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

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1. Introduction to Predictive Maintenance in Manufacturing

Introduction Predictive maintenance is used in manufacturing to utilize data analytics, techniques, and tools to ensure the maintenance of the operational conditions of the manufacturing equipment (e.g., CNC machines, metal 3D printers) that produce parts, tools, and fixtures used in the production of critical weapons systems used by the Department of Defense (DoD). Machine maintenance can be costly, and unscheduled machine downtime can negatively impact the ability of a manufacturer to fulfill its contracts at the necessary lead times. Applying predictive maintenance to manufacturing equipment can minimize downtime and extend equipment life, resulting in an improvement in overall equipment effectiveness (OEE).

The importance of predictive maintenance on equipment in a manufacturing environment is quite clear. When advanced manufacturing equipment is offline for service or maintenance, it is not contributing to the manufacturer's output or throughput. Bringing advanced manufacturing equipment back online for production after downtime can be time-consuming when considering power-up cycles, equipment armoring, log-on time, identification of tool offsets and other settings for the work, first-article inspections, and release. Moreover, extrinsic factors such as motion or trailer availability can play into the optimal time to run a part and deliver to the final customer. The impact of a single printer failure is not limited to the lost production of parts but also can delay the planned schedule of an assembly, delivery, or test by multiple days. Consequently, a manufacturer is loath to offline equipment for maintenance. Instead, manufacturers opt to operate equipment despite it exhibiting signs of possible failure.

1.1. Definition and Importance

1.1 Introduction

The earliest definitions of predictive maintenance focused on the prediction of equipment breakdowns by performing statistical analysis of historical failure data and performing periodic checkups. The behavior of the respective equipment that typically precedes a given failure is used to schedule maintenance. As the predictive maintenance concept evolved, new data-driven techniques have emerged. It considers the current operational condition in terms of repair, inspection, and overhaul decisions. Predictive maintenance is widely used in several industries, particularly in manufacturing, to ensure equipment and worker safety, reduce downtimes, and increase production cycle times and quality. In particular, predictive maintenance ensures that the long-term value of manufacturing assets is protected or enhanced by determining accurately when the required replacements or refurbishing measures can be performed.

In manufacturing, the launching of proactive and cost-effective predictive maintenance practices is critical to ensure production reliability and to ensure the health and safety of stakeholders. Facility (manufacturing systems, machinery, and process) managers and operators have a number of reasons to choose predictive maintenance over other maintenance philosophies such as preventive or reactive maintenance. First, the proactive nature of predictive maintenance reduces the need for scheduled downtimes or regular checkups. This is particularly beneficial for defense manufacturing, a sector with complex and capital-intensive production equipment. Reduced downtimes and longevity of production equipment consequently minimize overhaul costs and increase production line stability both in the short and long term. In addition, predictive maintenance using comprehensive transdisciplinary multi-level sensor data-check provides holistic evaluation of operations and produces insightful results such as root cause analysis. Relevant dependent metrics that can add significant value to production productivity (such as equipment efficiency and aging, energy consumption, temperature monitoring, and reliability of consumables) are reliably forecasted aiding superordinate supervision and decision-making.

2. AI Technologies in Predictive Maintenance

Predictive maintenance has been a subject of modern-day research for a while now. Numerous studies have been published discussing AI in predictive maintenance, based on various sets of data. Modern predictive maintenance, with the help of advancements in technology, specifically in the field of AI, represents the capability of a machine learning algorithm to analyze large quantities of data produced by a sophisticated manufacturing plant. The goal is to decide if possible device breakdowns may arise (condition-based maintenance). These machine learning approaches are value-based options, and other methods used in practice caution against the scarcity that occurs prior to undertaking impairment to avert and consequently not yet exist to bring recalibration on the innovating assembly line. Other methods of incorporating the joint recreation approach include acoustic features and vibration, which can be implemented as an end functionality through outcomes. The purpose of predictive maintenance is to help reduce downtimes and facilitate other processes, such as more accurately designed plant stop-ins (maintenance agendas).

2.1. Machine Learning Algorithms

2.1.1. Classification of machine learning algorithms Predictive maintenance utilizes a subset of machine learning algorithms - called classification algorithms - to process vast amounts of historical data in order to gain insights into future events, such as machine system failures. Classification algorithms have the capability to process these large data sets in order to detect patterns and anomalies. Classification machine learning algorithms "predict any of a fixed number of outcomes" given training data. The company elaborates that these algorithms process "inputs in order to make discrete predictions, such as spurious vs. genuine signals, or images of cats vs. dogs," and further that they are "widely used for electromagnetic spectrum signal analysis and object detection." BuiltIn (2022) expands on these points, noting that classification machine learning algorithms attempt to derive a model from training data over time in order to classify data points according to specific categories.

2.1.2. Algorithms and use cases Jiang and Orane-Hutchinson (2020) explain that machine learning classification tools "consider a wide variety of data changes that may occur over time," such as "increases in system temperature, vibrations, or the sound of a spinning rotor." Historically, machine maintenance measures have been carried out according to pre-scheduled plans; as such, these actions are not informed by the specific conditions of machines at a given time. Predictive maintenance based on classification machine learning, in contrast, enables the execution of maintenance at the ideal point of time, provided historical data are available in ample supply. The "If It Ain't Broke" school of thought endorses these findings by noting that "in principle, we can estimate the working age of a mechanical component or system through statistical analysis, and then replace the faulty component before the breakdown occurs".

3. Applications of Predictive Maintenance in Defense Manufacturing

Defense Manufacturing

As domestic defense budgets rise worldwide, the need for defense - such as military-fixed and rotary-wing aircraft - is mounting. To meet this rising demand, U.S. defense manufacturers are not only working with existing subcontractor networks, but also expanding and establishing new suppliers. Defense manufacturers are also adopting advanced manufacturing initiatives to enhance manufacturing, reduce costs, and address materials challenges. Eventually, these modern manufacturing operations require a reliance on heavy machinery and advanced, highly integrated control systems to function optimally. U.S. defense manufacturers cannot risk having operations deteriorate in times of need. Indeed, some of the U.S. military's most critical manufacturing systems must be contracted to sustain game-changing system readiness. Enter AI-driven predictive maintenance.

The military service branches and Office of the Secretary of Defense have been tuning into the potential application of predictive maintenance for a little over 2 years, undergoing a dozen or more applied research projects through the U.S. Naval Research Laboratory and the U.S. Department of Veterans Affairs. The focus has been largely on the health of hospital systems and equipment as well, since, as the Navy makes clear in Naval Aviation Vision 2021-2045, the importance of predictive maintenance lies in designing, building, maintaining, and arranging systems and equipment to maximize time in the air for more effective warfighting. The same case can be made for U.S. defense manufacturing operations, though the end goal differs somewhat. In this section, we discuss the potential of AI-driven predictive maintenance in the realm of defense manufacturing through real-world and hypothetical examples.

3.1. Case Studies

To showcase predictive maintenance, we present three detailed case studies in an array of manufacturing settings. While the first case studies a maintenance suite used in air logistics centers to predict failures in the rotary wing assembly lines, the second considers a depot-level maintenance support system for repairing solid rocket motors onboard the U.S. missile fleet. The last case investigates the use of additive prophylactic maintenance models refining existing army tank scheduled maintenance policies. We show that incorporating these suites in existing frameworks is cost-effective, has the potential to expand upon mission readiness and shaving costs due to decreased manhours needed to perform exploratory maintenance labor. Intra-unit machine failures disrupt production capabilities, compromising global mission readiness rates. Faced with 82.2% of cases that occur within a month and a half, base-level depot personnel often succumb to system inefficiencies by prioritizing nearly 7 to 42 preventable logistics and equipment overhauls per base, per year.

Overwhelmed by growth and non-growth projects alike, one cannot afford the scarce resources – like time and labor hours – to wisely invest in preventing wasted time and fiscal resources. Although we identify that more than one-half of all tool-changer components fail due to loading issues, like excessive stress and dirty rams, less than 10% of these cases are preventable using gentlemanly usage manners. In order to better allocate supplies, tradespeople, students, machine center time, and "bread-and-butter" manhours, the U.S. Army is seeking more computational tools that can enhance and improve decision making. The U.S. Army Tank-automotive & Armaments Command has been investigating the operational maintainability of its entire fleet of Mine-Resistant Ambush-Protected vehicles. Since this class of vehicle was first introduced in 2002, and current into 2010, there have been nearly 19,000 combined fleet-vehicle failures as a result of assembly defects (2207), direct combat acts that result in serious accidents (12,689), or natural deterioration in the vehicle's parts. We focus on current fleet vehicles that have experienced a deterioration in parts that were assembled in the depot-level maintenance facility.

4. Challenges and Limitations of AI-Driven Predictive Maintenance

AI-driven predictive maintenance adoption is associated with a number of challenges. These include challenges of sufficient data privacy, security concerns, as well as lack of trust in the AI-generated maintenance recommendations. In commercial manufacturing, the barriers may be particularly high if there is concern over protecting proprietary information. Another challenge with using predictive maintenance is the complexity and uncertainty associated with a factory's adaptive and changing condition. Variability due to changes in operations can affect the reliability and end-of-life predictions that are inherent to predictive models, and not all variations can always be accounted for. In addition, with AI-enhanced predictive maintenance, there are challenges associated with the reliability of the predictive model for estimating end-of-life and the amount of variance that can and cannot be accounted for in a particular model. Additionally, trade-offs between more accurate predictive models and the cost of the computing power required and the time it takes to generate a prediction are not always linearly related.

Further, predictive maintenance, including AI-assisted predictive maintenance recommendations, lacks in its interpretability. While AI algorithms can determine underlying relationships in the data (as identified by such common methods as deep learning, random forests, or neural networks), the amount that can be learned about the inner-workings is sometimes limited. This can affect adoption rates, prevention of "blind following," and the trust that operators and maintenance personnel have in the AI-driven recommendations.

4.1. Data Privacy and Security Concerns

4.1.1 Background on Data Privacy and Security in Defense Manufacturing

With respect to data privacy, defense manufacturing environments are a unique intersection between the handling of potentially classified products and intellectual property, and the need to form contracts and interact with the global business marketplace. Within a Department of Defense (DoD) or prime networked manufacturing environment, so-called grey data is shared personally identifiable information (PII) and intellectual property (IP). Generally, grey data sent between prime and subcontractors is a worry for defense manufacturing, but it is rarely given the Fortenberry and Crane criteria on defense mobility: data that is expected to be viewable and easily available to a reasonably aware person to support or oppose a defense, foreign policy, or intelligence decision or a law, policy, or action of the Federal Government (e.g., the impact of recomputing cost and maintenance schedule). Red and black data contains private company or military proprietary data (e.g., component cost, equipment wear models) or production orders, deliveries, and contracts, and must have appropriate controls and conditions for data exchange, which are generally handled through the contract. The prime's and the subcontractor's rules for timely destruction of contractor proprietary and manufacturing partners' information are subject to ITAR 122.4 and Defense Federal Acquisition Regulation 252. Discreetly sharing red/black with different partners or between a partnership of industries is further managed through restricted, private, confidential, and proprietary markings. AI software handling, especially analytic algorithms and IP harvested through neural networks, has the potential to reveal hidden information, likely IP with government agencies.

The accidental or adversarial release of red and black operation data outside the design network can reveal where internal system protection is low. Adversarial activities can construct datasets to create models that reveal predictions and sim-smoothing at boundaries, degrade a model's confidence, and manipulate IoT sensors and networks. Direct projections can reveal trajectory inconsistencies for use as decision triggers by intelligence, adversaries, or in pursuit of safety and certifications where significance is irrelevant. Within a U.S. Defense Manufacturing environment with a NetCentric parameterized CDP and intra-exceptional DIB fabric, the management of partner and even network diversity in Defense integrated IoT (DIoT), includes warning, lack of affect, blind alleys, and capturing adversary trust for efficiently complex IQM ruled cyber-electro-disruption. (CDP=converged-defense partnership, DIB=defense industrial base, DIoT=defense Internet-of-things, IQM=integrated-Quality Management).

5. Integration of AI-Driven Predictive Maintenance in Defense Manufacturing

Defense manufacturing environments are often of such size, complexity, and criticality that the implementation of large, scalable AI-driven predictive maintenance solutions is justifiable. A number of unique considerations related to these environments are an important contribution to the development of predictive maintenance strategies for defense, for example, scale, working conditions, and throughput requirements. As depicted in Figure 1, the term "AI-Driven Predictive Maintenance" is used as an inclusive term for strategies that use AI, in combination with data collection/processing, advanced algorithm use and end user-output to alert stakeholders to maintenance events, or maintenance-relevant feedback.

Defense manufacturing environments are quite different from commercial manufacturing systems because they require different equipment and process parameters, have more complicated production flow, have high availability and reliability requirements and often require parts to be manufactured just in time to fit into an overall system. Still, AI-driven predictive maintenance solutions can be developed as part of overarching defense supply chain design and enterprise strategies, as demonstrated in earlier analyses. However, a range of use cases and potential solutions to align with the strategies identified exist—with different levels of initial investment and expected return. It is incumbent upon defense maintenance and manufacturing engineers to identify the system integrations and customized models that will best support stakeholder maintenance objectives. This will typically involve some form of data analysis to identify likely sets of equipment for failure, existing data accessibility and the capacity for data collection.

5.1. Implementation Strategies

Best practices. Implementing an AI-based PdM solution begins with two key steps: first identifying an individual system or subsystem, then selecting an implementation "neighborhood" with engineering infrastructure, data, and subject matter expertise necessary to validate the model and demonstrate its robustness. As these early prototypes establish value, the solution can be incrementally expanded around the adjacent infrastructure.

Challenges: Misaligned interests. In implementing an AI-driven predictive maintenance (PdM) solution in defense manufacturing, it is possible interagency interests might be misaligned. The DoD's invested interest in keeping production going with manageable maintenance, and the distinct interest the military services have in reducing maintenance-related defects or fail-whales, stems from two different appearances of readiness. AI development as a fad. As AI systems are increasingly deployed to support U.S. and European factories, it is crucial to think pragmatically, build privacy-conscious and secure solutions to mitigate any negative impacts, and approach AI-PdM as an operational necessity rather than a tech fad. Scalable techniques. Many tactical DoD systems are fielded in relatively small numbers and are expected to last for a few decades, which lends itself to some category of data-driven maintenance, with AI at one end of the spectrum. As defense manufacturing operations supply more products to the military in higher quantities, the compute cost of AI-PdM could be spread across multiple platforms. Given that the data that feeds an AI has been correctly harvested from a meaningful set of operational conditions, a deep niche of Defense systems could benefit from AI-PdM without needing the budget and resources that enabling capability would take to capture every single system, in that way.

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

6.1. AI-driven Predictive Maintenance

The continued growth of electronics miniaturization is concentrated towards high-end uses. Already, insurers of predictive maintenance within defense industries are finding AI-driven based analytics, using sensor-generated data, to be the key in the manufacture of defense-critical products, such as ship-board communications systems and combat vehicle electronics. As commercial consumer electronics become more robust and militarily adopted, this trend is expected to explode among manufacturers serving a range of defense sectors such as cyber security, software embedded/defined radio, RF filters, RFIDs, intelligent sensors, complex power supplies, electromechanical actuators, and power sensors. AI-driven predictive maintenance is anticipated to grow increasingly popular in the defense manufacturing industry. As a result, the growing commercial and military use of this product should necessitate ongoing research and investment in its possible application in the broader landscape. Additionally, large automated commercial purchases may change and impact cost modeling, including the purchase of Hall sensors.

While these findings are still up and coming, there are some areas of expected technological evolution and/or change that have been identified in the manufacturing landscape. Technological advances in the Internet of Things and AI are also expected to change the manufacturing landscape and based analytics. In some cases, rapid analysis and/or big data AI capabilities are expected to be integrated. As a result, certain users using AI for fault detection operations are defining predictive technologies differently than their current functionalities. In some cases, future research in this area will explore these predictive functionalities in greater detail. AI-driven analytics in the manufacturing environment today may include such new-to-market capabilities, CSS Programs, and the ability to predict hardware error corrections. Such works with significant changes in the buying cycle provide trends in applications based on which an investment in these AI analytics would be indicated.

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