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Budget Forecasting for US Marine Corps Corrective Maintenance Costs

November 4, 2019

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Graduate School of Defense Management

Naval Postgraduate School

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Abstract

This project develops methodologies to better forecast corrective maintenance costs of the 1st Marine Division. Nearly half of 1st Marine Division's budget, approximately $25 million, is used for maintenance. The current budgeting process has a number of weaknesses, which includes insufficient detail to defend against funding cuts, and over reliance on historical execution and expert opinion, and is therefore ill-equipped to adapt to changing requirements or communicate impacts on readiness. This project identifies quantitative forecasting methodologies to improve accuracy of budgeting corrective maintenance costs.

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 models 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 the models can provide a more quantitative and accurate methodologies for 1st Marine Division planners to build, justify, and defend its corrective maintenance budget.

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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, or 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 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 a forecasting model 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 technical report is organized into seven sections. Section 2 introduces the background information of the project, which includes the 1st Marine Division's organization and its corrective maintenance budgeting process, and the characteristics of the vehicles selected for forecasting analysis. Section 3 provides a brief overview of forecasting theory, and a review of relevant literature. Section 4 discusses how data was collected, its quality, and formatting issues. Section 5 defines the forecasting models used and presents the results of the analysis. Section 6 provides conclusions and recommendations for forecasting corrective maintenance costs at the 1st Marine Division. Finally, Section 7 suggests recommendations for future research.

Background

This section provides additional background information about the 1st Marine Division, its current budget methodology, and characteristics of vehicles selected for performing a forecast of their corrective maintenance costs.

The 1st Marine Division

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, 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, California 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, California.

The 1st Marine Division is one of the major subordinate commands of I MEF. In the Marine Corps, a Division, a Marine Logistics Group, a Marine Information Group, and a Marine Air Wing all fall underneath one of three Marine Expeditionary Forces (MEF). Each of the three MEFs fall underneath a Marine Corps Forces (MARFOR) command. The MARFORs fall underneath Headquarters Marine Corps (HQMC). Operations and Maintenance funding is allocated by HQMC and works its way down the chain of command where the 1st Marine Division is allocated part of I MEF's funding (Department of Defense [DoD], 2018).

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.

Current Budgeting Method

When building the annual budget, the 1st Marine Division currently uses an Excel workbook tool called the Cost to Run a Marine Expeditionary Force, or C2RAM. A C2RAM Excel workbook is completed by each battalion and consolidated into a single budget for 1st Marine Division. Three steps are included in the process of creating a budget:

Step 1. Exercise List

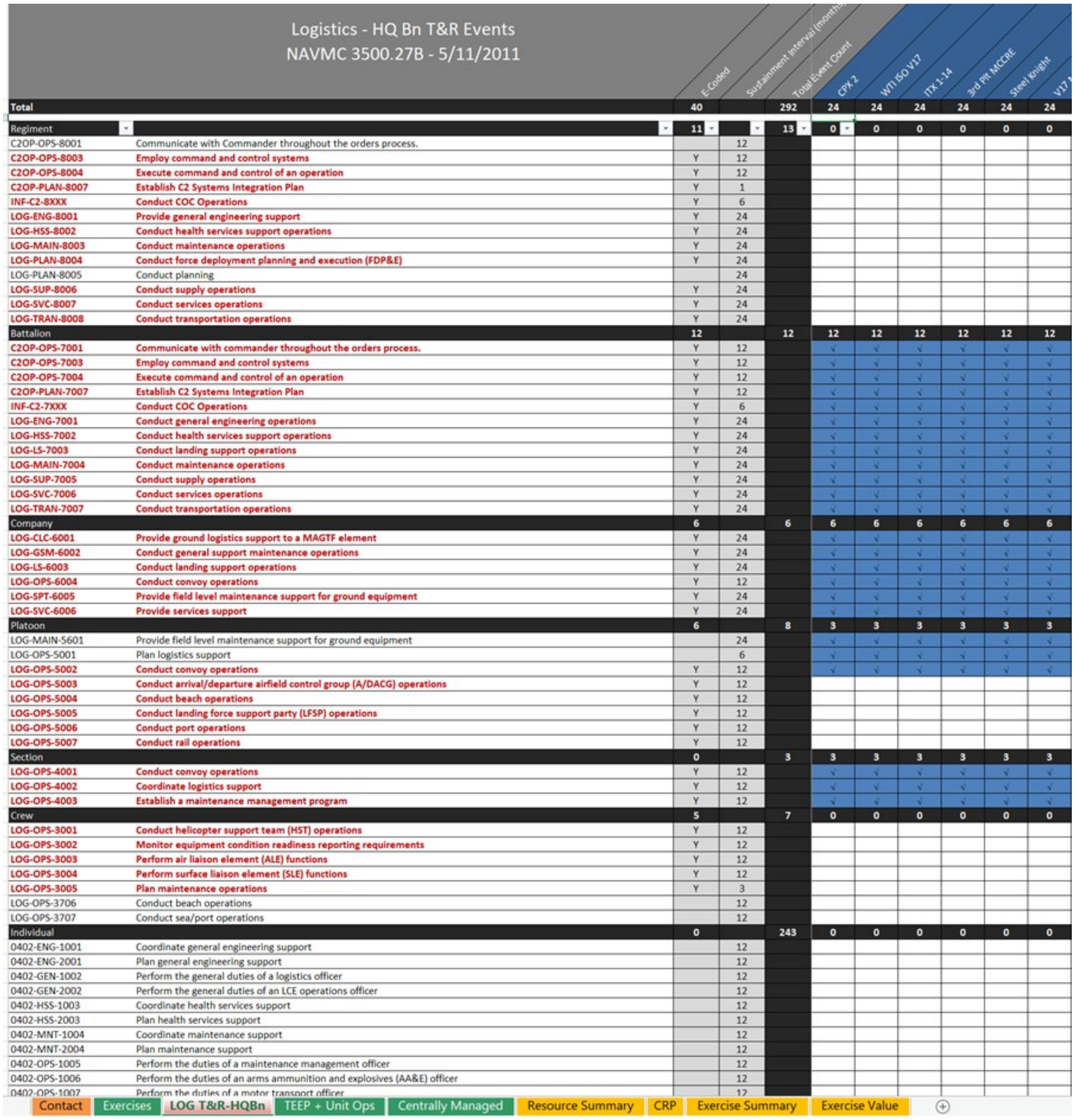
The first tab of the Excel workbook asks the battalion to list all of the exercises they plan to participate in during the upcoming fiscal year. At least 35 rows of data are collected for each exercise, such as the name of the exercise, duration in days, number of personnel involved, and the cost of specific items such as Port-a-johns, fuel, rental vehicles, supplies, and transportation. Of note, there is only a single line item for maintenance. Maintenance cost is incredibly hard to predict for a specific exercise. Sometimes an exercise requires very little maintenance due to luck. For other exercises, it seems like every piece of gear breaks down. Equipment incurs wear and tear every time it is used, and there is no sure way to predict exactly when various components will finally fail. As a result, battalion supply officers generally fall back on historical maintenance cost for similar exercises and add in a healthy fudge factor when developing an estimated maintenance cost. An example of this step is shown in Figure 1 below.

Step 2. Training and Readiness Standards

On the second tab of the C2RAM workbook, all of the exercises listed on the first tab will reappear on the second tab as columns. On this tab, the training and readiness (T&R) standards that will be tested for each exercise are marked. An example of this step is shown in Figure 2 below.

			Example	1	2	3
		Exercise Number	*Example*	1	2	3
		Total Exercise Cost	*$ 56,695*	$ 24,000	$ 19,000	$ 75,000
		Marine Training Days	*120*	-	1,575	1,260
		Exercise Name	*Directed FEX (EXAMPLE)*	CPX 2	WTI ISO V17	ITX 1-14
		Standard Exercise Name		Bn CPX	WTI	ITX 1-XX
Exercise Details		Exercise Description	*The Platoon goes out around CLNC to do patrol training*	Command Post Exercise to confirm comm architecture and EDL for SK14.	General Motor T support for V17.	General Motor T support for V35
		Requirement Source	*MEF*	Unit	Unit	Unit
		Type of Exercise	*Directed Training*	Unit Training	Unit Training	Unit Training
		Executing Unit Level	*Battalion*	Battalion	Platoon	Platoon
		Location	*On Duty Station/Location*	On Duty Station/Location	Off Duty Station/ Location	Off Duty Station/ Location
		Total Duration (Days)	*5*		45	36
		Training Duration (Days)	*3*		45	36
		Average Shift Duration (Hours)	*10*		14	14
		PAX	*40*		35	35
		Primary Limiting Factor	Range		None	None
		Limiting Factors Description	*Ranges on CLNC do not allow us to do maneuvers with the entire battalion.*			
		Additional Information for the Exercise	*We primarily use range F-17 and can supplement this training with the SAVT simulator.*			
Exercise Resources	OCC	Special Interest Code (SIC)	*2V0*			
		Job Number Local Use (JNLU)	*0R30*			
	250	Portable Toilets Cost	*$ 420*	$ 1,000	$ -	
		Portable Toilets Funding Source	*Reimbursed (1106 Green)*	Organic (1106 Green)	Organic (1106 Green)	
	210	Rental Vehicles Cost	*$ 2,000*	$ -	$ -	
		Rental Vehicles Funding Source	*Reimbursed (1106 Green)*	Organic (1106 Green)	Organic (1106 Green)	
		Rental Vehicles Description	*3 Marines required 1 rental vehicle for three weeks*		0	
	260	Fuel Cost	*$ 1,275*	$ 10,000	$ 16,000	$ 30,000
		Fuel Funding Source	*Reimbursed (1106 Green)*	Organic (1106 Green)	Organic (1106 Green)	Organic (1106 Green)
		Fuel Description	*4 HMMWVs & 3 7 Tons using ~300 gallons JP8; 3 rental vans using gas*	7 tons, and HMMWV's	3 7 Tons	20 7 Tons, 45 HMMWVs
	260	BOM Cost	*$ 1,500*	$ 10,000	$ -	$ 20,000
		BOM Funding Source	*Reimbursed (1106 Green)*	Organic (1106 Green)	Organic (1106 Green)	Organic (1106 Green)
		BOM Description	*Chem Lights, Razor Wire, Sand Bags*	Chem Lights, Razor Wire, Sand Bags,	n/a	sand bags, razor wire, chow stuff,
	260	Corrective Maint POL (III) Cost	*$ 1,000*			
		Corrective Maint POL (III) Funding Source	*Reimbursed (1106 Green)*			
		POL (III) Description	*Typically, the HMMWV drive lubrication costs*			
	260	[SMU Pass] Corrective Maint (IX) Cost	*$ 3,000*	$ 3,000	$ 3,000	$ 25,000
		[SMU Pass] Corrective Maint (IX) Funding Source	*Reimbursed (1106 Green)*	Organic (1106 Green)	Organic (1106 Green)	Organic (1106 Green)
		[SMU Pass] Corrective Maintenance (IX) Description	*Typically, the HMMWV parts drive maintenance costs at this exercise*	Typically, the HMMWV parts drive maintenance costs at this event	Typically, the HMMWV parts drive maintenance costs at this event	Typically, the HMMWV parts drive maintenance costs at this event
	210	TAD Cost	*$ 5,000*		$ -	
		TAD Funding Source	*Organic (1106 Green)*		Organic (1106 Green)	
		TAD Description	*Lodging and per diem for 5 Marines for 10 days*			
	210	TOP Cost	*$ 20,000*			
		TOP Funding Source	*MEF Support Account*		Organic (1106 Green)	
		TOP Description	*5 Marines TAD via plane before the exercise; 20 Marines usually get Stratlifted to the exercise*			
	220	TOT Cost	*$ 15,000*		$ -	
		TOT Funding Source	*MEF Support Account*		Organic (1106 Green)	
		TOT Description	*MEF G4 funded transportation of 6 HMMWVs*		n/a	
	260	MEDLOG (VIII) Cost	*$ 2,500*			
		MEDLOG (VIII) Funding Source	*Organic (1106 Green)*			
		MEDLOG (VIII) Description	*Our unit reimbursed MEDLOG for 1 AMAL*			
		Custom Cost 1 Type	*BOM Cost*			
		Custom Cost 1	*$ 5,000*			
		Custom Cost 1 Funding Source	*Organic (1106 Green)*			
		Custom Cost 1 Description	*Unit paid for extra targets and building materials to enhance training*			

Figure 1. Exercise Tab of a C2RAM Workbook



Logistics - HQ Bn T&R Events
NAVMC 3500.27B - 5/11/2011

		E-Coded	Sustainment Interval (months	Total Event Count	CPX 2	WTI ISO V17	ITX 1-14	3rd Plt MCCRE	Steel Knight	V17
Total		40		292	24	24	24	24	24	24
Regiment		11		13	0	0	0	0	0	0
C2OP-OPS-8001	Communicate with Commander throughout the orders process.		12							
C2OP-OPS-8003	Employ command and control systems	Y	12							
C2OP-OPS-8004	Execute command and control of an operation	Y	12							
C2OP-PLAN-8007	Establish C2 Systems Integration Plan	Y	1							
INF-C2-8XXX	Conduct COC Operations	Y	6							
LOG-ENG-8001	Provide general engineering support	Y	24							
LOG-HSS-8002	Conduct health services support operations	Y	24							
LOG-MAIN-8003	Conduct maintenance operations	Y	24							
LOG-PLAN-8004	Conduct force deployment planning and execution (FDP&E)	Y	24							
LOG-PLAN-8005	Conduct planning		24							
LOG-SUP-8006	Conduct supply operations	Y	24							
LOG-SVC-8007	Conduct services operations	Y	24							
LOG-TRAN-8008	Conduct transportation operations	Y	24							
Battalion		12		12	12	12	12	12	12	12
C2OP-OPS-7001	Communicate with commander throughout the orders process.	Y	12		√	√	√	√	√	√
C2OP-OPS-7003	Employ command and control systems	Y	12		√	√	√	√	√	√
C2OP-OPS-7004	Execute command and control of an operation	Y	12		√	√	√	√	√	√
C2OP-PLAN-7007	Establish C2 Systems Integration Plan	Y	12		√	√	√	√	√	√
INF-C2-7XXX	Conduct COC Operations	Y	6		√	√	√	√	√	√
LOG-ENG-7001	Conduct general engineering operations	Y	24		√	√	√	√	√	√
LOG-HSS-7002	Conduct health services support operations	Y	24		√	√	√	√	√	√
LOG-LS-7003	Conduct landing support operations	Y	24		√	√	√	√	√	√
LOG-MAIN-7004	Conduct maintenance operations	Y	24		√	√	√	√	√	√
LOG-SUP-7005	Conduct supply operations	Y	24		√	√	√	√	√	√
LOG-SVC-7006	Conduct services operations	Y	24		√	√	√	√	√	√
LOG-TRAN-7007	Conduct transportation operations	Y	24		√	√	√	√	√	√
Company		6		6	6	6	6	6	6	6
LOG-CLC-6001	Provide ground logistics support to a MAGTF element	Y	24		√	√	√	√	√	√
LOG-GSM-6002	Conduct general support maintenance operations	Y	24		√	√	√	√	√	√
LOG-LS-6003	Conduct landing support operations	Y	24		√	√	√	√	√	√
LOG-OPS-6004	Conduct convoy operations	Y	12		√	√	√	√	√	√
LOG-SPT-6005	Provide field level maintenance support for ground equipment	Y	24		√	√	√	√	√	√
LOG-SVC-6006	Provide services support	Y	24		√	√	√	√	√	√
Platoon		6		8	3	3	3	3	3	3
LOG-MAIN-5601	Provide field level maintenance support for ground equipment		24		√	√	√	√	√	√
LOG-OPS-5001	Plan logistics support		6		√	√	√	√	√	√
LOG-OPS-5002	Conduct convoy operations	Y	12		√	√	√	√	√	√
LOG-OPS-5003	Conduct arrival/departure airfield control group (A/DACG) operations	Y	12							
LOG-OPS-5004	Conduct beach operations	Y	12							
LOG-OPS-5005	Conduct landing force support party (LFSP) operations	Y	12							
LOG-OPS-5006	Conduct port operations	Y	12							
LOG-OPS-5007	Conduct rail operations	Y	12							
Section		0		3	3	3	3	3	3	3
LOG-OPS-4001	Conduct convoy operations	Y	12		√	√	√	√	√	√
LOG-OPS-4002	Coordinate logistics support	Y	12		√	√	√	√	√	√
LOG-OPS-4003	Establish a maintenance management program	Y	12		√	√	√	√	√	√
Crew		5		7	0	0	0	0	0	0
LOG-OPS-3001	Conduct helicopter support team (HST) operations	Y	12							
LOG-OPS-3002	Monitor equipment condition readiness reporting requirements	Y	12							
LOG-OPS-3003	Perform air liaison element (ALE) functions	Y	12							
LOG-OPS-3004	Perform surface liaison element (SLE) functions	Y	12							
LOG-OPS-3005	Plan maintenance operations	Y	3							
LOG-OPS-3706	Conduct beach operations		12							
LOG-OPS-3707	Conduct sea/port operations		12							
Individual		0		243	0	0	0	0	0	0
0402-ENG-1001	Coordinate general engineering support		12							
0402-ENG-2001	Plan general engineering support		12							
0402-GEN-1002	Perform the general duties of a logistics officer		12							
0402-GEN-2002	Perform the general duties of an LCE operations officer		12							
0402-HSS-1003	Coordinate health services support		12							
0402-HSS-2003	Plan health services support		12							
0402-MNT-1004	Coordinate maintenance support		12							
0402-MNT-2004	Plan maintenance support		12							
0402-OPS-1005	Perform the duties of a maintenance management officer		12							
0402-OPS-1006	Perform the duties of an arms ammunition and explosives (AA&E) officer		12							
0402-OPS-1007	Perform the duties of a motor transport officer		12							

Contact | Exercises | LOG T&R-HQBn | TEEP + Unit Ops | Centrally Managed | Resource Summary | CRP | Exercise Summary | Exercise Value

Figure 2. Training and Readiness Tab of C2RAM

Step 3. Operating Costs

On the final tab of the C2RAM workbook, other costs not directly tied to an exercise are listed by cost per month, and the exercises from the first tab are dropped onto a monthly schedule. These overhead costs include travel expenses, fuel, office supplies, and printing costs. The combination of exercise spending per month and overhead spending per month creates a battalion's monthly spend plan. An example of this step is shown in Figure 3 below.

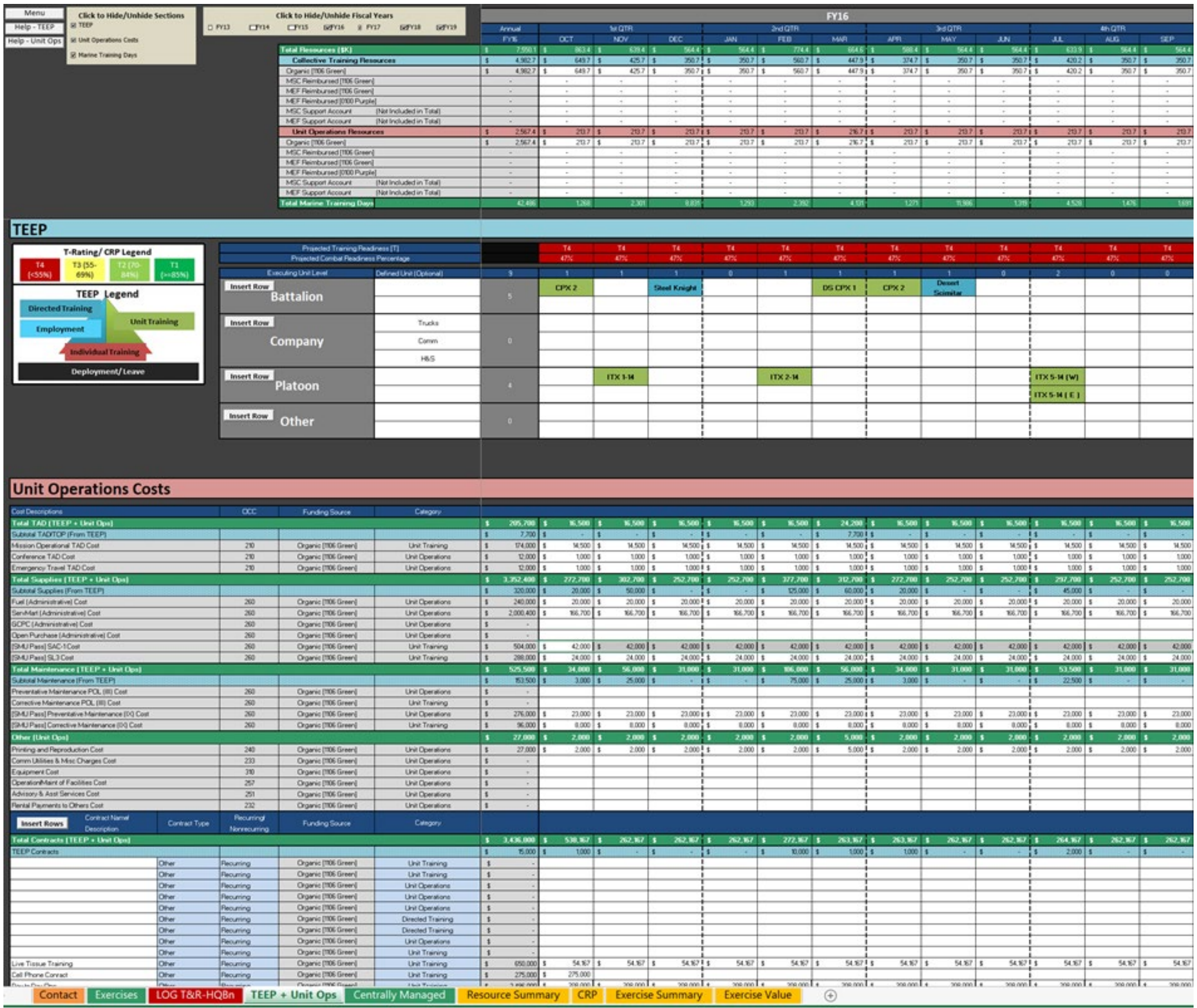


Figure 3. Unit Operating Costs

There are several weaknesses inherent to the C2RAM budgeting tool. C2RAM is unable to indicate why a given expenditure is incurred on any particular item. While it can detail line items, it does not show what drives those costs. Justifications to defend any particular line item must be submitted separately. Moreover, C2RAM cannot provide information as to whether funds are effectively spent. The 1st Marine Division could therefore use a system akin to activity based costing to alleviate this shortcoming but at this time does not do so. Further research is needed to reveal whether budgeted amounts are in line with actual spending and whether or not there is unnecessary waste. Historical spending, which C2RAM frequently relies upon, is not always a good predictor of future expenditures, especially when budgets are shrinking, equipment is changing, and missions are shifting. C2RAM also fails to adequately defend maintenance dollars. Maintenance accounts for almost half of the Division's budget, but very few line items are devoted to explaining how maintenance dollars are spent. There is just one line item for maintenance for each exercise, and another line item for maintenance not attributed to an exercise in the operating costs section of C2RAM. There is simply not enough detail to adequately defend half of the budget. C2RAM collects an immense amount of detail, but does not provide pertinent and useful data with regards to maintenance.

Perhaps the biggest problem with C2RAM is that it cannot measure the impact of budget cuts on readiness. If approved budgets fall below the amount requested in the C2RAM workbook, the entire workbook must be resubmitted, and battalions must submit a separate explanation detailing how they believe their readiness will be impacted. C2RAM fails to show which equipment is most likely to be impacted by the cut or specifically articulate which training will need to be reduced and by how much.

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 table of authorized material control number (TAMCN) D00037K (D0003) a variant of the Medium Tactical Vehicle Replacement (MTVR) cargo truck and the TAMCN D00307K (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 (Deller, unpublished data).

The D0003 MTVR, produced by Oshkosh Defense, a subsidiary of the Oshkosh Corporation, is an armored medium tactical all-terrain vehicle designed for cargo and troop transportation. The 1st Marine Division uses the D0003 primarily to move personnel and cargo for operations and training.

The D0030 HMMWV, manufactured by AM General, is an expanded capacity armament carrier HMMWV that can mount and fire various weapon systems with a 360 degree arc of fire. The D0030 HMMWV is designed for both road and off-road use in all weather conditions and has a maximum payload of 3,340 pounds. The 1st Marine Division primarily utilizes the D0030 HMMWV for convoy protection and command and control.

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Literature Review

This section is organized into two subsections: Forecasting Theory, and Review of Relevant literature. The first subsection gives a brief overview of forecasting theory, and the second subsection reviews previously scholarly studies with similar research objectives.

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, …, 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:

1. Moving averages
2. Simple exponential smoothing
3. Holt's exponential smoothing
4. Winter's exponential smoothing
5. 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 et al., (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 casual 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 useful to investigate whether causal models alone or in combination with time series models provide better forecast for corrective maintenance costs.

Data and Methods

This section discusses how data was collected, its quality, and formatting issues. Additionally, we define the variables used in our analysis and explain our forecasting methodology.

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 1 October 2013 to 29 June 2018, encompassing four full fiscal years (FY14-FY17) and the first nine months of FY18, totaling $553 million. These amounts are not adjusted for inflation, and GCSS-MC replaced Asset Tracking Logistics and Supply System (SASSY) in late 2012, so obtaining earlier data would be difficult to integrate (Griffin, 2011).

GCSS-MC Data Formatting and Processing

The formatting and processing of the maintenance data involved a five-step process: 1) obtain the raw data, 2) add a fiscal year column, 3) check for and remove duplicates, 4) remove outlier, and 5) analyze data using Excel pivot tables.

Once completed, various pivot tables were created in order to pull relevant data required for analysis. For example, pivot tables were created from the raw GCSS-MC data in order to isolate the sum of all corrective maintenance costs. For example, a pivot table for all D0003 MTVRs was created per vehicle serial number and year to count the total number of corrective service requests opened. Table 1 shows the Excel pivot table used to organize data for forecasting.

Table 1. Example of D0003 MTVR Corrective Maintenance Costs (FOUO)

GCSS D0003 Pivot Table for Forecast Modeling								
	Column Labels							
	2016		2017		2018		Total Sum of COST	Total Count of SR_NUMBER
Serial Number	Sum of COST	Count of SR_NUMBER	Sum of COST	Count of SR_NUMBER	Sum of COST	Count of SR_NUMBE		
561012	18155.36	58	558.48	11			18713.84	69
590817					227.65	7	227.65	7
590850	301.43	11	6644.71	17	2277.45	25	9223.59	53
590868			6799.25	37			6799.25	37
590896	2343.33	10	4108.32	63			6451.65	73
590897	657.77	1					657.77	1
590905			5744.4	9	308.61	12	6053.01	21
590916	851.94	2	1297.48	5	1779.64	1	3929.06	8
590929	2472.67	3	9679.59	58	2948.06	8	15100.32	69
590959	4953.02	20	3294.65	8	211.97	9	8459.64	37

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 TCPT system is an online information system that provides near term transportation planning, management, and execution capabilities tool to the Operating Forces in a Web based environment. TCPT is the overarching information system used to task and dispatch vehicles. It provides the ability to assess transportation capacity for various units, provide situational awareness of transportation missions, task subordinate units to complete transportation missions, and keep a historical log of all completed transportation missions.

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. Because TCPT is a cloud-based system, historical data can be downloaded by account holders for the units they have access to. This usage data contains TCPT user field inputs for dispatching vehicles and organized by the month and year the vehicles were dispatched. The user sets date parameters to return all TCPT dispatch entries between the date range and then downloads the usage data in Excel spreadsheet(s). The TCPT data fields are described in the Table 2.

Table 2. TCPT Data Field

Data Fields	Description
Unit	Unit within 1st Marine Division that dispatched the vehicle
Date	Date the vehicle was dispatched
TAMCN	Table of Authorized Material Control Number i.e. D0003
Model	Specific Model of the TAMCN i.e. AMK23 is model of D0003
Serial	Unique serial number to identify individual vehicles
Odometer Out	Odometer Reading of vehicle before it is dispatched
Odometer In	Odometer Reading of vehicle when it returns
Equipment Miles	Miles the vehicle traveled based on odometer readings
Time Disp	Time in hours:mins the vehicle was dispatched
Fuel Used	Gallons of fuel used while dispatched
Oil Used	Quarts of oil used while dispatched
Cargo	Pounds of cargo transported while dispatched
PAX	Number of Passengers transported while dispatched
Fuel	Gallons of fuel transported while dispatched
Water	Gallons of water transported while dispatched

The range for the data set includes all vehicles dispatched by the 1st Marine Division units between 1 January 2016 and 16 May 2018. Over this time period, there were 99,714 rows of data representing each time a vehicle was dispatched by the 1st Marine Division. The Excel TCPT data was emailed via military accounts for use in this project. This data set will be used to establish the independent variables in the multiple regression analysis of this project.

TCPT Data Quality

TCPT's ability to log and track all usage of transportation assets, particularly vehicles such as the D0003 and D0030, is effective in theory but not always in practice. Similar to GCSS-MC, there are a number of variables that affect the quality of the TCPT data. First, TCPT data is typically entered by entry-level dispatch clerks and mistakes are common. These clerks manually enter all TCPT logs by typing in values to the dispatch log for items such as serial number, odometer readings, cargo, and passengers. While these Marines are talented professionals, there are cases where human error will come into play because the dispatchers manually enter most of the data. As with GCSS-MC, there is a potential "Garbage in, Garbage out" problem with TCPT data.

A second problem with the data set is that vehicle operators must report data to the dispatcher using a physical, paper copy called a “trip ticket.” The dispatch clerk then enters the hand-written data on the trip ticket into TCPT to create and/or update the dispatch log. Again, human error is likely prevalent. For example, a vehicle driver must look at the odometer reading of the vehicle, write it down on the trip ticket, and give it to the dispatch clerk to enter the information in TCPT. Not only does the dispatch clerk have to enter the information by hand, but also rely on the vehicle driver to give them accurate information. This additional manual step in this game of telephone compounds data entry errors.

A third issue with the data quality is that many of the data entries are “best guesses” when entering them into TCPT and are determined by the vehicle operator. An example of this is the cargo weight that vehicles transport. While some loads are weighed for accurate weights, many are not. In some cases, cargo weight can be estimated based on USMC technical manuals and other publications for how heavy the cargo is. In other cases, many units just use their judgement to give an estimate of the cargo weight to enter into TCPT.

Another issue with TCPT is that each unit creates their own standard operating procedures (SOPs) for how to dispatch vehicles. While each unit must ensure that their own SOP is nested with their higher headquarters’ and Technical Manual 4700-151H, they have the ability to determine their unit level SOP. Because of this, each unit will have their own ways to collect and record data into TCPT. For example, as mentioned previously, each unit can have its own methods to record cargo weight and relay information between vehicle operators to dispatches. Therefore, TCPT data has some underlying quality issues and may not be perfectly accurate. This reconfirms what was found in the literature review, especially from Foley that vehicle data sources are not all very accurate. This will likely increase the variance of our data and skew the results of our analysis.

TCPT Data Formatting and Processing

The raw TCPT data in Excel spreadsheets obtained from the 1st Marine Division had to be formatted and reviewed for accuracy before inclusion in the forecast models. The data was formatted in a similar fashion as the GCSS-MC data.

First, the TCPT data was aggregated to get all TCPT data from multiple Excel sheets that contained all dispatch records during a month of a given year to single sheets that contained all dispatch logs per calendar year. Once aggregated by year, the data was then filtered and sorted to obtain only D0003 data with each calendar year in its own sheet. Excel's pivot table functions were then utilized to count specific variables to serve as independent variables in a multiple regression analysis model. Table 3 shows the Excel pivot table used to collect data on all D0003 MTVRs in 2016.

Table 3. Example TCPT Data for D0003 MTVRs (FOUO)

TCPT D0003 Pivot Table for Forecast Modeling					
Serial Number	Sum of EQUIP MILES	Sum of TIME ADJ (HRS)	Sum of CARGO (LB)	Sum of PAX	Count of Times Dispatched
561012	243	166.25	0	16	4
590731	74	118.99	0	12	2
590817	579	218.64	0	143	10
590850	2681	688.73	112150	234	20
590896	107	60.73	500	94	5
590905	160	60.41	0	53	4
590916	1189	1229.26	65700	290	23
590929	650	383.28	48970	155	25
590959	738	343.44	43300	481	29
590962	602	493.73	39400	289	12

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Forecasting Analysis

In this section we present the results of a 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 *k* independent variables, x_1, x_2, ..., x_k, that are believed to impact the value of the dependent variable where as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (1)$$

In the multiple regression model, $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ are the parameters of the intercept and the *k* independent variables respectively. The error term ε accounts for the variability in *y* that cannot be explained by the linear effect of the *k* independent variables. One of the assumptions is that the mean or expected value of ε is zero. Consequently, the expected value of *y*, denoted $E(y)$, can now be written as follows:

$$E(y) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \qquad (2)$$

Since the exact values of parameters $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ are not known, a simple random sample collected from the data set is used to compute the sample statistics $b_0, b_1, b_2, \ldots, b_k$ that are used as estimators of the parameters $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$. In our case these sample statistics provide the following estimated multiple regression equation:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_4 + b_5 x_5 + b_6 x_6 + b_7 x_7 \qquad (3)$$

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 6. As discussed earlier, about data quality and confirmed by these statistics, there is considerable variability in the TCPT and GCSS-MC data. Observe, that all coefficients of variation are larger than 0.8, suggesting poor reliability of the means at hand.

Excel's regression tool was used to run the multiple regression models. Table 7 shows how the data is arranged in Excel. Excel's regression tool is a comprehensive tool that performs a complete regression analysis, including analysis of variance (ANOVA), and provides the necessary statistics to perform significance tests.

A multiple regression analysis was performed on the D0003 MTVRs and D0030 HMMWVs for the 2016, 2017, 2018 years.

Analysis of the D0003 Regression Results

The D0003 regression analysis results are summarized in Table 8. 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 years 2016, 2017, and over the period time spanning the 2016-2018 years; it is not significant for 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.

Table 4. 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

Table 5. Example of 2017 D0003 Excel Regression Spreadsheet (FOUO)

Multiple Regression Model								
Source of Data	GCSS	TCPT	TCPT	TCPT	TCPT	TCPT	GCSS	TCPT
Variable	Y (dependent)	X1	X2	X3	X4	X5	X6	X7
Vehicle Serial Number	Corrective Maintenance Cost ($)	Distance Driven (mi)	Time Dispatched (hrs)	Cargo Hauled (lbs)	Passengers Hauled (people)	Dispatch Frequency (# Count)	Frequency of CM Service Requests (SR) (# Count)	Max Odometer Out (Miles)
561012	558.48	494	1271.68	3200	164	6	11	47613
590850	6644.71	1148	418.46	22530	202	27	17	87380
590905	5744.4	58	8.14	0	4	3	9	6889
590959	3294.65	46	163.24	1300	13	2	8	33459
590962	3625.86	33	1.5	0	2	1	20	18370
590974	1525.09	954	495.68	14340	229	14	26	5025
591015	7413.26	829	468.3	14900	216	6	3	18904
591122	1646.78	132	422.64	850	161	3	21	14950
591303	2927.84	907	1185.93	62600	325	15	21	7185

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 6. 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

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.

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 border-line 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 9 summarizes the results of the D0030 regression analysis. A closer look at the 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, which was discussed earlier.

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.

Table 7. 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

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:

$$F_{t+1} = \alpha X_t + (1-\alpha) F_t \qquad (4)$$

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.

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 ten 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:

$$F_t = \alpha X_t / S_{t-p} + (1-\alpha)(F_{t-1} + T_{t-1}) \quad (5)$$

$$S_t = \beta X_t / F_t + (1-\beta) S_{t-p} \quad (6)$$

$$T_t = \gamma (F_t - F_{t-1}) + (1-\gamma) T_{t-1} \quad (7)$$

$$W_{t+m} = (F_t + m T_t) S_{t+m-p} \quad (8)$$

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.

If the data does contain both trend and seasonality, Holt-Winters will provide an accurate forecast. This model requires four to five observations per season, has a short to medium forecast horizon, and moderate sophistication (Wilson et al., 2002).

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 than can be utilized to make better forecasts. The Box-Jenkins method utilizes the *Autoregressive Integrated*

Moving Average (ARIMA) technique which combines autoregressive and moving average models (Wilson et al, 2002). The mathematical equation for Box-Jenkins is as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + e_t + W_1 e_{t-1} + W_2 e_{t-2} + \ldots + W_q e_{t-q} \qquad (9)$$

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

$W_{1,2,\ldots,q}$ = 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

It is often rare to find one model that is always best for any given business or data set. In order to evaluate the accuracy of forecasting models over a number of time periods forecast errors are generally computed. Lower values of the forecast errors indicate that the method produces accurate 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 MAPE is expressed mathematically below:

$$\text{MAPE} = \frac{\sum |(A_t - F_t) / A_t|}{n} \tag{10}$$

where:

A_t = Actual value in period t

F_t = Forecast value in period t

n = Number of periods used in the calculation.

The MAPE as one of the easiest error terms to interpret as it is not dependent on the magnitude of the data and the error can be explained 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. The mean square error is the sum of the differences between the actual and forecasted values squared divided by the number of observations. RSME is one of the most widely used error criterion and is one of the easiest ones to use due to utilizing the same statistical concept as standard deviation. The RMSE is expressed mathematically as follows:

$$\text{RMSE} = \sqrt{\frac{\sum (A_t - F_t)^2}{n}} \tag{11}$$

where:

A_t = Actual value in period t

F_t = Forecast value in period t

n = Number of periods used in the calculation.

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.

The software used to run the time series models was ForecastX version 3.8 developed by John Galt Development, Inc and included in Wilson et al. (2002). ForecastX is an Excel add-in that is designed to not only run forecast models of the users choosing, but also has a Procast feature which lets the software analyze the data and determine which forecasting model provides the best forecast based on a selected error term to minimize. In addition, ForecastX has the ability for "data cleansing" which gives the user the option to remove outliers. ForecastX provides forecasted values, error terms, and graphs which allows the user to quickly and easily compare multiple forecasts.

The data for the time series forecasting comes from GCSS-MC and organized by a specific time interval. In the case of the forecasts for this study, all time intervals are in months or quarters in order to have enough data points to run the time series forecasts.

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 10 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.

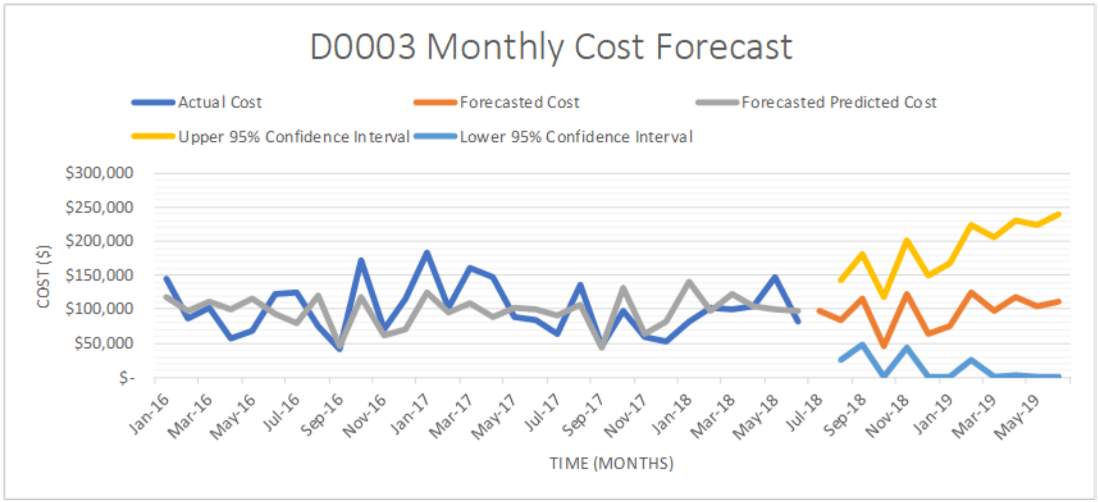
Table 8. D0003 Time Series Forecasting Results

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 ForecastX 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 gave 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.

Let us take a closer look the "Holt-Winters Start Jan16" forecast executive report shown in Figure 4 below. The graph shown 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 forecast has an average forecasted monthly cost of $96,194.94 with a maximum of $124,859.59 and minimum of $44,929.97. An example of a monthly forecasted cost for January 2019 is $124,859.59 with a 95% confidence that the cost will range between $25,499.26 and $224,219.92. Also, this summary specifies that this Holt-Winters forecast is 15% more accurate than merely using the historical average to forecast costs of future months. Finally, the 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 4. 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 11 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.

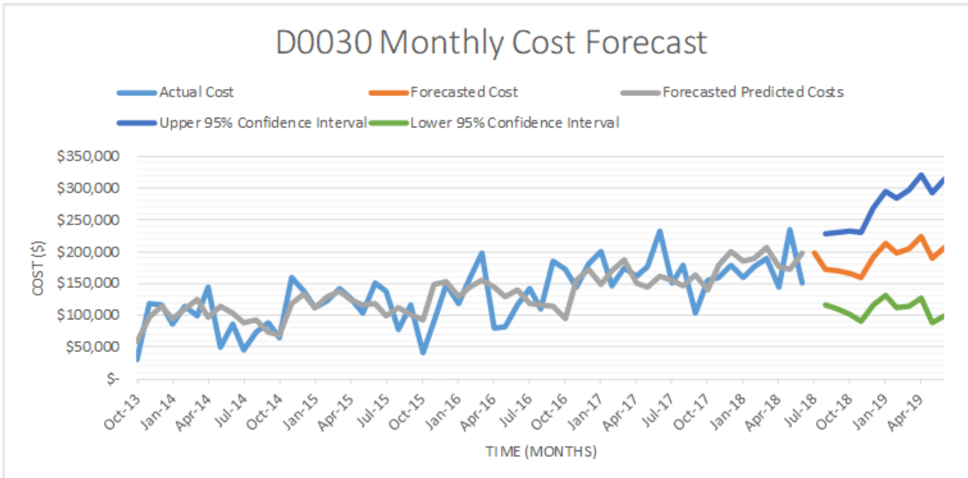
Table 9. D0030 Time Series Forecasting Results

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 RSME, the software selected simple exponential smoothing and Holt-Winters respectively as the best models to minimize those two error terms. A final forecast was run utilizing Procast to minimize the RSME with outliers removed.

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, 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.

Let us take a closer look the "Holt-Winters method with RSME minimization and outlier removed" forecast executive report shown in Figure 5 below. The graph shown 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.



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 5. D0030 Holt-Winters Forecast Results

This forecast has an average forecasted monthly corrective maintenance cost of $191,852.82 with a maximum of $222,762.63 and minimum of $160,385.31. Also, each month's forecasted cost and its upper and lower cost limits are given. For example, the forecasted cost for January 2019 is $197,433.71 with a 95 % confidence that this cost will range between $111,292.44 and $283,547.98. Also indicated is that this forecasted cost is 7.49% below the forecasted cost of the previous month of December 2018. Further, this summary specifies that this Holt-Winters forecast is

42.81% more accurate than merely using a simple average of the historical vales to forecast values of future months. 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 Table of Authorized Material Control Number (TAMCN) items that undergo corrective maintenance in the 1st Marine Division. Due to the large number of items in this category, 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. This type of analysis allows leaders to focus on the most important, most expensive items that drive the majority of expenditures. Table 12 shows TAMCNs classified into A, B, and C Types.

The 20 Type A items are listed in Table 13. 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.

Table 10. ABC Classification of TAMCN Equipment

Type	Percent of Maintenance Spending	Number of TAMCN
A	80	20
B	15	53
C	5	379
Total	100	452

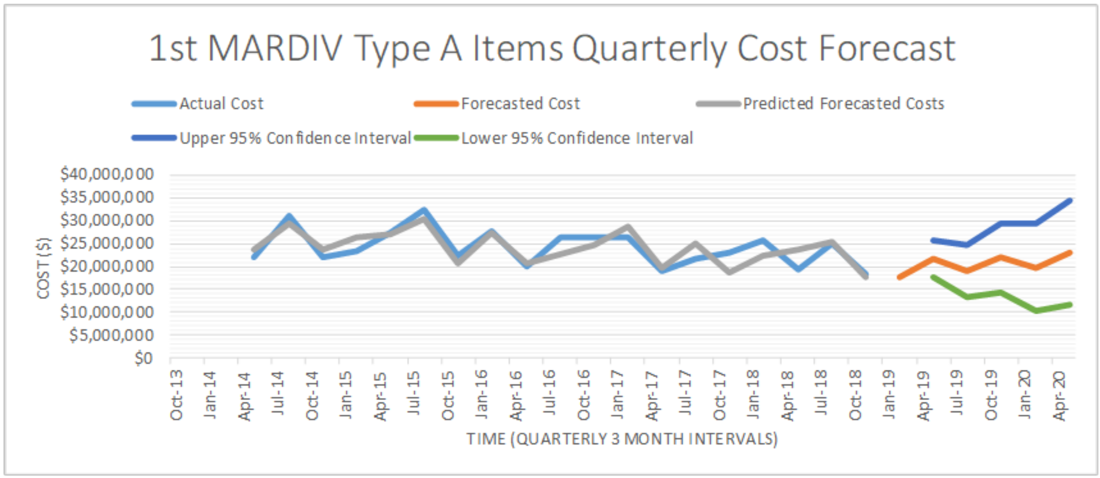
The ability to forecast 80% of the corrective maintenance costs for the most important and expensive equipment motivated us to focus on developing forecasting methods for this group of items. Accurate forecast of the corrective maintenance costs of these items will not only help prepare more accurate budgets, but also provide solid justification of how much funding is needed.

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. The historical corrective maintenance costs per quarter were extracted from the GCSS-MC data set by each TAMCN from the Type A equipment. These values were then aggregated to create the total cost of all Type A items per fiscal quarter, totaling 19 quarters. The Type A corrective maintenance costs were analyzed in ForecastX utilizing Procast to minimize RMSE without any outlier removal as there was much less variance in the "pooled" data as there is for individual equipment such as the D0003 MTVR and D0030 HMMWV. As expected, ForecastX recommended using the Holt-Winters method to forecast corrective maintenance costs of Type A items.

Table 11. 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%

Let us take a closer look at results shown in Figure 6 obtained using the Holt-Winters method. 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.



Forecast -- Holt-Winters Selected

Date	Forecast Quarterly	Forecast Annual	95% - 5% Upper	95% - 5% Lower	% Change 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 6. Type A Items Holt-Winters Forecast Results

This method produced an average forecasted quarterly cost of $20,691,589 and a 95% confidence interval ranging from $16,435,540.35 to a $23,106,224.94. 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.

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Conclusions

A review of the forecasting results developed in this research 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. Considering the GCSS-MC monthly corrective maintenance cost data, we were able to find the most accurate models to forecast future corrective maintenance costs for D0003 MTVRs, D0030 HMMWVs, and all 1st Marine Division type A items with a reasonable degree of accuracy. 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.
3. With the availability of GCSS-MC data and the flexibility provided by such software as ForecastX to test a variety of forecasting techniques, every unit within the 1st Marine Division could conduct the same analysis to make more accurate, quantitative budget estimates. The ability of ForecastX to provide a 95% confidence interval for every monthly forecast it generates should motivate logistical and fiscal planners to develop a quantitative-based forecasts for the corrective maintenance costs.
4. 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.

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. Software similar to ForecastX would be ideal to assist in completing the forecasts with speed and accuracy. With the amount of available data and the speed and accuracy of forecasting software, there is opportunity to leverage these opportunities to make more accurate forecasts. With the 1st Marine Division's quarterly corrective maintenance spending forecasted to average over $20 million each quarter per Figure 6, investing in forecasting software has potential to provide a huge return on investment by protecting and justifying the budget.
3. 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. Additionally, steps need to be taken to standardize data entry and collection of usage data. As discussed earlier in TCPT data quality, there is too much variation in the recorded data which leads to poor data analysis results.

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.

1. One possible variable to look into is the actual age of the vehicles. This data was not available in the collected data set and could be useful to explain the correlation between vehicle age and maintenance costs.
2. A second variable that we did not have information about is the location of where these vehicles are utilized. The 1st Marine Division vehicles operate almost exclusively in either Camp Pendleton or Marine Corps Air Ground Combat Center in Twentynine Palms, CA. These are two very different environments (desert vs ocean coast) and could be impacting maintenance costs. At hand data identifies who owns each vehicle and therefore its location. However, this might not be accurate as throughout the year, vehicles will occasionally go back and forth between the two bases and operate at both locations for training and exercises.
3. A third variable that should be examined further is individual unit trends and their standard operating procedures (SOPs). While the 1st Marine Division has an overarching maintenance management policy for equipment, each unit has its own individual maintenance management and dispatch SOPs. It would be interesting to look at how corrective maintenance cost varies between individual units (Regiments and Battalions) of the Division and then look at their SOPs to see why some unit costs are lower than others. Best practices can be identified and recommended to other units in the Division.
4. Another variable to further consider would be the preventive maintenance costs. While preventive maintenance costs are captured in the GCSS-MC data, an additional variable to add would be how much preventive maintenance was done by vehicle, month, or unit and see if there is a significant relationship between such preventive maintenance and corrective maintenance. For example, if a vehicle has more preventive maintenance costs, it should have lower corrective maintenance costs. The same logic could apply to a unit at large. If the unit is spending more on preventive maintenance than other units with respect to a certain vehicle type, then one should expect that the unit's corrective maintenance spending would be lower in relation to other units.
5. Like the age variable discussed previously, our data set does not contain any reliability data such as the actual or manufacture's Mean Time Between Failures (MTBF) of certain parts or subsystems of vehicles. However, it might be of interest to a reliability study on such parts or subsystems of vehicles, to not only confirm or infirm the manufacturer's MTBF claims, but also to

investigate whether or not a relationship exists between MTBF and corrective maintenance costs.

Finally, while our analysis focused only on forecasting the 1st Marine Division corrective maintenance costs, it would be interesting to compare the corrective maintenance costs in this division to those of the 2nd and 3rd Marine Divisions located in North Carolina and Okinawa, Japan respectively. If corrective maintenance costs across these divisions are radically different, then one could investigate what drives those differences. While some variation is expected due to different climates and usage, extremely large discrepancies could be an opportunity to identify and implement best practices fleet wide.

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