NSRP RA Project 2024-01

Building "Failure Data and Prediction Models" for **Ship Construction and Sustainment Support**

(Focus on Artificial Intelligence Model Development)
Project Final Technology Transfer Presentation

NSRP Business Technologies Panel Meeting
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Project Participants

NSRP RA Project 2024-01

- Newport News Shipbuilding (HII-NNS)
- Ingalls Shipbuilding (HII-Ingalls)

- NAVSEA 05Z with NSWC Philadelphia & USCG Surface Forces Logistics Center
- NOAA, MSC

Problem Statement

- Sustainment costs for ships continue to be a large and difficult to manage cost for the Navy and other services
- Considerable effort is being spent on sensing and measurement of parameters that may help identify and predict failures
- Opportunities remain to extract much more value from the amount of data already being collected

Challenges Affecting Navy Ships Availability	*Ticonderoga*-class cruiser (CG-47)	*Nimitz*-class aircraft carrier (CVN-68)	*Arleigh Burke*-class destroyer (DDG-51)	*Freedom*-class littoral combat ship (LCS-1)	*Independence*-class littoral combat ship (LCS-2)	*America*-class amphibious assault ship (LHA-6)	*Wasp*-class amphibious assault ship (LHD-1)	*San Antonio*-class amphibious transport dock (LPD-17)	*Whidbey Island*-class dock landing ship (LSD-41)	*Harpers Ferry*-class dock landing ship (LSD-49)
Service life longer than anticipated	●	●							●	●
Unexpected replacement of parts and repairs		●	●	●	●		●	●		●
Access to technical data		●								
Delays in depot maintenance	●	●	●	●	●	●	●	●	●	●
Delays in intermediate maintenance	●		●		●		●			
Shortage of trained maintenance personnel	●		●	●	●	●	●	●	●	●
Unscheduled maintenance	●	●	●	●	●	●	●	●		
Diminishing manufacturing sources	●	●	●		●		●			
Parts obsolescence	●	●	●	●	●		●	●		●
Parts shortages and delays	●	●	●	●	●		●	●	●	●

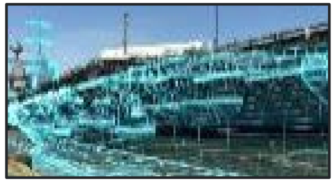
● Applicable maintenance issue

Source: GAO analysis of Navy information. | GAO-23-106673

Amphibious Assault Ships

Destroyers

Submarines



Aircraft Carriers

NSRP RA Project 2024-01 FINAL REPORT

1. **Provide a failure data readiness/quality assessment and develop a roadmap for government fleet owner/operators and shipyards to:**

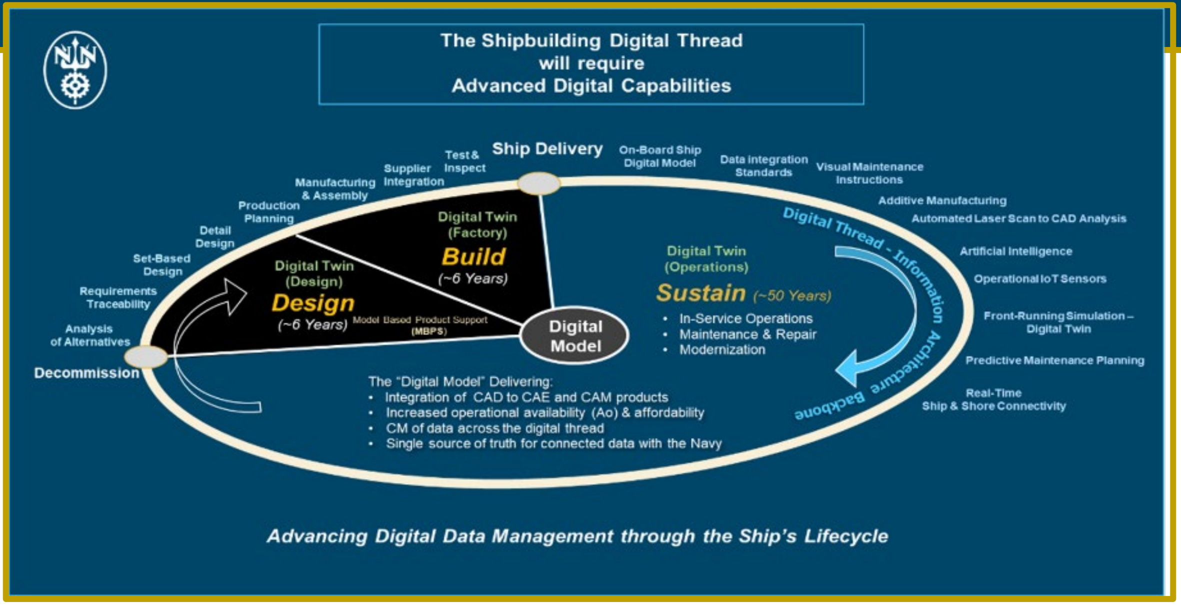
   (1) Optimize yard availabilities

   (2) Provide feedback to follow-on vessels using advanced data analytics of available ship condition

2. **Lay the foundation for increased use of advanced data analytics that:**

   (1) Reduce the cost and improve the predictability of scheduling for yard availability periods for ships

   (2) Reduce the total cost of ownership of ships produced and sustained by yards, especially due to unrecognized vulnerabilities and material conditions that lead to failures



What Do Artificial Intelligence-Based Machinery Analytics Provide?

Anomaly Detection

Insights to make data-driven operational & maintenance decisions *(active and pro-active)*

- Detect incipient issues (<u>prior to potential failure</u>) > reduce unplanned failures
- Identify target areas for closer monitoring
- Augment upcoming planned maintenance > condition based
- Plan for corrective action (when failures confirmed) > flexibility

Disposition

- Provide most likely and actionable IP
- Continuous program improvement
- Identify additional components or failure modes

RAMS (Reliability, Availability, Maintainability and Safety)

Insights for Planning & Optimization

- Understanding system reliability & trends
- Identify bad actors and/or systemic FMs
- Detect emergent reliability-related risks
- Perform vessel-to-vessel benchmarking
- Insights for ABS surveyors: inputs to PCM; targeted & focused
- Identify data quality issues
- Potential insights using CMMS data:
    - Parts and spares
    - Maintenance cycles
    - Vessel operations

Salient Features

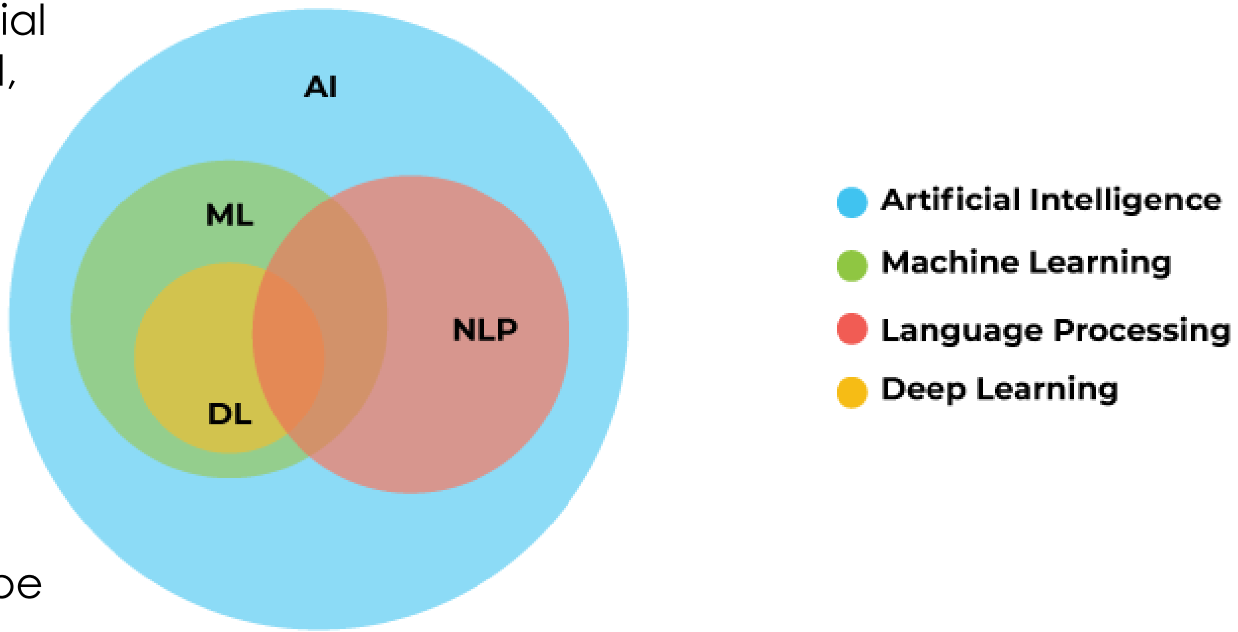
- Data-driven tools to <u>augment</u> customer's decision-making
- Insights to assist with planning, maintenance scoping and operational inputs
- Customer-ABS current processes undergo <u>***no***</u> change…only data-driven insights to support decision-making
- Perform continuous improvement in algorithms and data quality processes

AI Tools Used to Preprocess the Data: NLP

Natural Language Processing (NLP) is a field of artificial intelligence which enables computers to understand, interpret and generate language

Some Common Tasks:
- **Text Classification**
- Machine Translation
- **Named Entity Recognition**
- Summarization

Objectives:
- Ingest and prepare the data
- Determine processes by which key data will be extracted from text
- Explore data-driven insights into common failure modes for machinery
- Provide solutions and next steps to reduce downtime & improve reliability



Machine Learning	Deep Learning
Simple (regression, tree based)	Complex (neural net, transformer)
Interpretable	Black box
More preprocessing	More contextual understanding

Artificial Intelligence (AI) refers to computer systems that can perform complex tasks normally done by human-reasoning, decision making, creating, etc. AI algorithms are used to analyze large amounts of data and identify patterns and trends that can inform the design of more efficient and effective ships.

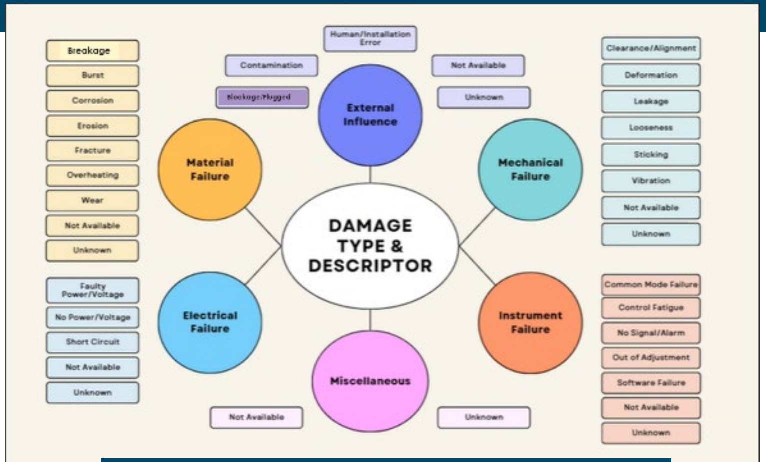
Accessing Data & Categorization

Open Architectural Retrieval System (OARS) – maintained by NAVSEA logistics center
(All fleet data from all hulls go into that database)

- DCACA Program (old term) Data collection, analysis and corrective actions
- FRACAS (New Term) = Failure reporting analysis and corrective actions
- We track by part number; systems could have multiple parts
- Each ship class has their own list of what are the mission-critical systems to track

OARS – Data Structure

Program Class	Period of Failure Tracking	Equipment & Failures Track	Failure Type	Report forms	Solution
Any Naval Ship	Latest 9 years, from delivery to operation	EVERYTHING	EVERYTHING	Database	We run a query and review the results

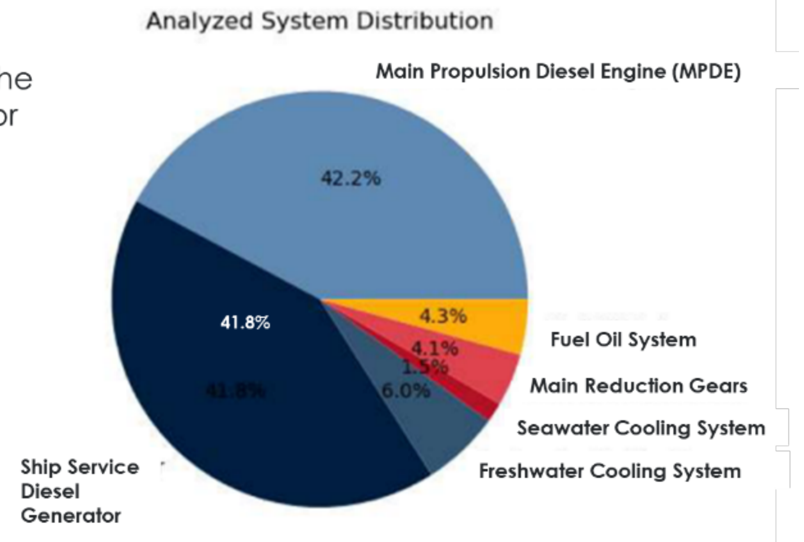


Damage Data Categorization

Representative Data Sets for Data Analytics Demonstration Cases

The data utilized in this analysis consists of multiple structured files (excel) sourced from the Navy's ESWBS system, with one file provided for each vessel system of interest:

1) Main propulsion diesel engine
2) Ship service diesel generator
3) Main reduction gears
4) Seawater cooling system
5) Freshwater cooling system
6) Fuel oil system



* ESWBS = Extended ship work breakdown structure

Training Data

Normalization & Feature Engineering

Where is our data coming from?

- Multiple sources that have been labeled by a Subject Matter Expert (SME)
- Supplemented with a few thousand rows of LPD-17 data

Which columns are we looking at when it comes to model training?

- We're focused on the text columns that SME uses for classification task

What systems are we looking at?

- Main propulsion diesel engine
- Ship service diesel generator
- Main reduction gears
- Seawater cooling system
- Freshwater cooling system
- Fuel oil system

SIMULATED DATA for Presentation

Job Summary	Description	Solution
1B MPDE LOP FASTENERS	DURING NORMAL OPERATION, S/F FOUND THAT NR 2, NR 3, & NR 4 LUBEOILPUMP FASTENERS WER MISSING 1 HOLD DOWN FASTENER EACH.	S/F RECOMMENDS ER04 ASSIST IN THE RECRETION OF 3 LUBE OIL PUMP FASTENERS.
JW EXP. TNK TLI OOC	DURING ROUTINE MAINTENANCE, SHIP'S FORCE DISCOVERED THAT THE JACKET WATER LEVEL INDICATION WAS FAULTY. UPON FURTHER INBESTIGATION, IT WAS DETRIMINED THAT THE LEVEL SWITCH WAS CORRODED AND IN NEED OF REPLACE.	SHIP'S FORCE WILL ORDER AND INSTALL NEW PARTS

Normalization:

- Misspellings
- Abbreviations/entity linking
  - OOC -> out of compliance
  - xfrmr -> transformer
  - ER04 -> engine room #4
- Spaces/NoSpaces
  - Mpdecrankcase -> MPDE crankcase

Feature Engineering:

- How can we make features as meaningful as possible?

  NAVSEA S6430-AE-TED-010

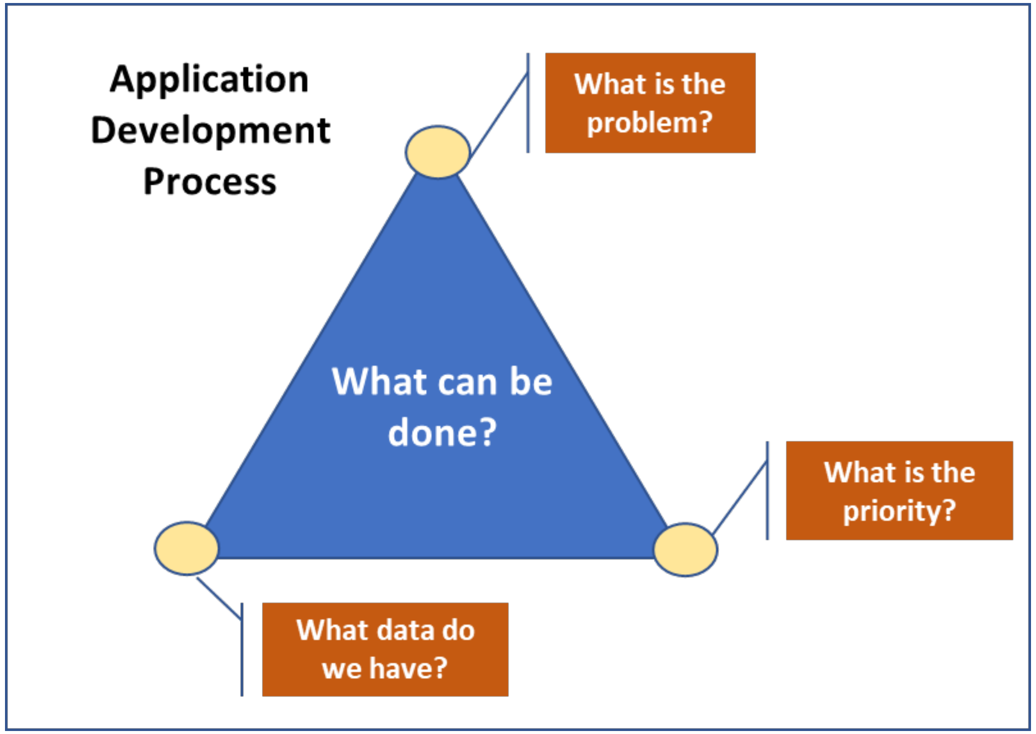
  NAVSEA HANDBOOK S9233-DL-HBK-010

Job Summary	Description	Solution
1B MPDE LUBE OIL FASTENERS	DURING NORMAL OPERATION, SHIP'S FORCE FOUND THAT LUBE OIL PUMP FASTENERS WERE MISSING 1 HOLD DOWN FASTENER EACH.	S/F RECOMMENDS ENGINE ROOM 4 ASSIST IN THE RECRETION OF 3 LUBE OIL PUMP FASTENERS.
JACKET WATER EXPANSION TANK TANK LEVEL INDICATOR OUT OF COMPLIANCE	DURING ROUTINE MAINTENANCE, SHIP'S FORCE DISCOVERED THAT THE JACKET WATER LEVEL INDICATION WAS FAULTY. UPON FURTHER INVESTIGATION, IT WAS DETERMINED THAT THE LEVEL SWITCH WAS CORRODED AND IN NEED OF REPLACE.	SHIP'S FORCE WILL ORDER AND INSTALL NEW PARTS

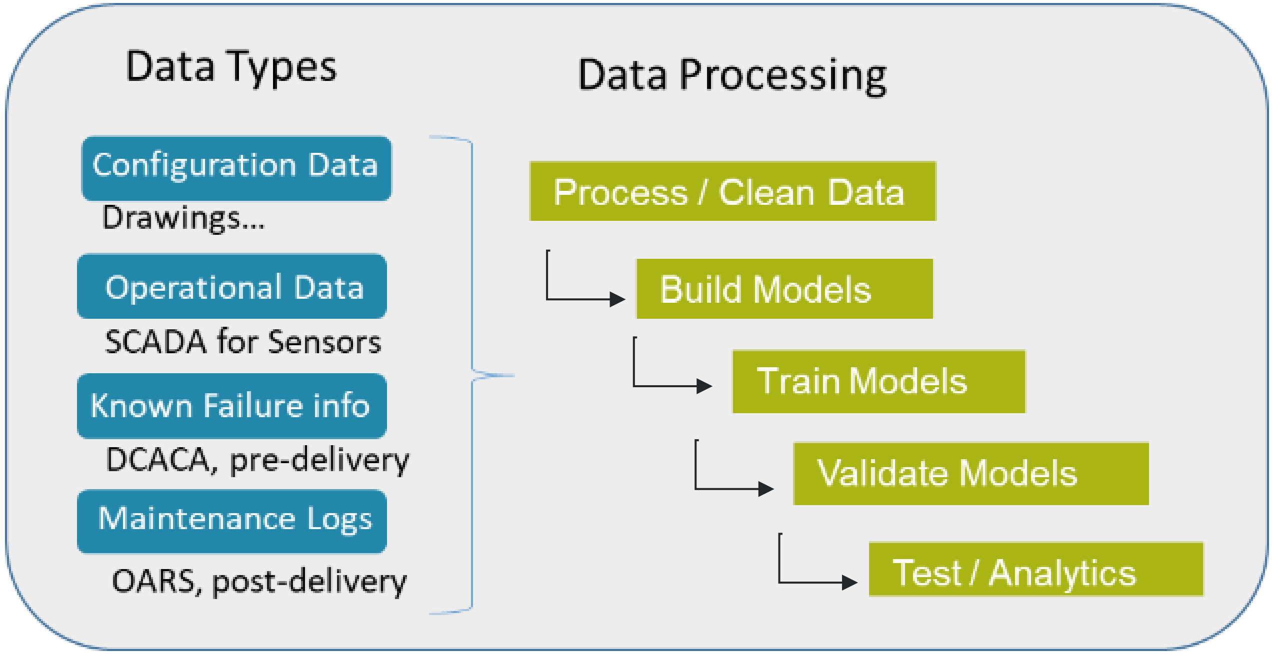
ABS Failure Data Processing "User Guide" (DELIVERABLE)

A key deliverable for this project is the **ABS User Guide**. This will provide guidance on the sequence of work (the *what to*) necessary to develop an AI architecture to support ship sustainment activities.

Primary steps in the User Guide will include:



Data Management Process



ABS Program "Roadmap" (DELIVERABLE)

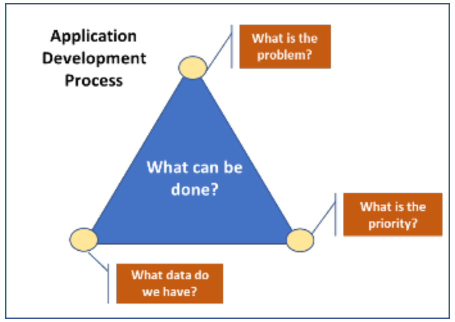
Identify Problem
(Develop Use-Cases)

Application Development
What can be done?

What is the problem?

What is the priority?

What data do we have?



Identify & Gather Data

Configuration Information

Operational Data
(SCADA sensors data)

Equipment, Yard Data
(DCACA data)

Maintenance Logs
(OARS)

Generating Value
(Ops, Maintenance, etc.)

Data Prep & Pre-Processing

Build models

Train/Validate Models

Test Models

Post-Processing

Key Insights
(Feedback to detail design and construction process)

1. Parts & System
2. Systemic issues affecting vessels to incorporate into present & future yard activities
3. Major damage types & damage descriptors affecting equipment in fleet vs specific vessels
4. Estimated reliability vs. expected reliability for major systems
5. Identify training needs: yard labor
6. Evaluate data types, sensors & process improvements to be planned for future construction
7. Improvements in maintenance (CMMS) systems to answer critical questions
8. Areas for potential process improvement

Decision Making & Creating Value

1. Incipient failure detection
2. Reliability benchmarking across fleet
3. Emergent risks for critical systems
4. Bad-actors: Unavailability risk

Final values to be determined during implementation

Expected Benefits

1. Inputs for yard availability planning
2. Informs processes for parts & design selection, affecting supply chain management
3. Potential inputs for operational decision-making

ABS Guidance on current NSRP effort

ABS

GUIDANCE ON

Leveraging Data Analytics to Optimize Vessel and Shipyard Availability

JUNE 2026

American Bureau of Shipping
Incorporated by Act of Legislature of
the State of New York 1862

ABS
1701 City Plaza Drive
Spring, TX 77389 USA

ABS developing a guidance on 'Leveraging Data Analytics to Optimize Vessel and Shipyard Availability'

Discusses topics related to critical technologies and methods used as part of this program

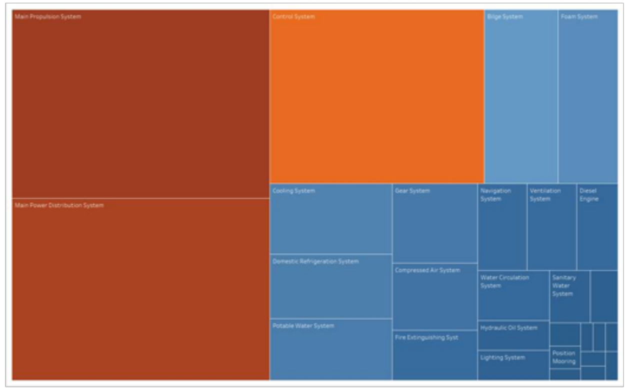
Will be made available post-internal review process

Estimating Reliability Metrics using actual CMMS data

Bad Actors

Quantify operational RAM risks

- Benchmark current reliability of major sub-systems.
- Identify emergent reliability risks
- Provide reliability trends over time
- Quantify the relative risk in reliability amongst multiple maintenance facilities

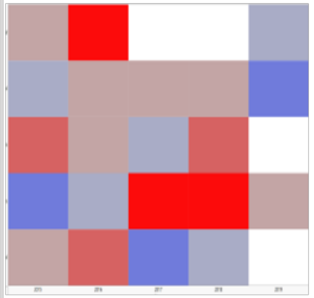


Quantify Asset to Component Level Risks

- Statistical & Risk models to benchmark baseline reliability risks
- Fleet wide risk assessment
- System to Component level models

People or Process or Product ?

- Identify main factors causing RAM risk
- Data improvement



Sensor-Based Anomaly Detection

Detecting anomalous signatures for proactive maintenance planning

Performance Analysis

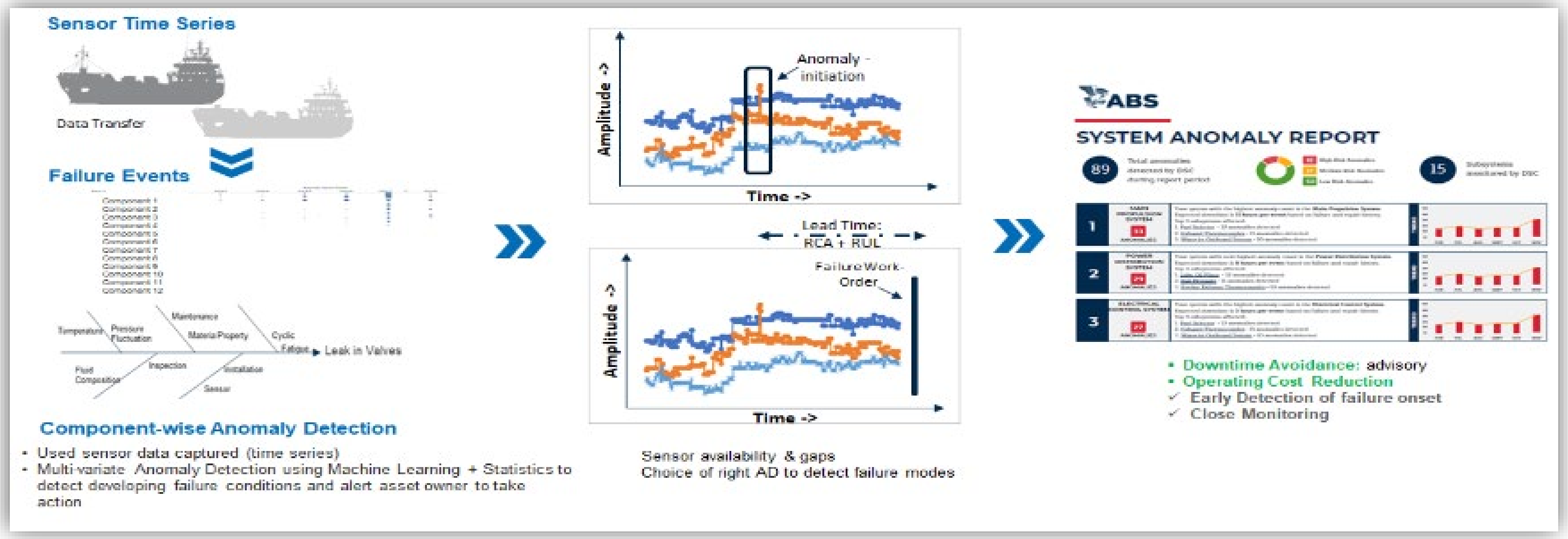
Detailed analysis of the machinery performance for an asset or a fleet of assets

Collect Additional Data

- Fusion of sensor, survey & customer data
- Signature analysis & pattern mining

Identify, Monitor and Predict Anomalies

Reoccurring reports & alerts of identified anomalies



Project Summary

- ✓ We have provided processes to unlock the power of failure/condition data sets through advanced analytics, including tools such as Artificial Intelligence (AI) and Machine Learning (ML), as well as more traditional reliability engineering techniques, by:
    1. Alignment of the many stakeholders engaged in the availability planning / execution process
    2. Providing the critical technical insights to identify and address early failures for planned and scheduled corrective action
    3. Providing a feedback loop to eliminate vulnerabilities during construction of subsequent ships in a vessel class
- ✓ We have provided a failure data readiness/quality assessment user guideto improve ship availability work identification process and accurately schedule to reduce unscheduled work and time-at-dock
- ✓ We will evaluate the AI OARS model for use on additional ship classes and integrate into our processes

Delivered: Failure Data & Prediction Models Roadmap posted to NSRP ATI site RA 2024-01

Delivered: Failure Data & Prediction Models User Guide posted to ABS site

Thank you for your attention

Discussion…

Building "Failure Data & Prediction Models" for Ship Construction & Sustainment Support