Deep Analytics for Readiness Impacts of Underfunding Spares Backlogs

Ying Zhao, Ph.D., Naval Postgraduate School, Monterey, CA, USA, yzhao@nps.edu 10/2021



Naval Postgraduate School

# **Background, Needs, and Goals**

Navy ships' aviation and maritime units may lack funding to buy spare parts. The requirements accumulate in a financially restricted work queue (FRWQ) awaiting resourcing while the systems with these parts support are still fielded, and the fleet still generates requirements to replace these parts.

**OPNAV N4 Material Readiness & Logistics needs to** 

- 1) compare fleet demands against requirements in a financially restricted work queue (FRWQ), where, when not funded, spare requirements accumulate awaiting resourcing
- 2) assess items in an FRWQ against high priority demands such as in a casualty report (CASREP) and an aviation unit's casualty report, i.e., non-mission capable supply (NMCS)
- design a tool that periodically scores and prioritizes the items in an FRWQ

#### Goals:

- Enhance total force readiness and project combat power across the whole range of military operations and spectrum of conflict at any time
- Adopt advanced and deep business intelligence (BI) analytics to understand to address the need.

# Methods

Two methodologies are considered:

- **1. Baseline methodology:** Score and prioritize items based on the DoD Manual 4140.01-V2 (2018) using different points:
- Coefficient of variance points: The ratio of the standard deviation of the demand to the average demand.
- Intermittency points: The percentage of total historical demand periods (e.g., months in a year) that have non-zero demand.
- Platform/type points: afloat units have higher priority than shore units.
- **2. Lexical link analysis (LLA) methodology:** The unsupervised machine learning method, used as a "Market basket analysis"
- Hypothesis 1: Items that appear together in the same baskets are associated with the same cause, so they could be demanded together.
- Hypothesis 2: Centrality measures from the LLA word feature networks provide mechanisms to score and prioritize items in an FRWQ.

### Weapons System Criticality Criteria

Use IMEC/ WSG to determine essentiality
Source: DODManual 4140.01-V2, Chapter 5

### Fleet Demand Criteria

Score Intermittency and CV
Source: DODManual 4140.01-V2, Chapter 7

## Data Sets

Priority scores of items based on the baseline method and LLA method used two historical raw demand data sets:

- Raw Demand Data Set 1 (Aviation): Historical raw demand for items related to aviation readiness and NMCS
- Raw Demand Data Set 2 (Maritime): Historical raw demand for items related to maritime parts and CASREPs



Figure 1. Data Sets Generated and Used in This Study.

## **Conclusions and Recommendations**

 Use the baseline methodology as the foundation for the design of an application to score and prioritize the items in an FRWQ periodically. The tool should take an input of FRWQ and match/score it against raw demand data from the ship and the IMEC code and platform/hull priority from the corresponding databases, and it should output a priority list of items.



Figure 2: The Baseline Methodology of Prioritizing Items for a FRWQ

## **Results**

**Result 1**. There are 611,335 unique baskets (i.e., Job Control Numbers) and 280,762 unique items in the Maritime data set. We found 2,093,633 statistically significant associations that were used in the LLA analysis to determine the priority of a National Item Identification Number.

**Result 2**. FRWQ items have been prioritized and ranked meaningfully and reasonably from the baseline methodology and have been validated by subject matter experts (SMEs).

**Result 3**. Association patterns discovered by LLA are meaningful based on the SMEs' evaluation (SME, Hypothesis 1). However, the association patterns in this use case do not conclude better and more meaningful rankings of the items than the baseline method based the SMEs' evaluation (Hypothesis 2). From the correlations of LLA scores and baseline points in Table 1, LLA suggests using the "degree out weight" scores as the total estimated impact to other items' probability of demand (POD), which has a correlation of 0.34 with the baseline total points. *Table 1. Correlations of LLA and Baseline Points* 

Total PointsCVIntermittencyIMECPlatform/Type

- Future research should derive item priorities and FRWQ decisions using one set of historical data and test on another to see if the prioritizing methods would reduce casualty reports and non-mission capable supply.
- Navy Ships may need to adopt more deep business intelligence (BI) analytics for a wider spectrum or end-to-end logistic planning.
- Business processes should be reviewed at a holistic level to plan for a whole class of ships or a whole fleet for a period (e.g., the CVN-74, USS John C. Stennis group for last a few years).
- To perform more feasible deep analytics and other BI methods, more and accurate data are needed. A study could collect consequences, feedback, penalty, or reward data on item prioritizing and resource allocation decisions, which might impact future readiness.

#### Publication

Zhao, et al. (2021). Leverage artificial intelligence to Learn, Optimize, and Wargame (LAILOW) for Navy Ships. In the Special Webinar *Developing Artificial Intelligence in Defense Programs and Proceedings for* the 18<sup>th</sup> Annual Acquisition Research Symposium, Virtual, March 3, 2021. <u>https://dair.nps.edu/handle/123456789/4396</u>

POD	0.34	0.34	0.36	0.09	-0.09
Degree in weight	0.20	0.10	0.25	0.16	-0.11
Degree out weight	0.08	0.06	0.19	-0.019	-0.06
Degree	0.07	0.03	0.15	0.012	-0.04
Betweenness	0.17	0.07	0.19	0.18	-0.13

This indicates LLA's centrality measure "degree out weight" does not use demand as signals for deciding the importance of an item. This may also indicate the hypothesis of causality learning that one item's demand might cause another item's demand may not fit this problem. The low-demand and high-impact items may not exist in an FRWQ data set. For example, the item mission essentiality code (IMEC) defines the items that are highly important so that they usually fail less, thus they are generally in less demand. However, should these items fail such as CASREPs, their impact to other associated items' POD are not as obvious as in predicting the probability of failure in different LLA applications (Zhao et al., 2021).



#### Researcher: Dr. Ying Zhao (PI), <u>yzhao@nps.edu</u>,

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