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RELIABILITY MODELING TO INFORM THE DEVELOPMENT OF ON-PLATFORM PREDICTIVE ANALYTICS

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ABSTRACT

Implementing Prognostic and Predictive Maintenance (PPMx) for the U.S. Army's ground vehicle fleet requires the design and integration of on-platform predictive analytics. To support the design process, U.S. Army DEVCOM Ground Vehicle Systems Center (GVSC) and Applied Research Laboratory (ARL) Penn State researchers are developing a systematic approach that uses reliability modeling in a guiding role. The key steps of the process are building the initial reliability model from available data (e.g., system diagrams and physical layouts), augmenting with information on observed states and failure modes via subject matter experts, and then conducting trades on additional sensors and algorithms to determine a suitable predictive analytics capability. In this paper we provide an example of this process as applied to an Army ground vehicle, first focusing on a simplified sub-problem to demonstrate the technique, then providing statistics on the large scale process.

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1. INTRODUCTION

Although the Army has been conducting ground vehicle Condition Based Maintenance Plus (CBM+) related efforts for years, there has been a resurgence of interest and resources put toward this area in the recent decade. This area of interest has gone through a name change, and is now referred to as Prognostics and Predictive Maintenance (PPMx). With improved data collection technologies, as well as increased capabilities in data transmission, processing and analysis, the Army is working to apply the benefits of these new and improved predictive analytical capabilities in order to provide advanced troubleshooting techniques and insights for every echelon of decision making – from the enterprise, to the Program Manager, to the maintainer.

One of the biggest challenges in beginning to implement PPMx data collection and analysis techniques to large Army ground vehicle platforms is to determine what data is available, what data should be collected and monitored, and how that data will be used. Although it sometimes sounds appealing to collect more data, that is not always necessary, nor are there always the analytical resources to consume that additional data. One technique that is a powerful tool in determining what data is necessary to collect and what critical components / subsystems to focus on for PPMx algorithms is Reliability-Centered Maintenance (RCM) Analysis. According to MIL-STD-3034A [1], "Reliability-Centered Maintenance (RCM) Process," there is a strong relationship between RCM and CBM+/PPMx. As outlined in Appendix F of MIL-STD-3034A, "The objective of CBM is that maintenance is performed based on objective evidence of need. RCM is the foundation for CBM; it is the process that is used to develop the maintenance tasks needed to implement CBM." According to DODI 4151.22-M [2] on Reliability Centered Maintenance, "CBM+ is maintenance performed on evidence of need provided by RCM analysis and other enabling processes. CBM+ uses a systems engineering approach to collect data, enable analysis, and support the decision-making processes for system acquisition, sustainment, and operations."

Throughout this paper, we will discuss reliability modeling and its crucial role in designing and developing on-board predictive analytics. These reliability models can be used for RCM analysis to determine which failure modes and components are the best candidates for monitoring and implementation of PPMx.

A key component of a PPMx system for the U.S. Army's ground vehicle fleet is *on-platform predictive analytics*. Implementing the predictive analytics requires determining what additional sensors are needed for health monitoring, and what algorithms to use to identify current, and predict future, health states. Evaluating a notional predictive analytics solution requires simulating the system, exercising its different failure precursors and failure modes, and evaluating the success of the solution in detecting and predicting the failures.

To support the design of the predictive analytics, U.S. Army Ground Vehicle Systems Center (GVSC) and Applied Research Laboratory (ARL) Penn State researchers are developing a systematic approach that uses reliability modeling in a guiding role. The reliability model captures failure modes and statistics for individual components of a system, then through interconnections of components it captures how component failures propagate to system failures. It also captures the (potentially) observable parameters of the system operation (e.g., voltages, pressures) that can be sensed to develop an understanding of the system's health state.

The key steps of the process developed by GVSC and ARL Penn State are building the initial reliability model from available data (e.g., system diagrams, manuals, and physical layouts), augmenting the model with information on observed states and failure modes via subject matter experts, and then conducting trades on additional sensors and algorithms to determine a suitable predictive analytics capability. The approach implemented by this team is shown in Figure 1.

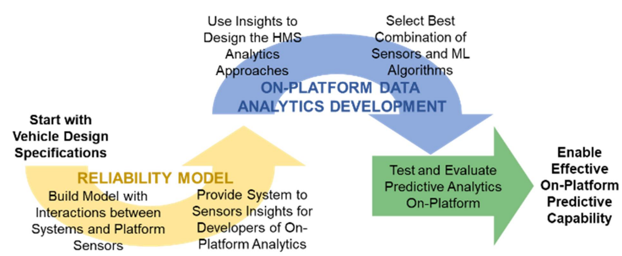

Figure 1: Approach for developing health monitoring system (HMS) technology

In the remainder of the paper we first provide an overview of the predictive analytics design problem, and where reliability modeling plays a role. Next we discuss the modeling environment and approach adopted. The implemented process is demonstrated on a simplified sub-problem to highlight the steps in building and exercising the model. Then the entire system model is addressed, presenting statistics on model complexity and failure processes. The paper concludes with a summary of results and next steps.

2. PREDICTIVE ANALYTICS PROBLEM

The fundamental problem for predictive analytics (PA) is to observe the system under consideration and infer the system's state of health from the available sensor information, as shown in Figure 2. In this paper, we use the Joint Light Tactical Vehicle (JLTV) as the example ground vehicle. It is important to note that the example in this paper uses a simplified example, meaning the representation of the JLTV cooling system is modified – not an exact, detailed representation of all of the components and connections found in the actual JLTV design. It is a generic example assigned to an actual Army ground vehicle platform in order to demonstrate the relevance of this type of modeling and optimization process to the PM.

The ideal state of vehicle health monitoring is that at each moment the PA is able to assess the health of every component in the system. However, this is both unrealizable due to the sensing that would be required, and unnecessary due to the high reliability or lack of criticality of many of the components. Therefore, the PA is typically designed to infer the state of a critical subset of failure modes and the components that cause and are affected by them. This is derived via a *Failure Modes, Effects, and Criticality Analysis* (FMECA), conducted with the aid of subject matter experts. According to the Defense Acquisition University (DAU), "The FMEA/FMECA is a reliability evaluation/design technique which examines potential failure modes within a system and its equipment, in order to determine the effects on equipment and system performance. Each mode is classified according impact on mission success and safety to personnel and equipment [3]."

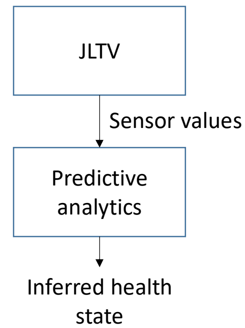

Figure 2: Predictive analytics

A key decision in developing the PA is determining the suite of sensors to use to infer the health state. Systems like the JLTV already have sensors as part of the system - the designer can choose to augment the system with additional ones in order to gain the necessary insight.

PA can infer failed components via at least two means; from direct measurement, and from inference using other measurements and knowledge of the observed system. As sensors have a cost, add weight/complexity to the sensed system, and can themselves fail, it is desirable to use only a minimal set of sensors while accurately determining system health.

This is where reliability modeling can impact PA design. Reliability modeling decomposes systems into their constituent subsystems and on down until modeled at individual components (or some level of abstraction). Properties such as sensed outputs and failure modes can be captured. Next, connections are captured for components, subsystems, and up to the system level. The *connections*, which can also be labeled as *couplings* or *flows*, are one of two types: explicit or implicit. The explicit connections are as captured in the documentation, for example the flow of hydraulic fluid from pump to actuator. System schematics will clearly show these for the systems, and they can be captured in the reliability model directly. The reliability model can then reason about them, and infer that if one fails then so does the other (if in sequence).

The implicit couplings are where components are not directly coupled as part of the design, but they are coupled due to proximity in the physical layout. For example, two components co-located in a space may couple directly (e.g., data flow) but may also couple thermally and through vibration due to their proximity to each other. This may result in their failures in the physical system being coupled. While the reliability model will not identify their coupling, subject matter experts can model their dependency via other means, ensuring their interconnection is captured.

Sensors for the components and their connections are also added to the model. As physical components, they also have failure modes and interdependencies the same as the basic system components, and their addition drives up system complexity. In designing the PA, there is a natural tradeoff between maximizing health state knowledge through sensing, and minimizing system complexity and cost.

A reliability tool can now analyze the components and their connections, and automatically develop fault trees that map component failures to subsystem and system failures. And as is critical to PA design, *the ability of sensors to localize the failures to specific sets of components can be assessed*.

A PA designer now has two key capabilities: the first is the ability to experiment with different sensor suites and easily determine whether they enable sufficient localization of top level faults to components. Second, the reliability model contains the fault tree information needed for the designer to build an advanced predictive analytics capability that can infer component failures for the case where the failed component cannot be localized just from the sensor data.

3. MODELING PROCESS EXAMPLE

This section discusses the modeling approach that ARL Penn State used, based on PHM Technology's *MADe* software [4, 5] for the reliability modeling of a Joint Light Tactical Vehicle (JLTV). While the full vehicle model capturing all of the system's complexities is being used for the analysis of possible additional sensor(s) that would add value based on the criticality of the failure modes detected, only a simple model of a subsystem is provided here as an illustrative academic example.

The process starts with the development of a functional model from its design specifications. With the primary emphasis on optimizing the design of predictive analytics technologies, the vehicle's subsystems and components are modeled and the functional dependencies between the components are mapped. This allows the team to conceptualize the vehicle as both a system and as independent components. A simplified example of the JLTV cooling system is shown in Figure 3.

Each component in the model contains physical properties that are capable of being monitored. These properties consist of the temperatures, pressures, volumes, etc. that flow between components and affect the performance of the system.

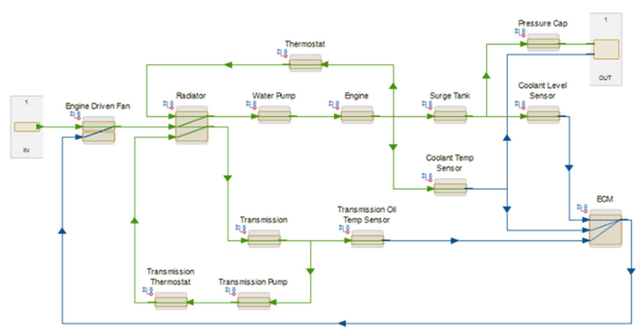

Figure 3: JLTV simplified cooling system – no additional sensors suggested by MADe

3.1. Aids in Selecting Sensor Sets

The MADe reliability modeling software contains a *Predictive Health Monitoring* (PHM) module that can determine, for a particular sensor, which component failures it can detect; and for a particular component failure, which sensors detect it. The module further provides the set of components that a failure can be narrowed to based on a sensor reading (the *ambiguity set*). Of particular utility is the ability to designate key failures and components to be monitored (and ones that can be ignored) and have the PHM module identify potential sets of existing and added sensors that will identify failures with a specified level of acceptable ambiguity.

The ARL Penn State team created a separate, simplified model of the JLTV's cooling system to experiment with the MADe PHM module's capabilities and explore its usefulness to predictive algorithm development. Figure 4 shows the legacy set of sensors that are organic to the cooling system, then candidate sensor sets to be considered. For each sensor set, the tool provides information on which faults can be detected and which components can be localized. The size and members of ambiguity sets, and other key attributes of interest to a PA designer are also obtained through use of the tool.

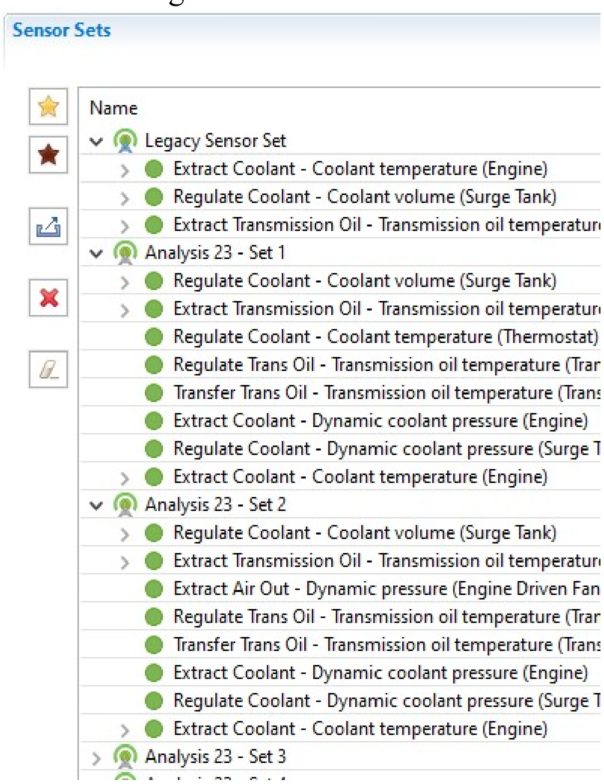

Figure 4. Candidate Sensor Sets for the JLTV cooling system

3.2. Aids in Designing PA Algorithms

The process used to develop the reliability model provides critical information for the engineers and data scientists responsible for developing on-platform predictive analytics. These developers may not be familiar with the platform or the interactions between its components. A reliability model, including those created using the MADe software, can provide the algorithm developers with an overview of the platform's component layout, details about physical properties and their flows between components (such as temperature and pressure), and locations of existing and recommended sensors.

Interdependencies become clear as relationships and feedback between equipment are displayed, allowing the engineers to visualize how faults can propagate through the system. They can use this knowledge to select combinations of sensors and machine learning (ML) techniques that can extend detection beyond direct sensing, and allow the ability to predict future failures based on observed trends.

As an example, the simplified JLTV cooling system sub-problem used here has clearly identified the existing sensors and component interactions to the ARL Penn State predictive algorithm development team. A top failure identified by a subject matter expert for the JLTV is an engine overheat caused by a blocked radiator. The ARL Penn State team was able to use the MADe reliability model to quickly determine that the JLTV cooling system cools both the engine coolant and the transmission oil, and therefore both the existing engine coolant temperature and transmission oil temperature sensors could be used as inputs to an Engine Overheat predictive algorithm. The interdependencies between components, even in separate subsystems, becomes apparent by using the model. These interactions may not be obvious by looking at a spreadsheet of failure modes or reading through an instruction manual. By having a visualization of the functional relationships and failure propagations throughout the vehicle system, engineers and analysts can efficiently identify the data flows and states that need to be measured on a vehicle in order to accurately identify the conditions surrounding faults, failures, and degraded operation. The cooling system example contains less than 15 components. As one can imagine, the value of using the model increases exponentially when dealing with hundreds of Line Replaceable Units (LRUs) on a given system. The interdependencies between these components (1st order, 2nd order, 3rd order, etc.) can be less easily traced manually. The sensor set optimization algorithms which present coverage of failure modes simplifies the work of the analyst as well, as the goal is not only covering as many critical components as possible, but also multiple failure modes on those components, which can have varying degrees of criticality themselves.

We modeled the major components of JLTV, breaking the vehicle down into the following major subsystems: Engine, Transmission, Driveline, Suspension-Hydraulics, Pneumatics-Brakes-Central Tire Inflation, HVAC, and Fire Suppression. Failure modes were implemented based on input from subject matter experts. Analyses were conducted on each subsystem as well as the entire vehicle to develop sensor set solutions.

The next step will be algorithm development based on the sensor set options provided, trading on the number of sensors and usability of the sensor data by the algorithms to provide the desired PA component coverage. The model will be refined to account for the algorithms in reducing the required amounts of sensors. The model will also be updated as "new" failure modes are encountered and discovered through testing and operational usage of the vehicle. Maintenance strategies will be developed based on this information to increase reliability and maximize availability.

4. CONCLUSION

Developing predictive analytics involves identifying what parameters of a system need to be sensed, and implementing algorithms to process the sensor data to infer current and predict future failures. The key to both of those tasks is developing a model that can assess the ability of a set of sensors to identify and localize faults, and that contains information on the dependency of system health on the health of its subsystems, as well as individual components. A reliability model contains both of these attributes. By incorporating reliability modeling into the health monitoring system design process, we will be able to demonstrate the ability to create a more optimum on-platform predictive analytics capability, central to the Army's efforts to better achieve higher states of system readiness.

5. REFERENCES

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