SYM-AM-20-053

Proceedings
of the
Seventeenth Annual Acquisition Research Symposium

Acquisition Research:
Creating Synergy for Informed Change

May 13–14, 2020

Published: April 10, 2020

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Defense Management at the Naval Postgraduate School.

Budget Forecasting for U.S. Marine Corps Corrective Maintenance Costs

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Abstract

This project presents some methodologies to forecast corrective maintenance costs of the 1st Marine Division. Nearly half of the 1st Marine Division's budget, approximately $25 million, is used for maintenance. The current budgeting process has a number of weaknesses, which include insufficient detail to defend against funding cuts and overreliance on historical execution and expert opinion, and is therefore ill-equipped to adapt to changing requirements or communicate impacts on readiness. By combining and analyzing data from a variety of independent sources, including financial, maintenance, and transportation data, two classes of models were developed to assist maintenance budget planners develop accurate forecasts of corrective maintenance costs. The first class, consisting of causal models, is used to identify cost drivers impacting corrective maintenance costs of two vehicles among the 20 most expensive vehicles used by the Division. The second class, consisting of time series techniques, is used to forecast corrective maintenance costs of the Division's Type A items (or items consuming 80% of the maintenance budget). The analysis indicates that the models can provide a more quantitative and accurate methodologies for 1st Marine Division planners to build, justify, and defend its corrective maintenance budget.

Introduction

A large portion (about 60%) of the 1st Marine Division's annual budget goes towards paying for maintenance. From October 2014 through June 2018, the 1st Marine Division spent over $553 million on maintenance alone. The reasons behind this high spending are not well understood, and there is therefore a need to study and discover the principal drivers behind this expenditure.

In developing corrective maintenance budgets for principal end items, financial management personnel, battalion supply officers, and comptrollers typically rely on historical expenditure data to estimate next year's expenditures. In effect, they use a simple forecasting method referred to in the literature as the naïve forecast model whereby the forecast for the next period expenditure is merely taken to be the same as the most current expenditure. In practical terms, this approach assumes the adage: "We spent this much last year, so we'll probably spend about the same next year." Although this model is easy and requires minimal data, the forecasts generated are poor and generally of small practical value. In particular, there are two primary weaknesses of the naïve forecast model used to budget maintenance expenditures of the 1st Marine Division.

The first problem is that the historical ability to spend a certain maintenance budget is not a defensible justification to guard against cuts in a competitive or fiscally constrained environment. Execution of the allotted budget alone is not evidence that funds are being effectively and efficiently spent. Building a budget based on historical amounts also fails to detect or mitigate fraud, waste, and abuse, which further saps critical resources. A more compelling defense of existing resources can explain why historical amounts were spent, rather than simply stating the amounts that were spent.

The second weakness of this naïve forecast model is its inability to account for trends and drivers of maintenance costs. The equipment set fielded by the 1st Marine Division typically changes every year as obsolete items are disposed of and replaced by new variants with new capabilities, and worn-out material is exchanged for identical refurbished units. The impact of the new mix of equipment and its effects on maintenance spending are rarely considered when establishing maintenance budgets for future years. This constitutes a glaring risk to the 1st Marine Division's ability to fully fund all maintenance requirements considering the varying amount of resources that maintenance consumes every year.

By considering multiple sources of historical data (financial, maintenance, transportation, and training plans), this research proposes to use statistical analysis to develop forecasting models that will overcome many of the limitations of the current approach, and produce more accurate forecasts. In particular, this research will take a closer look at all relevant principal end item factors such as the equipment set fielded to each battalion, its usage, its failure rate, and repair costs and determine if any significant statistical relationship exists between these factors and the incurred corrective maintenance costs. Conclusions derived from this statistical analysis will produce a deeper understanding of maintenance cost drivers and their impact on budgets.

This paper is organized into seven sections. The following section introduces the background information of the project, which includes the 1st Marine Division's organization and its mission. Next, a brief overview of forecasting theory and a review of relevant literature are provided. The next section discusses how data was collected, and characteristics of vehicles used in this study. Then the forecasting models used are defined and the results of the analysis are presented. Next, conclusions and recommendations for forecasting corrective maintenance costs at the 1st Marine Division are provided. Finally, the last section suggests recommendations for future research.

Background

The 1st Marine Division is a multi-role, expeditionary ground combat force. According to 1st Marine Division's website, it is the oldest and largest Marine Corps division with 27 independent battalions, 18,000 personnel, $3 billion worth of equipment, and an annual budget that ranges between $50 and $70 million dollars and is commanded by a two-star general. It is employed as the ground combat element of the I Marine Expeditionary Force (I MEF) and can be task organized to perform assault operations, amphibious forcible entry, and/or subsequent land operations.

Composed of three infantry regiments, an artillery regiment, two light armored reconnaissance battalions, a tank battalion, an amphibious assault battalion, a combat engineer battalion, a reconnaissance battalion, and a headquarters battalion, the 1st Marine Division is headquartered in Camp Pendleton, CA, with the majority of its subordinate units. A few subordinate units such as the 7th Marine Regiment and its battalions and the 1st Tank Battalion are located in Twentynine Palms, CA.

Literature Review

Forecasting Theory

Forecasting is a necessary prerequisite to most operational activities. It is a necessity since it allows management to cope with the ever-changing shifts in demands and costs. A military organization with an oversupply of spare parts in inventory, for example, incurs undue costs caused by stocking, deterioration, or obsolescence of the items. With an undersupply of spare parts, loss of readiness may result. Reliable forecasts are therefore essential for the warfighting capability of the military organization.

Forecasting techniques can be categorized into three groups. The first category referred to as *qualitative*, where all information and judgment relating to an item are used to forecast the demand of such an item. This technique is often used when little or no demand history is available. The forecasts may be based on marketing research studies, the Delphi method, or similar methods.

The second group called *causal* consists of methods seeking to establish a cause-and-effect type of association. Here, the forecaster seeks a relation between an item's demand and other factors, such as business industrial and national indices. This relationship, once identified, is capitalized upon to forecast the future demands of the item. Chief among the causal models is regression analysis. Regression analysis consists of building a statistical model to estimate the mathematical relationship between the variable for which we want to develop a forecast (or the dependent variable usually referred to as Y) and one or more k independent variables (usually referred to as $x_1, x_2, \ldots, x_k$) that are believed to impact the value of the dependent variable.

The third group is called time-series *smoothing* analysis, where a statistical analysis of past demand is used to generate the forecasts. The basic assumption here is that the underlying trends of the past will continue into the future. Time-series smoothing techniques use a form of weighted average of past demand values to smooth short-term up-and-down fluctuations in past values. These fluctuations are assumed to represent random departures from some smooth curve that, once identified, can be extrapolated into the future to produce a forecast. This group consists of the following five popular methods: Moving Averages, Simple Exponential Smoothing, Holt's Exponential Smoothing, Winter's Exponential Smoothing, and Adaptive-Response-Rate Single Exponential Smoothing

Relevant Literature

In this subsection, we focus on reviewing studies that addressed maintenance cost of military vehicles, for the purpose of discovering the drivers of their maintenance costs.

Shukri, Jusoh, Ramlan, and Anuar (2013) conducted a study for the National Defense University of Malaysia to identify the operating and maintenance cost drivers of a three-ton military vehicle. They concluded, by means of regression analysis, that a significant relationship exist between such variables as weather and terrain are vehicle costs.

Andrzejczak and Selech (2017) used non-military vehicles to conduct a study that investigated the trends of corrective maintenance costs of public transportation vehicles. In their study, they identify factors contributing to unscheduled maintenance and conducted an analysis of variance (ANOVA) to understand what was driving costs in public transportation vehicles. They found that mileage did not have a significant affect in terms of average cost of unplanned maintenance. This study found that mileage was not a significant variable when looking at the causal relationship of corrective maintenance and miles the vehicle was driven.

Lavin, McNabb, and Sullivan (2017) examined the question of whether equipment age affected the operational availability and operating costs of 47-foot Motor Lifeboats in the U.S. Coast Guard. While this study focused primarily on operational availability, it did conduct a regression of operational availability of the Motor Lifeboats with age as the independent variable. This study found that age played a significant role in the operational availability of the Motor Lifeboats.

Goguen and Purcell (2013) conducted a cost analysis for life-cycle preventive maintenance, administrative storage, and condition-based maintenance of MTVR vehicles, which includes the D0003 MTVRs. They investigated MTVR storage and their maintenance costs trends to determine the best way to store unused vehicles.

Reuter (2007) conducted a reliability study on the cargo variant MTVRs (similar to the D0003) used in Operation Iraqi Freedom. He identified the importance of the quality of the data and refinement of the data for MTVRs and provided additional context into MTVR usage including miles driven as primary variable of his system reliability analysis.

Foley (2015) looked at another reliability study that looked at data quality and reliability analysis of USMC ground vehicle maintenance records. In his study, Foley used generalized linear regression models to determine the expected number of dead lining events for vehicles. His results showed that scheduling more than one maintenance event in a year reduced the quantity of dead lining events. More importantly, he also highlighted the high level of inaccuracy of vehicle odometer readings.

Mimms (1992) conducted an analysis on USMC ground equipment maintenance data to forecast future maintenance events. He used historical maintenance data to simulate future repair and failure times of different types of ground equipment.

Based on the aforementioned review, it appears that the current qualitative method to forecasting corrective maintenance budgets could benefit from the use of advanced forecasting methods. While some of the relevant previous work reviewed herewith applied some quantitative approaches to forecast corrective maintenance costs in similar civilian and military organizations, none of these studies applied causal and time series models using the same data set. It is therefore useful to investigate whether causal models alone or in combination with time series models provide better forecast for corrective maintenance costs.

Data and Methods

Data for this research is collected from the 1st Marine Division sources including Transportation Capacity Planning Tool (TCPT) and Global Combat Support System–Marine Corps (GCSS-MC) data which are For Official Use Only (FOUO) sources.

Global Combat Support System–Marine Corps

The Global Combat Support System–Marine Corps (GCSS-MC) is the information system the Marine Corps uses to collect and record maintenance and requisition data for ground equipment. The data set was pulled from 18 tables of data that are consolidated by Headquarter Marine Corps commonly referred to as the R-001 report by Logistics Command, at Headquarters Marine Corps, based on custom specifications. The final data set contains approximately 450,000 records from October 1, 2013, to June 29, 2018, encompassing four full fiscal years (FY14–FY17) and the first nine months of FY18, totaling $553 million.

Vehicle Characteristics

Two vehicles were identified for forecasting analysis based on the total of their maintenance costs and available usage data. The two vehicles were the D0003, a variant of the Medium Tactical Vehicle Replacement (MTVR) cargo truck, and the D0030, a variant of the High Mobility Multipurpose Wheeled Vehicle (HMMWV). These vehicles are prevalent in the 1st Marine Division, as there are 331 D0003 MTVRs and 514 D0030 HMMWVs in service as of June 2018.

Transportation Capacity Planning Tool

Transportation Capacity Planning Tool (TCPT) is the information system the Marine Corps uses to operationally manage most of its transportation equipment, including the D0003 MTVR and the D0030 HMMWV. The most important aspect of TCPT for the purposes of this study is its historical logs that contain usage data. Each time a vehicle is dispatched, a TCPT log is created to keep a record of the vehicle's usage. The range for the data set includes all vehicles dispatched by the 1st Marine Division units between January 1, 2016, and May 16, 2018.

Forecasting Analysis

In this section, we present the results of our forecasting analysis using two groups of models: a *causal* model by means of multiple linear regression and several time series *smoothing* forecasting models.

Multiple Linear Regression

Multiple regression analysis consists of building a statistical model to estimate the mathematical relationship between the dependent variable for which we want to develop a forecast *y* and one or more of seven independent variables, x_1, x_2, ..., x_7, that are believed to impact the value of the dependent variable where as follows:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_5 x_5 + b_6 x_6 + b_7 x_7 \qquad (1)$$

where:

$\hat{y}$ = predicted value of corrective maintenance cost (in dollars),

x_1 = miles driven by the vehicle,

x_2 = dispatched time (in hours) of the vehicle,

x_3 = weight of cargo (in pounds) hauled by the vehicle,

x_4 = number of passengers transported by the vehicle,

x_5 = number of times the vehicle was dispatched per year,

x_6 = number of times per year the vehicle had a corrective maintenance service,

x_7 = odometer reading of the vehicle.

The summary statistics of the independent variables data for the D0003 and D0030 vehicles over the three fiscal years of 2016, 2017, and 2018 are shown in Table 1. Observe that all coefficients of variation are larger than 0.8, suggesting poor reliability of the means at hand.

Analysis of the D0003 Regression Results

A multiple regression analysis was performed on the D0003 MTVRs and D0030 HMMWVs for the 2016, 2017, and 2018 years. The D0003 regression analysis results are summarized in Table 2.

Overall the R-square values show little correlation between the corrective maintenance costs and the six independent variables over the three fiscal years of 2016, 2017, and 2018 taken separately, or in combination. Moreover, the F-test values suggest that while the overall model is significant at 5% level of significance for the years 2016, 2017, and over the period time spanning the 2016–2018 years, it is not significant for the year 2018 when considered separately.

Except for the Corrective Maintenance Service Request Frequency (x_6), none of the other independent variables considered in this study are statistically significant at the 5% level, implying that they are not significant drivers of corrective maintenance costs of the D0003 vehicle. However, the Corrective Maintenance Service Request Frequency is not the best indicator of causality for corrective maintenance as corrective maintenance service requests are created in GCSS-MC every time a vehicle bears a corrective maintenance cost. Therefore, the significance of this variable may be misleading.

One notable takeaway from these regression models is that each has a large intercept coefficient representing a large upfront maintenance cost and many independent variables have negative coefficients. This suggests that corrective maintenance costs would actually decrease the more mile a vehicle was driven, the longer a vehicle was operating, the more passengers hauled, etc. For example, in 2017, the D0003 model suggests each MTVR will have at least $2,027.25 in corrective maintenance costs. For every hour and every instance a vehicle is dispatched (x_2 and x_5 respectively), corrective maintenance costs would decrease by $2.24 and $19.63 respectively.

Table 1. Descriptive Statistics of the D0003 and D0030 Vehicles (FOUO)

	D0003 Summary Statistics				D0030 Summary Statistics			
	Observations	Mean	Standard Deviation	Coefficient of Variation	Observations	Mean	Standard Deviation	Coefficient of Variation
Y (Corrective Maintenance Cost)								
2016	170	3936.87	4878.80	1.24	272	3278.58	3440.30	1.05
2017	153	4284.14	4923.96	1.15	275	4006.26	4630.51	1.16
2018	91	2705.88	3602.51	1.33	137	2606.01	3590.47	1.38
All Years	414	3794.63	4674.37	1.23	684	3436.43	4017.94	1.17
X1 (Miles Driven)								
2016	170	818.00	756.72	0.93	272	454.90	426.00	0.94
2017	153	1020.95	920.81	0.90	275	506.02	470.69	0.93
2018	91	376.51	375.09	1.00	137	205.12	247.28	1.21
All Years	414	795.96	796.72	1.00	684	425.43	431.00	1.01
X2 (Time Dispatched)								
2016	170	455.87	390.85	0.86	272	298.79	272.91	0.91
2017	153	604.87	454.76	0.75	275	324.74	267.38	0.82
2018	91	314.18	384.96	1.23	137	154.07	156.51	1.02
All Years	414	479.79	427.78	0.89	684	280.23	259.30	0.93
X3 (Cargo Hauled)								
2016	170	32539.21	43145.77	1.33	272	1157.38	2429.77	2.10
2017	153	45862.15	57297.068	1.25	275	1593.65	2764.03	1.73
2018	91	11175.96	17495.31	1.57	137	434.25	1165.22	2.68
All Years	414	32767.12	46935.83	1.43	684	1187.95	2420.40	2.04
X4 (Passengers Hauled)								
2016	170	239.36	244.97	1.02	272	60.48	57.03	0.94
2017	153	320.60	335.23	1.05	275	60.24	51.44	0.85
2018	91	137.98	150.94	1.09	137	26.23	33.91	1.29
All Years	414	247.10	274.83	1.11	684	53.52	52.61	0.98
X5 (Dispatch Frequency)								
2016	170	17.55	14.14	0.81	272	7.72	6.56	0.85
2017	153	19.42	13.93	0.72	275	7.60	6.43	0.85
2018	91	7.90	5.98	0.76	137	3.01	2.99	0.99
All Years	414	16.12	13.44	0.83	684	6.73	6.24	0.93
(X6) Corrective Maintenance Service Request Frequency								
2016	170	11.21	11.53	1.03	272	14.31	10.10	0.71
2017	153	16.56	13.80	0.83	275	23.16	22.20	0.96
2018	91	7.89	8.23	1.04	137	15.88	15.99	1.01
All Years	414	12.45	12.28	0.99	684	18.18	17.50	0.96
X7 (Max Odometer Out)								
2016	-	-	-	-	272	14875.29	21343.01	1.43
2017	153	25296.36	21869.75	0.86	275	17379.85	27703.84	1.59
2018	91	24888.16	19427.79	0.78	137	11275.42	11750.90	1.04
All Years	-	-	-	-	684	15161.21	22829.39	1.51

Other years are similar except instead of time dispatched (x_2), it is miles driven (x_1) or passengers hauled (x_4).

The large intercept coefficient and the negative independent variable coefficients lead us to believe that a vicious cycle of deteriorating operational readiness is in effect for the 1st Marine Division D0003 MTVRs. This vicious cycle, as described by Kang and Apte (2007), is a cycle of deteriorating maintenance readiness caused by increasing system failures that negatively impacts military readiness. The vicious cycle has a serious and direct impact on life-cycle costs and the operational availability of vehicles.

Table 2. D0003 Regression Analysis Results

D0003 Regression Analysis				
	2016	**2017**	**2018**	**All Years**
Intercept	2586.25	2027.25	1887.38	2191.99
P-Value	**0.0005**	**0.0274**	**0.0440**	**0.0000**
X1 (Miles Driven)	-1.040	0.3864	-2.1103	-0.3788
P-Value	0.2099	0.6950	0.2267	0.5046
X2 (Time Dispatched)	0.0424	-2.2485	1.0457	-0.7915
P-Value	0.9698	0.0675	0.3565	0.2391
X3 (Cargo Hauled)	0.000382502	0.0085	0.0087	0.0050
P-Value	0.9659	0.2624	0.7336	0.3400
X4 (Passengers Hauled)	0.5606	2.2473	-0.4241	1.8884
P-Value	0.8192	0.3467	0.9216	0.2017
X5 (Dispatch Frequency)	-11.992	-19.635	38.216	-21.908
P-Value	0.7841	0.6979	0.7442	0.4540
(X6) Corrective Maintenance Service Request Frequency	200.390	136.610	102.064	161.227
P-Value	0.0000	0.0000	0.0339	0.0000
X7 (Max Odometer Out)	-	0.009	0.006	-
P-Value	-	0.6143	0.7804	-
Observations	170	153	91	414.0000
Significance F	**0.0000**	**0.0007**	0.2793	**0.0000**
R Square	0.2920	0.1575	0.0962	0.1894

While the regression models cannot identify with confidence what is driving the corrective maintenance costs of the D0003 MTVRs, they do suggest a counterintuitive model that has a large up-front corrective maintenance cost that decreases the more vehicles are used. These results point to a maintenance vicious cycle. This vicious cycle becomes evident, as there are so many D0003 MTVRs that have high corrective maintenance costs but show little usage in any of the independent variables. MTVRs that break down and have the highest corrective maintenance costs are not used, and therefore, those more reliable and operational D0003 MTVRs are utilized more and more, hence the negative independent variable coefficients. This will eventually lead to more and more vehicles breaking down requiring corrective maintenance actions, and fewer vehicles to meet the 1st Marine Division operational requirements. Without taking measures to correct the vicious cycle, the 1st Marine Division D0003 MTVR readiness will likely suffer and result in rising corrective maintenance costs.

With poor confidence indicators among the independent variables, simple linear regression models of corrective maintenance cost against each independent variable taken individually for each time period were run to see if multicollinearity was affecting the results of the multiple regression models. As was the case for multiple regressions, the simple regressions did not yield any significant results. When accounting for multicollinearity, several independent variables were removed from the model if strongly correlated over 0.7. For example, in the D0003 2017 regression model, x_2, x_4, and x_5 were found to be strongly correlated with x_1 Miles Driven. Even when x_2, x_4, and x_5 were removed from the regression model and the model was recalculated, it did not improve any of the regression statistics of the remaining independent variable *p*-values or the models *R* square values.

Overall, the D0003 MTVR regression models could not reveal with any statistical significance what the leading cost drivers were for corrective maintenance costs. The 2017 model suggested Time Dispatched was borderline significant, but none of the other models showed that such variable was significant. The main conclusion from the D0003 MTVR regression analysis is finding evidence of a vicious maintenance cycle affecting the 1st Marine Division D0003s, which needs further analysis and action in order to prevent further readiness deterioration and increased corrective maintenance costs.

Analysis of the D0030 Regression Results

Table 3 summarizes the results of the D0030 regression analysis. A closer look at the *p*-values of the independent variables show that except for dispatch frequency in 2016 and miles driven in 2018, which are significant at the 5% level, and passengers hauled in 2018, which is significant at the 10% level, the rest of the independent variables are not. Hence, like in the case of the D0003, there were no other common trends of significant individual variables that could be used to confidently conclude which one of these variables was driving corrective maintenance costs.

Again, like in the case of the D0003, it can be inferred that a vicious cycle is apparent in D0030 HMMWVs as well. Observe, for example, that the All Years model starts with an upfront corrective maintenance cost of $1,958.92. There are then negative coefficients for x_1, miles driven, and x_5, dispatch frequency, which is counterintuitive as these results suggest the more miles the vehicle is driven and the more often it is dispatched, the lower is the corrective maintenance cost, when higher costs are theoretically expected in such cases. This suggest that the D0030 HMMWVs that are operating more frequently suffer lower corrective maintenance costs, while those that are mostly dead-lined incur higher corrective maintenance costs. This is possibly due to the fact that when a vehicle sits for extended periods, fuels, oils, and rubber materials inside the vehicle deteriorate causing mechanical problems when the vehicle is restarted. Without a revision of the vehicle long-term storage policy, this vicious cycle will continue to degrade D0030 HMMWV vehicle readiness and continue to increase corrective maintenance costs.

Again, like with the D0003, simple linear regressions were run and correlation of all the independent variables was measured for each model to see if multicollinearity was affecting the results. The simple linear regressions did not reveal any significant relationship between corrective maintenance costs and the individual independent variables. Also, when the independent variables that were correlated over 0.7 were removed from the multiple regression models, the remaining individual variables showed little significance of relationship with the dependent variable.

Regression Analysis Conclusions

Overall, the results of the multiple regression analysis for both the D0003 MTVR and D0030 HMMWV were disappointing. While all the models, except for the 2018 D0003 MTVR, showed overall significance albeit with low correlations, we could not conclude with any confidence that any of the seven independent variables were the main cost drivers of corrective maintenance cost. While some variables showed individual significance in a single model, there were not enough models with similar values to conclude with reasonable level of confidence which of these variables are the cost drivers for the 1st Marine Division to focus on when forecasting D0003 and D0030 corrective maintenance costs. We believe this is mainly due to the high variance and poor quality of the TCPT data. One surprising result of the multiple regression models was our finding of the vicious maintenance cycle in both vehicle types. If it is present in both vehicles, then it is likely to be prevalent in most motor pools for the majority of all vehicle types in the 1st Marine Division. This is a serious operational readiness and maintenance cost budgeting issue that will need further analysis and attention by the 1st Marine Division.

Time Series Analysis

There are many time series models available as discussed earlier in the literature review. Several models were used in order to determine which models provided the best forecast based on their forecast error values and fit. The models chosen for analysis in this research are simple exponential smoothing, Holt-Winters, and Box-Jenkins.

Simple exponential smoothing is the best time series forecast when the data does not contain trend or seasonality components. Exponential smoothing uses a single parameter, the smoothing constant. Exponential smoothing takes a weighted average of all the previous data points while giving more weight to recent observations using this single parameter. The mathematical equation for simple exponential smoothing is as follows:

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t \qquad (2)$$

where:

F_{t+1} = Forecast value for period $t+1$

α = Smoothing constant ($0 < \alpha < 1$)

X_t = Actual value of demand in period t

F_t = Forecast value for period t.

Table 3. D0030 Regression Analysis Results

D0030 Regression Analysis				
	2016	**2017**	**2018**	**All Years**
Intercept	2670.12	2259.05	1085.96	1958.92
P-Value	**0.0000**	**0.0000**	**0.0446**	**0.0000**
X1 (Miles Driven)	0.0837	-0.0785	-4.9421	-0.3436
P-Value	0.9225	0.9328	**0.0234**	0.5602
X2 (Time Dispatched)	-0.6783	0.1527	2.2138	0.0268
P-Value	0.5997	0.9072	0.4228	0.9749
X3 (Cargo Hauled)	0.0260	0.0507	-0.2831	0.0311
P-Value	0.7622	0.5851	0.2454	0.5983
X4 (Passengers Hauled)	9.5579	-7.4241	28.0100	4.2390
P-Value	0.2140	0.4183	0.0707	0.4311
X5 (Dispatch Frequency)	-118.925	-57.462	23.525	-69.257
P-Value	**0.0438**	0.4154	0.8911	0.1052
(X6) Corrective Maintenance Service Request Frequency	91.736	109.191	109.053	105.817
P-Value	**0.0000**	**0.0000**	**0.0000**	**0.0000**
X7 (Max Odometer Out)	-0.0154	0.0006	-0.0197	-0.0070
P-Value	0.1112	0.9433	0.3880	0.2593
Observations	272	275	137	684
Significance F	**0.0001**	**0.0000**	**0.0000**	**0.0000**
R Square	0.1087	0.2831	0.3280	0.2265

If the historical cost data has no seasonality or trends in it, this method will provide an accurate forecast as it weights the most recent data points in the data set as the most important. This model requires at least five to 10 observations, has a short forecast horizon, and has little sophistication. Therefore, this method is best when looking just for the next period forecast.

Holt-Winters exponential smoothing as the best used for data that exhibit both trend and seasonality. Holt-Winters model uses three-parameters $\alpha, \beta,$ and γ to account for both trend and seasonality as follows:

where:

$$F_t = \alpha X_t / S_{t-p} + (1-\alpha)(F_{t-1} + T_{t-1}) \quad (3)$$

$$S_t = \beta X_t / F_t + (1-\beta) S_{t-p} \quad (4)$$

$$T_t = \gamma (F_t - F_{t-1}) + (1-\gamma) T_{t-1} \quad (5)$$

$$W_{t+m} = (F_t + mT_t) S_{t+m-p} \quad (6)$$

where:

F_t = Forecast value for period t

α = Smoothing constant for the data ($0 < \alpha < 1$)

X_t = Actual value of demand in period t

F_{t-1} = Average experience of series smoothed value for period $t-1$

T_{t+1} = Trend Estimate

S_t = Seasonality estimate

β = Smoothing constant for seasonality ($0 < \beta < 1$)

γ = Smoothing constant for trend estimate ($0 < \gamma < 1$)

m = Number of periods in the forecast lead period

p = Number of periods in the seasonal cycle

W_{t+m} = Winters' forecast for m periods into the future.

The Box-Jenkins method is the most technically sophisticated way of forecasting a dependent variable based on historical time series data. It utilizes the most recent data points as starting values to analyze forecasting errors to determine future forecasts as well as looking for patterns in the data that can be utilized to make better forecasts. The mathematical equation for Box-Jenkins is as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + e_t + W_1 e_{t-1} + W_2 e_{t-2} + \ldots + W_q e_{t-q} \quad (7)$$

where:

Y_t = The moving-average time series generated

$A_{1,2,\ldots p}$ = Autoregressive coefficients

$Y_{1,2,\ldots,t-p}$ = Lagged values of the time series

e_t = White noise series

$e_{t-1,t-2,\ldots,t-q}$ = Previous values of the white noise seires

$\mathrm{W}_{1,2,\ldots,q}$ = Moving-average coefficients

The Box-Jenkins method, however, requires large amount of data, typically at least 50 observations, in order to provide an accurate forecast. Overall, this model must have a stationary data pattern, is highly sophisticated, and can provide short, medium, or long-term forecasts.

Evaluating Forecasts

Two forecast errors were examined to compare the forecasts. The first error term examined was the Mean Absolute Percent Error (MAPE). The MAPE is the computed average of absolute differences between the forecasted and actual values, expressed as a percentage of the actual values. The second forecast error considered herein is the Root Mean Squared Error (RMSE). RMSE is the square root of the mean square error. These two error terms will be the primary method to determine the accuracy of the forecasts and which method of time series forecasting best fits the data at hand.

Time series analysis was completed for D0003 MTVRs, D0030 HMMWVs, and Type A items. We will discuss later herein how Type A items were identified. Each time series analysis included 57 monthly cost data points from October 2013 to June 2018 unless otherwise noted. The forecasts were completed using various methods as described in the methodology.

Analysis of the D0003 Time Series Results

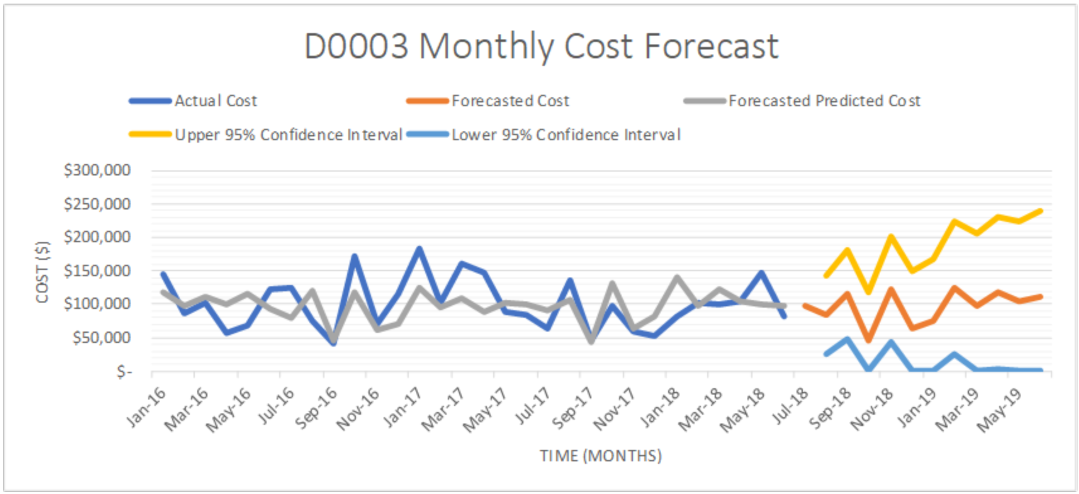
Corrective maintenance cost time series forecasts were conducted for the D0003 MTVRs. Table 4 shows the forecasted corrective maintenance cost estimate for the next six months, and the highest and lowest forecasted values obtained by the three forecasting methods (Simple Exponential Smoothing, Holt-Winters, and Box Jenkins) along with their forecast error values. The table shows time series forecasting methods used organized by error terms and follow on monthly forecasts starting in July 2018. Green highlighted cells denote the smallest error terms and forecasted values while red highlighted cells represent the largest.

Table 4. D0003 Time Series Forecasting Results

D0003 Time Series Comparision								
	Error Terms		Monthly Forecasts					
	MAPE	RMSE	1 (Jul-18)	2 (Aug-18)	3 (Sep-18)	4 (Oct-18)	5 (Nov-18)	6 (Dec-18)
Simple Exponential Smoothing	79.17%	70,393.56	94,317.65	94,317.65	94,317.65	94,317.65	94,317.65	94,317.65
Holt-Winters	75.87%	65,043.41	65,292.00	91,649.83	87,419.14	111,448.95	99,792.45	152,772.03
Box Jenkins	66.51%	72,651.62	78,548.07	78,123.69	78,082.10	78,078.01	78,077.61	78,077.57
Procast (Min RSME, Remove Outliers)	31.11%	32,014.68	93,390.39	93,390.39	93,390.39	93,390.39	93,390.39	93,390.39
Holt-Winters Start Jan16	29.08%	34,507.91	83,857.93	114,728.06	44,929.97	122,692.89	63,429.96	74,636.49
Box Jenkins Start Jan16	33.56%	38,198.00	93,918.42	93,613.48	93,621.49	93,621.28	93,621.29	93,621.29

As seen in the above table, simple exponential smoothing had the highest MAPE value and Box Jenkins had the highest RMSE. The Procast model utilized by ForecastX—the forecasting software used in this study—to minimize RMSE while also removing actual cost outliers that were greater than two standard deviations from the actual cost mean. Procast chose exponential smoothing as its method for forecasting, which returned the lowest RMSE but only produced one forecasted value. The last two forecasts were completed utilizing Holt-Winters and Box Jenkins but the forecast was started at January 2016 as the majority of the variation in the corrective maintenance cost spending forecasted was in 2013–2015. Removing 2013–2015 monthly cost data points still left 30 monthly cost data points to forecast. This led to “Holt-Winters Start Jan16” as the best forecast as it had the lowest MAPE value, second lowest RMSE, and forecasted values that reflected trends and seasonality that ForecastX detected in the data.

The graph shown in Figure 1 below gives a visual depiction of the actual historical cost, predicted historical costs based on the Holt-Winters model, along with future forecasted cost, and a 95% confidence interval of these forecasted values. This graph reveals that the D0003 maintenance costs are fairly stable over this 21-month period.



Forecast -- Holt-Winters

	Forecast			95% - 5%	95% - 5%
Date	Monthly	Quarterly	Annual	Upper	Lower
Jul-2018	83,857.93			142,928.65	24,787.22
Aug-2018	114,728.06			180,220.74	49,235.38
Sep-2018	44,929.97	243,515.96		117,004.92	0.00
Oct-2018	122,692.89			201,470.23	43,915.54
Nov-2018	63,429.96			149,001.61	0.00
Dec-2018	74,636.49	260,759.33	504,275.29	167,074.08	0.00
Jan-2019	124,859.59			224,219.92	25,499.26
Feb-2019	98,593.47			204,922.24	0.00
Mar-2019	117,065.33	340,518.39		230,399.81	3,730.84
Apr-2019	104,382.94			224,753.90	0.00
May-2019	112,166.15			239,599.26	0.00
Jun-2019	92,996.48	309,545.57		227,513.35	0.00
Avg	96,194.94	288,584.81	504,275.29	192,425.73	12,264.02
Max	124,859.59	340,518.39	504,275.29	239,599.26	49,235.38
Min	44,929.97	243,515.96	504,275.29	117,004.92	0.00

Summary Comments	
The forecast has an average error of	29.08%
The data has a standard deviation of	38,197.53
The forecast exceeds the accuracy of a simple average by	15.57%

Report Details
Run Date: 11/02/2018 17:30
Report Creator: Matt Biesecker
Note: Forecast generated using ForecastX by John Galt Development, Inc.

Figure 1. D0003 Holt-Winters Forecast Results

Analysis of the D0030 Time Series Results

Corrective maintenance cost time series forecasts were conducted for the D0030 HMMWVs. Table 5 shows the forecasted corrective maintenance cost estimate for the next six months, and the highest and lowest forecasted values obtained by the three forecasting methods (Simple Exponential Smoothing, Holt-Winters, and Box Jenkins) along with their forecast error values. Table 5 shows time series forecasting methods used organized by error terms and follow-on monthly forecasts starting in July 2018. Green highlighted cells denote the smallest error terms and forecasted values while red highlighted cells represent the largest.

Table 5. D0030 Time Series Forecasting Results

D0030 Time Series Comparisions								
	Error Terms		Monthly Forecasts					
	MAPE	RMSE	1 (Jul-18)	2 (Aug-18)	3 (Sep-18)	4 (Oct-18)	5 (Nov-18)	6 (Dec-18)
Simple Exponential Smoothing	33.09%	45,371.75	171,490.38	171,490.38	171,490.38	171,490.38	171,490.38	171,490.38
Holt-Winters	34.26%	42,638.23	186,164.29	185,612.18	180,265.57	200,855.48	184,562.95	208,834.37
Box Jenkins	34.79%	44,483.31	170,013.18	169,892.47	169,774.63	169,659.61	169,547.34	169,437.74
Procast (Min RMSE)	33.21%	41,728.82	178,539.19	174,814.09	184,328.58	163,493.29	217,232.10	200,054.54
Procast (Min MAPE)	33.09%	45,371.75	171,490.38	171,490.38	171,490.38	171,490.38	171,490.38	171,490.38
Procast (Min RSME w/ Outlier Removal	25.75%	34,417.87	172,267.01	170,082.42	166,129.94	160,385.31	192,016.45	213,429.45

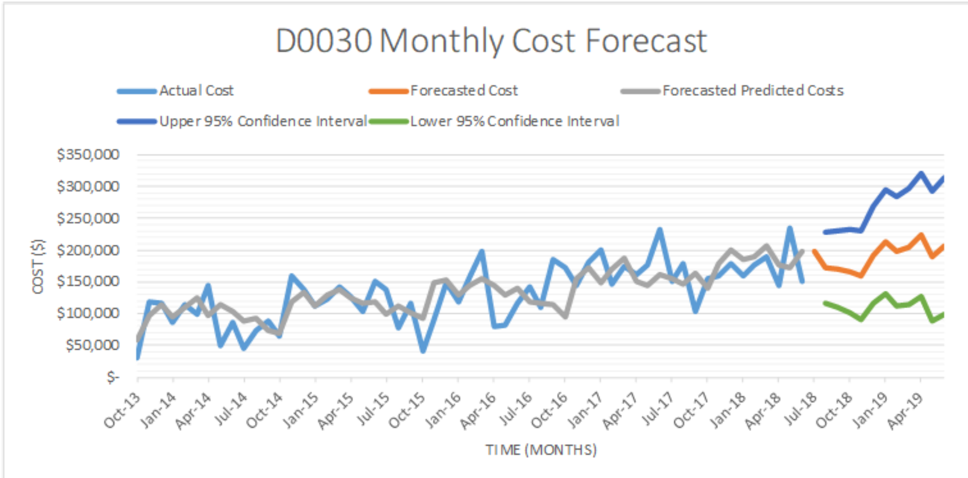
Observe that simple exponential smoothing had the highest RMSE and Box-Jenkins had the highest MAPE for the D0030 forecasts. When the selected objectives were to minimize MAPE and RMSE, simple exponential smoothing and Holt-Winters produced respectively the best forecasts. Unlike the D0003 MTVR, the D0030's data did not exhibit much variability between 2013 and 2015, so all 57 months of historical cost data was used in the forecasts. However, outlier removal was utilized in the final model to again remove values that were more than 2 standard deviations away from the mean. This final forecast, "Procast (Min RSME w/ Outlier Removal)" utilizing Holt-Winters, was the best forecast as it had the smallest MAPE and RMSE and accounted for trend and seasonality in the data. This is therefore the recommended forecast method to use when forecasting D0030 HMMWV corrective maintenance costs.

The graph shown in Figure 2 gives a visual depiction of the actual historical cost, predicted historical costs along with future forecasted cost, and a 95% confidence interval of these forecasted values, using the Holt-Winters method with RSME minimization as an objective and outlier removed. This is a much-improved accuracy over the D0003 forecast discussed earlier. The graph also suggests that D0003 MTVR maintenance costs are on an increasing trend over the past five years and projected to continue increasing.

Type A Items Time Series Results

In addition to the D0003 and D0030 vehicles the collected data included 452 items that undergo corrective maintenance in the 1st Marine Division. An ABC analysis was undertaken to group these items into three categories labelled A, B, and C wherein A items account for the top 80% of total maintenance spending, B items account for the middle 15%, and type C items are composed of the cheapest items that make up the lowest 5% of expenditures. The 20 Type A items that resulted from the ABC analysis are listed in Table 6.

As one might expect, the expensive items tend to be the heavy mechanized items like tanks, AAVs, light armored vehicles (LAVs), cargo trucks, artillery pieces, and radios. The vast majority of these items represent the most important Marine Corps items for readiness and operational availability. Any cuts to maintenance spending are most likely to affect these items the most. Any significant cost savings are most likely to be found by finding ways to control costs for these most expensive items.



Forecast -- Holt-Winters Selected

	Forecast			95%-5%	95%-5%	% Change
Date	Monthly	Quarterly	Annual	Upper	Lower	In Forecast
Jul-2018	172,267.01			228,360.71	116,173.32	
Aug-2018	170,082.42			230,979.94	109,184.90	-1.27%
Sep-2018	166,129.94	508,479.37		231,937.48	100,322.40	-2.32%
Oct-2018	160,385.31			231,186.97	89,583.65	-3.46%
Nov-2018	192,016.45			267,879.73	116,153.17	19.72%
Dec-2018	213,429.45	565,831.21	1,074,310.58	294,409.20	132,449.71	11.15%
Jan-2019	197,433.71			283,574.98	111,292.44	-7.49%
Feb-2019	204,618.05			295,958.28	113,277.82	3.64%
Mar-2019	222,762.63	624,814.39		319,333.20	126,192.06	8.87%
Apr-2019	189,621.10			291,448.56	87,793.64	-14.88%
May-2019	206,043.76			313,150.75	98,936.77	8.66%
Jun-2019	207,443.98	603,108.84		319,849.95	95,038.01	0.68%
Avg	191,852.82	575,558.45	1,074,310.58	275,672.48	108,033.16	2.12%
Max	222,762.63	624,814.39	1,074,310.58	319,849.95	132,449.71	19.72%
Min	160,385.31	508,479.37	1,074,310.58	228,360.71	87,793.64	-14.88%

Summary Comments	
The forecast has an average error of	25.75%
The data has a standard deviation of	45,917.19
The forecast exceeds the accuracy of a simple average by	42.81%

Report Details
Run Date: 11/02/2018 15:25
Report Creator: Matt Biesecker
Note: Forecast generated using ForecastX by John Galt Development, Inc.

Figure 2. D0030 Holt-Winters Forecast Results

The same approach as that applied in conjunction with the D0003 and D0030 was used except in this case the data was organized into fiscal year quarters rather than months. Here also, the Holt-Winters model produced the most accurate forecasts. Results shown in Figure 3 obtained using indicate that the Holt-Winters forecast minimizing MAPE had an average forecast error of 8.24% and produced forecasts that are 61.26% more accurate than just using a simple average approach of the historical values. The graph also shows that quarterly costs are trending down mildly; the forecasted quarterly costs are projected to increase from the last historical quarterly corrective maintenance cost.

Table 6. List of Type A Items (FOUO)

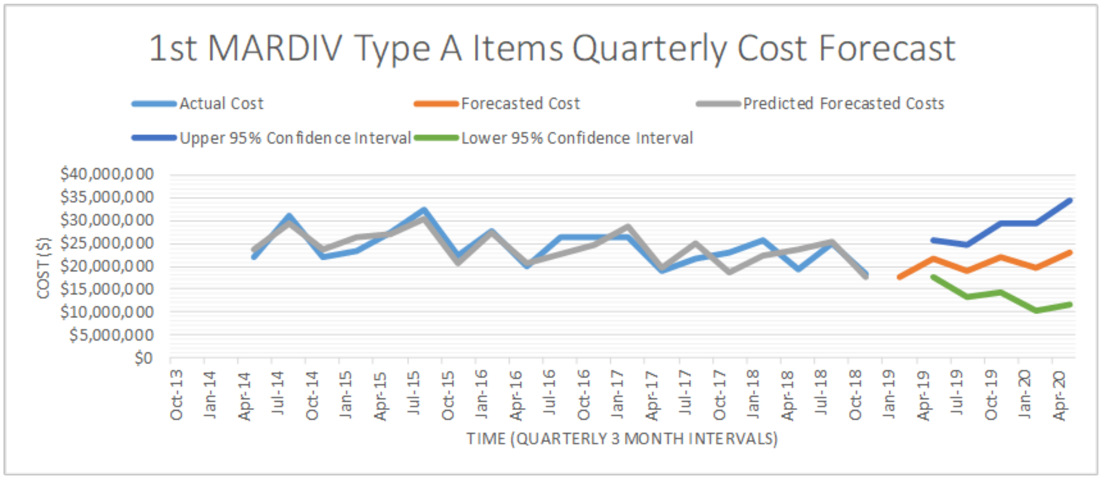
Nomenclature	TAMCN	Total Maintenance Cost (Oct 14 - Jun 18)	% of Total Maintenance Spending (Oct 14 - Jun 18)
AAV	E08467K	$ 112,422,870	20.32%
Tank	E18887M	$ 81,651,538	14.76%
Radio	A00977G	$ 47,668,650	8.62%
Howitzer	E06717M	$ 27,075,847	4.89%
Radio	A20687G	$ 26,953,311	4.87%
Radio	A20427G	$ 18,250,910	3.30%
Recovery Vic	E13787K	$ 18,127,905	3.28%
Radio	A03367G	$ 16,984,110	3.07%
Radio	A01297G	$ 16,551,370	2.99%
Assault Breacher	B01607B	$ 14,266,759	2.58%
Radio	A03527G	$ 10,082,373	1.82%
Utility Truck	D00307K	$ 7,859,675	1.42%
LAV	E09477M	$ 7,630,549	1.38%
Cargo Truck	D00037K	$ 6,161,396	1.11%
Radio	A20757G	$ 5,771,191	1.04%
Radio	A00677G	$ 5,716,656	1.03%
Radio	A03877G	$ 5,456,952	0.99%
Cargo Truck	D01987K	$ 5,227,996	0.94%
Radio	A01267G	$ 5,182,841	0.94%
NVG	E11542B	$ 5,011,770	0.91%

Conclusions

A review of the forecasting results developed in this study lead us to formulate the following conclusions:

1. The regression analysis performed on the D0003 MTVR and D0030 HMMWV vehicles lead us to believe that these vehicles likely suffer from a vicious maintenance cycle. Too many of these vehicles that are largely contributing to corrective maintenance costs actually experienced little usage or contribution to mission requirements. This suggest that the vehicles that are operating more frequently suffer lower corrective maintenance costs, while those that are mostly dead-lined incur higher corrective maintenance costs. This is possibly due to the commonly held belief that when a vehicle sits for an extended period of time, fuels, oils, and rubber materials inside the vehicle deteriorate, causing mechanical problems when the vehicle is restarted. Without a revision of the vehicle long term storage policy, this vicious cycle will likely continue to degrade the D0003 MTVR and D0030 HMMWV readiness and unnecessarily use up valuable corrective maintenance funding.
2. With respect to forecasting Type A items, the Holt-Winters forecasting method proved to be the most accurate method due to its ability to detect

trends and seasonality in the historical data from quarterly funding allocations and predictable major exercises. This method could also be applied to any type of equipment or maintenance type data available in GCSS-MC.



Forecast -- Holt-Winters Selected

	Forecast		95% - 5%	95% - 5%	% Change
Date	Quarterly	Annual	Upper	Lower	In Forecast
Jan-2019	21,691,589.80		25,724,313.61	17,658,865.99	
Apr-2019	18,945,877.23		24,743,131.94	13,148,622.53	-12.66%
Jul-2019	21,854,191.57		29,492,370.34	14,216,012.79	15.35%
Oct-2019	19,823,551.84	82,315,210.44	29,334,792.55	10,312,311.12	-9.29%
Jan-2020	23,106,224.94		34,506,836.19	11,705,613.68	16.56%
Apr-2020	16,453,540.35		29,752,881.92	3,154,198.79	-28.79%
Avg	20,312,495.95	82,315,210.44	28,925,721.09	11,699,270.82	-3.77%
Max	23,106,224.94	82,315,210.44	34,506,836.19	17,658,865.99	16.56%
Min	16,453,540.35	82,315,210.44	24,743,131.94	3,154,198.79	-28.79%

Summary Comments	
The forecast has an average error of	8.24%
The data has a standard deviation of	3,912,402.12
The forecast exceeds the accuracy of a simple average by	61.26%

Report Details
Run Date: 11/02/2018 23:21
Author: Matthew Biesecker
Note: Forecast generated using ForecastX by John Galt Development, Inc.

Figure 3. Type A Items Holt-Winters Forecast Results

Corrective Maintenance Forecasting Recommendations

Based on the conclusions of this research, we recommend that the 1st Marine Division adopt the following approach to forecast corrective maintenance expenditures:

1. Use time series forecasting models to budget and forecast corrective maintenance costs. The time series forecasting models are best suited for reoccurring events that typically have large amounts of historical data that is not expected to vary much from year to year. Of these models, the Holt-Winters model proved to be the most accurate in predicting the 1st Marine Division corrective maintenance costs. The use of such model will provide more accurate and quantitative ways to forecast corrective maintenance costs, which in turn will help build, defend, and justify future maintenance budgets.
2. Collect and/or obtain usage data for Type A items to develop cost per usage estimates. Obtaining additional usage data for other equipment would enable

spending analysis and cost forecasting to be done individually on all Type A items.

3. While these time series methods are great tools, users must remember that these forecasting techniques are completely reliant on past events and may not work well in situations where the future is subject to drastic changes from the past; therefore, time-series forecasting is merely one methodology that can be used by the 1st Marine Division to forecast defend their corrective maintenance budgets.

Future Research Recommendations

Identify additional independent variables to include in the multiple regression model. Due to poor results obtained from our regression model, there are likely other variables that we did not account for that are better, more significant drivers of corrective maintenance costs. Additional independent variables may include the following:

1. Age of the vehicles.
2. Location of where these vehicles are utilized.
3. Standard operating procedures (SOPs) of vehicles.
4. Preventive maintenance intensity of vehicles.
5. Reliability data such as the Mean Time Between Failures (MTBF) of vehicles.

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Acknowledgements

The research reported in this paper was supported by the Acquisition Research Program (ARP) at the Naval Postgraduate School (NPS) through an FY2019 Navy DACM Research grant. The opinions expressed here are those of the author and do not represent the views of ARP or NPS.

The author would like to acknowledge the contributions of Capt Matthew B. Biesecker and Capt Paul S. Deller, two NPS MBA students, for collecting and organizing the data used in this report.

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