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Implementation of Predictive Maintenance in the Army

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Abstract: The Army is looking to implement predictive maintenance by 2030, so identifying the optimal applications of predictive maintenance is crucial. Although adding predictive measures to all parts of the maintenance system in the Army is ambitious, there are also areas where adding predictive maintenance is not feasible or necessary. This paper explores the implementation of predictive maintenance within the U.S. Army to provide a model that identifies the platforms and components that would most benefit from predictive technology. The paper highlights the work done on developing a framework for component and platform selection through our simulation model, maintenance model, assessment of stakeholders and associated risks, and continuous improvement processes. Our research and findings lay some of the necessary groundwork for the development and implementation of predictive maintenance in the Army.

1. Introduction

With the growing utilization of Artificial Intelligence (AI) in commercial sectors and the military domain, the Army is actively exploring ways to integrate predictive factors into its existing maintenance cycles to increase its efficiency through predictive maintenance. Predictive maintenance is a proactive maintenance technique that uses real-time asset data (collected through sensors), historical performance data, and advanced analytics to forecast when asset failure will occur (Wilke, 2020). Predictive maintenance represents a new approach to maintenance that incorporates new technologies and AI to help monitor systems and platforms. Implementing AI and machine-based learning predictors in the current maintenance process has the potential to positively impact the Army's readiness and allow it to operate more effectively by improving upon conventional strategies that often lead to premature or delayed maintenance actions. In a recent systematic literature review of predictive maintenance in the military domain, Dalzochio discusses the different types of models used for predictive functions ranging from machine learning models, deep learning models, probabilistic, hybrid, and reasonable models, and physics-based models (Dalzochio et al., 2023). To tackle Predictive Maintenance within the military domain, our capstone group adopts a systems approach to address the question: **"How does the Army determine which platform sand components could best benefit from predictive maintenance models?"** In answering this question, our capstone dove into the existing maintenance practices within the Army, the current landscape of predictive maintenance, the challenges associated with its implementation, and its potential impacts. Given the many types of equipment and their various applications within the Army, we provided a comprehensive literature review, developed models, conducted stakeholder analysis, and assessed risk to provide value to our clients, The US Army Artificial Intelligence Integration Center (AI2C) in their development of AI and machine-based predictors. This paper outlines the background of predictive maintenance, identifies our methodology, presents models showcasing predictive maintenance applications, and offers preliminary findings from our simulation model.

2. Background and Literature Review

In the Army, maintenance procedures significantly impact unit readiness and success. Current Army maintenance relies on scheduled checks and procedures that are categorized into sustained maintenance, supported field maintenance, and organic field maintenance based on part availability and required maintenance level. These procedures are conducted at various intervals, including weekly, monthly, semiannual, and annual inspections. Additionally, maintenance tasks are based on part availability and required maintenance level ("Department of the Army Pamphlet 750–1", 2023). In the current maintenance process, adding accurate predictors of failures can help increase the efficiency of Army maintenance while reducing maintenance downtime and costs. Currently, the Army has shifted its focus to approaching maintenance with a more proactive stance rather than a reactionary stance. As the Army is moving towards predictive maintenance, there are many levels of stakeholders that are involved in the development and implementation of predictive maintenance in the Army. With these stakeholders comes a large landscape consisting of differing priorities and risks associated with each stakeholder.

Predictive maintenance when implemented efficiently would directly benefit its users which would be operational units. By decreasing mechanized units' vehicle downtime, predictive maintenance would have a direct impact on the Army's lethality and readiness. Although army units will be the primary users of predictive maintenance, many other stakeholders play a role in the development, training, and implementation of Predictive Maintenance in the Army. While working with stakeholders like CASCOM (Combined Arms Support Command), Army Futures Command, Contractors, PEOs (Program Executive Officers), AMC (Army Materiel Command), and other entities, they must comprehend the way the Army currently does maintenance and where to effectively implement predictive maintenance. The Army has emphasized this goal in its Material Maintenance Procedures Pamphlet 750-1 by adding a focus on condition-based maintenance and predictive maintenance through its current maintenance procedures ("Department of the Army Pamphlet 750–1", 2023). As the Army is looking into ways to develop and implement predictive maintenance into its units, the commercial sector is also currently investing and using AI and machine based learning models in operation to help minimize maintenance costs and downtime.

First, by accurately predicting potential failures before they occur, the Army can avoid the high costs associated with unplanned downtime and emergency repairs, which often require expedited shipping of parts and can lead to operational delays. Second, predictive maintenance allows for the optimization of maintenance schedules, reducing the frequency of routine checkups that may not be necessary, thereby saving on labor and material costs. Commercially, researchers are trying to reduce the number of failures in equipment and avoid breakdowns within the shipping industry by using an artificial intelligence model that uses real-time monitoring data (Jimenez, Bouhmala, & Gausdal, 2020). In the agricultural field, many organizations are attempting to apply research and development that are focused on industrial manufacturing and maintenance for agricultural machines (Lã, 2018). In aviation, condition-based maintenance is being used as a way to check the safety of the aircraft, however, predictive maintenance could be implemented to provide additional benefit to the aviation community (Lin, Luo, & Zhong, 2018). Although there are many benefits to efficiently implementing predictive maintenance into the Army's current operating procedures, the many different technologies, data types, and models, pose a multitude of challenges (Theissler, PérezVelázquez, Kettelgerdes, & Elger, 2021).

3. Methodology

3.1. Scope and Significance

As we focused on implementing predictive maintenance, we conducted a thorough evaluation of our current maintenance system to identify where predictive maintenance would capitulate the greatest effectiveness. We initially identified several key value measures crucial for decision-making. These value measures expand our understanding of how easily military personnel and systems can implement predictive maintenance, and if it is worth the lag time and resources to implement predictive maintenance. We will specifically focus on three value measures: operational readiness level increase, percent time saved if predicted, and total time from failure to replacement. We focused on these three value measures as data availability and stakeholder inputs suggested these were the most critical. Operational Readiness Level Increase is vital because it directly correlates with the primary mission of the Army—ensuring that units are combat-ready at all times. Predictive maintenance has the potential to significantly reduce equipment downtime, thereby enhancing overall operational readiness. By prioritizing this measure, we aim to focus on the direct link between maintenance efficiency and mission readiness. We also focus on the percent time saved if predicted because time is a critical asset in military operations, and any reduction in maintenance downtime

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directly translates to increased operational availability. Focusing on the percent time saved through predictive maintenance allows us to quantify efficiency gains and justify the investment in predictive technologies. The total time from failure to replacement provides insight into the life-cycle management of equipment, emphasizing the efficiency of the maintenance process from a failure to its correction. By concentrating on these three key value measures we ensure that our implementation of predictive maintenance is both data-driven and strategically aligned with broader mission objectives.

3.2. Stylized Implementation

While there are other maintenance models that focus on the platform level and above, our model primarily focuses on the impact that individual parts and components make on the status of an individual platform. By focusing on individual components, our model aims to fill the gap between models that look at unit data and individual part data. When used in aggregate, our model can also show the impact of implementing predictive measures on individual components on a unit level. With the ability to develop and implement Artificial intelligence in vehicles to predict part failures, our model attempts to take current component-level data and run simulations that output the effect predictive maintenance has on maintenance operations. With outputs like the percentage of vehicles operational, the percentage of time a platform is operational, and the percentage of waiting time saved, our model can pinpoint specific components where predictive AI is efficient and worth implementing.

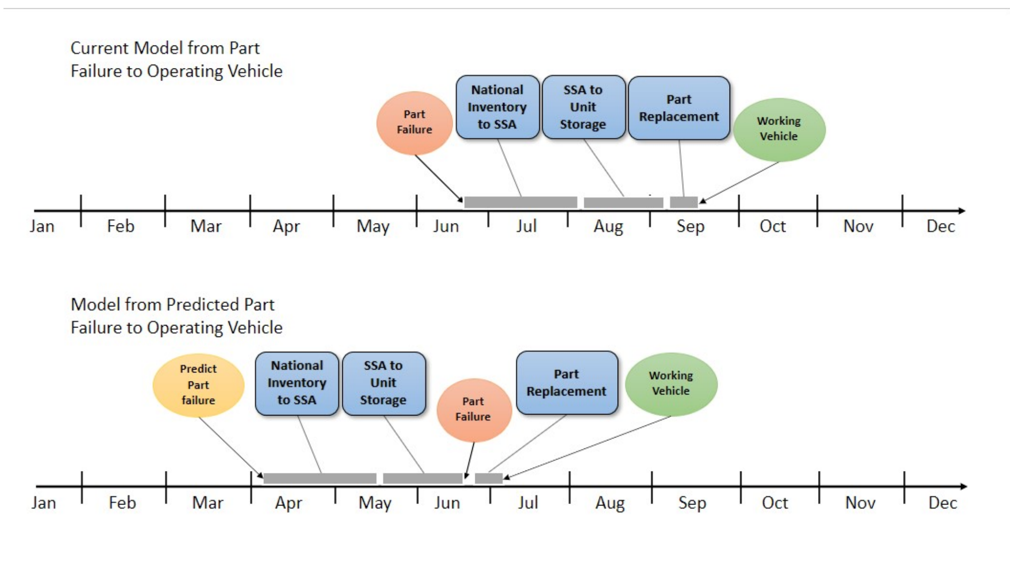

Figure 1: Flow Chart: The main benefit of predictive maintenance that our team identified is the ability to decrease the wait time of a vehicle for parts necessary for maintenance. By adding a predictive measure, a unit would be able to order the necessary parts before the part failure which limits the wait time and allows mechanics to fix or replace failures immediately after a failure. The top timeline shows the current model for responding to part failures, highlighting the sequence of events from the moment of failure to the return of a working vehicle. The bottom timeline showcases a predictive maintenance model, where part failures are anticipated and addressed proactively, potentially reducing downtime.

3.3. Simulation Outline

Our simulation quantitatively assesses the effectiveness of implementing predictive maintenance strategies within the Army, supported by the scope and objectives outlined in Section 3.1. The simulation uses inputs including mean and standard deviation for failure rates, repair times, shipping delays, and maintenance schedules, which were derived from real component level data from the Bradley Fighting Vehicle. These inputs are a reflection of the implementation of predictive maintenance shown in the bottom timeline of Figure 1. The model simulates the Mean Time Between Failure (MTBF) and Mean Time to Repair (MTTR) which are used to estimate the mean time to failure (MTTF) and integrate customer wait times. Our model

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estimates the total time from part failure to vehicle readiness, which is extremely valuable information for maintenance policies to enhance operational readiness and reduce downtime. The simulation outputs are classified by component status (up, down, undergoing maintenance, or waiting for parts), which provides a way to quantitatively represent and further describe the model shown in Figure 1. The results and insights from the simulation help Army Organizations not only better understand the current maintenance strategy but also predict and improve future maintenance operations. Our approach provides a tool for decisionmakers to optimize resource allocation and maintenance strategies that align with operational demands.

3.4. Use-Case Selection

For the use case in our simulation, we selected the Bradley Fighting Vehicle due to the comprehensive data access provided by the Combat Capabilities Development Command Data and Analysis Center (CCDC DAC), which included detailed component-level data and a summary data report covering the years 2016-2019. The specified inputs for our model consisted of time-based data, including individual component part repair times, part shipment times from national storage to the Supply Support Activity (SSA), and from SSA to the unit. This data also included metrics like man hours per action, which helped us estimate the MTTF and MTBF, which are key factors in predicting maintenance needs and scheduling.

We used these metrics, along with the MTTR, to incorporate the customer wait time into our simulation, providing a rough estimate of the total time from part failure to vehicle operational status. Our analysis of the data allowed us to prioritize the maintenance of significant parts based on their impact on vehicle readiness and operational downtime. By selecting 15 components, with a range of predictability, our simulation aims to reflect the maintenance cycle's response in practical scenarios.

3.5. Inputs

The inputs that our simulation needs are component specifications: Mean and standard deviation for failure rate, repair time, shipping delays, and maintenance schedules. The simulation uses these input parameters: How many weeks we want to simulate, the maximum amount of repairs per week, and the failure rate increase factor (simulates degradation of components).

3.6. Key Assumptions

Key assumptions that affect our simulation and results are that failures and repair times are normally distributed and cannot have negative attributes. Our next key assumption is that failure rates increase linearly with usage beyond the first week. Our final assumption is that a fixed threshold determines the maximum number of repairs per week, which simulates the limited time and resources of mechanics.

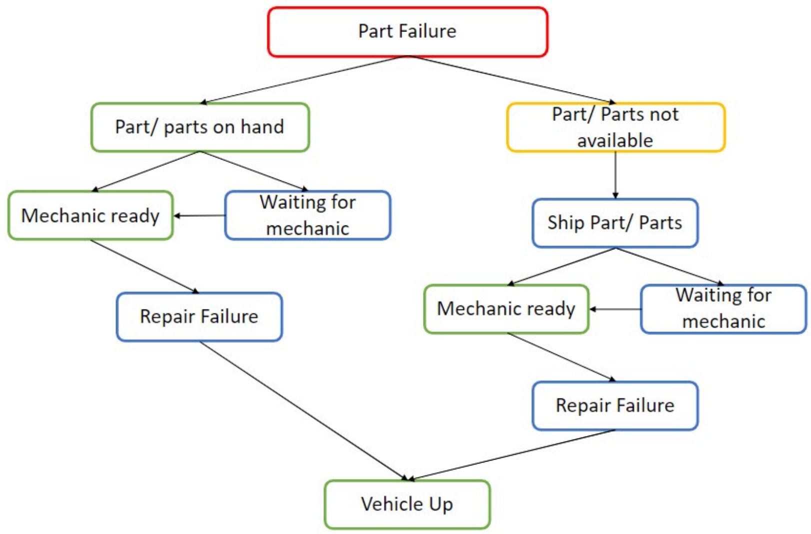

Figure 2: Decision Tree: This Figure demonstrates the process mechanics will go through when a part fails. It outlines the functionality and concept behind our simulation. While there are many other activities that must happen once a vehicle or part goes down, this flow chart outlines the steps that take place in our simulation when modeling the maintenance process with and without a predictor.

3.7. Simulation Structure

For each component, we generated non-negative, normally distributed values for failure rate, repair time, and shipping delays. First, our simulation conducted a maintenance check. When a component was scheduled for maintenance, we updated its status and skipped to the next component. After a part failure, as shown in Figure 2, the path split based on parts availability. If parts were not immediately available, the simulation accounted for the shipping time. A part was scheduled for repair when a mechanic was available and repair capacity allowed. If not, it remained in a waiting state or was added back to the waiting list. This simulation approach enabled us to realistically model the dynamic nature of maintenance logistics, highlighting the importance of efficient parts management and mechanic availability to reduce downtime and increase operational readiness. The waiting time for components decreased each week. If waiting time was up and repair capacity wasn't reached, we scheduled for repair. Otherwise, we continued waiting or added back to the waiting list if repair capacity was reached. Furthermore, we implemented cumulative usage for a singular component. For each week, *cumulative_usage* increased by 1 for each component. If *cumulative_usage* was greater than 1, we adjusted the failure rate based on usage and failure rate increase factor. Now, addressing our failure simulation, the simulation used a Poisson distribution to estimate failures based on the adjusted failure rate. From this, we updated the component status to ’down’ if failures occurred and set them to wait for repair with a specified shipping delay. Otherwise, we marked components as ’up’.

3.8. Sample Simulation Output

The output is a detailed week-by-week timeline showing components' statuses: up, down, undergoing maintenance, being repaired, or waiting for parts, as seen in Figure 3.

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	Week	Component 1 Status	Component 2 Status	Component 3 Status	Component 4 Status	Date	Month
0	1	Up	Up	Up	Up	2024-02-15	2
1	2	Up	Up	Up	Up	2024-02-22	2
2	3	Up	Up	Up	Up	2024-02-29	2
3	4	Maintenance	Maintenance	Maintenance	Maintenance	2024-03-07	3
4	5	Up	Down	Up	Up	2024-03-14	3
5	6	Up	Waiting for Parts	Up	Up	2024-03-21	3
6	7	Up	Waiting for Parts	Up	Up	2024-03-28	3
7	8	Maintenance	Maintenance	Maintenance	Maintenance	2024-04-04	4
8	9	Down	Waiting for Parts	Up	Up	2024-04-11	4
9	10	Waiting for Parts	Waiting for Parts	Up	Down	2024-04-18	4

Figure 3: Simulation output that shows a component and its status. In comparing the outputs before and after adding predictive measures, we can then compare the downtime and readiness of a unit and see the difference that predictions make in a unit's operational readiness.

3.9. Simulation Use

The simulation developed in this research serves as a foundational framework designed to support Army organizations in implementing predictive maintenance strategies effectively. Adopting organizations must recognize key assumptions that significantly influence the simulation's applicability and results. Organizations looking to utilize this simulation must consider these assumptions and may need to adjust these parameters to better fit their specific operational contexts and data characteristics. By doing so, they can enhance the simulation's accuracy and reliability, ensuring that predictive maintenance strategies are both realistic and effective in improving operational readiness and reducing downtime.

4. Results and Future Work

The simulation and modeling efforts provided here demonstrate a framework for evaluating the utility of predictive maintenance by quantifying the decrease in vehicle downtime which can significantly improve unit availability. The scope of our research could be expanded with access to more diverse data sources, which would allow for a broader analysis of Army operations across a wide variety of platforms. Furthermore, our modeling approach introduces a simulation that could be expanded with additional features and additional input data. One additional feature worth considering is incorporating the error rates of the predictive models and the impact of predictive model quality in the simulation. This would provide a more realistic view of implementation.

In conclusion, this paper demonstrates the significant advantages of predictive maintenance in the Army's Maintenance Process. The shift from a reactive to a predictive maintenance model has the potential to revolutionize army asset management, and also directly improve readiness and effectiveness on a larger scale.

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