2018 NDIA GROUND VEHICLE SYSTEMS ENGINEERING AND TECHNOLOGY SYMPOSIUM
SYSTEMS ENGINEERING (SE) TECHNICAL SESSION
AUGUST 7-9, 2018 - NOVI, MICHIGAN

SIMPLIFIED APPROACH ON DEVELOPING PREVENTIVE AND CORRECTIVE MAINTENANCE STRATEGY

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ABSTRACT

Developing preventive and corrective maintenance strategies for military ground vehicles based on asset readiness and lifecycle cost is a challenge due to the complexity associated with the collection and storage of maintenance and failure data in the operational environment. Many of the past reliability centered maintenance efforts have encountered significant challenges in collecting, identifying, accessing, cleaning, enhancing, fusing, and analyzing the data. Another challenge is creating and maintaining complex simulation models that require significant effort and time to produce business value. The work described in this paper is the result of a collaborative effort among multiple US Army organizations to simplify the approach in order to gain valuable insight from the existing data. It is shown how the resulting process can be used to develop simplified models to optimize corrective and preventive maintenance programs. Details are provided on how to work with the existing data sources in order to develop and implement methods at the program management level. The simulation results demonstrate the benefits for the maintenance teams, logistics teams, operation teams, fleet planners, and warfighters.

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INTRODUCTION

Embracing emerging technologies and leveraging new methods of data analysis are at the heart of the Army's effort to advance predictive analytics to create more efficient maintenance strategies. In addition to sensor data, historical maintenance data can be utilized to implement time and cost efficient maintenance strategies. Leveraging maintenance data is the cornerstone behind Reliability Centered Maintenance (RCM). The RCM helps to focus on the Preventive Maintenance (PM) rather than the Corrective Maintenance (CM). Reliability is the probability that an item will perform without failure for a certain period [2]. Increasing reliability and availability are achieved by identifying the mission critical systems, subsystems, and components of the asset. In addition to the cost savings from efficient maintenance scheduling, the availability of the fleet would increase.

Successful implementation of RCM can help develop maintenance and logistic strategies, improve asset readiness, reduce risk, and manage lifecycle cost (refer to Figure 1).

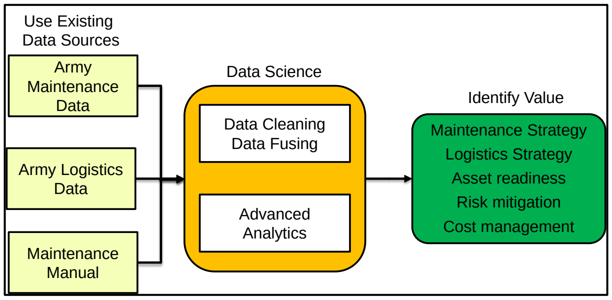

Figure 1. Implementing RCM

Due to the complexity in collection and storage of failure and maintenance data, few RCM efforts are implemented successfully. Efforts are being made to use existing Army maintenance data to develop models that will allow performing PM and aid in implementing predictive maintenance (PdM). A simple and clear methodology to perform a data-driven RCM effort is needed to identify necessary data sources and to develop failure models. A reliability block diagram (RBD), a simple model in which "blocks" correspond to component(s) at the line-replaceable unit (LRU), is a useful method for representing the interactions and dependencies in a vehicle subsystem.

Several RBDs can be connected together to model a complex, multi-leveled vehicle system, however, a model's results can only be as good as the data that is used to create it. Thus, finding reliable and clean data is critical and is often times one of the most difficult steps in any analytical process. The analysis approach discussed in this paper is generalizable to maintenance programs for ground vehicles. The approach includes the following:

1. Identification of vehicle systems, subsystems, and components
2. Identifying failures & successes
3. Development & validation of mathematical models

Implementation of a vehicle fleet simulation algorithm is also presented as it is used to help develop maintenance strategies. Depending on the selected ground vehicle programs and their data sources, these techniques can be refined and replicated.

In general, a RCM approach focuses maintenance activities on preserving the functionality of the assets. RCM programs should be able to define maintenance strategies that optimize operational availability and affordability of the vehicles. One of the important performance metrics for the Army is asset readiness or availability. Reliability and maintainability play significant roles in the computation of the availability metric. Therefore, asset readiness or availability prediction can be performed once the reliability and maintainability events are modeled correctly.

STANDARD APPROACH TO RELIABILITY

The general approach of creating a method to build RCM predictive capability consists of problem definition, data exploration, modeling, validation, and implementation.

1. **Problem definition**: Understand the context and formulate what problem of the asset will be solved. It is an important aspect of the process. During this step, understanding the intended use of the asset is very critical. It can vary depending on the asset owners/customers.

2. **Data exploration**: Identify relevant data, clean it, and do the exploratory data analysis (EDA) to get insight about the problem domain.

3. **Modeling**: Build models, either descriptive or predictive, and make sure that the assumptions are realistic.

4. **Validation**: Need to validate the model and make sure that the model satisfies the business needs.

5. **Implementation**: Implement the model so that the business user start using it to make evidence-based decisions, also determine how often the models need to be updated.

Based on the performed study, the standard approach was uniquely modified for the Army vehicle programs of interest. Current and historical maintenance records of the components of the assets should be used to develop a predictive model. However, these details are very hard to gather in a large organization such as the US Army. Furthermore, the data sources can vary depending on the vehicle program. Therefore, a tailored version of the standard approach was used in practice.

RCM RECIPE

Based on the recent study on a US Army vehicle platform, the following information is needed:

1. Identify maintenance data sources
    a. Historical maintenance data sources
    b. Current maintenance data sources

2. Identify components by part number or National Stock Number (NSN)

3. Identify failures / success and quantity / life
    a. What failed?
        i. System
        ii. Subsystem
        iii. Components
    b. How many failed?
        i. Failure count
        ii. Success count (suspension count)[1]
    c. How did it fail?
        i. Standardized words to identify failures
        ii. Free form text by maintenance personnel
    d. When did it fail?
        i. Hours
        ii. Miles
        iii. Days

4. Identify cost
    a. Components or system cost
    b. Maintenance cost
    c. Down time cost or opportunity cost

IDENTIFYING DATA SOURCES/GAPS

Identifying Data Needs

As mentioned previously, identification of reliable data sources is a critical component to any analytical process. If not all of the data can be found in one data source, there must be an effort to discover the data sources.

During the gap analysis of this study, no single data source was found to have all of the necessary information to conduct the reliability analysis. Therefore, multiple data sources were used in conjunction. This situation is typical in large organizations such as the US Army. Thus, developing techniques that utilizes a combination of data sources is crucial.

Substantial effort was needed to combine existing Army data sources that met the requirements of performing a LDA on a specific ground vehicle platform. The study team consulted with the Original Equipment Manufacturer (OEM), Program Management office (PM), Army Command Logistics Support Activity (LOGSA), Army Materiel Systems Analysis Activity (AMSAA), and Global Combat Support System (GCSS).

After the maintenance data from each organization were merged and analyzed, it was determined that the Army does in fact have sufficient historical data to proceed further with their efforts to implement reliability centered maintenance strategies.

Figure 2 shows how the key information was gathered and used.

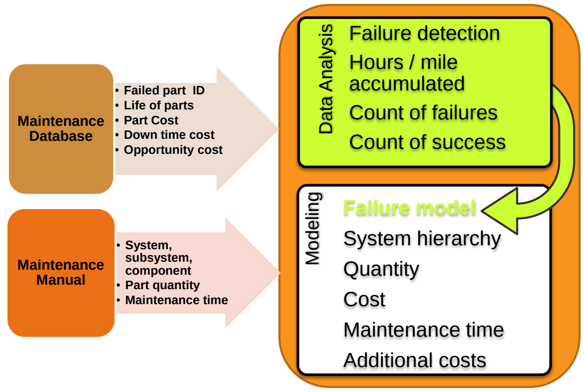

Figure 2. Data Sources Information

Identifying Failure

From the maintenance database, identifying what part failed is confusing and challenging. Due to the current maintenance practice and record keeping methods, large uncertainty is introduced in the army maintenance records. Future programs should address these concerns to improve the maintenance programs.

Typically, the maintenance records capture failed part number, replaced part number, failure observation comments / complaints, and maintenance action. It is necessary to understand what these terms mean in the context of the data collection.

1. Failed part number: This is the part number of the component that failed. This record may not be reliable because the maintenance mechanics, presumably, do not have the means to verify the part number before entering into the maintenance database. In addition, no robust process is implemented to identify root cause of the failure.

2. Replaced part number: This information is typically reliable because correct part should be ordered or checked out from the parts crib. The study used replaced part number to infer failed part number. The accuracy of linking actual part failure to replaced part number depends on how robust the maintenance program and its record keeping practice. Few observations suggest that there are evidence of “no” failures on parts that deemed failed parts in the maintenance records.

[1] *“Success” and “Suspension” have the same meaning in reliability analysis. Suspension is the hours and miles accumulated on the components that are still in operation without failure [1]***.**

3. Failure observation and comments: Capturing detailed failure information is critical to having a successful RCM program. This is typically a text record that will take one of three forms:
    a. Detailed explanation of the failure
    b. A few words about the failure
    c. Left blank or N/A

4. Maintenance action: Knowing if the part is replaced as part of preventive maintenance or corrective maintenance makes a difference in the reliability analysis.

Implementing reliability centered maintenance programs requires significant attention early in the program to reap its full potential. Once it is implemented correctly where good quality data are collected, implementing optimized maintenance strategy becomes straightforward.

Quantifying Failure

To perform a good reliability prediction, it is important to know how many specific parts failed and how many parts are still in operation. As shown in Figure 3, the vehicles that failed are part of failure data and the vehicles that are still in operation are part of suspension data.

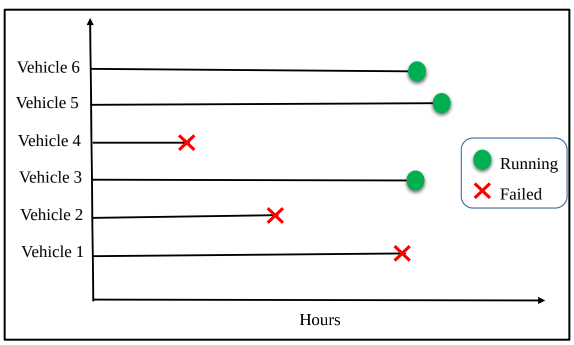

Figure 3. Failure and suspension needed

This type of data is called right censored data. For the ground vehicle programs, identifying failures and suspension of vehicle systems, subsystems, and components require further processing from the maintenance data. Many vehicles do not have start of service date or manufactured date in the maintenance database.

To establish zero hour on the vehicle, you can search the very first record and assume it as the zero hour. To establish suspension data, you have to find out the latest record of the vehicle in the maintenance record. No failure entry in the maintenance record is a data point for suspension.

Model Configuration

Another major obstacle in performing effective RCM is the creation of a model, which accurately represent the systems and subsystems. Depending on the level of detail in the model, there may be several layers of subsystems and many complex relationships between components in the subsystems, such as redundancy or k-out-of-n configurations. Models must not only represent the failure characteristics of the LRU components, but also contain the complete system hierarchical relationships between components, subsystems, and systems.

In this study, one of the most useful documents was the Interactive Electronic Technical Manual (IETM) provided by LOGSA. The IETM provides comprehensive details on the system, subsystems, components, maintenance process, and tools needed for maintenance of the vehicle. For RCM, this manual can be used to identify part numbers or NSN numbers in order to build RBDs for the systems and subsystems. The manual contains assembly pictures and depictions of the relationship between all components and subsystems contained within the vehicle. The subsystem-system breakdown structure used in most IETMs is an intuitive method for creating functional working groups for modeling purposes. Thus, this was the method used in this study. For example, all components contained within the IETM's power pack subsystem were grouped together within the same power pack diagram in an RBD.

Along with the specific installation instruction for pre-assembled parts, the IETM contains the exact quantity of all parts used within a subsystem. This part count is an important data feature needed for life data analysis (LDA). The LDA uses a statistical method in determining the behavior of the life of a component. LDA is best performed at the LRU component level. Based on the Army maintenance data gathered from the IETM, every repairable system is composed of non-repairable items at this LRU component level that can be replaced with a new part.

In this study, the models created from the life data analysis estimate the failure rate of the components as a function of either hours, miles, or days and probability of failure at a given age or for a given period. The resulting failure rate is a mathematical representation of the failure and is given as a series of continuous functions to allow for simulations and experimental analyses. The accuracy of these subsequent simulations is heavily dependent on the quality of the failure data collected.

The probabilistic models are based on the statistical distributions. Figure 4 shows the most commonly used statistical distributions.

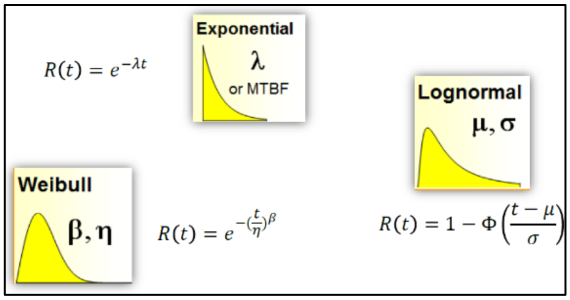

Figure 4. Commonly used statistical distribution

As discussed previously, reliability is a statistical measure based on function of time or usage. For the Army maintenance program, it is important to define and collect "failure time." It is also important to collect the suspension details of the components.

SOFTWARE ANALYSES

Life Data Analysis

After identifying the necessary data sources to perform a life data analysis and create a system model, the next stage is data processing in order to create a methodology for identifying failures at the LRU level. Data processing can vary depending on the data and data sources. There are multiple programming languages available as open source codes (e.g. R & Python) that can be utilized efficiently to clean and analyze the data. Before conducting any type of data analysis or data cleaning, performing an exploratory data analysis (EDA) helps expedite the analysis process.

EDA helps to gain insight about the problem domain. In this study, the EDA was conducted on the following variables:

1. Vehicle Identification Number
2. Odometer Hours
3. Odometer Miles
4. Failed Part Number
5. Failed Part Description
6. Ordered Part Number
7. NSN Number
8. Failure Identification or Complaints Failed
9. Part Description

It was found during the EDA, neither the failed part number nor the failed part description was recorded consistently throughout the entire collection period. However, the ordered part number was recorded consistently. Therefore, this detail was used to infer failure part description. As discussed before, this assumption can be challenged if the part is replaced without conducting an investigation of a failure.

In order to perform the LDA on this particular Army Vehicle platform and calculate the failure rate of a specific component, the ordered part number was used to identify the instances the component failed, the hours or miles accumulated before the failure, and the life of the component itself. The maintenance database was searched using this ordered part number. However to identify a unique part, the National Stock Number (NSN) is more reliable than using the part number. IETM can provide the part number and NSN number details for a systems or subsystems. After the failure times are found for each component, a failure rate or failure model must be calculated.

Reliability Model

For this study, a multi-platform software, ReliaSoft, was used. The reliability model for each component was linked in the RBDs. If the component level model is updated with new data, the system level model and RBDs are updated automatically.

As mentioned previously, building a vehicle RBD model using component level LRU is the best approach. These components or blocks should be connected into subsystems or into a hierarchy of subsystems that make up a system to develop the maintenance strategy. Figure 5 shows a simplistic example of a vehicle hierarchical breakdown.

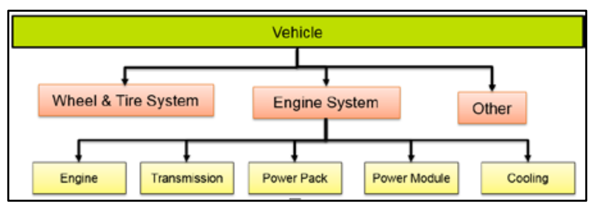

Figure 5. Example Vehicle RBD Hierarchy

Reliability Simulation

Once a model is configured as a hierarchy of components, subsystems, and systems, number of additional business details can be added to build more realistic and detailed models to perform scenario simulations. Each component should be given its part cost, corrective task, preventative maintenance schedule, opportunity cost, etc. All of these details and the features attributed to an individual component are contained within the component's individual block as its Universal Reliability Definition (URD).

Now, the user can run the simulation for any desired length of life cycle time such as 10,000 hours of operation. Upon completion of the simulation, metrics and graphs for availability, downtime, cost, etc. can be populated to develop future maintenance strategies.

SIMPLIFIED RCM APPROACH

A reliability analysis process was developed specifically for a ground vehicle program. However, this process can be replicated across multiple vehicle programs after careful review. This section outlines the steps how to build the life data analysis and RBDs, which will help develop the maintenance strategy.

Step 1: Identify vehicle system hierarchy

From the engineering design point of view, understanding functional interaction helps to prioritize design improvements. From the maintenance point of view, understanding failure rates helps to prioritize maintenance work.

The vehicle can be hierarchically broken down to major systems, subsystems, and components. The engineering hierarchy and the maintenance hierarchy could be different. In this study, the maintenance hierarchy view was considered. Therefore, maintenance practice needed to be understood to define the hierarchy. This hierarchy is used in order to develop the reliability model, which will be used for the simulation. See Figure 6 for an example of a vehicle system, subsystem, and component breakdown. In this example, the power pack was studied. Subsystem and the components that failed for the power packs were modeled in the reliability block diagrams as shown in the green boxes in Figure 6.

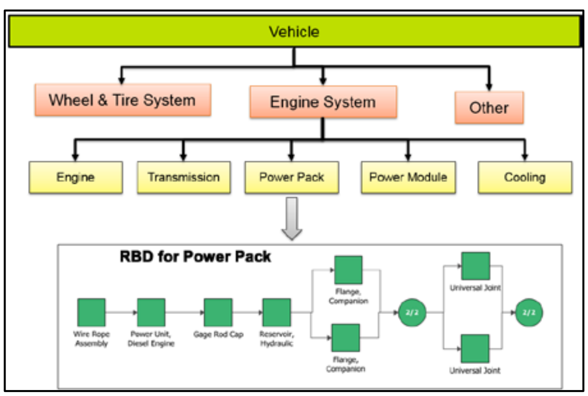

Figure 6. System Breakdown

Step 2: Identify the population and extract failures from that population

In order to do the reliability analysis on a group of vehicles, the first step is to identify a 'homogeneous' population of vehicles. Here the meaning of "homogeneous," is a population of vehicles that were manufactured during a specific period. It is assumed that the vehicles have similar engineering designs, manufacturing process, and applications. The intent behind constraining the study to this homogeneous population is to have similar mechanisms of failure for these vehicles.

The next step is to identify a part number of interest along with a specific failure mode for that part number. However, in the historical data set that was analyzed, failure modes were not consistently captured. Therefore, all the failures for that specific part number from the defined population were included. Maintenance records that included battle damage repairs, resets, accidental damage, and overhaul records, must be omitted as 'non failure' records such that the analysis considered only the records with 'true' failures/replacements. By using this well-defined logic, 'true' failures/replacements can be extracted. Depending on the data source used for the reliability analysis and its features, data extraction logic has to be implemented to capture only 'true' failures/replacements.

Additionally, the accumulated miles and hours for a component's failure need to be captured and used for the RCM analysis. The study discovered that the current maintenance database does not have this information. Therefore, for life data analysis, accumulated miles and hours information needs to be gathered from a different data source. When combining multiple data sources to estimate miles and hours for the failed component, extreme care should be taken for the data quality.

When a single part number is used in multiple locations on a single vehicle, the specific location where the component failed must be known. However, this information was rarely captured in a structured manner in the maintenance data. For example, the Universal Joint is used in two locations, one in the front, and one in the rear of the drive shaft as shown below in Figure 7.

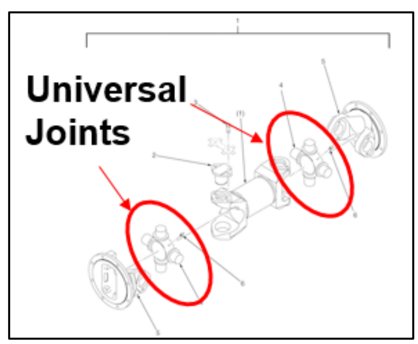

Figure 7. Vehicle Universal Joints

Based on the historical maintenance data, when this part failed, the joint location (front or back) was not specified. In the reliability analysis, it is essential that the specific location of the component is known.

In the example shown in Figure 8, two scenarios are presented to explain this issue. In Case 1, it is assumed that the same location failed each time, which is a very conservative scenario. In Case 2, it is assumed that

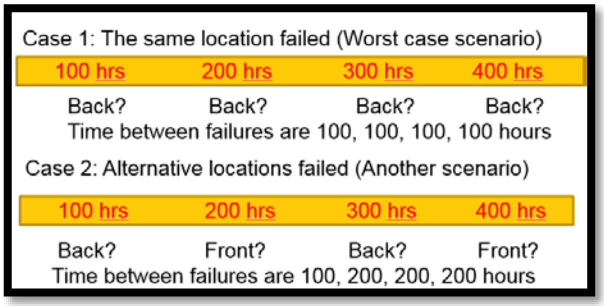

Figure 8. Example of four failures on a single vehicle

alternative locations failed, which is a more optimistic scenario.

In real life, it is unknown what happened unless the failure was recorded carefully and therefore, a realistic assumption has to be made for the failure location (i.e. front or back). The logic used in this study used randomized logic to overcome this issue. Failures were 'randomly' assigned to either one of the two locations and this simulates the 'real life' as close as possible. Using this process, failed part number can be uniquely identified with its location in the vehicle. In summary, every part can be uniquely identified if that part is used in multiple places in a vehicle or in an asset. It is a requirement to perform the life data analysis.

Step 3: Identify failure times and success times

In order to do the life analysis, historical maintenance data is generally used. Both failure data and 'success' data are used in the analysis, so that credit is given to 'success' (or non-failures). There are two types of 'suspension' data, which are illustrated in the following example.

For example, assume that a part number "Part 1" is used in a fleet of two vehicles (homogeneous population of two vehicles). Assume that Part 1 failed in Vehicle 1 at 100 hours and then at 300 hours shown below in Table 1.

At both failures, the part was replaced. At the time of the analysis, the vehicle has accumulated 600 hours and has not fail after the last failure at 300 hours. In order to perform the life modeling, two columns of data need to be created. Column 1 consists of failure/success times. Column 2 consists of failure/success label. In this example, Vehicle 1 failed at 100 hours, then again in 200 hours (300 hours minus 100 hours: the time between failures), then it did not fail but accumulated 300 hours (600 hours minus 300 hours: time since the last failure). This period of 300 hours can be considered as 'suspension' (or 'success') hours and is labelled as 'S'. Therefore, the entries in column 1 for Vehicle 1 are 100, 200, 300 hours. In column 2, the entries are F (Fail), F (Fail), and S (Suspension/Success).

Table 1. Tracking failure and suspension data for Vehicle 1

Hours	Fail/Suspension Flag
100	F
200	F
300	S

Table 2. Merging failure and suspension data for Vehicle 2

Hours	Fail/Suspension Flag
100	F
200	F
300	S
800	S

Now consider another scenario: Part 1 did not fail in Vehicle 2. At the time of the analysis, Vehicle 2 has accumulated 800 hours. For Vehicle 2, since there are no failures, Column 1 will have only one data point of 800 hours and Column 2 will have a label of "S" (Suspension/Success). Table 2 shows the data for the two vehicles combined.

It is important to consider the time between failures and give 'credit' for 'successes', such as in the process defined above. Also, note that either hours or miles can be used in the analysis. For engine failures, hours of usage may be more relevant and for wheels/tire failures, miles of usage may be more relevant.

For any unique part in the vehicle, using the maintenance data, two-column table is generated. For this example, a Weibull distribution was used to fit the data. Any reliability software tool can be used to fit a two-parameter Weibull model to the data set. This

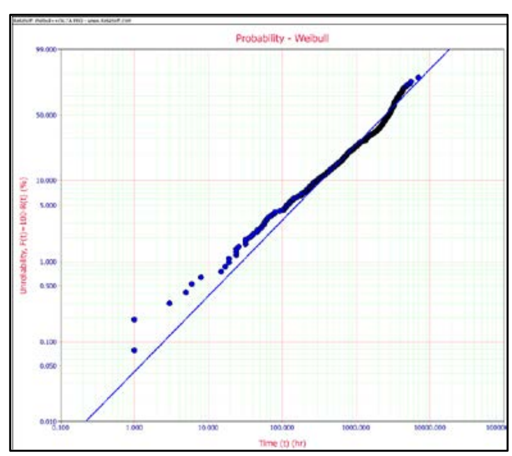

Figure 9 Weibull plot of a component

Weibull model can then be used for prediction purposes.

Figure 9 shows an example Weibull distribution for a component. This model can be used to answer the question, 'what is the likelihood that the power pack will fail at 5,000 hours?' This occurs about 75% mark using the plot. This answer can be used to make informed decisions regarding maintenance practice. For example, one can decide to replace the part in the vehicle proactively at 4,900 hours of operation (Predictive Maintenance – PdM). On the other hand, if the likelihood of failure is less than 1%, then one can decide to wait and replace the part when it fails (Corrective Maintenance – CM). In summary, the life model can be used to make informed maintenance decisions at the part-number level in order to optimize the availability with minimal maintenance costs.

Step 4: Validation

A validation process was used to ensure that the model is accurate enough to be useful, given all the assumptions that have been made. In this example, there were about 380 vehicles in the population. The 'training set' of data was formed by randomly selecting 80% of this population. The remaining 20% of this population is called the 'test set' of data. Then, a Weibull distribution was fit to the 'training set' of data. Using the Weibull model, the predicted the number of failures in the 'training set' was compared to the actual number of failures. It is expected that the predicted numbers of failures would be 'close' to the actual number of failures.

Figure 10 shows an example for the same component that was considered in the previous figure. The blue dot curve is 'predicted' number of failures and red dot curve is for 'actual' number of failures. Note that the population is not completely 'dead' yet and hence we would expect more failures at 'high' hours. Also, note that the predicted number of failures at the 'high' hours is greater than the actual number of failures, which is expected.

This validation process is then repeated for the test set, which has not been used yet. The test set is 'new' and has not been analyzed before.

Figure 11 shows the results of the component using the test set of data. The blue curve is the 'predicted' number of failures using the Weibull model and the red curve is for 'actual' number of failures. Again, the same pattern is observed in that the predicted number of failures at the 'high' hours is greater than the actual number of failures.

In both the training set and the test set, the actual vs predicted number of failures is relatively 'close'. This means that the assumptions and the modeling process are reasonable. Hence, this process can be used to model other part numbers and make maintenance-

Figure 10. Validation on the training set

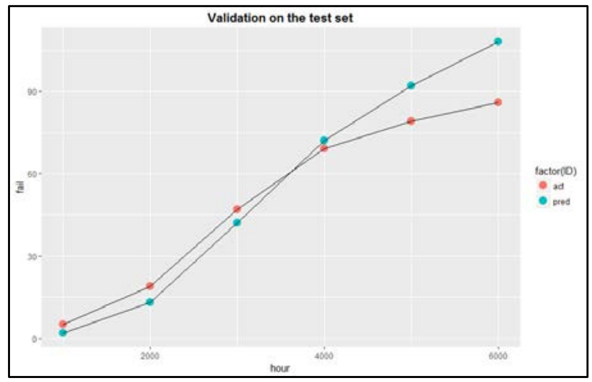

Figure 11. Validation on the test set

related decisions, using this process, with reasonable confidence. Once the validation has been done using a handful of part numbers, and if the results are reasonable, then this process can be implemented. The users do not need to do the validation step on a daily basis. Periodically, the validation process needs to be done by 'modeling experts' to ensure that all the assumptions are reasonable.

Step 5: Fleet Simulation

The previous steps have described the use of a life model to help make decisions at a single part number level. However, the analysis can be expanded to incorporate a fleet of vehicles. For example, assume there are 1,000 vehicles. This means that multiple part numbers in each vehicle must be considered. In order to do PdM in an efficient manner, multiple part numbers should be combined together. Assume that the PdM model suggests that for Part 1 is replaced at 2,000 hours and Part 2 at 2,200 hours. This means that the vehicle would need to be taken to the depot 2 times within 200 hours. Rather it would be more efficient to do PdM once at 2,000 hours for both part numbers together. Since there are thousands of part numbers in a vehicle, it is a cumbersome process to do it manually. Hence, a simulation process is used to model the entire fleet. To conduct a fleet-level simulation, RBDs for a single vehicle should be built and used to conduct scenario simulations. The results of these simulations can be scaled to represent the entire fleet of vehicles.

PM AND CM FLEET SIMULATION

This section discusses one of the usages of fleet simulation using the RCM approach discussed in the previous sections. The example uses notional data and demonstrates the capability of establishing an optimal preventive maintenance strategy, which is relatively easy by using simulation methods based on historical maintenance data [3].

This example considers a fleet of vehicles that has a 2-parameter Weibull failure distribution. Downtime cost is $20/hour and the PM cost is $10 per incident. Life cycle goal is 10,000 hours of operation for each vehicle in usage. Using simulation, the optimum preventive maintenance interval can be computed for the required fleet readiness. The “Time to Failure” block shown in Figure 12 can use failure data given in this example to generate a historical failure model.

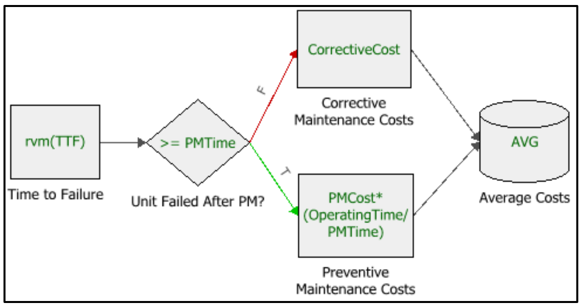

Figure 12. Simulation process for an optimal preventive maintenance interval

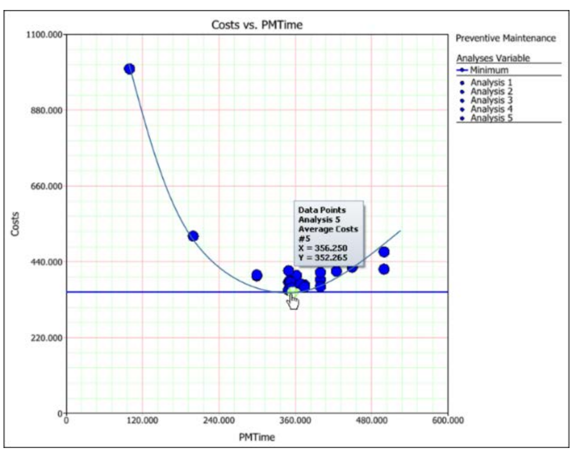

Figure 13. Preventive maintenance time for lowest cost using notional data

When a failure occurs before the preventive maintenance time (PMTime), the repair cost uses the corrective maintenance cost for the total cost calculation, but if the failure occurs after the PMTime, the preventive maintenance cost is used instead. By combining both costs, the average cost of the simulated fleet can be calculated.

Figure 13 shows a plot of the simulated preventive maintenance times and the cost associated with each preventive maintenance schedule strategy for an example using notional data. The variable in the x-axis is the preventive maintenance time and y-axis is the average cost of the fleet. Multiple runs were conducted and they are represented by the data points. The lowest point on the plot found is 352 hours. Therefore, to minimize cost, the preventive maintenance for this example asset should be performed at an interval of 352 hours.

Once the reliability models are built for the fleet, they can be used for many different applications. Simulation tools and methods are already available from the commercial tool developers or from the open source codes. However, as discussed previously, the greatest challenges are bringing together all the data sources, identifying the necessary information, and preparing the data to build reliability models.

CONCLUSIONS

By combining customized data cleaning, data enhancing, and data fusing techniques, the US Army can implement Reliability Centered Maintenance programs based on the existing data sources. Currently, the required data sources are not stored in one location, so they must first be identified and assembled. This effort requires support from the PM office maintenance personnel and maintenance source managers.

The results of this study demonstrate that it is possible to combine data from multiple sources in order to build reliability models using advanced analytics and statistical techniques and thereby develop a maintenance strategy. In order to implement RCM and PdM at the enterprise level, the US Army may want to include additional enabling technologies such as cloud computing and machine learning to link multiple data sources and perform advanced analytics. This could lead to increased asset readiness, reduced lifecycle cost, and improved safety.

ACKNOWLEDGMENTS

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The Authors would like to acknowledge financial and technical support for this research provided by the US Army TARDEC, under the Simulation Based Reliability & Safety (SimBRS) program.

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