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PRODUCT SUPPORTABILITY THROUGH LIFECYLE MODELING AND SIMULATION

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ABSTRACT

Current changes in DoD budgeting processes and in the constraints on available funding have resulted in inadequate support for our warfighter's needs. The decision environment evolves into a key question impacting our warfighter capabilities: How should the funding be distributed to achieve the optimal balance between readiness, performance, and cost? This paper outlines the fundamentals of successful Product Life Cycle Management, a method to monitor systems towards fulfilling the operational needs at the lowest possible Total Ownership Cost (TOC). The paper discusses critical decision points in different phases of the system's life cycle and suggests an approach to use modelling and simulation tools to answer key questions and provide the required decision support.

1 INTRODUCTION

Today's constraints on funding the acquisition of systems and their associated lifecycle support costs requires a rigorous and consistent analytical process to ensure the systems and supporting processes provide capabilities that are worth the expenditures. These funding constraints come at a time when many of our systems are very mature and "war-weary." This fact exacerbates an already complex decision environment. The decision environment evolves into a key question impacting our warfighter capabilities: How should the funding be distributed to achieve the optimal balance between readiness, performance, and cost?

Key Points: Recent DoD policies and guidance make significant strides towards identifying and promoting broad-based Product Lifecycle Management (PLM) strategies to design, field and sustain more affordable and ready warfighting capabilities. The practical implementation and institutionalization of these strategies, however, has not kept pace with available analysis capabilities. The most significant barriers to attaining the desired implementation and institutionalization of these strategies are:

- The deep-rooted divisions between systems engineering, lifecycle product support, programmatic and cost functions.
- Divergence between policy requirements and organizational business strategies/ investments in enterprise-wide lifecycle process and knowledge management.
- Sustainment data from the many "stove-piped" information sources within each of the services/organizations that needs to be extracted, transformed, and loaded into a common information analytics data warehouse with other PLM data sources and capabilities.
- The need for developing and employing a comprehensive "Big Data" strategy to effectively use the large volume of sustainment data and resolve the complexities involved with effective integration of this data.
- A scarcity of competency and proficiency in structured analytics, business intelligence, Reliability, Availability, Maintainability and Cost (RAM-C) trade studies, lifecycle product support package design, and PLM technologies.
- In addition, the complexity of the decision environment is increased by:

- The potential cost growth of continuing to operate systems that have been significantly degraded by war-fatigue or have had their original operational life extended many times.
- The decreased budgets and increased costs to maintain systems, ultimately leads to a realization that spreading budget cuts across every program is probably no longer a viable solution.
- Early decisions regarding concepts, requirements, and choice of supplier will impact the TOC more than anything.

This paper outlines the fundamentals of successful PLM, a method to monitor systems towards fulfilling the operational needs at the lowest possible TOC. The paper discusses critical decision points in different phases of the systems life cycle and suggests an approach to use modelling and simulation tools to answer key questions and provide the required decision support.

Advances in Lifecycle Modeling and Simulation technologies have provided a significant opportunity for the DoD to address these complex issues. Lifecycle Management (LCM) simulation tools and techniques have been developed to automate and modernize the collection, aggregation, measurement, and visualization of system and platform performance from the In-Service Engineering Agent's (ISEA's) perspective, with potential for providing valuable information to the service components and to the acquisition community. These new technologies assist with the capture, retention, translation, and aggregation of numerous forms of structured data. There are numerous databases being used that perform just as many tasks and the primary purpose is to aggregate their data. In some cases, tools can translate database data elements so that they are compatible with other databases' data elements. Data translation then paves the way for data integration. Data aggregation and integration reveal data relationships not otherwise known to program managers and subject matter experts.

Additionally, early decisions regarding concepts, requirements and choice of supplier will impact the TOC more than anything else. Unfortunately, these decisions need to be made without exact knowledge about all influencing parameters. To make these kinds of decisions under major uncertainties calls for an efficient and systematic decision-making process, using modelling and simulation tools to analyze the consequences of the decisions. Figure 1 shows the basic Data Modeling and Analysis Process.

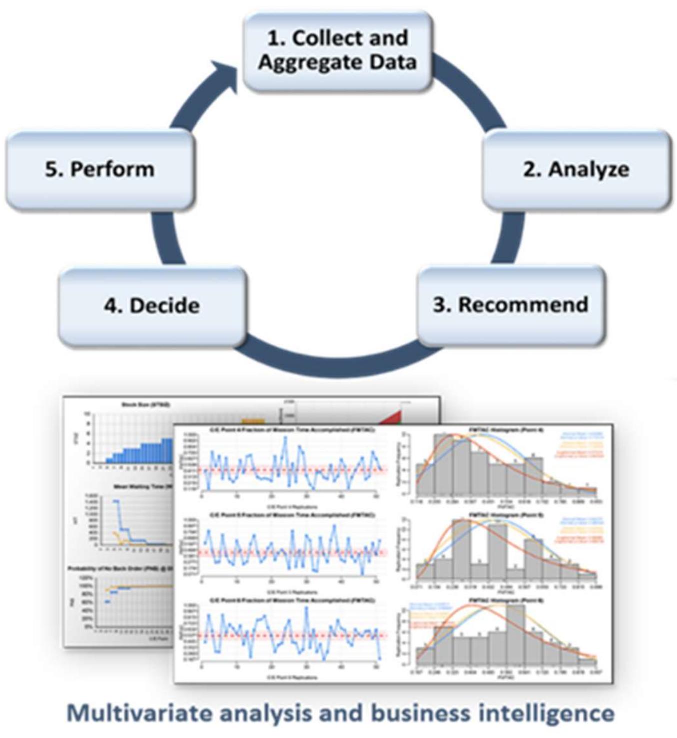

Figure 1: Data modeling and analysis process.

2 SUPPORTABILITY IN THE DESIGN AND ACQUISITION PHASES

From a customer and owner perspective, any system typically goes through several phases starting with concept definition, specification, and acquisition, continuing with system design and development, production, entry to service, operations, and maintenance and finally disposal. All through the life cycle a program or product manager needs to make many decisions regarding the technical system, its operations and maintenance and the logistic support. The important point here is that consequences of decisions made will may not be exposed until many years after a decision is made. That is the background to the classic characteristics of a Lifecycle Cost Curve (LCC) curve shown below in Figure 2.

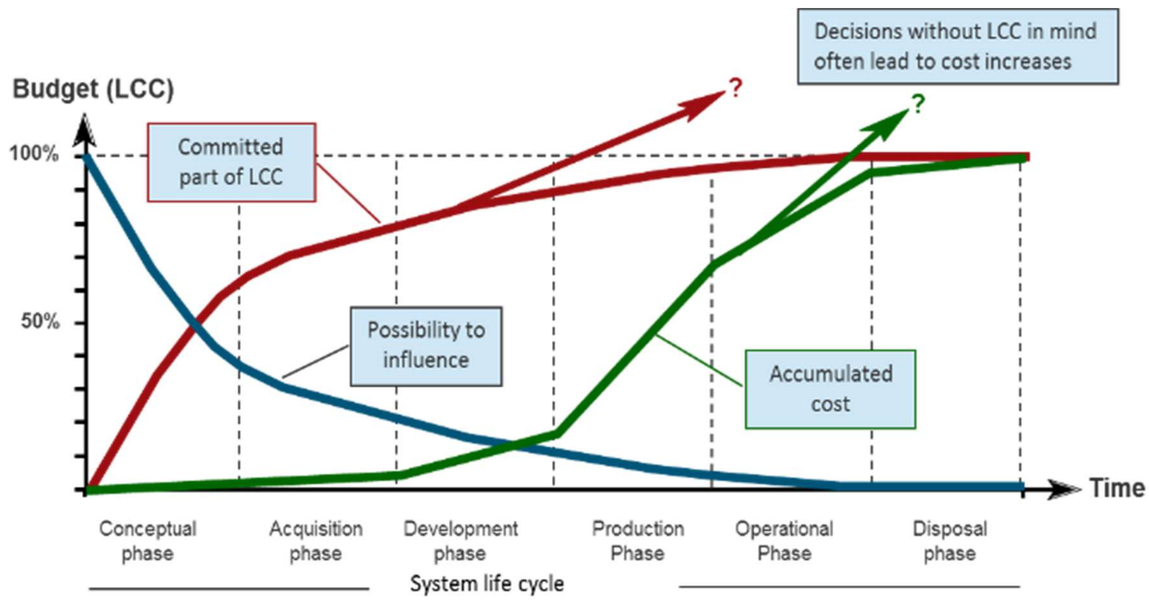

Figure 2: Characteristics of a life cycle cost curve (LCC).

The green curve shows the actual expenditures (both CapEx and OpEx) for a system throughout its life cycle. The red curve, however, describes when stake holder(s) decisions make them commit to the costs, which usually occur long before the actual expenditures. Thus, their possibility to influence the total ownership cost will decrease during the system´s life cycle according to the blue curve.

It is also important to note that if decisions are made in later phases without analyzing the potential consequences on operational performance and life cycle cost, there is a great risk that one commits to future cost increase.

3 COST/BENEFIT ASSESSMENT DURING PRODUCT LIFECYCLE

When should replacement of fleet of systems take place? What requirements should be put on a new system? Which systems should be purchased? What investments in logistic support, spares and other resources should be chosen? What improvements are most cost-effective to make to enhance my operations?

These are some examples of major questions for a system manager. They all require an understanding of what the consequences of the choices at hand will be on operational performance and total cost of ownership. The questions are complicated to answer since there are so many influencing parameters. Figure 3 below illustrates the decision problem and the three main influencing domains.

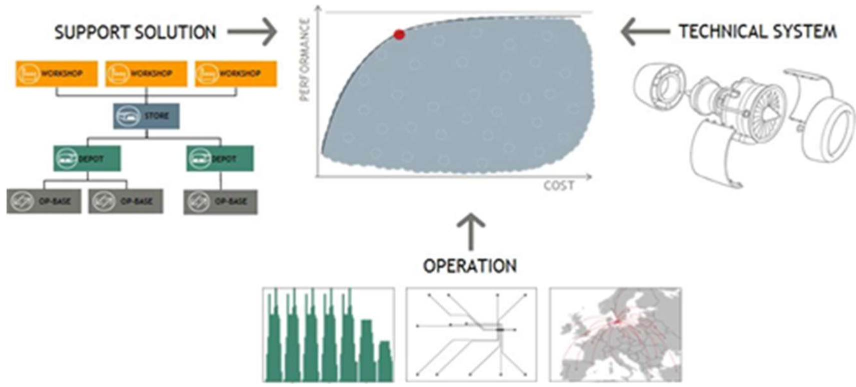

Figure 3: The dimensions that influence the relationship between cost and availability.

To be able to assess consequences of alternative solutions in a systematic and consistent way throughout the system's life cycle there is a need to use an analytical approach supported by efficient decision support models—a combination of tools to assess different aspects of a decision. Typically, an optimization tool is used to identify the best logistic support solution from a cost effectiveness perspective and to optimize the spares assortment. A simulation tool is used to validate sustainability and ability to handle different scenarios and to dimension fleet size, personnel, repair equipment and other resources. A cost calculation tool is used for LCC comparisons, identification of cost drivers, budgeting, and cost analysis. These tools work together as a suite to provide decision support for each type of decision and helps finding the optimal trade-off between cost and availability.

A general approach when working with LCM analyses includes the following:

- Define a system and scope, the decision at hand and the alternative solutions.
- Define prerequisites and limitations for operations and maintenance.
- Define influencing parameters and create a model.
- Acquire input data. Begin with a rough data model.
- Validate the model and the data quality and improve data that has significant impact on the decision at hand.
- Perform analyses and evaluate the results.
- Perform sensitivity analysis, identify drivers of cost and effectiveness, iterate to find the best solution.

As per Figure 4, in the early phases stake holder(s) make the major decisions which will commit most of the future life cycle costs. This means that it is in the early phases that stake holder(s) need to put in most of the effort. Nevertheless, to achieve the availability performance and the life cycle cost that the early decisions have made possible, stake holder(s) need to carry on making decisions in a systematic way throughout the rest of the systems life cycle. Otherwise, there is a great risk that stake holder(s) will suffer from uncontrollable increasing costs or poor availability performance. Managing decisions over the lifecycle with overall requirements and goals on macro level in focus, modelling detailed data on micro level is a true lifecycle management challenge.

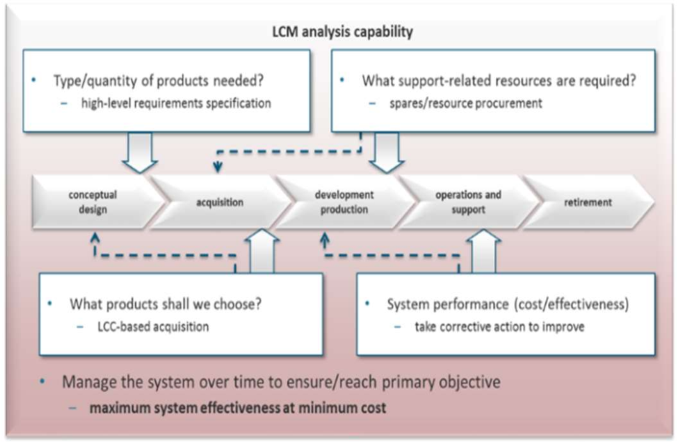

Figure 4: Lifecycle maintenance analysis capability.

4 SAMPLE TEST CASES

4.1 CASE 1

Objective: A power utility company wants to investigate and analyze if it would be cost effective to invest in the procurement of spare transformers. Additionally, they need to determine the storage location for each of the transformers to optimize Operational Availability (Ao) of the power plant and operational costs.

4.1.1 CASE 1 Sample Data

The power utility company used the following data in Table 1.

Table 1: Available transformer data.

Parameter	Description
Power Plant	Name of power plant
Manufacture	Manufacturer of transformer
Apparent Power	The magnitude of the complex power [VA]
Voltage Ratio Max/Min	Ratio between LV and HV side
Vector Group	Winding configuration of 3-phase
Existing Spare Transformer	If spare units exist and its location
Quality/Reliability	Reliability of transformer
Transformer Price	Price of transformer [EUR]
Downtime in case of spare	Time duration required to replace if spares
Downtime in case of no spare	Time duration required to replace if no spares exist
Expected annual gross margin of block	Expected gross margin per annum if no unavailability

The data concerning down times with and without spare units, and the data concerning the expected margin, enabled the utility to assess what possible down times would imply in terms of lost profit. Together with the reliability data and the price of each transformer the risk of losing profit could be evaluated against the risk mitigation of investing in spare units.

4.1.2 CASE 1 Methodology

The utility used a spare part and logistic support optimization tool to model and analyze their transformer case. The basics of the methodology is depicted below in Figure 5. This tool uses turn-around-times, reliability, and price data together with other logistics, maintenance, and technical data to calculate the optimal assortment and allocation of spares from a system cost-efficiency perspective.

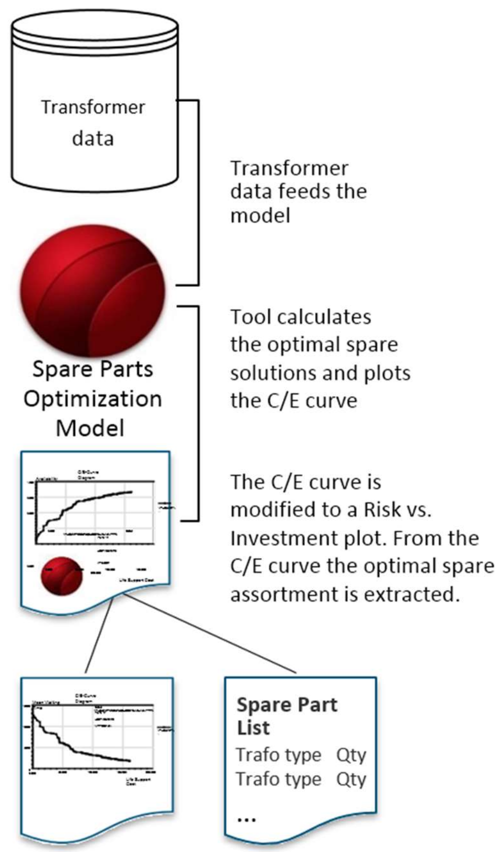

Figure 5: Overview of the analysis method.

The spare part and logistic support optimization tool generates a Cost/Effectiveness (C/E) curve that plots the spares investment against the availability of the whole system, i.e., the average availability of all transformers. Each point on the C/E curve represents the optimal sparing solution for a specific budget frame, and as one progresses to the right in the C/E curve the spares investment increases as power utility company invests in more transformers. As a consequence of the larger spares investment, the resulting availability also increases.

As the value of availability can differ between transformers in this case, the utility took advantage of the possibility to prioritize the plants in the model and used the expected annual gross margin as the priority factor in the input model.

Once the C/E curve had been established, the utility extracted the availability for each transformer in the case, and for each point on the curve. Together with the information about the expected annual gross margin the C/E curve was modified to a Risk vs. Investment curve.

4.1.3 CASE 1 Results

Figure 6 shows how the investments in spares influence the lost profits due to down time caused by transformer failures. Naturally, lost production, and hence lost revenues, decreases with higher investment levels in spare transformers.

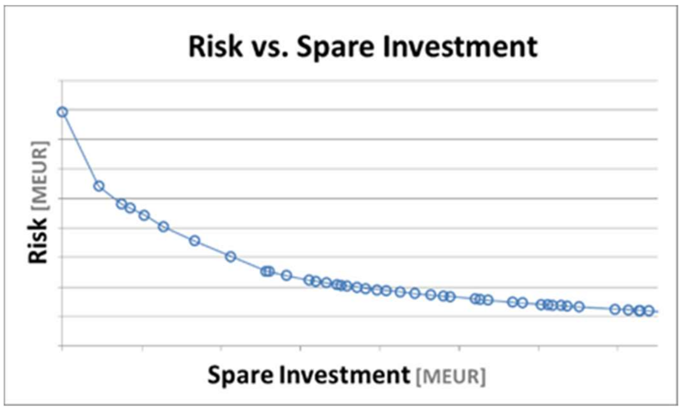

Figure 6: Risk vs. spares investment.

The power utility company was interested in evaluating how many, and which, transformers that could be economically motivated to purchase as spares. Therefore, the delta risk reduction was divided with each respective spares investment to create Figure 7 below.

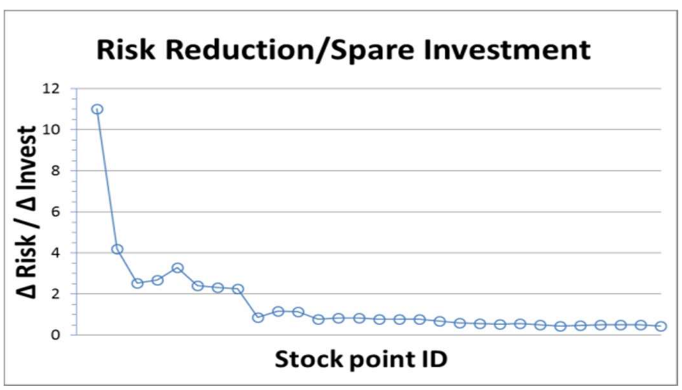

Figure 7: Delta risk/delta investment.

In the plot above the dimensionless ratio between risk reduction in dollars and investment in dollars is depicted. If this ratio is below one (1) the investment is inevitably not profitable. However, all ratios above one (1) will not necessarily prove themselves profitable since there are some uncertainties built into the risk value.

The power utility company opted to vary different input parameter, e.g. the failure frequencies of the transformers, in order to study the sensitivity of the results. Results from three scenarios with different failure rates are shown below in Figure 8.

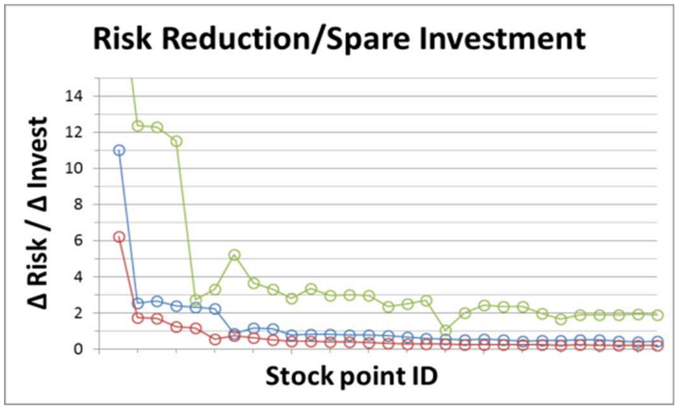

Figure 8: Delta risk/delta investment at different failure scenarios.

Properly investigating the sensitivity of the results was an integral part of the analysis. To find the absolute availability level was not the priority of the analysis, more so was formulating a short list of transformers in which to invest in. After evaluating the case in different scenarios, the power utility company could select a ratio between risk reduction and spare investment with good judgment and formulate a short list of transformers for their investment program.

4.2 CASE 2

Objective: Navy Type Commanders (TYCOM) want to make sure that all the ships pass their Board of Inspection and Survey (INSURV) inspections. Ships are typically notified one year prior to the conduct of this upcoming INSURV. What can the TYCOM do to mitigate the risks to the ships to failing an INSURV and where should they focus their limited resources? Develop a statistical model to prioritize ship departments for focus of upcoming INSURV inspections.

4.2.1 CASE 2 Sample Data

The TYCOM used the following data in Table 2.

Table 2: INSURV data.

Parameter	Description
INSURV	Material Inspection (MI) Data
3-M	Maintenance Material Management Data
Training Sets	Prior INSURV MI data

4.2.2 CASE 2 Methodology

Develop a statistical inspection model using Binomial Logistic Regression using the following parameters:

- Formula

$$D = x_R + x_{Am} + x_i + x_{Av} - 1$$

where

$$D = Discrepancy\ (binary)$$

$$x_R = Root\ Cause\ Code$$

$$x_{Am} = Ship\ Age\ (months)$$

$$x_i = i^{th} Inspection$$

$$x_{Av} = number\ of\ Availabilities$$

$$-1 = No\ intercept$$

- Training Set = InspectionDate ≤ 2016
  (90 Inspections)
- Test Set = InspectionDate > 2017
  (24 Inspections)
- There is no equivalent R^2 for logistic regression
- McFadden R^2 index (0.2-0.4 = excellent fit)
- Receiver Operating Characteristic (ROC) Area Under Curve (AUC) is a (preferred?) binary classifier performance measurement (1.0 is ideal)

4.2.3 CASE 2 Results

Figure 9 shows approximately 9 times out of 10 that the model correctly identified a specific discrepancy will occur within this AS Department with a root cause (i.e. Model is a realistic representation of predicting root causes).

- Anti-Submarine (AS) Department
- R2 = 0.353
- Fit vs Actual Accuracy = 0.889
- AUC = 0.848

Figure 10 shows the Probability the Defect (Pd) will occur for a particular area on the ship. ELEX/CCA/MODULE Component failure is rated the highest probable defect in the Reliability Area (A). This provides a heads-up to the TYCOM team for particular discrepancy area prior to the actual inspection. They may ask the ship to conduct additional Preventative Maintenance in order to mitigate these issues.

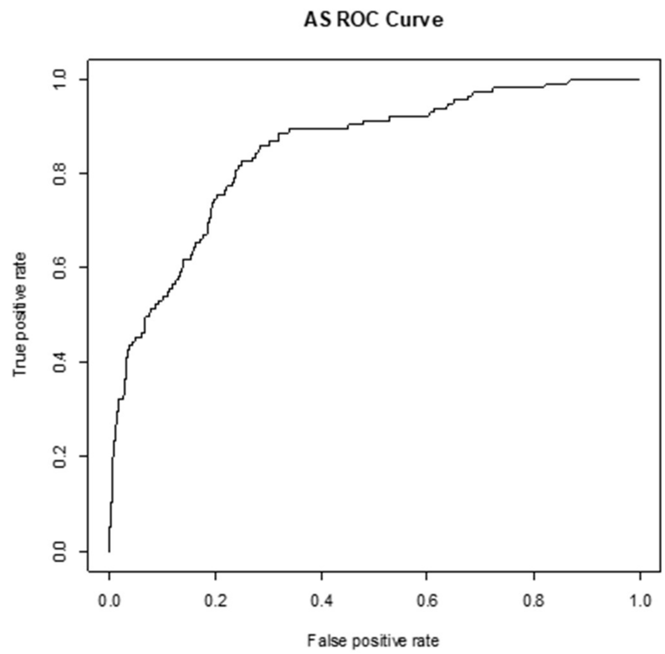

Figure 9: Model fidelity curve.

	P(d)	Discrepancies per Inspection	Avg EOC	Average EOC +/- 1 Standard Deviation (68%)
A-RELIABILITY				
1-MANUFACTURING DEFECT	17.48%	1	$x-1\sigma$ 0.26 x 0.50 $x+1\sigma$ 0.73	
2-INSTALLATION DEFECT	23.30%	28	$x-1\sigma$ 0.24 x 0.48 $x+1\sigma$ 0.71	
3-INADEQUATE DESIGN	12.62%	1	$x-1\sigma$ 0.34 x 0.56 $x+1\sigma$ 0.78	
4-ELEX/CCA/MODULE COMPONENT FAILURE	64.08%	7	$x-1\sigma$ 0.41 x 0.63 $x+1\sigma$ 0.85	
5-COMPONENT FAILURE	41.75%	3	$x-1\sigma$ 0.39 x 0.61 $x+1\sigma$ 0.83	
6-SEAL FIGURE	28.16%	4	$x-1\sigma$ 0.38 x 0.63 $x+1\sigma$ 0.89	

Figure 10: Probability of discrepancy per INSURV area.

5 CONCLUSIONS

This paper has presented a tool-based methodology to enhance supportability. These models can be used for optimizing spares and predicting areas where failures can occur. By conducting the analysis, the customers will be better prepared to provide informed decisions. The methodology quantifies the risks. Moreover, the case presented in this paper shows how Logistics Modeling tools can be successfully employed, and deliver fact-based results, also in cases with low failure frequency systems.

AUTHOR BIOGRAPHIES

JUSTIN WOULFE is a principal and co-founder of Systecon North America with expertise in Systems, Logistics, and Cost Optimization. For the past decade, he has focused on balancing cost and capability within the Aerospace & Defense industry. Justin has a BS in Electrical Engineering from Virginia Military Institute, an MS in Engineering Management from Drexel University and a MS in Supply Chain Management from Syracuse University through the DoD LOGTECH program. His research and analysis has resulted in billions of dollars in savings and increases in readiness on large, complex acquisition and sustainment programs. His work in Model-Based-Systems-Engineering, optimization, and readiness analysis is widely published and taught in both university and DoD programs.

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