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Hello Readers,

I hope you and your family are safe and well. We are grateful that our ALE staff and their families have remained healthy during the COVID-19 pandemic and we extend well wishes to all those who have been affected by COVID-19. While the future of the pandemic crisis is unknown at this time, ALE continues to remain open and committed to our customers' success.

Inside this newsletter, the first article highlights a real-world example of when the traditional reliability prediction approach was modified to include the conduct of a Monte Carlo simulation. At ALE, we are always looking for new and innovative ways to expand our capabilities and provide meaningful insights to our customer's programs. This article showcases how there is no one-size-fits all analysis, and that conducting a tailored analysis will instill greater confidence in the results.

The second article focuses on the impact that robust data has on developing an effective and responsive Support System. ALE's customers rely on high-quality data products, and this article describes the many ways design and logistics data are used throughout a program's lifecycle and how to ensure that high-quality data products are produced and maintained.

Thank you for your readership and I hope you continue to stay safe.

Renee Coogan

Renee Coogan, President

About Acquisition Logistics Engineering

The ALE Advantage:

WOMAN OWNED SMALL BUSINESS

ISO 9001:2015 CERTIFIED

NIST SP 800-171 COMPLIANT

DCAA APPROVED ACCOUNTING SYSTEM

SEAPORT NXG PRIME CONTRACT HOLDER

CAGE: 1Z220
DUNS: 16-125-2218
NAICS: 541330, 541614, 541715

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When Basic Reliability Models Fall Short
A Real World Example

By Rodney Benson

BACKGROUND •••

Often times reliability models are straightforward and routine, and a standard model is sufficient to show compliance with reliability requirements. However, there are times when a standard model will not provide the needed answers; so how do we successfully address reliability of systems with complex architecture and associated definition of system failure? Over the years, ALE has encountered many unique challenges where routine reliability models and approaches are inadequate and do not provide truly meaningful insights. The following provides a generalized discussion of a more recent example where ALE reliability engineers developed an in-house, tailored analysis tool to assist a customer in demonstrating reliability compliance given their "unique" system design and performance requirements.

The methodology used in this reliability analysis is based on Monte Carlo simulation theory. Monte Carlo simulation is a standard methodology used in many mathematical, engineering, and financial areas such as optimization, numerical integration, and selecting from probability distributions. Many good resources are available via a quick internet search to provide more information about Monte Carlo simulation.

SAMPLE PROBLEM •••

In this particular example, the results of a standard Monte Carlo simulation would not accurately model actual application of the system under development. The customer's system is designed to allow non-linear degradation in performance over time while the overall system continues to operate, successfully satisfying key performance parameters. The system (A), illustrated below, consists of 2 sub-systems (A_1 and A_2), each independent of the other and each contain a set of controllers (A_{1-1} – A_{1-19}, A_{2-1} – A_{2-19}). Each of the 38 independent controllers control a set of 30 components (A_{1-1-1} – A_{1-1-30}, A_{1-2-1} – A_{1-2-30}, etc.), resulting in a total of 1,140 individual components in the system. Failure of a higher-level subsystem results in a loss of functionality of the lower level elements which they control, but the remainder of the system remains functional.

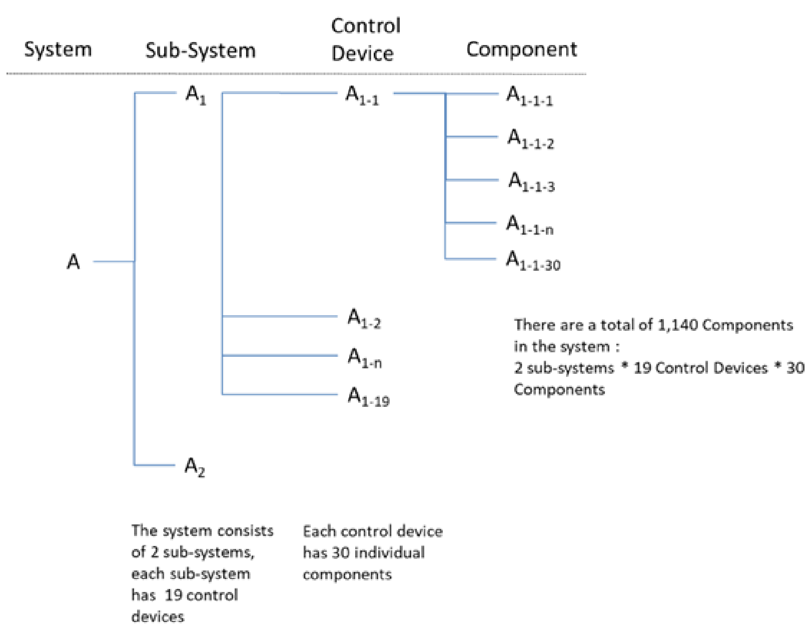


Figure 1. Simplified System Diagram

An approach was needed that would simulate the occurrence of failures of low-level hardware (i.e. sub-systems, controllers, and/or components) over time and calculate the resulting level of system performance degradation. As shown by the system diagram, a failure of one sub-system will result in 570 components being non-operational (19 controllers * 30 components = 570 components). Similarly, a failure in one controller will result in 30 components being non-operational. As long as the number of functional components remain above the minimum required, the system will satisfy the performance requirements and the simulation will continue. When the model indicates the system has accumulated more than the pre-established maximum number of failures in any combination of sub-system(s), controller(s), and components, the simulation categorizes the system as failed.

Hourly probabilities associated with hardware failures were calculated using failure rates developed as part of the system hardware reliability prediction effort using standard reliability methods. To determine if a failure has occurred, the simulation generates a random number between zero and one, which is used as the seed probability. The model compares the seed to the system failure probability and makes a determination as to whether the entire system is failed. If the system is determined not to have failed, a new seed is generated and compared to the failure probability of the first sub-system. This iterative process continues through the second sub-system, all device controllers, and all components, with the program maintaining a running record of the failed components. The resulting component failures are summed to determine whether the system is still considered functional. If the system is functional, the time period is incremented, and the process repeated until the system fails. Upon system failure, relevant data, including time of failure and the number of failed components, is logged and the system reset to a fully operational state for the next iteration.

As the number of simulation runs are increased, the average failure time converges asymptotically with less variance between runs as illustrated in Figure 2. This average failure time was used to calculate the predicted failure rate of the system using standard reliability equations. Figure 2 shows that running the simulation 5 times at 5,000 iterations each provided a mean time to failure of 13,985 hours. The confidence in this result is much higher than running the model for 1,000 or 2,500 iterations. However, there is a tradeoff in increasing the number of iterations with the significant increase in computing time. Graphing the results will help identify the optimal number of iterations at which increasing the number of iterations has a minimal change to the average failure time.

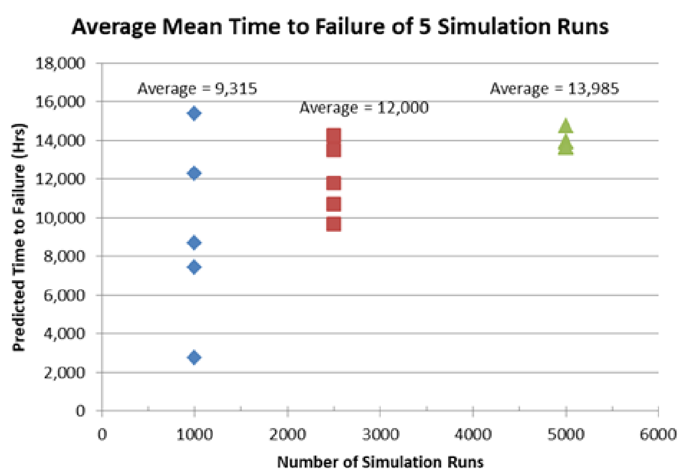


Figure 2. Simulation Results

CONCLUSIONS •••

In developing the simulation as a stand-alone application, ALE leveraged our experience and knowledge of reliability analysis methodologies to address the real world challenge of demonstrating compliance with performance requirements for our customer; a feat not achievable using standard reliability models. Had the model demonstrated the system was unlikely to meet performance requirements, additional insights into system architecture could be obtained to support trade studies of potential design changes towards increasing system reliability and satisfying program requirements. Data recording aspects of the model were further customized to record individual component failures over time. This data was used to provide a real-time visual model that illustrated the state of the system throughout the simulation, a level of customization that would not be achievable using a prebuilt simulation model. ■

A Support System is Only as Good as the Data Used to Build It

How Design Data Availability and Maturity Influences the Effectiveness of the Support System

By Elizabeth Schwartz

The title of this article says it all. A Support System is only as good as the data used to build it. The consistent access to and application of design and field data during all stages of a program's life cycle will ensure that Support Systems meet program needs. This article breaks down each phase of programs' life cycles to show how data can be used by logistics teams to make better Support System decisions.

PRELIMINARY DESIGN

The Preliminary Design Phase requires the Support System designer to be flexible. During this phase, the design data is incomplete and likely from a comparable system and not the actual design. While working with incomplete or projected data can be a challenge, valuable insights into creating an appropriate Support System design can still be discovered.

One tool ALE employs during (and sometimes prior to) the Preliminary Design Phase to conceptualize a reasonable Support System is the Front End Analysis (FEA). An FEA consists of a series of trade-off studies that produces a relational impact model of varying factors. An FEA might predict that by lengthening a vessel by 20%, the maintenance cost will increase 40%; or that by reducing the fleet size by 5% reduces the number of spare parts needed by 15%.

FEAs can be performed using whatever data is available combined with sound assumptions from subject matter experts. While the data requirements are minimal, the results can have a large impact on the Support System design.

During the Preliminary Design Phase is also when Configuration Management (CM) processes are established. Ensuring that a robust CM process is followed throughout the program will build confidence in the available data and logistics products and eliminate countless issues down-the-road. Imagine going to repair a system, only to discover outdated spare parts were ordered. The resulting extended downtime of the system could have been eliminated through following the CM process because the provisioner would have had the correct data for ordering the spare parts.

DETAILED DESIGN & PRODUCTION

When a program moves into the Detailed Design and Production Phase, the Support System truly starts to take form. More detailed trade-off studies and Level of Repair Analysis (LORA) can be accomplished using data for the actual design. It is advisable that interfaces for exchanging the most current data are established early between the Support System designers in the Integrated Logistics Support (ILS) Team and the Design Team, Test Engineers, System Safety and Human Factors Analysts, Logistics Product Team, Provisioning, etc.

The ILS Team will utilize the data from the Design Team, Test Engineers, etc. to develop a detailed, fieldable Support System. The comprehensiveness and accuracy of data that funnels through the ILS Team directly impacts the quality of the Support System. For example, if Test Engineers test a system using environmental parameters true to those anticipated for a fielded system as opposed to generic environmental parameters, the resulting data will help create a Support System that better matches the true preventive and corrective maintenance needs.

FIELDING & SUSTAINMENT

During a system's Fielding and Sustainment is when having utilized good data to design the Support System truly pays off. The data challenge transitions from gathering initial data and making fundamental Support System design decisions to maintaining the data. When systems are upgraded or obsolete parts are replaced, the associated data must also be added to and/or updated in the logistics product data (LPD) database and be reflected in all associated products (technical manuals, parts lists, etc.). The last thing a maintainer wants to experience is to be repairing a system in the field and an obsolete part has no replacement, or a system cannot be calibrated because the technical manual does not reflect the fielded system configuration. Errors in data management results in extended system downtime.

The Support System should continue to be evaluated for effectiveness throughout sustainment. Like making changes to the design, making changes to the Support System should follow the established CM process for documenting all relevant data changes. A documented Support System that is reflective of the fielded Support System allows for accurate inventory and spares management, timely performance of maintenance, and increased confidence in the availability of the system.

CONCLUSION

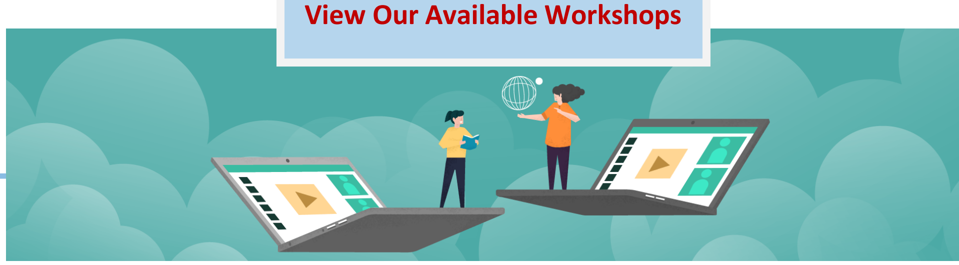
Access to good data ultimately helps the Support System designers make better decisions, which results in successful fielded Support Systems. From Preliminary Design to Detailed Design and Production to Fielding and Sustainment, data drives the Support System design and functionality. Implementing and following rigorous CM processes early and throughout a system program will contribute to maintaining system availability. ■

VIRTUAL WORKSHOPS BY ALE

To meet the training needs of our customers, several of ALE's workshops are going virtual during the COVID-19 pandemic. Attendees will receive the same level of instructor interaction and high-quality content that our customers expect from an ALE workshop.

To express interest in attending a virtual workshop, contact staff@ale.com or call us at (614) 436-1609. We are actively developing our future workshop schedule, and your input is greatly valued.

View Our Available Workshops



➲ COMING LATE 2020 ➲

Say Farewell to *The Logista*. ALE's Latest News and Insights have a New Home.