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APPLYING INVENTORY CLASSIFICATION TO A LARGE INVENTORY MANAGEMENT SYSTEM

ABSTRACT

Inventory classification aims to ensure that business-driving inventory items are efficiently managed in spite of constrained resources. There are numerous single- and multiple-criteria approaches to it. Our objective is to improve resource allocation to focus on items that can lead to high equipment availability. This concern is typical of many service industries such as military logistics, airlines, amusement parks and public works. Our study tests several inventory prioritization techniques and finds that a modified multi-criterion weighted non-linear optimization (WNO) technique is a powerful approach for classifying inventory, outperforming traditional techniques of inventory prioritization such as ABC analysis in a variety of performance objectives.

KEYWORDS | Multi-criteria inventory classification, priority schemes, ABC analysis, nonlinear programming, spare parts management.

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INTRODUCTION

The logistics unit of a large navy is denominated WSS (weapons system support). It is responsible for spare parts support for all maritime and aviation assets in this military force. This support includes procurement, production, repair, and transportation. The unit's responsibility is uniquely complex relative to other military or civilian organizations due to the size of its inventory (400,000+ unique parts) and its multi-item, multi-indenture, multi-echelon inventory system. The WSS planners individually analyze and plan (both long-term and short-term) the supply for each spare part. Once the support plan is determined, contracting specialists place that stock-keeping unit (SKU) on production or repair contracts, a decision based on vendor, budget, and other variables for each item. Planners and contracting specialists currently respond to each part requirement, primarily, on a first-come-first-serve basis. The current system does not allocate limited resources, time and budget, to the items most important to operations. If there are immediate operational needs, supply officers contact WSS to request prioritization of certain items, regardless of their attributes. The suboptimal resource allocation leads to less-than-ideal performance on key metrics, such as fill rate (fraction of initial orders fulfilled from stock), delay (time to release material for shipment), backorders (unfilled orders awaiting fulfillment), and response time (time between requisition and delivery). This multi-criterion decision making process impacts equipment availability, the primary goal of the enterprise.

To increase fill rate of its maritime inventory, WSS is implementing a four-category inventory classification system called WSS4. The goal of this system is to focus WSS resources on items in the highest category to minimize the unfilled orders on those items. The system considers demand and two other factors to classify items: *casualty reports* (CASREP) and *platform readiness drivers*. CASREP are emergency requisitions for parts required to fix a system that is critical to a mission. Platform readiness drivers are items that were identified as problematic, either because of their impact on equipment availability or because their supply chain is unreliable. The system considers only demand, casualty reports, and platform readiness drivers to group items into the four categories, but the thresholds used to define the boundaries of these categories are set by inventory managers, based on what they deem a manageable workload within each group.

Although the WSS4 method adopts some prioritization, there are other factors that influence equipment availability. A model that considers only requisitions and CASREP may not be the best technique for improving resource allocation.

This study evaluates existing inventory prioritization methods and compares them against WSS4, the method currently in use. Before we present other methods, we briefly introduce ABC Analysis, the seminal inventory categorization technique.

Research objective

The purpose of this study is to determine an effective classification approach for a large spare parts inventory management system by comparing some of the classification methods in the literature. We use input from inventory planners to identify the factors that have most significant impact on WSS's primary goal, equipment availability. Based on those factors, an ABC-like model is tailored for WSS inventory management needs. Once the model is built, we test it with inventory data collected by the ERP system. The model is contrasted with alternative prioritization schemes, including the WSS4 method being implemented by WSS. Raw spare parts demand data for this study was provided by WSS.

The remainder of this paper is organized as follows: Section 2 presents the literature of inventory prioritization with focus on the approaches used in our analysis. Section 3 overviews the data selected for testing our prioritization model. Section 4 presents a subset of the many variables available for each transaction in the ERP. The section culminates in subsection 4.6 where we present the final variable selection, supported by the expert judgement of WSS inventory planners. Section 5 explains the methodology behind the WNO approach to inventory prioritization, followed by the WNO model analysis in Section 6. Subsection 6.2 compares the WNO model with other inventory prioritization approaches. It shows that the WNO model outperforms all other multi-criterion approaches in a variety of performance metrics. Section 7 discusses the analysis.

LITERATURE REVIEW

The WSS4 method and the other methods explored in this paper are derived from Always Better Control (ABC) analysis (Dickie 1951). ABC analysis is an inventory categorization technique used to prioritize

stock items into different levels of management attention. It is based on Pareto's law, which states that the significant items in a group usually constitute only a small fraction of the total number of items in that group (Zimmerman 1975). Pareto's law can be applied to many fields of study, and is particularly applicable to inventory management. ABC uses a single dimension, demand value, the product of demand rate and unit price, as its primary metric (Silver et al. 1998). The reasoning is that there are a finite number of dollars available for inventory management, and those dollars must be used wisely.

Spare parts inventories can be extremely difficult to manage. The ABC analysis is the first of many classification schemes used by inventory managers. By focusing on the business drivers, the ABC classification method allows businesses to significantly reduce inventory costs while minimizing stock-out rates. Other methods may focus on different metrics, and their applicability varies, as shown in Table 1 (Gopalakrishnan 2004). With business models varying across industries, these methods are often tailored to fit specific needs.

Table 1. **ABC-derived classification techniques (Gopalakrishnan 2004)**

Type	Definition	Metrics
ABC	Always Better Control	Annual demand value
XYZ	N/A	Inventory value at the closing of annual accounts
HML	High-Medium-Low value	Unit value (price or cost)
FSN	Fast-Slow-Non Movement	Stock rotation
VEIN	Vital-Essential-Important-Normal Criticality	Performance, warranty, reliability, safety, maintainability, criticality
VED	Vital-Essential-Desirable Criticality	Performance, warranty, reliability, safety, maintainability, criticality
GOLF	Government-controlled, Ordinarily available, Locally available, Foreign imported	Availability, Lead time
SDE	Scarce or single-source, Difficult or Easy to obtain	Availability, Lead time
SOS	Seasonal and Off-Seasonal	Availability, Lead time

As business models evolved and computing power increased, complex multi-criteria inventory models were developed. Regardless of the model most applicable to a particular business, Pareto's law remains the underlying principle behind most inventory classification techniques in use today. This paper explores alternative factors that may provide more value to managing spare parts than just targeting fill rates.

Pareto's law is the original theory behind the ABC inventory management technique. Some advanced multi-criteria inventory classification (MCIC) variations have been developed using the Pareto principle. They aim to achieve the same goal of prioritizing items either on a categorical or individual basis. We explore eight specific multi-dimensional models in detail regarding their applicability to WSS business requirements. These variants include joint-criteria matrix,

MUSIC-3D, operations-related groups, analytic hierarchy process, genetic algorithm for multi-criteria inventory classification, weighted linear optimization, simple classifiers for multiple-criteria ABC analysis, and weighted non-linear optimization models.

Flores and Whybark introduced a joint-criteria model by which demand value is combined with criticality to create a 3x3, nine-category classification matrix. Criticality refers to the potential loss incurred from being unable to fulfill an order. An example of a stock-out loss is the likelihood of losing a customer's future business to another supplier. The opportunity cost of losing that customer could be much higher than just the revenue loss of a single sale. Category "AA" represents the highest priority category (highest demand value and criticality) and "CC" represents the lowest priority category (lowest demand value and critical-

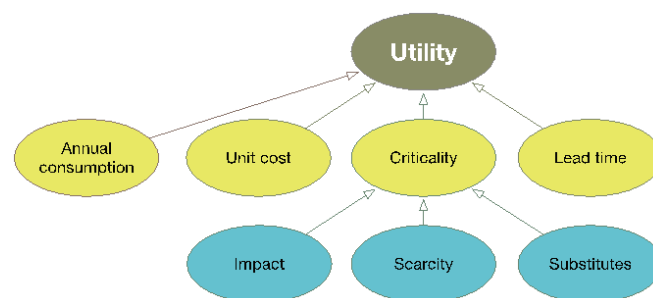
ity). Items not directly falling on one of the diagonal categories (“AA”, “BB”, or “CC”) are subjectively moved to the diagonal category best representing their priority (Flores and Whybark 1987). This approach is reasonable with two factors (demand value and criticality), but it becomes more unwieldy with more factors. Our multi-factor analysis overcomes these limitations.

Gopalakrishnan introduced the MUSIC-3D model as a 3-D matrix focusing on finance, operations, and criticality. Each of the three dimensions is split in two levels: “High/Low consumption value (HCV/LCV)”, “Long/Short Lead Time (LLT/SLT)” and “Critical/Non-critical (C/NC)”. Each item in inventory is classified and located in one of the eight 3D cells such as LCV-NC-LLT. The cells are ranked one dimension at a time, such that all HCV items are ranked higher than LCV items. Among HCV (or LCV) items, all Critical items are ranked higher than Non-critical items. Finally, among Critical (or Non-Critical) items, all LLT items are ranked higher than SLT items. Consequently, the cells are ranked following the sequence: HCV-C-LLT, HCV-C-SLT, HCV-NC-LLT, ..., and LCV-NC-SLT. This classification is quite subjective, but it is easy to implement (Gopalakrishnan 2004). As with the joint-criteria model, this approach does not scale well with additional factors and requires a certain amount of subjective ranking by the decision maker.

Cohen and Ernst introduced Operations-Related Groups as another MCIC method. Inventory items are clustered based on statistical procedures using operational constraints such as market attributes, production- and distribution-related parameters, and financial data to minimize the impact resulting from the shortage of a few items (Cohen and Ernst 1988). Flores, Olson and Dorai applied Saaty’s Analytic Hierarchy Process (AHP) as yet another MCIC method. The AHP arranges complex and unstructured data into a hierarchy of nodes with branches, and assigns relative weights to specified item criteria, which are then used to create and assign scores to inventory items (Saaty 1977, Flores et al. 1992). Items are ranked based on their scores. Figure 1 shows the initial structure of AHP applied to inventory categorization. Three criteria make up “criticality,” while four criteria, including “criticality,” make up “utility.” A “relative importance” scale could be used to assign values to the criteria. Scores for each item would then be calculated, and the items’ score would be used to prioritize them. Our primary approach has similarities to AHP in that we score each item based on a weighted sum of criteria.

We determine the weights using a different method that does not require the pairwise comparisons in AHP.

Figure 1. **AHP Structure (Flores et al. 1992).**



Artificial Neural Networks (ANN) and Genetic Algorithm for Multi-criteria Inventory Classification (GAMIC) use genetic algorithms to build upon the AHP method. They have been used to alleviate a few of the assumptions and restrictions of AHP, such as measurement of units of criteria and subjective scale assignments, creating consistency between comparisons (Guenir and Erel 1998). It is able to detect and extract nonlinear relationships and interactions among predictor variables (Partovi and Murugan 2002). GAMIC relaxes these assumptions by using a sample of classified items to assign criteria weights.

Ramanathan introduced Weighted Linear Optimization (WLO), a weighted additive function used to aggregate the performance of an inventory item, in terms of different criteria, to a single optimal inventory score (Ramanathan 2006). To eliminate the requirement for optimization software while also providing comparable results, a Simple Classifier for Multiple-Criteria (SCMC) analysis was created (Ng 2007). This model also converts all criteria measures into a scalar score, but it differs from WLO by transforming the criteria to a comparable base.

Improving upon SCMC, a simple weighted non-linear optimization model (WNO) that combines the positive qualities from both SCMC and WLO was developed (Hadi-Vencheh 2010). Like SCMC, WNO transforms the criteria to a comparable base. WNO assigns a weighted aggregate score to each item based on a simple optimization problem consisting of nonlinear constraints. The constraints for WNO differ from both the SCMC and WLO models by using squared weights, which expands the feasible region, leading to more precise scoring. This is the most applicable model for our inventory classification goals. It creates a prioritized list based on any number of items, variables, and variable priority rankings. Though

the model is simple enough to run without advanced software, it has the flexibility to add and change constraints and factors as needed. Similar attempts to multi-criteria inventory classification (MCIC) include (Bacchetti et al. 2013, Hatefi et al. 2014, Lolli et al. 2014, Millstein et al. 2014, Park et al. 2014, Roda et al. 2014, Soylu and Akyol 2014, Babai et al. 2015).

DATA OVERVIEW

In this large organization, WSS is responsible for providing wholesale- and retail-level support for both maritime and aviation platforms. The introduction of a new enterprise resource planning (ERP) system provided the organization with a single interface to manage its entire inventory, with the ability to track all aspects of parts flow through the organization's multi-indenture, multi-echelon inventory distribution structure. We filtered the data to include just the spare parts for maritime operations with demand over the three-year period from April 2011 through March 2014. Items that did not receive any order during that period were excluded from the analysis. We also used the item's maturity as filter. Maritime items experience five life-cycle phases: initial operational capability, pre-material support date, demand development interval, maturity, and sunset. Most items are in the mature life-cycle phase, and we only included these in our analysis.

In summary, of the 272,000 WSS-managed maritime items, 131,000 items are in the mature phase of their life cycles. By restricting to a demand history of at least one unit in the specified three-year time frame, only 17,587 items remained in our sample.

Relevant attributes

The reports provided by the ERP include more than 70 different attributes for each item in the system. These attributes are organized in five data categories: demand, lead times, repair capability, price, and classifications. As expected, *demand* has a significant influence on equipment availability. The primary variables associated with demand are demand forecast, demand deviation (forecast error), requisition frequency, requisition size, regeneration demand, and attrition demand. *Demand forecast* is the expected demand of an item, obtained by analyzing its time-series. *Demand deviation* is a measure of forecast error. *Requisition size* and *requisition frequency* represent the average number of units per order and the number of orders per quarter, respectively. *Regeneration demand*

is the fraction of demand fulfilled with the repair of recycled items, while *attrition demand* is the fraction of demand fulfilled with the purchase of new items.

The next category, *lead time*, includes the average time and its sigma (deviation) for procurement, production, procurement administrative, repair, and repair administrative. These times represent the expected delays associated with particular portions of the supply chain. These parameters are used for setting inventory safety levels and demand forecasts.

The *repair capability* category includes forecasts for item survival, carcass (i.e., an item requiring repair) return, and pipeline loss. *Survival rate* represents the probability that a carcass is repaired successfully by the repair facility. *Carcass return rate* represents the probability that inoperable items are returned to the repair facility. *Pipeline loss rate* represents the fraction of carcasses that is lost due to repair and non-repair reasons.

Numerous *prices* are associated with each item, including standard, net, replacement, and repair. They measure a part's reparability, the cost to repair it, and the cost to replace it. *Standard* and *net prices* represent incoming revenue for WSS from internal transactions. *Replacement* and *repair prices* represent costs due to external transactions. The *standard price* of an item is charged to the customer's budget in the fleet for either a consumable part or a repairable part with no carcass turn-in. *Net price* is the rebate price charged to the customer when a carcass turn-in is provided as part of the transaction. *Replacement* and *repair prices* are those paid by WSS to replace and repair the inventory items, respectively.

The *classification* category is the largest portion of ERP's metadata. Classes, indicators, codes, identifiers, symbols, routers, and flags comprise approximately half of the data fields.

VARIABLE SELECTION

In this section we determine which item attributes to include in our analysis to prioritize items for resource allocation. We use a combination of regression analysis and subject matter expertise to determine the drivers of WSS's primary goals, fill rate and equipment availability.

The significant differences in type, measurement, and magnitude among the variables limit the data analysis techniques that we can use. We select the "random

forests” approach (Breiman 2001, Benyami 2012), a machine learning method that combines the qualities of advanced cluster analysis with regression analysis to classify observations and prioritize factors. It generates a multitude of decision trees from random data points in a large dataset, where each tree represents a predictive modeling approach to map an item’s qualities (predictor variables) to its dependent (response) variable.

For each tree in a random forest, a subset of random observations from a full observation set is chosen, and from these observations, random subsets of predictor variables are selected. An optimal binary split is made on each branch using the variable that best impacts the specified objective function. This process is repeated multiple times, decreasing the mean squared residual error at each split. The final product represents one tree in the forest. Ultimately, the random selections of observations and predictor variables produce an ensemble of independently constructed trees. Once the forest is fully assembled, the node split values are aggregated and used to create classification criteria. The variables are ranked against each other based on how often and at what level they were chosen as the node’s best binary split variable. Because the objective of this analysis is to identify and verify the key variables driving fill rate, the relative ranking of variables is the primary goal of our random forest analysis.

The objective of random forest construction is to minimize the error in predicting the fill rate based on item parameters. We construct random forests of 1,000 trees for full observation of the 17,587 items in our sample. We use fill rate (drawn from compiled sales document data) as the response variable. We start by including all available variables (70+ fields) as predictors. We then proceed in an iterative manual process of removing variables and rebuilding trees to narrow our set of relevant variables. We use common sense, item manager advice, and WSS analyst recommendations to further refine our list of variables and confirm that the random forest suggestions are reasonable. This iterative process allowed us to remove variables with limited significance for this study and highlight the relative importance of the remaining variables. We finally converge on variables associated with price, criticality, and the mean and variance of demand and lead-time as the most important factors.

In the following subsections we describe the variables

of interest for the period 04/2011 to 03/2014 to determine their applicability and contribution to a prioritization model. Specific categories include fill rate, demand, lead time, criticality, and price. Each category includes several variables.

Fill rate

Fill rate (FR), the response variable, is the fraction of requisitions immediately filled with on-hand inventory. It is the primary performance measure for WSS because it relates to all other customer-oriented metrics (such as average delay, backorders, and response time). The fill rate for an item is calculated by averaging the hit/miss binary values for each requisition. Table 2 displays the 36-month histogram for the 17,587 items in our analysis. It shows that the median fill rate was 78% and the mean was 62%, substantially lower than the 85% goal. All items in the upper quartile had a fill rate of 100%, but the lower quartile had a fill rate of 20% or less.

Table 2. **Fill rate**

	Overall Fill Rate
100%	1.00
90%	1.00
75%	1.00
Median	0.78
25%	0.20
10%	0.00
0%	0.00
Mean	0.62
Std Dev	0.41

Demand

Numerous variables are associated with item requisition and demand values. Table 3 displays information related to the *number of requisitions (X)*. The mean number of orders per item in the period was 13.64 and the median was 3, but one item had 4871 orders. With an upper quartile value of just 10, it is clear that just a few items generate most requisitions.

Table 3. Number of requisitions per item

	Requisitions
100%	4871
90%	27
75%	10
Median	3
25%	1
10%	1
0%	1
Mean	13.6
Std Dev	72.6

A repair program refurbishes used assets to reissue them for future use. In most cases, expensive parts may be repaired at much lower cost than completely replacing them (Ferrer and Guide 2002). Survival rate and pipeline loss rate measure the reparability of a particular item. *Repair survival rate* (ρ_R) is the fraction of assets that experience a repair attempt and are successfully repaired. Table 4 shows a median repair survival rate of 90% and the mean is 67%. *Repair pipeline loss rate* (ρ_{LOSS}) represents the fraction of assets in the repair pipeline that cannot be repaired. The pipeline loss rate table shows that the median ρ_{LOSS} is 13%,

meaning that more than half of the items in the dataset had less than 13% of the requisitions not repaired by the system.

Table 4. Repair survival rate and Pipeline loss rate

	Repair survival rate	Pipeline loss rate
100%	1.00	1.00
90%	1.00	1.00
75%	0.92	0.99
Median	0.90	0.13
25%	0.01	0.09
10%	0.00	0.03
0%	0.00	0.01
Mean	0.67	0.35
Std Dev	0.41	0.45

Demand (D) represents the annual demand for that item. The majority of the variables of interest relate to demand, not requisitions. Specific demand measures include quantity demanded, demand deviation, regeneration demand, and attrition demand. Table 5 displays the relevant information. One item faced demand of 40,567, but the demand for 90% of the items was lower than 39 in the 36-month period, and the median demand was 4.

Table 5. Demand, Demand deviation, Regeneration, and Attrition

	Demand	Demand deviation	Regeneration demand	Attrition demand
100%	40567	2167.77	1646.76	15423.00
90%	39	2.85	2.49	2.63
75%	12	1.14	0.82	0.48
Median	4	0.51	0.24	0.12
25%	2	0.22	0.00	0.03
10%	1	0.00	0.00	0.00
0%	0	0.00	0.00	0.00
Mean	38.41	3.51	1.46	8.78
Std Dev	486.11	37.23	15.56	165.86

The *demand deviation* (ε) is measured as a forecast error. It indicates the difficulty in forecasting demand for low-demand items. Though coefficient of variation (the ratio between the mean demand and its standard deviation) might be a better measure of relative uncertainty, forecast error is tracked by the ERP and is easy to obtain, so it is the uncertainty metric used throughout this analysis. *Regeneration demand* (D_R) is the demand fulfilled through repair, while *attrition demand* (D_{ATT}) is the demand fulfilled with new

purchases. These values play a large role in budget planning due to the high cost associated with purchasing new items. They reflect the importance of the repair pipeline.

Lead time

The random forest approach identified four lead-time metrics correlated with fill rate: procurement administrative, production, procurement, and repair turn-

around lead times. *Procurement administrative lead time* (L_{ADM}) is the time it takes to award a procurement contract to a supplier. The clock starts when the contracting office receives a purchase request, and ends when the contract is awarded. *Production lead time* (L_{PROD}) is the time that it takes to manufacture and deliver a purchase order. *Procurement lead time* (L_{PROC})

is the sum of the procurement administrative and production lead times. *Repair turnaround time* (L_R) is the time required to repair and deliver a repair order. Table 6 shows that the median lead times for each of the processes are relatively low, but their standard deviations are high.

Table 6. **Procurement administrative, Production, Procurement, and Repair time (days)**

	Procurement ad-min. lead time	Production lead time	Procurement lead time	Repair turnaround time
100%	240.00	894.25	984.25	461.73
90%	1.64	6.30	7.39	3.35
75%	1.04	4.00	5.20	2.41
Median	1.04	2.83	3.97	1.74
25%	0.99	1.70	2.74	0.88
10%	0.82	0.70	1.74	0.00
0%	0.00	0.00	0.30	0.00
Mean	4.73	8.84	13.57	2.53
Std Dev	17.92	35.85	48.18	11.79

Procurement problem variable (PPV) is a strong indicator of supply chain health for a particular item, and is defined in equation (1). It captures how much demand occurs while waiting for an ordered part (either

via replacement or repair). PPV identifies potential issues in the supply chain resulting from higher-than-forecasted demand and/or longer-than-expected lead times.

$$PPV = D * L_{PROC} * \rho_{LOSS} + D * L_R * (1 - \rho_{LOSS}) \quad (1)$$

Table 7 provides the statistics for PPV and *PPV variance* (σ_{PPV}^2). Once again, a small number of items is responsible for most cases of high PPV and high PPV variance values.

Table 7. **PPV and PPV variance**

	Procurement problem variable	PPV variance
100%	15423.00	6.80E+07
90%	6.73	31.39
75%	1.89	4.46
Median	0.63	0.88
25%	0.21	0.21
10%	0.02	0.00
0%	0.00	0.00
Mean	10.24	8977.81
Std Dev	166.69	539085.25

Criticality

The notion of criticality plays a major role in repair parts management. Though a high level of demand

indicates that the item is frequently needed, its criticality could range from insignificant to vital. For instance, consider two types of light bulbs. The first has an annual demand of 50,000 units because it fits every reading light socket in a ship. Without the bulb, one needs another light source for reading. The second bulb has a demand of just 5 units per year, but it lights a control panel required for safe navigation. Without the second bulb, that panel is out of commission. Though both types are important, the second bulb is critical to operational effectiveness and should be managed more carefully than first bulb.

Three types of criticality measures used for this analysis: “whisky” ($w = 0$ or 1) requisitions, requisition priorities ($H = 0$ or 1), and item management essentiality codes ($IMEC = 0$ - 5), as follow:

1. *Whisky* requisitions: If a system required to complete a mission becomes inoperable, it is reported as a casualty. A requisition for parts required to make a system operable is classified as w . The letter indicates that the absence of that part prevents

a ship from achieving its mission. Approximately 7% of all requisitions analyzed were classified as *w*. The first column in Table 8 shows that, while one particular item suffered 548 whisky requisitions, more than half of the items had none. The last column shows that the urgency of the whisky process has an impact, but it is somewhat limited: the mean fill rate of whisky requisitions is just 75%, compared to the 62% overall fill rate shown in Table 2.

Table 8. Whisky requisitions, Whisky fraction, and Fill Rate

	Whisky requisitions	Whisky requisition fraction	Whisky fill rate
100%	548	1.00	1.00
90%	4	0.67	1.00
75%	1	0.29	1.00
Median	0	0.00	1.00
25%	0	0.00	0.50
10%	0	0.00	0.00
0%	0	0.00	0.00
Mean	1.82	0.18	0.75
Std Dev	7.06	0.30	0.39

2. Requisition priority: Requisitions contain a priority code to identify the current operational status and its need for the part. It is derived as a combination of two variables – operational state and urgency – to indicate if the requisition is high priority. Table 9 provides the 36-month statistics for *high-priority requisition (H)* and the *fraction of high-priority requisitions (δ_H)* for each item. One particular item received 3669 high priority requisitions, and half of the items had at least 1 high priority requisition. The second column shows that all requisitions were high priority for at least 25% of the items, and half of the items had more than half of their requisitions considered high priority.

Table 9. High-priority requisitions and High-priority fraction

	High priority requisitions	High priority requisition rate
100%	3669	1.00
90%	15	1.00
75%	5	1.00
Median	1	0.50

25%	0	0.00
10%	0	0.00
0%	0	0.00
Mean	7.63	0.49
Std Dev	46.40	0.39

3. Item Management Essentiality Code: The final criticality measure considered in this analysis is the *Item Management Essentiality Code (IMEC)*, which is assigned to each part based on a combination of its *military essentiality code (MEC)* and *mission criticality code (MCC)*. The sum of these codes is the IMEC, an integer number from 0 to 5, which increases with the item's criticality. Table 10 provides the histogram of IMECs in the data.

Table 10. Item Management Essentiality Codes (IMEC)

	IMEC
100%	5
90%	4
75%	4
Median	3
25%	1
10%	1
0%	0
Mean	2.81
Std Dev	1.23

Price

Numerous prices are associated with each item. Four price types correspond to the potential revenue and inventory replenishment costs. *Standard price (P)* represents the worst-case scenario for the customer. If a customer is unable to return a carcass to the pipeline for possible repair and reissue, the standard price is charged for that order. On the other hand, if the customer is able to return the carcass, the *net price (P_{NET})* is charged. The incoming revenue for that order would be added back to the WSS inventory budget and used for further inventory replenishment. As WSS determines what inventory to replenish, it must decide between repairing and replacing assets. The supplier charges WSS with either the *repair price (P_R)* attached to the asset, if it is repaired, or the *replacement price (P_{PROC})*, if it is a new procurement. Table 11 shows the respective summary statistics.

Table 11. Standard, Net, Replacement, and Repair

prices

	Standard price	Net price	Replacement price	Repair price
100%	\$6,504,171.00	\$1,171,258.00	\$5,131,600.00	\$898,926.00
90%	\$40,465.60	\$12,977.20	\$31,145.80	\$9,772.55
75%	\$15,942.00	\$5,269.00	\$12,308.40	\$3,982.00
Median	\$5,460.00	\$1,549.00	\$4,260.00	\$1,187.52
25%	\$1,585.00	\$195.00	\$1,229.00	\$154.14
10%	\$290.78	\$-	\$209.64	\$-
0%	\$-	\$-	\$-	\$-
Mean	\$21,397.84	\$6,746.44	\$16,507.56	\$5,018.74
Std Dev	\$108,117.87	\$26,446.76	\$83,219.19	\$19,621.17

Final variable selection

Demand, reparability, lead times, criticality and price are primary fill rate drivers that affect WSS's ability to maximize equipment availability. Therefore, they must be present in any model used to prioritize items for resource allocation and management. We discussed 21 specific variables in this section as fill rate and equipment availability drivers, but we do not need to use all them to prioritize the items. They can be represented through various creative combinations and variable substitutions. We want to limit the number of variables in the final analysis to maintain a parsimonious framework, while capturing as much of the important data as possible. We whittle our list down to six variables: criticality, demand value, number of requisitions, requisition variance, PPV, and PPV variance. We now describe the logic behind these choices.

We first make a note about the period of interest. We include items with demand of at least 1 unit over a 36-month period ending in May of 2014. However, to compute each of the six variables of interest, we do not necessarily include information over that entire 36 months. For variables related to requisitions, requisition variance, and high-priority requisitions, we used data over a 24-month period. Whisky requisition data covers a range from April 2013 through March 2014. We chose the two-year requisition and one-year whisky requisition time frames because those time frames are most representative of future requirements. Conceiv-

ably, the item management processes would address any major supply issues prior to those time frames.

Number of requisitions (X) and *requisition variance* (σ_x^2) warrant their own individual model variables. Every requisition of an item affects fill rate the same way, regardless of criticality, price, or quantity. Requisition and requisition variance are the best tools to predict and plan for the volume and predictability of future requisitions. This proper planning then leads to requisition fulfillment and fill rate metrics.

To create one criticality variable, we incorporate high-priority requisitions over the past 24 months, whisky requisitions over the past 12 months, and the IMEC code. The formula used to calculate the criticality score is shown in equation (2).

$$K = 1.5 * W + H + 0.1 * IMEC * X \quad (2)$$

The formulation is subjective in nature, but proves to be a good approximation of the importance of each measure to the overall criticality score. A requisition is often under more than one priority criteria (whisky, high-priority, and high IMEC), so it may contribute in three different ways to the item's *criticality score* (K). In this formulation, whisky requisitions weigh 50% higher than high-priority requisitions, which may impact the items criticality more heavily than its IMEC code. Table 12 shows how criticality scores are calculated for 12 different items.

Table 12. Criticality scores and rankings for 8 hypothetical items

item	IMEC	Requisitions (X)	Whiskeys (W)	Hi-Pri (H)	Criticality (K)
1	4	2000	1173	891	3450
2	4	100	57	1	126

3	3	2000	1093	912	3151
4	3	100	51	16	122
5	2	2000	122	100	683
6	2	100	43	34	118
7	1	2000	606	315	1424
8	1	100	18	12	49

We also include procurement problem variable (PPV) and its variance (σ_{PPV}^2) in the model. They reflect the potential pipeline problems associated with each item, by integrating attrition demand, regeneration demand, procurement lead time, repair pipeline loss rate, and repair turnaround time. PPV and PPV variance are extremely important to fill rate goals because even if WSS knows exactly what the future demand is going to be, if the parts are not on the shelf due to pipeline issues, the requisition scores a “miss” and fill rate decreases.

There are several issues to consider when determining how to factor price into the model. Because WSS has more control over spending than it does over revenue, inventory cost proves to be the best basis for the model’s demand value variable. In summary, the *demand value* (V) considers unit demand, repair pipeline loss rate, repair price, and replacement price to calculate an expected cost for WSS to supply that unit demand.

The formulation used for demand value is shown below in equation (3).

$$V = \rho_{LOSS} * D * P_{PROC} + (1 - \rho_{LOSS}) * D * P_R \quad (3)$$

METHODOLOGY

We now turn to developing the machinery that will transform the values of the six variables from Table 13 into a score for each item. We can then prioritize them according to this score. Recalling the list of methods from Section , we focus on WLO, SCMC, and WNO as potential prioritization candidates. Because SCMC improves upon WLO, and WNO improves slightly upon SCMC, we start with WNO. To reiterate, the major benefits of the WNO model are the ability to run without specialized software, the ability to consider any number of criteria, the priority ranking of variables, and the ability to rank items individually.

Table 13. **Variables selected to prioritize items**

Variable	Attributes
Requisitions (X)	Number of requisitions
Requisition variance (σ_x^2)	Number of requisitions uncertainty, Requisition frequency
Criticality (K)	Whisky requisitions, Requisitions priority, IMEC
Procurement problem variable (PPV)	Regeneration demand, Attrition demand, Repair turnaround time, Procurement lead time, Repair pipeline loss rate
PPV variance (σ_{PPV}^2)	Regeneration demand uncertainty, Attrition demand uncertainty, Repair turnaround time variability
Demand value (V)	Demand rate, Pipeline loss rate, Replacement price, Repair price

The inputs for the WNO model are the relevant variables associated with each item and the subjective priority ranking of all variables established by the decision maker. We label the variables in ascending order according to the priority specified by the decision maker. Next, each item is scored for every variable according to its relative ranking among all items. If the value of the j^{th} variable for the i^{th} item is , then this item’s score according to the j^{th} variable is , the result

of the following expression (Ng 2007, Hadi-Vencheh 2010):

$$\alpha_{ij} = \frac{y_{ij} - \min_{i=1,2,\dots,I}\{y_{ij}\}}{\max_{i=1,2,\dots,I}\{y_{ij}\} - \min_{i=1,2,\dots,I}\{y_{ij}\}}$$

Considering the relative importance of each variable, an optimization specifies their weights by maximizing the weighted sum of the scores obtained by each item:

$$\begin{aligned} & \max_{w_j} \sum_j^J w_j \sum_{i=1}^I \alpha_{ij} \\ \text{subject to} \quad & \sum_{j=1}^J w_j^2 = 1 \\ & w_j \geq w_{j+1} \geq 0, j = 1, 2, \dots, J-1 \end{aligned} \quad (4)$$

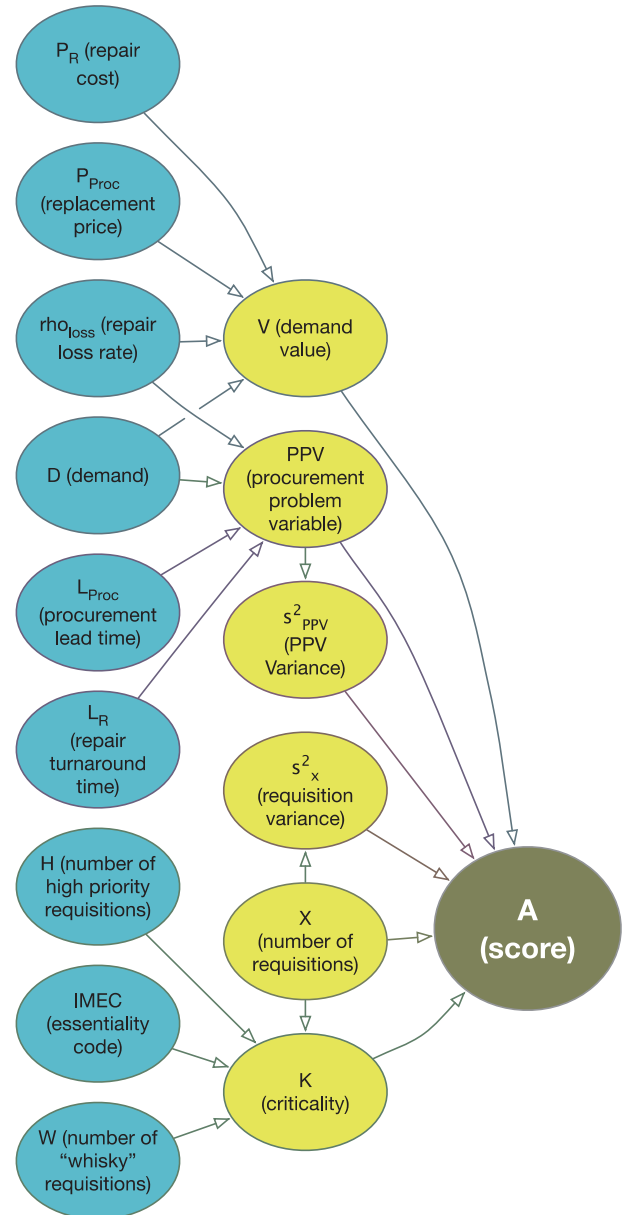
The objective function (4) intends to find the array of weights that maximizes the sum of final scores subject to the following constraints: the sum of the squared weights equals to 1, as recommended by Hadi-Vencheh, and the weights are monotonically increasing, according to the subjective ranking previously determined by the decision maker. By squaring the weights, we avoid results that assign the value of zero to some weights, an important consideration to ensure that all variables are represented in the prioritization scheme.

Our objective function is modified from the original WNO model proposed by Hadi-Vencheh. In that model, the user solves a separate optimization model for each item, rather than a single optimization over the sum of scores for each variable. Our simplification allows easy integration with ERP systems, an important concern if you have a large number of stock-keeping units or a large number of variables

In order to perform the optimization in (4), we must rank the selected variables ($X, \sigma_X^2, K, PPV, \sigma_{PPV}^2, V$) in order of importance. In addition to choice of time frame for data selection, this is the only subjective part of the model. All six variables include some measure of demand rate. Therefore, number of requisitions (X) is strongly represented regardless of the variable ranking. With that in mind, focus shifts to variables that encompass other aspects affecting equipment availability.

Criticality (K) represents equipment availability better than all other variables. The fact that just one small part could potentially render an entire warship not operationally ready is reason enough to designate criticality as the highest priority variable. Demand value (V) falls in line with the original theory behind ABC analysis. Resources committed to stagnant inventory severely diminish a business's ability to fund high-demand and/or highly critical stock. Stagnant stock not only limits replenishment of high-demand stock that drives fill rate, but also critical parts that strongly affect equipment availability. We assign demand value as the second highest priority variable to capture WSS's need to be efficient with its limited budget.

Figure 2: **WNO structure with selected variables**



Requisitions, requisition variance, procurement problem variable, and PPV variance are all heavily correlated with demand. Though PPV and PPV variance can identify potential pipeline problems created by long lead-times, high values aren't necessarily indicative of greater concerns. If inventory levels are set high enough for a high-PPV item, the pipeline may still be healthy. Still, the item does have the potential to quickly experience major issues due to demand or lead time volatility. On the other hand, high requisitions and requisition variance values do directly reflect higher importance to fill rate and equipment availability. Therefore, we ranked the remaining four variables in this order: number of requisitions (X), requisition variance (σ_X^2), procurement problem variable (PPV) and PPV variance (σ_{PPV}^2). Figure 2 shows how the

variables in the raw data participate in the variables selected in the model to build each item's score.

MODEL ANALYSIS

One of the major advantages of the modified WNO model is its simplicity. The input of the classification scheme is the set of weights associated with each variable in the objective function in section . To generate a score, we compute the weighted sum of the standardized variables associated with that item. The weighted sum of all criteria (A_i) becomes the final score for the i^{th} item used in the priority scheme.

$$A_i = \sum_j w_j * \alpha_{ij} \quad (5)$$

We then prioritize items by their individual scores. Table 14 presents the optimal weights for our WSS data. To generate the numbers in this table we find the coefficients w_j by solving the objective function in equation (4) using the Generalized Reduced Gradient (GRG) non-linear optimization algorithm available in the Solver add-in in MS Excel 2014 on a MacBook Pro 2.7 GHz. We specified a multi-start method with a population size of 250 random starting points, where each starting point was a different weight array.

Table 14. Optimal weights for the WNO model

Ranking	Variable	Weight
1	Criticality (K)	0.491
2	Demand value (V)	0.491
3	Requisitions (X)	0.491
4	Requisition variance (σ_x^2)	0.491
5	Procurement problem variable (PPV)	0.131
6	PPV variance (σ_{PPV}^2)	0.131

Recall that the WNO model constrains the sum of squared weights to 1 and that the weights must have non-increasing values according to the variable prioritization described above. In this case, WNO assigns criticality, demand value, requisitions, and requisition variance an equal weight. Based on the priority constraint, this suggests that the requisition variables are particularly crucial attributes. If the maximization were unconstrained, requisition variance would receive the highest weight.

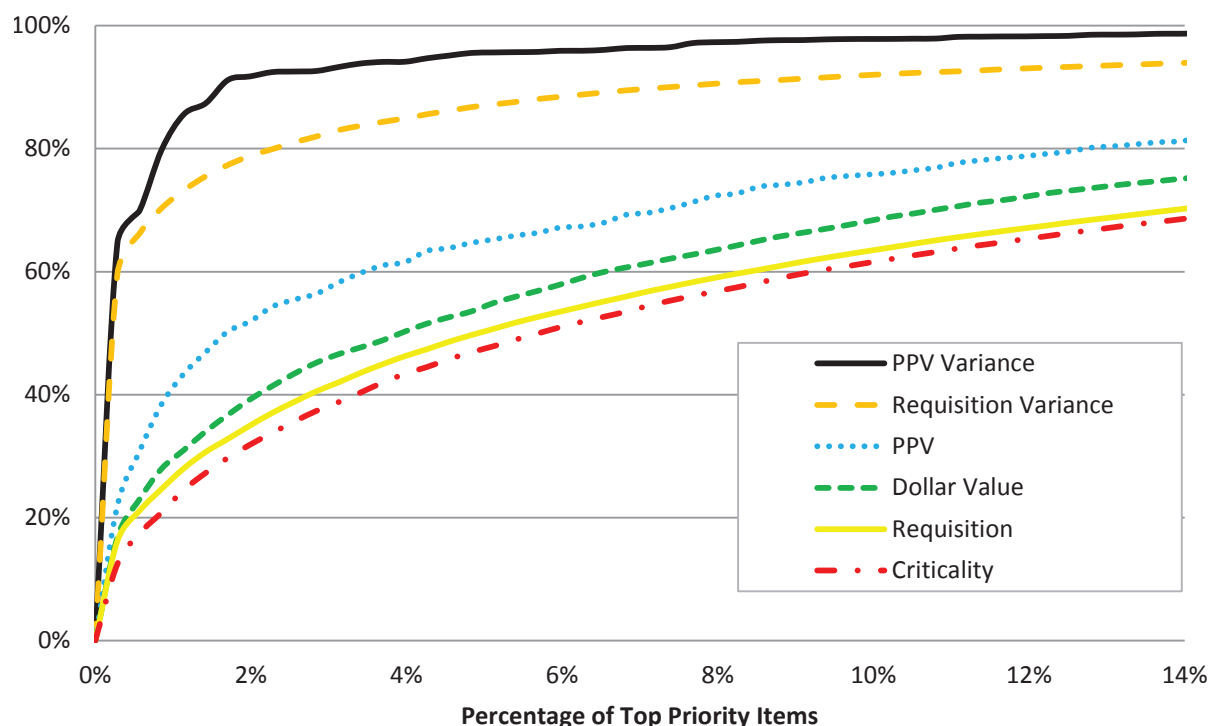
Given the optimal weights, we can score each item and evaluate our priority scheme against a few candidate prioritizations. To do this we focus on the Pareto nature of the original ABC analysis: if the WNO rankings are effective, a small fraction of the top ranked items (the "A" items) should capture a large fraction of the key business drivers. In the following section we create a Pareto plot to examine if the highest ranked items according to the WNO method capture a large fraction of requisitions, PPV, criticality and demand value.

WNO results

Figure 3 is a Pareto chart that shows the increasing amount of the six selected variables that are captured by the WNO model. Starting with the highest ranked item, it successively adds the highest ranked among the ones still remaining, one by one, as desired. Each curve refers to a single variable in the model. The x-axis represents the percentage of all 17,857 items ranked according to WNO. The y-axis represents the cumulative percentage of the variable captured by those items. The chart shows that PPV variance in the 17,857 items (black continuous line) is quickly captured by the first few items: just 2% of the items (351 items) ranked by WNO capture 92% of the PPV variance in the data. These same items also capture 79% of the requisition variance (long dashed line), 52% of the procurement problem variable (light dotted line), 39% of demand value (short dashed line), 35% of all requisitions (light continuous line) and 32% of the criticality (dot-dashed line) present in our dataset. Figure 3 illustrates the Pareto shape that we desire. A few items account for a large fraction of the metrics of interest. For all 6 metrics, 10% of the highest ranked items capture at least 60% of each variable identified as the key business drivers in the organization.

The approach adopted by this organization, the WSS4 method, categorizes 673 items as A. If we select the top 673 items of the WNO ranking (3.8% of the total), they capture 94%, 84.6%, 61.2%, 49.5%, 45.6%, and 42.6% of the data's total PPV variance, requisition variance, PPV, demand value, number of requisitions, and criticality, respectively.

Figure 3 illustrates the potential benefits of prioritizing items using our modified WNO method, as the top items capture most of the key drivers of fill rate and equipment availability. In the next section, we compare the WNO ranking scheme to other prioritization schemes.

Figure 3. **Impact by top priority items on each metric using WNO method**

Comparison of wno to alternative models

We perform similar analysis to Section for other prioritization methods. Currently WSS uses no prioritization. When an event that requires the attention of a planner occurs, that item joins a first-come-first-serve queue. If these events are independent of the metrics (e.g., “every X years an item must come up for reevaluation”), then the ranking of the items is essentially random, and we would expect the curves in Figure 3 to be roughly linear. That is the top 5% of items at the front of the queue would capture approximately 5% of demand value. Clearly the WNO model performs much better than the random approach, but there are other prioritization methods to consider.

In this section, we compare the performance of WNO to four other prioritization methods: WSS’s proposed WSS4 scheme, a prioritization based on number of requisitions (X), an ABC ranking based on demand value (V), and another based on criticality (K).

Figure 4 through Figure 7 present comparisons between our modified WNO method and the four other priority schemes. To create these figures, we first generate the Pareto numbers for each priority scheme that indicate what percentage of each variable of interest is captured by the top priority

items as ranked by that particular prioritization. Then, we subtract those numbers from the numbers created to generate Figure 3. A positive result indicates that the same percentage of items captures more of a variable with the WNO method. A negative result indicates otherwise. Thus, the positive regions in Figure 4 through Figure 7 show WNO outperforming the given alternative for a particular metric. The negative regions show the alternative scheme outperforming WNO. The line formatting in each figure is the same as in Figure 3. Because we are interested in identifying the items with greatest impact in the key business drivers, the left-hand side of each chart is more important than the right-hand side, which is why we only show the top 12% of each prioritization scheme.

The WSS4 prioritization scheme compares poorly with WNO (Figure 4). We notice that the top 2% of items in each ranking captures 30% more (in absolute terms) of the total PPV variance with WNO than with WSS4. They also capture 20% more of PPV and 11% more of the demand value. However, any number of top ranked items captures approximately the same amount of the requisition variance, number of requisitions or criticality by either prioritization method.

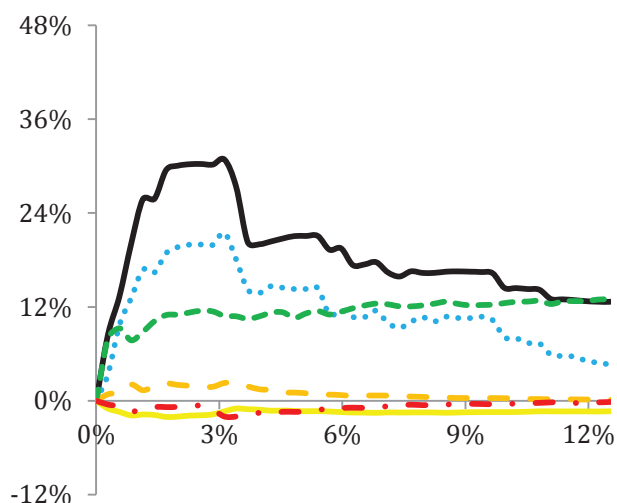
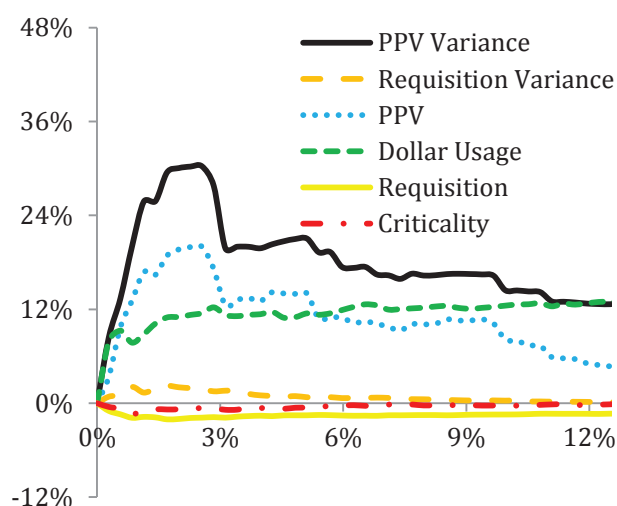
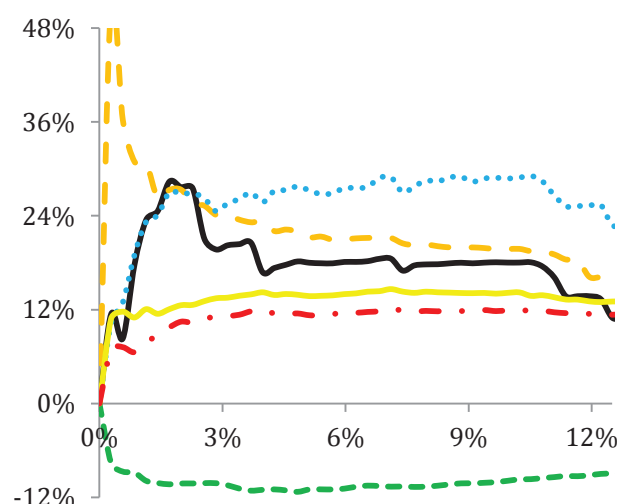
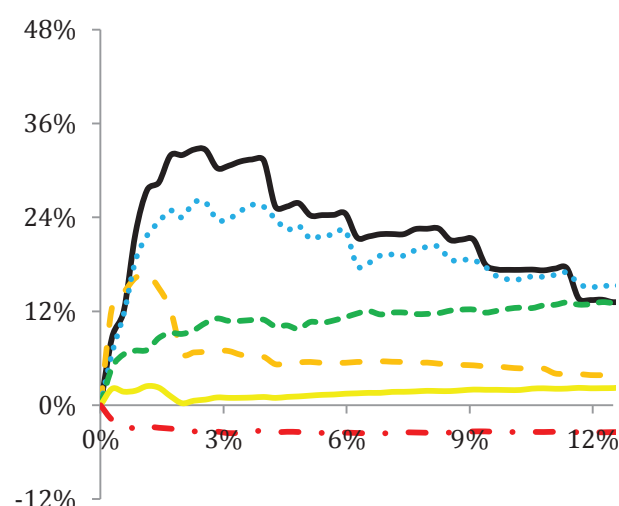
Figure 4. **WSS4 vs. WNO**Figure 5. **X vs. WNO**

Figure 5 yields essentially identical results: WNO performs better than a prioritization scheme based exclusively on number of requisitions, identifying the items that capture most of PPV variance, PPV and demand value, but both priority schemes capture nearly the same amount of requisition variance, number of requisitions and criticality. One would expect similarities between this scheme and WSS4, given that number of requisitions is a main driver of the WSS4. However, WSS4 also considers the number of whisky requisitions, but their impact on the method is marginal. This suggests that WSS might be better off just using the number of requisitions method, as it is simpler to adopt than WSS4 and it produces nearly the same results.

It is interesting to notice that WNO performs much better than the classic ABC method (Figure 6) for

Figure 6. **ABC vs. WNO**Figure 7. **K vs. WNO**

nearly all variables. WNO is only outperformed when considering demand value (V). Likewise, WNO outperforms the criticality method (Figure 7), except in the effort to identify items with highest criticality. Examination of Figure 4 through Figure 7 reveals that WNO performs worse for some metrics against ranking schemes that focus solely on a given variable (e.g., demand value or number of requisition), but it dominates in the other categories. That is, minor declines capturing a few variables using WNO are offset by significant improvements capturing other variables. While an approach using only the number of requisitions would improve fill rate, it would fail to address PPV and demand value. A demand value prioritization would promote tighter controls on budget and spending, at the expense of fill rate and other equipment availability variables.

Our modified WNO method captures the impact of most key variables with few inventory items (Figure 3). It also performs well against other possible prioritization schemes, generating robust results against a variety of schemes. The other prioritization methods usually underperform significantly in at least one metric, while WNO dominates in several metrics.

Before we conclude this section, we compare WNO with WSS4 in more depth, as these are two candidate prioritizations that WSS may actually implement. We examine how the two methods categorize the 17,587 items in the dataset. Applying the WSS4 logic, the A, B, and C classes contain 570, 636, and 1,329 items, respectively. Applying the same class sizes to the WNO-prioritized item list, we recreate A, B, C, D classes for the WNO method. The top 570 ranked items using WNO belong to group A, the next

636 belong to group B, the next 1329 to group C, and the remainder to group D. We can now compare how many of the WSS4 A items are also categorized as A by WNO, and so forth. Table 15 displays the classification comparison results: 78% of the items classified as A by WNO are also classified as A by WSS4, but 18% of the items classified as A by WSS4 are classified as B by WNO. The overlap is primarily due to the strong dependence of both models on number of requisitions. However, requisitions tell an incomplete story and it is important to consider other metrics. For example, 3% of the items classified as A by one method belong to the D class in the other method. Considering the superior ability to represent much of the inventory criticality with a small number of items, this suggests that WSS could see significant benefits from using WNO over WSS4 to account for factors related to equipment availability.

Table 15. **Discrepancy between WNO and WSS4 classification schemes**

		WNO classification			
		A	B	C	D
WSS4 classification	A	78%	18%	1%	3%
	B	15%	57%	14%	14%
	C	4%	20%	64%	12%
	D	3%	5%	21%	71%

Sensitivity analysis

In this section we examine how the results change when we consider subsets and extensions of our original dataset. Our original analysis considers regular requisitions data over 24 months and whisky requisitions over 12 months. We chose these timeframes based on perceived relevance by WSS experts. However, our data covers 36 months. We examined several other time windows to understand how they affect model performance. We considered combinations of time frames ranging from 36 months to 6 months for each type of requisition. The results are all very similar to what we presented in section and , and are not an artifact of the selected time frame.

Considering that WNO ranking is robust regarding the choice of time frames, we can now test the predictive capability of the WNO method. Sections and analyzed the data over a time period to identify the items that would capture the most of selected vari-

ables *during that same time period*. However, if the model is put into practice, it will rank the items using data from one time period, and it will use the results to prioritize the items in subsequent time periods. That is, we need the top-ranked items to capture a significant portion of the selected variables in a time window *outside of the one used to create the rankings*.

We use both the WNO and WSS4 methods to rank items using data from an 18-month time frame. We then use those rankings to determine each model's ability to capture the variables of interest in a future 18-month time frame. We use data from April 2011 through September 2012 to rank items. When we compute the fraction of each variable captured by the top WNO-ranked items for that *same* 18-month period, we create a figure very similar to Figure 3. However, when we use those WNO ranking to examine the fraction of variables captured for the *following* 18-month time period (October 2012 through March 2014) the performance decreases,

as expected, but the ranking remains useful. The PPV variance and Requisition variance, the two variables most captured by WNO, decrease 10-12% (in absolute terms), while the capture for the other variables decreases 5-10%. While the more realistic out-of-sample performance is worse than what we found in section 6.1, we still find that the top 10% of WNO ranked items capture over 50% of the metrics of interest in the future time frame. WSS4 faces similar degradation of out-of-sample performance.

Our final sensitivity analysis considers an additional three months of data from April to June 2014. Our items were originally ranked according to both WNO and WSS4 in sections and classifying 570 items as A, 636 as B, 1319 as C, and the remainder as D, using the time interval ending in March 2014. Between April and June 2014, there were 19,078 requisitions for 5,245 items. Only 1,075 of these requisitions were for items that were classified differently by our modified WNO model and WSS4, shown in Table 16. For instance 19 requisitions in that period were for items classified by WNO as A and by WSS4 as D.

Table 16. **Classification discrepancy for requisitions made in April-June 2014**

		WNO classification			
		A	B	C	D
WSS4 classification	A		0	0	0
	B	0		0	0
	C	0	227		551
	D	19	24	254	

Notice that most of these differences are for items that WSS4 ranked lower than WNO. Since the manager's main concern is with A items, discrepancies between C and D rankings are of very minor importance. Three months of requisition does not warrant much analysis, but it is still illuminating. Based on the active items that received lower ranking with WSS4, it seems that number of requisitions is not the only aspect WSS should consider; WSS should account for other business drivers, such as criticality and equipment availability, as well as demand value and PPV measures. An example of an item classified as A by WNO and D by WSS4 is an item that had only 11 requisitions over the 24-month timeframe. WSS4 classifies the item as a D because of its low number of requisitions. However, the item costs \$106,000, so WNO classifies it as an A due to its high demand value: \$1.15 million. The demand for this item in the recent 3-month interval was 3. Common sense dictates that WNO ranked it well, and planners should closely monitor and manage this item due to the potential budget impact.

The analysis in section reveals that our modified WNO method produces effective rankings that capture a significant portion of key metrics with a relatively small fraction of items. Furthermore, WNO is consistent, performing strongly across more met-

rics than other possible ranking schemes. These findings appear robust to different out-of-sample data considerations.

DISCUSSION

Decades of research and analysis have shown that ABC analysis is a viable concept that nearly any inventory management systems should employ, but the criteria used to prioritize inventory should be representative of business goals. For WSS, these goals include fill rate and equipment availability. Fill rate is a direct function of demand and inventory on hand, while equipment availability is based on both demand and the criticality measures of that demand. WSS cannot change business rules or prioritize items in an effort to directly impact demand, but it can impact the amount and stability of the on-hand inventory. We identified variables associated with demand, lead time, and price as the inventory qualities strongly affecting fill rate. Subject matter expertise was used to identify variables to create criticality factors.

Of all the explored ABC analysis methods, the multi-criteria weighted non-linear optimization (WNO) technique was shown to be the best option for WSS's prioritization goals. It optimally assigns weights to

priority-ranked factors to maximize the summation of factor-based scores across all items being ranked. This technique identifies the order in which items should be optimally managed based on the priorities specified.

We chose criticality (K), demand value (V), number of requisitions (X), requisition variance (σ_x^2), procurement problem variable (PPV) and PPV variance (σ_{PPV}^2) as the input variables to the WNO model. We compared its results to alternative prioritization schemes regarding how it captures key business variables. Other prioritization methods considered include WSS4 (a classification scheme currently under consideration), requisitions volume, criticality, and demand value. Although the alternative models slightly outperformed WNO in one or two metrics, WNO is the best overall method: Relative to the other models, WNO losses in capturing a few variables were countered with significant gains capturing much more of the remaining variables.

As opposed to a first-come-first-serve approach, any prioritization scheme that considers number of requisitions should improve fill rate and equipment availability. The largest increases in fill rate would result from the models that primarily focus on number of requisitions, such as the WSS4. Though these models meet short-term objectives, their use may not be the best long-term approach for WSS given their disregard for budget constraints.

The consideration of requisition variance, lead times, and demand value fosters inventory stability and the efficient use of a constrained inventory budget. Inventory level stability is aided by predictable and stable lead times, which can be improved through item manager attention. Likewise, inventory budget efficiency is aided by limiting the dollar value of on-hand inventory, which can be achieved through tighter controls by item planners. As budget allocation improves, resources become available to manage low demand items for which planning is so difficult.

The ability to apply the WNO model with any number of factors is yet another benefit of this model. Managers from any number of industries may customize the method by choosing other variables to use in the model. WNO's flexibility, compatibility, and ability to optimize based on multiple criteria render it superior to other prioritization methods considered. However, only experience will tell how much the fill rate and equipment availability can improve if managers adopt WNO; as any prioritization scheme, the

method is designed to focus the attention of the decision maker. The performance improvement comes from using that focus to make the right decisions.

FINAL CONSIDERATIONS

We used different measures to capture criticality. They may be valuable in many industries, but the correct usage of these variables require a thorough understanding of the impact of that part on operations. Developing and updating the criticality measures would enhance the effectiveness of the WNO model.

Our study has a subjective step that was mentioned earlier. The relative importance of the selected attributes was subjectively determined by the inventory managers. This is not an ambiguity of the method, but an approach to handle the complexity of meeting multiple objectives: either we decide that these attributes are equally important or we assign relative importance.

Our analysis only included items that were in their mature phase. We made this restriction because these items had sufficient history for making a sustainable classification. New items would have to rely on subjective classification by inventory managers until sufficient history is gathered. Also, we focused on the maritime wholesale supply chain for this military organization. The method should be used only on a set of items that is managed by a single organization, with a variety of objectives and constraints, in many industries. Natural candidates for this method are the environments that deal with a large variety of parts in their inventory management systems, such as airlines, amusement parks and public works.

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