Proceedings of the Annual General Donald R. Keith Memorial Conference
West Point, New York, USA
April 24, 2025
A Regional Conference of the Society for Industrial and Systems Engineering

A Data-Driven Approach to Evaluating Armored Brigade Combat Team Equipment Readiness

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Author Note: The authors would like to thank the members of the offices of the Deputy Assistant Secretary of Defense for Force Readiness, DASD(FR), the U.S. Army Chief of Armor (OCOA), and the Army Capability Manager Armored Brigade Combat Team (ACM ABCT) for their time and expertise. The views expressed herein are those of the authors and do not reflect the position of the United States Military Academy, the Department of the Army, or the Department of Defense.

Abstract: We present the key factors that influence an armored unit's vehicle readiness, based on our stakeholder analysis and literature review. Building on these insights, we propose a framework to assess whether these factors have a measurable impact on readiness. We also identify the format of the data required to implement this framework. Since such data was not available to us, we created a synthetic dataset that reflects the expected relationships among the factors. This allowed us to develop proof of concept demonstrating how the framework could be used to detect and quantify their impact. This framework along with the needed data could then be utilized to assist U.S. Armed forces in assessing equipment readiness.

Keywords: Equipment Readiness, Predictive Modeling, Maintenance

1. Introduction

A critical consideration in assessing the military's capacity to engage in conflict is the evaluation of unit readiness. The Deputy Assistant Secretary of Defense for Force Readiness, DASD(FR), has developed predictive models for the readiness of maritime and aviation units for future deployments. This paper evaluates a workflow for assessing ground force equipment readiness. We have scoped our focus to Armored Brigade Combat Teams (ABCTs).

Vehicle readiness in Armored Units is an important factor for commanders to predict when anticipating future deployments. Through this research, we provide a framework for a model that predicts the failure rate and mean time to repair for vehicles based on several different factors that can be measured at armored units. This framework was derived from our stakeholder analysis, in which we identified the three key determinants with the most significant impact on equipment readiness. These determinants were: fleet age, maintainer quality, and the time allocated for maintenance within each training cycle. Our framework will illustrate an example of specific data that could be used to quantify the impact of these factors.

2. Literature Review

To better understand the factors, we needed to incorporate into our model, we first explored how equipment readiness is currently assessed. As shown in Figure 1, we reviewed a RAND study, "Diagnosing the Army's Equipment Readiness", that examined the effects of vehicle age on operational readiness rate (Peltz, Robbins, Boren &Wolff, 2002). The study found a clear trend: as vehicles age, their operational readiness declines. This relationship between vehicle age and readiness informed the way we approached aging in our model.

In addition to equipment age, we also considered the structural context in which maintenance occurs. The U.S. Army uses the Regionally Aligned Readiness and Modernization Model (ReARMM) Unit Life Cycle Model (AST) to regulate the phases its units cycle through. As illustrated in Figure 2, this model includes three primary phases—Modernization, Training, and Mission—with an ideal rotation of eight months per phase. The Modernization Phase is especially relevant, as it is when units perform maintenance and conduct upgrades or resets on their vehicles.

However, the idealized cycle depicted in Figure 2 is not strictly followed in practice. According to the Army Unit Calendar (AST), which outlines the schedules of all Armored Brigade Combat Teams, many units deviate from the prescribed ReARMM cycle. This deviation often results from units being tasked with additional missions under FORSCOM or preparing for deployments, which causes a pulling of resources and personnel away from their scheduled phase activities.

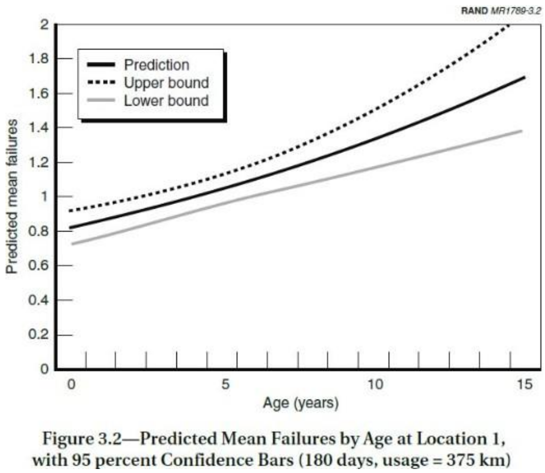

Figure 1: RAND Study

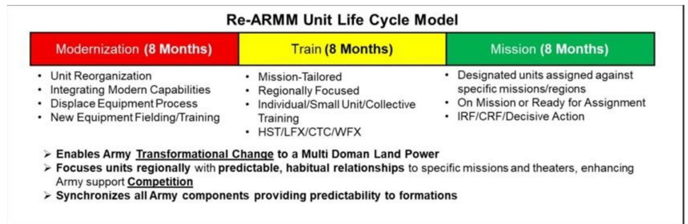

Figure 2: ReARMM

3. Stakeholder Analysis

For this research, we met with a variety of stakeholders for equipment readiness. Our research is sponsored by DASD(FR) and is intended to contribute to the Readiness Decision Impact Model (RDIM) they are developing. RDIM includes models for fixed-wing aviation and maritime force elements, and our work is meant to inform development of a ground forces model. We scoped our research down to ABCT equipment readiness specifically to help create a framework that could become a component of the RDIM ground forces model. Our in-progress review with DASD(FR) gave us valuable feedback on that initial scoping.

We also met with several of the foremost experts on armor equipment readiness in the U.S. Army. Members of ACM ABCT, a key stakeholder, which included Armor branch officers, NCOs, and civilian maintenance technicians, gave us insight on the variables that we decided to focus on for our literature review. Following this, we met with the U.S. Army Chief of Armor, who gave us important context on some of our initial research and guidance on how to further scope what we found during our literature review. These subject matter experts recommended that the relationships we should focus on quantifying were the impacts of age of fleet on vehicle failures, maintenance schedule windows' influence on overall maintenance time, and the impacts of maintainer quality on mean time to repair.

4. Methodology

To quantify those relationships for all eleven active duty ABCTs, this study develops a framework that could be used to evaluate the failure rates and mean time to repair of Bradley Fighting Vehicles and Abrams tanks. The framework incorporates three categories of factors potentially influencing vehicle readiness: vehicle age, the quality of maintainers, and the maintenance schedule phases assigned to each unit. To support this analysis, synthetic datasets were generated at the brigade level, capturing information on individual vehicles, assigned maintainers, and maintenance cycles. These synthetic datasets illustrate an example of the specific data that could be collected to provide insights into vehicle reliability and maintenance efficiency, enabling a data-driven approach for understanding the value, in terms of equipment readiness, that could be expected from vehicle modernization or programs to train and retain vehicle maintainers.

4.1 Vehicle Datasets

To facilitate the analysis, our code creates three distinct datasets of synthetic vehicle data: manufacture date, retirement date, and reset date. – The manufacture date dataset includes the Unit Identification Code (UIC), Vehicle ID, and manufacture date for every vehicle. The retirement date dataset contains the UIC, Vehicle ID, and date retired. These data are used to compute vehicle age, as well as to determine which unit the vehicle is assigned to in order to associate vehicles with maintainers. Our framework currently assumes that the time between manufacture and a vehicle being assigned to a unit is negligible, and that vehicles do not get reassigned to a different unit. Removing those assumptions would require minor modifications to our code. The reset dataset records the Vehicle ID and reset date, representing the instances when vehicles undergo a maintenance overhaul.

Including this in the models, in addition to date of manufacture, would allow us to quantify the amount of life these expensive overhauls add to vehicles in order to assess whether or not they are worth the cost.

4.2 Maintenance Windows

To understand the impact that maintenance windows have on the ability for an ABCT to repair vehicles from Not Mission Capable (NMC) to Fully Mission Capable (FMC), we used the Army's ReARMM doctrine. The Army's ReARMM doctrine outlines a mission phase, training phase, and a maintenance phase that prioritizes unit activities during the different periods of time. The baseline for each phase is prescribed to be an 8-month window. Upon reviewing the Army Unit Calendar, it became clear that many brigades do not strictly follow the 8-month schedules, with varying mission, training, and modernization phases: from as high as 12 months to as low as 6 months. We used similar time lengths for the ReARMM phases from 2015 to 2026 in the synthetic data that we created for the eleven ABCTs. Whenever a unit changes ReARMM phase, the synthetic dataset records the UIC, new ReARMM phase, and date of change. If the ReARMM phase is mission, the code also randomly chooses if the unit deploys (p=0.5 in the synthetic data that we created, although this is easily adjusted).

4.3 Maintainer Quality

We assessed maintainer quality based on three metrics recommended by ACM ABCT: time in grade, time in MOS, and certifications. The metrics are computed on only the Sergeant and Staff Sergeant maintainers in the unit. The first two metrics measure experience, and the last one measures technical competence. Time in MOS addresses a key issue that ACM ABCT highlighted: maintainers who reclassify from another MOS and fill E5 or E6 billets without having sufficient experience for the role. For the certification metric, we are not identifying any specific certification. Instead, the Army would need to decide which certifications to count.

Rather than aggregate personnel data containing these factors on every maintainer in an ABCT, we used a "design of experiments" inspired approach to replicate a brigade's maintainer quality at any moment of time, by creating eight different "unit snapshots" of the aforementioned factors. In each snapshot, each factor was assigned either the high or low level. The model focuses exclusively on maintainers in the ranks SGT and SSG, as they play a critical role in equipment maintenance. The assumed range of time in MOS for an SGT is between 3 and 4.7 years, while for an SSG, it is between 6 and 7.7 years. Additionally, we assume that the highest percentage of maintainers for a unit to hold maintenance certifications is 50 percent and the lowest is 10 percent. These levels were established based on insights gathered from subject matter experts during our stakeholder analysis, ensuring the model reflects realistic maintenance dynamics within an ABCT.

If the values of these factors are too similar across ABCTs and time, then our framework would not be able detect the impact of these factors at this level of granularity. In that case, data may need collected at the battalion or even company level. Another limitation of our model is that it does not account for maintainers from outside the organization performing maintenance on the unit's vehicles. Ideally, exactly which maintainers (active duty, DA civilian, or contractor) perform maintenance (preventative or corrective) on a vehicle, should be recorded with personnel IDs, vehicle serial numbers, and time stamps.

Table 1 shows the HHH snapshot, with all high levels for: time in grade (years), time in MOS (years) and percentage of maintainers certified. Table 2 shows the LLL snapshot. The other six snapshots contained the other possible combinations: HHL, HLH, HLL, LHH, LHL, and LLH. For each ABCT, we assign one of the snapshots for each month starting in January 2015 and ending in December 2025. We assigned one brigade to have highs across the board and one brigade to have lows across the board. The other brigades were each randomly assigned a different snapshot every 6 months in order to replicate changes in a brigade's maintainer quality as personnel transition into or out of the organization. In order to use our framework with actual personnel data, the individual data would need aggregated to brigade averages. Although we use monthly snapshots, our code as written would also accept daily snapshots.

Table 1: HHH Maintainer Quality Snapshot

Grade	MOS	Time In Grade	Time in MOS	Certification
E5	91A	2	4.7	0.5
E6	91A	2	7.7	0.5
E5	91M	2	4.7	0.5
E6	91M	2	7.7	0.5
E5	91H	2	4.7	0.5
E6	91H	2	7.7	0.5

Table 2: LLL Maintainer Quality Snapshot

Grade	MOS	Time In Grade	Time in MOS	Certification
E5	91A	1	3	0.1
E6	91A	1	6	0.1
E5	91M	1	3	0.1
E6	91M	1	6	0.1
E5	91H	1	3	0.1
E6	91H	1	6	0.1

4.4 Models

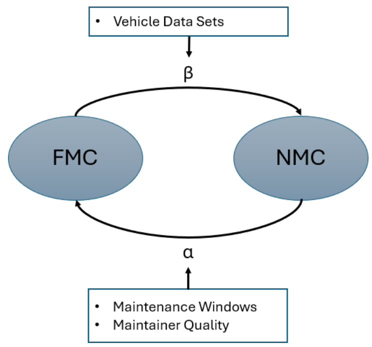

Figure 3: Concept of Model

4.4.1 Logistic Regression Model

$$y = \left[1 + e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\beta_4 x_4+\beta_5 x_5)}\right]^{-1} \quad (1)$$

- y is the predicted probability that a vehicle will break in a given day
- x_1 is vehicle age (time since manufacture) (years)
- x_2 is time since last reset (years)
- x_3 is a binary variable indicating that the ReARMM phase is Training
- x_4 is a binary variable indicating that the ReARMM phase is Mission
- x_5 is a binary variable indicating that the ABCT is deployed

This simple logistic regression model could quantify the impact to vehicle failure rate based on several key factors: vehicle age, whether the unit is in the Mission or Training phase of the ReARMM cycle (with the Maintenance phase inferred when a unit is in neither), the time elapsed since the vehicle was last reset (a maintenance overhaul), and whether the unit is currently deployed. For each day, a vehicle is assigned a value of 1 if it experiences a breakdown and 0 if it remains operational. By analyzing these outcomes alongside the predictor variables, the Army could assess how each factor contributes to the probability of a vehicle breaking down.

4.4.2 Linear Regression Model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 \quad (2)$$

- y is the predicted mean time to repair (hours)
- x_1 is average maintainer time in grade (years)
- x_2 is average maintainer time in MOS (years)
- x_3 is percentage of maintainers certified
- x_4 is a binary variable indicating that the ReARMM phase is Training
- x_5 is a binary variable indicating that the ReARMM phase is Mission
- x_6 is a binary variable indicating that the ABCT is deployed

The linear regression model could be used to quantify the impact that maintainer quality, ReARMM phase, and deployment have on the rate at which a unit is able to get a tank from NMC back to FMC. The framework queries the unit maintainer data (from the snapshot) for each vehicle repair in order to associate the time to repair that failure with the maintainer data for the maintainers available to repair it. As stated earlier, in the ideal scenario the maintainer data used would be the data for the exact maintainers who performed the repair, rather than the average of the maintainers in the unit. Since we used synthetic data, there was no loss of generality, since we can assume all of the synthetic maintainers in the unit were identical.

5. Experiment

Our framework is designed to enable the Army to analyze the impact to vehicle readiness from the previously mentioned factors. In order to assess the viability of the framework and verify our code, we generated synthetic failure data and repair data that contained known relationships to those factors, then used two simple models to see if we could accurately detect those known relationships.

The first model is a logistic regression to assess key factors influencing vehicle breakdowns. This includes when a vehicle was assigned to an ABCT, the date of its most recent reset, and the current ReARMM phase. By incorporating these variables, the model calculates the probability of a vehicle experiencing a failure and estimates the time intervals between breakdowns.

The second model is a linear regression to determine the factors contributing to the transition of a vehicle from Non-Mission Capable to Fully Mission Capable status. This analysis is driven by maintainer quality indicators such as time in grade, time in military occupational specialty, and the certifications maintainers hold. Additionally, the ReARMM phase is factored into account for variations in operational tempo and modernization efforts that may influence repair timelines.

The generate the known relationships, the code operates on a daily cycle, systematically analyzing each vehicle's operational status. For every vehicle in the dataset, it assesses unit assignment, age, last reset date, and ReARMM phase to determine the probability of a breakdown, then randomly chooses if the failure occurs based on that probability. If a failure occurs, the code shifts to the repair phase, using maintainer attributes—such as certifications, time in MOS, and time in grade to randomly choose a duration required to return the vehicle to FMC status.

Ultimately, the purpose of this experiment is not to validate the specific parameter values but to provide a proof of concept that the relationships can be detected in data containing these factors, at these levels, at this granularity.

6. Results

Both models accurately quantified the known relationships in the synthetic data as shown in Table 3 and Table 4 below, which compare the actual parameter values used to create the synthetic data and the parameter values fit by the models. One critique of our approach is that we used the same models to detect that we used to create the synthetic data. The main reason for this is that these capture the expected relationships based on our stakeholder analysis and literature review. However, if these expected relationships are not detected on real data, other more sophisticated models can easily be substituted. In particular, we used the scikit-learn Python library to implement these models, and the library has several other models available.

Table 3: Logistic Model Parameters

	actual	fit
x_1	0.16	0.173110
x_2	0.07	0.077212
x_3	0.50	0.560869
x_4	0.25	0.292666
x_5	0.543	0.616977

Table 4: Linear Regression Parameters

	actual	fit
x_1	0.00	-0.118289
x_2	-2.00	-1.972745
x_3	-3.00	-3.062675
x_4	2.00	2.181991
x_5	1.00	1.186693
x_6	4.00	4.315038

The comparison between actual and model is visualized in Figure 4, which shows the true (notional) and estimated (model) daily probability of a failure versus the age of the vehicle in years. The sampled (simulated) proportion of failures in the synthetic data is shown on the same graph. For all three plots, 6-month wide bins were used. The factors of all vehicles and their units during each bin were used with the actual/fit parameters to plot the true/estimated probabilities.

The second graph showcases one of the variables deemed statistically significant by the linear regression. Figure 5 examines maintainer time in MOS against the mean time required to repair a vehicle. The ordinate is on a logarithmic scale to highlight that, in addition to having a median repair time 60% longer, the inexperienced maintainers also had a much higher maximum repair time. Of course, this data is synthetic, but this is a demonstration of potential insights that could be discovered with this framework.

ISBN: 97819384969-9-8

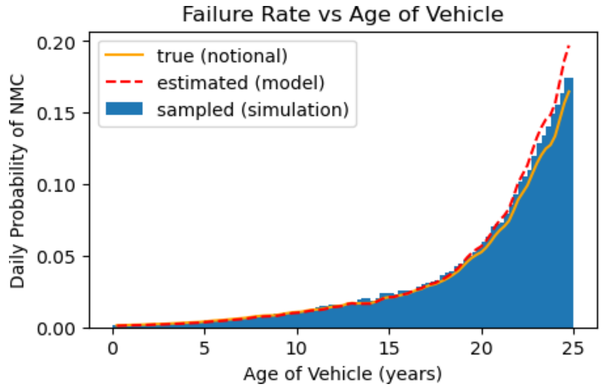

Figure 4: Failure Rate vs. Age of Vehicle

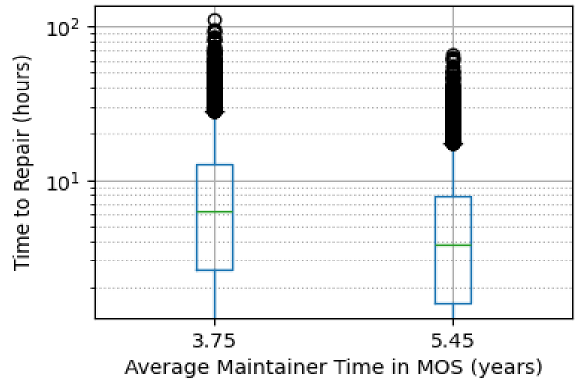

Figure 5: Time in Maintenance based on Maintainer Quality

7. Conclusion and Recommendation

To develop a more accurate model of equipment readiness, the Army must collect specific data on key factors influencing vehicle performance. During our research, we found that the necessary data was not readily available to build a precise and predictive model. Therefore, we recommend that the Army systematically track armored vehicle manufacture dates and vehicle reset timestamps to improve the accuracy of the age of fleet factor. Furthermore, consolidating detailed maintainer data, including rank, time in rank, certifications, MOS, and time in MOS, would significantly improve maintenance quality assessments. Ideally, every maintenance action would be recorded with the vehicle serial numbers, personnel IDs of the maintainers, and timestamp.

By collecting and integrating this data, the Army can develop more robust models to forecast equipment readiness, ultimately leading to a more comprehensive approach to ground forces sustainment. This effort would contribute to a fully integrated readiness model in all military domains, ground, maritime, and air, providing the Department of Defense with a clearer, data-driven understanding of the nation's ability to deploy forces quickly and effectively.

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