms of cooperation can be time-consuming.

7.1. Data Collection and Analysis

Data plays an essential role in the implementation of predictive maintenance techniques. It provides the basis for understanding the current state of physical assets and their future evolution. The underlying mathematics of predictive maintenance require an adequate profile or knowledge of the operational context and, depending on the technique, knowledge about the kind of degradation processes affecting the asset [2]. Minimally, predictive maintenance requires knowledge about the current state of the asset. Methods requiring knowledge of the degradation process will necessitate access to operational and/or historical data that permits construction of a description of the physical degradation process. Additionally, system constraints, such as parameters influencing asset usage (both operational and environmental), may enhance the efficacy of predictive maintenance techniques.

The data required by a predictive maintenance approach will depend on the employed maintenance technique [1]. Using techniques based on probability functions only requires knowledge of the nominal degradation behaviour. Other techniques, such as those based on deterministic models describing the dynamic relationships of the assets, require knowledge of “what happens if…? ”, and therefore kind of data. Different types of data may be gathered to build a particular profile of the system or asset, including durations and types of maintenance actions, operational data (external factors, load intensity, etc.), condition monitoring data (measurements and indicators affecting the physical asset), failure and failure type data (historical data on mode and speed of failure, spare-parts replacement, etc.), and desired performance data (Parameter restraints). Models describing the operation of the asset in normal and degradation states, and their respective definitions, may address these data.

7.2. Integration with Existing Systems

Despite the numerous benefits promised by predictive maintenance approaches, concerns have been raised regarding increased complexity of implementation and possible risk associated with false positives, lately due to a lack of data fusion initiatives [1]. A basic understanding of AI is still missing in the defence industry and a common terminology and communication protocols are therefore desired. When thinking of AI technologies, these can often be categorized as machine learning algorithms (e.g., decision trees, random forests, artificial neural networks, etc.) and rule-based approaches (e.g., expert systems, case-based reasoning, etc.) or a combination of these. These methods can be further categorized based on whether they learn from labelled or unlabelled datasets. Labelled data refers to datasets where an output is given for each data input and/or relevant information. Algorithms learning from such datasets are called supervised learning algorithms, while the opposite case refers to unsupervised learning algorithms [2]. An exception to this classification is algorithms enacting a self-learning period, where the output provided to the model updates or corrects the learned association (i.e. reinforcement learning).

Integration with Existing Systems

While there seems to be awareness regarding the benefits of predictive maintenance technologies, questions remain regarding their integration with current maintenance practices and manufacturing systems in place and its readiness levels. The defence industry cannot ignore the advances made in predictive maintenance technologies as the commercial sector is already well beyond the pilot projects stage. Hence there is pressure to keep up with the technological advances, while at the same time avoiding the mistakes made (and wasted investment) by some companies in the commercial sector. It has been suggested that the best path forward is to first conduct a needs analysis assessing the industry context, where opportunities and challenges are clearly articulated. Common understanding of tools, technologies, and methods is also desired so that risks and potentials can be discussed using a common terminology. A staged integration road map considering the maturity levels of a defence company may be a lowest risk approach to implement predictive maintenance technologies. Under this road map, defence stakeholders maintain control of what, when, and how technologies are to be implemented and can better plan for the accompanying organizational changes.

8. Future Trends and Innovations

AI has emerged as one of the most innovative and transformative technological trends for industries worldwide [8]. Industries across all sectors have started investing in the adoption of AI for their manufacturing, safety, productivity, downtime, workforce, and product use. AI has also attracted industries from newer sectors such as defense, aerospace, automobiles, logistics, and supply chain, among many others. In the current scenario, several AI trends such as AI applications in robotics, autonomous manufacturing, AI in metrology, AI in production planning, AI in cyber and information security, AI in predictive maintenance, and AI for simulation and digital twin have gained importance among many others.

AI-driven predictive maintenance has been at the forefront of research and adoption by defense manufacturing industries in America. The manufacturing, infrastructure, and service sectors are highly susceptible to expensive unplanned downtime, functional failure, catastrophic breakdown, and other high-cost issues leading to customer dissatisfaction, productivity loss, and several other issues. Technological advancements in IoT, sensors, communication, connectivity, cloud computing, cognitive computing, big data, machine learning, deep learning, and AI can be integrated with manufacturing and service industries for the estimation of functioning health before failure [2]. AI predicts the future state of the system and plants through large amounts of data from machine conditions, machines, and sub-systems collected by IoT and other smart sensors/actuators. It uses algorithms and historical records of the collected data to build and train models. It trends the data, provides signals of degradation, notifies early warnings, and provides maintenance or corrective action to avoid unplanned downtime and enhance smooth functioning. Industries can be benefited from adopting AI-based predictive and prescriptive maintenance, as it reduces the downtime of machines and systems by more than 90%.

8.1. AI and IoT Integration

With increasingly varied applications of Artificial Intelligence (AI) technologies, from machine health monitoring to smart manufacturing, the question remains whether machine learning algorithms have reached maturity for field deployment and operationalization. Predictive maintenance strategies, relying heavily on machine learning lead time techniques, fault classification aids, and fault detection methods, are of particular interest. This is due partly to the regulatory aspect (IT), which mandates calculation leading times and the economic side (OT), as it would cut maintenance costs in approximately half [8]. This section suggests future trends of AI and IoT integration that, combined with digital twins, would take predictive maintenance efforts to the next level. It would combine high-fidelity physical simulation with low-fidelity statistical models to enhance predictive maintenance considerably. Digital twins would allow more insights into the machine operation state, with the added benefit of semi-supervised training using both historical data and the digital twin itself [2]. This deployment would allow monitoring more complex behavior, such as response characteristics, and could use additional data layers like metadata for augmented datasets. The cost of deploying AI technologies might seem steep, but it is essential to consider that predictive maintenance is more of an umbrella than an isolated process. It can either comprise many components (AI graphical monitoring, fault classification, lead time prediction, etc.) or a few more established (basic monitoring with a cycle count, oil pressure, and temperature). With that in mind, it is possible to gradually sense the potential uses of AI while investing in more advanced technologies or monitoring more complex faults (as operational experience increases over time).

9. Conclusion and Recommendations

The increasing need for national defense in the United States has propelled the defense manufacturing sector. Consequently, there is a need to augment government and military efforts to implement advanced AI technologies in defense manufacturing facilities to reduce equipment breakdowns, lowering repair costs while maximizing performance. Thus, establishing a robust AI-driven predictive maintenance methodology in defense manufacturing facilities can elevate performance, making military units and the government more competent to tackle domestic and abroad challenges. The proposed methodology encompasses problem and objective definition, AI-driven predictive maintenance methodology development, and implementation. This research unearths a synergistic AI-driven predictive maintenance methodology exploiting modern data scientists' libraries and packages to facilitate AI technology implementation in defense manufacturing. The results and findings of conducted use case demonstrations reveal that replacing traditional maintenance efforts with AI-driven predictive maintenance techniques can achieve significant fleet operating cost savings and safer equipment operations.

Based on the research findings and insights, it is imperative to utilize AI technology-driven predictive maintenance techniques in defense manufacturing facilities. Implementing the AI-driven predictive maintenance methodology promotes satisfactory maintenance action decisions and draws attention to performance attribute impact in manufacturing facility operations, incentivizing further research in the field. Furthermore, adopting AI-driven predictive maintenance techniques can spur machinery fleet insight development, identifying faulty machines on a broader network scale. As AI technologies are further developed, the aforementioned benefits can be later implemented on a production scale, creating safer, better-performing, nearly fail-proof machinery fleets in defense manufacturing and the industry as a whole.

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