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VIABILITY OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN VEHICLE SYSTEM LIFE CYCLE MANAGEMENT

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ABSTRACT

Traditionally, the life cycle management of military vehicle fleets is a lengthy and costly process involving maintenance crews completing numerous and oftentimes unnecessary inspections and diagnostics tests. Recent technological advances have allowed for the automation of life cycle management processes of complex systems. In this paper, we present our process for applying artificial intelligence (AI) and machine learning (ML) in the life cycle management of military vehicle fleets, using a Ground Vehicle fleet. We outline the data processing and data mapping methodologies needed for generating AI/ML model training data. We then use AI and ML methods to refine our training sets and labels. Finally, we outline a Random Forest classification model for identifying system failures and associated root causes. Our evaluation of the Random Forest model results show that our approach can predict system failures and associated root causes with 96% accuracy.

1. INTRODUCTION

Systems Engineering is a widely used framework for developing a variety of complex systems, using traditional engineering tools and methodologies. Systems Engineering paradigms are frequently used in vehicle systems maintenance for data gathering, system health monitoring, degradation tracking, maintenance scheduling, task prioritization, and parts ordering. This is especially true for complex vehicle weapons platforms deployed in military operations where the cost of unforeseen failure comes with a steep price tag and potential loss of life. The Department of Defense in their Condition Based Maintenance Plus (CBM+) Guidebook states, “At its core, CBM+ is maintenance performed based on evidence of need provided by…enabling processes and technologies [using] a systems engineering approach to collect data, enable analysis, and support the decision-making process for system acquisition, sustainment, and operations.” [1]

The mission capability (mission readiness) of vehicle weapons platforms is of the utmost importance in military operations. It is important that all vehicle weapons platforms are Fully Mission Capable (FMC) prior to deployment, as the classification of a single system as Non-Mission Capable (NMC) or Partially Mission Capable (PMC) can be enough to cancel or alter a mission minutes before deployment. Oftentimes the mission readiness of a vehicle or weapons platform comes from the operator's testimony from pre and post operating checks and platform operation in training and combat exercises, which the maintenance crew is provided. The maintenance crew will receive operator or user reports and run diagnostic tests on the system to verify problems with platform subsystems and perform the necessary maintenance. The weakness of this approach is two-fold, 1.) It relies on humans-in-the-loop to both identify and diagnose platform subsystem health, and 2.) It requires expert level domain and environmental knowledge to verify the identified problem and diagnostic solution. There have been recent efforts to relieve the reliance of expert level domain knowledge by introducing state-of-the-art sensing technologies [2],[3]; however, the humans-in-the-loop remains to analyze sensing data and run diagnostic tests to identify root causes of system failures.

Recent advances in the fields of Artificial Intelligence and Machine Learning (AI/ML) have allowed for the automation of various aspects of the maintenance process. To this effort, Systecon North America set out to assess the viability and application of AI/ML in the maintenance lifecycle of active vehicle weapons platforms in accordance with the CBM+ guidelines.

This article will focus on the utilization of AI/ML models and associated software in fulfillment of the Systems Engineering objectives of CBM+. For this study, a Ground Vehicle (GV) platform will be examined.

The basic operations of a GV in the US Army are mission centric. The process starts on the day of a planned mission with an operator performing a pre-mission inspection for a go-no-go decision. This is followed by the execution of the mission where operating conditions and system failures are recorded by onboard systems and sensors. Post mission the operator will perform a post-mission inspection and provide comments on any failures encountered. These failures are given to the maintenance crew who verifies the mission readiness of the vehicle as FMC, PMC, or NMC, and performs the necessary maintenance.

The GV platform is composed of numerous subsystems that function both dependently and independently of each other and is effectively a System of Systems (SoS). Therefore, for the purposes of CBM+, the maintenance of a GV can be treated as the maintenance of several smaller independent subsystems. This will be the basis for our research in this paper.

2. DATA

Automated modeling and management of complex vehicle weapons platforms requires large amounts of historic mission and maintenance data to train accurate and reliable AI/ML models. For this study, we utilized a subset of historic mission and maintenance data for over one hundred GV systems spanning multiple years. We utilized generalized fleet and system data, mission record data, and maintenance forms for each GV platform.

2.1. Fleet and Systems Data

In any complex Systems Engineering problem domain knowledge is crucial to developing a successful system. We worked with the GV Subject Matter Experts to obtain the data dictionaries necessary to understand the connection between the different GV subsystems, the different GV failure modes and comprehensive Bill of Materials for each subsystem, and fleet specific knowledge about maintenance crew, operator, and units belonging to each GV system

2.2. Operating Records

The most important aspect of CBM+ is understanding the degradation timeline for a system. Without a degradation timeline it is impossible to know when a system has sufficiently degraded to the point of inoperability. estimate determining when and how to perform maintenance. Mission records are essential in understanding the inner workings and timeline for complex systems which necessitates large amounts of historical mission records. Thus, the most comprehensive data we utilized were the individual mission records for each GV system. These records include sensor readings from individual sensors, geo-location coordinates, and subsystem faults and warnings.

2.3. Maintenance Records

Understanding the maintenance process and workflow is crucial to linking system degradation patterns with maintenance events. As such, we utilized a comprehensive set of maintenance records including general maintenance records; part replacement forms; and logs. The general maintenance records contain general information about the initial reason for service, the maintenance task performed, the result of that maintenance task, and any subsequent maintenance tasks and their reasons and results. The part replacement logs catalog individual parts replaced in a GV system and their reason for replacement. The logs contain the daily and monthly manual mission readiness classifications (FMC, PMC, and NMC) for each system.

3. METHODS AND PROCEDURES

3.1. Data Preprocessing

With so many separate data forms and sets with differing timelines, degrees of completeness, and standardization it is necessary to perform extensive data processing, checking, and cleaning before any modeling takes place. There are many problems to look for when modeling a process or system with multiple moving parts, including but not limited to; gaps in data due to vehicle subsystems being turned on and off during maintenance or testing; a mismatch between the timelines of mission records and onboard sensor readings indicating potential problems with system clocks, software, or faulty hardware; and/or a given mission record could be a non-mission maintenance test mission, a period of short missions during maintenance events to validate service tasks.

The most important data for classifying mission readiness and reasons for maintenance are the onboard sensor readings. Each sensor generates sensor readings at different sampling rates; therefore, it is necessary to standardize the readings so that all sensors have a standardized sampling rate of one second. This gives an average reading from each sensor for each second of recorded mission that can be used to model and monitor subsystem/part degradation timelines.

Cross-referencing and validation of disparate datasets is a vital step in automating any complex Systems Engineering process involving data from multiple processes. Cross-referencing and validation will filter disparate datasets and timelines into parts that model a single congruent timeline. The Validation of the sensor and system failure timelines occurs with matching associated mission records. Any sensor or failure timelines that do not have a matching mission record cannot be used in modeling and are discarded. We then combined the remaining congruent sensor and failure timelines into a single degradation timeline for each GV system and its subsystems.

For degradation modeling and monitoring it is important that outliers such as maintenance test missions are avoided. Maintenance test missions muddy the data waters and create high intensity timelines of failure and repair that can confuse AI/ML models. The GV system and subsystem degradation timelines require further cleaning and processing, by matching them to associated maintenance events and periods. The timelines that model short frequent missions matching mission readiness periods of PMC/NMC are filtered out as maintenance test missions. The remaining data consists of usable degradation timelines that will be used to train and test AI/ML models to identify mission readiness or the remaining useful life of a system.

3.2. Data Exploration

Anomaly detection models [4] utilize existing sensor data to find statistical data abnormalities (anomalies) that indicate problems. For example, if the gearbox temperature sensor reading is unusually high or the oil pressure is close to zero, chances are there is a problem with the gearbox. Given a fleet of GV, used for similar missions in the same environment with the same sensors, a distribution can be modeled for each active sensor type in the fleet. These distributions are used to find outlying values, given normal operating conditions, which may indicate failure and decreased mission readiness.

Statistical anomaly identification does not fully explain the data nor is it always accurate in identifying invalid sensor readings. These cases oftentimes require additional domain knowledge to identify different operating regimes of a system. For example, the sensor readings and operation of an GV system may differ drastically between different operational regimes, e.g., low speed maneuvering, high speed operations, and idling. During high speed operations it may be common to see higher than normal fuel usage compared to when idling. The increased fuel usages could be normal for high speed operations and it could conversely indicate the failure of fuel pumps leading to fuel leakage while idling. A statistical anomaly detection model may miss these anomalies without sufficient knowledge of these operational regimes. Identification of these regimes should occur, and data categorized by regime; however, discovering these regimes is challenging because it requires simultaneous segmentation and clustering of the time series.

Subsequence clustering of multivariate time series is a useful tool for discovering repeated patterns in temporal data [5]. Once patterns have been discovered, complicated datasets can be interpreted as a temporal sequence of only a small number of states, or clusters (Regime).

The relationships and correlations between sensors in different Regimes can help identify the causation of sensor failure and is invaluable in understanding the root cause of a problem. For example, understanding that there exists a correlation between throttle position, rotor RPM, and vehicle speed is key. If increased throttle does not sufficiently increase vehicle speed but does increase engine RPM, there may be strong headwinds reducing vehicle speed. If increased throttle does not result in increased engine RPM there is likely a problem with the transmission assembly or engine. Understanding these correlations and important items helps identify the root cause of identified problems.

3.3. Modeling

Predictive modeling applications often utilize AI/ML algorithms and models. In our approach we trained multiple Random Forest [6] classifiers. A final model was selected by maximizing the F1 score on the validation set. The F1 score is used due to its ability to reward correct positive and negative classifications while penalizing incorrect classifications.

Random Forest models are nothing new to the field of AI/ML applied to sensing technologies; however, the utilization of such models has not seen wide adaptation in CBM of complex systems due to the "black box" nature of such models. The outputs of traditional AI/ML models do not intrinsically explain the route that model inputs (sensors and failures) map to obtain the model's output (mission readiness), nor is the importance of each input explained by the model.

To fill this gap and provide a transparent model we incorporate the Shapley Additive Explanations (SHAP) values [7]. SHAP values allow "black box" ML models to provide explanations for their outputs, including the importance of each input. These SHAP values are crucial for understanding which sensors are the root cause of system failure and impact mission readiness.

Use of SHAP values for each mission readiness prediction help identify the sensor importance to the mission readiness prediction, and the relationship between system failure and the individual subsystems/parts in an GV system and to further use these relationships to identify the root cause of mission readiness. We used maintenance testimony and verified maintenance logs to validate the accuracy and conclusions of our AI/ML model.

4. RESULTS

The Random Forest model achieved a final F1 score of 97% and accuracy of 96% on the test set. This proves that AI/ML is indeed a viable candidate for use in life cycle management for vehicle systems.

5. CONCULSION AND FUTURE WORK

In this study we have proven the viability of utilizing AI/ML in Systems Engineering process for the lifecycle management of complex vehicle weapons platforms. We have identified that with proper data cleaning and regime identification it becomes possible to construct meaningful sensing timelines for use in predicting asset degradation and readiness. This in combination with model explanation through SHAP analysis allows for the detection and remediation of system failures without necessitating human involvement. We leave the topics of; using forecasting models to model future mission readiness; incorporating environmental variables and domain knowledge into degradation models; automated maintenance scheduling and prioritization; and intelligent parts selection for future research efforts.

6. REFERENCES

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