Impact of Environmental Temperature Variation on Vibration-Based Fault Detection for Air Compressors

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Abstract

Condition-Based Maintenance Plus (CBM+) aims to enhance operational readiness for U.S. Navy assets by using predictive models to forecast equipment failures. Applying CBM+ in the U.S. Navy faces a unique challenge: ships operate globally for extended periods, exposing machinery to a wide range of ambient air and seawater temperatures that alter their characteristic vibration signatures and can compromise model performance. This paper investigates the extent to which these seasonal temperature variations degrade the performance of a vibration-based fault detection model for a naval air compressor.

Using data from controlled testing, vibration data was collected under healthy and various induced-fault conditions during both winter and summer to create two environmentally distinct datasets. Power Spectral Density analysis was used to extract features for training classifiers. Results show that models trained exclusively on data from one season performed poorly when tested against data from the other, confirming that environmental shifts significantly degrade predictive accuracy. In contrast, a model trained on a combined dataset incorporating data from both seasons demonstrated substantially improved and more generalized performance. These findings underscore that the development of robust, field-ready CBM+ systems is critically dependent on training ML models with comprehensive and environmentally diverse datasets that reflect the full spectrum of anticipated operational conditions.

1. Introduction

Condition-Based Maintenance Plus (CBM+) elevates traditional CBM by incorporating predictive analytics and knowledge-based systems to forecast, rather than simply detect, equipment failures (DoD, 2018). While conventional CBM triggers maintenance based on real-time asset monitoring, CBM+ employs predictive algorithms – including machine learning and artificial intelligence – to estimate an asset's Remaining Useful Life (RUL). This advanced, prognostic capability allows organizations to transition from a reactive to a truly proactive maintenance strategy. The result is optimized repair schedules, minimized unscheduled downtime, and a significant improvement in overall system reliability and operational efficiency (DoD, 2018).

The U.S. Navy is a strong advocate for the implementation of CBM+ and strives to incorporate CBM+ early in the design of new technologies. At a high level, a U.S. Navy ship represent an industrial environment like any other setting using heavy-duty machinery. However, it is no secret that these ships can be anywhere in the world on any given day. It is possible that a ship can start her deployment in the winter in the Arctic Circle for several months and then migrate towards the equator in the summer for several more months. The vibration signatures of the machinery onboard a ship with this mission will change significantly due to changes in ambient temperatures. Building a machine learning (ML) classifier model generalized enough to detect faults across not just these two extreme scenarios, but also the potential environment in between them will be challenging.

This project focuses on deploying prognostics and health management (PHM) technologies to enable CBM+ for the U.S. Navy (Baker et al., 2020). New ship construction offers a unique opportunity to affordably implement an advanced hull, mechanical, and electrical (HM&E) monitoring system that integrates sensor data collection, processing, visualization, and machine learning-based predictive analytics. The application of these embedded CBM+ capabilities is expected to significantly reduce sailor troubleshooting workload, lower lifecycle sustainment costs, minimize preventive maintenance actions, and increase overall ship reliability.

A critical requirement for developing effective predictive analytics is the availability of representative, vibration-based fault data to train and validate the machine learning algorithms. To address this, the paper discusses an initiative undertaken by the Naval Surface Warfare Center, Philadelphia Division (NSWCPD) to conduct controlled fault testing on critical ship systems. This effort focuses on generating the essential datasets needed to develop, train, and validate robust predictive models.

Using data from this initiative, this paper seeks to address two key questions: 1) To what extent does seasonal temperature variation degrade the performance of a vibration-based fault detection model? and 2) Can this degradation be overcome by training a model on a more environmentally diverse dataset? The central hypothesis is that a model's performance is strongly dependent on the environmental conditions represented in its training data.

2. Test Equipment and Faults Studied

Every system onboard these ships is mission critical; without their reliable performance over the length of a mission, the chances of that mission's success degrade significantly. This testing focuses on implementing CBM+ on one of those essential systems: compressed air. Air compressors provide ships with compressed air that serve a wide range of applications essential for day-to-day operations. This compressed air enables buoyancy control for routine surfacing and emergency ascents for submarines, powers main propulsion startup, and supports weapon system launch mechanisms. Furthermore, they control numerous pneumatic systems critical for daily operations, including valve actuators, control systems, instrumentation, and emergency life support redundancy. The compressed air system is integral for many other systems onboard a ship as well, underscoring the necessity of continuous, reliable air compressor operation for maintaining ship readiness and operational effectiveness.

Faults develop over time in any industrial equipment deployed to a harsh environment. Air compressors have several common faults. Air leaks, both internal and external, constitute a common category of compressor problems. Internally, valve-related issues frequently arise due to the high-pressure and cyclic loading inherent in compressor operations, causing wear on valve seats and internal valve components. Valves can become stuck or break because of mechanical stress or carbon buildup from oil carryover. Valve leaks due to improper seating or damaged seals further degrade compressor efficiency and reduce output pressure (Cui, et al., 2009). Similarly, piston rings, cylinder liners, rod packaging, and other sealing elements are subjected to significant stress and wear, leading to blow-by, reduced compression efficiency, increased oil consumption, and potential oil carryover into the compressed air stream. External leaks are also common, typically originating from fittings, hoses, gaskets, or component casings. These leaks can result from vibration, pressure cycling, corrosion, or improper assembly, contributing significantly to operational inefficiency.

Inlet air restrictions typically result from fouled intake filters or malfunctioning inlet valves. Such restrictions reduce airflow into the compressor, causing decreased output capacity and efficiency. Fouled or clogged intake filters can occur due to particulate ingestion, while inlet valves may become stuck or damaged due to mechanical issues or contaminants. Reduced inlet airflow increases the workload placed on the compressor and leads to elevated operating temperatures and accelerated component wear.

Cooling water restrictions represent another significant source of compressor faults. Multi-stage compressors depend heavily on efficient intercoolers and after-coolers. A sea strainer filters raw seawater before reaching the air compressor, and this strainer requires routine maintenance as debris restricts flow over time. Blockage at the sea strainer directly impedes heat transfer efficiency, resulting in overheating and increased wear rates over time. Additionally, improper condensate management—caused by inefficient cooling or faulty condensate traps—can allow excess moisture to enter the compressed air system, negatively affecting air quality and compressor reliability.

To represent the range of faults a compressor might encounter, we collected data from eight conditions:

- Off: the compressor is powered down
- Baseline: normal function, with the compressor warmed up
- Air Leak A & Air Leak B: two different types of air leak
- Faulted Piston: a worn piston was placed in the compressor
- Restricted Inlet Air: the air inlet was partially covered
- Restricted Inlet Seawater: the seawater inlet was partially obstructed
- Restricted Inlet Air & Seawater: both air and seawater flow were limited.

2.1. Challenges in Fault Detection for the U.S. Navy

The unique integration of machinery onboard U.S. Navy ships complicates detecting and isolating faults in a device from another event onboard. All equipment is installed in confined spaces that complicate routine visual inspections or direct measurements during underway operations. Additionally, vibration signatures from other onboard mechanical systems may mask subtle early-stage faults (Kumar, 2025), while load variations further complicate diagnostics (Kibrete et al., 2024). Ambient temperature is the only environmental factor addressed in this paper.

The ambient operating environment machinery spaces onboard U.S. Navy ships commonly changes for three main reasons: (1) seasonal variation in air and seawater temperature; (2) the ship has relocated to a different location where the air and seawater temperatures have changed; and (3) other machinery in the same space as an air compressor power on and off. The temperature of the air in a space onboard a U.S. Navy ship changes dramatically depending on how many other machines are powered on. For example, an engine room with an electric generator and two gas turbines running at full power generates much more heat than if they were shutdown. This means the inlet air that an air compressor ingests will be significantly warmer, leading to changes in vibration signatures. Developing a predictive ML model that is robust enough to detect these changes across all potential operating environments will require very diverse datasets for training, testing, and validation.

A key obstacle in developing advanced ML algorithms for PHM is the scarcity of representative historical fault data. Real-world compressor failures occur infrequently and with little to no warning, so comprehensive datasets representing diverse faults under realistic operational conditions are limited. Inducing specific faults aboard operational equipment is both impractical and potentially unsafe. Thus, dedicated laboratory testing initiatives are essential to generate diverse, representative fault datasets critical for effective predictive algorithm development.

3. Vibration-Based Fault Detection

This study compares two datasets collected in a lab at NSWCPD during different parts of the calendar year. Each dataset contains vibration data from a mix of both healthy and faulty conditions. The only difference between these datasets is that one was collected in the winter while the other was collected in the summer. The raw data are cleaned and inspected before the most important features are extracted to train and test the models (see Eklund, *et al.* (2025) for details of the analysis). Figures 1 and 2 show the temperature distributions of the inlet air and the coolant of the air compressor for both the winter and summer datasets.

Each test event conducted at NSWCPD is comprised of three distinct phases: data acquisition and preprocessing, feature extraction and selection, and training, testing, and deploying a model onto an edge device for real-time diagnostics. Vibration data was collected under controlled operating conditions. The collected data underwent preprocessing followed by extraction of condition indicators via frequency-domain analysis.

3.1 Data Collection & Feature Extraction

For each data collection run, we first established a baseline by operating the compressor for 20-30 minutes under normal conditions. A specific fault was then introduced, and the compressor ran for approximately 10 minutes to collect data under steady-state fault conditions. Vibration data was sampled continuously using three orthogonally mounted accelerometers sampling at a rate of 10,000 Hz.

Vibration analysis for mechanical fault detection is based on the principle that mechanical defects alter the dynamic behavior of rotating or reciprocating machinery, inducing distinct patterns in measured vibration signals. These vibration signatures reflect changes in the mechanical energy distribution within the system and manifest as shifts in amplitude, frequency content, or phase characteristics of the measured acceleration signals.

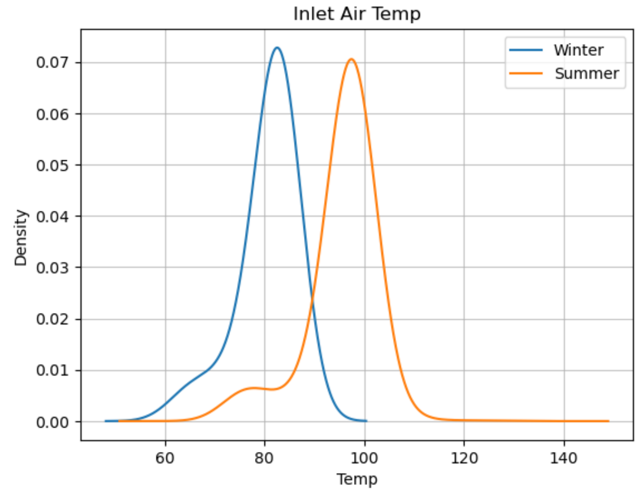

Figure 1. Distribution of ambient air temperature by season.

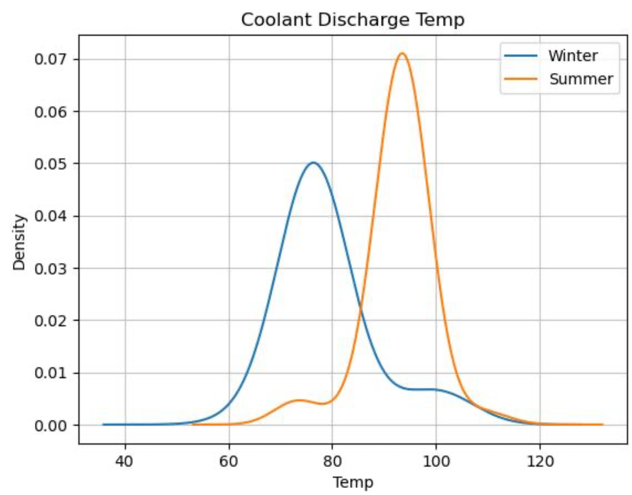

Figure 2. Distribution of coolant temperatures by season.

Power spectral density (PSD) is a frequency-domain analysis method that identifies the characteristic signatures of vibrations. PSD analysis, derived from the Fast Fourier Transform (FFT), quantifies the distribution of signal power over frequency, enabling the identification of characteristic fault frequencies and their harmonics. Under the assumption that vibration signatures change when a piece of equipment is degraded, PSDs provide the optimal method of identifying what those deviations are. An ML classifier model trained on these PSDs can identify the specific frequencies that change the most and use it to make fault predictions.

The hardware used to collect data is discussed in depth in Farinholt, et al. (2019) and Banks, et al. (2022). The details of the analysis are described in Eklund *et al*. (2025).

Note that the cooling water restriction fault was not implemented as planned during testing. While a 50% flow restriction was intended, later analysis indicated only approximately 15% actual restriction occurred. This discrepancy explains the relatively poorer detection performance observed for this fault condition, including why it was primarily mislabeled as Baseline, in the results below.

3.2 Seasonal PSD Comparison

Data was collected as described above in both the summer and winter, using a common set of sensors. Figure 3 shows the PSD of a healthy, baseline condition in the morning of the winter dataset versus another baseline condition in the morning of the summer dataset; the range of the axes is the same in both plots.

There are clear differences between the two PSDs. While certain frequencies exhibit similar behaviors, others show dramatic differences. For a machine learning model to accurately estimate RUL in machinery onboard a U.S. Navy ship, the training data will need to be diverse enough to capture these different PSD behaviors. Moreover, these two PSD plots do not represent all the varying environments an air compressor encounters during normal operations – they simply demonstrate the need for this work.

While a data-driven approach (Eklund, *et al.*, 2025) successfully identified key frequencies to differentiate between normal and faulty operation, we discovered that the optimal features were highly dataset-dependent. For instance, a model built using features selected from a "winter" dataset could not effectively identify faults in a "summer" dataset. A separate analysis of the summer data revealed that its most important predictive frequencies were distinctly different from those found in the winter data. This demonstrates that a feature set optimized for one operational environment does not guarantee success in another, highlighting the need to identify more robust, environment-invariant features for reliable fault detection.

These results also demonstrate a hazard of attempting to field an algorithm based solely on data collected on relatively sterile laboratory conditions. Future data collection efforts will focus on intentionally exposing the system to the full range of expected operational and environmental conditions, such as varying temperatures, humidity, and workloads. Creating and testing against such a diverse dataset is a prerequisite for developing a truly robust model that can transition successfully from the laboratory to the field

3. Classifier Performance

Several Random Forests (RF; Breiman, 2001) were built to classify state of the compressor. One RF was trained on PSD features extracted from the winter dataset and tested against the summer dataset (Figure 4). Additionally, a separate RF was trained on PSD features from the summer dataset and tested against the winter dataset (Figure 5). The goal of this test was to determine how accurate each model was when tested against data taken under different environmental conditions. Feature selection and model development are described in detail in Eklund *et al.*, (2025).

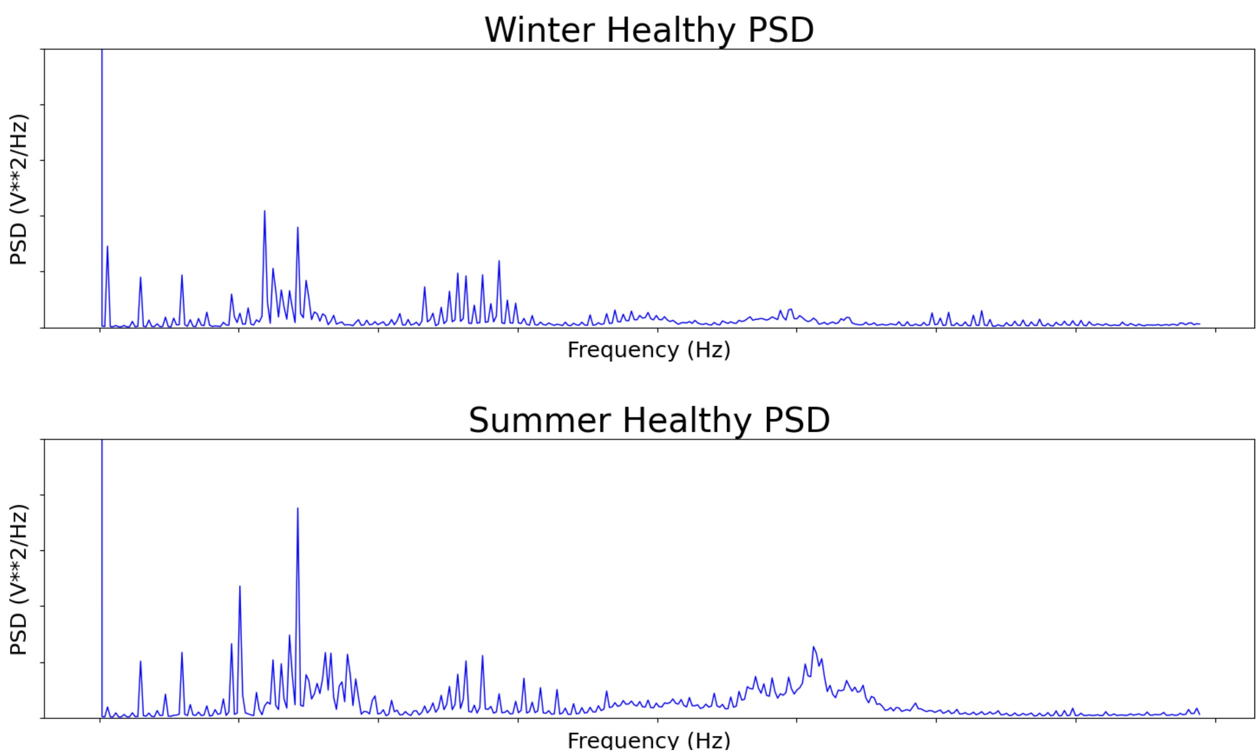

Figure 3: Seasonal variation in power spectral density during normal operation.

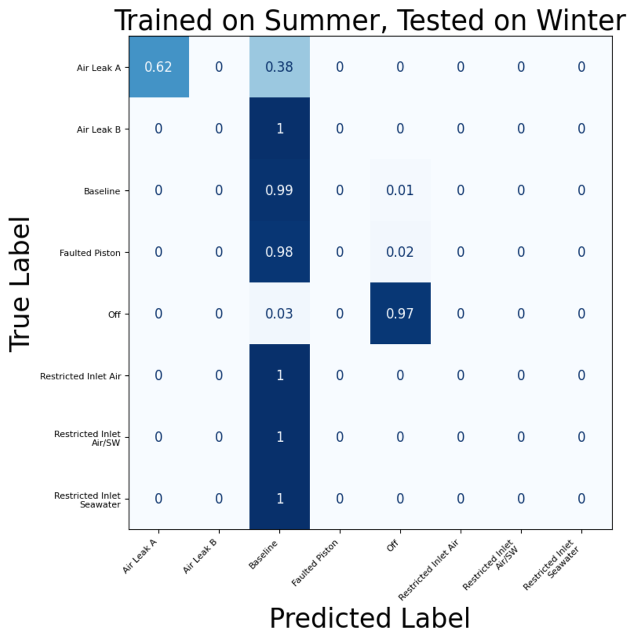

Figure 4. Cross-seasonal evaluation: winter-trained model on summer data

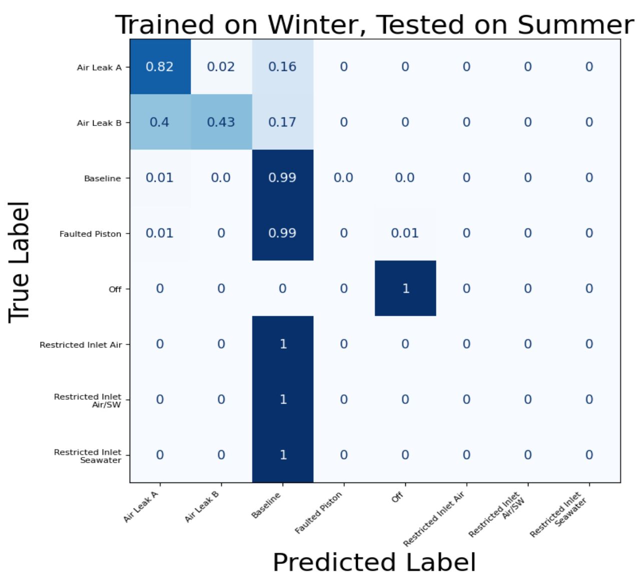

Figure 5. Cross-seasonal evaluation: winter-trained model on summer data.

These two confusion matrices show that the models did not perform well when tested with data from a different environment. This performance degradation occurred because the PSD signatures for any given fault are significantly different across calendar seasons. This variation is a direct result of how environmental temperature affects the compressor's mechanical operation.

For example, seasonal shifts in the temperature of the inlet air and cooling water alter fundamental operating parameters. Colder, denser winter air changes the load on the compressor, while warmer summer temperatures can reduce the viscosity of lubricants and cause thermal expansion in mechanical components. These factors can slightly change critical clearances in bearings and shafts, altering the machine's overall vibration signature. These subtle, temperature-driven changes in the physical system manifest as distinct shifts in the PSD data, ultimately causing a model trained on one set of thermal conditions to fail when presented with another.

A third model was constructed, training on both the winter and summer dataset, under the expectation this is this model would be much better at predicting operational conditions when the environmental impacts from both seasons are included in the training set. This combined model performed significantly better than the previous two individual models, although there are still opportunities for improvement (Figure 6).

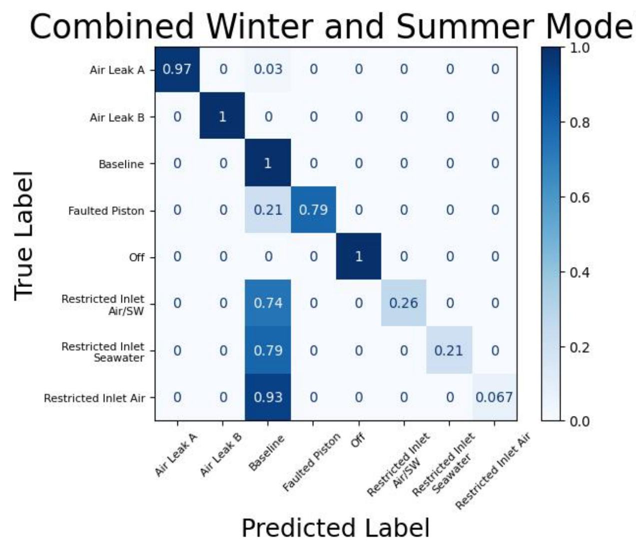

Figure 6. Overall performance: combined-season model

5. Discussion

While this study supports the feasibility of implementing CBM+ technologies in variable naval environments, the results also highlight critical challenges that must be overcome to field an impactful solution. The analysis of the model performance reveals areas for improvement in experimental design, sensor strategy, and data collection.

A key finding is the consistent failure of all three models to detect the "Restricted Inlet Air" fault. This poor performance suggests two potential issues. First, the performance of any vibration-based diagnostic model is fundamentally constrained by the quality and placement of its sensors. It's possible that the accelerometer locations were not well suited to capture the subtle dynamic changes associated with an airflow restriction. Therefore, a crucial next step is to systematically evaluate sensor placement, either by relocating existing sensors closer to the air intake system or by augmenting the setup with additional accelerometers in targeted areas. A similar strategic relocation of sensors could also enhance the detection of faults related to “Restricted Seawater Cooling”.

Second, it is possible that the induced fault condition was not large enough to generate a distinct and measurable change in the compressor's performance. A subtle fault may be masked by the machine's baseline operational noise, making it difficult for a model to distinguish. Future experiments should aim to induce a more pronounced fault by further restricting the inlet air or seawater supply, thereby creating a more robust signal.

Beyond these specific faults, this study's primary conclusion is the critical importance of data diversity. Building a generalized model that can reliably detect faults across a wide range of operating environments requires a comprehensive training set inclusive of as many conditions as possible. As demonstrated by the superior performance of the combined model, collecting more data and engineering feature sets that encompass multiple operational environments directly lead to more robust and accurate predictive maintenance tools.

6. Future Work

The findings of this study provide a clear roadmap for future research, which will focus on refining the current experimental approach while simultaneously expanding its scope to better replicate the complexities of a naval operational environment.

Immediate future work will concentrate on improving the existing single-compressor test setup. This involves acquiring more extensive data across a wider range of environmental conditions to build a more generalized and robust training set. Concurrently, a systematic optimization of sensor locations will be undertaken to enhance the detection of previously challenging faults. This effort will be complemented by the exploration of alternative and more advanced machine learning classifiers, which may better capture the nuanced relationships between vibration signatures and fault states across different thermal profiles.

A significant next step will be to transition from testing the air compressor in isolation to evaluating it within an integrated system loop. This is critical because ambient temperature is not the only environmental factor that influences vibration signatures aboard a U.S. Navy ship. The proximity of other equipment introduces sympathetic vibrations and operational noise that can mask the signatures of developing faults. Testing within a complete loop will allow for the evaluation of the model's ability to isolate true fault conditions from the complex vibration landscape of an active machinery space.

Finally, the long-term research plan includes applying these validated methodologies to different types of naval machinery. By performing similar analyses on a variety of systems, the goal is to develop a framework for evaluating which equipment is best suited for PHM technologies and provides the most return on investment for CBM+ implementation across the fleet.

References

Baker, W., Nixon, S., Banks, J., Reichard, K., & Castelle, K. (2020). Degrader analysis for diagnostic and predictive capabilities: a demonstration of progress in DoD CBM+ initiatives. *Procedia Computer Science*, *168*, 257-264.

Banks, J., Belella, M., Nixon, S., Polter, S., & Farinholt, K. (2022). *Development of machine learning-based predictive techniques for navy submarine CBM*. Paper presented at the AMTS Conference, 2022.

Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.

Cui, H., Zhang, L., Kang, R., & Lan, X. (2009). Research on fault diagnosis for reciprocating compressor valve using information entropy and SVM method. *Journal of loss prevention in the process industries*, *22*(6), 864-867.

Darst, B. F., Malecki, K. C., & Engelman, C. D. (2018). Using recursive feature elimination in random forest to account for correlated variables in high dimensional data. BMC genetics, 19, 1-6.

(DoD) U.S. Department of Defense. (2018). *Condition based maintenance plus (CBM+) for materiel maintenance* (DoD Instruction 4151.22). Washington Headquarters Services.

Efroymson, M. A. (1960). Multiple regression analysis. *Mathematical methods for digital computers*, 191-203.

Eklund, N., Wechsler, A., Polter, S., Van, K., Dingley, C., Chukwuemeka, A., Pale, A. (2025). Enhanced Operational Readiness through Vibration-Based Fault Detection in Air Compressors. In *Proceedings of the American Society of Naval Engineers Intelligent Ships Symposium (ISS) 2025*. American Society of Naval Engineers.

Fang, Z., Wang, W., Cao, Y., Li, Q., Lin, Y., Li, T., & Wu, S. (2024). Reciprocating compressors intelligent fault diagnosis under multiple operating conditions based on adaptive variable scale morphological filter. *Measurement*, *224*, 113778.

Farinholt, K., Polter, S., Hipwell, N., Chaudhry, A., Meekins, R., Kim, M., Thompson, E., & Castillo, K. (2019). Embedded sensing system for condition monitoring of hydraulic actuators. In *Intelligent Ships Symposium 2019 (ISS 2019)*.

Kibrete, F., Woldemichael, D. E., & Gebremedhen, H. S. (2024). Multi-Sensor data fusion in intelligent fault diagnosis of rotating machines: A comprehensive review. Measurement, 114658.

Kumar, A. (2025). Research overview and prospect in condition monitoring of compressors. *Expert Systems with Applications*, 127284.

BIOGRAPHIES

Colin Dingley, CISSP, M.S. Cyber Security from Penn State (2024), has spent his entire nine-year career at NSWCPD, becoming an expert in HM&E systems on various naval vessels. He began as a Machinery Control Systems In-Service Engineering Agent, developing and installing the control software sailors use to operate and monitor HM&E equipment. He then migrated to the Unmanned Surface Vehicle program, where he used his HM&E expertise to evaluate how AI/ML based solutions control and manipulate autonomous ships. Now he contributes to this research by leveraging his experience in Machine Learning and HM&E systems to design test environments that allow for proper detection of fault conditions.

Neil Eklund, Ph.D., FPHMS, is a leading expert in Asset Health Management and a seasoned technologist with over 25 years of experience in data science, industrial artificial intelligence, and machine learning. He has led high-impact projects across industries including aerospace, energy, healthcare, and oil & gas, resulting in 16 patents and over 70 technical publications. Dr. Eklund is one of the co-founders the Prognostics and Health Management Society and serves on its board of directors. His career includes significant roles at General Electric Research, Xerox PARC, and Schlumberger, where he was the Chief Data Scientist. At Schlumberger, he led the development of the first successful deployed Internet of Things (IoT) application in the oil industry, generating over $20 million in its first three months of operation. Dr. Eklund's extensive collaboration with organizations like DARPA, NASA, the DoD, Lockheed Martin, ExxonMobil, Ford Motor Company, and Boeing highlights his impact on both commercial and government sectors. His contributions extend beyond industry, having taught graduate-level courses in machine learning and classes through the PHM Society.

Adam S. Wechsler, M.S. in Data Science from Northwestern University, Chicago, IL, USA (2023). He has been involved in data analytics projects with a focus on anomaly and fault detection for Naval Surface Warfare Center Philadelphia Division (NSWCPD) since 2017. He has generated anomaly and fault detection models for a variety of mechanical equipment as part of the development of an embedded condition-based monitoring data acquisition system. He has also generated anomaly detection and predictive maintenance models from historical ship system and maintenance data. He has recently pivoted some of his effort toward software development for a ship equipment health-monitoring dashboard. Prior to joining NSWCPD, he had worked as a high school mathematics teacher for 16 years, and his involvement in education continues as a co-lead for the SeaGlide high school robotics competition.

Sherwood Polter, received MSEE in Acoustics and Power Systems Engineering from University of Idaho, is involved with machinery silencing R&D projects since 1996. Mr. Polter is program manager for embedded condition-based monitoring leading to acquiring data in relevant environments for machine learning models to inform predictive maintenance technology development for auxiliary machinery HM&E systems at NSWCPD. Mr. Polter has co-authored papers in CBM applications for the American Society of Naval Engineers, IEEE PHM and PHM Society. Mr. Polter has one patent for resilient mount measurement used in damping and noise control applications. Mr. Polter has led efforts with the development of acoustic noise control applications with design, testing, evaluation and inspection for auxiliary machinery systems.