Applications of Machine Learning to Smart Provisioning and Predictive Sparing

Dawson Miller

Machine Learning Engineer

Eric Schneider

Principal Investigator

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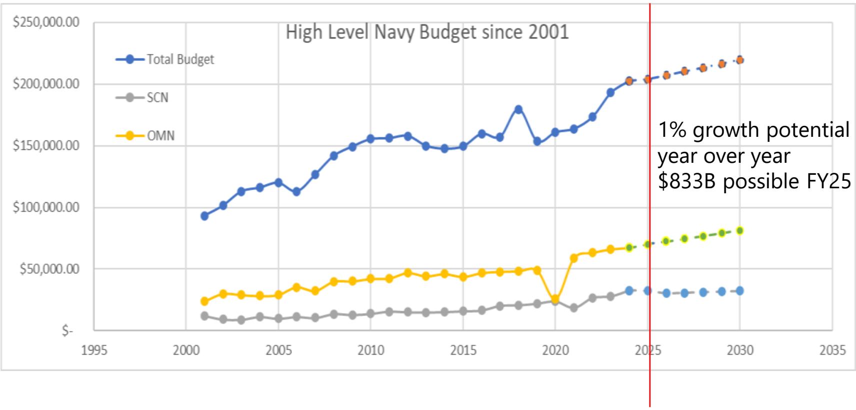
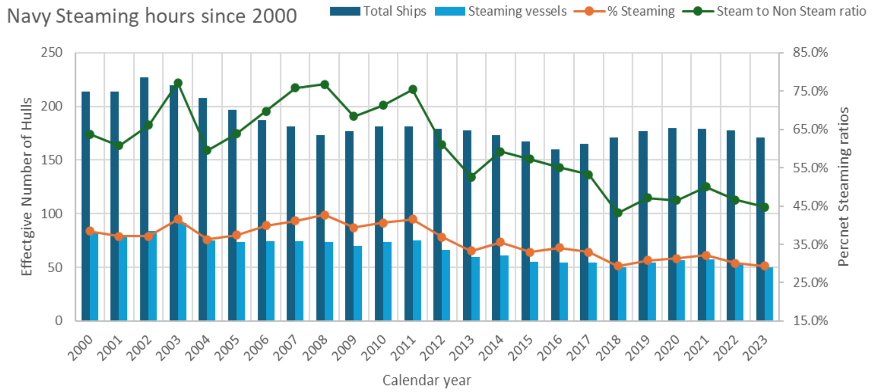
For the best of reasons

Motivation

Meeting 80% combat surge ready ships by 2027 with a lagging shipbuilding programs, budget constraints and hampered global supply chain – the **readiness** of ships is even more **paramount**



Davidson Window (2027)



Potential for 20 ships to leave inventory by 2030 with only 5-6 planned replacements

Reduced, Flat Budgets

– Material, resources, and people impacted by shortfalls

Global Supply Chain

Increased OPTEMPO & Global Tensions

– Davidson window

How do we get more ships?

Readiness

– Personnel, Equipment, & Training

Sustainment

– Maintenance & Modernization

Approach

Digital Engineering and Machine Learning (ML) that enable intelligent automation and bolster readiness and sustainment

Upstream

Delivery of Fleet

- Build configuration baseline for a ship's service life
- Allowance Parts List (APL), configuration files, technical manuals, engineering operational sequencing system (EOSS), and planned maintenance system (PMS)
- Increased automation
- Quality improvements
- De-duplication in configuration records (anomaly removal)

Mid & Downstream

Sustainment of Fleet

- Changes to Integrated Logistics Support (ILS) and technical documents
- Modernization scheduling
- Sustainment of supply and maintenance needs
- Anomaly detection
- Implement changes and feedback to upstream

Digital Engineering & ML: Overview of Accomplishments

Upstream

Automating Configuration

- Prototyped ML pipeline to analyze part requirements across ships

Predictive Sparing

- Prototype for projecting part requirements during ship's deployment
- Automated APL / Demand Matrix for discovering parts to configuration mismatches

Mid & Downstream

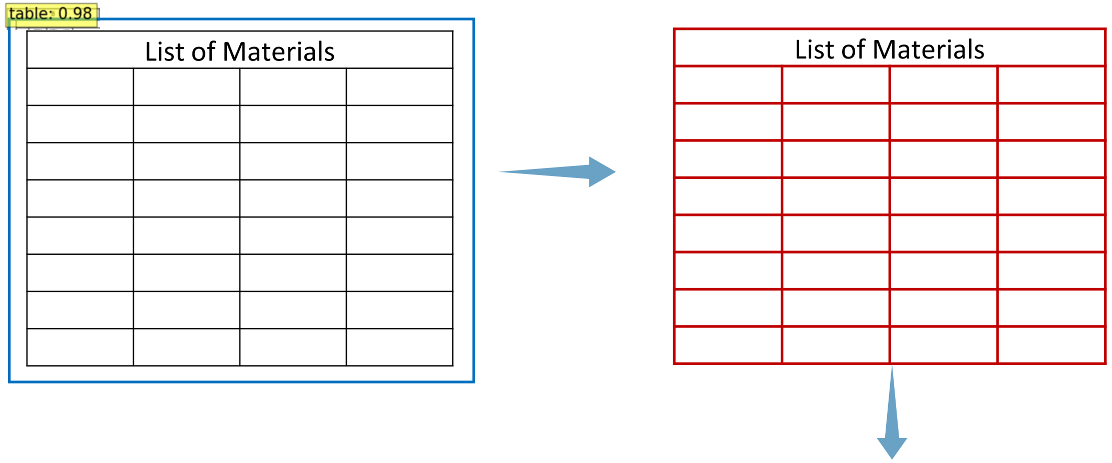
Predictive Maintenance

- Anomaly Detection
- Categorize parts according to historical patterns of demand and supply

Upstream: Analyzing Part Requirements

Process Overview — Original PDF

- Detect **List of Materials** (LoM) table on page using pre-trained, state-of-the-art neural network table detection model
- Infer structure of table using classical computer vision
- Read text within each cell of the table and output to excel
- Usually, text is extracted perfectly



Part	Metadata
Sample part 1	-
Sample part 2	-

Process Overview — Scanned Copies

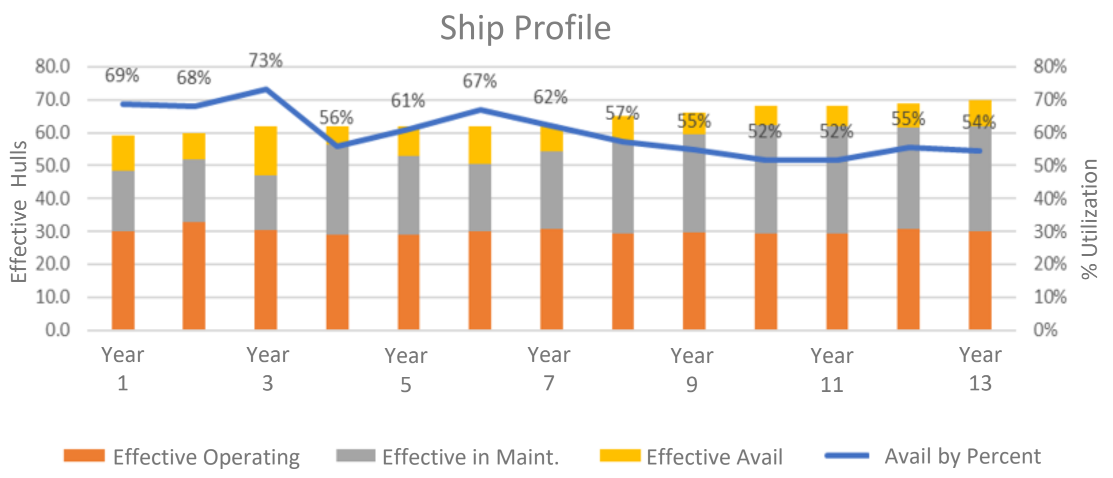
- Detect LoM table on page using pre-trained, state-of-the-art neural network table detection model
  - Not always possible
    - Sometimes table is not detected
- Infer structure of table using computer vision
  - There is some additional noise relative to having the original PDF
- Use pre-trained OCR model to extract text
- Use the bounding boxes to associate extracted text with inferred table cells
- In general, much noisier than having the original

List of Materials	
Column 1	Column2
#####	#####
#####	#####
#####	#####
#####	#####
#####	#####
#####	#####
#####	#####

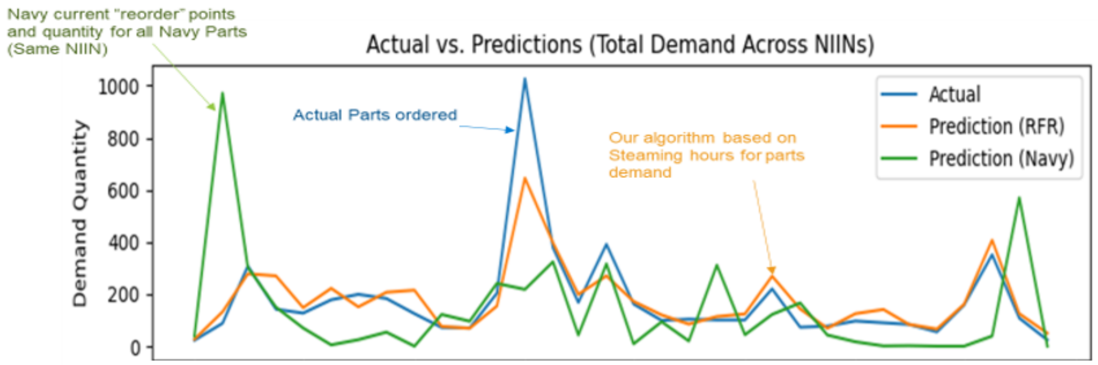
Upstream: Predictive Sparing

Predictive Sparing – what will need to happen to supply parts to get to **80% surge ready combatants** – can we predict part usage by operation for targeting the 120-day supply?

By steaming days and maintenance days for given ship class only



System part demand for given ship class: Is it possible to model the demand for parts using operating and projected hours?



ORANGE is our prediction model based on steaming hours
BLUE is actual parts demand
GREEN is current order / restocking points by Navy – calendar based

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Mid & Downstream: Predictive Maintenance

Predicting a maintenance need can eliminate growth work, eliminate incorrect repairs and save parts, leading to cost reduction while improving uptime and on-time delivery

- Abundance of sensor data
- Apply ML to continuously monitor and analyze ship's operations
- Burden reduction
- Support transition from time-based to condition-based maintenance

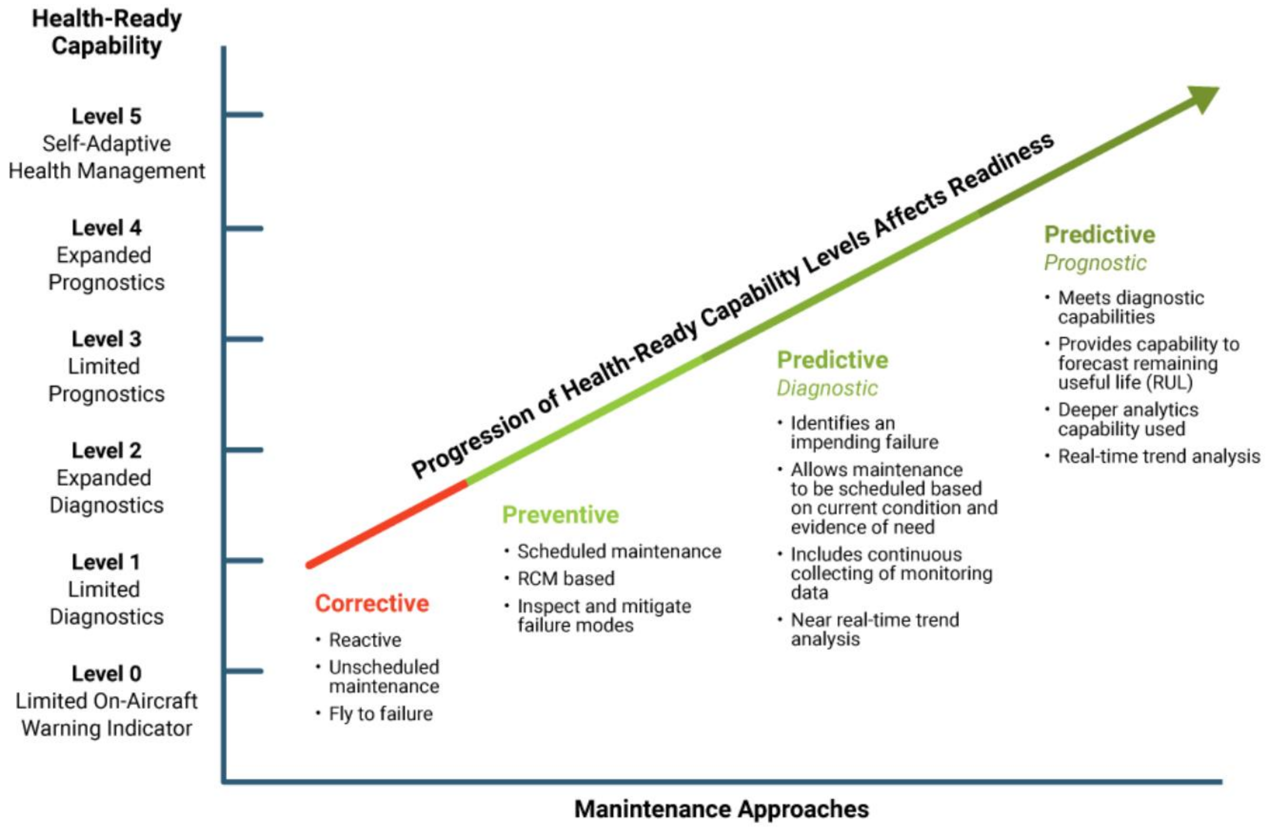

Figure 1. The U.S. Navy is moving towards predictive maintenance procedures which are prognostic in nature. (Source: Brief to Deputy Assistant Secretary of the Navy on Condition Based Maintenance.)

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Predictive Maintenance via Anomaly Detection

Types of anomalies

Point, subsequence, shift, trend, and variance

Prototype with Synthetic Data

- Ground truth is known
- GAN for generating synthetic data
- Inject anomalies with Anomaly Generator on Time Series (AGOTS) library

Methods

- Clustering
  - K-means, DBSCAN
- Predictive
  - ARIMA, LSTM, Autoencoders, Scalable Unsupervised Outlier Detection (SUOD)

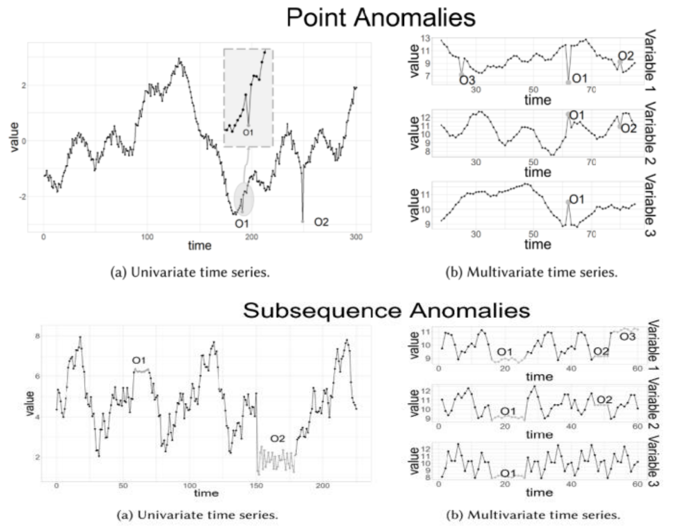

Figure 2. Point and subsequence anomalies for univariate or multivariate time series.[1]

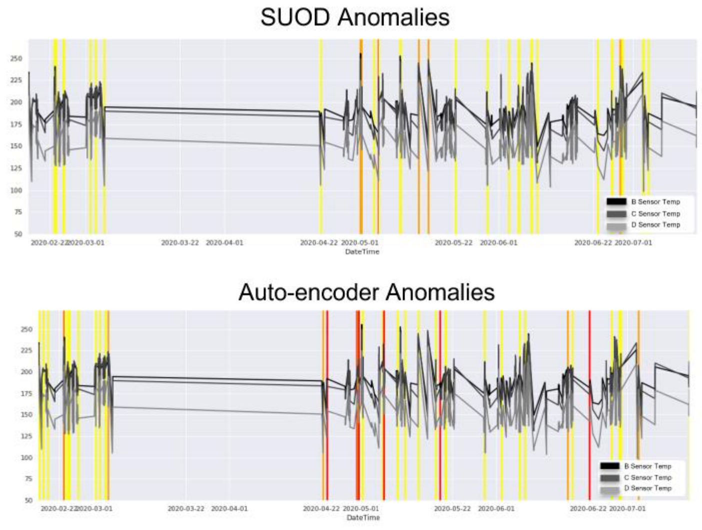

Figure 5. Examples of anomalies detected by SUOD and autoencoder-based anomaly detection methods

Downstream: Focus on Problem Parts

Utilize order history to identify problem parts across ship lifecycles, reducing complexity of sparing and on-time delivery

- Identify the problem parts based on part order statistics
- Bucket parts according to a ship's cycle (deploy, work up, maintenance)
  - Can we predict order trends on a per-part basis?
  - On-time delivery
- Inform upstream:
  - Improve sparing
  - Combine with configuration for natural language applications that help determine the right parts

Total Parts (niins)	82,362
Total Part Orders	8,337,794
% of Parts per 80% of Orders	3.9%
% of Parts per 50% of Orders	0.4%

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Where We’re Headed

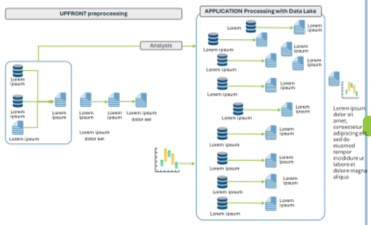
Using AI/ML and Digital Engineering, optimize the parts we have and parts we need, and enable actionable interactions between the upstream and downstream workflows

Ingest various unstructured data

Drawings
Engineering change
Tech Feeback
Remedy Feedback

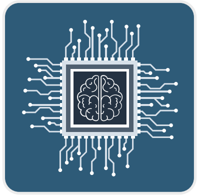
ILS Cert
Provisioning Technical data
APL
Configuration
SW configuration
PMS
OSS
maintenance requirements
test equipment
SISCAL
Training Requirements
Obselecnce

Create data “Lakehouse”



Prediction using

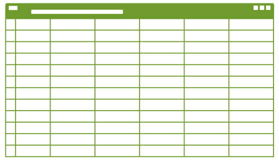
- Forecasting
- NLP
- Anomaly detection



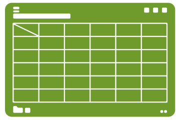
AI/ML

Outputs

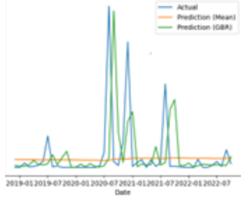
ILS certs



Configuration Validations for systems / by class



Ao / Maintenance Improvements



Spare Part Prediction Modeling based on steaming days

- ☐ More accurate configuration
- ☐ Target need for maintenance when combined with Failure prediction (CBM)
- ☐ Prediction modeling and stock on hand modeling

Measure	Equation
Inherent Availability	$A_i = \frac{MTBF}{MTBF + MTTR}$
Operational Availability	$A_o = \frac{MTBM}{MTBM + MDT}$

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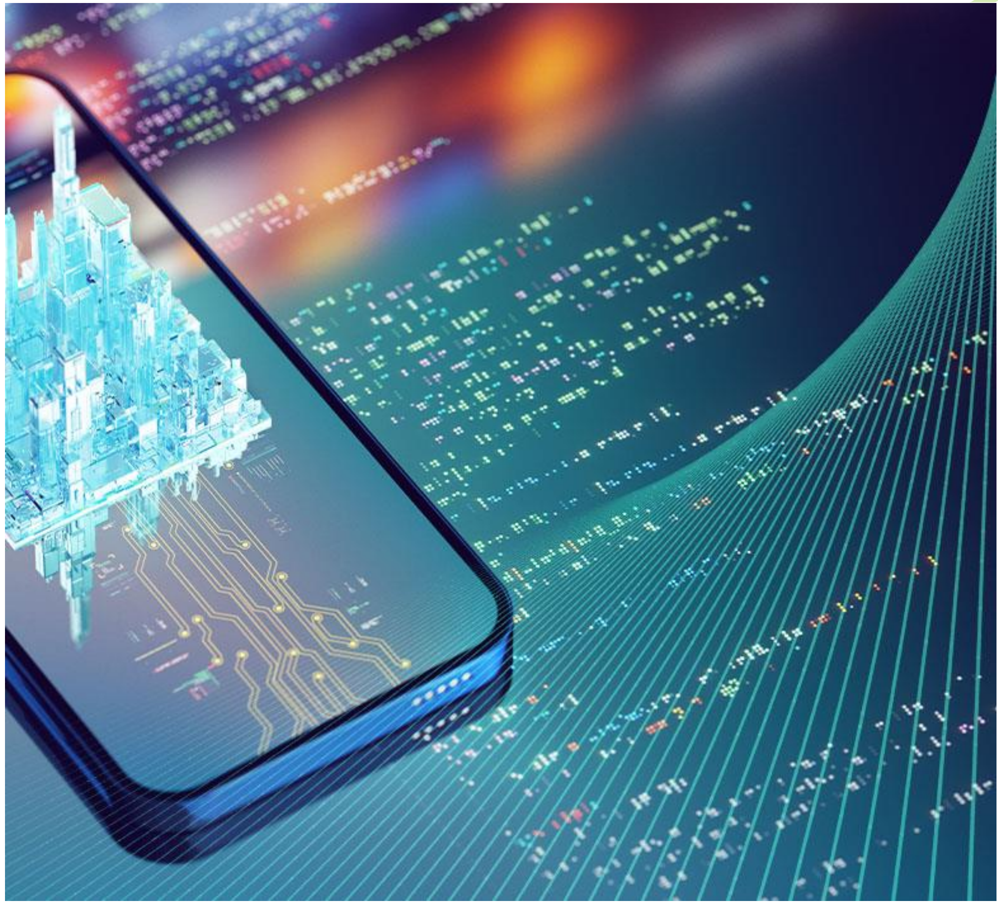
Thank You

Dawson Miller
Machine Learning Engineer
dawson.miller@noblis.org

Eric Schneider
Principal Investigator
eric.schneider@noblismsd.com



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