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Leveraging Machine Learning and AI to Identify Alternative Parts to Increase Parts Availability and Improve Fleet Readiness

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Abstract

As competition between the United States and near-peer adversaries intensifies, the U.S. Navy faces increasing challenges to its sea dominance. Fleet readiness, backed by superior Naval capabilities, is critical to credibly project U.S. power and deter conflict in the region.

The speed and agility of the U.S. industrial base to maintain operational availability (Ao) is foundational to readiness. However, obsolescence issues such as parts shortages plague weapon systems, negatively impacting Ao. Leveraging artificial intelligence and machine learning (AI/ML) processes to quickly identify potential alternative parts can greatly speed up the time required to identify replacement parts.

Currently, to remedy these issues, engineers must manually scour hundreds of sources and compare a multitude of technical characteristics to identify alternative parts, a time- and labor-intensive process. To address this need, this study developed an LLM-base AI model to quickly compare multiple parts, rank them based on similarity to the part under investigation, and ultimately identify feasible alternatives. The output is a prioritized ranking of parts, based on model-determined similarity of form, fit and function of the parts. The model-recommended parts are then analyzed for current stock on hand to identify the most viable parts that could also be quickly accessed.

Introduction

Traditionally, Navy engineers are notified once a part is unable to meet fleet requirements and tasked with identifying alternatives to maintain shipyard availability schedules. This manual process is time-consuming, labor-intensive, and does not always yield fruitful results, sometimes overlooking potential replacement solutions. Without the ability to compare the potential form, fit and function across a multitude of potential parts at scale, this process will continue to be a bottleneck to addressing fleet sustainment challenges. Without a way to speed up this process and ensure fleet readiness, the U.S. Navy risks diminished or loss of advantage in the maritime domain.

To ensure an accelerated and robust process for identifying parts replacements, Govini developed a repeatable and scalable methodology, which leverages a large language model (LLM) to analyze the potential form, fit and function of parts and prioritize potential alternate parts in order to provide Navy engineers a starting point for their process. The methodology examines part inventory and supply levels to heavily prioritize parts that the U.S. Navy has stock on hand for in a nearby location to further speed up part delivery to the Fleet. To accomplish this task, the study leveraged machine learning and artificial intelligence (ML/AI) to first identify the baseline dataset of relevant parts and associated characteristics and then identify similar alternates to potentially problematic parts.

The insights from the study can aid decision-makers in the Department of the Navy (DoN), Defense Department, and broader U.S. government as they grapple with instilling processes to address the challenges extended ship and submarine lifetimes put on fleet sustainment and maintaining U.S. maritime superiority.

Key Findings

Implementing AI/ML processes is key to proactively identifying parts that pose high risk to shipyard availability schedules. Once these target parts have been identified, the LLM can be leveraged to identify potential solutions and speed up remediation actions.

- **Ohio Class Submarine parts have a lead time of up to 1,261 days.** Extremely long lead times can negatively impact shipyard availabilities due to lack of part availability once the part requirement is identified. Lead times of multiple years are untenable, and mitigations need to be identified.
- **18,007 total parts with a lead time of over 1 year.** Out of the 123,564 unique parts identified associated with the Ohio Class Submarine, ~14% of these parts have a lead time of over 1 year.
- **Of the 18,007 with lead times over 1 year, the LLM identified 10,703, which have similar parts with stock on hand.** The average similarity score of this cohort of potential alternate parts is 0.88 out of 1, which indicates a high probability of the similar parts being acceptable alternates.

Methodology

Govini’s National Security Knowledge Graph (NSKG) was leveraged to identify all relevant structured and unstructured data that could be used to describe the form, fit and function of parts for a selected weapon system. The NSKG is driven by Govini's ML-powered Object Fusion data engine that continuously ingests, normalizes, and integrates new data sources with existing data catalogs. Govini analysts leveraged the vast information in the NSKG to construct the associated part landscape views across the Ohio Class Submarine through the use of ML algorithms. This comprised the baseline dataset for analysis. This study focuses on the Ohio Class Submarine as an exemplar case, but any predetermined set of parts can be utilized. The list of all the weapon system designator codes (WSDC) utilized can be seen in Appendix A.

The first phase of this study utilized an LLM-enhanced model to quantify the form, fit and function similarity between parts, leveraging all of the NSKG-derived information described in the previous paragraph. The LLM-based model was trained using input identified by subject matter experts. The relevant part identifying information that this application uses includes a wide variety of part-specific elements that describe the part in specific detail. Examples include the part’s weight, material, size, description, etc. This allows for scanning for parts that share similar features that could also be quick, low-cost alternatives to long lead time parts.

In the second phase, the baseline dataset of all Ohio Class Submarine parts was evaluated to identify the top 10 long lead parts. These parts were then run through the LLM model to identify similar parts. Potential similar parts with stock on hand are prioritized for these long lead parts to provide a prioritized list of potential alternates for these long lead items.

Analysis

A training set was generated to train the model across the Ohio Class Submarine parts cohort. This model evaluated 3,106 unique types of inputs across the part cohort. The model outputs vector embeddings, which are utilized to determine which parts are similar. Vectors will be closer together if the parts are more similar. This can then be used to generate a similarity score to more easily compare various parts.

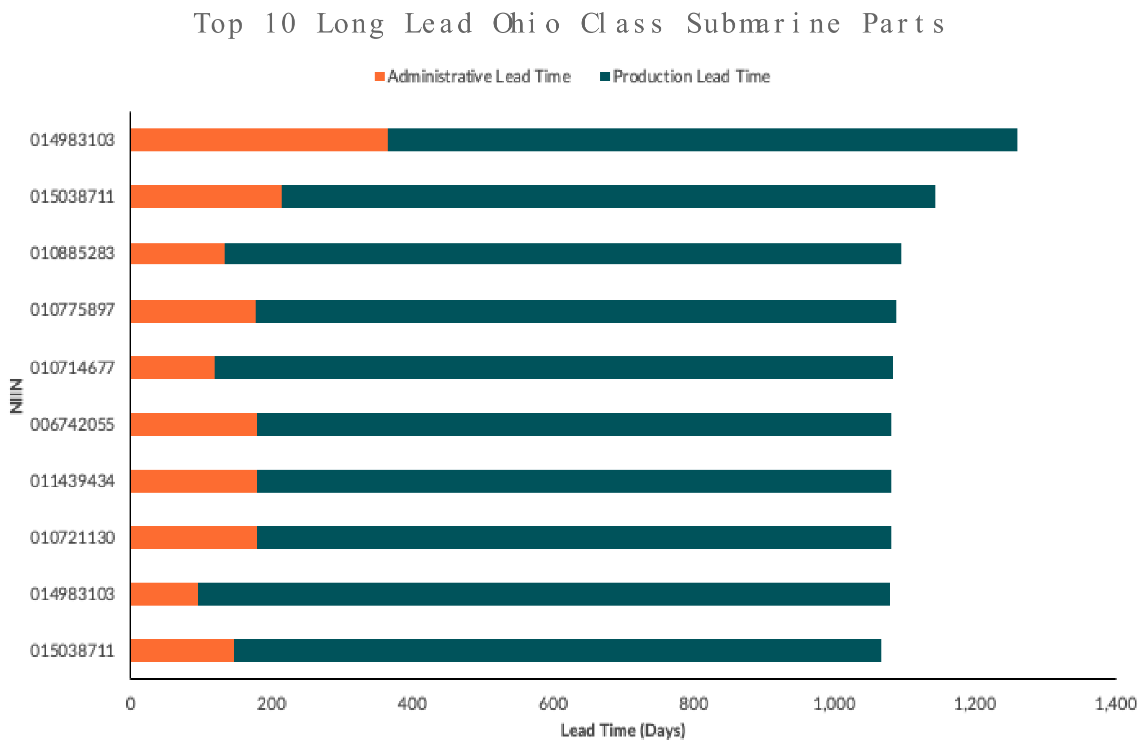

Figure 1. Top 10 Long Lead Ohio Class Submarine Parts

There are approximately 123,564 unique parts associated with the Ohio Class Submarine identified by 25 different WSDCs defined by the Defense Logistics Agency (DLA). As seen in Figure 1, some of these parts have lead times as high as 1,261 days. This means that if this part is needed to support a Submarine in a shipyard availability, it could take as long as 42 months to get the part to the Submarine and get the Submarine repaired, greatly impacting overall fleet readiness.

Running the Ohio Class Submarine parts through the LLM provides 68,569 unique parts with similar parts that have a similarity score over 90; 90 is utilized as a threshold to ensure all parts have a higher probability of being selected by engineers and subject matter experts as acceptable alternates. These lists are then further prioritized by filtering out parts with no available stock on hand. This subset represents the subset of parts that should the similar part be approved as an alternate part, have stock on hand to most quickly be utilized to leverage any schedule delays during a shipyard availability.

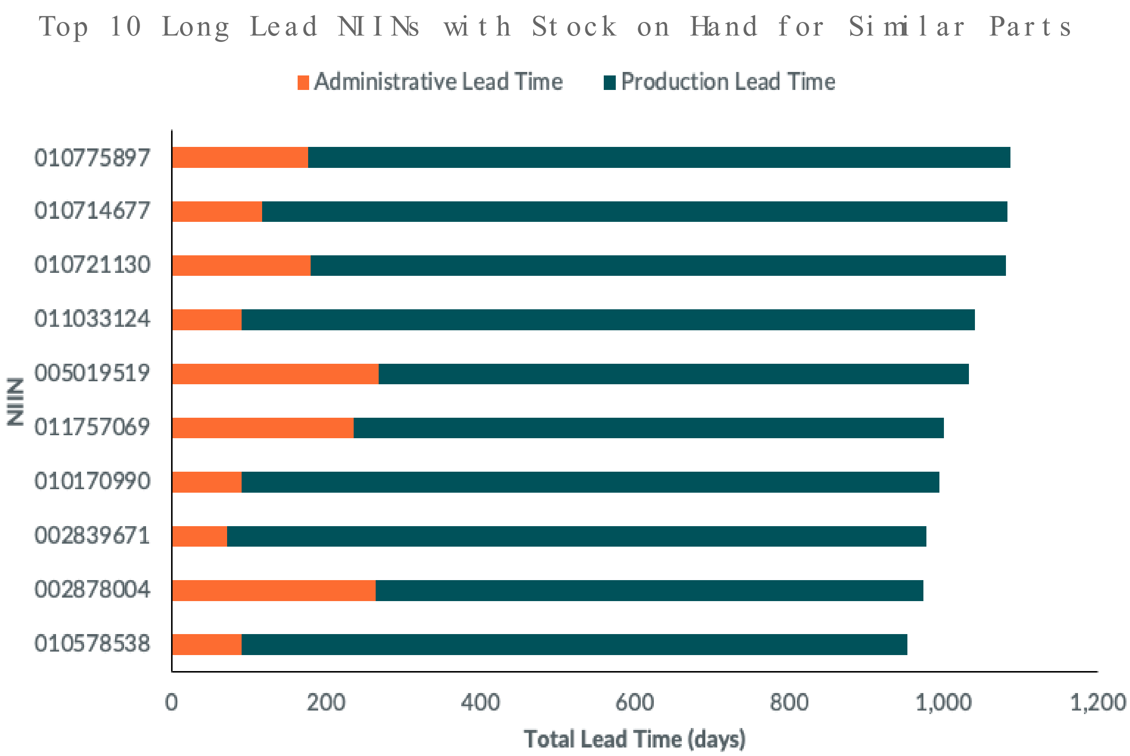

Figure 2. Top 10 Long Lead Ohio Class Submarine Parts With Highly Similar Parts With Stock on Hand

Figure 2 shows the breakdown of administrative lead time and production lead time of these top Ohio Class Submarine parts. All of these parts have multi-year lead times and could possibly cause schedule delays. The LLM outputs a number of similar parts for each of the NIINs shown in Figure 2, which can be analyzed further. This study focuses on highlighting one of these parts for in-depth analysis.

NIIN 005019519 is an Annular Ball Bearing, which is part of an auxiliary system on the Ohio Class Submarine. With a lead time of over 1,000 days, if this part is not available when it is needed, it could severely impact shipyard schedules.

Table 1. Top Similar NIINs for Annular Ball Bearing (NIIN 005019519)

Similarity Score	Similar NIIN	Similar NIIN Stock on Hand
0.987	000039270	62
0.976	006138004	13
0.983	001426059	39
0.976	010800812	15

During the detailed, manual evaluation, 18 unique technical characteristics associated with this part were compared across all parts within Govini's NSKG to identify similar parts. This detailed comparison can be seen in Appendix B. Table 1 shows the top similar NIINs for this part, which also have stock on hand. This short list can then be provided to engineers to confirm that one of these similar parts can be used in place of the original part. The stock on hand can then be utilized to quickly solve the part availability issue.

In this study, AI/ML processes were able to seamlessly analyze the 123,564 unique parts in the Ohio Class Submarine, identifying risk factors including long part times, low stock on hand, and lack of alternates. Ultimately, the LLM identified potential alternate parts to mitigate high risks of causing operational disruption.

Implications for the Navy

With the ability to quickly identify alternative parts, the U.S. Navy can more effectively maintain shipyard availability schedules and overall fleet readiness. Leveraging AI and ML to analyze large data sets at scale will expedite a previously manual process. Tactically, utilizing these technologies will save the Navy time and man-hours, freeing up man-hour time to focus on other priorities. Strategically, faster discovery of alternate parts can mitigate overall schedule impacts. In the future, the U.S. Navy can leverage this methodology to proactively identify alternative parts for parts that are long lead critical path items. This can be leveraged during the availability planning process, instead of only after a part availability issue has been identified.

Next Steps

In order to further refine the results from this study, the team would conduct initial discussions with U.S. Navy leadership and technical subject matter experts to better understand critical parts technical characteristics. This will allow for further refinement of the LLM to ensure the model takes into account the characteristics that engineers deem more critical to speed up evaluation. Additional part data will also be ingested into the NSKG to broaden the scope of parts being evaluated as similar parts. The methodology used in this study could be applied to another baseline set of parts such as SPY-6, DDG-51, or Columbia Class Submarines as well. Expanded utilization of additional data within the NSKG would make it possible to further filter down the stock on hand based on location to determine if the stock on hand is near the shipyard where the Submarine is undergoing its availability to even further speed up access of the part to the Submarine.

Appendix A. Ohio Class Submarine Weapon System Designator Codes

List of all 25 Weapon System Designator Codes (WSDC) utilized to generate baseline dataset for this analysis. WSDCs are predefined groupings of parts and defined by DLA.

Weapon System Designator Code (WSDC)	Weapon System Name
23N	Ohio Class Submarine
86N	BQQ-6
A3N	Sonar Acoustic Missianeous
DQN	Submarine Vertical Launch System
MYN	BPS-15/16
MZN	BQQ-10
RHN	Submarine Data Processing System

SCN	SLMM Mine(s) Countermeasures
SJN	Towed Array Handling Equipment
SMN	Submarine Auxiliary System
SRN	Submarine Outfittings & Furnishings
TXN	Submarine Electrolytic Oxygen System
TYN	Submarine Interior Communication Systems
WCN	Submarine Atmosphere Control & Compressed Air/Gas System
WFN	Submarine Auxiliary & Miscellaneous Systems
WHN	Submarine Armament & Fire Control Systems
WJN	Submarine Miscellaneous Sonar & ADP Systems
WKN	Submarine Surveillance Systems
WLN	Submarine Acoustic Sonar Systems
WMN	Submarine High Pressure Air System
WPN	Submarine Atmosphere Analyzing System
WRN	Submarine Co/H2 Burner & Co2 Removal System
WSN	Submarine Ventilation
WTN	Submarine Gas Management Systems
WWN	Submarine Hydraulic Systems

Appendix B. Similar Parts Comparison for NIIN 005019519

Detailed breakdown of some of the relevant part identifying information compared to generate similarity score during this study.

NIIN	005019519	000039270	001426059	006138004	010800812
Item Name	BEARING,BALL,ANNULAR	BEARING,BALL,ANNULAR	BEARING,BALL,ANNULAR	BEARING,BALL,ANNULAR	BEARING,BALL,ANNULAR
Similarity Score		0.98749	0.982939	0.976174	0.975602
Stock On Hand		62	39.0	13.0	15.0
Bearing Seal Type	Contact	Contact	Contact	Contact	Contact
Bore Diameter	10.0 Millimeters Nominal	4.00 Millimeters Nominal	1.2500 Inches Nominal	60.0 Millimeters Nominal	30.00 Millimeters Nominal

Bore Shape	Straight	Straight	Straight	Straight	Straight
Internal Fit-Up Designation	Loose	Standard	Standard	Standard	Loose
Load Direction	Radial	Radial	Radial	Radial	Radial
Lubrication Material	Grease	Grease	Grease	Grease	Grease
Lubrication Material Document And Classification	Mil-G-81322 Mil Spec Single Material Response	Mil-G-81322 Mil Spec Single Material Response	Dod-G-24508 Mil Spec Single Material Response	Dod-G-24508 Mil Spec Single Material Response	Mil-G-81322 Mil Spec Single Material Response
Material	Steel Comp E52100 Outer Ring,Steel Comp E52100 Inner Ring,Steel Comp E52100 Ball,Steel Comp E52100 Retainer	Steel Comp E52100 Outer Ring,Rubber Synthetic Seal,Steel Comp E52100 Ball,Steel Comp E52100 Retainer,Steel Comp E52100 Inner Ring	Steel Comp E52100 Ball,Steel Comp E52100 Outer Ring,Steel Comp E52100 Inner Ring,Steel Comp E52100 Retainer,Rubber Synthetic Seal	Steel Retainer,Rubber Synthetic Seal,Steel Comp E52100 Ball,Steel Comp E52100 Outer Ring,Steel Comp E52100 Inner Ring	Steel Comp E52100 Inner Ring,Steel Comp E52100 Outer Ring,Rubber Synthetic Seal,Steel Comp E52100 Ball,Steel Retainer
Material Document And Classification	66 Fed Std Single Material Response Ball,66 Fed Std Single Material Response Outer Ring,66 Fed Std Single Material Response Retainer,66 Fed Std Single Material Response Inner Ring	66 Fed Std Single Material Response Outer Ring,66 Fed Std Single Material Response Inner Ring,66 Fed Std Single Material Response Ball,66 Fed Std Single Material Response Retainer	66 Fed Std Single Material Response Ball,66 Fed Std Single Material Response Inner Ring,66 Fed Std Single Material Response Outer Ring,66 Fed Std Single Material Response Retainer	66 Fed Std Single Material Response Outer Ring,66 Fed Std Single Material Response Inner Ring,66 Fed Std Single Material Response Ball	66 Fed Std Single Material Response Inner Ring,66 Fed Std Single Material Response Ball,66 Fed Std Single Material Response Outer Ring
Overall Outside Diameter	30.0 Millimeters Nominal	16.00 Millimeters Nominal	2.2500 Inches Nominal	130.0 Millimeters Nominal	62.00 Millimeters Nominal
Overall Width	9.0 Millimeters Nominal	5.0 Millimeters Nominal	0.5000 Inches Nominal	31.0 Millimeters Nominal	16.00 Millimeters Nominal

Retainer Fabrication Method	Pressed	Pressed	Pressed	Stamped	Pressed
Seal Quantity	2	2	2	1	2
Special Features	Ty 111 Cl 8 Gr 00	Nan	Nan	Nan	Nan
Standard Tolerance Designation	Abec No.1	Abec No.1	Abec No.1	Abec No.1	Abec No.1
Style Designator	Non-Loading Groove, Non-Separable	Non-Loading Groove, Non-Separable	Non-Loading Groove, Non-Separable	Non-Loading Groove, Non-Separable	Non-Loading Groove, Non-Separable
Surface Finish	Ground	Ground	Ground	Ground	Ground

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