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Report Documentation Page				Form Approved OMB No. 0704-0188	
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1. REPORT DATE 2013		2. REPORT TYPE		3. DATES COVERED 00-00-2013 to 00-00-2013	
4. TITLE AND SUBTITLE Measuring the Value of Renewal: Age, Operational Tempo, Deployment, and Reset Effects on the Readiness and Maintenance Costs of Army Vehicles				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S)				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) RAND Corporation, Arroyo Center, 1776 Main Street, P.O. Box 2138, Santa Monica, CA, 90407-2138				8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution unlimited					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT					
15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT Same as Report (SAR)	18. NUMBER OF PAGES 97	19a. NAME OF RESPONSIBLE PERSON
a. REPORT unclassified	b. ABSTRACT unclassified	c. THIS PAGE unclassified			

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DOCUMENTED BRIEFING

Measuring the Value of Renewal

Age, Operational Tempo, Deployment,
and Reset Effects on the Readiness and
Maintenance Costs of Army Vehicles

Lisa Pelled Colabella • Aimee Bower • Lionel A. Galway • Ellen M. Pint • Jason Eng

Prepared for the United States Army

Approved for public release; distribution unlimited



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The research described in this report was sponsored by the United States Army under Contract No. W74V8H-06-C-0001.

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Published 2013 by the RAND Corporation
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Preface

Equipment renewal is currently an Army imperative due to several causes: aging legacy fleets, recent high operational tempos (OPTEMPOs) and operating conditions in Southwest Asia (SWA), and anticipated deployment needs. The renewal program includes equipment reset (return to combat-ready condition), overhaul, and recapitalization (overhaul and upgrade). While anecdotal reports suggest that renewal programs have been valuable, quantitative analyses are needed to measure their impact and inform decisions about when and how often a vehicle should be renewed. The Army recently sponsored a RAND Arroyo Center study to address this need. This documented briefing describes that study, which assessed the impact of age, usage, deployment, and reset on the readiness and maintenance costs of ground fleets. Our findings have implications for equipment reset planning and funding decisions and are likely to be of interest to resource planners, logisticians, and weapon system managers and analysts.

This research was sponsored by the Office of the Deputy Chief of Staff, G-4, Headquarters, Department of the Army. The research was conducted in RAND Arroyo Center's Military Logistics Program. RAND Arroyo Center, part of the RAND Corporation, is the United States Army's federally funded research and development center for policy studies and analyses.

The Project Unique Identification Code (PUIC) for this study is DAL0C10455.

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Summary

Background and Purpose of Study

Faced with a complex and rapidly changing security environment, the Army has been pursuing multiple initiatives to increase preparedness for a wide range of contingencies. One such initiative is the renewal of ground systems. Renewal refers to equipment reset (return to combat-ready or “10/20” condition),¹ overhaul, or recapitalization (overhaul and upgrade to return vehicle to “zero hours/zero miles condition” (Boucher, 2007)). Anecdotal reports (e.g., Lorge, 2008) suggest that the renewal program has been valuable; however, there is a need for quantitative analyses measuring its impact and, more generally, whether the effects of age, usage, and deployed operating environments on a vehicle justify renewal.

Two prior RAND studies (Peltz et al., 2004; Pint et al., 2008) conducted multivariate analyses of the effects of age (years since manufacture date), annual usage (miles traveled during a year or portion of a year), and location (site of usage) on readiness and maintenance costs. However, both studies were based on one to three years of peacetime data per vehicle, as the policy of archiving usage and mission-critical failure records was fairly new when data were gathered for those studies.² Also, maintenance costs were based on mission-critical failures that had part orders; they did not include the costs of repairs

¹ The term “reset” can also be used more broadly, to refer to renewal in general. For example, the *2010 Army Posture Statement* describes reset as the “repair, recapitalization, or replacement of equipment to a desired level of combat capability commensurate with a unit’s future mission” (HQDA, *2010 Army Posture Statement*). However, consistent with the repair facilities that provided data for this study and with other Army sources, this study treated reset as work performed to technical manual (TM) 10/20 standards (Bacchus, 2010; Dwyer, 2009).

² Data gathering for the Pint et al. (2008) study began in 2004, and analyses were completed in 2005.

without part replacements or repairs that were non-mission-critical. Additionally, the studies did not assess renewal effects, as the Army's renewal program had not yet begun. (Overhauls had occurred but were not routinely tracked.) Other studies of age and/or usage effects on Army equipment (Simberg, 2001; Congressional Budget Office, 2007) used similar data and methods and were based on maintenance actions before the current comprehensive renewal initiative.

Thus, there was a need to build on prior studies by using data from deployed operating environments, incorporating more observations (vehicles and years of data), expanding the set of maintenance costs in analyses, and assessing renewal effects. The present study aimed at meeting that need, assessing the impact of vehicle age, usage, Southwest Asia (SWA) deployment, and specifically the reset level of renewal on mission-critical failures and unscheduled field maintenance costs.

Method

We prepared two datasets, each integrating serial number-level data from multiple sources. The first dataset (hereafter called the "SDC dataset") included vehicle usage, location, and field maintenance records from the Army Materiel Systems Analysis Activity (AMSAA) Sample Data Collection (SDC) program; vehicle manufacture dates from both SDC and the Logistics Integrated Database (LIDB); and reset dates and costs from Tank-automotive and Armaments Life Cycle Management Command (TACOM) and the Defense Logistics Agency (DLA). The second dataset (hereafter called the "EDA dataset") included mission-critical failure records from the Equipment Downtime Analyzer (EDA); vehicle manufacture dates, usage (odometer readings), and locations from LIDB serial number usage reports;³ and reset

³ Unit Identification Codes (UICs) identified the location at which a vehicle was operated each month. We needed to use LIDB UICs (locations) rather than locations in EDA maintenance records because our predictor variable was the location of *operation*

dates and costs from TACOM and DLA. We analyzed both the SDC and EDA datasets to assess effects on system mission-critical failures, and we analyzed the SDC dataset alone to assess effects on maintenance costs and subsystem failures.

Our analyses focused on three fleets: (1) M2 and M3 series Bradley Fighting Vehicles; (2) M1 Abrams tanks; and (3) Family of Medium Tactical Vehicles (FMTV) M1078 series trucks. The Bradley sample included the M2A2, M2A2 Operation Desert Storm (ODS), M3A2, and M3A2 ODS variants. The Abrams sample included M1A1, M1A1 AIM, M1A2, and M1A2 SEP tanks. The FMTV sample included M1078, M1078 with winch (W/W), M1078A1, and M1078A1W/W trucks. The bases for selecting these fleets were that they had large SDC sample sizes relative to other fleets; had multiple years of EDA data; were used in SWA and in CONUS; and had reset data available.⁴

Our analyses called for multiple variables at the vehicle serial-number level. Key predictor variables were vehicle usage (miles driven), age, the location

(usage) of a vehicle. Many times a vehicle was used in a particular year but had no mission-critical failures during that year. There was no EDA record—and thus, no EDA location information—for the vehicle in such cases. Also, consistent with prior studies (Peltz et al., 2004; Pint et al., 2008), the intent was to see the effect of operating a vehicle under different conditions. The UIC translation file (UIC_history), which we obtained from the Integrated Logistics Analysis Program (ILAP), had some inaccurate translations, and an alternative source of translations was not available.

⁴ Standard Army Management Information Systems (STAMIS) generally do not contain vehicle reset and recapitalization dates and costs by serial number. The Logistics Support Activity (LOGSA) stores any renewal data it receives (via form 2408-9) in a Recap-Rebuild-Overhaul table, but most of the data in the table are overhauls that occurred prior to 1998. PM Bradley and the Abrams Mobility Group at TACOM Integrated Logistics Support Center (ILSC) maintain detailed reset (10/20 repair) and recapitalization records by serial number for Bradley Fighting Vehicles and M1 Abrams tanks, however. The Bradley renewal data spanned FY 2005 to FY 2009, and the Abrams renewal data spanned FY 2003 to FY 2010. Also, a contact at HQDA G-48 provided 10 years of DLA data on vehicles that went through Red River Army Depot (RRAD). These included “dates received” for FMTVs arriving from Kuwait, the port at Beaumont, Texas, and the port at Charleston, South Carolina. Given that FMTVs are reset at RRAD, we treat the year of the date received as the year of reset.

at which a vehicle was driven, reset, and national stock number (the variant of a particular vehicle). The primary outcome variables in the study were vehicle mission-critical failures and field maintenance costs.

To assess the impact of predictor variables on mission-critical failures of systems and subsystems, we used Poisson and negative binomial regressions. To assess the impact of predictor variables on vehicle maintenance costs, we used a technique called two-part or “hurdle” regression. The final regression models served as the basis for plots showing the predicted effects of vehicle age, usage, location, and reset on failures and costs. Based on the cost of reset versus the maintenance savings due to reset, we calculated, via net present value, when reset becomes cost-effective—or, the cost-effective number of years between resets of a vehicle.

Findings

Analyses for the three systems in this study revealed a set of noteworthy patterns. First, age increased mission-critical failures very mildly, and only up to a point. Plots corresponding to SDC as well as EDA data consistently showed a downturn in the tail region of failure-versus-age curves. This downturn may reflect the limitations of measuring age based on manufacture date. That is, the age measure did not capture the age of vehicle components—the component replacement history). Some older vehicles may have had newer components, and therefore fewer failures, than some younger vehicles.

Second, for the heavy combat vehicles (Bradley and Abrams), usage had stronger effects than age, and power train and electrical systems were among the key drivers of those usage effects. The magnitude and form of usage effects differed in the SDC and EDA analyses, however.

Several factors may account for discrepancies in the SDC and EDA usage findings, including the tendency for SDC curves to show larger usage effects but, in some cases, to have unexpected dips. The usage data in SDC are much higher quality than the LIDB usage data used in the EDA analysis. Thus, even though the LIDB/EDA dataset has the advantage of a large sample size, the

LIDB/EDA usage effect may be underestimated. However, since the SDC dataset is cross-sectional while the EDA dataset is longitudinal, the shape of the SDC curve is potentially more susceptible to confounding factors; additionally, the smaller SDC sample size may make the shape of the curve more susceptible to influence from outliers.

In addition to usage effects, there were sizable location effects in this study. Heavy combat vehicle location clearly affected failures and costs; however, after controlling for usage, some CONUS locations were associated with higher expected failure counts and costs than Iraq.

Another key finding was the effect of reset. Both Bradley and Abrams reset reduced predicted annual mission-critical failures and maintenance costs by as much as 50 percent. The net present value of maintenance savings versus reset cost indicated that, for vehicles driven 1,000 miles per year, both Bradley and Abrams reset became cost-effective four years after reset. However, more frequent reset could be appropriate if justified by readiness gains; if the vehicle reset cost decreases; or if vehicles have higher usage.⁵ In general, reset decisions should be based not only on time since reset, but also on usage and location.

Implications

The small age effects found in this study suggest that while a vehicle's original manufacture date merits some consideration when developing reset plans for ground systems, it should not be the sole criterion—or even a key criterion—for inducting vehicles into the program. By the same token, being located in SWA is not a sufficient criterion for reset induction; vehicles driven few miles in SWA may not need reset immediately after redeployment. Rather, a combination of vehicle attributes may help identify suitable candidates for reset. The relatively strong impact of usage and location (not necessarily

⁵ At higher usage levels, predicted maintenance savings from reset are greater.

deployment) in this study support including those attributes among key reset selection criteria.

This study also provides statistical evidence that national reset (returning vehicles to 10/20 condition) yields substantial readiness benefits and maintenance cost savings for heavy combat vehicles. By demonstrating that current reset programs are bearing fruit, the study suggests that funding of such programs is a sound investment.

Additionally, the finding that reset becomes cost-effective after four years (for Bradley and Abrams) may inform Army decisions about when and how often vehicles should be renewed. However, most of the vehicles in our analyses had been reset once. Over time, once the reset program has a longer history, it would be worthwhile to assess the effects of multiple resets on the same vehicle.

Other follow-up steps may also be valuable extensions of the analyses completed to date. First, it is important to further investigate the reasons that some of the SDC findings were not identical to the EDA findings; this may help identify additional steps needed to resolve inconsistencies (where possible) and assess the validity of findings that emerged with one dataset but not another. Second, a regression of downtime on predictor variables may provide a fuller picture of how age, usage, deployment, and reset affect vehicle readiness. Third, further examination of subsystem effects may shed more light on the factors behind the relatively strong usage effects in this study. Finally, the effects of other types of renewal, especially recapitalization, need to be assessed.

Acknowledgments

We would like to thank LTG Mitchell Stevenson, HQDA G-4, for sponsoring this work, and we are grateful for the valuable feedback that Chris Lowman, Director of HQDA G-44M, provided at each Interim Project Review. James Jones and Felicia Walter were also very helpful, ensuring that we were able to gather data needed for the study and facilitating communication with Army groups conducting related research.

The Sample Data Collection (SDC) files that Henry Simberg of the U.S. Army Materiel Systems Analysis Activity (AMSAA) prepared for us were critical to our analyses. We very much appreciate the time that he took to assemble them, explain them, and ensure that they met this project's needs. Additionally, discussions with Clarke Fox, Mark Mossa, Greg Wyant, Steve Kratzmeier, and John Nierwinski at AMSAA; Ken Rebstock at the Logistics Innovation Agency (LIA); and Dan Kenny at HQDA G-4 prompted informative sensitivity analyses and improvements in the presentation of findings.

At RAND we received very useful guidance from Ken Girardini (director of RAND Arroyo Center's Military Logistics Program) and Rick Eden (its associate director). Also, Pam Thompson and Patrice Lester provided excellent administrative support for this project.

The authors also benefited from thoughtful and constructive feedback from their RAND colleague John Adams and from Paul D. Rogers, Deputy PEO, Ground Combat Systems.

Glossary

AIM	Abrams Integrated Management
AMSAA	Army Materiel Systems Analysis Activity
ARNG	U.S. Army National Guard
CONUS	Continental United States
DLA	Defense Logistics Agency
EDA	Equipment Downtime Analyzer
FMTV	Family of Medium Tactical Vehicles
FORCES	Force and Organization Cost Estimating System
FORSCOM	U.S. Army Forces Command
HQDA	Headquarters, Department of the Army
ILAP	Integrated Logistics Analysis Program
ILSC	Integrated Logistics Support Center
LIA	Logistics Innovation Agency
LIDB	Logistics Integrated Database
LOGSA	Logistics Support Activity
MC	Mission Critical
NMC	Non Mission Capable
NPV	Net Present Value
NSN	National Stock Number
O&S	Operations and Support
OCONUS	Outside the Continental United States
ODS	Operation Desert Storm
OLS	Ordinary Least Squares
OPTEMPO	Operational Tempo

OSMIS	Operating and Support Management Information System
PM	Program Manager
RRAD	Red River Army Depot
SDC	Sample Data Collection
SEP	System Enhancement Package
SSF	Single Stock Fund
STAMIS	Standard Army Management Information Systems
SWA	Southwest Asia
TACOM	U.S. Army Tank-automotive and Armaments Life Cycle Management Command
UIC	Unit Identification Code
ULLS	Unit Level Logistics System
USAREUR	U.S. Army Europe

1. Background and Purpose



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Age, Usage, Deployment, and Reset Effects on Readiness and on Maintenance Costs

September 2010

Sponsor: HQDA G-4

Lisa Colabella, Aimee Bower, Lionel Galway, Ellen Pint, Jason Eng

Faced with a complex and rapidly changing security environment, the Army has been pursuing multiple initiatives to increase preparedness for a wide range of contingencies. One such initiative is the renewal of ground systems. In this context, renewal refers to three levels of repair and refurbishment. In order of increasing scope and expense, the levels are *reset* (return to combat-ready or “10/20” condition),⁶ *overhaul*, or *recapitalization* (overhaul and upgrade to

⁶ The term “reset” can also be used more broadly, to refer to renewal in general. For example, the *2010 Army Posture Statement* describes reset as the “repair, recapitalization, or replacement of equipment to a desired level of combat capability commensurate with a unit’s

return vehicle to “zero hours/zero miles condition” (Boucher, 2007)).

Equipment renewal is currently an Army imperative because legacy fleets are aging; vehicles have been subjected to harsh conditions and high operational usage in Southwest Asia (SWA) operations; and combat-ready equipment, as well as new capabilities, are needed for current and future deployments.

The scope of the renewal program is vast. For example, between 2002 and 2009 the Army reset over 470,000 pieces of equipment, including (but not limited to) 2,702 aircraft; 4,622 tracked vehicles; 33,721 High-Mobility Multipurpose Wheeled Vehicles (HMMWVs) (includes reset and recapitalization); 6,550 trucks; 3,819 trailers; 214,484 small arms; and 20,170 generators (Chiarelli, 2009). Although the program, which has cost on the order of \$10 billion per year for the past few years, is currently funded through the Overseas Contingency Operations (OCO) request, renewal is widely recognized as an enduring Army mission (Magnuson, 2009).

Anecdotal reports suggest that the reset component of the Army’s renewal program is valuable and effective. According to Lorge (2008), a Headquarters, Department of the Army (HQDA) G-8 general observed that “The reset program has been a tremendous success . . . The proof is that when our units deploy, commanders have what they need to do their jobs.” Other officials have reported that reset creates financial efficiencies that save taxpayer dollars (Buckley, 2008; Cole, 2010) and “takes away the effects of the high usage and operations in a harsh environment” (AMC official quoted by Cole, 2010).

However, there is a need for quantitative analyses measuring the impact of reset—and, more generally, whether the effects of age, usage, and deployed operating environments on a vehicle justify renewal. As reported by Magnuson (2009), a tactical vehicle product manager noted that

future mission” (HQDA, *2010 Army Posture Statement*). However, consistent with the repair facilities that provided data for this study and with other Army sources, this study treated reset as work performed to technical manual (TM) 10/20 standards (Bacchus, 2010; Dwyer, 2009).

he can no longer go to senior Army leadership and ask for more truck capabilities without a cost-versus-benefit analysis in hand.

“There are those who question the utility of our reset strategy and the need to spend the amounts of money we’re spending,” he said.

Thus, the cost-effectiveness and readiness benefits of reset need to be evaluated. In addition, assessing age, usage, and deployment effects may help determine appropriate criteria for inducting vehicles into renewal programs.⁷

⁷ A current method used to select vehicles for restoration is the maintenance expenditure limit (MEL). Technicians inspect a vehicle, estimate its repair costs, and compare the estimate to the MEL. If the estimate exceeds the MEL, then the Army may decide to send the vehicle to the Defense Reutilization and Marketing Office (DRMO), rather than repairing it (Tandoi, 2010). If vehicle age, usage, and location can help identify likely reset candidates, then fewer vehicle inspections may be needed.

Project Purpose and Tasks

Purpose

Conduct analyses to determine the value of vehicle reset programs (return to 10/20) and facilitate decisions about such programs

Tasks

- 1. Build fleet analysis datasets for selected LINs**
 - **Integrate multiple Army data sources**
- 2. Assess the effects of age, usage, deployment, and reset on mission-critical failures (equipment readiness) and field maintenance costs**

RAND

Several prior RAND studies conducted multivariate analyses of the effects of age (years since manufacture date), annual usage (miles traveled during a year or portion of a year), and location (site of usage) on readiness and maintenance costs. Peltz et al. (2004) found that age had a log-linear relationship and usage had a log-quadratic relationship with predicted mean failures of M1 Abrams tanks. Also, the geographic region of the tanks' owning unit was a significant predictor of mission-critical failures. Pint et al. (2008) found that age and usage had curvilinear effects on downtime and maintenance costs; they also found a significant effect of vehicle location. However, both studies were based on one to three years of peacetime data per vehicle, as the policy of archiving usage and mission-critical failure records was fairly new when data were gathered for those

studies.⁸ Also, maintenance costs were based on mission-critical failures that had part orders; they did not include the costs of repairs without part replacements or repairs that were non-mission-critical. Additionally, the studies did not assess renewal effects, as the Army's reset program had not yet begun. (Overhauls had occurred but were not routinely tracked.)

An Army Materiel Systems Analysis Activity (AMSAA) study (Simberg, 2001) assessed the effect of age (both in years and in lifetime miles accumulated) on part replacement costs and reliability. The study primarily used Field Exercise Data Collection (FEDC) data, with Sample Data Collection (SDC) data used for several of the newer systems. Although an aggregate analysis found no evidence of an aging effect on most systems, a serial number-level statistical analysis found that part replacement costs per mile and unscheduled maintenance visits per mile generally increased between the first and second halves of a system's life at the National Training Center (NTC). While the findings suggested an aging effect, they were based on small samples at training sites (e.g., 200 M88A1 vehicles) and did not reveal the form of the aging effects.

In a study examining whether Army equipment can sustain high usage, the Congressional Budget Office (CBO, 2007) made several strong assumptions—e.g., a 50,000-mile lifetime limit per Bradley and “that the Army's systems are being properly maintained while operating at their current high rates and that unexpected conditions are not degrading their performance” (p. 15). Although the CBO research team inferred that usage in SWA would not stress equipment beyond its capacity, they did not directly assess usage and location effects on vehicles.

Thus, there was a need to build on prior studies by using data from deployed operating environments, incorporating more observations (vehicles

⁸ Data gathering for the Pint et al. (2008) study began in 2004, and analyses were completed in 2005.

and years of data), expanding the set of maintenance costs in analyses, and assessing reset effects. This study aimed at meeting that need.

The overall purpose of the study was to conduct analyses that would help assess the value of vehicle renewal and facilitate renewal planning. Specific tasks consisted of (1) integrating data from multiple sources to build datasets for analyses of selected fleets; and (2) using those datasets to assess the impact of vehicle age, usage, SWA deployment, and reset on mission-critical failures and unscheduled field maintenance costs. (Note: The goal of our analysis is to see what the effect is on mission-critical failures (MC failures) of usage, age, deployment, and reset, controlling for other variables. Our data consists of records of non-mission-capable repairs (NMC repairs), for which actions are taken in response to MC failures. We therefore use both terms depending on whether we are discussing the goal or the data analysis.)

2. Method

<i>Data Came from Two Primary Sources, Each Supplemented by Others</i>	
1. Sample Data Collection (SDC)	2. Equipment Downtime Analyzer (EDA)
<i>Strengths</i> • Includes field maintenance (mostly organizational) & costs • High-quality usage & location data gathered by AMSAA data collectors <i>Weaknesses</i> • Cross-sectional data (harder to determine causality) • Smaller sample size than EDA	<i>Strengths</i> • Longitudinal data (more confidence in causality) • Large sample size, including active & reserve component <i>Weaknesses</i> • Includes mission-critical (MC) failures only • Dataset with EDA depends on LIDB usage & location data, which are lower quality than SDC
cleaned LIDB age data	cleaned LIDB age, usage, location data
Reset Data from PM Bradley, TACOM ILSC, DLA	

Data Sources

We prepared two datasets, each integrating serial number–level data from multiple sources. The left-hand side of the above chart describes the first dataset. The major portion of the first dataset (hereafter called the “SDC dataset”) consisted of vehicle usage, location, and field maintenance records from the AMSAA SDC program. In the SDC program, data collectors visit selected units (identified through a cluster sampling technique) in garrison environments and combat areas and gather equipment usage and maintenance data at the serial number level (AMSAA, 2008; HQDA Pamphlet 700-24,

2007). Because equipment usage and maintenance data are the focus of SDC data collectors, those data tend to be of very high quality.

Although SDC data also include manufacture dates (age data), these data tend to be moderate in quality. We found that a portion of the manufacture dates were missing, and others did not correspond to the serial number sequence or variant. Manufacture dates from another source, the Logistics Integrated Database (LIDB), also had such quality problems. We took steps (described later, in the “Study Variables” section) to improve the accuracy of manufacture dates and then used cleaned-up manufacture dates from LIDB to fill in and correct the manufacture dates in SDC, as needed. Vehicle reset dates came from program manager, TACOM Integrated Logistics Support Center (ILSC), and Defense Logistics Agency (DLA) records.

The right-hand side of the above chart shows the second dataset in the study. A portion of the second dataset (hereafter called the “EDA dataset”) consisted of mission-critical failure records from the Equipment Downtime Analyzer (EDA). Another portion of the dataset—vehicle manufacture dates, usage (odometer readings), and locations—came from LIDB. Just as we took steps to improve the accuracy of manufacture dates, we used statistical imputation to improve the quality of LIDB usage data (again, see “Study Variables” for a description of this process). The remaining portion of our EDA dataset consisted of vehicle reset dates and costs from the program manager (PM), TACOM, and DLA.⁹

We used both the EDA and SDC datasets because each has unique features needed in our analyses. The EDA dataset is longitudinal, often with five or more years of usage and maintenance data per vehicle. This feature helps assess causal relationships—e.g., whether usage is causing failures. Additionally,

⁹ PM Bradley and PM Tactical Vehicles provided Bradley and FMTV national reset costs as of 2009. The Abrams reset cost was based on an article stating that General Dynamics Land Systems received a \$20 million delivery order as part of a \$37 million contract to reset 36 M1A1 AIM tanks (Defense File, 2007).

the larger sample size in the EDA dataset increases the likelihood of detecting meaningful effects. As Lenth (2001:2) states, a sample “must be ‘big enough’ that an effect of such magnitude as to be of scientific significance will also be statistically significant.”

The SDC dataset is cross-sectional (not longitudinal) and has smaller sample sizes than the EDA dataset; however, it has a different set of strengths. As mentioned earlier, SDC usage and location data are higher quality than those in LIDB (the source of usage and locations in the EDA dataset). Also, SDC data include parts costs and labor hours associated with unscheduled field maintenance—both NMC and non-NMC. The EDA data, in contrast, only have parts costs (not labor hours) associated with mission-critical failures (i.e., NMC repairs only). Thus, the SDC data are more conducive to assessing effects of predictor variables on maintenance costs. We analyzed both the SDC and EDA datasets to assess effects on system mission-critical failures, and we analyzed the SDC dataset alone to assess effects on maintenance costs and subsystem failures.

The approach of conducting similar analyses with the EDA and SDC datasets constituted *method triangulation*. Method triangulation entails assessing the consistency of findings generated by different data-collection methods (see, e.g., Burns and Grove, 2005)—e.g., sample data collectors versus unit reporting via the Unit Level Logistics System (ULLS). Triangulation can increase confidence in results if two independent analyses and datasets yield consistent findings. If findings from one dataset do not corroborate findings from another, then further studies may be warranted to draw more definitive conclusions.

***Data Availability and Quality Led to Focus on
Three Ground Systems***

Weapon System	Variants	SDC Sample	EDA Sample
M2/M3 Bradley	M2A2, M2A2 ODS, M3A2, M3A2 ODS	3,076 vehicle-location-years	15,244 vehicle-years
M1 Abrams	M1A1, M1A2	6,489 vehicle-location-years	22,271 vehicle-years
FMTV	M1078, M1078WW, M1078A1, M1078A1 WW	3,015 vehicle-location-years	56,179 vehicle-years

RAND

Samples

Our analyses focused on three fleets: M2 and M3 series Bradley Fighting Vehicles, M1 Abrams tanks, and Family of Medium Tactical Vehicles (FMTV) M1078 series trucks. The bases for selecting these fleets were that they had large SDC sample sizes relative to other fleets; had multiple years of EDA data; were used in SWA and in CONUS; and had renewal data available.¹⁰

¹⁰ Standard Army Management Information Systems (STAMIS) generally do not contain vehicle reset and recapitalization dates and costs by serial number. Logistics Support Activity (LOGSA) stores any renewal data it receives (via form 2408-9) in a Recap-Rebuild-Overhaul table, but most of the data in the table are overhauls that occurred prior to 1998. PM Bradley and the Abrams Mobility Group at TACOM ILSC maintain detailed reset (10/20 repair) and recapitalization records by serial number for Bradley Fighting Vehicles and M1 Abrams tanks, however. The Bradley renewal data spanned FY 2005 to FY 2009, and the Abrams renewal data spanned FY 2003 to FY 2010. Also, a contact at HQDA G-48

The Bradley sample included M2A2, M2A2 Operation Desert Storm (ODS), M3A2, and M3A2 ODS variants. We limited analyses to these variants in order to focus on Bradleys that were not remanufactured vehicles. That is, we excluded the M2A3, M3A3, and M3A3 BFIST variants, which PM Bradley (Fader, 2010) indicated are remanufactured M2A2 and M3A2 vehicles, as a comparison of remanufactured and non-remanufactured Bradleys is likely to be a follow-up to the analyses described in this report.

The Abrams sample included M1A1, M1A1 AIM, M1A2, and M1A2 SEP tanks. In this case, we included Abrams Integrated Management (AIM) and System Enhancement Package (SEP) tanks in the analysis, even though they were recapitalized versions of M1A1 and M1A2 tanks; this decision was based on the age ranges of the tanks. Specifically, the M1A1 vehicles in the sample were manufactured between 1986 and 1993, while M1A1 AIM vehicles were produced from 2000 to 2008. The M1A2 vehicles were manufactured largely between 1994 and 1999, while the M1A2 SEP vehicles were produced from 1999 to 2008. Thus, excluding recapitalized vehicles would have limited the sample to vehicles manufactured before 1999. We chose to include recapitalized vehicles to ensure that the dataset encompassed newer as well as older tanks.¹¹

The FMTV sample included M1078, M1078 with winch (W/W), M1078A1, and M1078A1W/W trucks. The FMTV does not yet have a recapitalization program.

As mentioned earlier, SDC data are essentially cross-sectional. Each vehicle has, on average, about 300 days of SDC usage and maintenance data, and those 300 days typically span two years (e.g., 150 days in 2005 and 150

provided 10 years of DLA data on vehicles that went through Red River Army Depot (RRAD). These included “dates received” for FMTVs arriving from Kuwait, the port at Beaumont, Texas, and the port at Charleston, South Carolina. Given that FMTVs are reset at RRAD, we treated the year of the date received as the year of reset.

¹¹ In the Bradley sample, recapitalization was less confounded with age, so we were able to include vehicles with manufacture dates ranging from 1986 to 2008 without having recapitalized vehicles in that sample.

days in 2006). Because a vehicle's age changes from one year of usage to the next (e.g., age 10 in 2005 and age 11 in 2006), it was important to take the year of usage into account when structuring the dataset. Also, a small number of vehicles had SDC data from more than one location during the same year. Thus, we structured the SDC dataset so that each observation was a vehicle-location-year (e.g., serial 2ADR0077F-Iraq-2005). The third column in the above slide lists the SDC sample sizes (number of vehicle-location-years) for the Bradleys, Abrams tanks, and FMTVs in this study.

In the EDA dataset, each observation was a vehicle-year, rather than a vehicle-location-year. If a vehicle was used at more than one location during a year, the location selected was the one at which the vehicle spent the most months during that year. The reason for this less fine-grained treatment of location was that the LIDB location data used in the EDA dataset were lower quality—i.e., not sufficiently precise to warrant a lower level of analysis.¹² The fourth column in the above slide lists the EDA sample sizes (number of vehicle-years) for the Bradleys, Abrams tanks, and FMTVs in this study. The Appendix provides additional detail about each of the samples analyzed. As we discuss in the results section, the annual usage for all vehicle fleets is, as expected, skewed toward lower annual mileages. This leads to greater uncertainty in our analyses at higher mileages. Charts in the Appendix show the annual mileage distributions for the various fleets in this study.

¹² Unit Identification Codes (UICs) identified the location at which a vehicle was operated each month. We needed to use LIDB UICs (locations) rather than locations in EDA maintenance records because our predictor variable was the location of *operation* (usage) of a vehicle. Many times a vehicle was used in a particular year but had no mission-critical failures during that year. There was no EDA record—and thus, no EDA location information—for the vehicle in such cases. The UIC translation file (UIC_history), which we obtained from ILAP, had some inaccurate translations, and an alternative source of translations was not available.

The Study Called for Data at the Vehicle Serial-Number Level

- **Usage** = miles vehicle traveled in a given year (or fraction of year)
- **Age** = year of usage – manufacture date of vehicle
- **Location** = where vehicle was used
- **Reset** = whether a variable had been reset, as of the year of usage
- **National Stock Number** = variant of the vehicle
- **Updays** = the number of days in a year that a vehicle was available for operations (not having a mission-critical failure)
- **Mission-critical failures** = number of deadlining failures during vehicle study period
- **Maintenance action indicator** = 0-1 binary indicator of whether vehicle had maintenance action during study period
- **Field maintenance cost** = cost of parts and labor associated with unscheduled field maintenance on the vehicle during study period

RAND

Study Variables

Our analyses called for multiple variables at the vehicle serial-number level. Predictor variables included vehicle usage, age, location, reset, national stock number, and updays. The primary outcome variables (dependent variables) in the study were vehicle mission-critical failures, a maintenance event indicator, and field maintenance costs. Below are the variable descriptions.

Predictor Variables

Usage. Usage was measured as the miles traveled by a vehicle during a given calendar year or portion thereof. When we received SDC usage data from AMSAA, the file contained miles traveled per month by serial number. We summed those values to obtain usage by vehicle-year. For example, suppose a vehicle had 10 months of SDC data, including five months in 2005 and five

months in 2006. The vehicle would then have two observations in the SDC dataset, one for each of those two years. Its usage during 2005 would be the sum of the miles it traveled during the first five months, and its usage during 2006 would be the sum of miles traveled during the second five months.

In the EDA dataset, our primary source of usage data consisted of LIDB odometer readings. Due to the quality problems with those readings, obtaining usage values for the EDA analyses called for more steps. First, if a vehicle in LIDB had a monthly usage reading in SDC, we used the SDC usage reading for that month. If not, we made corrections to improve usage calculations based on LIDB. For example, obvious decimal point errors in odometer readings were corrected. Also, we treated a monthly odometer reading as missing if it was (1) lower than the reading a month earlier; or (2) more than 2,000 miles greater than the reading a month earlier. Monthly usage was then calculated as the difference between two consecutive monthly odometer readings.

If the calculated usage for a vehicle was a missing value in a particular month, we set the vehicle's usage equal to the company mean for that month—i.e., the average usage of other vehicles in the same company. This statistical imputation technique, known as “mean substitution,” was also applied to address usage data gaps in a prior study (Peltz et al., 2004). After we completed this process and had cleaner monthly usage values, we summed those values by vehicle-year, obtaining the miles covered by a vehicle during a given calendar year.¹³

Age. Age was computed as the difference between the year of usage and the year of manufacture. For example, recall that if a vehicle had usage during 2005 and 2006, then it had two observations (vehicle-years) in a dataset. If it was manufactured in 1995, then its age was 10 (i.e., 2005–1995) in the first vehicle-year and 11 (i.e., 2006–1995) in the second vehicle-year.

¹³ A reviewer noted two additional potential problems with M1A2 usage data: a potential confusion during data entry of kilometers versus miles driven (due to odometer readout selections) and a possible odometer reset when software is upgraded.

As mentioned earlier, manufacture dates had quality issues in both the SDC dataset and the EDA dataset, for which LIDB was the source of the year of manufacture. Through deductive imputation and vehicle data plate readings provided by some Army units, we “cleaned” LIDB manufacture dates—then, where possible, used the LIDB dates to correct and fill in SDC dates.¹⁴

Location. Location was the CONUS installation or OCONUS geographic region in which a vehicle was operated during the study period. In the SDC dataset, a vehicle’s location was where the data collector gathered usage and maintenance data from the vehicle; thus, it was likely to be highly accurate. In the EDA dataset, the location was based on the UIC reported by the unit when the unit provided a monthly usage report to LOGSA. We translated monthly UICs into vehicle locations using an Integrated Logistics Analysis Program (ILAP) table called UIC_history.

Reset. Reset was a dichotomous variable equal to 1 if the vehicle had been reset by a given vehicle-year and equal to 0 if the vehicle had not yet been reset. For example, a vehicle that was reset in 2004 and had usage data in 2005, 2006, and 2007 would have reset equal to 1 for all three vehicle-years. If the vehicle was not reset until 2006, then reset would equal 0 in 2005 but 1 in 2006 and 2007.

National Stock Number (NSN). NSN was a categorical variable indicating the type or variant of a vehicle. For example, each of the four variants of the Bradley Fighting Vehicle in our datasets (M2A2, M2A2 ODS,

¹⁴ Deductive imputation is the process of deducing the value of a variable based on the value of another variable. Because serial numbers were assigned in order of production, we were able to deduce the manufacture dates of some vehicles from their serial numbers. LIDB—more specifically, the portion of LIDB called the TAMMS Equipment Database (TEDB)—contains more vehicle serial numbers and manufacture dates than SDC. A longer sequence of serial numbers and manufacture dates is more conducive to deductive imputation; it is more feasible to determine how serial number patterns are associated with manufacture dates. We therefore began by imputing manufacture dates in LIDB and then used those to fill in gaps or correct errors in SDC dates.

M3A2, M3A2 ODS) had an NSN. When a vehicle had n NSNs, there were $n - 1$ dummy variables in the regression equation. The coefficients of those variables indicated the magnitude of the effect of a particular variant, relative to the “referent” variant in the regression equation.

Updays. This variable measured a vehicle’s “exposure”—that is, the total number of days it had an opportunity to fail during each vehicle-year. For the EDA data, which covered all vehicles in the fleets we analyzed, updays was the total number of days in the calendar year minus the number of downdays (days a vehicle was undergoing NMC repairs). For the SDC data, where a particular vehicle might not be in SDC for an entire year, updays equaled the number of days in the SDC during that year minus the downdays recorded in the SDC for that vehicle in that year.

Outcome Variables

Mission-critical failures. The readiness measure in this study was the number of mission-critical failures a vehicle had during a given vehicle-year. In the SDC dataset, this variable was a count of maintenance events identified by “date in” and NMC_Flag. Specifically, we treated a mission-critical failure as any maintenance on a vehicle that had the same “date in” and was flagged by AMSAA data collectors as an NMC repair (i.e., had “NMC_Flag” equal to “Y”). If several NMC maintenance actions had the same date in, we counted them as a single maintenance event.

In the EDA dataset, a mission-critical failure included all of a vehicle’s maintenance actions with the same job order number (JON). (The SDC data did not contain JONs.)

Based on the parts ordered for SDC repairs, we counted subsystem failures associated with vehicle MC failures. For example, if a vehicle NMC repair called for 3 electrical parts and 2 chassis parts (but no other parts), then we counted that repair as 1 overall vehicle failure, 1 electrical subsystem failure,

and 1 chassis failure.¹⁵ This approach to counting subsystem failures was also used in subsystem analyses by Peltz et al. (2004).

Maintenance event indicator. For the purposes of our cost analyses (to be described later), we also had a dichotomous (0/1) variable that indicated whether the vehicle had at least one field maintenance event during a given vehicle-year. (The variable, which was based on SDC data, allowed us to assess the probability of a vehicle having field maintenance during a year.) In this case we did not restrict the NMC_Flag variable; that is, for the purpose of assessing costs, a maintenance event could be either an NMC or a non-NMC repair.

Field maintenance costs. The second outcome variable used in our cost analyses was maintenance cost, defined as the parts and labor cost associated with a field maintenance event in the SDC data. Parts costs were those listed with the SDC maintenance records, and AMSAA indicated that the parts costs were the FEDLOG prices minus credits as of December 2009 (Simberg, 2010a, 2010b). Per AMSAA guidance (Simberg, 2010b), the unit part costs were multiplied by the quantity ordered, but the labor hours did not need to be adjusted for quantity.

To convert labor hours to labor costs, we used 2010 Military Composite Standard Labor Rates obtained from the Force and Organization Cost Estimating System (FORCES) database. For an earlier study (Pint et al., 2008), TACOM had provided approximate percentages of FMTV maintenance labor performed by grades E-3 to E-8 as of 2004. Those percentages were about 23.3% E-3, 32.0% E-4, 20.0% E-5, 13.7% E-6, 8.5% E-7, and 2.5% E-8. As of 2010, the hourly salaries for those grades were \$28.65 E-3, \$33.00 E-4,

¹⁵ Parts were classified into subsystems based on Federal Supply Class (FSC). For example, FSC 3010 (torque converter) was in the Power Train subsystem; FSC 1240 (optical sighting) was in the Fire Control subsystem; and FSC 4720 (flexible hose/tubing) was in the Hydraulic subsystem. We based our FSC-to-subsystem mapping on that of Peltz et al. (2004), who had the mapping reviewed by Army maintenance personnel. Multiple FSCs corresponded to each subsystem. The primary subsystems included weapon, fire control, chassis, power train, hardware, hydraulic, and electrical.

\$40.11 E-5, \$48.23 E-6, \$56.77 E-7, and \$63.47 E-8. A weighted average of the E-3 to E-8 labor rates came to \$38.27 per hour. We assumed that overhead increased this figure by 10 percent, so we multiplied labor hours by \$42.10/hour to obtain labor costs in the present study.

We Used Regression Techniques to Assess Effects of Predictor Variables on Outcome Variables

- **Conducted statistical analyses of each dataset to assess effects of predictors on outcome variables**
 - **Used Poisson and negative binomial regressions when outcome variable was count of MC failures, i.e., non-mission-capable (NMC) repairs**
 - **Log of vehicle “up days” (exposure time) as offset variable**
 - **Model included higher-order age and usage terms**
 - **EDA analysis used random effects model; random intercept for each vehicle was included due to multiple, potentially correlated observations (vehicle-years) for same vehicle**
 - **Used two-part “hurdle” regression when outcome variable was cost/year**
 - 1) **Logistic regression to assess probability of a maintenance action**
 - 2) **Ordinary Least Squares (OLS) regression to assess expected cost given maintenance occurs**

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Analytical Techniques

Assessing Effects on Readiness

Our primary analytical technique was regression analysis. To assess the effects of predictor variables on mission-critical failures of systems and subsystems, we used Poisson and negative binomial regressions. Typically, count data—e.g., number of failures—tend to have a Poisson distribution, in which the variance across all observations equals the mean of those observations. In some cases, however, count data have a negative binomial distribution, with the variance greater than the mean. For each system and subsystem in the study, we began with a Poisson regression that had the following full model:

$\ln(\text{mean vehicle failures during study period}) =$

$$\begin{aligned} & \beta_0 + \ln(\text{updays}) + \sum_{i=1}^c \beta_i (\text{location}_i) + \sum_{k=1}^3 \beta_{c+k} (\text{usage}^k) + \sum_{m=1}^3 \beta_{c+3+m} (\text{age}^m) \\ & + \sum_{t=1}^w \beta_{c+6+t} (\text{NSN}_t) + \beta_{c+7+w} \text{reset}, \end{aligned}$$

where c = number of locations in the sample and w = number of NSNs in the sample.

We then used backward elimination to arrive at the final, reduced model for the system. Backward elimination is a process in which one removes nonsignificant terms from the model, one by one, based on the Likelihood Ratio Test Statistic.

Several features of the regression model should be noted: First, the variable $\ln(\text{updays})$ was an offset variable to control for the “exposure time” or opportunity for a vehicle to have a mission-critical failure. Without an offset in the model, the relationship of the other variables with the failure rates would be confounded with the time a vehicle was in operation, e.g., a doubling in exposure time would lead to a doubling in failures observed, even if the values of none of the other independent variables changed. An offset variable always has a coefficient of 1. Second, since the EDA dataset was longitudinal, we ran the model two ways in the EDA analysis: (1) with lagged usage (assessing the impact of the previous year’s usage—the impact of usage in year $n - 1$ on failures in year n); and (2) with usage in the same year as failures. Third, because the EDA dataset had, on average, about five years of data per vehicle, we used a random effects model in our EDA analyses. That is, we used a random intercept for each vehicle to account for the possibility that multiple observations (vehicle-years) corresponding to the same vehicle were correlated.

When the deviance ratio (the model deviance/degrees of freedom) of the model was close to 1, we concluded that the Poisson regression model had a good fit. When the deviance ratio was greater than 2 or less than 0.5, we

followed the same procedure described above but used a negative binomial regression instead, provided the deviance ratio improved.¹⁶

Also, to determine how age, usage, deployment, and reset affect each vehicle *subsystem*, we used the same Poisson and negative binomial regression approach. However, the outcome variable was then the number of subsystem (e.g., chassis) MC failures, rather than the number of vehicle MC failures.

Assessing Effects on Maintenance Costs

To assess the effects of predictor variables on vehicle maintenance costs, we used a technique called two-part or “hurdle” regression, which was used in a prior study of maintenance costs versus age, usage, and location (Pint et al., 2008) and has also been used in studies of individual health care expenditures (e.g., Liu, Long, and Dowling, 2003; Diehr, Ash, and Hornbrook, 1999). Specifically, we first used logistic regression to assess the impact of predictors on the likelihood of a vehicle having at least one maintenance event in a year. We began with the following full model and then reduced it via backward elimination:

maintenance action indicator =

$$\begin{aligned} & \beta_0 + \ln(\text{updays}) + \sum_{i=1}^c \beta_i (\text{location}_i) + \sum_{k=1}^3 \beta_{c+k} (\text{usage}^k) + \sum_{m=1}^3 \beta_{c+3+m} (\text{age}^m) \\ & + \sum_{t=1}^w \beta_{c+6+t} (\text{NSN}_t) + \beta_{c+7+w} \text{reset} , \end{aligned}$$

¹⁶ An indicator of the goodness of fit of a Poisson model is the deviance for the model divided by the degrees of freedom. The deviance is “two times the difference of the log likelihood of the maximum achievable model . . . and the log likelihood under the fitted model.” If the model fits the data well, then the ratio of the deviance to degrees of freedom in the model (deviance/DF) should be close to 1 (UCLA: Academic Technology Services, Statistical Consulting Group, no date).

where c = number of locations in the sample and w = number of NSNs in the sample. The maintenance action indicator was a binary indicator of whether or not a vehicle had a maintenance action—i.e., incurred a maintenance cost—recorded in SDC during the period that usage and maintenance data were collected for the vehicle.

Next, we used ordinary least squares (OLS) regression to assess the impact of predictors on a vehicle's expected maintenance cost per year, given that the vehicle had at least one maintenance event. For this OLS regression, we began with the following full model and then reduced it via backward elimination:

$\ln(\text{maintenance cost/year, given a maintenance action occurs}) =$

$$\begin{aligned} & \beta_0 + \sum_{i=1}^c \beta_i (\text{location}_i) + \sum_{k=1}^3 \beta_{c+k} (\text{usage}^k) + \sum_{m=1}^3 \beta_{c+3+m} (\text{age}^m) \\ & + \sum_{t=1}^w \beta_{c+6+t} (\text{NSN}_t) + \beta_{c+7+w} \text{reset}, \end{aligned}$$

where c = number of locations in the sample and w = number of NSNs in the sample. We used cost per year and usage per year in this OLS regression because we did not control for updays; OLS regressions do not have offset variables. The reason for transforming cost per year into $\ln(\text{cost per year})$ was to change the distribution from skewed to approximately normal.

We then multiplied the predicted value in the first regression by the retransformed predicted value in the second equation (as well as a Duan smearing correction factor) to obtain the overall predicted maintenance cost per year for the vehicle.¹⁷

¹⁷ Because we transformed costs per year into $\ln(\text{costs per year})$ before entering it into the regression equation, we needed to take an additional step after retransforming the predictions in the OLS regression: We multiplied the predictions by Duan's (1983) smearing estimate to correct for retransformation bias.

Plotting Predicted Values

To illustrate the effects detected with these analyses, we began by generating plots of expected mission-critical failures (i.e., the predicted mean failures for a vehicle) versus age and usage. For the predicted failures versus age curve, we let updays equal 365, annual usage equal 1,000 miles, and reset equal 0, and we selected a single location and NSN value to use. After entering these updays, usage, reset, location, and NSN values into the regression equation and holding them constant, we varied the value of age that we entered into the regression equation. In this manner, we obtained predicted failures versus age, controlling for other variables. Because the predictions in the Poisson and negative binomial regression equations are logarithmic values—i.e., $\ln(\text{mean failures})$, we transformed the values via the exponent function before plotting them.

For the predicted failures versus usage curve, we took the same approach, except that, instead of holding usage constant, we held age constant at 10 years and varied the value of usage in the regression equation. By doing so, we obtained predicted failures versus usage, controlling for other variables.

To see the effect of location, we plot the failure versus age curve for all of the locations, in each case setting one location dummy variable equal to 1 and the others equal to 0. Similarly, to see the effect of reset, we plot the failure versus age and/or failure versus usage curves with the reset variable equal to 1 and with the reset variable equal to 0.

For the cost versus age and cost versus usage curves, we used almost the same approach that we used for the failure curves, except that we took each part of a two-part regression into account when generating a cost curve. For example, to generate a cost versus age curve, we varied age in the logistic and OLS regression equations, holding other variables constant. We then multiplied the two predicted values (including the Duan smearing factor) to obtain predicted values for the final cost versus age curve.

The next section of this documented briefing presents and discusses plots corresponding to the Bradley, Abrams, and FMTV regression models. It is

important to keep in mind that the plots are predicted values based on the full samples described earlier. We did not partition samples by location, variant, or other variables, as doing so would have reduced the statistical power of the models. For example, the SDC regression model and corresponding plots for the Bradley were based on the full SDC dataset for the Bradley, including all locations and variants. The partial correlation coefficients in the regression equations allowed us to distinguish the effect of one location and variant from another.

3. Findings

The M2 and M3 Bradley Fighting Vehicle

Table 3.1 shows results of the Poisson regression of mission-critical failures on predictor variables in the SDC analysis.

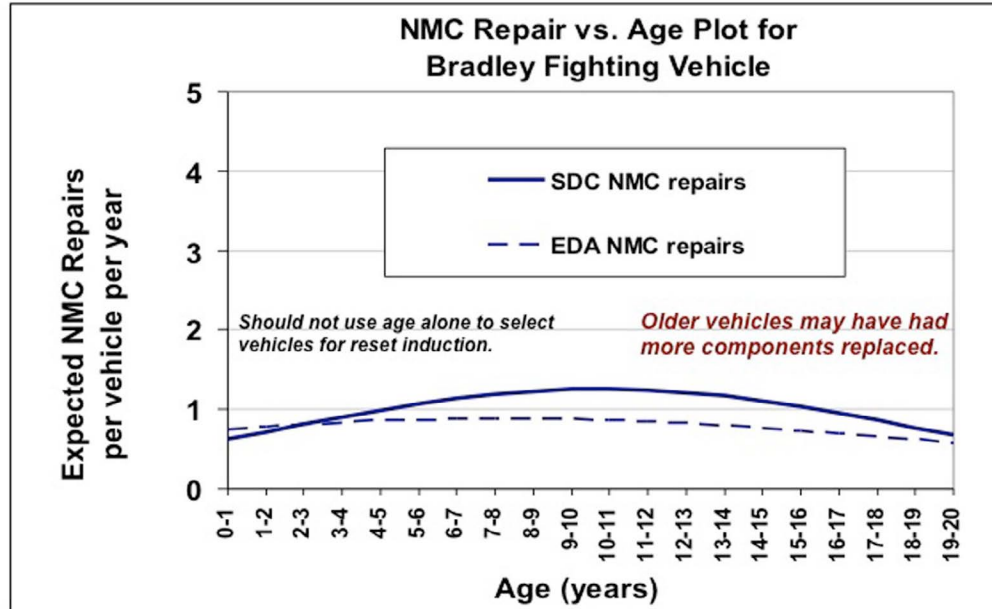
Table 3.1
Poisson Regression of Bradley Failures on Predictors

Parameter	Bradley Mission-Critical Failures
	Estimate
Intercept	−0.7656***
Reset	−0.2176*
(Age)squared	−0.0073***
Age	0.1426***
(Usage)cubic	0.0167***
(Usage)squared	−0.2685***
Usage	1.2181***
Location A	−0.6842***
Location B	−1.3329***
Location C	0.7809***
Location D	1.1790***
Location E	1.5138***
Iraq	0.0000 [other location coefficients show effects relative to effect of Iraq]
Type: M2A2	0.0951
Type: M3A2	0.8263***
Type: M2A2 ODS	0.0170
Type M3A2 ODS	0.0000 [other type coefficients show effects relative to effect of M3A2 ODS]
Deviance: Value/DF = 4691/3052 = 1.5	
Ln(updays) was an offset variable in the regression; this is equivalent to being a parameter with estimate = 1.	
* $p < .05$; ** $p < .01$; *** $p < .001$	

The final model had a quadratic age effect, cubic usage effect, and significant effects of location and variant.¹⁸ The deviance value/DF of 1.5 indicated a good fit of the Poisson regression model. Subsequent plots illustrate the effects listed in this table as well as those from the separate analysis of EDA data for Bradleys.

¹⁸ In Poisson and negative binomial regressions with log links, linear, quadratic, and cubic effects are actually log-linear, log-quadratic, and log-cubic effects, as the regression coefficients specify the impact of predictors on the natural log of mean failures.

For Bradleys, Age Has Modest Effect on Mission-Critical Failures (Consistent with Other Studies)



Predicted curve for location A, type = M2A2 ODS, no deployment, up 365 days, usage = 1,000 miles

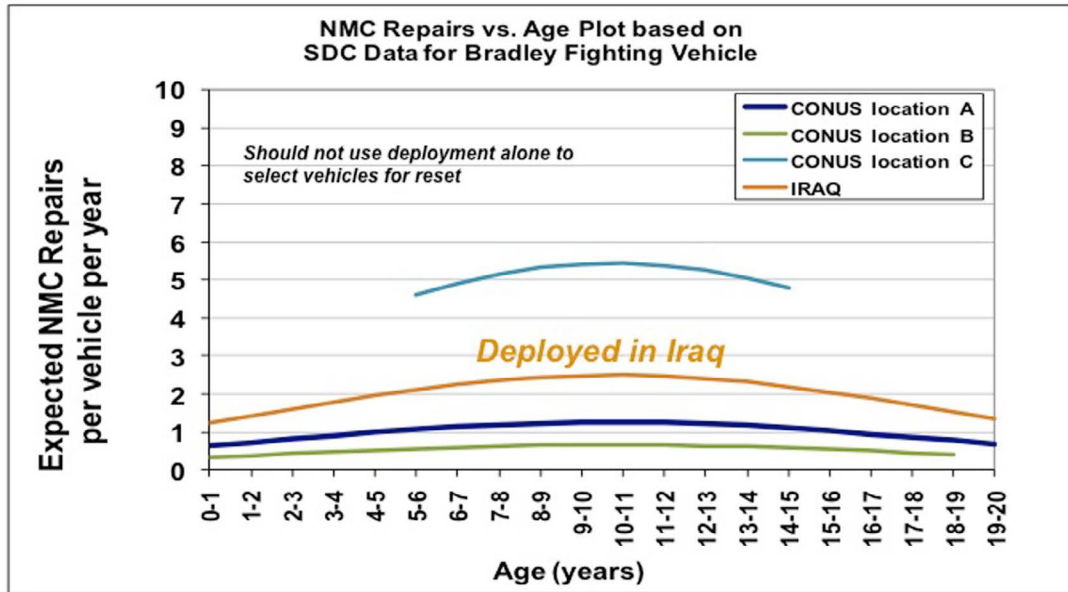
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Our statistical analysis of the Bradley SDC dataset yielded a regression model in which age had a quadratic association with mission-critical failures, such that failures increased mildly with age up to a point (age 10) and then began to decrease. The solid blue curve in the above chart shows the age effect found with the SDC dataset for the Bradley, controlling for usage, location, NSN (type of vehicle), reset, and updates. The downturn in the tail region of the curve may be a result of component replacements that occurred in older vehicles. New components may effectively make such vehicles younger than their original manufacture dates suggest. We did not have data on the age of vehicle components or the component replacement history of vehicles before they were tracked in SDC and EDA.

The dashed blue curve in the above chart shows the age effect found with the EDA dataset for the Bradley, controlling for usage, location, NSN, reset, and updates. (Using lagged usage did not alter this finding.) In this second

analysis, age once again had a mild quadratic effect on mission-critical failures. Both results suggest that age has a statistically significant but mild effect on mission-critical failures and therefore should not be a key criterion for inducting vehicles into renewal programs.

Mission-Critical Failures for Bradleys Deployed in Iraq Were Lower Than in Some CONUS Locations



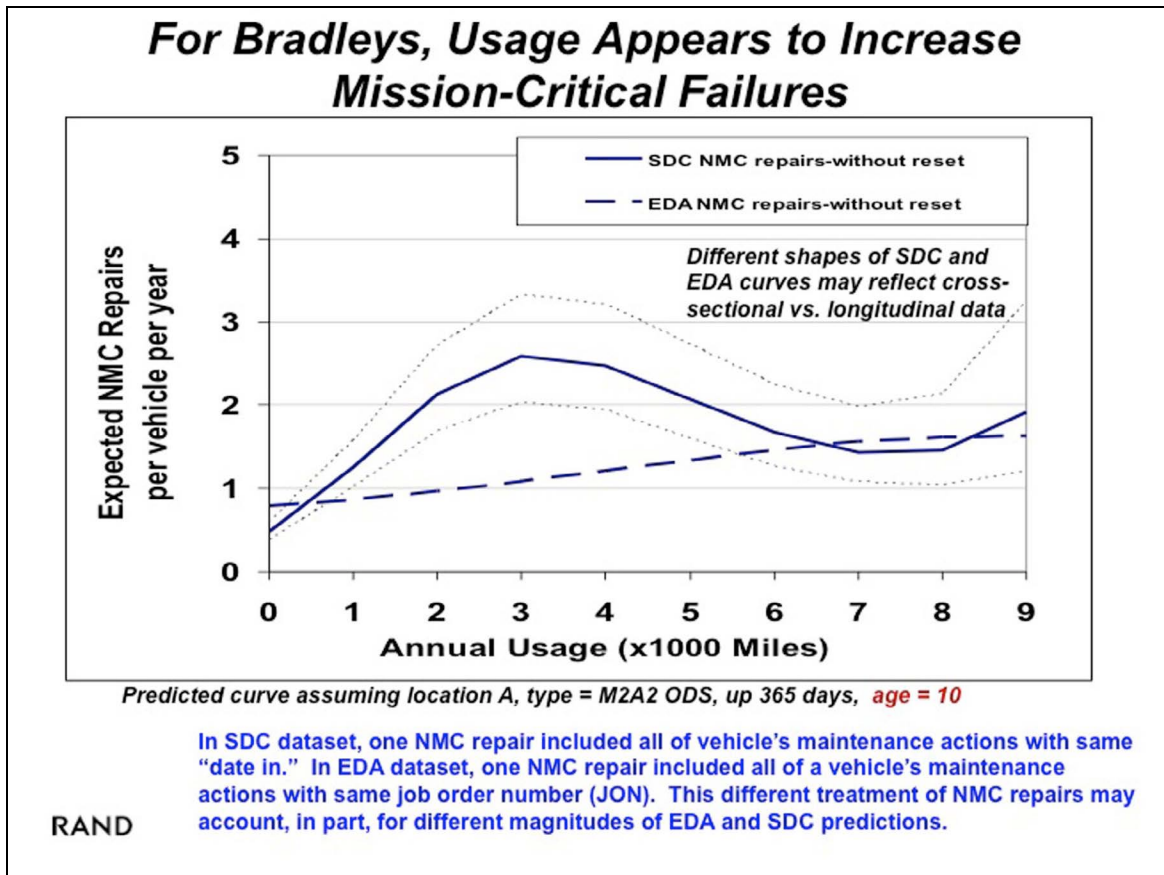
RAND

The location dummy variables had significant effects in both the SDC and EDA analyses. However, our plots of location effects focus on those found with SDC analyses, given that the locations recorded in SDC are not subject to the translation errors and quality issues that affect LIDB location data.¹⁹ As the above curves illustrate, the predicted failure versus age curve was higher for some locations than for others. The different intercepts of the curves reflect location differences. It is particularly noteworthy that *vehicles in some CONUS locations had more failures than vehicles in Iraq*, after controlling for usage and other factors. That is, if one separates the effect of location from usage, vehicles

¹⁹ It is important to keep in mind that although we refer to the second dataset as the “EDA dataset,” the sample was determined by the vehicle-years in LIDB. A vehicle could still have usage without having a mission-critical failure. Thus, the location of usage came from LIDB, rather than from EDA.

located in Iraq do not necessarily need renewal more urgently than vehicles located in CONUS.

As noted by Peltz et al. (2004), different locations may have different environmental conditions, training schedules, maintenance practices, and command policies. Further investigation is needed to determine what accounts for the location effects found in this study. However, based on the observed patterns, a reasonable inference is that deployment alone is not a sufficient criterion for induction into reset.



The solid curve in the above chart illustrates the cubic usage effect found in the SDC analysis of Bradley data. Mission-critical failures increased sharply with vehicle usage until vehicle usage was about 3,000 miles per year. At that point a downturn occurred, followed by a second inflection point in which failures begin increasing again. In contrast, in the EDA analysis Bradley usage had a *slightly* quadratic (almost linear) effect on mission-critical failures.

While both the SDC and EDA analyses suggest an overall upward trend—i.e., that failures tend to increase with usage—there are considerable differences in the magnitudes and shapes of the curves. Several factors may account for these differences. In particular, the usage data in SDC are much higher quality than the LIDB usage data used in the EDA analysis. The magnitude (gradient) of the LIDB/EDA usage effect may therefore be an underestimate.

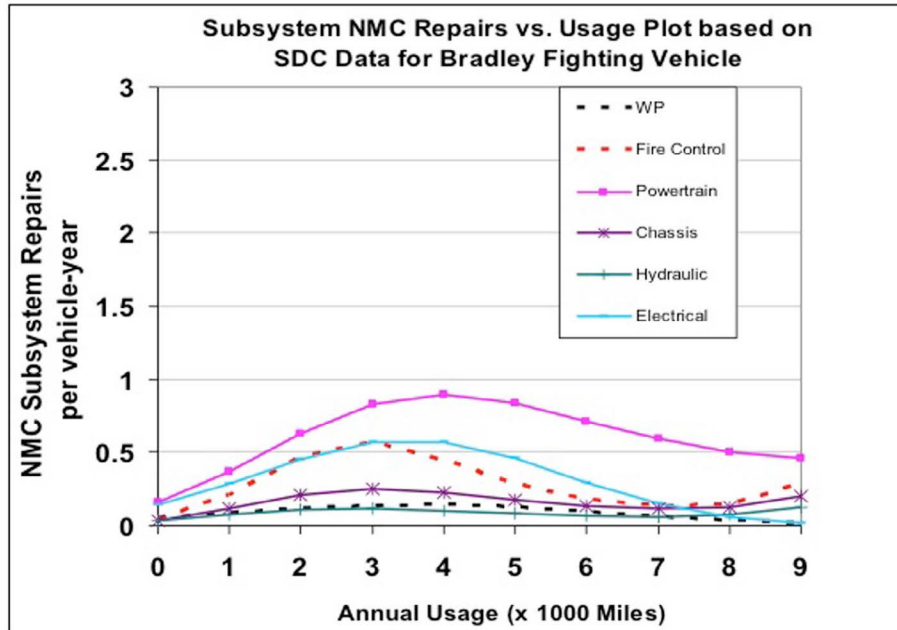
However, the smaller SDC sample size may make the shape of the SDC curve more susceptible to outlier effects. Also, since the SDC dataset is cross-sectional while the EDA dataset is longitudinal, the shape of the SDC curve is potentially more susceptible to other confounding factors. As Pierret (2005:4) has noted,

A classic econometric problem is the existence of unobserved personal characteristics that may be correlated with both the dependent variable of interest and an independent variable that is hypothesized to cause the dependent variable . . . Longitudinal data give us the ability to control for individual effects by using multiple observations of the same individual.

By the same token, because the LIDB/EDA dataset had multiple observations on the same vehicle and allowed a random effect analysis, we were able to control for the confounding effect of unmeasured individual vehicle characteristics. This was not possible with the SDC data.

It is also important to keep in mind that, due to fewer data points, the shapes of the usage curves are less certain in the high-usage region. The dotted curves, which show the 95 percent confidence bands for the SDC curve, become increasingly far apart after about 2,000 miles per year of usage.

Power Train, Electrical, and Fire Control Failures Drive Usage Effects on Bradley Mission-Critical Failures

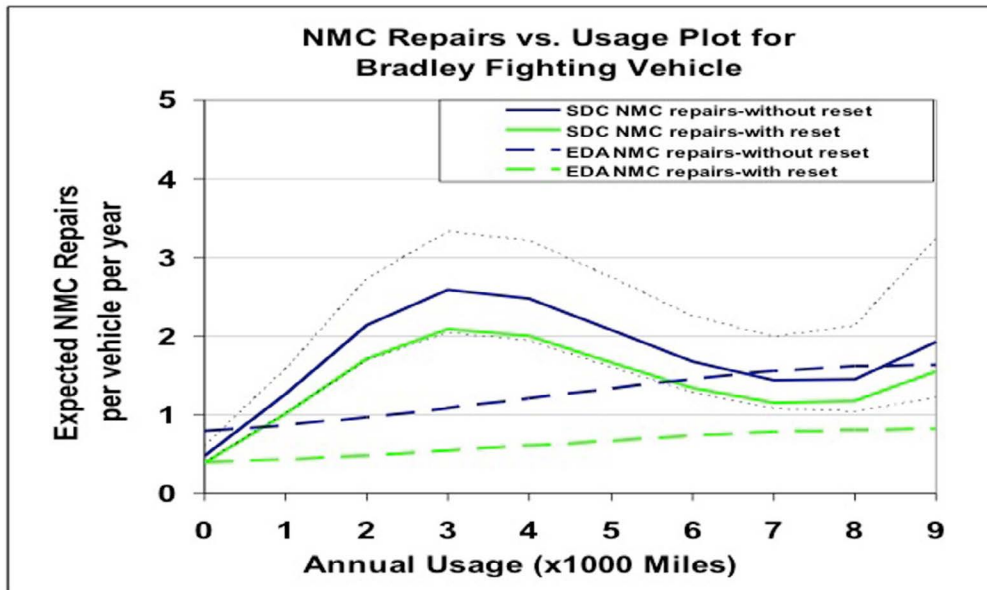


Predicted curve for location A, type = M2A2 ODS, up 365 days, age = 10 years (in usage curve)

RAND

Regressions of Bradley subsystem mission-critical failures on predictors also revealed curvilinear usage effects. The relative heights of the curves suggest that power train, electrical, and fire control failures were the primary drivers of the association between Bradley usage and mission-critical failures. Consistent with the power train finding, during early Operation Iraqi Freedom Boyd (2005:21) noted that “the high usage in the area of operations are causing frequent failures of [Bradley] transmissions.” When Boyd made this observation, in the 2005 timeframe, Bradley usage was reportedly about 5,000–6,000 miles per year—near where peak MC failures occur in the above curve (Korb, Thompson, and Wadhams, 2006; Office of the Secretary of Defense, 2005).

For Bradleys, Reset Reduces Mission-Critical Failures

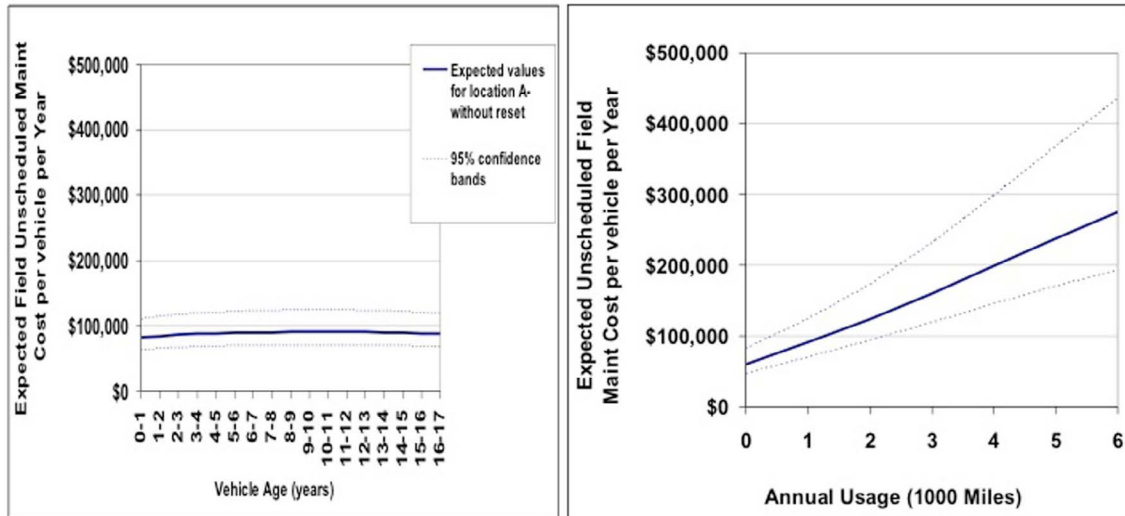


Predicted curve assuming location A, type = M2A2 ODS, up 365 days, age = 10

RAND

In both the EDA and SDC analyses, Bradley vehicles had significantly fewer mission-critical failures after reset than before reset. The blue solid and dashed curves show, respectively, SDC- and EDA-based predicted MC failures versus usage *without* reset. The green solid and dashed curves show, respectively, SDC- and EDA-based predicted MC failures versus usage *with* reset. Predicted MC failures were 20 percent lower for reset vehicles in the SDC dataset and 50 percent lower for reset vehicles in the EDA dataset.

For Bradleys, Annual Parts and Labor Costs Per Vehicle Rise with Usage but Change Little with Age



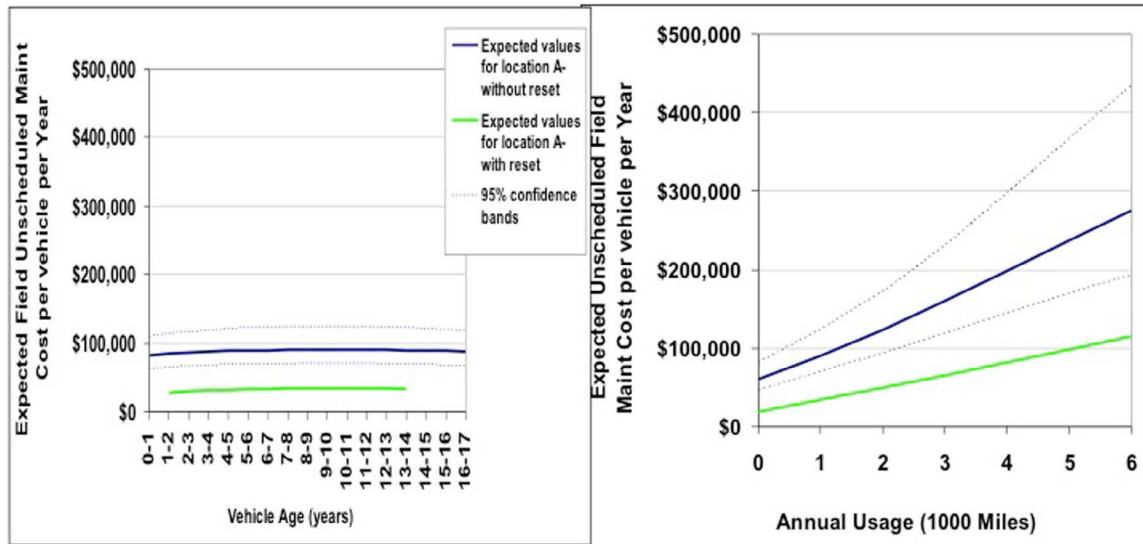
Based on SDC data. Predicted curve assuming location A, type = M2A2 ODS, up 365 days, annual usage = 1,000 miles (for age curve); age = 10 years (for usage curve)

RAND

The above plots were generated from the two-part cost regression for the Bradley. Although the logistic regression (first part of the two-part regression) indicated that age had a slight quadratic effect on the probability of unscheduled field maintenance in a given year, the OLS regression (second part of the two-part regression) indicated that age did not have a significant effect on the magnitude of costs once a maintenance event occurred. As the left-hand plot indicates, the two parts in combination suggested that expected unscheduled field maintenance costs changed little with Bradley age.

However, as the right-hand plot indicates, such costs did increase steadily with usage. Usage had significant quadratic effects on both the probability of maintenance and the costs given that maintenance occurs. As indicated by the 95 percent confidence bands, predictions for higher usage were less certain.

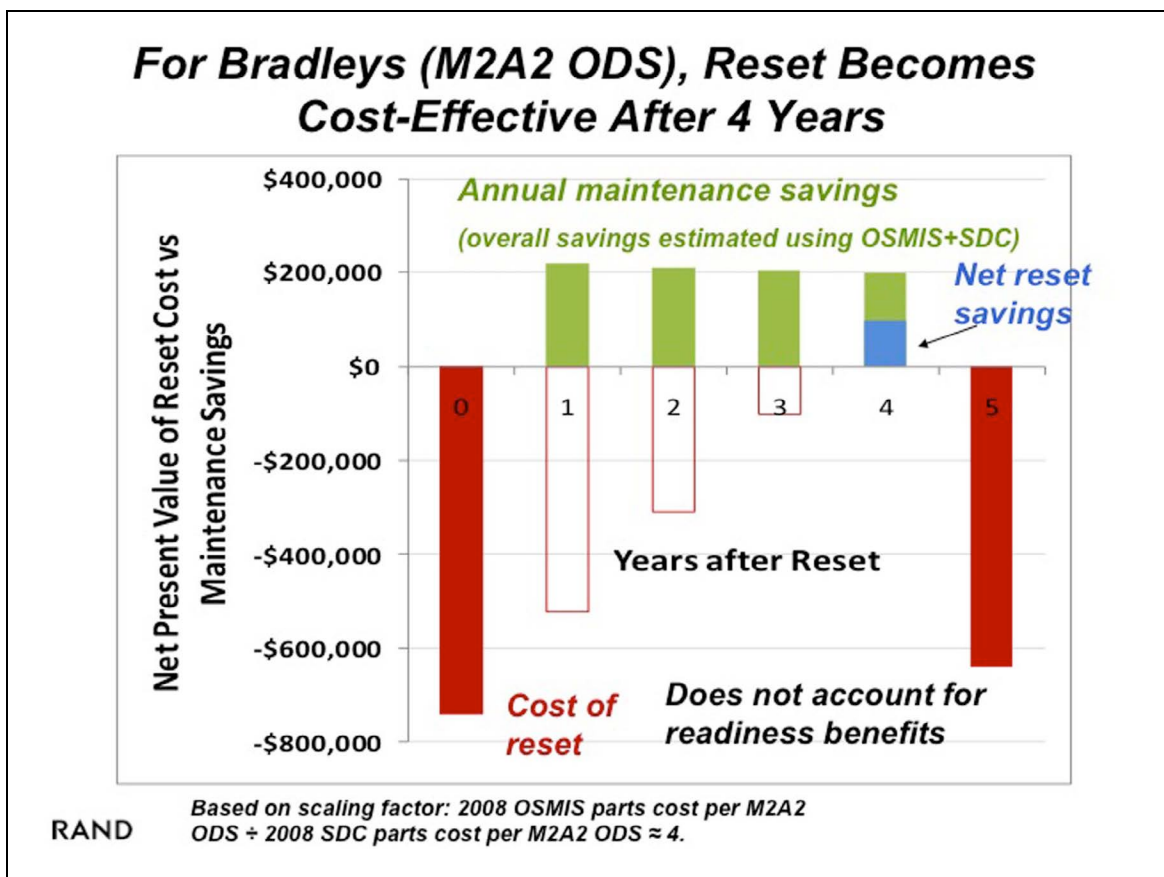
For Bradleys, Annual Parts and Labor Costs Per Vehicle Decrease Substantially After Reset



Based on SDC data. Predicted curve assuming location A, type = M2A2 ODS, up 365 days, annual usage = 1,000 miles (for age curve); age = 10 years (for usage curve)

RAND

The two-part regression also revealed that reset was a significant predictor of unscheduled field maintenance costs. The plot on the left-hand side of the above chart shows that without reset, a Bradley vehicle's expected annual unscheduled field maintenance costs were approximately \$89,000 and changed little with age. With reset, however, expected annual unscheduled field maintenance costs were approximately \$33,000. This suggests that when annual usage is 1,000 miles, reset yields an annual maintenance savings of about \$56,000 per Bradley ODS vehicle. (We used the more precise figure of \$56,300 in subsequent calculations.)



Based on the estimated field maintenance savings of \$56,300 per Bradley per year, we were able to calculate roughly when Bradley reset becomes cost-effective. We began by scaling up the \$56,300 figure to account for maintenance costs other than those SDC captures. OSMIS has average overall parts costs per system by year. The FY 2008 OSMIS FORSCOM and USAREUR parts costs (from SSF O&S Class IX Summary) per M2A2 ODS were \$78,766. This figure was about four times higher than 2008 SDC *parts* costs (not parts + labor) for the same vehicle.²⁰ Thus, we multiplied the savings

²⁰ The SDC data primarily captured costs associated with organization-level repairs. The OSMIS data we used captured all parts demands for vehicles at similar locations. To ensure that parts demands associated with reset were not part of this OSMIS figure, we excluded vehicles owned by AMC from the calculation of OSMIS average parts costs per vehicle for the Bradley.

of \$56,300 by 4 to estimate the overall annual parts and labor savings per vehicle due to reset: \$225,200 per year. Given that M2A2 ODS reset cost is about \$740,000 per vehicle, a net present value (NPV) calculation suggests that maintenance savings compensate for reset costs after about four years, as shown in the above slide. This figure is based on a discount factor of 3 percent and the assumption that annual reset benefits (maintenance savings) do not diminish during those four years.

Also, while Bradley reset may be cost-effective if it occurs every four years, this calculation does not consider readiness benefits. That is, readiness improvement may justify more frequent reset, even if the cost-versus-savings benefits do not.

Summary of Bradley Findings

Predictor Variable	Effects
Age	• Modestly increases MC failures, to a point • Little effect on maintenance costs
Usage	• Increases MC failures, although increase may not be steady • Steadily increases maintenance costs • Largely driven by power train, electrical, and fire control failures
SWA deployment	• Associated with more MC failures and costs than some CONUS locations but less than others
Reset	• Substantially reduces MC failures and costs

RAND

Above is a summary of our analysis results for the Bradley Fighting Vehicle. Age was associated with modest increases in MC failures—and only up to a point; a downturn in the predicted MC failure versus age curve occurred after age 10. Also, vehicle age had a very weak—almost negligible—effect on field maintenance costs.

Usage, however, was associated with greater increases in MC failures and maintenance costs. The power train, electrical, and fire control subsystems were the primary drivers of the Bradley usage effect on MC failures.

Although some Bradley locations had significantly more MC failures and higher maintenance costs than others, the SWA location was not consistently associated with more failures than CONUS locations. That is, when we “partialled out” the effect of high usage and looked strictly at location, vehicles deployed in SWA had fewer MC failures and costs than those in some CONUS locations.

Of particular note is the strong effect of reset. Predicted MC failures were 20–50 percent lower for reset Bradleys than for those that had not been reset. The SDC analysis suggested 20 percent, while the EDA analysis suggested 50 percent. The different magnitudes may stem from having a greater number of reset vehicles, and more post-reset data, in the EDA dataset. As more resets occur over time, subsequent studies may shed further light on such reset effects.

The M1 Abrams Tank

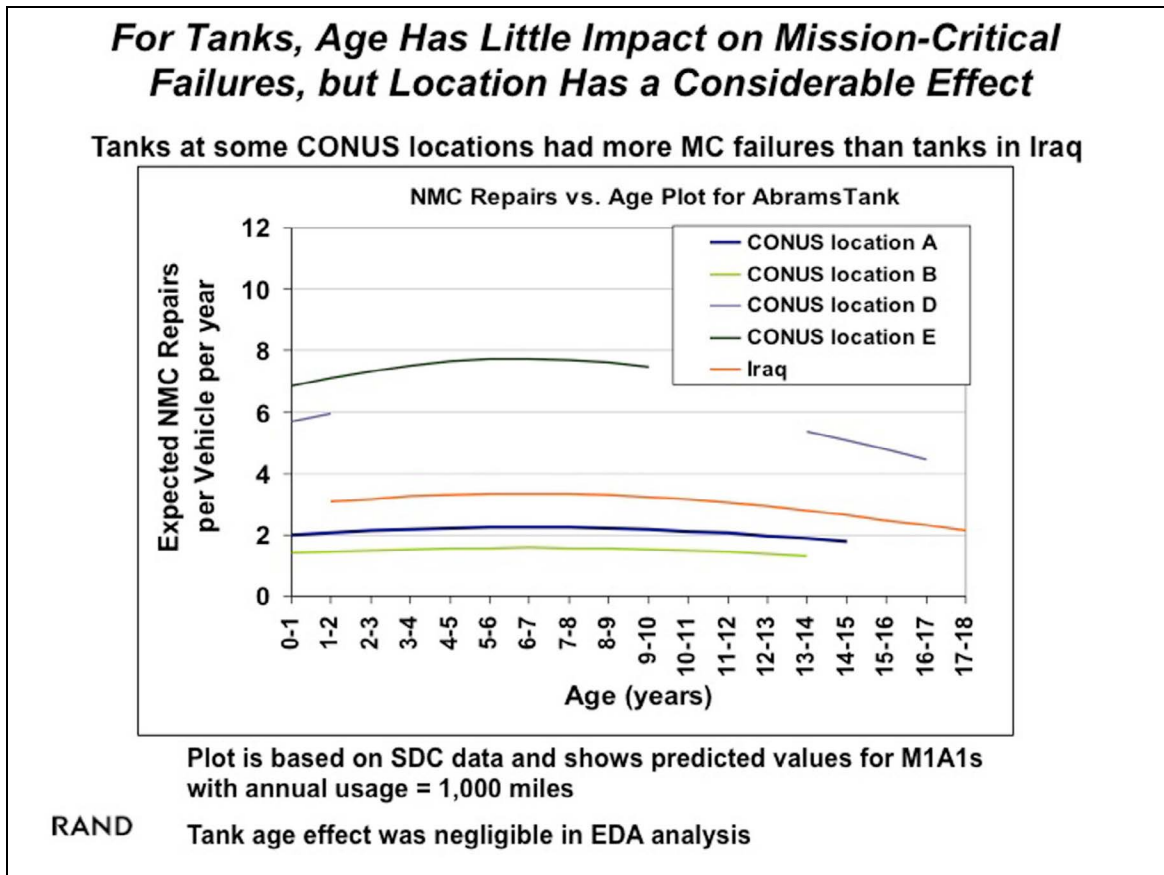
Table 3.2 shows results of the Poisson regression of mission-critical failures on predictor variables in the M1 Abrams SDC analysis.

Table 3.2
Poisson Regression of M1 Abrams Failures on Predictors

Parameter	M1 Abrams Mission-Critical Failures
	Estimate
Intercept	0.7171***
Reset	-0.4855***
(Age)squared	-0.0036**
Age	0.0422*
(Usage)cubic	0.0441***
(Usage)squared	-0.3472***
Usage	1.0817***
Location A	-0.3947***
Location B	-0.7502***
Location C	1.2139***
Location D	0.6576***
Location E	0.8376***
Iraq	0.0000 [other location coefficients show effects relative to effect of Iraq]
Type: M1A1	-0.4114***
Type: M1A2	0.0000 [other type coefficients show effects relative to effect of M3A2 ODS]
Deviance: Value/DF = 6445/6421 = 1.0	
Ln(updays) was an offset variable in the regression; this is equivalent to being a parameter with estimate = 1.	
* $p < .05$; ** $p < .01$; *** $p < .001$	

The final model had a quadratic age effect, cubic usage effect, and significant effects of location and variant.²¹ The deviance value/DF of 1.0 indicated a good fit of the Poisson regression model. Subsequent plots illustrate the effects listed in this table, as well as those from the separate analysis of EDA data for tanks.

²¹ In Poisson and negative binomial regressions with log links, linear, quadratic, and cubic effects are actually log-linear, log-quadratic, and log-cubic effects, as the regression coefficients specify the impact of predictors on the natural log of mean failures.

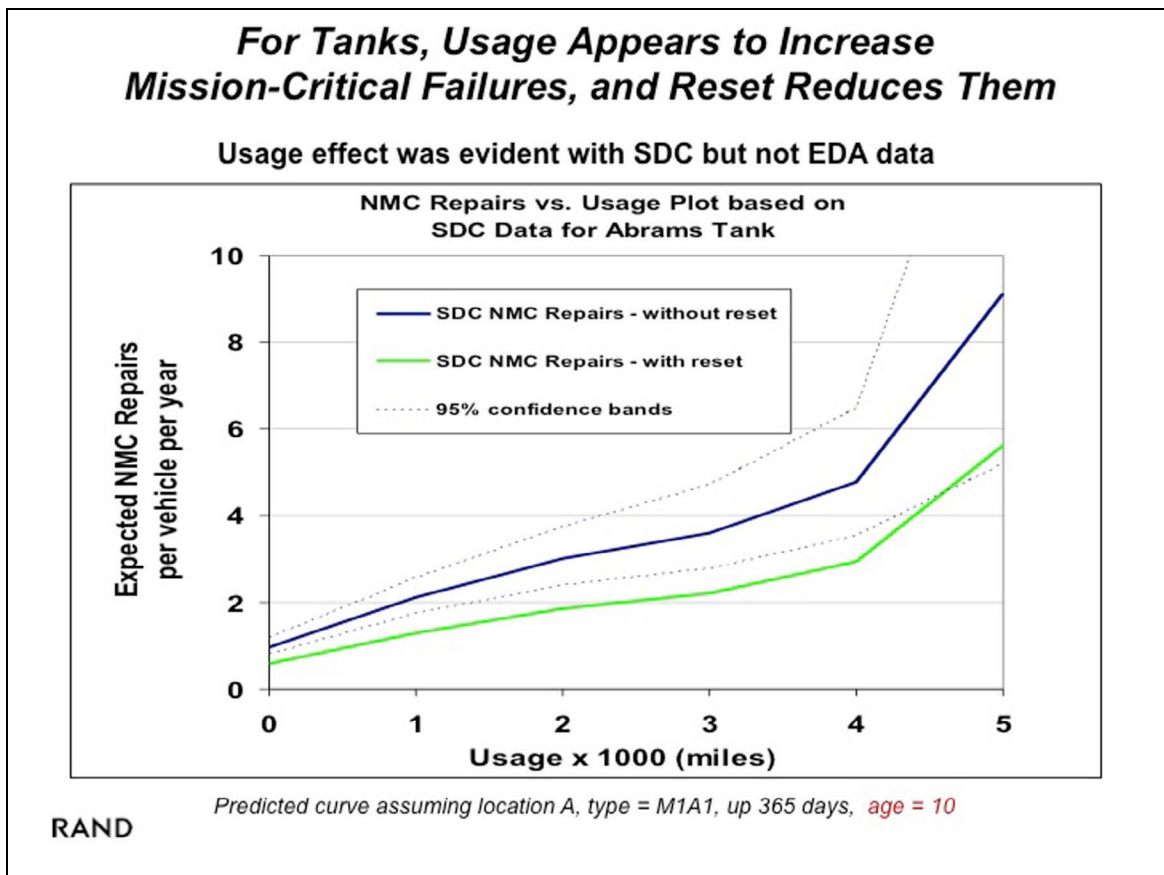


As with the Bradley, SDC analyses revealed that age had a modest curvilinear effect on expected M1 Abrams tank MC failures; however, the age effect was even milder than it was for the Bradley. Also, in the EDA analysis, the age effect on tanks was not statistically significant. This EDA finding differs from an earlier finding with EDA data (Peltz et al., 2004). It should be noted, however, that the current study has a different M1 fleet composition and more longitudinal EDA data than the earlier Abrams study.

While there were few M1A1 AIM and M1A2 SEP tanks when data were gathered for the earlier study (1999–2000), currently they have a significant presence in the fleet. Of 4,470 tanks (22,271 vehicle-years) in the EDA sample for the present study, approximately 623 of the vehicles (3,573 vehicle-years) were M1A2 SEP tanks, and 285 of the vehicles (1,478 vehicle-years) were M1A2 AIM tanks. The newer tanks in the present study, those manufactured from 2000 to the present, were almost exclusively AIM and SEP tanks, which

were upgraded versions of earlier tanks. Separate analyses of older tanks (manufactured before 2000) and newer tanks (manufactured after 2000) may reveal aging effects within those subsamples; such subsample analyses may be a worthwhile avenue to pursue in follow-up work.

As reflected in the different intercepts of the curves in this plot, location had a significant impact on tank MC failures. However, as with the Bradley, SWA was not consistently associated with more failures than CONUS locations.



The blue curve in the above plot shows that in the SDC analysis, M1 Abrams usage significantly increased expected MC failures. The slope of the curve becomes steeper when usage is 3,000+ miles per year—and steeper yet after 4,000 miles per year, suggesting that this effect of usage on failures becomes stronger at high usage; however, the 95 percent confidence bands indicate that predictions are less certain in that range.

In the EDA analysis, the effect of usage on expected MC failures was *statistically* significant but, practically speaking, negligible.²² Recall that for the

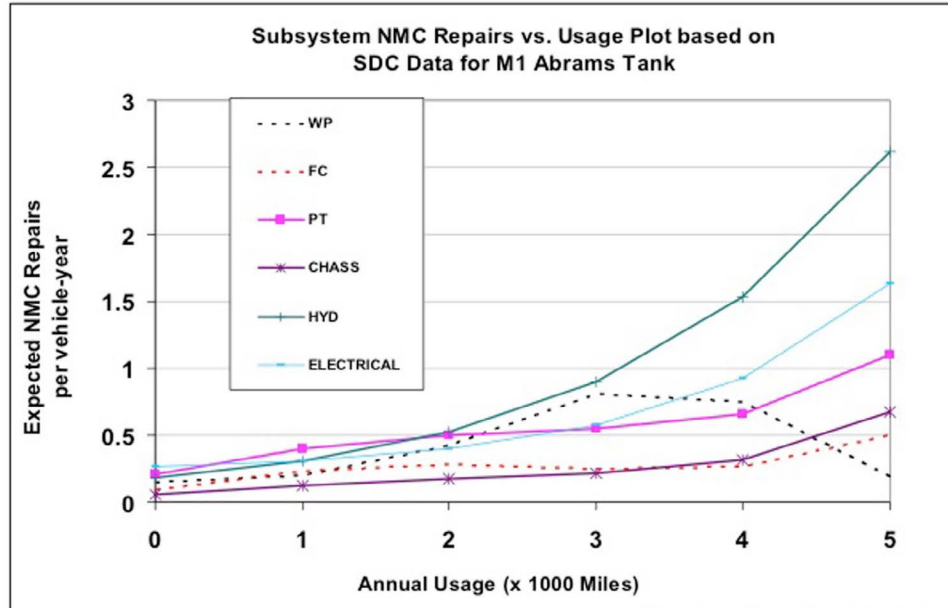
²² The effect was hardly visible in a failure versus usage plot, even when the y-axis scale was 0 to 1 failures. In the Peltz et al. (2004) study using LIDB and EDA data, the Abrams usage effect was stronger (e.g., with predicted MC failures increasing from 0.8 per 180 days to 1.7 per 180 days when usage increased from 0 to 1,000 kilometers). As with the age effects, it is important to keep in mind that the composition of the Abrams fleet has changed

Bradley, the EDA analysis also suggested a milder usage effect than the SDC analysis. For both the Abrams and the Bradley, higher-quality SDC usage data may, in part, be responsible for discrepancies in the usage effects found with the SDC and EDA datasets.

The green curve shows that in the SDC analysis, reset reduced the predicted MC failures of Abrams tanks by about 38 percent. In the EDA analysis, the effect of reset on Abrams tanks was also significant, but the benefit was milder and delayed. That is, reset reduced predicted failures by about 13 percent, but not until two years after the vehicle was reset.

since 2001, when data were gathered for the Peltz et al. study. Also, the time horizon and set of locations in the Abrams LIDB and EDA data have changed.

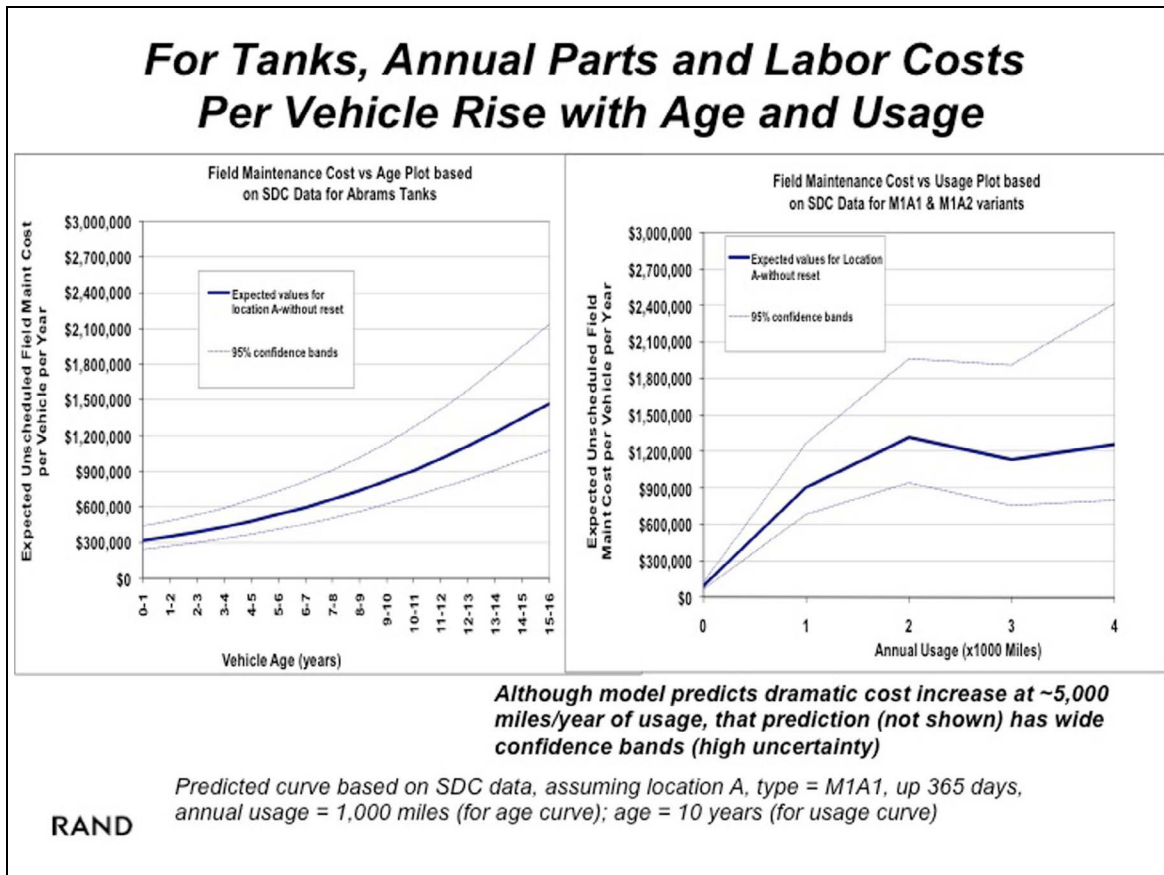
Hydraulic, Power Train, and Electrical Failures Drive M1 Abrams Usage Effects on Mission-Critical Failures



Predicted curve for location A, type = M1A1, up 365 days, age = 10 years (in usage curve)

RAND

Analyses of Abrams subsystem MC failures in the SDC dataset revealed that the usage-failure curve for most subsystems (except the weapon subsystem) was similar in form to the overall M1 usage-failure curve. The relative heights of the curves, however, suggest that the hydraulic, power train, and electrical failures were the primary drivers of the association between tank usage and mission-critical failures. The weapon (main gun) subsystem had a considerable role in the M1 usage-failure relationship at lower usage.

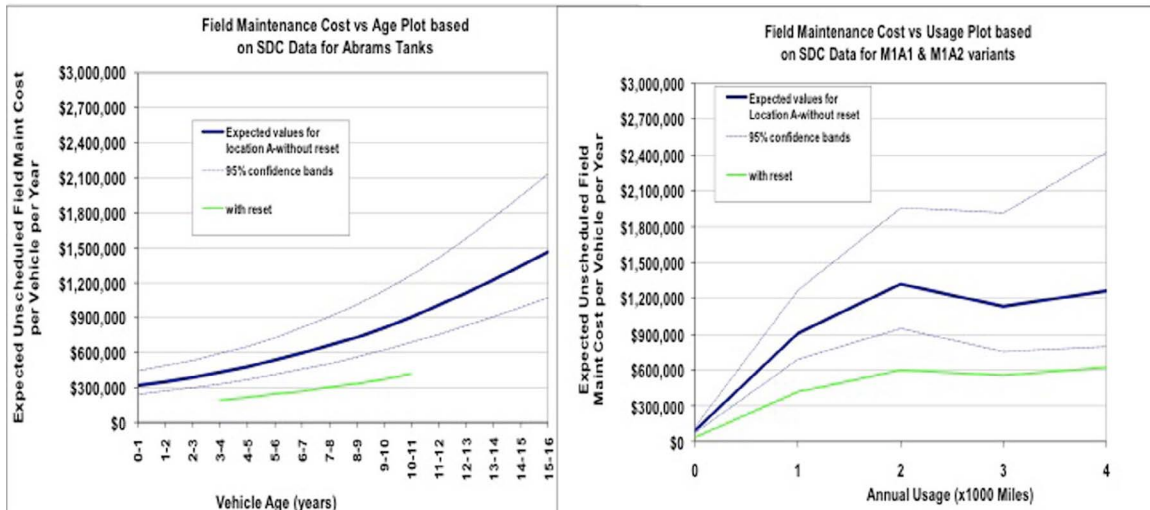


The two-part cost regressions for the Abrams indicated that tank age had a relatively strong effect on expected unscheduled field maintenance costs per vehicle per year, as the left-hand plot above indicates. That is, even though NMC repairs (MC failures) changed very little with vehicle age, the costs of unscheduled field maintenance in general—both NMC and non-NMC—steadily increased with age.

As the right-hand plot indicates, predicted maintenance costs also increased with usage but reached a plateau after approximately 2,000 miles per year of usage. At this plateau, the predicted costs for 10-year-old M1A1 tanks at a CONUS location were about \$1.2 million per vehicle per year. (High tank maintenance costs were often associated with replacement of the power pack with container, having a part cost of greater than \$500,000.) Although the regression model predicted a dramatic tank maintenance cost increase after

5,000 miles per year of usage, the 95 percent confidence bands became too far apart for predictions to be meaningful at that point.

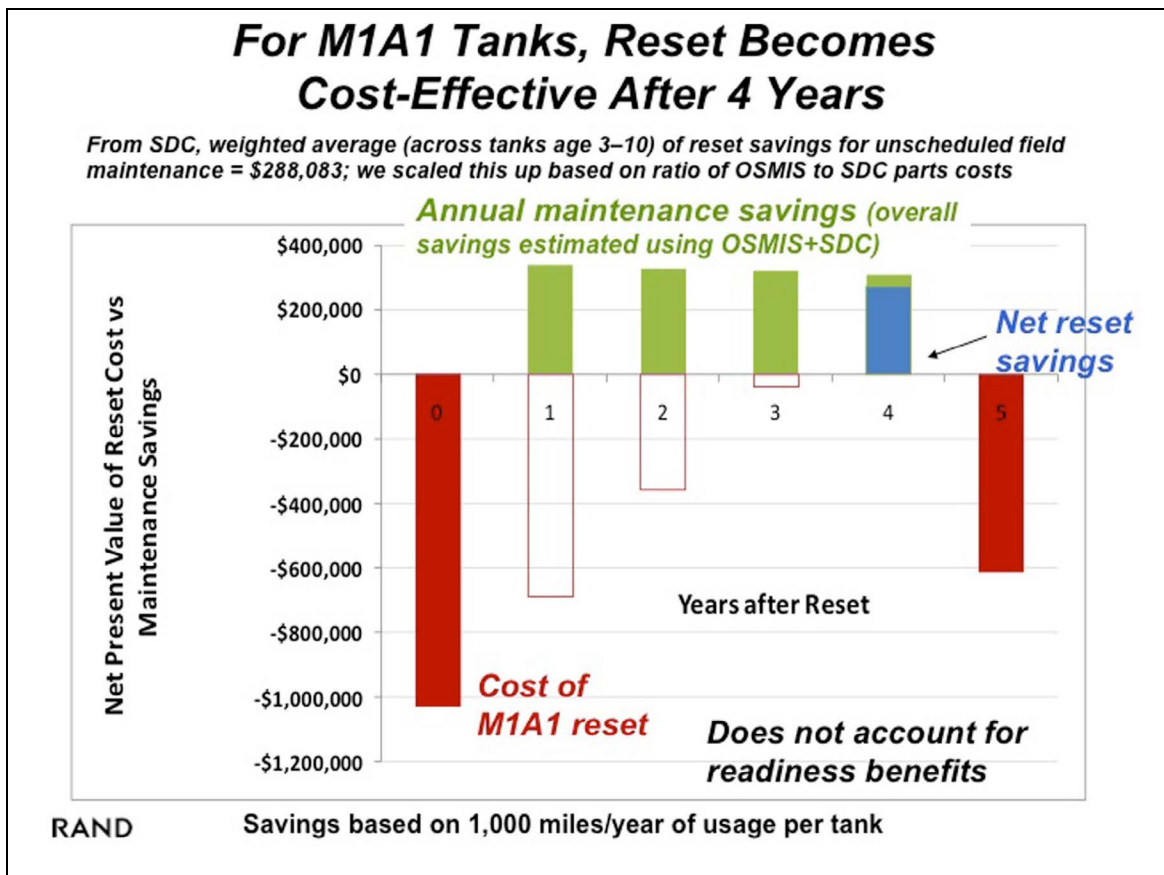
For Tanks, Annual Parts and Labor Costs Per Vehicle Decrease Substantially After Reset



Based on SDC data. Predicted curve assuming location A, type = M1A1, up 365 days, annual usage = 1,000 miles (for age curve); age = 10 years (for usage curve)

RAND

The two-part regression also revealed that reset was a significant predictor of M1 Abrams unscheduled field maintenance costs. In the plot on the left-hand side of the above chart, the average difference between the blue curve (maintenance costs without reset) and green curve (maintenance costs with reset) across age groups was approximately \$288,000. This suggests that when annual usage is 1,000 miles, reset yields an annual maintenance savings of about \$288,000 per M1 Abrams tank. (We used the more precise figure of \$288,083 in subsequent calculations.)



Based on the estimated field maintenance savings of \$288,083 per tank per year, we were able to calculate roughly when Abrams reset becomes cost-effective. We began by scaling up the \$288,083 figure to account for maintenance costs other than those SDC captures. OSMIS has average overall parts costs per system by year. The FY 2008 OSMIS FORSCOM and USAREUR parts costs (from SSF O&S Class IX Summary) per M1A1 Abrams were \$182,934. This figure was about 1.215 times higher than 2008 SDC *parts* costs (not parts + labor) for the same vehicle. Thus, we multiplied the savings of \$288,083 by 1.215 to estimate the overall annual parts and labor savings per vehicle due to reset: \$350,068 per year. Given that M1A1 AIM reset cost is about \$1,028,000 per vehicle, an NPV calculation suggests that maintenance savings compensate for reset costs after about four years, as shown in the above slide. This figure is based on a discount factor of 3 percent and the assumption that annual reset benefits (maintenance savings) do not diminish in that time.

Also, the cost-effectiveness calculation does not consider readiness benefits. As mentioned earlier, readiness gains may justify more frequent reset, even if the cost-versus-savings benefits do not.

Summary of Abrams Findings

Predictor Variable	Effects
Age	• Very modestly increases MC failures, to a point • Steadily increases maintenance costs
Usage	• May steadily increase MC failures (effect found with SDC but not EDA) • Increases maintenance costs to a point • Largely driven by hydraulic, power train, and electrical failures
SWA deployment	• Associated with more MC failures and costs than some CONUS locations but less than others
Reset	• Substantially reduces MC failures and costs (stronger effect found with SDC data)

RAND

In general, findings for the M1 Abrams tank were similar to those for the Bradley. Above is a summary of our Abrams analysis results. Age had a minimal effect on the expected annual MC failure (NMC repair) count per tank, increasing failures very mildly up to a point; however, age steadily increased field maintenance costs associated with NMC and non-NMC repairs.

Usage was associated with greater increases in Abrams MC failures and maintenance costs. The hydraulic, power train, and electrical subsystems were the primary drivers of the Abrams usage effect on MC failures.

Although some Abrams locations had significantly more MC failures and higher maintenance costs than others, the SWA location was not consistently associated with more failures than CONUS locations. As with the Bradley, when we “partialled out” the effect of high usage and looked strictly at location effects on the Abrams, vehicles deployed in SWA had fewer MC failures and costs than those in some CONUS locations.

Like Bradley reset, Abrams reset reduced predicted MC failures and field maintenance costs, becoming cost-effective after four years. However, unlike Bradley reset, Abrams reset had a stronger impact in the SDC analyses than in the EDA analyses. Again, as more resets occur over time, subsequent studies may provide more definitive information about the magnitude of reset benefits.

The FMTV M1078 Series Truck

Table 3.3 shows results of the Poisson regression of mission-critical failures on predictor variables in the FMTV SDC analysis.

Table 3.3
Poisson Regression of FMTV Failures on Predictors

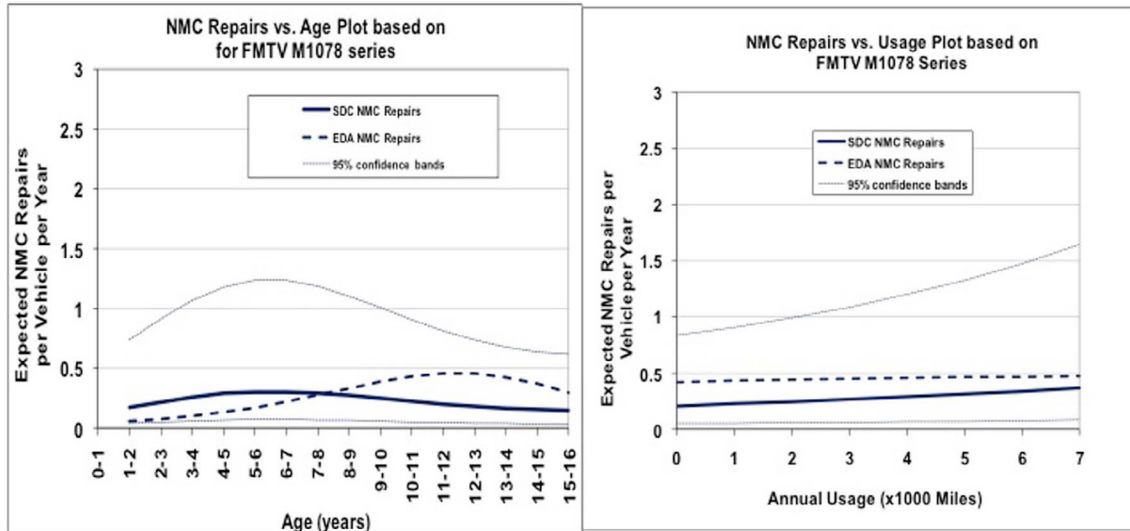
Parameter	FMTV M1078 Series Mission-Critical Failures
	Estimate
Intercept	2.8958***
(Age)cubic	0.0014**
(Age)squared	-0.0036**
Age	-0.0445**
Usage	0.0822*
Location A	-0.2953
Location C	0.7118
Location E	0.1477
Location F	0.6717
Location G	-0.3427
Location H	0.3556
Location I	0.0388
Iraq	0.6957
Misc low-density sites	0.0000
Type: M1078	1.0458***
Type: M1078W/W	1.4654
Type: M1078A1W/W	-0.0129
Type: M1078A1	0.0000
	[other type coefficients show effects relative to effect of M3A2 ODS]
Deviance: Value/DF = 2001/2992 = 0.67	
Ln(updays) was an offset variable in the regression; this is equivalent to being a parameter with estimate = 1.	
* $p < .05$; ** $p < .01$; *** $p < .001$	

The final model had a small cubic age effect and linear usage effect.²³ FMTV variant had significant effect, but location did not. The deviance value/DF was 0.67 for the Poisson regression model and 0.45 when we ran a negative binomial regression; thus, the Poisson model had a better fit. Subsequent plots illustrate the effects listed in this table, as well as those from the separate analysis of EDA data for tanks.

²³ In Poisson and negative binomial regressions with log links, linear, quadratic, and cubic effects are actually log-linear, log-quadratic, and log-cubic effects, as the regression coefficients specify the impact of predictors on the natural log of mean failures.

For FMTV M1078 Series Vehicles, Age and Usage Have Very Little Effect on Mission-Critical Failures

No significant reset effect found



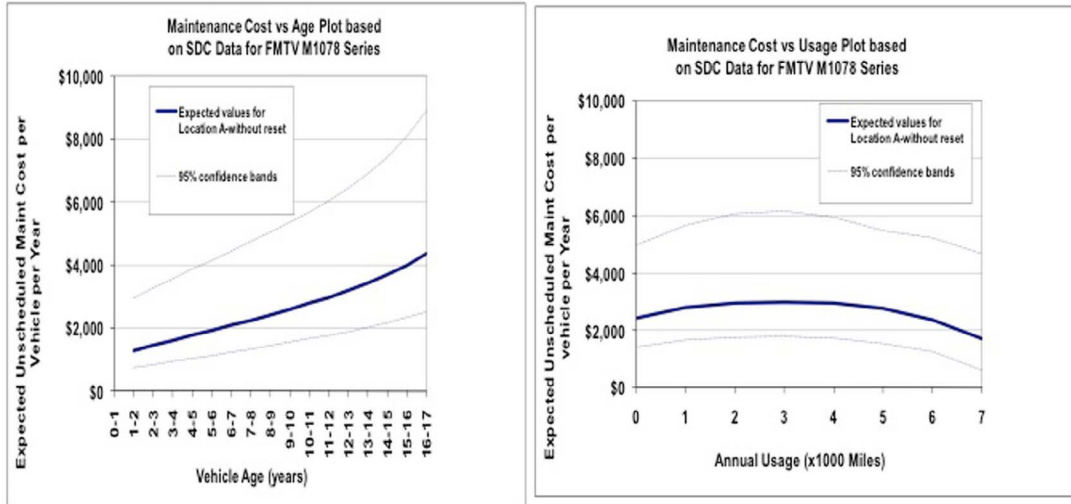
*Predicted curve for location A, type = M1078, no deployment, up 365 days, usage = 1000 miles
(age curve), age = 10 (usage curve)*

RAND

The above failure versus age and failure versus usage plots showed that both age and usage had very little impact on FMTV MC failures. The solid blue curves are the predictions based on SDC analyses, and the dotted blue curves are the 95 percent confidence bands surrounding those predictions. The *dashed* blue curves are the predictions based on EDA analyses. The SDC and EDA findings for FMTV were similar: modest age and usage effects and no significant reset effect. The small gradient of the failure versus usage curve suggests that the FMTV has a much higher tolerance for high usage than do heavy combat vehicles (Bradley and Abrams).

For FMTV M1078 Series, Expected Parts and Labor Costs Increase with Age but Remain Relatively Low (<\$5K per year)

Reset was not a significant predictor of maintenance costs, possibly due to limited number of reset vehicles in the sample. Even if effect were significant, maintenance savings not likely to compensate for the ~\$92K FMTV reset cost.



Predicted curve for location A, type = M1078, no deployment, up 365 days, usage = 1000 miles (age curve), age = 10 (usage curve)

RAND

The two-part cost regressions for the FMTV M1078 series indicated that vehicle age increased expected annual unscheduled field maintenance costs—an effect that was roughly linear, as the left-hand plot above indicates. However, costs remained below \$5,000 per year, even at the high end of the age range.

As the right-hand plot indicates, predicted annual maintenance costs increased slightly with FMTV usage and then decreased. The curvature in the plot reflects the first part (the reliability piece) of the two-part regression: usage had a quadratic effect on the probability of at least one maintenance action in a given year. (In the second part of the two-part cost regression, usage did not have a significant effect on expected costs given that maintenance occurred.) As mentioned earlier, the SDC data were cross-sectional, so the downturn in the tail region may indicate that unmeasured individual vehicle characteristics had a confounding effect.

Summary of FMTV Findings

Predictor Variable	Effects
Age	• Very modestly increases MC failures, to a point • Steadily increases field maintenance costs, but not beyond \$5,000 per year
Usage	• Very modestly increases MC failures, roughly linearly • Very modestly increases maintenance costs to a point
SWA deployment	• No significant location effects found
Reset	• No reset effect found

RAND

Above is a summary of our analysis results for FMTV M1078 series trucks. Both the age and usage effects on MC failures were very small. Age had a more substantial effect on field maintenance costs, but the costs were low (under \$5,000 per year) even in the oldest vehicles. No significant location or reset effects were detected.

The low maintenance costs, minimal effects of age and usage, and lack of a significant reset effect may raise questions about the value of FMTV M1078 series reset. As of October 2008, the cost of CONUS FMTV reset by RRAD/BAE Systems was \$91,825 per vehicle (PM, Heavy Tactical Vehicles, 2009).

Overall Summary of Findings

- **Modest effects of age**
- **Stronger effect of usage on heavy combat vehicles**
- **Power train and electrical subsystems tend to drive usage effects on heavy combat vehicles**
 - Hydraulic subsystem more of a factor for Abrams than Bradley
- **Heavy combat vehicle reset yields readiness benefits and maintenance savings**
 - Bradley and Abrams reset cost-effective after ~4 years
- **Location (proxy for differences in training, maintenance practices, and operating environment) has significant effect on Bradley and Abrams readiness and costs**
 - However, controlling for usage and other predictors, some CONUS locations had more mission-critical failures and higher maintenance costs than Iraq

RAND

When we compared findings for the three systems in this study, a noteworthy set of patterns emerged. First, age only increased mission-critical failures mildly, and only up to a point. (Recall that the downturn in the tail region may reflect the limitations of measuring age based on manufacture date. This age measure did not capture the age of vehicle components—i.e., the component replacement history. Some older vehicles may have had newer components, and therefore fewer failures, than some younger vehicles.) Second, for the heavy combat vehicles (Bradley and Abrams), usage had stronger effects than age, and the power train and electrical systems were among the key drivers of those usage effects. Third, for vehicles driven 1,000 miles per year, both Bradley and Abrams reset became cost-effective four years after reset. Fourth, heavy combat vehicle location clearly affected failures and costs, but after controlling for usage, some CONUS locations were associated with higher expected failure counts and maintenance costs than Iraq.

4. Discussion and Implications

Implications of Age-Usage-Deployment Analyses

- **Should not use age or deployment alone to determine when to reset a vehicle**
- **Generally, reset reduces mission-critical failures, but benefit varies by weapon system**
 - Clear for Bradley and Abrams
 - FMTV warrants further investigation
- **Reset also reduces field maintenance costs**
 - Cost-effective timing of reset depends on reset cost versus maintenance savings for a given system
- **Cost of reset should be evaluated against both reduction in support costs and improved readiness**

RAND

The small age effects found in this study suggest that while a vehicle's original manufacture date merits some consideration when developing reset plans for ground systems, it should not be the sole criterion—or even a key criterion—for inducting vehicles into the program. Recent AMSAA analyses of tactical wheeled vehicles similarly found that age was not a universal predictor of reliability and maintainability (RAM) and costs per mile (Fox et al., 2010a).

By the same token, being located in SWA is not a sufficient criterion for reset induction; vehicles driven few miles in SWA may not need reset immediately after deployment. At a recent AMSAA, LIA, HQDA G-4, and RAND meeting (Fox et al., 2010b) discussing the organizations' respective fleet

management studies, participants concluded that promising vehicle selection criteria for reset may include a combination of usage, cumulative usage (total vehicle mileage), location, and past maintenance history. The relatively strong impact of usage and location (not necessarily deployment) in this study support including those attributes among key reset selection criteria.

This study also provides statistical evidence that national reset (returning vehicles to 10/20 condition) yields substantial readiness benefits and maintenance cost savings for heavy combat vehicles. By demonstrating that current reset programs are bearing fruit, the study suggests that funding of such programs is a sound investment at current usage.

Additionally, the finding that reset becomes cost-effective after four years (for Bradley and Abrams) may inform Army decisions about when and how often vehicles should be reset.

Anticipated Follow-up

- **Further investigate possible reasons for differences in Bradley and Abrams usage effects found with SDC versus EDA, including role of**
 - maintenance data discrepancies
 - proportion of AIM and SEP vehicles in datasets
- **Assess effects on downdays (additional indicator of readiness)**
- **Delve further into subsystem effects: e.g., effects on transmission and engine failures**
- **Assess impact of recapitalization on readiness and maintenance costs**

RAND

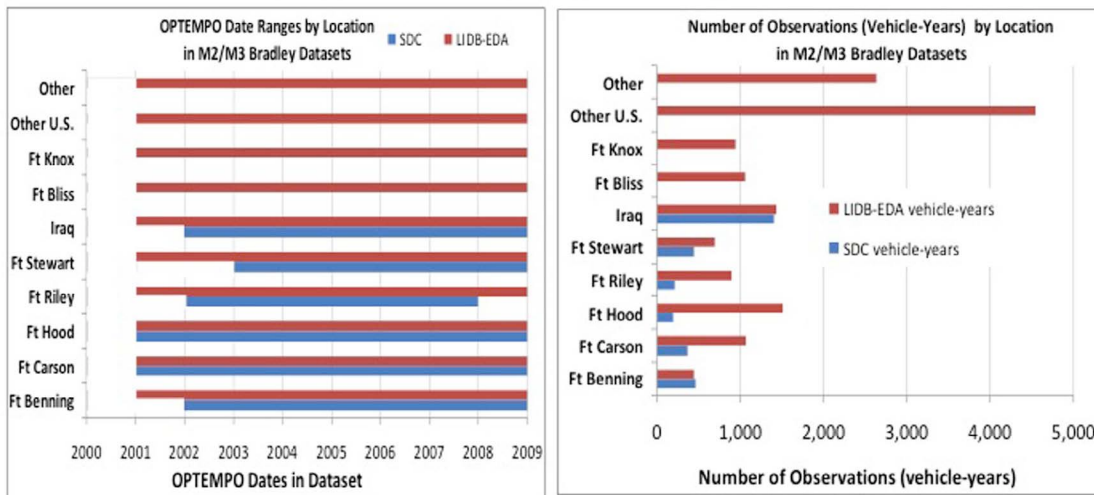
A series of follow-up steps may be valuable extensions of the analyses completed to date. First, it is important to further investigate the reasons that some of the SDC findings were not identical to the EDA findings. Several reasons—the higher-quality usage data in SDC and longitudinal structure of the EDA dataset—were discussed earlier. However, other possible factors—specifically, the degree of overlap in SDC and EDA maintenance data and the role of AIM and SEP vehicles in the two datasets—merit investigation. Second, a regression of downtime on predictor variables may provide a fuller picture of how those predictors affect vehicle readiness. Third, further examination of subsystem effects may shed more light on the factors behind the relatively strong usage effects in this study. Finally, the effects of other types of renewal, especially recapitalization, need to be assessed. Such efforts are likely to expand the contributions of this study to Army fleet management.

Appendix: Sample Profiles

This Appendix provides additional information about the SDC and EDA datasets used in the Bradley, Abrams, and FMTV analyses.

Bradley Data in SDC and LIDB/EDA Datasets Covered Multiple Locations, and Data Collection Dates Ranged from 2002 to 2009

LIDB data for Bradleys cover more locations; however, locations reported in SDC are more accurate



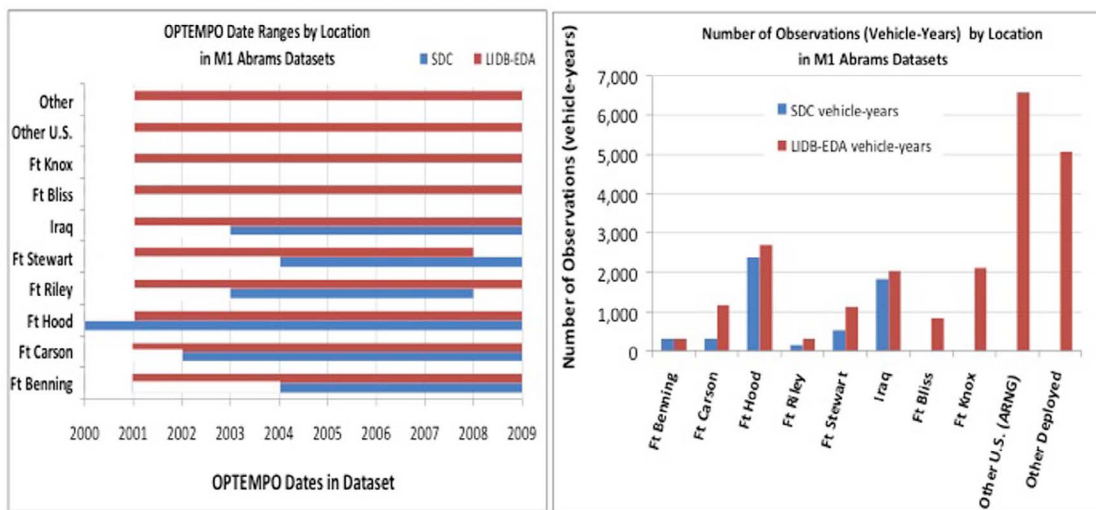
RAND

In this slide, the left-hand bar chart shows the Bradley locations in the SDC and LIDB-EDA datasets and the date range for each location. Both datasets had observation dates ranging from 2002 to 2009. However, each vehicle in the SDC dataset typically had only 365 days of usage data spanning two of those years. In contrast, each vehicle in the LIDB-EDA dataset had about five years of data.

The right-hand bar chart shows the number of observations (vehicle-years) by location in the SDC and LIDB-EDA datasets. Most of the Bradley (M2A2, M2A2 ODS, M3A2, M3A2 ODS) observations in SDC were at Iraq, Fort Stewart, and Fort Benning; none were at other deployed locations or U.S. Army National Guard (ARNG) sites. In contrast, the LIDB-EDA data included many Bradleys at CONUS ARNG sites and deployed locations other than Iraq. It is important to keep in mind, though, that the locations recorded in LIDB were less accurate than those in the SDC dataset.

M1 Abrams Data in SDC and LIDB/EDA Datasets Covered Multiple Locations and Years of Data Collection

Although LIDB data for tanks cover more locations and dates, locations reported in SDC are more accurate

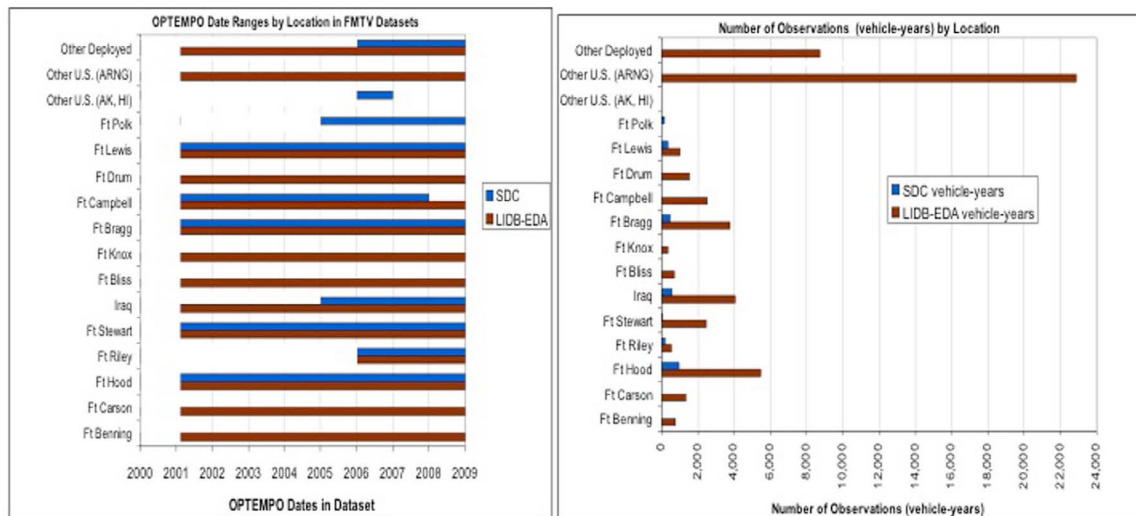


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For the M1 Abrams analyses, the SDC date ranges varied by location, with a wide range of dates (2000–2009) at Fort Hood and narrower ranges at other sites. The LIDB-EDA data that we used spanned the years 2001 to 2009 at each location.

In the SDC dataset, most of the Abrams observations (tank-years) were in Fort Hood and Iraq. In the LIDB-EDA dataset, the primary locations were CONUS ARNG sites and deployment sites other than Iraq; however, many of the remaining Abrams observations were in Fort Hood, Iraq, and Fort Knox.

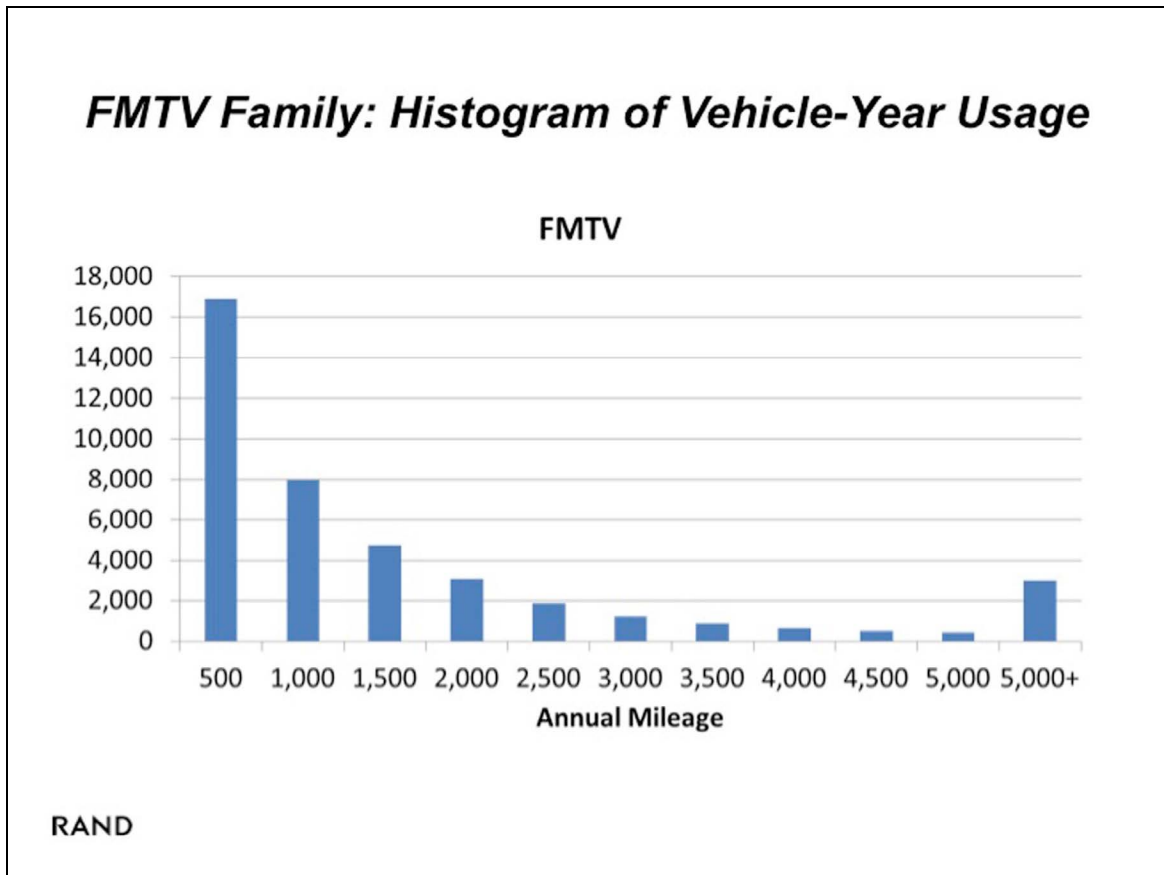
FMTV M1078 Series Data in SDC and LIDB/EDA Datasets Covered Multiple Locations, and Data Collection Dates Ranged from 2001 to 2009



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For the FMTV analyses, the SDC date ranges at Fort Hood, Fort Bragg, and Fort Lewis were 2001 to 2009, but the date ranges were narrower at other locations. The LIDB-EDA data that we used spanned 2001–2009 at each location.

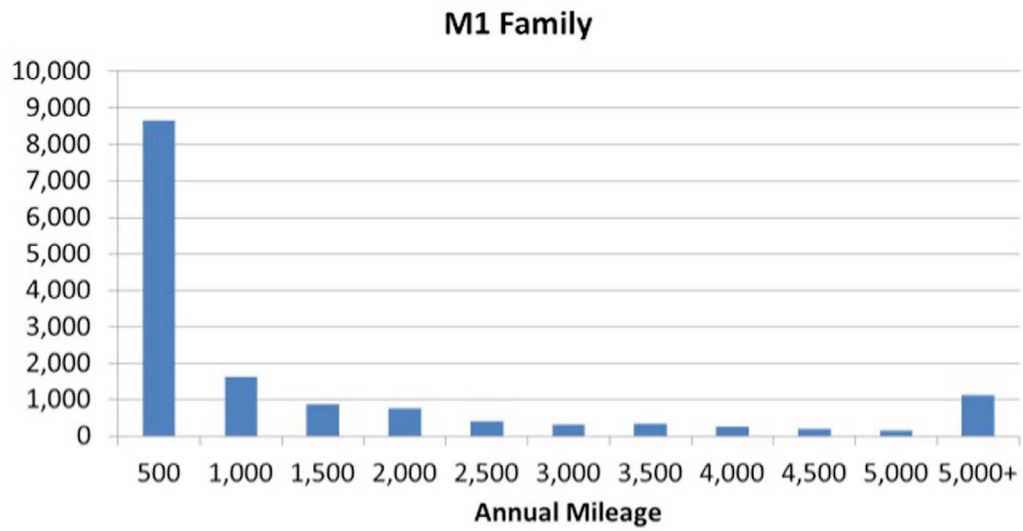
In the SDC dataset, most of the FMTV M1078 series observations were in Fort Hood, Iraq, and Fort Bragg. In the LIDB-EDA dataset, the primary locations were CONUS ARNG sites and deployment sites other than Iraq; however, many of the remaining FMTV observations were in Fort Hood, Iraq, and Fort Bragg.



This chart shows the annual usages for the FMTVs in the study. Each vehicle contributes a variable number of observations: one mileage number for each year in the study. As noted above in the text, the skewness toward the low end of the usage scale means that regression models and predictions are more accurate at lower usages.

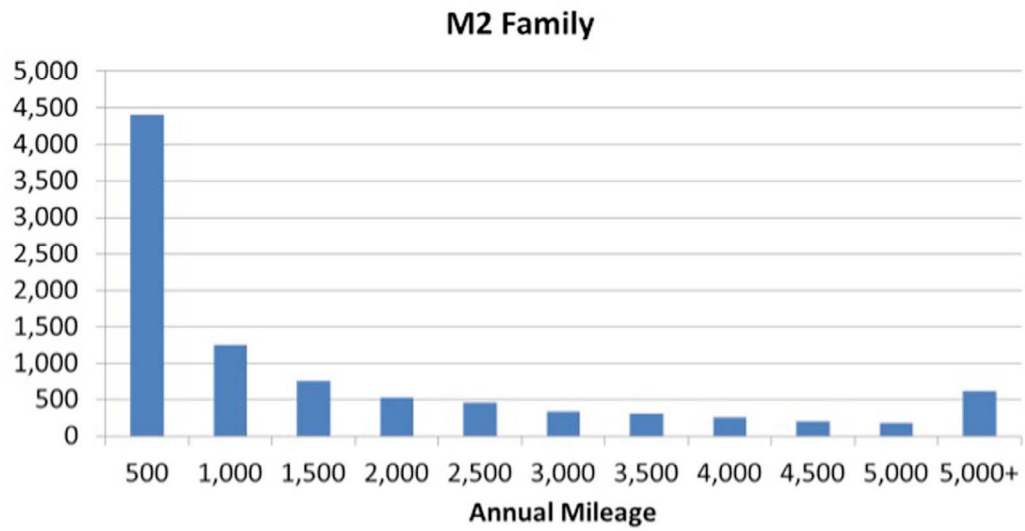
The following two slides show analogous histograms for the M1 and M2 fleets.

M1 Family: Histogram of Vehicle-Year Usage



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M2 Family: Histogram of Vehicle-Year Usage



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Bibliography

Army Materiel Systems Analysis Activity (AMSAA), Field Studies Branch,
2008. As of October 11, 2010:

http://www.amsaa.army.mil/field_studies_branch.htm

Bacchus, Jennifer, "ANAD's Speedy M1A2 Reset Praised," *www.army.mil*
news, July 9, 2010. As of September 30, 2010:

<http://www.army.mil/-news/2010/07/09/42011-anads-speedy-m1a2-reset-praised/>

Boucher, Jacqueline, "Depot Repairs Battle-Damaged Equipment: Subtle,
Distinct Differences in Recap, Reset, Overhaul Repair Programs,"
Tobyhanna Reporter, 2007.

Boyd, Jermaine, "PMCS: Key to Readiness During Deployment," *Army*
Logistician, November–December 2005, pp. 20–21. As of October 25,
2010:

http://www.almc.army.mil/alog/issues/NovDec05/pdf/nov_dec_05.pdf

Buckley, COL John, "A Complement to FCS: Resetting, Upgrading
Capabilities Will Help Speed Modernization," *Army Times*, 2008. As of
October 7, 2010:

http://www.armytimes.com/community/opinion/army_backtalk_modernization_080121/

Burns, Nancy, and Susan K. Grove, *The Practice of Nursing Research: Conduct,
Critique, and Utilization, 5th Edition*, St. Louis, MO: Elsevier/Saunders,
2005.

Chiarelli, General Peter W., *Statement Before the House Armed Services
Committee on Readiness, First Session, 111th Congress, on United States Army
Reset*, July 9, 2009. As of November 11, 2010:

<http://armedservices.house.gov/pdfs/Joint-CHIARELLI.pdf>

Cole, Natalie, "Army's Big Move: R2TF Critical Link in Iraq Drawdown Management," *Army.mil news*, September 21, 2010. As of October 7, 2010: <http://www.army.mil/-news/2010/09/21/45483-armys-big-move-r2tf-critical-link-in-iraq-drawdown-management/>

Congressional Budget Office, *Replacing and Repairing Equipment Used in Iraq and Afghanistan: The Army's Reset Program*, September 2007. As of October 7, 2010: <http://www.cbo.gov/ftpdocs/86xx/doc8629/09-13-ArmyReset.pdf>

Defense File, "General Dynamics Awarded \$20 Million for M1A1 Abrams Reset," August 28, 2007. As of October 25, 2010: http://www.defensefile.com/Customisation/News/Military_Vehicles/Armoured_and_tracked_vehicles/General_Dynamics_Awarded_20_Million_for_M1A1_Abrams_Reset.asp

Diehr, P., D. Yanez, A. Ash, and M. Hornbrook, "Methods for Analyzing Health Care Utilization and Costs," *Annual Review of Public Health*, Vol. 20, 1999, pp. 125–144. As of October 15, 2010: <http://www.annualreviews.org/doi/pdf/10.1146/annurev.publhealth.20.1.125>

Duan, Naihua, "Smearing Estimate: A Nonparametric Retransformation Method," *Journal of the American Statistical Association*, Vol. 78, No. 383, 1983, pp. 605–610.

Dwyer, James C., *Recapitalization*. Briefing presented at AUSA's 2009 Annual Meeting and Exposition, Washington, D.C.: Walter E. Washington Convention Center, October 5, 2009. As of September 30, 2010: http://www.ausa.org/meetings/Documents/CMF20II20_20Army20Moderization20Post20FCS.pdf

Fader, Eric, PM Bradley, personal communication, February 2010.

Fox, Clarke, personal communication at meeting to discuss findings from recent AMSAA, HQDA G-4, LIA, RAND fleet management studies, RAND Washington, D.C., office, September 13, 2010a.

Fox, Clarke, Mark Mossa, and Greg Wyant, personal communication at meeting to discuss findings from recent AMSAA, HQDA G-4, LIA, and RAND fleet management studies, RAND Washington, D.C. office, September 13, 2010b.

Headquarters Department of the Army, *2010 Army Posture Statement*. As of September 30, 2010:

https://secureweb2.hqda.pentagon.mil/vdas_armyposturestatement/2010/2010_army_posture_statement.pdf

Headquarters Department of the Army, *Pamphlet 700-24: Logistics Sample Data Collection*, January 30, 2007.

Korb, Lawrence J., Loren B. Thompson, and Caroline P. Wadhams, *Army Equipment After Iraq*, April 2006. As of October 25, 2010:

http://www.americanprogress.org/kf/equipment_shortage.pdf

Lenth, Russel V., "Some Practical Guidelines for Effective Sample-Size Determination," University of Iowa Department of Statistics and Actuarial Science Technical Reports, March 1, 2001. As of October 6, 2010:

<http://www.stat.uiowa.edu/techrep/tr303.pdf>

Liu, Korbin, Sharon K. Long, and Krista Dowling, "Medicare Interim Payment System's Impact on Medicare Home Health Utilization," *Health Care Financing Review*, Vol. 25, No. 1, 2003, pp. 81–97. As of October 15, 2010:

<http://www4.cms.gov/HealthCareFinancingReview/Downloads/03fallpg81.pdf>

Lorge, Elizabeth M., "Reset Program Maintains Troop Readiness,"

Army.Mil News, August 15, 2008. As of October 7, 2010:

<http://www.army.mil/-news/2008/08/15/11713-reset-program-maintains-troop-readiness/>

Magnuson, Stew, "Military Services Ponder Future of Their War-Worn Trucks," *National Defense*, April 2009. As of October 7, 2010:

<http://www.nationaldefensemagazine.org/archive/2009/April/Pages/MilitaryServicesPonderFutureofTheirWar-WornTrucks.aspx>

Office of the Secretary of Defense, *Ground Force Equipment Repair, Replacement, and Recapitalization Requirements Resulting from Sustained Combat Operations: Report to the Congress*, April 2005. As of October 25, 2010:

http://www.ndu.edu/library/docs/crs/stress_on_equipment.pdf

Peltz, Eric, Lisa Colabella, Brian Williams, and Patricia M. Boren, *The Effects of Equipment Age on Mission-Critical Failure Rates: A Study of M1 Tanks*, Santa Monica, CA: RAND Corporation, MR-1789-A, 2004.

http://www.rand.org/pubs/monograph_reports/MR1789.html

Pierret, Charles, "The National Longitudinal Survey of Youth: 1979 Cohort at 25," *Monthly Labor Review*, February 2005. As of November 10, 2010:

<http://www.bls.gov/opub/mlr/2005/02/art1full.pdf>

Pint, Ellen M., Lisa Pelled Colabella, Justin L. Adams, and Sally Sleeper, *Improving Recapitalization Planning: Toward a Fleet Management Model for the High-Mobility Multipurpose Wheeled Vehicle*, Santa Monica, CA: RAND Corporation, TR-464-A, 2008.

http://www.rand.org/pubs/technical_reports/TR464.html

Program Manager, Heavy Tactical Vehicles, "CONUS Reset vs. Theater Provided Equipment Refurbishment Cost Comparison," calculated October 2008 but provided to RAND team in February 2009.

Simberg, Henry, personal communication during RAND-AMSAA meeting at Aberdeen Proving Ground, MD, August 16, 2010a.

Simberg, Henry, personal communication via emails received August 30 and 31, 2010b.

Simberg, Sheilah, *Analysis of Aging Trends on Army Legacy Vehicles*, U.S. Army Materiel Systems Analysis Activity (AMSAA), TR-698, December 2001.

Tandoi, Valerie, "DOL Gets to Reset Combat Vehicles from Overseas," *Defense Video & Imagery Distribution System*, March 2010. As of October 7, 2010: <http://www.dvidshub.net/news/48006/dol-gets-reset-combat-vehicles-overseas>

UCLA: Academic Technology Services, Statistical Consulting Group, "SAS Annotated Output-Poisson Regression," no date. As of October 18, 2010:
http://www.ats.ucla.edu/stat/sas/output/sas_poisson_output.htm