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EFFECTIVE MODELING AND SIMULATION OF INCREASED COMPLEXITY IN COMBAT SYSTEM DESIGN

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ABSTRACT

Defensible and Effective Model Based Engineering (MBE) requires capable tools for optimization and simulation to verify that the current system design can meet mission performance, availability and affordability requirements. Legacy Army tools have failed to meet those needs and a new generation of capabilities are now available to allow program managers to continuously update input variables and assess the system's Operational Availability (A_o) Key Performance Parameter (KPP) and Lifecycle O&S cost Key System Attribute (KSA).

INTRODUCTION

Program Executive Office Ground Combat Systems (PEO GCS) is responsible for providing world-class affordable, relevant and sustainable ground combat equipment to Joint Warfighters. With a focus on developing advanced technologies, PEO GCS is leading the design and development of the Army's Future Fighting Vehicle and Armored Multi-Purpose Vehicle, the Army's highest priority combat vehicle.

PEO GCS is developing 21st century, technically complex, systems designed to perform a critical mission in remote environments, across a full spectrum of operations and multiple terrain sets. As the design matures through development, production, and fielding, the associated performance and cost models become increasingly complex. Decisions made at every milestone can dramatically impact the future readiness of the system as well the operating support costs. It is essential for program managers to leverage defensible and effective modeling capabilities to understand how the design will perform when fielded, what it will cost to operate and support, and the expected impact of the logistics support system to achieve desired mission objectives. Embracing model-based engineering inserts a feedback mechanism to the design and product support teams. This allows for evidence based support for ECP funding, validating program decisions and understanding system performance as operating environments evolve in a way that maintains affordable readiness.

WHY BUILD A MODEL?

An effective Modeling and Simulation tool for Product Lifecycle Management, must be comprehensive and allow for a realistic model to be produced, not a "dumbed down" simplistic representation that is quickly built to check a CDRL deliverable box. A comprehensive set of inputs, such as technical system design, support system design, environmental factors, reliability, maintainability, supportability, and operational requirements must be utilized. The tool should also leverage advanced algorithms which optimize product support results as well as fast simulation to understand risk and probable outcomes in support of Analyses of Alternatives (AoAs). The comprehensive modeling capability should quickly provide results across the program leveraging a common baseline to allow for important decision analyses to be made, including operational effectiveness, availability, costs, required spare parts, resources allocations and impacts of changing OPTEMPO as well as understanding how changes to any one area ripples across the program to impact performance capability and readiness.

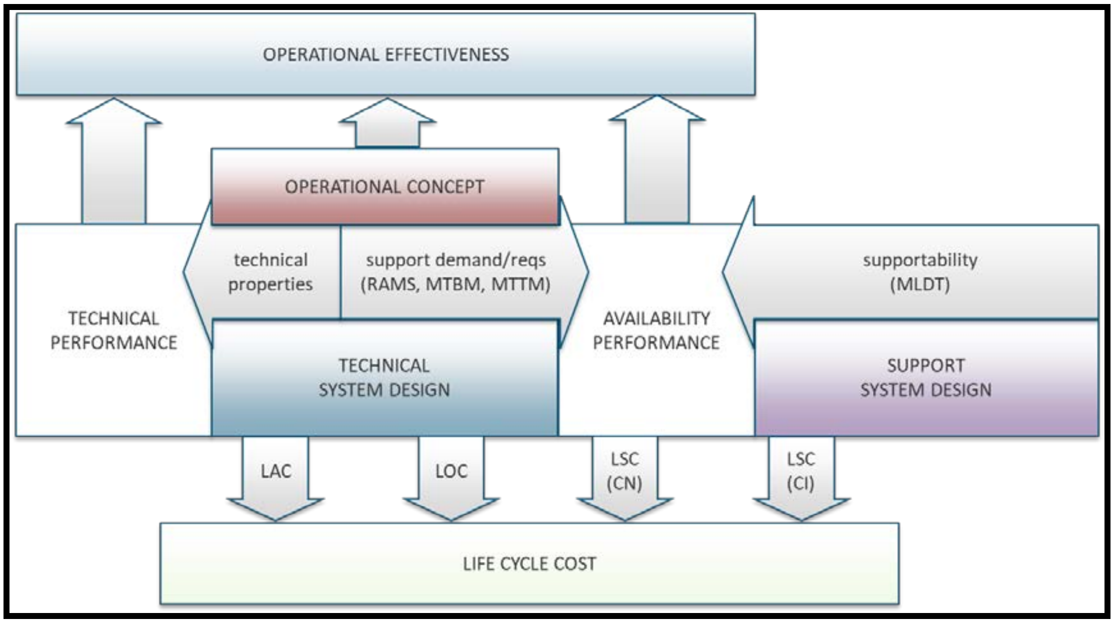

Figure 1: All program impacts impact cost and capability and should be simultaneously modeled.

Figure 1 shows the complex interrelationship between cost and operational effectiveness. Models used by the program should simultaneously consider the operational concept, the technical system design and the support system design and provide feedback to the program on the best courses of action to allow for the most "bang for your buck" regarding effectiveness, cost, or both. Focusing on the technical system design, it is important to model the entire system. Perhaps early on in the program only MTBF is available for each component. Later, after a FMECA is completed failure modes and their impact on the system will be understood. It is important the model be able to handle data in whatever format is available. Perhaps the technical system capabilities are dependent on the operational concept. If we were to build a reliability block diagram of the system, perhaps when conducting certain mission only some elements of the system are critical or have redundancy, while in other missions they are not. The model should capture all these complexities to accurately predict effectiveness and requirements on the support system (spares, manpower, etc). When designing the support system, it is not acceptable to look only at spare parts. We must understand the impact that all product support elements have on readiness and cost and optimize them simultaneously with a system perspective. Focusing only on spares or one component at a time prevents us from understanding the big picture (system capability) and risks "fixing" a problem that doesn't exist or implementing solutions to readiness issues that we don't truly understand and don't address the real problem.

MODELING IN ACTION

An example, produced with Systecon's Opus Suite, of how optimization and simulation can be used to verify that the current system design can meet mission performance, availability and affordability requirements specifically applied to ground vehicle systems is below. Leveraging advanced optimization and simulation tools allows the systems engineering team to continuously update input variables and assess the system's Operational Availability (A_o) Key Performance Parameter (KPP) and Lifecycle O&S cost Key System Attribute (KSA).

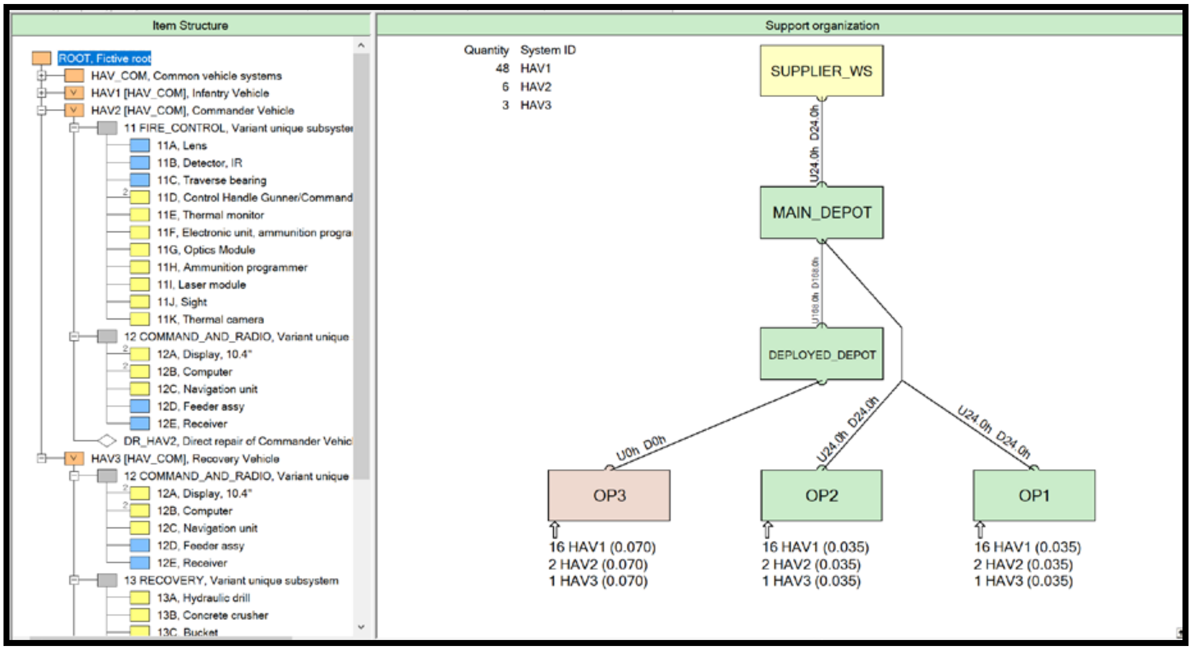

Figure 2: Model of three armored vehicles with many common components deployed across three operational locations

In this example we will study the availability and mission effectiveness of an armored vehicle shown in Figure 2. This vehicle consists of three different variants deployed in varying quantities and OPTEMPOs across three locations, one of which is deployed OCONUS. The sites are supported by a main depot and the OEM. Each component has a failure rate, RTAT, maintenance concept, task/resource requirements, and transport time/cost included in the model. Also modeled are the current on hand spares and manpower levels to support operations.

Figure 3 shows the availability of the systems by variant and location as calculated by the modeling and simulation tool. The output displays availability on the Y axis and cost on the X axis. The first point for each curve is the current on hand spares and manpower levels while each subsequent point is the optimal set of manpower and spare parts to achieve that readiness level. From the graph one can see that for a very small investment it is possible to make large improvements in readiness. Eventually, very large investments are required to achieve smaller and smaller gains in availability. In this example, somewhere between 80% and 90% availability is the "knee in the curve." Taking a point from this curve, we can simulate mission effectiveness over a deployment period, show causes of downtime, and drill down into achievable performance. These results of the baseline can be seen in Figure 4.

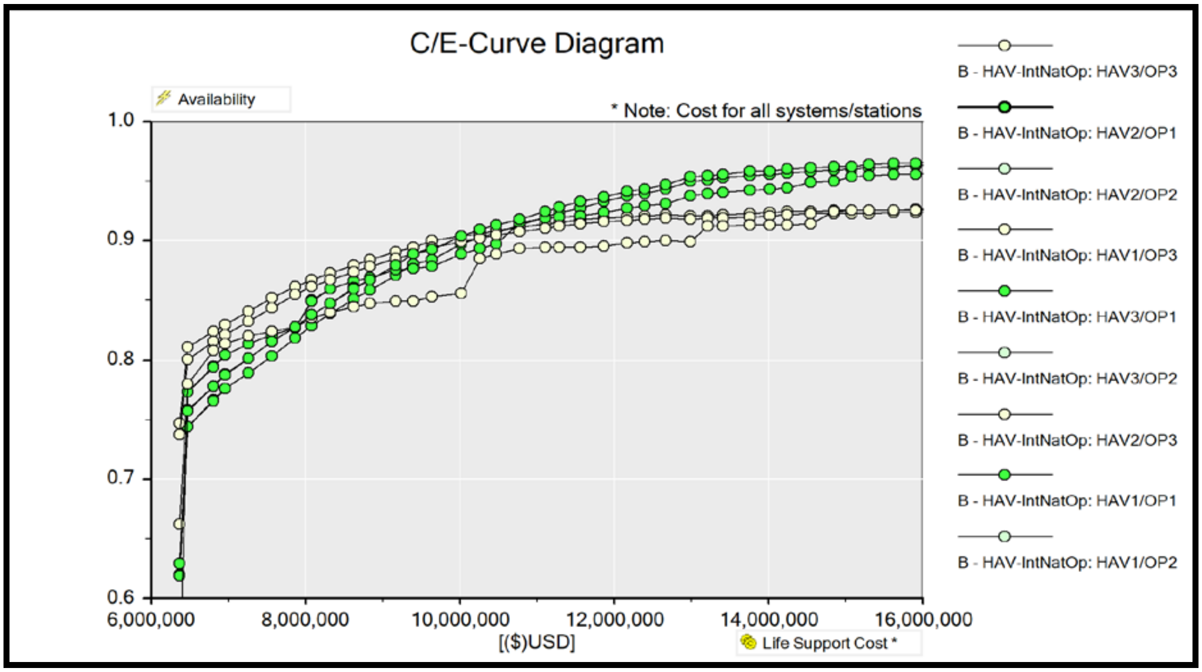

Figure 3: Availability by system variant and location

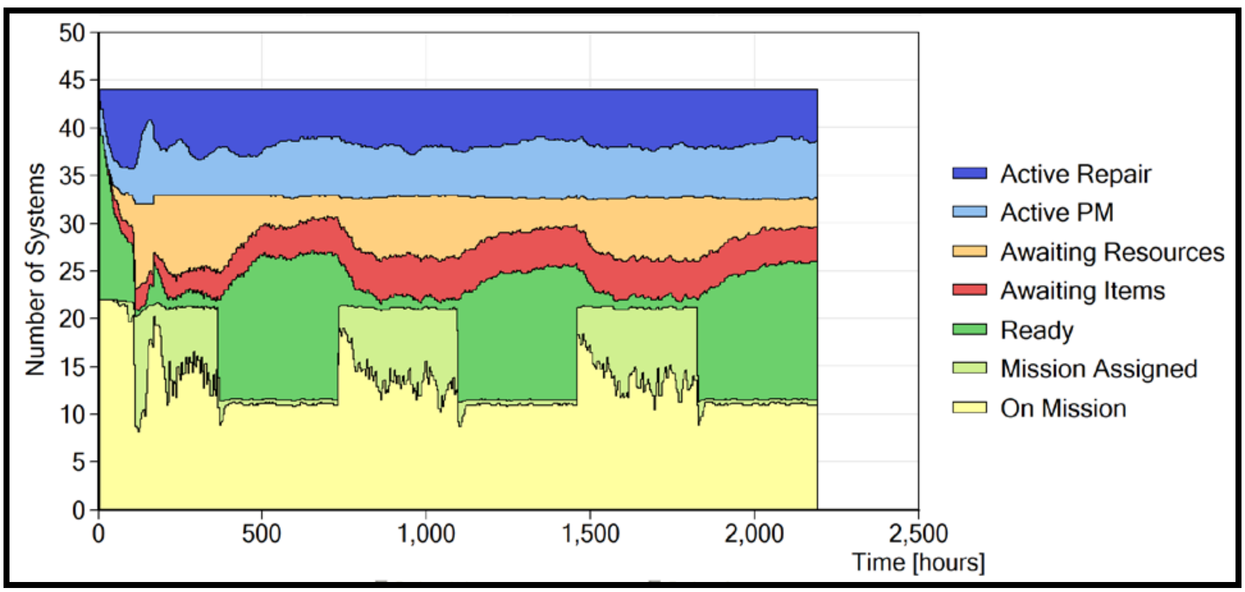

Figure 4: System states associated with the current on-hand spares and manpower levels

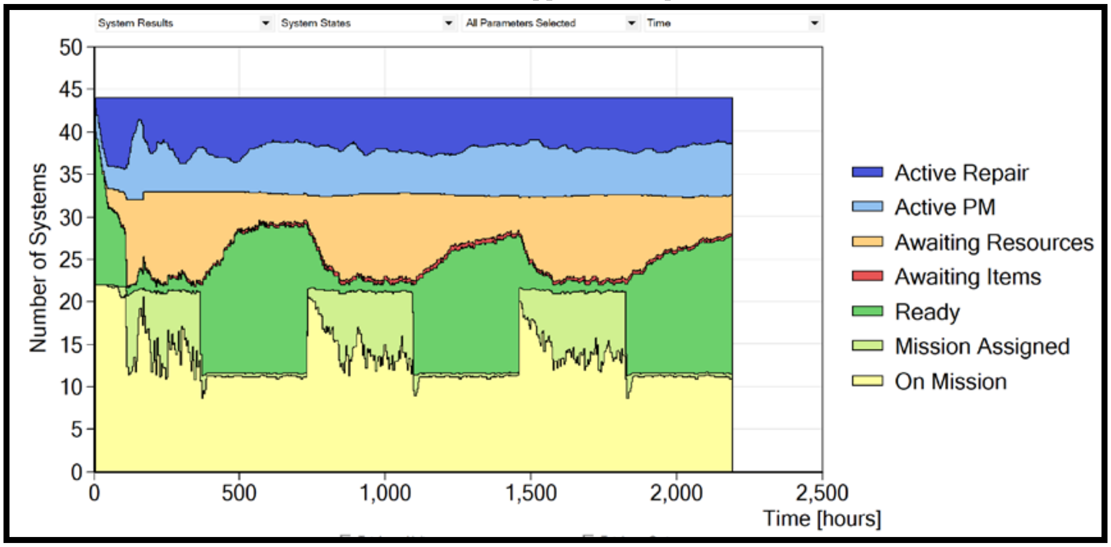

Figure 5: System states associated with only improving spares. Little improvement is noted as spares shortages are not the primary issue

Figure 5 demonstrates what happens when decisions are made without modeling the entire system, and it's support solutiuon. In this potential course of action, only investments in spare parts were considered. By focusing only on supply as the problem, one can easily infer from the output graph the we have replaced waiting for parts with waiting for resources (in this case manpower) with little impact on the overall availability or mission effectivness of the systems. In many cases, leadership wonders why models prodict an increase in a particular metric but see no resultant readiness impact. Often times this is due to using imcomplete and non-comprehensive models that don't holistically consider all system aspects and attributes. In this case, focusing only on parts does nothing to improve operational effectiveness. Figure 6 shows the results when considering both spares and manpower.

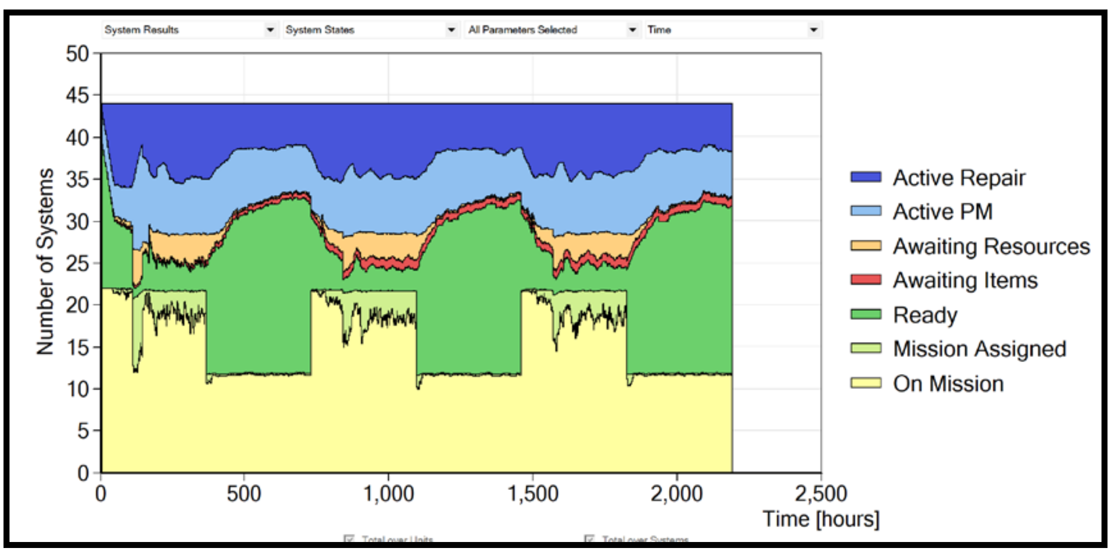

Figure 6: System states associated with improving both on-hand spares and manpower levels

The resultant modeling outcomes can be seen side by side in Figure 7. From the results it is clear that improving only spares has a minimal impact on both availability and mission effectiveness. A holistic approach that simulataneously optimizes both spares and manpower allows the program to achieve better results for the same cost. Legacy tools were not able to optimize in this way so decisipon makers often ignored tool results or only used them to check a milestone rather than gain valuable insight.

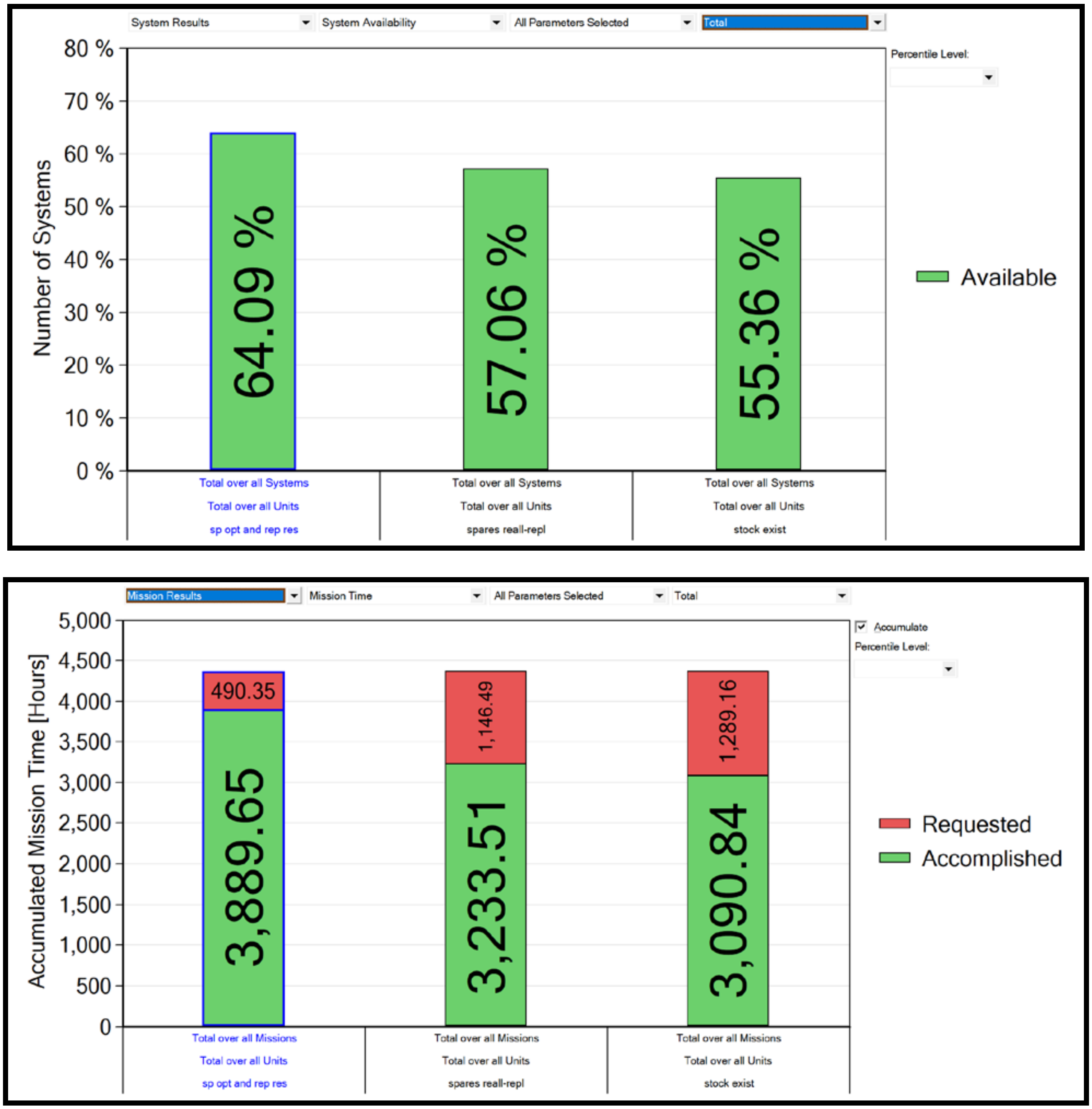

Figure 7: Availability and Mission Effectiveness of the baseline, improving only spares, and improving both spares and manpower in a holistic manner.

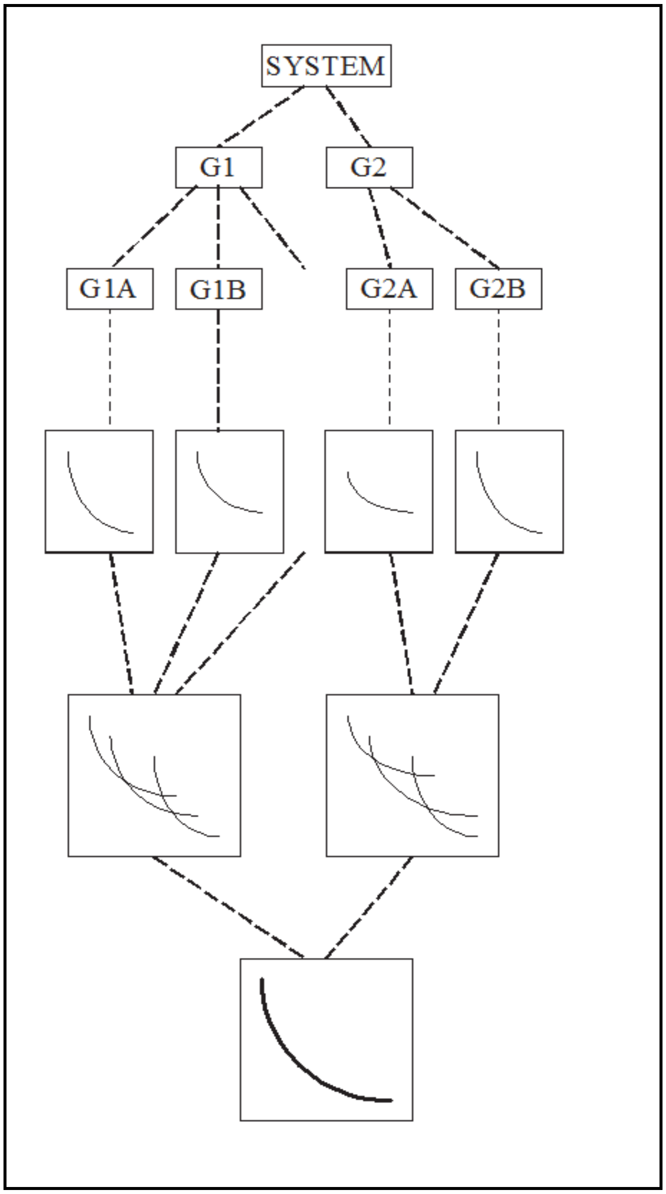

Figure 8: A graphical depiction of convexification. G1 and G2 represent subproblems for each resource group. A and B represent feasible resource allocations alternatives for each subproblem. The curves below represent the optimal curves for each allocation alternative, and the final curve is the optimal of all the previous curves.

It is important to note that modeling and simulation is not just a tool for designing a logistics support solution. This same model can (and should be used) as part of the design process and when planning for system upgrades and modifications. In the system definition and design phases, models are used to analyze alternative system concepts and designs, the design of support organizations, and make decisions about the optimal repair strategy. As new data is made available once a system is operational, this information can be used to update the optimization and simulations to ensure system readiness is maintained. Adjustments to the maintenance solution are continuously made throughout the program life cycle and through disposal. Figure 8 shows a prioritized list of components driving readiness. These drivers are excellent candidates for evaluation to determine if there is more reliable alternative available, if the system could be redesigned to mitigate a failure mode in one of the components, or if we must simply accept the component as is and optimize the support solution appropriately.

THE ALGORITHMS

The theory of the OPRAL optimization technique is based around the powerful concept of convexification. The convexification of a function f (x), is defined as the maximum over all convex functions g(x) such that g(x) $\leq$ f (x) for all x. For some values of x it holds that f c (x) = f (x), that is, the function coincides with its convexification. We refer to these x as convex points (for the function f). In other words, convexification is the idea of finding the optimal curve from a group of curves. The OPRAL algorithm optimizes in a way similar to many multi-echelon models, but instead of finding the optimal function from a large set of possible points, it takes the optimal curves of the different maintenance candidates and finds a single optimal function to simultaneously optimize both parts and resources (manpower, test equipment, etc).

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