Autonomous Vessel Energy and Readiness Management

Final Report

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Acronyms and Abbreviations

Term	Definition
AI	Artificial Intelligence
Ao	Operational Availability
APS	Autonomous Planning and Scheduling
CBM	Condition-Based Maintenance
CBM+	Condition-Based Maintenance Plus
CFM	Critical Failure Mode
CTMA	Commercial Technologies for Maintenance Activities
DAQ	Data Acquisition System
DDG-1000	Zumwalt Class Guided Missile Destroyer
DOD	Department of Defense
EPRI	Electric Power Research Institute
ESA	Electrical Signature Analysis
FM	Failure Mode
FMECA	Failure Modes, Effects and Criticality Analysis
FOQM	Fuel Oil Quality Monitor
FRP	Full Rate Production
HM&E	Hull, Mechanical, and Electrical
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
LOQM	Lube Oil Quality Monitor
LRU	Line Replaceable Unit
MASS	Maritime Autonomous Surface Ships
MCCS	Machinery Centralized Control System
MIP	Maintenance Index Page
ML	Machine Learning
MPE	Main Propulsion Engine
MRC	Maintenance Requirement Card
MRSS	Mission Readiness Support System
MTBF	Mean-Time-Between-Failure
MTTR	Mean-Time-to-Repair
MUSV	Medium Unmanned Surface Vessel

NCMS	National Center for Manufacturing Sciences
O&S	Operations and Support
ODASD-MR	Office of the Deputy Assistant Secretary of Defense, Materiel Readiness
OEM	Original Equipment Manufacturer
PHM	Proportional Hazard Model
PreMA	Predictive Machinery Analyzer
RCM	Reliability Centered Maintenance
RE-CBM+	Reliability Engineering-Condition-Based Maintenance Plus
RUL	Remaining Useful Life
SBIR	Small Business Innovation Research
SSDG	Ship's Service Diesel Generator
SURFDEVRON1	Surface Development Squadron One
UNACORN	Universal Naval AI CORe eNvironment
U.S.	United States
USN	United States Navy
USV	Unmanned Surface Vessel

Units of Measure

kW	kilowatt(s)
V	Volt(s)
HZ	Hertz
mm	millimeters
gpm	gallons per minute
psi	pounds per square inch
rpm	revolutions per minute
HP	Horsepower

1. Executive Summary

Energy intensity must be reduced, and readiness increased in all aspects of commercial and public enterprise. Effective monitoring and analytics allowing prediction of equipment health will enable convenient scheduling of equipment maintenance and allow cost-effective supply chains avoiding interruptions in production or the need for expensive expedited delivery. Timely knowledge about operational and logistics requirements can minimize energy consumption and allow pro-active parts delivery for maintenance and sustainment of ready, efficient, and effective industrial and public sector transportation and manufacturing infrastructure. Current maintenance and sustainment costs are too high, and readiness is too low across the board. New data-driven, artificial intelligence/ machine learning (AI/ML) technologies implemented in an effective decision support ecosystem offer the promise of increasing readiness of platforms at reduced operations and support (O&S) cost.

The intent of this project was to develop a solution for major business functions applicable to commercial and public business today which are:

- Continuous management of asset energy and life consumption in commercial and public infrastructure.
- Early definition of failures in mechanical and electrical systems and resulting impact to production.
- Pro-active ordering of replacement parts to quickly restore systems to full performance.

Readiness issues driven by maintenance and sustainment plague all commercial enterprises. Reduction in energy consumption across all enterprises is critical to combating climate change and transition to a green environment. These challenges can only be met by increased visibility into the inner workings of equipment used in production, transportation, and defense. The U.S. Navy is facing extreme challenges in readiness and cost of maintenance and sustainment and must develop a feasible solution to these issues. The U.S. Navy will demonstrate to the public what solutions are possible. As such, this project utilized U.S. Navy infrastructure as a surrogate for an eventual industry solution that satisfy an important public need. Efforts focused on issues specific to the Sea Hunter Medium Unmanned Surface Vessel (MUSV). The results are expected to be easily transferable to commercial industry, positively impacting delivery of products to the public.

Funding was secured for the collaborative initiative through the National Center for Manufacturing Sciences (NCMS) Commercial Technologies for Maintenance Activities (CTMA) Program and the Office of the Deputy Assistant Secretary of Defense, Materiel Readiness (ODASD-MR).

1.1 Problem/Proposed Solution

Realized energy efficiency and equipment reliability through extant maintenance processes is insufficient for competitive industrial operations in all manufacturing and transportation sectors. Time directed maintenance results in over or under-maintained equipment, heavy labor investment, and too-frequent interruptions due to unanticipated failure. Lack of adequate monitoring and analytics of energy efficiency and actual equipment life consumed prevent the enterprise from effectively managing maintenance and sustainment of their equipment and processes. An analysis based on rigorous reliability engineering analysis identifying critical faults and necessary sensors provides the basis for implementation of an effective AI/ML-based energy and readiness management system that can significantly improve system reliability and energy efficiency at reduced cost can improve commercial sector competitiveness.

The Navy suffers from a situation where ships are not as available as they need to be, and expenditures associated with maintenance and sustainment are untenably high. The challenge is recognized at the highest levels and substantial investment has been made for decades to improve the situation through Condition-Based Maintenance Plus (CBM+) – an approach of maintaining equipment only when quantitative measures indicate that it is worth doing – which has been under development for several decades. Recent advances in technology, especially AI/ML and Edge Computing have the opportunity to change the calculus. A commercially developed CBM+ application (from U.S. Navy Small Business Innovation Research (USN SBIR) seed funding) is a part of the acquisition of the new CONSTELLATION Frigate. Called the Mission Readiness Support System (MRSS), it was conceived and specified under the Zumwalt Class Guided Missile Destroyer (DDG-1000) program, but budget constraints prevented full implementation on the ship, which subsequently resulted in over-burdened sailors and inadequate readiness at extreme cost.

Autonomous vessels planned for extremely long mission times (months) without people on board to tend to the equipment exacerbate the problem. Built from standard commercially available hull, mechanical, and electrical (HM&E) equipment, these platforms will be unable to complete their assigned missions. Surface Development Squadron One (SURFDEVRON1), the operators of the Sea Hunter/Sea Hawk platforms, identified an interest in “using data and AI/ML to realize CBM+”. That interest resulted in the Autonomous Vessel Energy and Readiness Management project described herein.

The solution proposed was to implement the MRSS, which is being developed on CONSTELLATION, on the Sea Hunter, and to evaluate the ways that it can be used to inform an autonomous vessel and ensure operational availability (Ao) during critical mission segments. Implementing an edge-based ship system analytics on an autonomous vessel with no underway manning is equally useful for even manned ship applications. If people are not needed for maintenance and sustainment activities over long periods of operation at sea, the benefits of reduced manhours applied to unneeded maintenance accrue to both military as well as commercial operations where the crew’s efforts can be applied to more meaningful tasks than equipment maintenance and associated paperwork drudgery. Monitoring, reporting, mitigating, planning, and resource scheduling will all be automated and not require (but allow) human intervention.

The unmanned maritime platforms under development combat the threats of today as well as those of coming decades. Implementation of the MRSS on MUSV (Sea Hunter/Sea Hawk) will inform the specifications and design of all unmanned surface vessel (USV) types. Experience gained also mitigates risks for the MRSS on the FFG-62 Class. It also supports application to other classes, especially other unmanned platforms. Successful completion of this work resulted in demonstrating that increased reliability, improved energy efficiency, and increased mission readiness facilitating the envisioned long (30, 60, 90, 120-day) mission times of the unmanned surface platforms is achievable by implementation of the MRSS on Unmanned Maritime Systems. This initiative provided new functionality that could be used by the operational forces, increasing productivity, and providing a streamlined process for all Forces to utilize. Furthermore, the positive results achieved from numerous aspects of this initiative can be leveraged toward public maintenance and sustainment business processes.

1.2 Tasks

As the industry participant, The DEI Group, executed the project in support of the Unmanned Maritime Systems Program Office (PMS-406) from December 2022 to September 2023 with the following tasks performed:

1. Conducted CBM+ engineering on Sea Hunter and identified sensor gaps for readiness and energy management on:
   - Main Propulsion
   - Power Generation
   - Fuel System/Seawater Service System
2. Established accounts and familiarity with open AI/ML data repository and ecosystem and accessed the available Sea Hunter data.
3. Designed implementation to address sensor gaps to realize readiness and energy management.
4. Developed and implemented a Predictive Machinery Analyzer (PreMA) software configuration using Power Generation system to demonstrate the functionality and capabilities of the predictive analytics.

1.3 Results

Reliability Engineering-Condition-Based Maintenance (RE-CBM+) Analysis

The engineering analysis performed during the project was to support the development and implementation of a revised maintenance strategy for achieving high mission reliability. The process applied Reliability Engineering principles for supporting the implementation of CBM+ approach to improve the readiness management of all equipment on the Sea Hunter using the MRSS technology. The engineering analysis established what was needed to implement an advanced CBM platform which was a step towards a highly automated autonomous vessel managing equipment line-up based on predicted mission risk. Figure 1 shows the results of the CBM+ engineering analysis for all the systems that identified the number of failure modes (FMs), the number of critical FMs, and the number of FMs that could be monitored using advance predictive analytics.

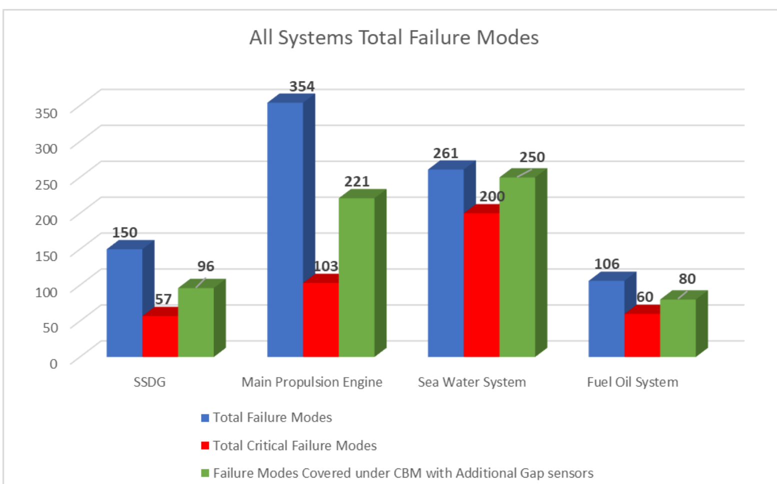

Figure 1. Total Failure Modes

To be able to monitor all FMs seen in Figure 1, a Sensor Gap analysis per system was performed and the results are shown in Figure 2 for all the systems. The Sensor Gap analysis was performed using the following process:

1. Map each FM to appropriate features to be used for health assessment.
2. Map each feature of interest to sensors required to be used.
3. Map each stress event profile to sensors required to be used.
4. Identify appropriate Tasks against FMs, with their associated threshold-based triggers.

Continuous awareness through monitoring to the component FM level and application of AI/ML analytics to identify mechanical distress that negatively impacts energy consumption and eventual failure holds the promise of substantial energy savings by avoiding wasted energy from mal-operating equipment and by optimizing machinery alignment for energy savings. It is important to note that "autonomous" and "unmanned" are not equivalent terms. A vessel may be unmanned but not autonomous, for example, if it is remotely controlled. The International Maritime Organization's "four degrees of autonomy"[1] framework reflects this distinction where a "Degree Three" ship is remotely controlled from another location with no seafarers onboard; whereas a "Degree Four" ship is fully autonomous and "the operating system of the ship is able to make decisions and determine actions by itself."

For Sea Hunter, this project highlighted the lack of sensors, as seen in Figure 3, to allow Sea Hunter to become a fully autonomous ship. A fully autonomous ship means that the operating system of the ship can make decisions and determine actions by itself. But to be able to do that, they must be equipped with a range of advanced technologies, such as right sensors, autonomy system connected to the machinery control system, navigation systems, and AI to provide for reasoning. Autonomous ships rely on sensors to provide real-time information about the ship's environment, such as its location, speed, and direction but also information about equipment current and future reliability risks. Only using these technologies will enable them to make decisions and operate safely and efficiently. As can be seen from Figure 3, many critical FMs cannot currently be monitored using the existing onboard sensors.

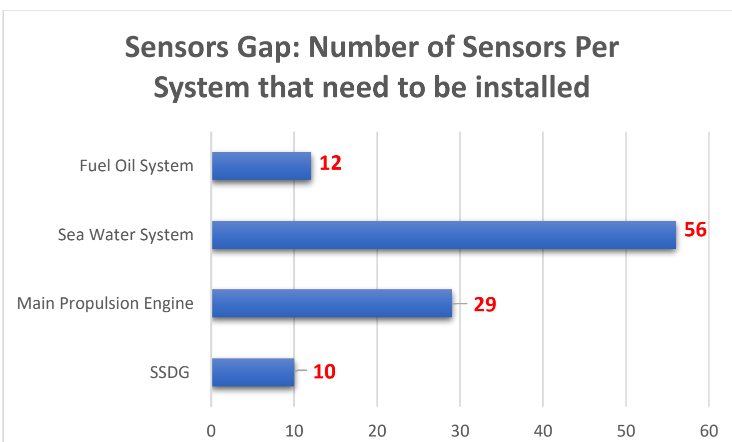

Figure 2. Sensor Gap

[1] The IMO's Maritime Safety Committee approved the framework and methodology for the regulatory scoping exercise on Maritime Autonomous Surface Ships (MASS) during its 100th session held on December 3-7, 2018.

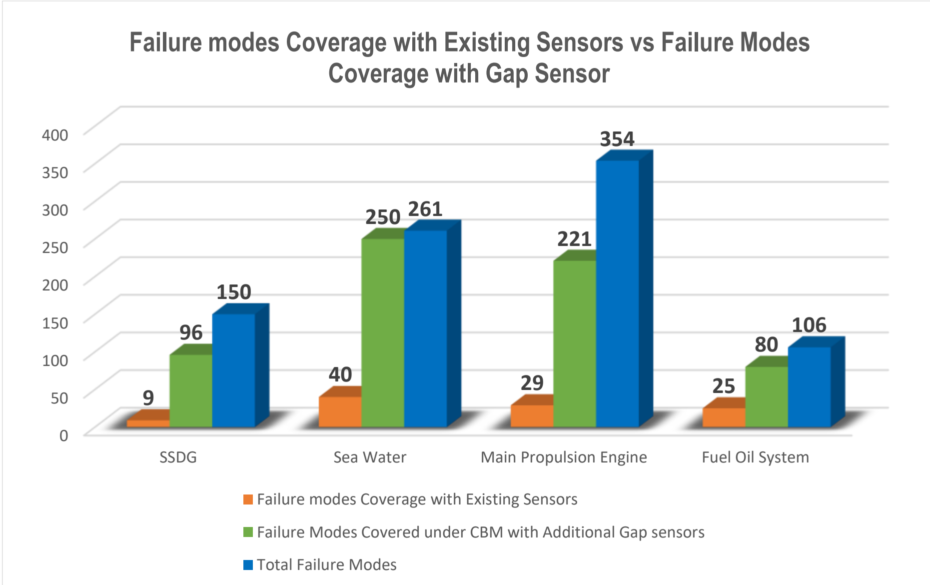

Figure 3. Failure Modes Coverage with Existing Sensors

1.4 Benefits

By implementing the right sensors and the advanced technology such as MRSS, ship system efficiency, safety and mission reliability will be greatly improved; MRSS will allow equipping the ships with advanced technologies such as AI, ML, and the Internet of Things (IoT) based data management, which will help optimize vessel operations, enhance safety, and reduce the possibility of human error.

- Data-Driven Operations: Autonomous ships generate a vast amount of data, which can be analyzed to improve decision-making, reduce costs, and enhance safety. The use of engineering context-based ML algorithms and predictive analytics can help identify patterns, predict outcomes, and optimize vessel operations.
- Reduce Fuel Consumption: Brake Specific Fuel Consumption of Diesel Engines expected to be 3%-5% less with the analytics-based maintenance performed during in-port periods.
  - 56 Propulsion Engine Efficiency Impacting FMs, for example:
    - Injector degradations degrade engine combustion efficiency by 0.5%
    - Cylinder liner and ring wear contribute to loss in combustion power conversion to delivered torque by 1%
  - 37 Ship's Service Diesel Generator (SSDG) Efficiency Impacting FMs, for example:
    - Injector degradations degrade engine combustion efficiency by 0.5%
    - Cylinder liner and ring wear contribute to loss in combustion power conversion to delivered torque by 1%.
- Improved readiness by knowing what needs to be corrected on mission critical systems prior to mission periods.
- Improved failure prediction and part requirements, providing for reduced in-port downtime, and subsequent increase in ship availability for missions.

- Longer sustained missions since predictive simulations will reduce the uncertainty of mission risks by identifying the high value tasks to be accomplished.

Projected Extended Outcomes

- Reduced Maintenance: 30-40% reduction in full rate production (FRP) sustainment costs.
- Earliest FY that benefits will be realized is expected to be starting one year following implementation of the technology.
- For Hardware/Software: FY of first ship install.

1.5 Recommendations

To take advantage of the engineering analysis performed under this project, and the expected benefits achievable, it is recommended that a detailed design, development, and implementation project be defined on one USV type ship. The scope of the project should also include the integration with the autonomy system for autonomous ship system readiness management, as well remote connectivity with a Digital Twin to provide the continuous visibility of ship system reliability risk, and the autonomous advance planning and scheduling of in-port availability work scope.

1.6 Technology Transition

Using the data analysis and best practices from this initiative, DOD activities and the public will have a greater understanding of variables relating to energy usage, causes of inefficiencies and autonomous behavior in unmanned vehicles' systems. In addition to the analytic results of the energy consumption by the major ship systems, the project will also contribute to accurate forecasts for equipment component degradations that may contribute to inefficiencies and eventual loss of reliability. Technology transition for this project involves the government being able to effectively use the provided AI/ML system to perform "what if" scenarios during operation, effectively increasing efficiency, reliability, and maintainability. Data derived from this project can have far-reaching applicability to other military and commercial unmanned and manned systems.

1.7 Invention Disclosure

☐ Yes Inventions ☒ No Inventions
DD882 Invention Report sent to NCMS ☒

1.8 Project Partners

- U.S. Navy – Naval Surface Warfare Center, Carderock
- U.S. Surface Forces Command, Pacific
- U.S. Marine Corps *(observer)*
- The DEI Group
- National Center for Manufacturing Sciences (NCMS)

2. Introduction

2.1 Background

Energy intensity must be reduced, and readiness increased in all aspects of commercial and public enterprise. Effective monitoring and analytics allowing prediction of equipment health will enable convenient scheduling of equipment maintenance and allow cost-effective supply chains avoiding interruptions in production or the need for expensive expedited delivery. Timely knowledge about operational and logistics requirements can minimize energy consumption and allow pro-active parts delivery for maintenance and sustainment of ready, efficient, and effective industrial and public sector transportation and manufacturing infrastructure. Current maintenance and sustainment costs are too high, and readiness is too low across the board. New data-driven, artificial AI/ML technologies implemented in an effective decision support ecosystem offer the promise of increasing readiness of platforms at reduced O&S cost. The Navy suffers from a situation where ships are not as available as they need to be, and expenditures associated with maintenance and sustainment are untenably high. Autonomous vessels planned for extremely long mission times (months) without people on board to tend to the equipment exacerbate the problem. Built from standard commercial HM&E equipment, these platforms will be unable to complete their extended assigned missions. Recent advances in technology, especially AI/ML and Edge Computing can change the calculus. The readiness challenge is recognized at the highest levels and substantial investment has been made for decades to improve the situation through CBM+ − an approach of maintaining equipment only when quantitative measures indicate that it is worth doing − has been under development for several decades. A commercially developed CBM+ application (from USN SBIR seed funding) is a part of the acquisition of the new CONSTELLATION Frigate. Called MRSS, it was conceived and specified under the DDG-1000 program, but budget constraints prevented full implementation on the ship, which has subsequently resulted in over-burdened sailors and inadequate readiness at extreme cost.

SURFDEVRON1, the owner of the Sea Hunter/Sea Hawk platforms, identified an interest in “using data and AI/ML to realize CBM+” such as the MRSS that is part of the acquisition of the CONSTELLATION Frigate. That interest resulted in the Autonomous Vessel Energy and Readiness Management project described herein.

2.2 Purpose

The solution proposed was to implement the MRSS, which is being developed on CONSTELLATION, on the Sea Hunter, and to evaluate the ways that it can be used to inform an autonomous vessel and ensure Ao during critical mission segments. Implementing an edge-based ship system analytics on an autonomous vessel with no underway manning is equally useful for even manned ship applications. If people are not needed for maintenance and sustainment activities over long periods of operation at sea, the benefits of reduced manhours applied to unneeded maintenance accrue to both military as well as commercial operations where the crew’s efforts can be applied to more meaningful tasks than equipment maintenance and associated paperwork drudgery. Monitoring, reporting, mitigating, planning, and resource scheduling will all be automated and not require (but allow) human intervention.

- Preventively scheduling of pre-planned tasks based on predicted ship system risks associated with the operational demands of the upcoming missions.
- Pro-active ordering of replacement parts to quickly restore systems to full performance.

The intent of this project was also to develop a solution for major business functions applicable to commercial and public business today addressing the following:

- Continuous management of asset energy consumption and equipment life consumption in commercial and public infrastructure.
- Early definition of failures in mechanical and electrical systems and resulting impact to production readiness.

Readiness issues driven by maintenance and sustainment plague all commercial enterprises and DOD sector. Reduction in energy consumption across all enterprises is critical to combating climate change and transition to a green environment. These challenges can only be met by increased visibility into the inner workings of equipment used in production, transportation, and defense. The U.S. Navy is facing extreme challenges in readiness and cost of maintenance and sustainment and must develop a feasible solution to these issues. The U.S. Navy will demonstrate to the public what solutions are possible. As such, this project was to utilize U.S. Navy infrastructure as a surrogate for an eventual industry solution that satisfies an important public need. Efforts focused on issues specific to the Sea Hunter MUSV. The results are expected to be easily transferable to commercial industry, positively impacting delivery of products to the public. The unmanned maritime platforms under development combat the threats of today as well as those of coming decades. Implementation of the MRSS on MUSV (Sea Hunter/Sea Hawk) will inform the specifications and design of all USV types. Experience gained also mitigates risks for the MRSS on the FFG-62 Class. It also supports application to other classes, especially other unmanned platforms. Unlike previous technology disruptions that were often unpredictable, enterprise management tools can now track possible and developing issues, anticipate their impacts and provide mitigation. Forward-thinking leaders can get ahead of the game, develop their strategies, and ride the results into new markets. However, the investment is substantial. Maintenance and sustainment intensive industries across the country know that to remain competitive, huge investments in building digital platforms executing engineering-based AI analytics will be necessary. But as in many cases, resources are limited and so is the tolerance for risk. Demonstrating a solution for the U.S. Navy’s autonomous platform energy and readiness management will provide commercial industry with critical knowledge to help successfully obtain an appropriate, cost-effective digital enterprise strategy beneficial to end customers. This initiative provided new functionality that could be used by the operational forces, increasing productivity, and providing a streamlined process for all Forces to utilize. Furthermore, positive results from numerous aspects of this initiative can be leveraged toward public maintenance and sustainment business processes.

The main purpose of the project was to:

- Perform reliability/CBM engineering analysis of four mission critical systems on the Sea Hunter platform.
- Identify sensor gaps to enable full coverage of all critical FMs.
- Implement the engineering analysis results of the Power Generation system into the MRSS configuration for a shore-side simulation-based limited demonstration.

2.3 Scope/Approach

A collaborative effort was deployed that embraced both Government and Industry participants. Industry provided the reliability engineering services to model important relationships between mission capabilities and individual FMs, platform hosted software and sensors able to continuously monitor consumption of equipment life during operations, continuous prediction of future risk to mission completion onboard the vessel and reporting to the autonomous controller. The Government provided functional and tacit knowledge, value opportunity definition and capture. The Sea Hunter and/or Sea Hawk MUSV prototype vessels were used to demonstrate an integrated implementation of energy and readiness management linked with a development pipeline for further AI/ML tools for HM&E equipment sustainment.

The following scope was performed:

1. Conducted rigorous Reliability Engineering-based analysis to identify FMs of interest and the associated reliability model, which would then be used to design the most effective early detection of equipment cumulative damage causing loss in efficiency and reliability and provide for identifying appropriate maintenance requirements scheduling based on predicted estimated risk. The scope of the analysis included only the main equipment, but the control system elements required to safely control start-up, operation, and shutdown of the equipment. If this is of interest, then the analysis boundary also needs to be extended to the control logic elements (Programable Logic Controller components) as well.

2. Shifted the current periodic time and machine hours-based maintenance to a CBM program, where applicable, through addition of sensors, with the intention of conducting maintenance based on predicted degradation and loss in reliability (remaining useful life) of the equipment rather than a pre-determined calendar or machine hours-based schedule.

3. Performed the Sensor Gap analysis using the following process:
   - Mapped each FM defined in the Failure Mode, Effects and Criticality (FMECA) to appropriate features to be used for health assessment.
   - Mapped each feature of interest to sensors required for extracting the features.
   - Mapped each stress event profile to sensors required to capture the stress event.
   - Identified appropriate Maintenance Requirement Card (MRC) tasks against FMs, with its associated threshold-based triggers.

4. Established accounts and familiarity with Universal Naval AI CORe eNvironment (UNACORN) and access the available Sea Hunter data. Conducted training on the system to access the data.

5. Designed implementation to address sensor gaps to realize readiness and Energy Management. (To be installed in follow-on work when funding becomes available).

6. Configured the MRSS and performed demonstration for the SSDG system.

2.4 Deliverables

The following deliverables were provided from the project:

- Comprehensive Project Plan
- RE-CBM+ Analysis for:
  - Main Propulsion Report
  - Power Generation Report
  - Seawater Service System Report
  - Fuel System Report
- Report that identified any recommended Gap CBM Sensors
- Summary of Projected Results Report with Existing Sensors and with added Gap Sensors
- Financial Status Reports
- DEMO of MRSS for Power Generation System

3. Project Narrative

Sustainment of equipment function, usually defined as maintenance, is a crucial process for the operation of USV. Ineffective maintenance due to incorrect maintenance strategy, lack of required knowledge of what and when to fix, spare parts and service equipment demand, or the availability of right personnel can result in increasing downtime of shipboard systems. Excessive downtime causes mission days lost for the platform operator. To avoid this problem, it is necessary on the one hand, to be able to estimate the equipment maintenance needs in advance, to avoid unforeseen breakdowns and mission interruption. On the other hand, advance planning of resources and spare parts become more important for ensuring spare parts availability when the ship returns from missions. To address these issues, the MRSS software was developed to implement advanced AI/ML predictive analytics that provide greater autonomy, flexibility, and adaptability. The continuous equipment monitoring and prognostics functionality of MRSS allows detection of faults and the performance of diagnostics in real time on the ship. Machine health monitoring at the component FM level provides the input to the prognostic analytics which will extend machine operating life, and shore-side real-time access to machine health and predicted reliability information benefits the entire USV operation. Such continuous insight into present and future health/reliability of machines and their components, as well as the information flow infrastructure enable the move to intelligent autonomous systems based on intelligent prognostics, where maintenance actions are synchronized with the overall operation of the system as well as with the necessary maintenance resources and spare parts. Such synchronization of onboard machinery management with maintenance actions and information flow infrastructure will enable autonomously triggering of services and ordering of spare parts, yielding near-zero downtime system operation through proactive, cost-effective maintenance that is the least intrusive on the normal function of the system.

The project performed the following subtasks:

- Defined the target Critical Failures of Interest through a rigorous reliability engineering analysis FMECA.
- Defined a predominantly on-line maintenance strategy for the monitored equipment.
- Established target dominant equipment FMs of interest required to be managed.
- Provided Sensor Gap analysis relative to recommended instrumentation to be installed.
- Configured MRSS for a limited DEMO on the DEI server for Power Generation System that:
  - Automatically analyzed the data to calculate current health, current reliability (cumulative damage), predicted reliability (30, 60, 90, 120-days), and Remaining Useful Life (RUL) of components at the FM level. RUL is defined as where 63% of life has been consumed, and forecasted reliability is below 37%.
  - Had continuous access to real-time analysis, notification, and display of analysis results.

3.1 Technical Approach

The RE-CBM+ methodologies have been developed as an effective **preventive maintenance strategy** that seeks to maximize equipment performance by applying the right activities to the equipment component, at the right stage in its *working age*. The concept of *working age* accounts for the damage accumulated by the component, thereby defining its current reliability, as a result of not just how long the equipment has operated, but under what conditions (stresses). The reliability-based maintenance triggers have no set periodicity (for example, every two months), but are variable based on the duty cycle experienced by the equipment, and the threshold of unacceptable reliability defined for mission readiness. The DEI Group developed RE-CBM+ methodologies for specific equipment at the Line Replaceable Unit (LRU) level, taking into account the full range of operational and environmental stress inducing factors applicable to Sea Hunter which were:

- Understanding the functions of the equipment and systems.
- Understanding how degradation and failures occur because of internally and externally induced stresses unique to identical equipment on diverse ship classes.
- Understanding how degradations and failures impact the ability to meet system functional requirements.
- Converting FMs and mechanisms into mathematically computable models.
- Developing and generating regular pre-planned maintenance tasks that must be performed on equipment to achieve defined objectives.
- How is the equipment deployed, and what are the ranges of duty cycles, environmental factors, and operator actions considered to accelerate component ageing on specific ship types?
- What are the “right” things (tasks) to do, on an estimated cumulative damage basis, to keep the equipment running better and longer?
- What data must be collected to assess equipment current and future conditions, trigger the correct task, and document work accomplished?
- What tasks are currently being done that seem to have little value, and can be eliminated?
- Are some technologies better than others at providing the condition assessment information that is needed?

Good condition equipment design characteristics and assessment information is critical when it comes to building confidence toward eliminating maintenance tasks which have been accomplished for many years, and the following are important to assess:

- What monitoring instrumentation would be beneficial to install on a marine platform given the known operating and environmental conditions?
- How to determine the best “risk levels” at which to perform tasks to attain the maximum benefit?
- What are the current planned maintenance actions for the equipment/system and how do they relate to equipment FMs?
- What is the relationship between the existing maintenance strategy and the currently achieved MTBF (Mean-Time-Between-Failures) and mission reliability. In establishing the “base” inherent equipment reliability, the current maintenance practice needs to be considered, since many of the legacy preventative maintenance and periodic overhaul practices corrupt the estimation of equipment component design life (characteristic life).

The RE-CBM+ process analysis steps were:

- Reviewed all available equipment technical manuals to fully understand the design of the equipment and its expected behavior during the full range of operating profiles.
- Analyzed previously available collected operating data.
- Thoroughly examined the latest release of the applicable equipment Maintenance Index Page (MIP) and MRCs from the latest Force Revision disk were, as this was the baseline against which any improvements were to be demonstrated.
- Performed analysis on calendar triggered PMS tasks that could be replaced or modified based on advance predictive analytics methods and condition monitoring.
- Performed the FMECA, and CBM engineering analysis. FMECA is a qualitative analysis approach intended to recognize and evaluate the potential failures of an equipment, and the effects of that failure. For each FM, functional failures occur when the FM causes the equipment to be unable to fulfill a function to a standard of performance which is acceptable to complete the mission requirement in a safe manner. Criticality is associated with the relative impact of the failure on the mission identified the following attributes associated with recognizing and managing the FMs of interest:
  - Failure causes
  - Failure mechanisms
  - FM detectability
  - FM anomalies
- Established the hierarchical equipment breakdown structure-based model consisting of:
  - System
  - Subsystem
  - LRU
  - FM
- Performed CBM+ engineering analysis to identify applicable and effective methods to manage the FM using advanced predictive analytics methods and condition monitoring techniques. Condition monitoring techniques are designed to detect potential failure inception indications (such as changes in vibration characteristics, changes in temperature, accumulated particles in lubricating oil, etc.). For each FM the following was identified:
  - Symptoms of each FM
  - Failure inducing events which initiate and propagate the FM
  - Degradation indicating measurements related to the FMs
  - Machine operating states requisite for qualifying these symptoms and events
  - Diagnostic features
  - Failure effects (local and systemic) – Failure effects describe the consequences of failure, which are useful for determining critical FMs to monitor.
  - Characteristic life of FM (eta) – For the diesel engines, extensive use was made of the work performed by The DEI Group on Chevron Tanker diesel generator engines and propulsion main engines as regards to MTBF of sufficiently similar marine engines. Typically, it had been found that commercial marine engines are designed with good

reliability margins as related to operations within the design envelop, and periodic unneeded intrusive maintenance tends to reduce the reliability realized

- Stresses creating failure mechanisms
- Reliability model characteristics
- Prognostic model types and requisite inputs.

- Performed the reliability engineering analysis to model the FMs, and their relationship to system reliability, which ensured that the maintenance tasks and triggers selected allowed the equipment to meet its intended function, at an acceptable level of reliability, during mission periods. In addition, using sensor-based predictive analytics, inspection tasks were to be eliminated where on-line analytics would provide sufficient confidence that a corrective task could be generated prior to reaching an unacceptable level of equipment reliability, while in its present operating context. The Reliability Centered Maintenance (RCM) process was satisfied by identifying the correct applicable/effective tasks, associated with the FMs which were identified during the FMECA process.

(Note: *Detailed approach of the above RE-CBM+ described process for each system and results was provided directly to the government partner.*)

3.1.1 Failure Mode, Effects and Criticality (FMECA) Analysis for Identified Critical Systems, Subsystems, and Components

The following were performed:

- <u>Identified the equipment and its functional description</u> – A clear understanding and articulation of the equipment and its function within the parent system under consideration was important. This understanding simplified the process of analysis by assisting the reliability engineer to identify those equipment uses that fall within the intended function and which ones fall outside. It was important to consider both intentional and unintentional uses since equipment failure often ends in human safety or mission impacting events.
- <u>Identified FMs</u> – A FM is defined as the way a system, subsystem, equipment, LRU could potentially fail to meet the design functional intent. A FM in one component can serve as the cause of a FM in another component. Each FM was listed in technical terms. FMs were listed for the function of each component. At this point the FMs were classified relative to likelihood of occurrence.
- <u>Analyzed each FM's effects</u> – For each FM identified, the immediate and ultimate effect was determined. A failure effect is defined as the result of a FM on the function of the equipment as it affects current and future mission readiness. This step identified both onboard operational risk effects as well as shore-side logistic impact effects.
- <u>Identified Severity</u> – A numerical ranking for the severity of the effects was established. A common industry standard scale uses 1 to represent no effect and 10 to indicate very severe with failure affecting system operation and safety without warning. The intent of the ranking was to help the analyst determine whether a failure would be a minor nuisance or a catastrophic occurrence. This enables prioritization of the failures and addresses the most critical issues first.

- Identified the causes for each FM – A failure cause is defined as a physical process that may result in a failure. The potential causes for each FM were identified and documented.
- Identified the cause probability factor assignment – A numerical weight were assigned to each FM cause that indicated how likely that cause was (probability of the cause occurring). A common industry standard scale uses 1 to represent not likely and 10 to indicate inevitable.
- Determined the detection likelihood – Detection likelihood is an assessment of the ability to recognize an early inception of the FM or the cause of the FM, thus preventing it from reaching a level that will create the undesirable effects. The detection likelihood was also ranked from 1 to 10.
- Identified operating modes – Measured conditions must be separated by operating mode. Each condition was identified for a particular mode of operation such as full power, idling, transient states, and steady states.
- Determined the measurements and trends that are required to identify the condition.
- Identified the sensor data to monitor and trend for the condition and provide a gap between available sensors and recommended sensors – The sensor gap analysis was performed using the following process:
  - Map each FM to appropriate features to be used for health assessment.
  - Map each feature of interest to sensors required to be used.
  - Map each stress event profile to sensors required to capture the stress events.
  - Identify appropriate Tasks against FMs, with their associated threshold-based triggers.

The process steps are provided in the graphical view in Figure 4.

3.1.2 CBM+ Subtasks

The following subtasks were performed:

- Developed Reliability Models for each FM at the Lowest Replaceable Unit Reliability
  - Developed failure models for the target FMs of interest, taking into account availability of sensors to support gap analysis, expected operating profile, and external stress inducing factors.
  - Identified appropriate Tasks for triggering and intervals (Calendar/Run Hours/Condition Based/Risk Based).
- Configured the MRSS Application for the limited DEMO for Power Generation
  - Analog data values
  - Digital data values
  - Failure inducing events
  - Configure the calculation engine to recognize the Symptoms of failure defined during the maintenance design activity into a mathematical relationship
  - Configure the Machine state validation rules used prior to symptom analysis
  - Configure the symptom output relationships into a diagnostic relationship definition represented as a diagnostic based Rule Pattern
  - Configure the Reliability models for each LRU FM of interest
  - Configure the base hazard function

- Configure the covariate projection and weighting function
- Configure the stress inducing factor function
- Configure user interface for FMs

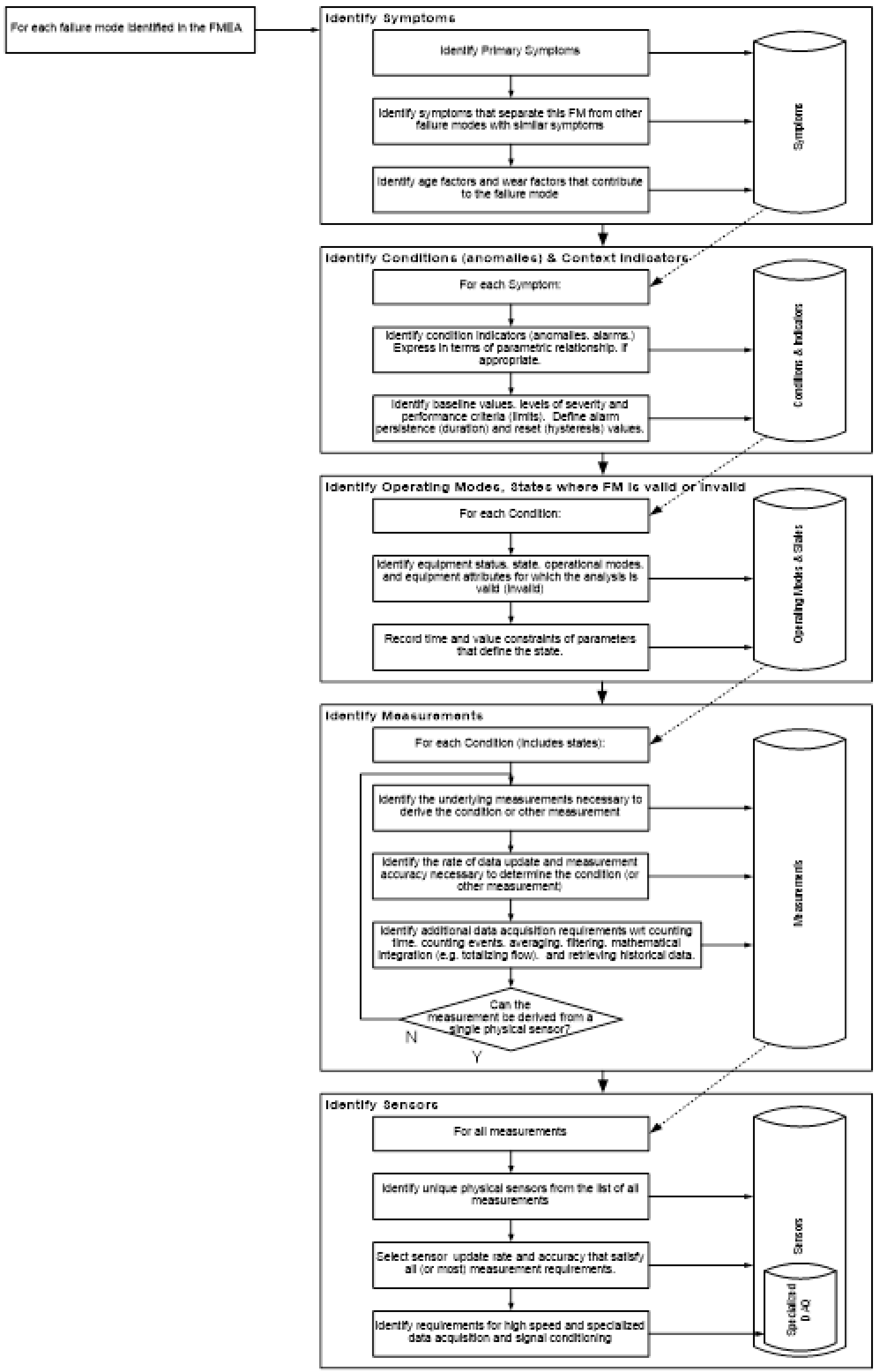

Figure 4. FMECA Process

3.2 Results

3.2.1 SSDG Report Analysis

Caterpillar was selected to supply the SSDGs. The main function of the SSDGs is to provide the Sea Hunter with electrical power by converting chemical energy in the form of fuel oil into electrical power. There are two generators on the Sea Hunter. For this report, the analysis for one is shown. The SSDGs are Model C4.4. They are 4-cylinder in-line, turbocharged engines, with a bore of 105mm and a stroke of 127mm. They have an output rating of 118 kW, 450 V 60 HZ, and produce 3-phase power. The SSDG interfaces with the following ship systems:

- Electrical Distribution
- Fuel Oil System

Figure 5 shows the analysis results.

A rigorous RE-CBM+ analysis was conducted that identified FMs of interest and the associated reliability model, which were then used to design the most practical means of reducing maintenance requirements and adjust maintenance task scheduling based on predicted estimated risk. Key benefit of identifying Critical Failure Modes (CFMs) was to provide the means to recognize high-criticality vs. low-criticality FMs to reduce the level of uncertainty and focus on high-priority maintenance tasks. Critical CFMs were defined by impact to:

- Loss of equipment operability
- Safety (failure results in loss of ship, injury, or damage to the environment)
- Impact to other ship mission critical systems

For SSDG, a total of 150 FMs were identified from which a total of 57 were CFMs.

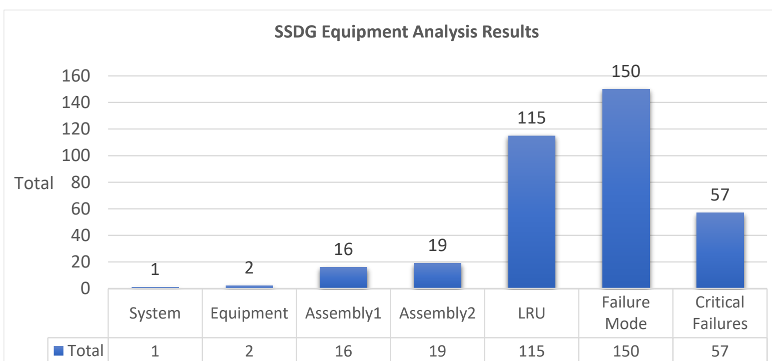

Figure 5. SSDG Analysis Results

Figure 6 shows the reliability models that were developed for each FM.

Reliability Models are defined as: *time-dependent mathematical models that are capable of computing current cumulative damage and predicting RUL when operated in the performance of a pre-defined mission profile. In essence, RUL can be converted to the probability of failure in future time under defined operating conditions.*

FM is the actual physical condition in a component that causes a particular functional failure.

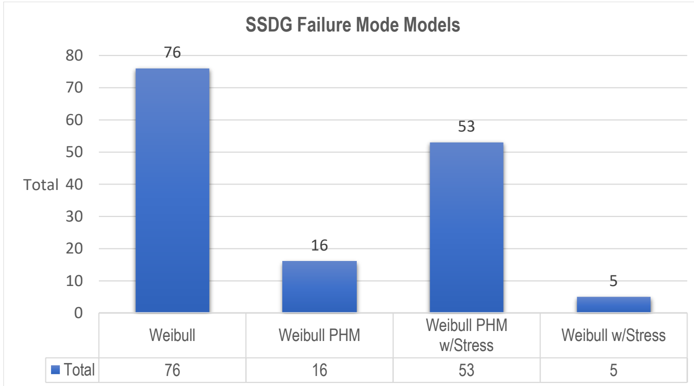

Figure 6. Reliability Models

FM Model Type are the mathematical constructs, which represent FM condition (health), and working age based on cumulative damage, providing a basis for estimating RUL (prognostics).

The model types are:

- **Weibull** – a static, historical failure rate based statistical model, represented by a two-parameter distribution function.
- **Weibull with Stress Events** – design life-based statistical model, which considers damage accumulation due to normal operating hours as well as the occurrences of events which are known to accelerate component ageing.
- **Weibull Proportional Hazard Model (PHM)** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of component health.
- **Weibull PHM with Stress Events** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of health, as well as the accumulation of captured stress events associated with accumulation of damage.

Maintenance strategy is a combination of maintenance task types performed on equipment, over a period, considering design, operational objectives, and constraints. A maintenance strategy was defined for FMs, based on the results of the selected FM model.

The maintenance strategies are:

- **Predictive** – Pre-Planned Maintenance that is scheduled based on estimation of RUL of FMs of interest. Sensor data is used to capture operating hours and estimate component health and current cumulative damage at the FM level using operating duty cycle and externally induced stresses (such as insufficient lubrication, high ambient temperature.). With the availability of projected SSDG utilization demand, the RUL of components is estimated until failure risk probability will impact mission readiness.
- **Condition-Based** – Pre-Planned Maintenance that is scheduled based on a threshold trigger on current health of a pre-defined component FM of interest. Appropriate sensor data, combined with periodic visual inspections, as appropriate, are evaluated continuously to assess the current health of the equipment against pre-established thresholds.

- **Run to Failure** – Pre-Planned unscheduled (reactive) corrective maintenance triggered following the component failure event.
- **Periodic Preventative** – Pre-Planned periodic tasks based on machine hours, number of starts, number of trips, or calendar, to either inspect and replace components as needed, or perform task without inspections regardless of condition, such as replace filter.

The selected Maintenance Strategy Types are shown in Figure 7.

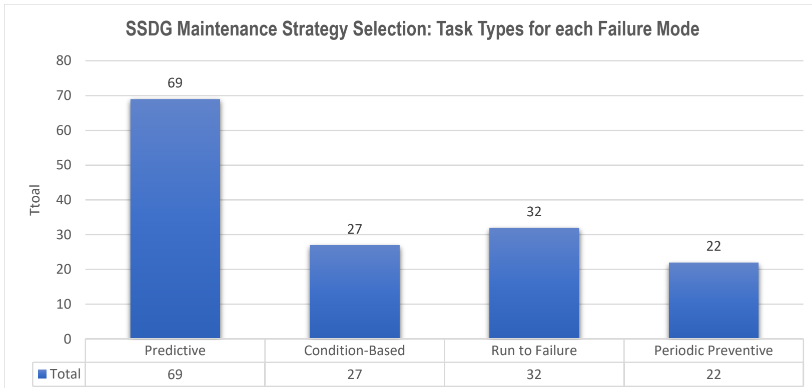

Figure 7. Selected Maintenance Tasks

3.2.1.1 SSDG Sensor Gap Report

Since sensors provide evidence of both equipment operational profile, as well as operating conditions as compared to design, they are very important for implementing an intelligent predictive analytics-based maintenance strategy. Typically, original equipment manufacturers (OEMs) provide installed sensors primarily to support start-up, shut-down, and supervisory control related functions. The full suite of sensors required for comprehensive, first principles-based analysis could be expensive to buy and implement. Therefore, one of the objectives of the detailed CBM+ analysis was to define the optimal sensor suite for managing the dominant FMs of interest. Each FM model includes information relative to what condition indicating and stress inducing parameters are needed. It identifies what to collect, when to collect it, how to collect it, and what features of the measurements are needed for anomaly detection, FM condition assessment, and remaining life estimation. The analysis focused on maximum use of a small sensor suite that is needed to provide a higher confidence factor for managing critical FMs.

The sensor types that MRSS uses are:

- Direct sensor measurements, whose values are acquired through networked data acquisition devices.
- A specific feature (attribute), as calculated by an intelligent sensor such as the amplitude of a narrow band harmonic, provided by the Electrical Signature Analysis (ESA) analytics, through the high-speed data acquisition device. By using advanced signal processing methods in selecting good feature subsets can help both in use of minimal sensors suite while enhancing the data analysis (e.g., classification performance) through a more stable data representation. The extraction of complex patterns from each sensor allows transforming each complex pattern (features) into virtual sensors that are used to further decipher meaningful information from the acquired data.

- A calculated value (virtual sensor), whereby several other parameter values from the sensor map are used to calculate an attribute, such as motor air gap integrity, pump work deviation from expected, etc. The output of the calculation will be the value in the sensor register assigned to the calculated value.

The official signal list from the Sea Hunter Machinery Centralized Control System (MCCS) available on the Sea Hunter was not available at the time of the analysis. Assumptions for currently available sensors were made using the SSDG technical manual, by looking at the typically installed sensors listed in the drawings.

The sensor gap analysis was performed using the following process:

- Map each FM to appropriate features to be used for health assessment.
- Map each feature of interest to sensors being used.
- Map each stress event profile to sensors being used.
- Identify appropriate Tasks against FMs, with their associated threshold-based triggers.

Sensor Gap Report for SSDG System is shown in Table 1.

Table 1. SSDG Gap Sensors

Sensor Type	Sensor Count	Sensor Gap? Y/N	Sensor Source	Inputs to FMs
Pressure	4	N	MCCS	6
Temperature	5	N	MCCS	29
Pressure	1	Y	MCCS	12
Temperature	4	Y	MCCS	24
Lube Oil Quality	1	Y	MCCS	16
Electrical Sensors	4	Y	MRSS DAQ	34

3.2.1.2 Conclusion for SSDG With Gap Sensors

Of the 150 FMs of the SSDG, 96 FMs (64%), are proposed to be managed under a predictive or condition-based approach. The 54 remaining FMs (36%) are non-critical FMs and are recommended to be managed under a "run to failure" or periodic preventative strategy; however, these will still have a RUL estimation relative to the average population baseline represented by a fleet level Weibull failure distribution (failure rate), but not to the specific SSDG being monitored.

This will provide visibility into estimated risk, with a broad variance, but still allowing planning for servicing and materials acquisition at the discretion of shore-side support crew. In effect, all FMs will be managed under a reliability driven CBM+ based strategy.

3.2.1.3 Conclusion for SSDG Without Gap Sensors

Figure 8 shows that only 9 of the 150 FMs are managed under a predictive or condition-based approach vs. 96 FMs that could be monitored with the additional sensors gap. "*As is*" will not support the autonomous operations as Sea Hunter is expected to perform 90 days mission without intervention for the shore.

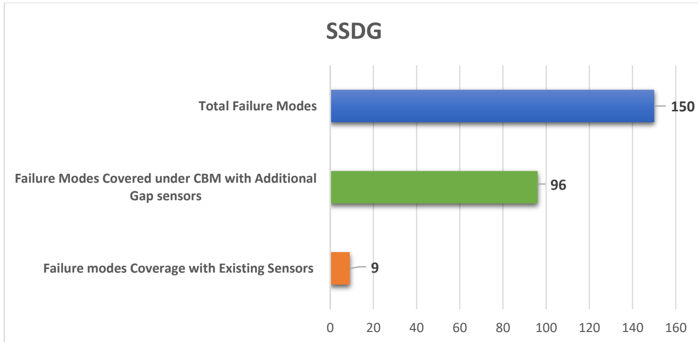

Figure 8. SSDG Without Gap Sensors Failure Coverage

3.2.2 Main Propulsion Engine (MPE)

MTU Detroit Diesel was selected to supply the MPEs. The function of the two MPEs is to provide propulsion power for the Sea Hunter. The MPEs are Model 12V 2000 m94. They are V-type 12-cylinder turbocharged engines, with a bore of 135mm and a stroke of 156mm. They have a rating of 1432 kW and rotate at 2450 rpm.

The MPE interfaces with the following ship systems:

- Fuel Oil System
- Drivetrain

Figure 9 provides the results of the FMECA analysis.

A rigorous RE-CBM+ analysis was conducted that identified FMs of interest and the associated reliability model, which were then used to design the most practical means of reducing maintenance requirements and adjust maintenance task scheduling based on predicted estimated risk. Key benefit of identifying CFMs was to provide the means to recognize high-criticality vs. low-criticality failure modes to reduce the level of uncertainty and focus on high-priority maintenance tasks. CFMs were defined by impact to:

- Loss of equipment operability
- Safety (failure results in loss of ship, injury, or damage to the environment)
- Impact to other ship mission critical systems

For MPE, a total of 354 FMs were identified from which a total of 103 were CFMs.

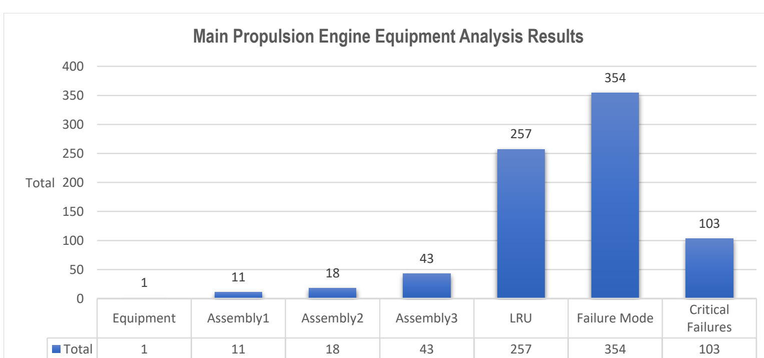

Figure 9. MPE

Figure 10 shows the reliability models that were developed for each FM.

Reliability Models are defined as: *time-dependent mathematical models that are capable of computing current cumulative damage and predicting RUL when operated in the performance of a pre-defined mission profile. In essence, RUL can be converted to the probability of failure in future time under defined operating conditions.*

FM is the actual physical condition in a component that causes a particular functional failure.

FM Model Type are the mathematical constructs, which represent FM condition (health), and working age based on cumulative damage, providing a basis for estimating RUL (prognostics).

The model types are:

- **Weibull** – a static, historical failure rate-based statistical model, represented by a two-parameter distribution function.
- **Weibull PHM** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of component health.
- **Weibull PHM with Stress Events** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of health, as well as the accumulation of captured stress events associated with accumulation of damage.

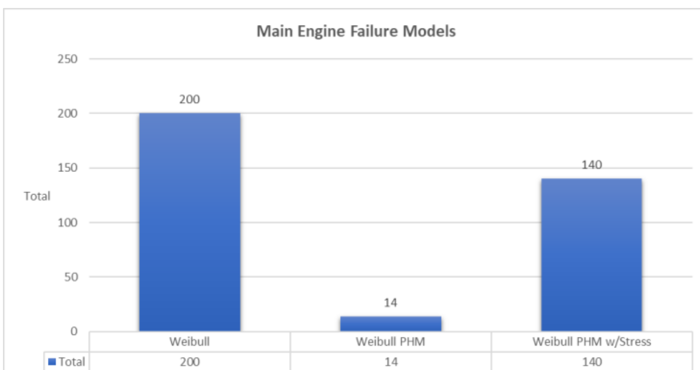

Figure 10. Main Engine Failure Models

Figure 11 shows the Maintenance Strategy that was selected for the Main Engine. Maintenance strategy is a combination of maintenance task types performed on equipment, over a period, taking into account design, operational objectives, and constraints. A maintenance strategy was defined for FMs, based on the results of the selected FM model.

The maintenance strategies are:

- **Predictive** – Pre-Planned Maintenance that is scheduled based on estimation of RUL of FMs of interest. Sensor data is used to capture operating hours and estimate component health and current cumulative damage at the FM level using operating duty cycle and externally induced stresses (such as insufficient lubrication, high ambient temperature.). With the availability of projected MPE utilization demand, the RUL of components is estimated until failure risk probability will impact mission readiness.

- **Condition-Based** – Pre-Planned Maintenance that is scheduled based on a threshold trigger on current health of a pre-defined component FM of interest. Appropriate sensor data, combined with periodic visual inspections, as appropriate, are evaluated continuously to assess the current health of the equipment against pre-established thresholds.
- **Run to Failure** – Pre-Planned unscheduled (reactive) corrective maintenance triggered following the component failure event.
- **Periodic Preventative** – Pre-Planned periodic tasks based on machine hours, number of starts, number of trips, or calendar, to either inspect and replace components as needed, or perform task without inspections regardless of condition, such as replace filter.

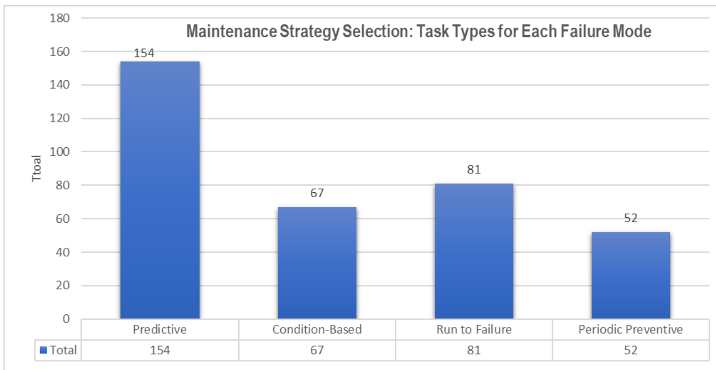

Figure 11. Maintenance Task Types

3.2.2.1 Sensor Gap Report for MPE

Since sensors provide evidence of both equipment operational profile, as well as operating conditions as compared to design, they are very important for implementing an intelligent predictive analytics-based maintenance strategy. Typically, OEMs provide installed sensors primarily to support start-up, shut-down, and supervisory control related sensors. The full suite of sensors required for comprehensive, first principles-based analysis could be expensive to buy and implement. Therefore, one of the objectives of the detailed CBM+ analysis was to define the optimal sensor suite for managing the dominant FMs of interest. Each FM model includes information relative to what condition indicating and stress inducing parameters are needed. It identifies what to collect, when to collect it, how to collect it, and what features of the measurements are needed for anomaly detection, failure mode condition assessment, and remaining life estimation. The analysis focused on maximum use of a small sensor suite that is needed to provide a higher confidence factor for managing critical FMs.

The sensor types that MRSS uses are:

- Direct sensor measurements, whose values are acquired through networked data acquisition devices.
- A specific feature (attribute), as calculated by an intelligent sensor such as the amplitude of a narrow band harmonic, provided by the ESA analytics, through the high-speed data acquisition device. By using advanced signal processing methods in selecting good feature subsets can help both in use of minimal sensors suite while enhancing the data analysis (e.g.,

classification performance) through a more stable data representation. The extraction of complex patterns from each sensor allows transforming each complex pattern (features) into virtual sensors that are used to further decipher meaningful information from the acquired data.

- A calculated value (virtual sensor), whereby several other parameter values from the sensor map are used to calculate an attribute, such as motor air gap integrity, pump work deviation from expected, etc. The output of the calculation will be the value in the sensor register assigned to the calculated value.

The official signal list from the Sea Hunter MCCS available on the Sea Hunter was not available at the time of the analysis. Assumptions for currently available sensors were made using the ME technical manual, by looking at the typically installed sensors listed in the drawings.

The sensor gap analysis was performed using the following process:

- Map each FM to appropriate features to be used for health assessment.
- Map each feature of interest to sensors being used.
- Map each stress event profile to sensors being used.
- Identify appropriate Tasks against FMs, with their associated threshold-based triggers.

MPE Sensor Gap Report is shown in Table 2.

Table 2. MPE Gap Sensors

Sensor Type	Sensor Count	Sensor Gap? Y/N	Sensor Source	Inputs to FMs
Pressure	8	N	MCCS	35
Temperature	5	N	MCCS	95
Pressure	1	Y	MCCS	26
Temperature	22	Y	MCCS	85
RPM	3	Y	MCCS	12
Torque Meter	1	Y	MRSS DAQ	60
Lube Oil Quality	1	Y	LOQM	13
Fuel Oil Quality	1	Y	FOQM	24

3.2.2.2 Conclusion from MPE Sensor Gap Analysis

The analysis showed that 221 (61%) of the 354 FMs can be managed under a predictive or condition-based approach, this provides a high coverage of the CFMs.

The 133 remaining FMs (39%) are non-critical and are recommended to be managed under a "run to failure" or periodic preventative strategy; however, these will still have a RUL estimation relative to the average population baseline represented by a fleet level Weibull failure distribution (failure rate), but not to the specific MPE being monitored.

This will provide visibility into estimated risk, with a broad variance, but still allowing planning for servicing and materials acquisition at the discretion of shore-side support crew. *In effect, all FMs will be managed under a reliability driven CBM+ based strategy*.

3.2.2.4 Conclusion for MPE Without Sensor Gap vs. Gap Sensors

Figure 12 shows that only 29 of the 354 FMs can be managed under a predictive or condition-based approach vs. 221 FMs that could be monitored with the additional sensors gap closure. "*As is*" will not support the autonomous operations as Sea Hunter is expected to perform 90 days mission without intervention from the shore.

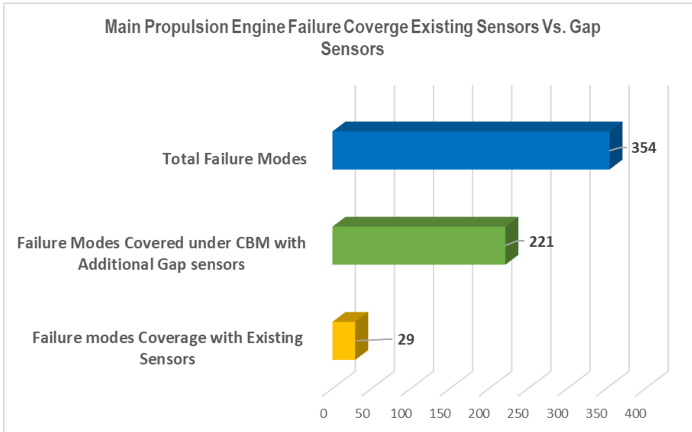

Figure 12. Main Engine Failure Coverage Existing Sensors vs. Gap Sensors

3.2.3 Seawater Service System

Viking Pump was selected as the Seawater Service pumps to supply the required seawater flow for the Seawater Service System. The main function of the Seawater Service is to supply seawater for cooling requirements of mission critical equipment onboard, including but not limited to the Heating, Ventilation and Air Conditioning (HVAC) system and Power Generation system. There are seven centrifugal type pump and motor units installed in the Seawater Service System. Each seawater pump has a capacity of 38.5 gpm at 17.5 psi. They are driven by a 1.5 Hp, 460 VAC, 3-phase, 60 Hz induction motor that rotates at 3450 rpm. The seawater pumps serve to provide cooling to several pieces of major equipment critical to ship operations and are in the following ship spaces:

- MG1 Pumps 1 & 2 AMR 1
- MG2 Pumps 1 & 2 AMR 2
- HVAC Pumps 1 & 2 AMR 1
- Main Deck Pump AMR 2

The Seawater Service System consists of the following equipment:

1. Sea Chests
2. Seawater Pumps
3. System Valves
4. System Strainers

The Seawater Service System interfaces with the following ship systems:

- Electrical Distribution

Figure 13 shows the results of the engineering analysis for Seawater System. A rigorous RE-CBM+ analysis was conducted that identified FMs of interest and the associated reliability model, which were then used to design the most practical means of reducing maintenance requirements and adjust maintenance task scheduling based on predicted estimated risk. Key benefit of identifying CFMs was to provide the means to recognize high-criticality vs. low-criticality FMs to reduce the level of uncertainty and focus on high-priority maintenance tasks. CFMs were defined by impact to:

- Loss of equipment operability
- Safety (failure results in loss of ship, injury, or damage to the environment)
- Impact to other ship mission critical systems

A total of 261 FMs were identified from which 200 were considered CFMs.

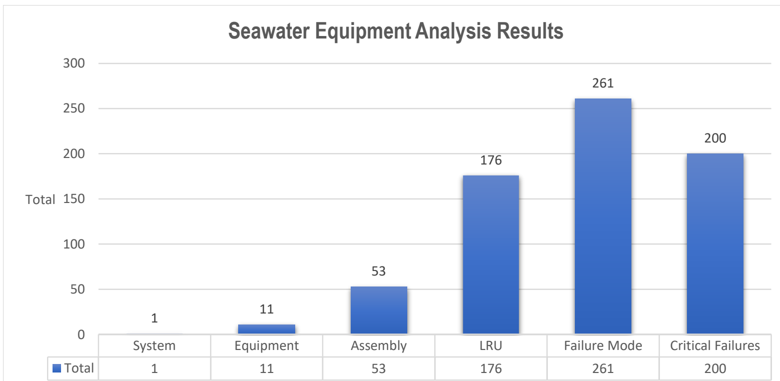

Figure 13. Seawater System

Figure 14 shows the reliability models that were developed for each FM.

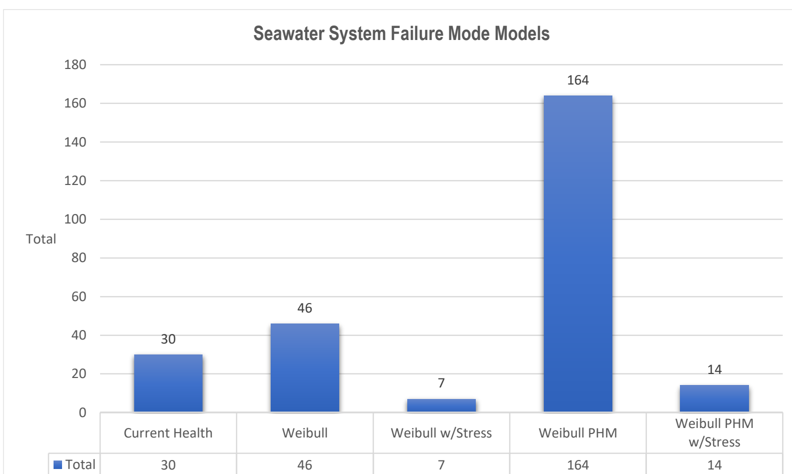

Figure 14. Failure Model Selection

Reliability Models are defined as: *time-dependent mathematical models that are capable of computing current cumulative damage and predicting RUL when operated in the performance of a pre-defined mission profile. In essence, RUL can be converted to the probability of failure in future time under defined operating conditions.*

FM is the actual physical condition in a component that causes a particular functional failure.

FM Model Type are the mathematical constructs, which represent FM condition (health), and working age based on cumulative damage, providing a basis for estimating RUL (prognostics).

The model types are:

- **Current Health** – based on a combination of parametric relationships (sensor data) compared against design or expected behavior.
- **Weibull** – a static, historical failure rate-based statistical model, represented by a two-parameter distribution function.
- **Weibull with Stress Events** – design life-based statistical model, which considers damage accumulation due to normal operating hours as well as the occurrences of events which are known to accelerate component ageing.
- **Weibull PHM** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of component health.
- **Weibull PHM with Stress Events** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of health, as well as the accumulation of captured stress events associated with accumulation of damage.

Figure 15 shows the Maintenance Strategy that was selected for the Seawater System. Maintenance strategy is a combination of maintenance task types performed on equipment, over a period, taking into account design, operational objectives, and constraints. A maintenance strategy was defined for FMs, based on the results of the selected FM model.

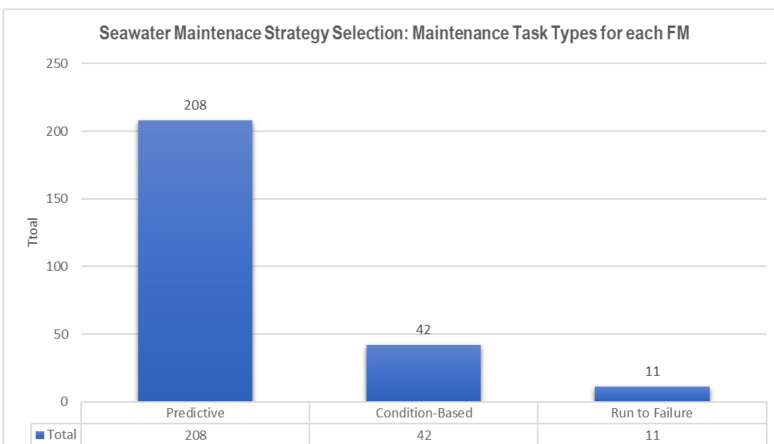

Figure 15. Maintenance Strategy Selection for Seawater

The maintenance strategies are:

- **Predictive** – Pre-Planned Maintenance that is scheduled based on estimation of RUL of FMs of interest. Sensor data is used to capture operating hours and estimate component health and current cumulative damage at the FM level using operating duty cycle and externally induced stresses (such as insufficient lubrication, high ambient temperature.). With the availability of projected Seawater Service System utilization demand, the RUL of components is estimated until failure risk probability will impact mission readiness.

- **Condition-Based** – Pre-Planned Maintenance that is scheduled based on a threshold trigger on current health of a pre-defined component FM of interest. Appropriate sensor data, combined with periodic visual inspections, as appropriate, are evaluated continuously to assess the current health of the equipment against pre-established thresholds.
- **Run to Failure** – Pre-Planned unscheduled (reactive) corrective maintenance triggered following the component failure event.

3.2.3.1 Sensor Gap for Seawater System

Since sensors provide evidence of both equipment operational profile, as well as operating conditions as compared to design, they are very important for implementing an intelligent predictive analytics-based maintenance strategy.

Typically, OEMs provide installed sensors primarily to support start-up, shut-down, and supervisory control related sensors. The full suite of sensors required for comprehensive, first principles-based analysis could be expensive to buy and implement. Therefore, one of the objectives of the detailed CBM+ analysis was to define the optimal sensor suite for managing the dominant FMs of interest. Each FM model includes information relative to what condition indicating and stress inducing parameters are needed. It identifies what to collect, when to collect it, how to collect it, and what features of the measurements are needed for anomaly detection, FM condition assessment, and remaining life estimation. The analysis focused on maximum use of a small sensor suite that is needed to provide a higher confidence factor for managing critical FMs.

The sensor types that MRSS uses are:

- Direct sensor measurements, whose values are acquired through networked data acquisition devices.
- A specific feature (attribute), as calculated by an intelligent sensor such as the amplitude of a narrow band harmonic, provided by the ESA analytics, through the high-speed data acquisition device. By using advanced signal processing methods in selecting good feature subsets can help both in use of minimal sensors suite while enhancing the data analysis (e.g., classification performance) through a more stable data representation. The extraction of complex patterns from each sensor allows transforming each complex pattern (features) into virtual sensors that are used to further decipher meaningful information from the acquired data.
- A calculated value (virtual sensor), whereby several other parameter values from the sensor map are used to calculate an attribute, such as motor air gap integrity, pump work deviation from expected, etc. The output of the calculation will be the value in the sensor register assigned to the calculated value.

The official signal list from the Sea Hunter MCCS available on the Sea Hunter was not available at the time of the analysis. Assumptions for currently available sensors were made using the Seawater System technical manual, by looking at the typically installed sensors listed in the drawings.

The sensor gap analysis was performed using the following process:

- Map each FM to appropriate features to be used for health assessment.
- Map each feature of interest to sensors being used.

- Map each stress event profile to sensors being used.
- Identify appropriate Tasks against FMs, with their associated threshold-based triggers.

Sensor Gap Report Summary is shown in Table 3.

Table 3. Sensor Gap for Seawater System

Sensor Type	Sensor Count	Sensor Gap? Y/N	Sensor Source	Inputs to Failure Modes
Pressure	25	N	MCCS	20
Temperature	4	N	MCCS	4
Actuator Signal	14	N	MCCS	30
Accelerometers	28	Y	MRSS DAQ	42
Electrical Sensors	28	Y	MRSS DAQ	126

3.2.3.2 Conclusion for Seawater With Sensor Gap

The analysis result shows that **250** (96%) of the 261 FMs can be managed under a **predictive or condition-based approach**. The **11** remaining FMs (4%) are non-critical and are recommended to be managed under a **"run to failure"** strategy; however, these will still have a RUL estimation relative to the average population baseline represented by a fleet level Weibull failure distribution (failure rate), but **not** to the specific seawater pump being monitored. This will provide visibility into estimated risk, with a broad variance, but still allowing planning for servicing and materials acquisition at the discretion of shore-side support crew. ***In effect, all FMs will be managed under a reliability driven CBM+ based strategy***.

3.2.3.3 Conclusion for Seawater Without Sensor Gap vs. Gap Sensors

Figure 16 shows that only 40 of the 261 FMs can be managed under a predictive or condition-based approach vs. 250 FMs that could be monitored with the additional sensors gap. "*As is*" will not support the autonomous operations as Sea Hunter is expected to perform 90 days mission without intervention for the shore.

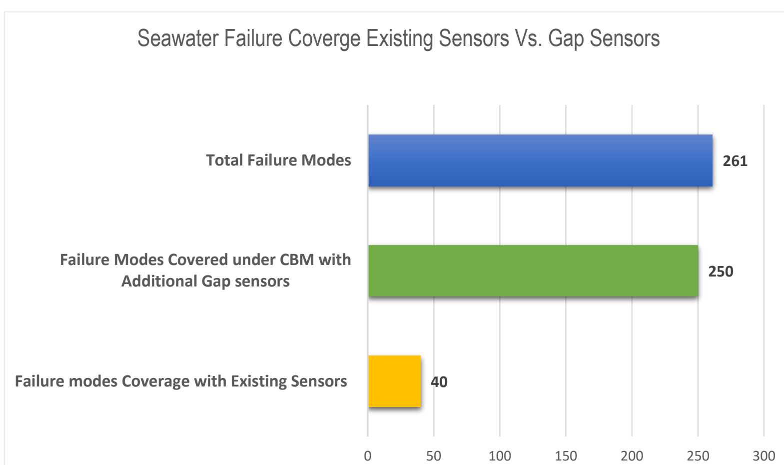

Figure 16. Seawater Failure Coverage Existing Sensors vs. Gap Sensors

3.2.4 Fuel Oil System

The main function of the Fuel Oil System is to provide marine-grade diesel fuel to the main engine and generators. Within the Fuel Oil System are two subsystems: the Fuel Transfer Subsystem and the Fuel Service Subsystem.

The Fuel Transfer Subsystem consists of three fuel oil storage tanks, fuel fill manifolds, redundant transfer filters, and redundant transfer pumps. The three storage tanks are in the following ship spaces:

- Fuel Storage Tank 1 AMR 1
- Fuel Storage Tank 2 AMR 1
- Fuel Storage Tank 3 AMR 2

Viking Pump was selected for the two fuel transfer pumps. They are gear type positive displacement pumps. Each pump has a rated capacity of 20 gpm. They are driven by a 1 Hp, 460 VAC, 3-phase, 60 Hz induction motor that rotates at 1740 rpm. The fuel transfer pumps are in the following ship spaces:

- Fuel Transfer Pump 1 AMR 1
- Fuel Transfer Pump 2 AMR 1

The transfer pumps take suction from the storage tanks, and discharge through a fuel transfer filter, to the two fuel service tanks.

The Fuel Service Subsystem consists of two fuel service tanks, fuel supply manifold, fuel return manifold, and a filter system for each engine and generator. The fuel oil service tanks are in the following ship spaces:

- Fuel Service Tank 1 C4N
- Fuel Service Tank 2 C4N

Each engine and generator have their own engine mounted fuel pump that supplies fuel oil to the respective equipment. The fuel passes through a filtration system before reaching the engine fuel injection components. The filtration system for each main engine consists of a 5 micron and a 1-micron filter, while the filtration system for each generator consists of a 3-stage filter.

The Fuel Oil System interfaces with the following ship systems:

- Electrical Distribution

Figure 17 shows the results of the engineering analysis for Fuel Oil System. A rigorous RE-CBM+ analysis was conducted that identified FMs of interest and the associated reliability model, which were then used to design the most practical means of reducing maintenance requirements and adjust maintenance task scheduling based on predicted estimated risk. Key benefit of identifying CFMs was to provide the means to recognize high-criticality vs. low-criticality failure modes to reduce the level of uncertainty and focus on high-priority maintenance tasks. CFMs were defined by impact to:

- Loss of equipment operability
- Safety (failure results in loss of ship, injury, or damage to the environment)
- Impact to other ship mission critical systems

A total of 106 FMs were identified from which 60 were considered CFMs.

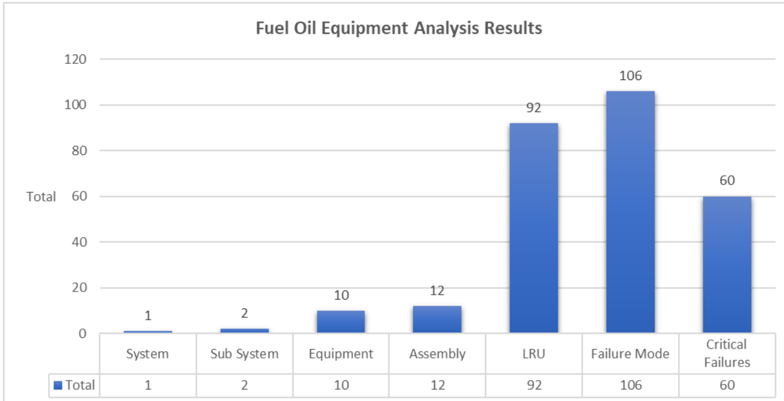

Figure 17. Fuel Oil FMECA Results

Figure 18 shows the reliability modes that were developed for each FM.

Reliability Models are defined as: *time-dependent mathematical models that are capable of computing current cumulative damage and predicting RUL when operated in the performance of a pre-defined mission profile. In essence, RUL can be converted to the probability of failure in future time under defined operating conditions.*

FM is the actual physical condition in a component that causes a particular functional failure.

FM Model Type are the mathematical constructs, which represent FM condition (health), and working age based on cumulative damage, providing a basis for estimating RUL (prognostics).

The model types are:

- **Current Health** – based on a combination of parametric relationships (sensor data) compared against design or expected behavior.
- **Weibull** – a static, historical failure rate-based statistical model, represented by a two-parameter distribution function.
- **Weibull with Stress Events** – design life-based statistical model, which considers damage accumulation due to normal operating hours as well as the occurrences of events which are known to accelerate component ageing.
- **Weibull PHM** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of component health.
- **Weibull PHM with Stress Events** – failure rate or design life-based statistical model (Weibull), dynamically integrated and updated continuously through the time history of sensor-based assessment of health, as well as the accumulation of captured stress events associated with accumulation of damage.

Figure 19 shows the Maintenance Strategy that was selected for the Fuel Oil System. Maintenance strategy is a combination of maintenance task types performed on equipment, over a period, taking

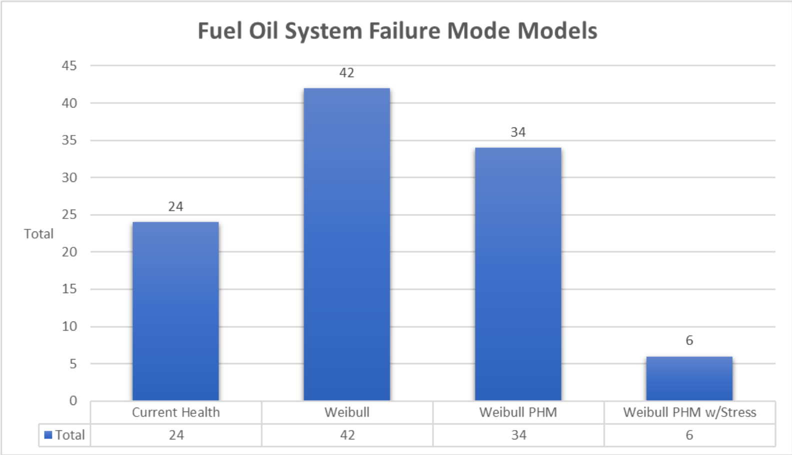

Figure 18. Fuel Oil Failure Modes

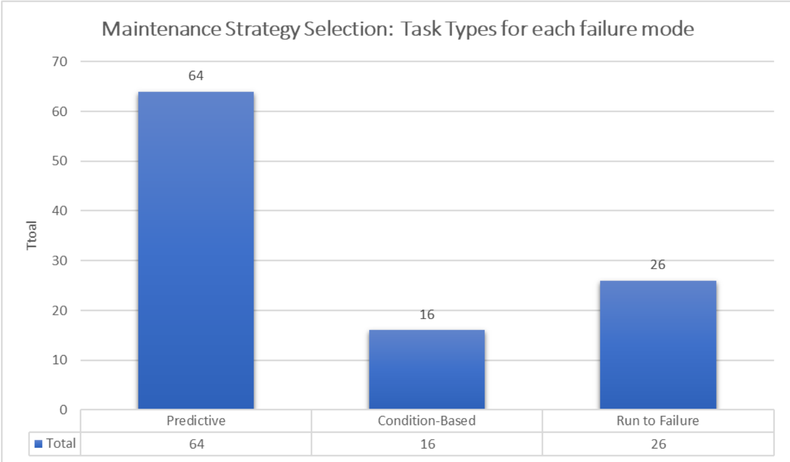

Figure 19. Maintenance Strategy Selection

into account design, operational objectives, and constraints. A maintenance strategy was defined for FMs, based on the results of the selected FM model.

The maintenance strategies are:

- **Predictive** – Pre-Planned Maintenance that is scheduled based on estimation of RUL of FMs of interest. Sensor data is used to capture operating hours and estimate component health and current cumulative damage at the FM level using operating duty cycle and externally induced stresses (such as insufficient lubrication, high ambient temperature.). With the availability of projected Fuel Oil System utilization demand, the RUL of components is estimated until failure risk probability will impact mission readiness.
- **Condition-Based** – Pre-Planned Maintenance that is scheduled based on a threshold trigger on current health of a pre-defined component FM of interest. Appropriate sensor data, combined with periodic visual inspections, as appropriate, are evaluated continuously to assess the current health of the equipment against pre-established thresholds.
- **Run to Failure** – Pre-Planned unscheduled (reactive) corrective maintenance triggered following the component failure event.

3.2.4.1 Sensor Gap Report for Fuel Oil System

Since sensors provide evidence of both equipment operational profile, as well as operating conditions as compared to design, they are very important for implementing an intelligent predictive analytics-based maintenance strategy. Typically, OEMs provide installed sensors primarily to support start-up, shut-down, and supervisory control related sensors. The full suite of sensors required for comprehensive, first principles-based analysis could be expensive to buy and implement. Therefore, one of the objectives of the detailed CBM+ analysis was to define the optimal sensor suite for managing the dominant FMs of interest. Each FM model includes information relative to what condition indicating and stress inducing parameters are needed. It identifies what to collect, when to collect it, how to collect it, and what features of the measurements are needed for anomaly detection, FM condition assessment, and remaining life estimation. The analysis focused on maximum use of a small sensor suite that is needed to provide a higher confidence factor for managing CFMs.

The sensor types that MRSS uses are:

- Direct sensor measurements, whose values are acquired through networked data acquisition devices.
- A specific feature (attribute), as calculated by an intelligent sensor such as the amplitude of a narrow band harmonic, provided by the ESA analytics, through the high-speed data acquisition device. By using advanced signal processing methods in selecting good feature subsets can help both in use of minimal sensors suite while enhancing the data analysis (e.g., classification performance) through a more stable data representation. The extraction of complex patterns from each sensor allows transforming each complex pattern (features) into virtual sensors that are used to further decipher meaningful information from the acquired data.
- A calculated value (virtual sensor), whereby several other parameter values from the sensor map are used to calculate an attribute, such as motor air gap integrity, pump work deviation from expected, etc. The output of the calculation will be the value in the sensor register assigned to the calculated value.

The official signal list from the Sea Hunter MCCS available on the Sea Hunter was not available at the time of the analysis. Assumptions for currently available sensors were made using the Fuel Oil System technical manual, by looking at the typically installed sensors listed in the drawings.

The sensor gap analysis was performed using the following process:

- Map each FM to appropriate features to be used for health assessment.
- Map each feature of interest to sensors being used.
- Map each stress event profile to sensors being used.
- Identify appropriate Tasks against FMs, with their associated threshold-based triggers.

Sensor Gap Report is shown in Table 4.

Table 4. Sensor Gap Fuel Oil System

Sensor Type	Sensor Count	Sensor Gap? Y/N	Sensor Source	Inputs to Failure Modes
Pressure	18	N	MCCS	10
Actuator Signal	10	N	MCCS	16
Electrical Sensors	8	Y	MRSS DAQ	38

3.2.4.2 Conclusion from Fuel Oil System Sensor Gap Analysis

The analysis results showed that 80 (75%), of the 106 FMs can be managed under a predictive or condition-based approach. The 26 remaining (25%) are non-critical FMs and are recommended to be managed under a "run to failure" strategy; however, these will still have a RUL estimation relative to the average population baseline represented by a fleet level Weibull failure distribution (failure rate), but not to the specific fuel transfer pump being monitored. This will provide visibility into estimated risk, with a broad variance, but still allowing planning for servicing and materials acquisition at the discretion of shore-side support crew. *In effect, all failure modes will be managed under a reliability driven CBM+ based strategy*.

3.2.4.3 Conclusion for Fuel Oil System Without Sensor Gap vs. Gap Sensors

Figure 20 shows that only 25 of the 106 FMs are managed under a predictive or condition-based approach vs. 80 FMs that could be monitored with the additional sensors gap. "*As is*" will not support the autonomous operations as Sea Hunter is expected to perform 90 days mission without intervention for the shore.

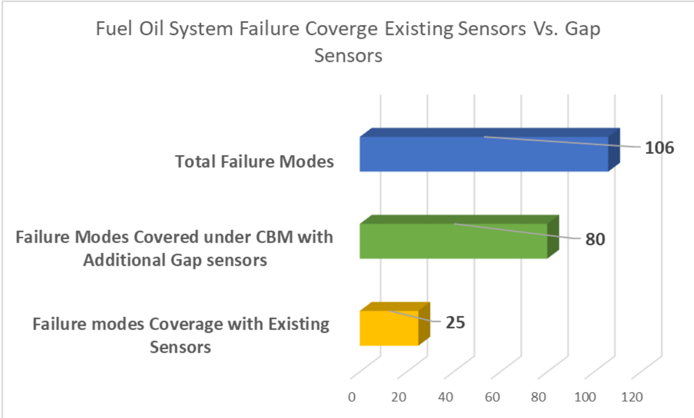

Figure 20. Fuel Oil Failure Coverage with Existing Sensors vs. Gap Sensors

3.2.5 Limited MRSS Demonstration for Power Generation System

As a deliverable under this project, a demonstration was provided to the Navy of the SSDG configuration within the MRSS framework, assuming availability of the sensor gaps as defined. MRSS is an AI/ML driven decision support system that integrates rigorous reliability engineering and data science expertise to be able to calculate equipment Current Health and Current/Future Reliability, which is then used to determine and schedule optimal maintenance actions autonomously or in interaction with other systems or humans as needed. Current and Future mission risk resulting from non-compliance to established requirements incorporates all known material requirements, including minimum reliability thresholds, against ship systems into a ship functional digital data model to be able to run a constrained maintenance optimization algorithm. The ship functional digital data model captures the System/Equipment Compliance to Mission Functions which are required to achieve Readiness.

MRSS framework contains two predictive analytics engines:

1. Predictive Machinery Analyzer (PreMA)
2. Autonomous Planning and Scheduling (APS)

Under this project only the PreMA engine was part of the configuration demonstration. The PreMA was created to provide intelligent prognostics at the component level. Based on automated analysis of trended information, the system efficiently collects data, stores, and analyzes, providing anomaly detection, diagnostics, and dynamic RUL estimation for the monitored systems. It captures the equipment current and future risk, can provide the analysis results to the onboard autonomy system for short-term management through equipment realignment, and long-term equipment failure risks with recommendations transferred ashore to the Digital Twin to:

- Support decisions related to maintenance advance planning.
- Leverage the shore-based maintenance support infrastructure to optimize the MTTR (mean-time-to-repair).

3.2.5.1 Predictive Machinery Analyzer Functional Processes

Condition Monitoring

Ship system condition monitoring sub-processes are executed to establish current condition of the equipment attributes, as related to the safe, compliant, and reliable operation of the equipment:

- Acquires the relevant data, at the prescribed frequency, and stores all parameters in the embedded data historian.
- Establishes the state of the equipment at the time the data was collected (on/off/steady state/dynamic).
- Compares qualified data to equipment operational design parameters, as represented by the assimilation and evaluation of measurable/observable indicators.
- Calculates and identifies deviations from expected values (anomalies).

The Condition Monitoring module’s primary function is to identify equipment anomalies as compared to base-line design, or as expected. PreMA provides the capability to define expected equipment behavior in several different formats. This includes steady-state performance curves or maps representing parametric relationships of equipment attributes, such as Load vs Exhaust Temperature, Pressure vs Flow, Heat Exchanger Logarithmic Mean Temperature Difference, etc. These models are built using a supervised ML approach. As the data is acquired and filtered, the performance models are evaluated for deviation, PreMA triggers various levels of alerts and alarms and are displayed in PreMA web Alert Manager. PreMA executes the Condition Monitoring Process continuously on-line using the available sensors.

<u>Output of the Condition Monitoring Process</u>: Compliance measure/deviation from expected, as compared to the requirement associated with the equipment attribute, is the process output, and it becomes the input to the next process element, System Condition Assessment.

Ship System Condition Assessment (Current Health) Process

Given the results of the Condition Monitoring process as an input, the System Condition Assessment process involves the qualitative evaluation of the Condition Monitoring results. The sensor-based condition monitoring, performed by PreMA is automatically analyzed against the baseline equipment performance requirements, and the deviation is processed by the PreMA diagnostic engine to establish an estimate of equipment current health at the FM level (condition relative to design.

Output of the Condition Assessment Process: Current health of managed equipment FMs of interest. These assessments become the input to the Current Reliability and Future Reliability evaluation of the current functional capability of ship systems to support current future defined mission requirements.

Ship System Current Reliability Estimation

Given the estimation of current ship system condition assessment, and results of the condition and event monitoring process outputs, the system current reliability estimation sub-process evaluates continuously the probability that all mission required functions are near-term supportable by the required ship systems. For the equipment FM related calculations performed by PreMA this estimation equates to the calculation of cumulative damage associated with the current state of the applicable equipment components.

Output of Current Reliability Process: Current reliability of ship systems for supporting mission reliability and availability and becomes an input to the Future Reliability calculations (prognostics).

Ship System Predicted Reliability Estimation and Estimated Remaining Useful Life (RUL)

The inputs of current health of the equipment, and the projected utilization as defined by duty cycles (loads and external environment during time periods), are used in the FM reliability models to determine the future behavior of the equipment dominant FM leading to equipment functional or structural failure. It provides failure risk probability, at discreet time frames far enough in the future, coupled with estimating RUL, to allow advance maintenance planning activities.

Output of RUL: Estimation of the 30, 60, 90, 120-day ship system reliability and estimation of RUL of components.

3.2.6 PreMA SSDG Configuration Demonstration

The Main Graphical Interface is shown in Figures 21, 22 and 23. For the purpose of this report, only a few representations of the main user interface are presented.

- **First Panel** (left Panel) shows the Systems/Equipment in a hierarchy tree. This panel serves as the navigation menu for the information on the second panel.
- **Second Panel** shows the contents related to the current selection.
- **Third Panel** is the Navigation Panel between Modules, always available regardless of Module.

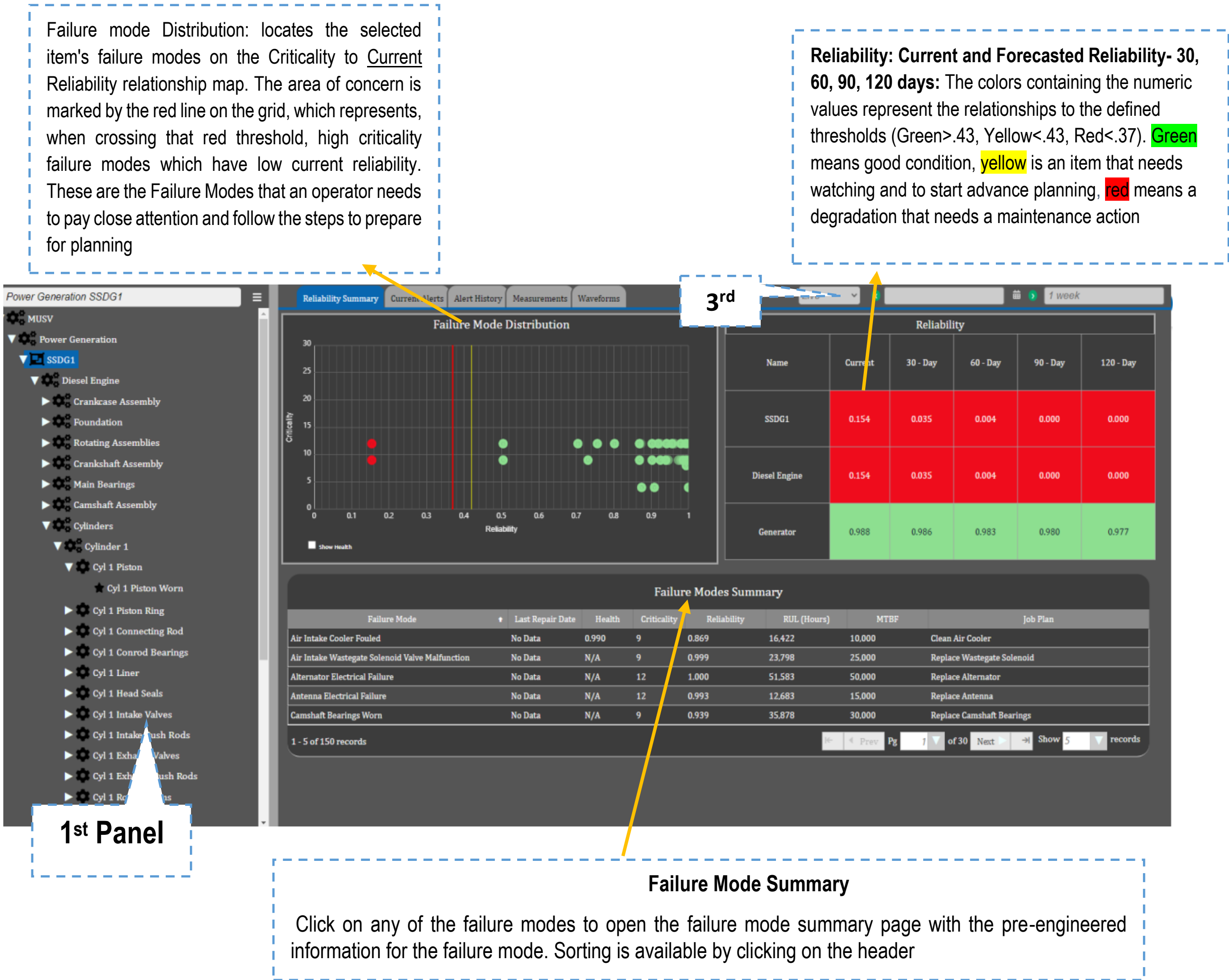

Figure 21. Main Graphical Interface

<u>The First Panel</u> represents the Power Generation systems hierarchy. The engineering configuration process builds the system/equipment models that contain all the attributes related to the FMs management. The system was decomposed into:

- System, equipment, component, LRU, and FMs. When an item of interest is selected, data associated with that selection will populate into the **Second Panel, in this case the reliability data was selected**.

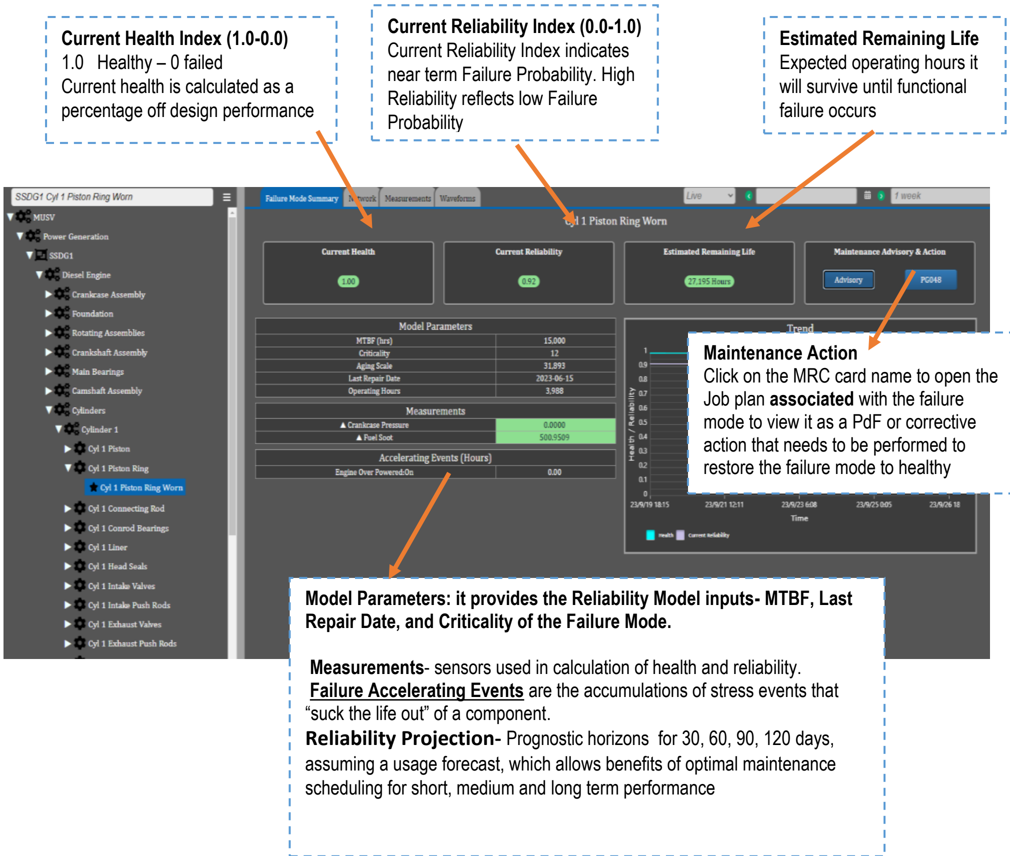

Figure 22. Main Graphical Interface

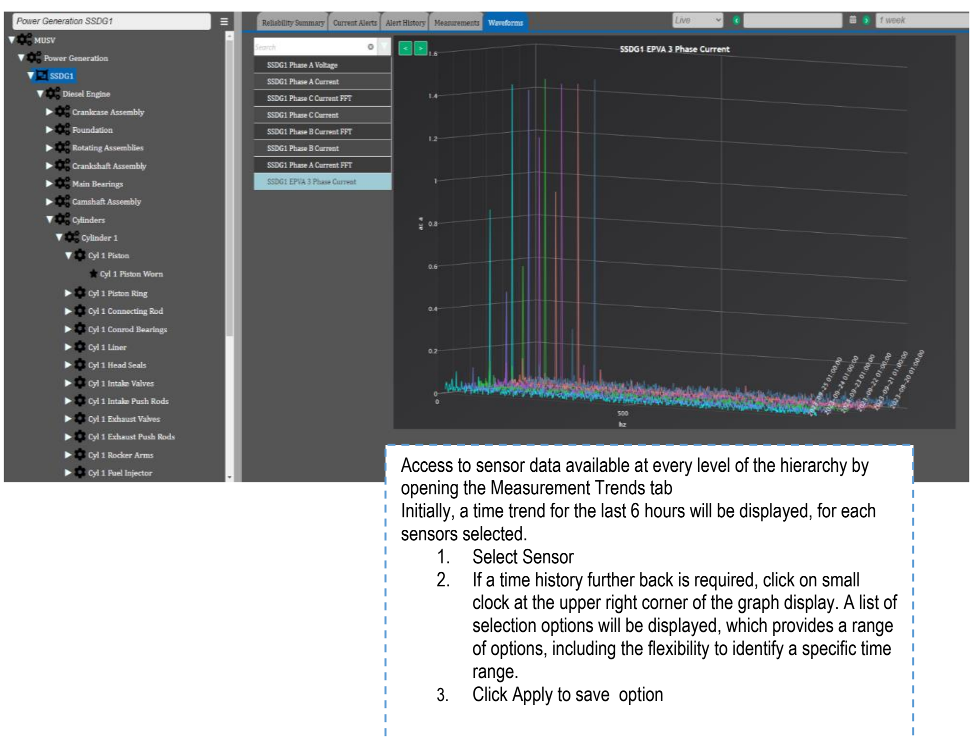

Figure 23. Main Graphical Interface

4. Conclusions

By accomplishing the Reliability Engineering analysis on the selected mission critical systems, a recommended sensor system was identified which when used by the appropriate reliability models, will provide the capability to estimate future mission risk with sufficient horizon to allow for pre-emptive performance of maintenance prior to start of mission.

The engineering analysis established what is needed to implement an advanced CBM platform which is a step towards a highly automated autonomous vessel. An innovative method that can greatly benefit both commercial and government shipping operations through the realization of autonomous vessels in which ships are intelligent and able to make decisions autonomously based on their embedded sensor data, getting from A-to-B on their own, all while communicating with other vessels and on-shore personnel to inform them what the ship needs, and will need in the future.

Timely knowledge about operational and logistics requirements can minimize energy consumption and allow pro-active parts delivery for maintenance and sustainment of ready, efficient, and effective industrial and public sector transportation and manufacturing infrastructure.

The Reliability Engineering Analysis and Maintenance Strategy Redesign task achieved three major objectives:

1. Developed and implemented a Reliability Engineering-based CBM+ (RE-CBM+) strategy for the selected equipment modeling the important relationships between mission capabilities and individual FMs, platform hosted software, and sensors to continuously monitor consumption of equipment life during operations and provide continuous prediction of future risk.

2. It showed that all CFMs can be monitored with the additional gap sensors, achieving required mission readiness based on the RE-CBM+ derived strategy.

3. It reduced the amount of scheduled and emergent maintenance requirements, with associated shore-side crew manhours, through an improved understanding of equipment health, current reliability (cumulative damage), and RUL of components before corrective actions need to be executed.

5. Project Benefits

5.1 Benefits for the General Public

By implementing the right sensors and the advanced technology such as MRSS, machinery system efficiency, safety and production reliability will be greatly improved; MRSS will allow equipping the machinery platforms with advanced technologies such as AI, ML, and IoT based data management, which will help optimize operations, enhance safety, and reduce the possibility of human error.

- Data-Driven Operations: Autonomously operated platforms generate a vast amount of data, which can be analyzed to improve decision-making, reduce costs, and enhance safety. The use of engineering context-based ML algorithms and predictive analytics can help identify patterns, predict outcomes, and optimize plant operations.
- Reduce Fuel Consumption: Brake Specific Fuel Consumption of Diesel Engines expected to be 3-5% less with the analytics-based maintenance performed during available maintenance periods.
    - 56 Propulsion Engine Efficiency Impacting FMs, for example:
        - Injector degradations degrade engine combustion efficiency by 0.5%
        - Cylinder liner and ring wear contribute to loss in combustion power conversion to delivered torque by 1%
    - 37 SSDG Efficiency Impacting FMs, for example:
        - Injector degradations degrade engine combustion efficiency by 0.5%
        - Cylinder liner and ring wear contribute to loss in combustion power conversion to delivered torque by 1%
- Improved machinery system readiness by knowing what needs to be corrected on critical systems prior to production periods.
- Improved failure prediction and part requirements, providing for reduced downtime, and subsequent increase in equipment availability.
- Longer sustained production periods since predictive simulations will reduce the uncertainty of risks by identifying the high value tasks to be accomplished prior to long production runs.

Projected Extended Outcomes

- Reduced Maintenance: 30-40% reduction in FRP sustainment costs. This is based on studies published by the Electric Power Research Institute (EPRI) as regards the cost relationships between Corrective, Preventive and Predictive maintenance strategies.

5.2 Benefits for DOD

By implementing the right sensors and the advanced technology such as MRSS, ship system efficiency, safety and mission reliability will be greatly improved; MRSS will allow equipping the ships with advanced technologies such as AI, ML, and IoT based data management, which will help optimize vessel operations, enhance safety, and reduce the possibility of human error.

- Data-Driven Operations: Autonomous ships generate a vast amount of data, which can be analyzed to improve decision-making, reduce costs, and enhance safety. The use of engineering context-based ML algorithms and predictive analytics can help identify patterns, predict outcomes, and optimize vessel operations.
- Reduce Fuel Consumption: Brake Specific Fuel Consumption of Diesel Engines expected to be 3-5% less with the analytics-based maintenance performed during in-port periods.
    - 56 Propulsion Engine Efficiency Impacting FMs, for example:
        - Injector degradations degrade engine combustion efficiency by 0.5%
        - Cylinder liner and ring wear contribute to loss in combustion power conversion to delivered torque by 1%
    - 37 SSDG Efficiency Impacting FMs, for example:
        - Injector degradations degrade engine combustion efficiency by 0.5%
        - Cylinder liner and ring wear contribute to loss in combustion power conversion to delivered torque by 1%
- Improved readiness by knowing what needs to be corrected on mission critical systems prior to mission periods.
- Improved failure prediction and part requirements, providing for reduced in-port downtime, and subsequent increase in ship availability for missions.
- Longer sustained missions since predictive simulations will reduce the uncertainty of mission risks by identifying the high value tasks to be accomplished.

Projected Extended Outcomes

- Reduced Maintenance: 30-40% reduction in FRP sustainment costs. This is based on studies published by EPRI as regards the cost relationships between Corrective, Preventive and Predictive maintenance strategies.
- Earliest FY that benefits will be realized is expected to be starting one year following implementation of the technology.
- For Hardware/Software – FY of first ship install.