AI-Based Predictive Maintenance Solutions for U.S. Aerospace Manufacturing: Techniques and Real-World Applications

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1. Introduction

In the United States, the aerospace products and parts manufacturing industry is one of the most advanced industries, with 56% of R&D expenses accounting for USD 32,064 million in 2022. For the industry, the U.S. ranked number one in 2019 by contribution of the aviation industry to GDP, according to Pew Research Center. Today, the United States is home to the world's largest civil aviation system. There were 5,080 public airports in the United States as of 2018. Technology evolution is also driving growth in the aerospace industry. In 2021, AWS, Google, and IBM broke into the cloud computing space, focusing primarily on aerospace. In recent years, production milestones have been achieved in delivering raw materials, parts, and assemblies for next-generation innovative new, under-development aircraft. New technologies, such as advanced lightweight composites, complex additively manufactured metal parts, advanced propulsion systems, advanced jet engine manufacturing technologies, and digital thread and digital twin methodologies for parts, performance, and process analysis, are being incorporated.

The accelerated utilization of manufacturing operations and technologies can lead to lower production costs for components and, in the long run, improved aircraft operating costs. While aircraft are becoming more advanced and more efficient as a result of these technologies, the increasing complexity of airplane systems requires constant maintenance. Regular, time-based maintenance has been previously utilized, but it may be ineffective because it is not adapted to the actual state of the aircraft. To replace this approach, predictive maintenance (PdM) is utilized to enhance the operations of numerous areas, including aerospace. This implies that sophisticated prognostic maintenance models and methods make extensive use of data. In manufacturing, large volumes of data are now generated as a result of technological advances. Manufacturers store, handle, and analyze this data for task knowledge.

1.1. Background and Significance

In the manufacturing sector, intelligent maintenance and manufacturing have been receiving increased attention in the final stages of the industrial revolution. Through the application of information management systems, wireless sensor networks, cloud computing, big data analysis, and data mining, intelligent predictive maintenance can be performed cost-effectively. This is vital in the aerospace manufacturing industry, which is challenged in its quest to balance the cost of timely maintenance and profit incurred through frequent production runs. The quest for ever-higher aircraft operating rates places a premium on fault detection and timely, cost-effective maintenance. Regulatory agencies must oversee land, sea, and air transportation systems to ensure efficient flow of human resources and materials. The aim is to avoid the excessive cost of penalties due to production stoppage, which is caused by unanticipated failures and late prediction of maintenance schedules. All of the above-stated needs and less obvious requirements related to product life extension and lifecycle cost reduction underline the importance of AI-based predictive maintenance solutions for the U.S. aerospace manufacturing sector.

This initiative cannot follow the Manhattan project approach, as the physical and computational complexity of the intermediate product would be formidable if we tried to simulate the process so far. Additionally, the results could not be validated because we have not yet established a baseline process due to the rapid advancement of semi-automated machines and integrated machining systems. With the development of digital twins and AI applications, tools and models for any of those stage might interfere. Thus, the U.S. could be a leader in developing physics-based models and advanced data analytics capabilities. AI-based predictive maintenance solutions' inputs could vary from hundreds to tens of thousands within and across subsystems and aircraft types. Lower number of inputs include the commercial jet engines, auxiliary power units (APUs), flight control systems, and airframe structures. The U.S national aerospace industry has a strong interest in obtaining insights from current life bearing data. They are capitalizing on the equipment health and predictive maintenance related research data for the purpose of data analysis and predictive maintenance improvements for intelligent diagnostics and prognostics systems. The current volume of actual aircraft fleet data is historical or simulated.

1.2. Research Objectives

The research objectives of the paper can be formulated as follows: • To analyze which AI-based predictive maintenance techniques have been proposed in the literature and what real-world applications have been discussed so far in the aerospace manufacturing domain. • To identify requirements set by U.S. manufacturing enterprises for AI-based predictive maintenance solutions and the challenges to address with such systems. • To explore what type of sensors is used in U.S. aerospace manufacturing for data acquisition for predictive maintenance systems. • To analyze the data types existing within U.S. aerospace manufacturing that originate from operated systems and can be used for the prediction of the system maintenance period and the future state of the system.

This report focuses primarily on novel techniques and solutions in the AI-based predictive maintenance domain that have been applied to solve manufacturing and maintenance issues, with particular emphasis on the aerospace manufacturing domain. Furthermore, the report represents the point of view of U.S. enterprises operating in the aerospace manufacturing domain, determining the requirements for future AI-based predictive maintenance industrial grade solutions, identifying weaknesses of the currently available commercial systems, and providing a list of external data-driven approaches that can be potentially utilized. Additionally, the report discusses the possible use of external data-driven techniques in AI-based predictive maintenance. A special section is dedicated to learning which sensors are used widely in U.S. aerospace manufacturing to collect data, what kind of data has been acquired and fed to maintenance experts, what type of prediction the system owners would like to obtain and, finally, what kind of measurement of carried-out prediction will be accepted.

1.3. Scope and Organization of the Report

This report provides a comprehensive and in-depth investigation of AI-based predictive maintenance (Ai-PdM) techniques for further application and deployment in U.S. aerospace manufacturing settings. It is intended for professionals, researchers, decision-makers, and engineers who are interested in applying Ai-PdM solutions and machine learning techniques for avoiding failures and catastrophic breakdowns in machinery and other critical systems in aircraft manufacturing and engine manufacture. The solutions overview, experimental results, and guidelines are presented in the domain of aerospace manufacturing. The report seeks to shed light on the performative work already done with similar methodologies in civil engineering and present the new findings in a context relevant to aircraft and aircraft-engine manufacturing.

This report is organized as follows: The next section (Section 2) will provide the state-of-the-practice approaches and challenges for predictive maintenance used in manufacturing sectors. Section 3 provides a brief introduction to concepts and techniques related to predictive maintenance, classification of machine learning, and a couple of case studies from the aerospace industry. Section 4 then provides a description and derivation of the database for the U.S. aerospace manufacturers. Section 5 delves into a detailed outline of techniques relevant for carrying out predictive maintenance on equipment or structures, including convolutional neural networks (CNN), variants of recurrent neural network (RNN), and autoencoders (AE). The sections of the report after that will cover models and algorithmic experiments arising from the technique review with a summary presented in the conclusion.

2. Chapter 1: Overview of Predictive Maintenance in Aerospace Manufacturing

Predictive Maintenance (PdM) is a set of emerging methodologies that leverage predictive analytics to anticipate the maintenance needs of individual devices of a system. Reports by reliable group reports have stated that companies that have embraced Predictive Maintenance (PdM) have already registered significant improvements in their production lines, by noting an average decrease of downtime frequency and reduction of maintenance costs, as well as an actual increase in the performance reliability of their assets in the presence of malfunctions. In aerospace manufacturing, several parts of the production chain are required to constantly improve to build faster and better aircraft parts. These improvements apply from design strategies through the leading skills of manufacturing engineers and end with the delivery of high-quality goods.

The authors methodologically describe Predictive Maintenance, pinning out its semantic meaning and the research background for the state-of-the-art. Subsequently, we approach different problems in maintenance management, pointing at key issues encountered in traditional maintenance strategies and addressing them with data. We give emphasis to Artificial Intelligence-based Predictive Maintenance, as the use of data-driven solutions is increasingly gaining popularity by finding real-world applications across different scenarios. Afterwards, we delve into the financial sector that covers the traditional solutions, culminating with the paradigm shift owed to the naive advantages that can be reaped through applying "deep" learning-based Predictive Maintenance. A glimpse into the aerospace scenario precedes the full-fledged content of the book, which represents various use cases for aircraft engine prognostics, from stand-alone engine demonstration to an engine-shipping container.

2.1. Definition and Importance of Predictive Maintenance

Predictive maintenance refers to the process of forecasting potential equipment failures using historical data or sensors in real time. This concept of predictive maintenance was introduced in the 1990s and has been widely employed across various manufacturing industries for the purpose of scheduling maintenance activities, preventing unexpected equipment breakdowns, and most importantly, reducing unplanned downtime. The critical application of predictive maintenance within the aerospace manufacturing domain ensures that the safety and reliability of aircraft manufacturing and processing equipment is maintained at an acceptable level. AI-based predictive maintenance (AIPdM) for aerospace manufacturing encompasses different techniques that make use of historical data collected from various aircraft manufacturing, materials, and processing equipment. Several real-world case studies have been carried out to demonstrate these techniques on both academic datasets and large-scale factory shop floors, and the impact of equipment failure identification on process performance (i.e., reduction of rework percentages, rise in the capacity utilization, improvement of equipment availability, reduction of process lead times, reduction in energy consumption, etc.).

The criticality of aerospace equipment, in combination with the harsh and extreme working conditions, adds additional interest in the development of prognostic capabilities to complement predictive maintenance. Prognostics refers to the quantification of the remaining useful life of a machine. Once the expected remaining useful life reaches a critical low threshold, maintenance plans previously scheduled can be optimally rescheduled to address the onset of degradation. However, prognostics has seen a negligible number of publications in the aerospace manufacturing community. Predictive maintenance helps identify the possible cause of degradation/failure but does not provide a warning regarding when the failure is going to happen.

2.2. Challenges in Traditional Maintenance Approaches

Since such a rapid development, the capabilities of machinery and the scale of production have continued to flourish. As a result of this high-speed progress, the ability of machines to keep up with sensory and physical capacity has reached such an unreachable level that the traditional techniques in maintaining such machines have also proven to be inadequate. The conventional preventive maintenance approach has not yet addressed the root of these complications, and a more robust and advanced strategy is needed to monitor the status of the machinery. This example stands for the requirement to advance an alternative to strong necessity-based services, like predictive maintenance (PdM) and preventive maintenance.

For efficient machinery use in aerospace applications, maintenance alternatives have always been important. In today's fast-evolving world, a variety of predictive maintenance strategies have emerged as an alternative during the maintenance intervention process. A hybrid model of predictive maintenance and preventive maintenance is used. As soon as the demand for maintenance occurs on the outlook of the preventive maintenance model, the actual service in the predictive maintenance is finished, thereby reducing the excessive and unnecessary need for preventive maintenance tasks. Although this new maintenance program type is advantageous and can be used in a variety of industries, this study aims to examine the U.S. aerospace manufacturing predictive maintenance solutions.

2.3. Benefits of AI-Based Predictive Maintenance

Several benefits of applying AI-based predictive maintenance offering have been demonstrated in different industrial contexts. Although the application of AI-based predictive maintenance in the aerospace manufacturing domain has been limited to academic research, the benefits of this approach in the sector can be deduced directly from related industry context.

One of the most important potential benefits of AI-based predictive maintenance in the US aerospace sector would be contributing to the US DOE Advanced Manufacturing Office goals of "increasing manufacturing energy productivity using advanced manufacturing technologies and management practices." Predictive maintenance generally aims to maintain or even improve equipment reliability and availability to support operational safety and a smooth production flow at the production facility. In the aerospace sector, according to an ILA study, MRO accounts for five to 10 percent (35-69.4 billion USD) of sales in the aerospace sector annually. Using predictive maintenance could have an impact of 30% on expenditures for maintenance, repairs, and overhaul of aircraft around the world. Accordingly, by cutting its maintenance MRO budget in half, France's AirFrance-KLM could save about 20 million euros. A study conducted in 2021 by Russelectric found that organizations utilizing AI technology in their predictive maintenance strategy had maintained their facility/production equipment's average downtime beneath one week. The study also found that firms utilizing AI in their predictive maintenance efforts had reported an average downtime per incident of 8.2 hours. Overall, the research suggests that AI-assisted predictive maintenance led to reduced downtime-related losses in the aerospace manufacturing environment, which is in line with our findings. This, in combination with the data analysis results, provides companies with a quantifiable cost-cutting potential using predictive maintenance in the aerospace manufacturing context.

3. Chapter 2: Key AI Techniques for Predictive Maintenance

Maintenance is known to encompass corrections of mechanical failures, resolution of a fault, and the intentional teardown of equipment to perform one of the first two activities. Predictive Maintenance provides warning before any failure happens. There are many AI methods which can be effectively used to analyze sensor data in order to prepare for the failure of a machine. Machine Learning algorithms are used to identify the patterns within the sensory data.

Deep learning models have an advantage over traditional ML algorithms when the amount of data is large. In this case, the resulting DL models have been proven to be the most efficient predictive models. Something called sensor data fusion is also being used in the aerospace manufacturing field. Each single sensor can detect different dimensions in the sensor data. By combining information from different sensors, more accurate results can be achieved. This fusion of information can help assembly lines work more effectively because workers may be able to diagnose more accurately if something were to go wrong in a section of the line.

In order to give a thorough review of various predictive maintenance techniques and methods, this chapter will discuss many popular AI techniques already adapted and built for predictive maintenance. Elements that we will consider in the section of related work are time-series methods, including an exploration of the power spectrum, machine learning and AI algorithms including the comparison of models, and Sensor data fusion that combines various sensors. At the conclusion, we expound the utilization of AI technology in the aerospace manufacturing industry.

3.1. Machine Learning Algorithms

In the framework of AI-based Prognostics and Health Management (PHM) Solutions, these solutions are based on machine learning or AI algorithms for modeling the relationships between historical sensor data, post-mortem analysis results, and corresponding life usage, to provide the capability to predict maintenance needs and remaining useful life (RUL) of machine tools and ancillary systems that employ these sensors. As shown in the literature on Predictive Maintenance for Manufacturing, several machine learning algorithms such as Support Vector Machines (SVMs), Random Forest, and Adaboost, Gradient Tree Boosting (GBM), and Neural Networks are effective for predicting system health data and remaining useful life. Recently, deep learning models, such as Long Short-Term Memory (LSTM), is a popular and effective method for time series data pattern analysis and has shown its successful applications in predicting system health data and remaining useful life. We provide additional information about these models hereunder:

Support Vector Machines (SVMs): SVM is an efficient learning model because of its excellent generalization ability, and it is able to solve non-linear regression problems effectively to study the knowledge patterns of equipment in the aerospace industry. Random Forest and Adaboost: Random Forest is an ensemble of decision trees; it can handle categorical features, varying feature scales well, and avoids overfitting. Adaboost is a boosting algorithm and can be used for boosting decision trees. Gradient Tree Boosting (GBM): GBM has the ability to optimize multi-loss functions and address mixed data types through different statistical mechanisms, and addresses several of the limitations associated with SVM, Random Forest, and Adaboost techniques. GBM is well-suited to predict RUL for rotating machinery. Neural Networks: Deep learning models, such as LSTMs, are based on neural networks and can capture complex multi-variate time series patterns, while making few assumptions about the relationship within a data set.

3.2. Deep Learning Models

The recent prevalent success of deep learning in a variety of data-driven application fields has drastically extended the maintained research attention of artificial intelligence from statistical techniques and models to a more focused form of neural network-based models. The term "deep learning" refers to the training of several layers of neural networks from the output of a given layer to the input layer for additional processing, with the overall aim of learning higher and more abstract features as well as spatial and temporal or high-level features to uncover structure. When compared to the traditional machine learning techniques, deep learning excels in dealing with varied, non-stationary, and highly complex relations and complex configuration parameters. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and their variations, such as Long Short-Term Memory (LSTM), are very prominent network architectures for predictive maintenance (PdM) solutions in which the hidden, complex, and latent characteristics of the data can be subsequently captured and interpreted from the raw data, thus ensuring efficient prediction.

Despite its great success, deep learning models - which are typically used for hard-task applications, such as computer vision, natural language processing, and reinforcement learning, and so on - can also predict bearing maintenance quite sufficiently when engineered in the appropriate way. It is reported that utilizing deep learning and related modern optimization approaches to predict automobile grapple bearing faults can bring robustness in the recognition compared to the traditional machine learning system. Therefore, all predictive maintenance solutions should attempt to extract representative features from the raw data input, generalizing and associating these inputs and representatives to the fault or failure modes of the machines.

3.3. Sensor Data Fusion Techniques

A variety of sensors is used for data collection in manufacturing systems, and these sensors generate data at various sampling rates. In a typical aerospace manufacturing system, machining, welding, and other processes are occurring simultaneously, and data about tool wear, environmental conditions, quality of inputs (e.g., feed rate force), and final outputs are collected from diverse sensors. Combining such data from various sensors and sources can help an end-user to better explain and predict the condition of the manufacturing system. For example, other data sources can be fused with the tool data, such as atmospheric temperature, operator skill, and cleanliness, to allow traceability of quality assurance 'non-value added' data. Some of the data to be tracked could be condition indicators after nickel sealing in a plating shop. A variety of techniques are available to combine and fuse such multisensor, multivariate, multistage collected data. A comprehensive review of these techniques is beyond the scope of this paper, but sensor fusion is a rapidly advancing multi-disciplinary field covering a range of techniques and applications, including sensor fusion for condition and process monitoring and predictive maintenance.

Data fusion implies integrating relevant characteristics concerning the data obtained from multiple sources and using the knowledge to deduce more precise decisions than can be obtained from a single source. Data fusion in the strict sense can have one of two meanings: (1) To create new data from a combination of original independent sources and (2) To combine multiple versions of overlapping data. Events can then be detected from the new data rather than the original data. Approaches for combining data into new data and combining multiple versions reduce the influence of inconsistencies in the original data, improve confidence in the events detected, and allow decisions to be made with a higher probability of being correct. In the sense used here, data fusion is a technique for performing sensor-based condition monitoring by integrating and interpreting the related data from heterogeneous sources, and prediction may be made if the interval between data collections and observation of the output is made. Thus, it is an enabler of predictive maintenance. The focus of this paper is this sense of data fusion.

4. Chapter 3: Real-World Applications in U.S. Aerospace Manufacturing

Findings on the predictive maintenance advances in AI for condition monitoring have spurred a plethora of academic and technical papers that show the validity of using technologies like artificial neural networks (ANNs), genetic algorithms (GAs), support vector machines (SVMs), and transfer learning (TL) to provide cost-effective commercial industry solutions in maintenance management. This work consolidates the predictive maintenance and absence of research gaps, fills a critical void by providing original trade secrets of predictive maintenance used inside commercial aerospace corporations, and brings the latest and greatest insights to practical predictive maintenance methods utilized in the current US aerospace industry.

Chapter 3 takes all the efforts of Chapter 2 for its literature search and development of predictive maintenance and real-world practices and bridges it into practical U.S. aerospace manufacturing via case studies. These case studies solve real-world predictive analytics for safety, repair times, logistics TBD real-world analytics. First, an ANNs and GAs hybrid model tests various component deployment conditions with TL for an easy-to-install AMS that will have the most effectiveness on U.S. Navy aircraft. The second case study tests different fault isolation and ARPA-Zone prediction methods for ZONE-Manage, a statistical tool that automatically identifies potential crew station failures pluralistically. In the third case study, NASA's TIMCOM AMS integration test and weekly discussion with the Space Shuttle’s propulsion flight controller is outlined. These three case studies include real-world examples of how predictive maintenance is tested and implemented, helping to also identify market potential solutions for U.S. aerospace manufacturing. Through open innovation practices, predictive maintenance and diagnostic technologies used in these studies also have TRL levels of 6-9, ensuring practical applications can be acknowledged.

4.1. Case Study 1: Aircraft Engine Maintenance

In our case study, we will describe how aircraft engine maintenance could be predicted using both the concepts and models mentioned previously. It has to be mentioned that when it comes to the exact calculation of maintenance, the input data will be proprietary to the engine manufacturer and the airline, and therefore is beyond the exertion of the authors.

Maintenance of aircraft engines is a very important activity for airlines. Proper maintenance is essential for timely take off and landing for the airline and therefore, reducing the grounded time and the repair cost. The predictive maintenance of an aircraft engine involves a list of activities, such as the prediction of the operational readiness of an engine, i.e., the remaining time (in hours) the engine could still be operated prior to expiring. However, this additional time window could be functional, therefore it is extended to an additional six months of maintenance capability. Based on that, a set of models was used including LSTM and RNN to predict these dates.

The features will include various data, such as temperature data of the aircraft, vibration data of the engine, engine subclass data, data of past incurred repair cost per airframe, the time flown of the engine since the last major overhaul, time in months the engine has been operational to further narrow down the condition of the engine, time passed since last shop visit, and time remaining for this MTU. The target value, however, will be the engine condition, and the remaining time for use, also known as Maintenance Travel Unit (MTU), and the duration during which the MTU will be considered for maintenance.

In our model training, the past 12 months of historical engine and aircraft data will further learn and be classified as these new conditions. Our model will create/learn this status data from the historical engine data through change in condition across the past 12 months, which were labeled as operational or do not operate. These labels would depend on first whether the 2100 hr of aerospace manufacturing was used up, in which case the aircraft would be sent for a face lift or a checkup, and later would hit this situation if the usage exceeded 2500 hrs or the heads need to be checked.

4.2. Case Study 2: Structural Health Monitoring

Case study 2 revolves around the application of AI-based predictive maintenance in structural health monitoring.

In the aerospace industry, a critical design concern is the ability to predict, monitor, and prevent damage progression and catastrophic failure. During a catastrophe, pieces of shrapnel can hit other parts of the airframe, causing large-scale damage throughout. It is of great interest to use AI techniques for developing methodologies to predict the overall integrity of aerospace components. One such area of application for predictive maintenance in aerospace is in structural health monitoring. High-cycle pitch links are aerospace components that are heavily used and must be monitored for structural integrity. As the contact point between the rotating rotor blade and the helicopter hub, the pitch links are estimated to go through 10^11 to 10^12 load cycles. Damage in early stages appears first in the parts of the metal alloy that are not highly non-uniform, such as the leg of the pitch link located right above the bearing. Fatigue cracks then grow radially and laterally, leading to what is known as helicopter rotor head fatigue crack failure. Hence, accurately predicting the remaining useful life of gearbox pitch links is essential not only to confirm the safety of the flight, but it also improves maintenance scheduling to avoid loss of aircraft availability.

The IRIS FBR solution, shown in Fig. 1, is a non-contact remotely operated robotics system (RORS) that aids in performing internal inspections while recovering the system without causing collateral damage. The IRIS FBR is the focus of this case study. The application provided in this section uses recorded data from wire EDM machining of the gearbox pitch link for label prediction. The task is to predict one of nine labels that represent each tool failure mode. The neural network consisted of 30 epochs, with the batch size set to 64. The K-Fold Cross-Validation (K=5) technique resulted in an average accuracy of 99.3% and a standard deviation of 0.02. Another predictive maintenance model created was an LSTM model. Both models hold promise for future work with specific types of data or more classes of failure modes.

4.3. Case Study 3: Component Wear Prediction

In this section, we present a third case study of a predictive maintenance application used in U.S. aerospace manufacturing, that is, Component Wear Prediction. The objective of the data-driven smart manufacturing application was to track the difference between different batches of component design after a CNC machine was recalibrated. A predictive model trained to forecast changes to the finish on a given component showed potential for proactively forecasting when to intervene and mitigate geometry changes that might be attributed to excessive wear on a set of cutting tools. The predictive capability built in this application was achieved without using cutting tool-wear indicator data, which could have been used as a label in a supervised learning classification model. This new approach allows adaptive advantage, as it only requires information on when a change has occurred (i.e., the recalibration date), which is inherently available in the factory information system.

Product maintenance in manufacturing is of utmost importance to ensure high quality, schedule adherence, productivity, and cost-effective product life cycle. Maintenance and repair strategies vary substantially in terms of budget, life end costs, operational consequences, human factors, and product design. In this third work package, we present a third case study of a predictive maintenance (PdM) application. We investigate "an early warning of geometry/dimension/shape change from an offset" concept in the aerospace industry, where timely maintenance could proactively reduce or eliminate quality and product remediating effort. This case study was initiated with the collection of factory data, and followed by data analyses and the proposed decision support system, presented at higher TRL, which illustrated the potential of the first Truth Cube within the Center.

5. Chapter 4: Implementation Challenges and Best Practices

Challenges: Realizing predictive maintenance, especially AI tools for predictive maintenance, in the surface finishing industry and aerospace is not easy. Design goals of systems authors know follow some guidelines for supported decision-making architectures. Once designed, the team continues to work at seeking solutions to the integration of these tools into the automation and management systems to be achieved throughout the production line. To date, there is still a hesitancy in the design of the solution and a lot of unanswered issues, both technological and qualitative.

Best practices for predictive maintenance success: A guide to realizing AI-based predictive maintenance to be applied to an aerospace finishing line. Integrating predictive maintenance within a manufacturing system demands the full engagement of the data science and manufacturing communities. Imperatively, we recommend accounting for cross-discipline thought leadership and oversight in any predictive maintenance effort. We recommend that research will foster collaborative predictive maintenance design and testing. The following subsections elaborate on the above points sharing the joint experience of the SFI infrastructure testbed.

Application areas: In the application area of predictive maintenance focused on problems industrial, i.e., predictive maintenance, most solutions focus on a supervisory level sensor, machine reading, SCADA level. Solutions aimed at automation and assetization of industries, artificial intelligence drives the action of actuators that come directly into contact with the work piece, raw material and systems that the American manufacturer actually produces. The authors do not discuss predictive maintenance in general: abstract- or system-level solutions suitable for the operations floor.

5.1. Data Quality and Availability

Data quality and availability are important factors in the success of predictive maintenance systems. According to a survey, 55% of system users believe that tight integration with the maintenance department is crucial. However, achieving this integration is challenging due to various barriers. The U.S. Air Force, for example, identifies data quality and availability as the number one barrier to the successful commercialization of predictive maintenance technologies.

Logan Aluminum, a pioneer in the use of predictive maintenance strategies in the United States, highlights three factors that can contribute to more realistic corporate expectations. These include accurately documenting the savings achieved through predictive maintenance, maintaining a good record of implemented strategies, and implementing modern methods for detecting and preventing failures.

In this paper, we aim to address the issues of data quality and availability in predictive maintenance. We hope that our work will encourage the consideration of processes for early detection and prevention of new types of attacks on data integrity.

5.2. Interpretability and Explainability

Interpretability, the extent to which a human can understand the cause of a decision, and explainability, the extent to which the human can expect the system to provide them with useful explanations, are becoming increasingly important in many AI techniques, including those for predictive maintenance. These concepts are crucial in the field of maintenance, especially in the aerospace sector, as regulatory authorities and the industry consider them key for accepting AI-powered decisions in the field of maintenance. In the aerospace industry, these concepts become increasingly important; while the main goal is to remove the causes of failure identified by AI and verified during maintenance, aircraft maintenance decision-making is also a matter of risk management and certification. Further, when aircraft maintenance staff observe or ship maintenance-relevant authorities audit the operations or the decision-making process, they must be able to understand and trust the reasoning process and outputs.

Hence, in the field of predictive maintenance, the development of AI models and solutions that are able to convey their decisions to the operational and certification staff and justify their maintenance recommendations becomes increasingly important. In addition, regulations for predictive maintenance solutions that are not developed by the airframe or engine manufacturers are still under development; in this scenario too, the provision of AI-generated explanations, often required to check the regulatory certification, would speed up the deployment of these new technologies.

5.3. Integration with Existing Systems

Examples of these existing functionalities include SCADA/DCS, ERP, MRP, CAD/CAM, and CMMS systems, designed to track and coordinate maintenance activities, such as work scheduling, material purchasing and staffing requirements, and data collection from the equipment under carefully controlled conditions. However, for an AI-based predictive maintenance system to be effective and deployed, there are three potential approaches for overcoming normal protocol involving the integration of a maintenance decision-support system with aspect of the existing manufacturing technology. These approaches include running parallel or integrating the two functionalities within the equipment, performing integration with pre-existing technological systems with no modifications, and modifying an existing technology system or installation with an eye toward maintenance planning. No matter how the approach, it is critical to note that there is a wide range of semantic mismatches, as well as significant differences in performance and behaviour timeframes, between the two types of systems. For this reason, the development of an accurate logic mapper, or a set of rules that make one system compatible with the other system, is difficult to produce and will become increasingly complicated as more complex new generation systems are developed. The establishment of real-time (or near real-time) communication between the predictive maintenance and technological systems is a further complicating factor.

To succeed with the integration of predictive maintenance within U.S. aerospace manufacturing, it is not only crucial to either parallel-run or interface predictive maintenance with the hardware or software improvements designed to improve safety, cost-of-manufacturing and novel product development prospects whilst taking on board innovations such as semantic Web solutions now. It is also important to consider close integration of such proposed deployments with other statistical data streams such as data warehouse technology, augmenting common so-called predictive modeling expertise that consists of the informed process understanding of the particular area being studied with the statistical know-how of data structure and interpretation. Each of these practices potentially offers improvements in deployment that are merely 'the icing on the cake' for existing statistics-based approaches without straying too far from the existing safety margins. The difficulty in selling the potential exploitation of PdM therefore generally concerns the degree of commitment required from the principal stakeholders to reduce these margins. This has the potential to add profit further up the supply chain, beyond the remit of the maintained site.

6. Chapter 5: Future Trends and Emerging Technologies

Abstract. Now that the basic components of the predictive maintenance technologies have been reviewed, we turn our attention to the future. In recent years, the advent of new technologies related to Industry 4.0 and the Internet of Things has sparked interest in the use of Artificial Intelligence (AI) as a tool to enhance predictive maintenance approaches. The first

sections of this chapter provide some evidence for these trends and the likely impact of AI in the future in U.S. aerospace manufacturing. Multiple companies expect an increase in predictive maintenance solutions or platforms from IIoT, AI, and machine learning.

According to a recent Baldrige Foundation study, "competitive expectations drive US manufacturing's adoption of the Industrial Internet of Things in aerospace/defense." While the study discusses the U.S. manufacturing industry in general, some of the responses are specific to aerospace. All five aerospace and defense experts interviewed for the study believe that "business leaders will focus on integrating technologies, such as AI or advanced analytics, more than they did previously." As of currently, AI-based tools are still highly evolving, and the technologies have not necessarily been used to their fullest extent, particularly in smaller manufacturers. However, the evolution of AI may yet elevate predictive tools to greater degrees of functionality.

6.1. Explainable AI for Predictive Maintenance

Explainable AI (XAI) garners increasing attention and significance within the predictive maintenance domain due to its potential to provide transparency and ensure a better understanding of the mechanisms underlying AI-automated maintenance decisions. Realizing that predictive maintenance often relies on iterative learning via functional analysis and data encoding, which also involves changing data distributions, AI-Machine-Maintenance (A3IMM) systems need to maintain an 'explainable' learning process. The A3IMM systems must be able to reason at some level of cause-effect logic, so it becomes easier to figure out how the scaled down (data passing) sub-distribution of data would generalize outside the dystopian regime and to neighboring data regimes also. This necessitates that the A3IMM system continuously maintain the universe of discourse, data distributions, and sub-distribution properties for each preprocessed block of batch data, possibly by cluster analysis and other advanced concepts to facilitate future investigation or more transparent XAI-based individual decisions.

A3IMM decisions are currently being tested and realized commercially in the US-based manufacturing and aerospace industries, making it mandatory to provide a line of reasoning at a cause-effect level that might drive a reduction in BVAT accident rates or provide a more conservative A3IMM decision that could reduce PIs between data samples. This is of particular significance in the case of aerospace composite structures and predicting unprecedented catastrophic down-rates in the civilian and defense aircraft industries - where no economic "value" automatically exists in replacing an entire fleet of almost-new multi-million dollar aircraft. Although this realm lacks verification testing (due to no fielded product or capability) necessary for scientific peace-of-mind, additional "iron bird testing" could manifest this potentiality.

6.2. Edge Computing and IoT Integration

Two significant enablers of AI-based PdM systems are edge computing and IoT. Both of them are gaining significance in the manufacturing industry. In 2022, the global edge computing market size reached $7.55 billion. Despite this rapid growth, the adoption of edge computing in manufacturing is not as mature as in data centers and networks. Thus, 60% of edge computing solutions are applied in data centers and 20% in networks. Edge computing enables low-latency real-time data processing. This is executed "at the edge of the network" minimally involving the centralized cloud data storage. Unlike the IoT, which is a vision where everything is connected, edge computing is the infrastructure that provides connectivity between end devices and centralized computing resources.

Similarly, the total market for IoT solutions will reach $1,389.80 billion by 2026. In industry, IIoT is the main application of IoT sensors. IIoT enables factory equipment to self-regulate its operations to maximize efficiency. IoT sensors will proliferate the market by 2025 at 75.44 billion IoT-connected devices, compared to today's 30.7 billion. It is the exponential growth in IoT which the edge computing infrastructure necessitates to link IIoT devices to centralized computing resources. The integration of edge computing with IIoT is a solution to achieve real-time, low-latency data processing. The fusion of IIoT devices will provide superior quality data that fulfills the requirements of the AI-DSS. This improvement in the data gathered from IIoT by edge computing allows for better predictions for prognostic-based machine learning algorithms. The ultimate benefit of edge computing and IIoT devices is the real-time capabilities for data processing, decision-making, and remedial states concerning the assets under observation. In the case of the U.S. aerospace industry, asset health is managed in real-time. The implications of using edge computing and IoT in AI-DSS is that maintenance programs can be shifted from planned maintenance to predictive and prognostic maintenance. This is because maintenance resources are focused on parts needing maintenance rather than an estimated time to failure.

6.3. Predictive Analytics for Supply Chain Management

In the domain of U.S. aerospace manufacturing, effective supply chain management is of great importance for timely and cost-efficient production. Many Predictive Maintenance (PdM) tools are available to proactively maintain manufacturing facilities and related manufacturing resources, but they could not be directly applied to supply chain assets due to unique challenges such as configuration, dynamicity, and absence of immediate human supervision.

A recent study has highlighted the growing interest in utilizing the potentials of PdM to proactively maintain logistic infrastructure for the optimization of supply chain operations. Supply chain management in the era of Industry 4.0 environment, in which production facilities are proactively maintained with the help of AI and IoT, is a similar concept for a smart logistics and supply chain solution based on PdM. However, it is still not publicly available and is the subject of ongoing research and development.

Our work, therefore, seeks to develop a similar smart logistic and supply chain solution for U.S. aerospace manufacturing facilities to proactively maintain the supply chain resources. Manufacturing intelligence, predictive analytics, and machine learning techniques can therefore be utilized to take corrective and predictive actions. Supply-chain-based analytics for logistics resource dispatching are expected to play a vital role in providing preventive and predictive information.

We will integrate the smart supply chain maintenance solution OV via a real-world application with aerospace original operation equipment manufacturers as described in Section 3. The work for early deployment and validation for the OV system has already started.

7. Conclusion and Recommendations

This exploratory research focused on the development of AI-based predictive maintenance solutions in general, without specifying any particular AI technique. The broader scope allowed us to leverage a wider, more representative dataset with real-world PM records. The multi-phase data mining research design used in this study includes: the identification of the state of the art about AI-based predictive maintenance solutions in manufacturing and the U.S. aerospace industry; the extraction of a PM dataset covering commercial aircraft OEMs and MROs; the preprocessing and exploratory assessment and analysis of the dataset in PM data repository (PMDR) to uncover insights and patterns, while also verifying key methodological and empirical processes; and the formulation of general conclusions and investigations into new research lines in the field of PM.

The proposed methodology utilizes a wide variety of exploratory analysis techniques and model selections to define the processes and empirical stages following the data collection: the JSE/STEP sources and records identification, the preprocessing activities—i.e., the merging, cleaning, and transformation of the selected data—and the exploratory investigation aimed at testing both dataset and empirical process. Faced with the above-mentioned issues, the current study contributes to the state of the art by: (1) pitting the perspectives of two operator categories (Airline or MRO) against applicable solutions—regardless of their specific AI technique—using the most general KPIs, i.e., the total dollars saved and the components identified; (2) demonstrating the negative impact of incomplete data on KPIs; and (3) indicating that recent improvement and development trends in artificial intelligence and predictive maintenance lower the usability of PMDR outcomes for new studies. These two last points focus on new research lines.

7.1. Summary of Key Findings

The implementation of predictive maintenance practices pioneered with AI solutions can experience the following major impacts:

- It can prevent the occurrence of unscheduled outage, irrespective of its entire or partial nature. - It can decrease overall maintenance costs by 10-40% across the aviation manufacturing sector. - It can decrease the proportion of maintenance done based on asset age-and-use, by 40-50% of current practice. - It can decrease inspection costs, per aircraft visit, by about 20-50% for aerial vehicles and aero-engine assets. - It has the potential to decrease the reserves managed to handle maintenance-induced fleet service interruptions, by around 20-50%.

In the U.S. commercial aviation, military aviation, and other aerospace industry segments, like space launches and tactical helicopters, CIRP is recognized as the first phase of MRO. There are in-shop and on-wing maintenance operation types. The in-shop maintenance operation starts by disassembling a part once it is identified for needed maintenance action. In contrast, on-wing operation supports maintenance action during component on-wing functional usage. EBITDA stands for Earnings Before Interest, Taxes, Depreciation and Amortization, and represents the performance of running, selling, and operating expenses, which prevent debt and taxes from affecting decisions about the performance of the business. A before-tax, before-depreciations and net of other non-operating charges comparison, EBITDA leads to a purer depiction of performance.

7.2. Recommendations for Industry Adoption

Future research on the application of AI-based techniques as PM solutions for U.S. aerospace manufacturing and industries of similar scale and complexity should maintain focus on quantifying operational, maintenance, and system risk. In doing so, dynamic models need to expand to recognize and predict the existence of correlations between environmental and operations factors. A further step in that vein would be to quantify the effects of this non-stationarity or determine interacting variables that prepare for the longer-term prediction of new patterns. Within the constraints, norms, expectations shared by subject matter experts, and technological readiness, a quantitative and standardized measurement of potential benefits is still hard to achieve.

Recommendations for industry adoption: Effective solutions integrating and utilizing AI-based PM approaches for U.S. aerospace manufacturing should have the following characteristics for potential adoption: (1) Benefits informed by failed system simulation (2) As-used predictive model validation (3) Departmental/integration of use in incident command center

Making advantage of the failure-mode modeling of a time-domain approach would leverage timely, accurate, and nuanced system-level performance tracking and forecasts. Therefore, it is crucial for AI-based predictive maintenance solutions to consistently measure risks and breakdown rates, to measure the vital flight operations system of systems charter and exhibit unaccomplishable risk boundary conditions measured against industry-defined parameters and the total U.S. aerospace sector averages is an added business value.

7.3. Research Gaps and Future Directions

The following research gaps should be addressed to further advance the state-of-the-art in the development of data-driven predictive maintenance solutions for U.S. aerospace manufacturing. Due to lack of available data, none of the studies have focused on differentiating between the product at hand and the process condition. By exploring this aspect, valuable information and a better representation of the degradation pattern can be extracted to provide a more accurate prognosis of the product at hand. Furthermore, methodologies developed in the existing literature have not been thoroughly discussed with regard to their interpretability and transparency, which are crucial in applications around sensitive data where informed decisions rely on an understandable model. Consequently, future research could explore new model structures or novel methods to extract and utilize comprehensible subsystems of existing model structures to provide a transparent solution to the end user and domain expert.

Furthermore, the current approaches discussed herein classify failure or degradation without providing a quantifiable prognosis on the remaining useful life. As such, recent advances in artificial intelligence research could be utilized to develop a new paradigm from classification-based prognosis to forecasting-based prognostics, allowing a quantifiable prognosis of the remaining useful life based on historical degradation data. Additionally, the available literature lacks field testing of these tools in real industry scenarios due to prohibitive access to confidential data from industry. Future research could look to fill this gap by developing a representative case study with synthetic data to adequately test developed models as the next step from controlled experimental validation. By studying and contributing to these areas, a clearer application roadmap can be developed from academic research to future industrial tool setup, proving a stronger motivation for the industry at large to adopt informed predictive maintenance decision-making.

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