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Predictive Modeling for Navy Readiness Based on Resource Investment in Supply Support and Maintenance

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PREDICTIVE MODELING FOR NAVY READINESS BASED ON RESOURCE INVESTMENT IN SUPPLY SUPPORT AND MAINTENANCE

EXECUTIVE SUMMARY

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Project Summary

The Navy invests substantial resources to fleet maintenance in terms of part supply, corrective maintenance, maintenance availabilities, and overhauls. In order to measure and prioritize weapon systems investment decisions, an endurance supply metric (E_s) is being developed to ensure these systems are ready for tasking across the full spectrum of operations. This research project attempts to develop models to determine self-sustaining stock levels of critical parts, for key ship systems, in order to operate for at least T_1 days without resupply, with a risk no greater than β_1 that part shortage will cause system failure. These models are developed for both a single deployed ship and multiple deployed ships in a battlegroup. Our model shows that a small number of spare parts can significantly increase E_s for a single deployed ship operating beyond the reach of a supply chain. For multiple deployed ships, our model suggests the desired endurance target can be reached with a limited number of additional spare parts if spare and redundant parts are pooled.

Keywords: *readiness, logistics, Endurance Supply, E_s, Monte Carlo Simulation, MCS, Reliability Block Diagrams, RBD*

Background

The chief of naval operations in his Navigation Plan provides his strategic vision and our Navy's four top priorities. Readiness, the ability to deliver a more-ready fleet, is an important one of these priorities. Nearly 70% of the Fleet in 2030 is already in service today. Sustaining our ships and aircraft is absolutely critical to meeting future demands. Towards this end, the Naval Supply Systems Command (NAVSUP) initiated an effort to develop a predictable supply model that ensures supply issues are not a primary cause of readiness shortfalls. A new metric called E_s or Endurance Supply is being developed to answer the question of how long the onboard inventory should be, to keep a system up and running. Traditional metrics such operational availability do not answer this question. Therefore, E_s is a measure of readiness in contested environments, without resupply.

The methodology used to guide this research is based on the Cross Industry Standard Process for Data Mining (CRISP-DM), a standard methodology and process model used to impose structure and improve success and efficiency of data science projects (Vorhies, 2016). The CRISP-DM methodology includes six phases that address the main requirements for a data science project. The six phases are undertaken in a cyclical and iterative manner and include: Business/Mission Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.

For the modeling phase we use both Monte Carlo Simulation (MCS) and Reliability Block Diagrams (RBD) (Tobias & Trindade, 2011) to predict performance of the system as fielded. In determining self-sustaining stock levels of critical parts for key ship systems to meet Endurance supply goals, we made heavy use of known results about Order Statistics (estimation of first, second, third, etc. failures) (David & Nagaraja, 2003; Nagaraja, 2006; Réyni, 1953).

Findings and Conclusions

For a single-ship E_s, we found that endurance could be improved with additional spare parts. In a simplified model consisting of 51 more-likely-to-fail parts aka National Item Identification Numbers (NIINs), we found that an E_s target of 90-day endurance with 85% probability could not be met without additional spares. However, the addition of just 41 additional parts would achieve that target. This finding assumes that redundant parts can be cannibalized from one readiness block in the SPY-1D, to keep another readiness block operational.

For a multi-ship E_s, we modeled a battlegroup that contained 3 SPY-1D radar and found that, if the three ships did not share spare parts, the battlegroup would fall well short of the endurance target. Without pooling, 354 spare parts (118x3) were required so that *all three* SPY-1D lasted at least 90 days with an 85% probability, far more than the single-ship requirement of 123 (41x3). However, with pooled spares and cannibalization of redundant parts across the battlegroup, we found that the battlegroup could endure for 90 days with an 85% probability with just nine additional spare parts (123 + 9 = 132).

We calibrated our predictions against the observed mean-days-to-failure of the SPY-1D of 86 days. Based on that calibration, we predict the NIIN we model cause approximately two-thirds of failures. We further predict that without additional spare parts, the probability a system will endure more than 18 days is less than 85%. The particular sparing plan that we recommend should be cross-validated before implementation.

Our model shows that a small number of spare parts can significantly increase E_s for a single ship operating beyond the reach of a supply chain. Based on our calibrated findings, we conclude that a ship be given 41 additional spares if they will need to operate beyond the reach of a supply chain for more than the 18 days.

Sparing a battlegroup with several SPY-1D radar for endurance beyond the supply chain is more difficult, because the battlegroup's capability is degraded by the *first-failure* of any SPY-1D. However, if spare and redundant parts are pooled, this requirement can be substantially reduced. If pooled, our model suggests the same endurance target can be reached with as few as nine additional spares. So, we conclude a policy of pooling and cannibalizing spare and redundant parts be implemented for any battlegroup that must go beyond the reach of the supply chain for more than 18 days.

We were given the task of examining whether spare parts could help a battlegroup endure for 90 days beyond the reach of a supply chain, and if so, what level of sparing would be required. Our model predicts that, as far as system failures that are caused by part failures, this is possible.

Recommendations for Further Research

Our sparing model captures only about 68% of the causes of SPY-1D system failure. A greater percentage of failure could be captured by extending the analysis to parts that are less-likely to cause failure. But other factors such as human error and operating environment (O'Haver, Barker, Dockery, & Huffaker, 2018) also cause system failures in phased radar systems. A substantial part of the unexplained 32% of failures in the field may not be caused by part failure, at all. In sum, spare parts can help the battlegroup endure significantly longer beyond the reach of a supply chain. But other sources of failure can still prevent an endurance target from being met.

So, in addition to the cross-validation of our work, we recommend additional work be done to examine and ameliorate other sources of failure on the SPY-1D. Until that is done, while our recommendations will certainly increase endurance and the probability of endurance, they are unlikely to provide the desired risk reduction. That is, until other sources of failure are investigated and ameliorated, our recommended sparing plan will provide less than an 85% chance of enduring for 90 days beyond the reach of a supply chain.

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Acronyms

CRISP-DM	Cross Industry Standard Process for Data Mining
E_s	Endurance Supply
MCS	Monte Carlo Simulation
NAVSUP	Naval Supply Systems Command
NIIN	National Item Identification Number
RBD	Reliability Block Diagrams