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Team 7: Total Life Cycle Management – Assessment Tool: An Exploratory Analysis

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INTRODUCTION

The United States Marine Corps continually works to shape logistics plans and policies in order to sustain excellence in combat effectiveness. Total Life Cycle Management (TLCM) is a vital part of the Marine Corps' vision of developing a force that is capable of performing and successfully completing the vast array of missions expected to be performed during the 21st Century. In an effort to improve the life-cycle management of assigned weapon systems, the Marine Corps contracted Clockwork Solutions to develop a tool capable of simulating life-cycle sustainment costs and performance metrics of operations, maintenance and supply for new and legacy weapon systems. Clockwork Solutions developed such a tool and named it Total Life Cycle Management-Assessment Tool (TLCM-AT).

During the IDFW-16, we focused our efforts on exploring several parameters and assumptions using TLCM-AT on a Marine Light Armored Vehicle (LAV-25). Our analysis involved the employment of the Nearly Orthogonal Latin Hypercube (NOLH) to help develop several scenarios based on a range of inputs for five critical parameters. Each scenario was replicated using TLCM-AT and the results were later analyzed in search of significant factors.

TLCM-AT Tool and NOLH

TLCM-AT is a stochastic modeling and simulation analysis tool developed by Clockwork Solutions. The tool's main objective is to provide a simplified representation of a system at some particular point in time intended to promote the understanding of the real system. Using this tool could enable decision makers and logisticians to perceive in a matter of minutes interactions and behaviors that would normally unfold over a very long time.

Clockwork Solutions included in the delivery of TLCM-AT five models covering the following weapon platforms:

- Amphibious Assault Vehicle (AAV)
- Joint Light Tactical Vehicle (JLTV)
- Light Armored Vehicle-25 (LAV-25)
- Lightweight 155mm howitzer (LW155)
- Medium Tactical Vehicle Replacement (MTVR)

Each of these models is implemented using a Microsoft Access 2003 database file. TLCM-AT uses these files to control both inputs and outputs, which are saved into the same file. In the context of this report a database file representing a weapon system will be called a model.

Using the provided LAV-25 baseline model, we ran the simulation tool 30 times and collected the results to determine the top ten LAV-25 degrading parts. This process of determining problem parts is done using a formula provided by Clockwork Solutions on their LAV-25 final report. The process uses the output from the out Waiting time and Unavailability output table. The formula is used to create a degrader index for each part on the weapon system. The formula is:

*Waiting Time * Requests * (Unavailability+1)*

Later parts are sorted by decreasing degrader index to determine the top ten degraders.

Employing the NOLH tool to efficiently maximize our sample space, we varied the starting state of the top ten degrader parts by varying five initial input parameters of each degrader. The five parameters controlled for our experiment are:

- Spare Levels (Total number of spares at each location)
- Induction Quantity (A limit on the number of inductions that can occur in the given quarter and year)
- Capacity (Number of parts that can be processed concurrently)
- Service Times (Time to service the part)
- Unscheduled Removal Rates (Part failure rate)

The Measure of Effectiveness (MOE) used was Operational Availability (Ao). Ao is defined as the number of operational platforms divided by the total number of platforms available fleet-wide at the end of 20 operational quarters. Table 1 shows the list of experiments in NOLH design format. Each row in Table 1 defines one experiment; later we will describe how these values are implemented into a model.

low level	1	0	1	0.5	0
high level	33	32	33	1.5	10
decimals	0	0	0	4	4
factor name	Spare	IQ	I Cap	Deg	ST
	11	32	27	0.875	2.5
	3	8	29	1.0625	0
	5	14	3	0.75	6.25
	7	20	11	1.5	5.625
	25	30	15	0.625	3.125
	33	10	13	1.3125	0.625
	21	6	33	0.8125	8.75
	19	28	25	1.4375	8.125
	17	16	17	1	5
	23	0	7	1.125	7.5
	31	24	5	0.9375	10
	29	18	31	1.25	3.75
	27	12	23	0.5	4.375
	9	2	19	1.375	6.875
	1	22	21	0.6875	9.375
	13	26	1	1.1875	1.25
	15	4	9	0.5625	1.875

Table 1: NOLH Design

Design Implementation

Each design was implemented using Table 1 as a guide. The factor names are Spare for spare levels, IQ for induction quantity, I Cap for capacity at the I- Level, Deg for unscheduled removal rates and ST for service times. The value of spare levels, induction quantity and capacity were set to the value on the NOLH for each degrader part. In the case of service times and unscheduled removal rates the current values of those parameters were multiplied by the value on the NOLH.

Data Generation and Flow

Due to the cumbersome nature of manipulating Access files manually, we were forced to create a Java application that could do the job for us. Figure 1 describes the process of design development and data generation flow. We were able to implement a Java tool that copies our baseline model into a working model that TLCM-AT can recognize when launched from the command line. Once the working model is created, our Java tool modifies the model to reflect the next design on the experiment; it then launches TLCM-AT from the command line. Our tool completes the process by collecting the necessary output from the current working model so it can be saved before a new working model representing the next design is created.

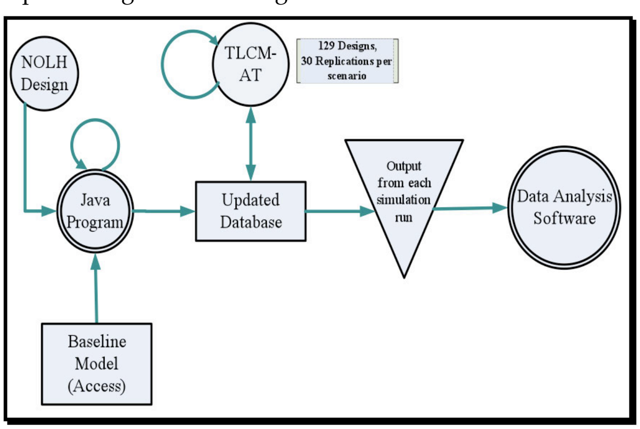

Figure 1: Data Generation and Flow

The output from our simulation is a CSV file containing every design value as listed on Table 1 and the achieved Ao for that design.

RESULTS AND ANALYSIS

Figure 2 shows how each design compares with respect to our MOE. The small difference range among all designs is explained by the fact that we only varied our parameters on ten parts. Limiting our analysis to only ten parts significantly improved the speed of our runs.

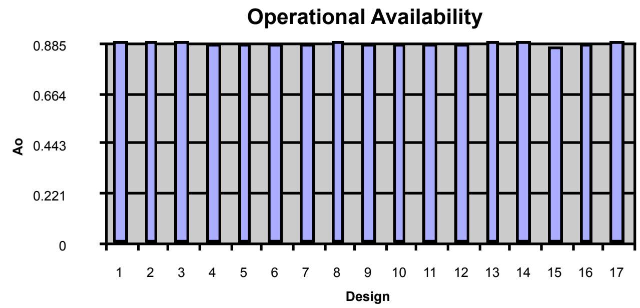

Figure 2: Operational Availability per design

Our initial analysis involved a main-factor-only multiple linear regression model. We expected to identify some significant main factors during this portion of the analysis, but surprisingly that was not the case. Figure 3 shows the parameter estimates for the linear regression model. The lowest p-value included on this model is 29 percent and the R-Squared equaled 17 percent strongly suggesting that this model is not adequate.

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.87646	0.005963	146.99	<.0001*
Spares	0.0001072	0.000127	0.85	0.4159
IQ	-2.79e-5	0.000127	-0.22	0.8299
Capacity	3.0247e-5	0.000127	0.24	0.8159
Degradation	0.0017899	0.004059	0.44	0.6678
ServTime	-0.000448	0.000406	-1.10	0.2929

Figure 3: Main Factors Regression Model

Our next step was to include second order interactions on our model perform stepwise regression to determine significant factors and interactions.

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.8693558	0.001984	438.16	<.0001*
Spares	0.0001072	3.452e-5	3.11	0.0267*
IQ	0.0001104	0.000041	2.69	0.0433*
Capacity	7.9242e-5	3.54e-5	2.24	0.0754
Degradation	0.0053867	0.001247	4.32	0.0076*
ServTime	-0.000356	0.000111	-3.20	0.0241*
(Spares-17)*(IQ-16)	-1.94e-5	8.777e-6	-2.21	0.0781
(Spares-17)*(Capacity-17)	8.8471e-6	4.588e-6	1.93	0.1117
(Spares-17)*(Degradation-1)	-0.000972	0.000208	-4.66	0.0055*
(Spares-17)*(ServTime-5)	0.0000504	1.233e-5	4.09	0.0095*
(Capacity-17)*(Degradation-1)	0.0013016	0.000283	4.60	0.0059*
(Spares-17)*(Capacity-17)*(Degradation-1)	-0.000138	2.223e-5	-6.22	0.0016*

Figure 4: Regression Model with Interactions

In this case it was discovered that the interaction among spares, capacity and degradation times was the most significant factor on the model. Figure 4 shows the Parameter Estimates for the regression model including second order interactions. The subsequent significant factors are interactions between spares and degradation times, capacity and degradation times and the main factor degradation times (significant in the presence of other factors).

Figure 5 shows the order of significance of all factors included on the model. R Squared for this latest model equaled 97 percent.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
(Spares-17)*(Capacity-17)*(Degradation-1)	-0.000138	2.223e-5	-6.22	0.0016*
(Spares-17)*(Degradation-1)	-0.000972	0.000208	-4.66	0.0055*
(Capacity-17)*(Degradation-1)	0.0013016	0.000283	4.60	0.0059*
Degradation	0.0053867	0.001247	4.32	0.0076*
(Spares-17)*(ServTime-5)	0.0000504	1.233e-5	4.09	0.0095*
ServTime	-0.000356	0.000111	-3.20	0.0241*
Spares	0.0001072	3.452e-5	3.11	0.0267*
IQ	0.0001104	0.000041	2.69	0.0433*
Capacity	7.9242e-5	3.54e-5	2.24	0.0754
(Spares-17)*(IQ-16)	-1.94e-5	8.777e-6	-2.21	0.0781
(Spares-17)*(Capacity-17)	8.8471e-6	4.588e-6	1.93	0.1117

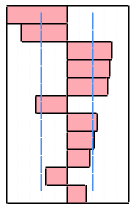

Figure 5: Parameter Estimates in Order of Significance

CONCLUSIONS

The results from this analysis are specific to the LAV model provided to us by Clockwork Solutions and it applies to the set of adjusted parameters and the way they were changed. The main conclusion is that investing in any one given resource in order to improve Operational Availability would not provide the best result if the underlying interactions among factors are not explored carefully. Running a base case scenario and comparing the results to those obtained by changing one factor at a time simply will not allow the analyst to estimate the interactions (synergies) among the many factors. From the initial results that were obtained during the workshop, one can clearly see that the interaction of the factors analyzed had the most significant impact on Operational Availability of the LAV. Decision makers need to consider the best mix of resources to maximize Ao; clearly the use of tools such as the TLCM-AT, combined with design of experiments, can provide insight into these interactions.

THE WAY AHEAD

During the previous months and during IDFW-16, a process has been developed to use DOE and the NOLH with the TLCM-AT. A simple scenario was used to test the mechanics of the Java implementation, and interesting results were obtained. The work accomplished here opens the door for researchers in the future to apply these techniques to real-world scenarios. Commonly, decision-makers are presented with several courses of action (COA) when trying to decide how to maintain material readiness of complex weapons systems. Each COA can be individually modeled in the TLCM-AT database, and design of experiments can be used to explore the significant factors that affect the desired end state for the fleet of a particular weapons system.