SYM-AM-16-047

PROCEEDINGS
OF THE
THIRTEENTH ANNUAL ACQUISITION RESEARCH SYMPOSIUM

THURSDAY SESSIONS
VOLUME II

Effective PBLs Through Simultaneous Optimization and Simulation of Maintenance, Manpower, and Spare Parts

Justin Woulfe, Executive Vice President, Technical Services, Systecon North America
Samantha Alpert, Analyst, Systecon North America

Published April 30, 2016

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

ACQUISITION RESEARCH PROGRAM
GRADUATE SCHOOL OF BUSINESS & PUBLIC POLICY
NAVAL POSTGRADUATE SCHOOL

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Business & Public Policy at the Naval Postgraduate School.

Panel 11. Enabling Successful Outcomes in Performance Based Logistics

Thursday, May 5, 2016	
9:30 a.m. – 11:00 a.m.	**Chair: Stan Soloway,** President and CEO, Celero Strategies, LLC ***Performance-Based Logistics: Examining the Successes and Challenges When Operating in Stressful Environments*** William Lucyshyn, Senior Research Scholar, Center for Public Policy and Private Enterprise, UMD John Rigilano, Faculty Research Assistant, Center for Public Policy and Private Enterprise, UMD Darya Safai, Graduate Research Associate, School of Public Policy, UMD ***Effective PBLs Through Simultaneous Optimization and Simulation of Maintenance, Manpower, and Spare Parts*** Justin Woulfe, Executive Vice President, Technical Services, Systecon North America Samantha Alpert, Analyst, Systecon North America ***Future Contracting for Availability*** Lou Kratz, Vice President and Managing Director, Logistics & Sustainment, Lockheed Martin Bradd Buckingham, Senior Market Research Planner, Logistics & Sustainment, Lockheed Martin

Effective PBLs Through Simultaneous Optimization and Simulation of Maintenance, Manpower, and Spare Parts

Justin Woulfe—is Executive Vice President, Technical Services, at Systecon North America. [jwoulfe@systecon.us]

Samantha Alpert—is an Analyst at Systecon North America. [salpert@systecon.us]

Abstract

The problem of determining the optimum repair strategy is sometimes called location-of-repair analysis, or LORA, while OPRAL is an analytical model for determining the optimal repair locations and spares allocations in a multi-level hierarchical support organization based on the spares optimization model OPUS10. The OPRAL optimization technique is based around the powerful concept of calculating the maximum function over all convex functions created from several different repair strategies in order to find the optimal one. The process of simultaneously optimizing LORA analysis, spare parts optimization and resource utilization is significant, hence why it is necessary to integrate the optimization techniques. These techniques can be instrumental in setting up and managing risk in Performance Based Logistics (PBL) contracts where a Product Support Manager (PSM) is responsible for a high level metric such as system availability, mission hours accomplished, etc., where optimizing all aspects of a system's operation is critical.

Introduction

Determining the optimal level of spares has been a use of the optimization software OPUS Suite (which consists of OPUS10, SIMLOX, and CATLOC) since the 1970s. Developed in Stockholm, Sweden, the software is now used to optimize spares in numerous countries for a wide span of projects that span across the commercial and defense sectors. However, the problem of determining the optimal repair strategy, called level-of-repair analysis or LORA, has become more prevalent, and as such, the ever-improving software had to accommodate.

The LORA calculation discussed in this paper is performed with the OPUS10 tool. OPUS10 contains an advanced LORA capability specifically created to optimize both spares and repair capabilities for Performance Based Logistics (PBL). This calculation is performed using an algorithm called OPRAL.

Background on OPRAL

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) ≤ 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 just like OPUS10, but instead of finding the optimal function from a large set of possible points, it takes the optimal curves of the different LORA candidates and finds a single optimal function.

As shown in Figure 1, the C/E-curves for different resource groups are combined to find the total C/E-curve. As in OPUS10, this curve represents maximum support system effectiveness when allocating a certain cost to the support system.

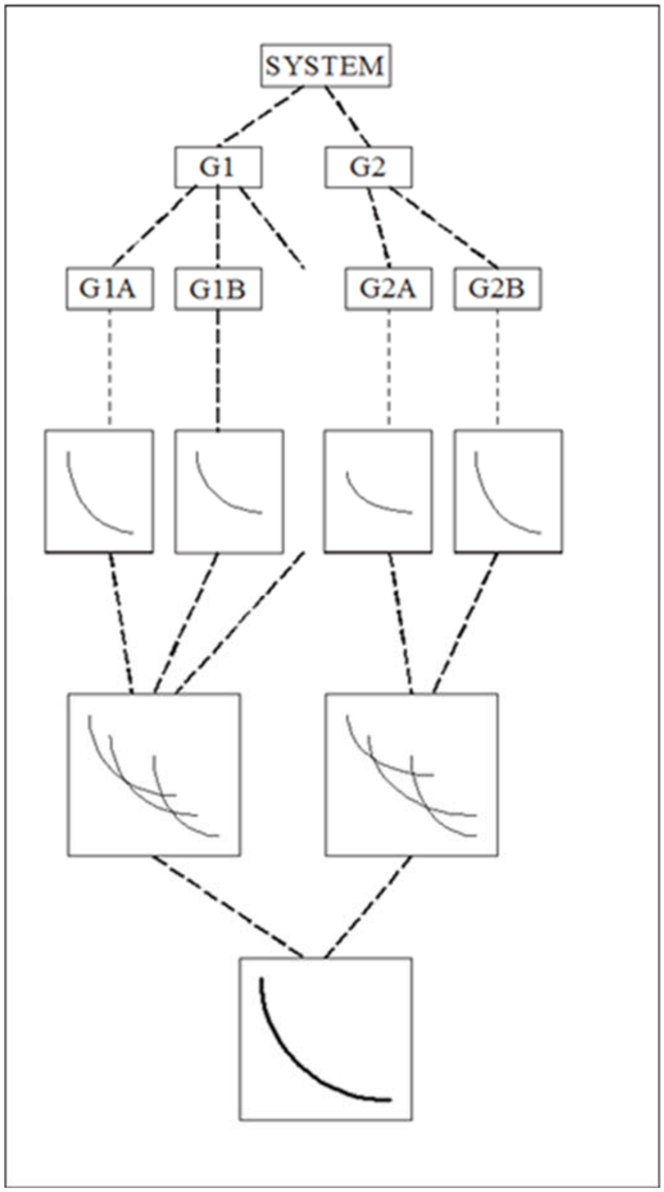

Figure 1. A Graphical Depiction of Convexification

Note. 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.

When thinking about a LORA model, the highest level questions are

- What repair strategy should be used for items of a given type?
- What sparing strategy should be used for items of a given type?

The choice of repair strategy concerns whether to discard or repair faulty items of a given type. Furthermore, if the item is to be repaired, it also concerns where the repair should take place.

One of the first techniques to approach this problem was the METRIC model from 1968 (Sherbrooke, 1968). Independently, yet concurrently, the first OPUS model was derived.

The step of marrying LORA and spare parts optimization is significant, which feeds into the next questions to be answered:

- If a given item fails, should it be repaired or discarded?
- If an item is to be repaired, where should the repair take place?

The correct answer to these questions depends on several things, for example, the cost of necessary resources to repair the item and the unit price of the item. Another issue that makes determining the optimal repair strategy difficult is the interrelation with sparing. The accessibility of spares will have an impact on how critical repair turn-around times will be. With large spare part stocks, we can allow longer repair turn-around times than with smaller stocks. Similarly, shorter repair turn-arounds will decrease the amount of spares required to reach a specified service performance.

The above-mentioned issues (that is, that repair decisions for different items) can be dependent on common expensive repair resources, and the relationship between sparing and repair complicates matters. Therefore, in the past, these issues have been ignored by traditional techniques and tools. However, a model aimed to accurately describe the real-world aspects of the problem must properly address them.

Performance Based Logistics

Because the OPUS Suite can simultaneously optimize manpower, spares and support and test equipment, and also simulate mission effectiveness of the optimal solution, the opportunity to effectively dimension and manage Performance Based Logistics, or PBL, contracts is significant.

Performance Based Logistics represents a potentially cost effective method for system sustainment. From the customer perspective, PBL means a shift away from buying parts to instead buying performance from the supplier. We can apply this concept at the system, subsystem, or major assembly level. A key element in PBL is the ability to measure the system performance in a well-defined way, either directly, like availability, or indirectly by measuring given logistic parameters, for example, backorders. Monitoring and following up logistic parameters in the supply chain can on its own be a driver for supply chain performance improvements. Applied correctly and tailored to the specific scenario, that potential is substantial. But as many Program Managers and Logisticians have experienced, setting up a PBL contract is a complex task. More importantly, if inadequately written, the outcome may be the opposite: increased costs and risks for government, contractor or both.

There are several success factors that can be realized through modeling and simulation as described by Olinger, Hell, and Wijk (2011):

- Success factor 1—A common pitfall in PBL contract design is that the supplier scope is not clearly defined and that the distinction between supplier and customer responsibilities is imprecise. A weak definition of this basic foundation of the contract can be detrimental and cause discussions and disagreements about what is included and not. It can also lead to the defined KPIs not corresponding to the actual interpretation of the contract scope.
- Success factor 2—Appropriate performance parameters (KPIs). The KPIs must be selected based on the nature and scope of the contract and give the customer performance, affordability and control. On the other side, KPIs must

give the contractor direction and incentive, but also maneuverability to build, adapt and manage the solution in the most cost effective way. To allow for the latter, a small number of well selected KPIs are preferable to many. It is a common mistake to try to compensate uncertainty with a long array of KPIs which are at best redundant and at worst conflicting and counterproductive.

- Success factor 3—Appropriate KPI target levels. It is crucial to understand the consequences of setting a certain target level in advance. For example, a target for average availability may seem acceptable if only considering a steady state situation, but can mean unacceptable sensitivity to changes or poor ability to handle peak loads. Meanwhile, a too high target typically escalates costs.
- Success factor 4—A clear and relevant incentive model. All involved should win when performance is on or above target, and, the very driving force of PBL, the revenue for the contractor must drop significantly when performing below target. The approach can be either penalties or rewards.
- Success factor 5—Performance measurement approach and intervals. The way performance is measured and calculated, and how often it is measured, can have a large impact on the outcome. Too long measuring intervals could for example mean that unsatisfactory performance over important periods can be averaged out by over-performing during the rest of the time. Too short intervals could mean that the contractor does not get enough time to adjust and correct deficiencies; hence the incentive to improve is lost.

Understanding the consequences of a PBL contract in advance, and the potential benefits, risks and costs involved, is equally important to customer and contractor. Design, evaluation and ultimately the negotiation of the terms in the contract should be based on thorough analysis by both parties.

Optimization in OPUS10 coupled with Monte Carlo simulation in a tool like SIMLOX can be used to design an effective incentive model and to set the performance levels and suitable measurement intervals, all based on proper decision support, mission understanding and consequence analyses.

A key element in PBL is the ability to measure the system performance in a well-defined way, either directly (e.g., availability) or indirectly by measuring given logistic parameters (e.g., backorders). Monitoring and following up logistic parameters in the supply chain can on its own be a driver for supply chain performance improvements.

The degree of PBL contract fulfillment has been shown to be able to be defined using a penalty function y(x), where y is the share (%) of the maximum penalty amount and x can be any logistics parameter of interest to mission capability. The parameter x is measured as an average over a time period T.

Using simulation, the time period T will influence the design of the penalty function y(x). In many cases, the backorder measure B is used for designing the penalty function Y(B), but the same approach can be used for any other logistics parameter. In fact, y(x) could be multidimensional (i.e., x being a vector of several types of logistics parameters).

Appropriate results collected from Monte Carlo simulations enable evaluation of alternative penalty (or reward) functions suggested in a PBL contract negotiation. Using these methods, a penalty function y(x) should be designed to meet the customer and supplier objectives in a satisfactory way for both parties.

It is important to consider different operational scenarios and the potential effects of the penalty function (e.g., mission success, mission readiness, and operational effectiveness) when designing the y(x) function. Typically, the penalty increases in steps if performance drops below target. Each step in y(x) should be simulated to demonstrate the capability impacts (positive and negative) of different outcomes. While requiring a thorough understanding of mission profiles, operational scenarios, and definitions of "success," this methodology allows both the customer and the supplier to make rational decisions and agree on a reward (or penalty) function commensurate with the relative impact of each y(x) step on overall mission readiness and mission capability. Simulation of mission readiness and capability instead of availability provide a y(x) function that aligns with operational realities and ensures cost effective capability to the warfighter.

LORA Example

When conducting a LORA, there are many factors to be considered. The measures of effectiveness are affected by the resources, spares, manpower, transportation, and much more. Using the tool OPUS10, we can measure how much each of your options for repair will change your results.

We connect each repair action at each possible location to a repair task. Those tasks can be broken into subtasks that can split the total repair time into specific steps. This is helpful when connecting the resources to those subtasks, causing the resources to only be used for the specific parts of the repair and not the entire repair turnaround time. The tasks are then divided by their complexity into task levels.

The task levels are used to create all of the different maintenance candidates. The maintenance candidates, or scenarios, are the possible combinations of places that will complete the task levels. All of these connections are shown graphically in Figure 2. OPUS10 optimizes each of the candidates as if it was its own model, then finds the optimal curve from the group. The result will show the most optimal candidate as well as the number of resources and spares required, where they should be, and how much they will all cost.

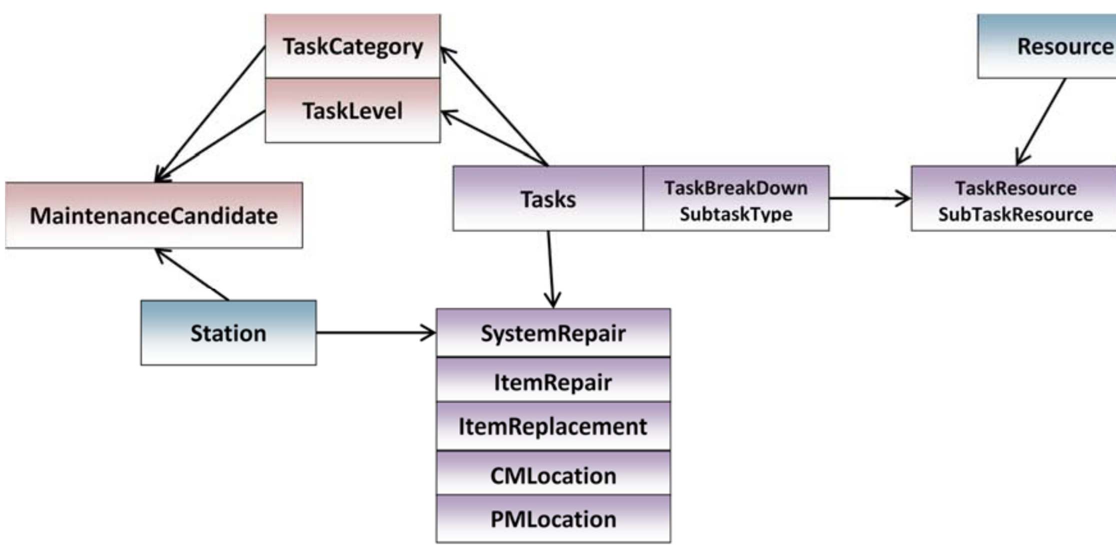

Figure 2. Connection Between Tables Built in OPUS10 to Perform LORA Calculation

Using the results of the OPUS10 calculation, we can make better decisions based on numerous metrics like availability of the system, total life support cost, investment costs, and more. Based on the different PBLs the analyst is optimizing for, there are many different reports that can be made from the results; some examples can be seen in Figure 3.

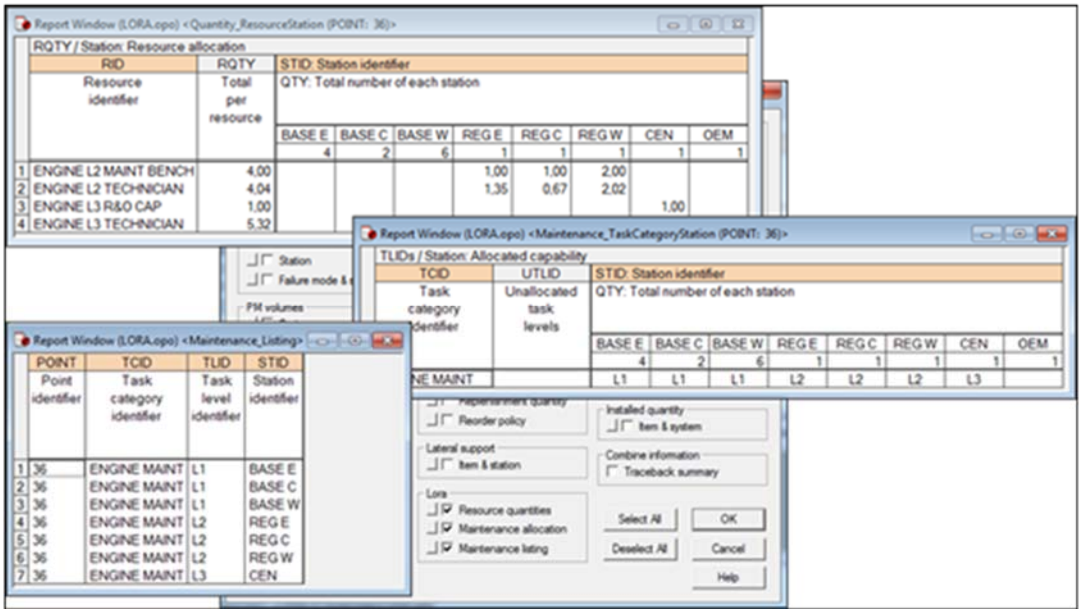

Figure 3. Examples of Reports Created From OPUS10 Calculations

Conclusion

To avoid a high cost with low effectiveness of a project, analytics must be performed. When a proper support structure has not been established, or the current structure has been shown to be suboptimal, a LORA must be conducted to assist with the decisions being made. In addition, the spares optimization cannot be ignored, nor should it be calculated separately. Combining these variables is key to truly optimal results.

References

Alfredsson. P. (1997). *On the optimization of support systems* (Doctoral thesis, KTH). Stockholm, Sweden.

Feeney, G. J., & Sherbrooke C. C. (1966). The (S-1,S) inventory policy under compound Poisson demand. *Management Science, 12,* 391–411.

Graves, S. C. (1985). A multi-echelon inventory model for a repairable item with one-for-one replenishment. *Management Science, 31*, 1247–1256.

Hadley, G., & Whitin, T. M. (1963). *Analysis of inventory systems*. Englewood Cliffs, NJ: Prentice-Hall.

Mahon, D. (2007). Performance-based logistics: Transforming sustainment. *Journal of Contract Management, 5*(1), 53–71.

Muckstadt, J. A. (1973). A model for a multi-item, multi-echelon, multi-indenture inventory system. *Management Science, 20*, 472–481.

OPUS10–Logistic support and spares optimization. (n.d.). Retrieved from http://www.systecon.se/

Palm, C. (1938). Analysis of the Erlang traffic formula for busy-signal arrangements. *Ericsson Technics, 5,* 39–58.

Sherbrooke, C. C. (1968). METRIC: A multi-echelon technique for recoverable item control. *Operations Research, 16,* 122–141.

Sherbrooke, C. C. (1986). VARI-METRIC: Improved approximation for multi-indenture, multi-echelon availability models. *Operations Research, 34*, 311–319.

Sherbrooke, C. C. (1992). *Optimal inventory modeling of systems: Multi-echelon techniques.* New York, NY: John Wiley & Sons.

SIMLOX—Simulation of logistics and operations. (n.d.). Retrieved from http://www.systecon.se/

Simon, R. M. (1971). Stationary properties of a two-echelon inventory model for low-demand items. *Operations Research, 19*, 761–773.

Systecon AB. (1998). *OPUS10 user's reference*. Stockholm, Sweden.

van Hoek, R. I. (1998). Measuring the unmeasurable—Measuring and improving performance in the supply chain. *Supply Chain Management, 3*(4), 187–191.

Wijk, O., Olinger, T., & Hell, R. (2011). Simulation as support for decision making in negotiations. *14th Annual System Engineering Conference.* San Diego, CA. Retrieved from www.systecon.se/documents/Simulation_as_support.pdf

ACQUISITION RESEARCH PROGRAM
GRADUATE SCHOOL OF BUSINESS & PUBLIC POLICY
NAVAL POSTGRADUATE SCHOOL
555 DYER ROAD, INGERSOLL HALL
MONTEREY, CA 93943

www.acquisitionresearch.net