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Degrader Analysis for Diagnostic and Predictive Capabilities: A Demonstration of Progress in DoD CBM+ Initiatives

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Abstract

This paper presents a modified reliability centered maintenance (RCM) methodology developed by The Applied Research Laboratory at The Pennsylvania State University (ARL Penn State) to meet challenges in decreasing life cycle sustainment costs for critical Naval assets. The focus of this paper is on the requirements for the development of the on-board Prognostics and Health Management (PHM) system with a discussion on the implementation progress for two systems: the high pressure air compressor (HPAC), and the advanced carbon dioxide removal unit (ACRU). Recent Department of Defense (DoD) guidance calls for implementing Condition Based Maintenance (CBM) as an alternative to traditional reactive and preventative maintenance strategies that rely on regular and active participation from subject matter experts to evaluate the health condition of critical systems.

The RCM based degrader analysis utilizes data from multiple sources to provide a path for selecting systems and components most likely to benefit from the implementation of diagnostic and predictive capabilities for monitoring and managing failure modes by determining various options of possible CBM system designs that provide the highest potential ROI. Sensor data collected by the PHM system can be used with machine learning applications to develop failure mode predictive algorithms with greatest benefit in terms of performance, sustainment costs, and increasing platform operational availability. The approach supports traditional maintenance strategy development by assessing the financial benefit of the PHM technology implementation with promising potential for many industrial and military complex adaptive system applications.

Keywords: Reliability Centered Maintenance; Condition Based Maintenance; High Pressure Air Compressor

1. Background

CBM capabilities, including implementation of continuous or periodic assessment of system condition via integrated sensors or at-platform tests and measurements, are built upon the foundation that is based on the idea that maintenance should be performed only when there is evidence of need from the asset being monitored.

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1.1. Condition Based Maintenance (CBM)

Operations and maintenance costs not only comprise a significant portion of the total ownership cost, they can be difficult to accurately assess at the outset of any acquisition project and even more difficult to control during the operation of an asset. CBM represents one of three maintenance philosophies that can be implemented over the lifetime of any asset, the other two being reactive maintenance and preventative maintenance. While all three strategies have valid applications for various asset types, successful implementation of a CBM philosophy has the ability to significantly decrease total asset lifetime cost by reducing overall maintenance costs associated with downtime for inspection and replacement or repair of components before their lifetime has been fully exhausted [1]. With proper implementation, CBM reduces unplanned downtime and increases asset availability, further enhancing the potential value of a successful program to asset owners and other stakeholders.

CBM relies on accurately assessing an asset's condition when making maintenance decisions regarding the asset. Given a defined CBM approach, regularly scheduled preventative maintenance inspections can be reduced if an asset is categorized in a condition of good health based on the sensor data analysis results. Components of the asset discovered in a condition of poor health that are likely to fail, are replaced before they undergo a catastrophic failure regardless of how long they have been in service. These potential benefits have not gone unnoticed – private companies from pulp and paper manufacturing to automotive assembly are investing heavily in CBM as an additional maintenance philosophy. CBM principles are now being adopted widely, leading to significant cost savings for many organizations by enabling improved maintenance and logistics practices for identifying and scheduling maintenance tasks through advances in business practices, engineering, maintenance tools, technologies, and processes, computer resources, and information systems. Many studies have demonstrated the efficiency and economic benefits of CBM strategies for applicable systems [2], including applications for detection of transient faults in the variable stator vane of aero gas turbine engines [3], detection and diagnosis of faults using Supervisory Control and Data Acquisition (SCADA) system data from wind turbines [4], predicting milling machine tool wear [5], and degradation trend analysis on turbofan engines [6]. Essentially, any field with complex mechanical/electrical systems and high operational readiness requirements can be a good candidate for CBM [7], where the ability to leverage monitoring of system performance conditions in real-time data for detection of failure and identification of recommended actions would enable an advantageous maintenance philosophy.

In recent decades, CBM has been embraced by the US Navy and DoD at large due to its ability to diagnose problems before they occur, reduce costs associated with maintenance, improve mission reliability, maintain or enhance safety, extend time between overhaul and reduce unnecessary downtime [7].

1.1. Condition Based Maintenance Plus (CBM+)

In 2002, the DoD instituted a policy in a memorandum signed by the Deputy Under Secretary of Defense for Logistics and Materiel Readiness directing CBM+ to be "implemented to improve maintenance agility and responsiveness, increase operational availability, and reduce life cycle total ownership costs" [8]. The policy requires that CBM+ tenets (many of which are basic concepts to CBM) are to be applied in both the maintenance and logistics realms across the DoD wherever they are found to be cost effective [8]. The original promulgation of the CBM+ strategy and related policy and instruction has since been updated and reissued, as it remains an essential readiness enabler and a recommended primary strategy for achieving cost-effective system lifecycle sustainment [9].

CBM+ is not a single process, rather it is a comprehensive strategy for selection, integration, and focus on a number of process improvement capabilities for maintainers and operators to cost-effectively attain the desired readiness across the total system lifecycle, particularly in operations and support (O&S) where roughly 65-80% of total ownership costs are incurred [10]. CBM+ strategies in organizations and programs include a variety of interrelated or independent capabilities and initiatives, both procedural and technical, that provides flexibility and optimization of maintenance tasks and reduces requirements for maintenance manpower and resources, facilities, and equipment [10]. The evolutionary approach seeks to improve accuracy of detection and prediction of early indications of fault or impending failure. CBM can be implemented to provide visibility of asset health status with monitored data over a usage period [11], to prompt maintenance and supply channels to correct system health prior to occurrence of a serious problem, while maintaining operational readiness and reduce life-cycle costs associated with scheduled or reactive maintenance.

Following CBM+ guidance involves "a conscious effort to shift equipment maintenance from an unscheduled, reactive approach at the time of failure to a more proactive and predictive approach that is driven by condition sensing and integrated, analysis-based decisions" [10].

2. Degrader analysis and implementation of CBM+

Degrader analysis, developed by ARL Penn State, is a modified reliability centered maintenance based methodology to determine where the implementation of platform health management technology could potentially provide the greatest value to stakeholders by decreasing total ownership costs, which are largely comprised of maintenance and sustainment costs (Figure 1) [12].

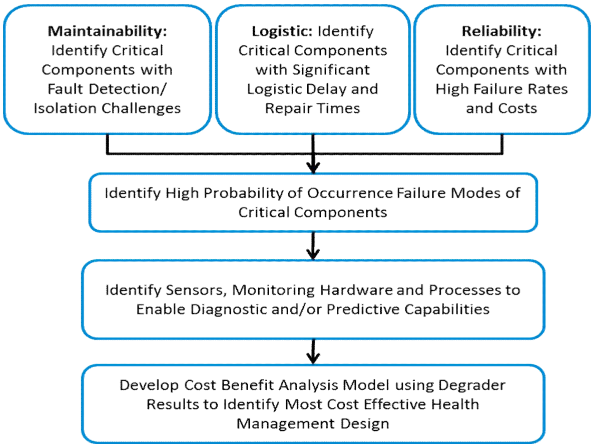

Figure 1. Degrader Analysis, adapted from [12]

This methodology was designed to meet requirements of Department of Defense CBM+ initiatives but is broadly applicable to any complex adaptive system to support enhanced, maintenance-centric logistics response by providing proactive and predictive capabilities.

Naval assets have demanding deployment and refit availability requirements, which contribute to the high total ownership costs for these platforms. Integrating Prognostics and Health Management (PHM) systems into the design and manufacturing of systems will better allow early prediction of degrading asset health and identification of supply and maintenance support needs [12]. The degrader analysis began with analysis of platform part replacement 3M data to provide a statistical based assessment of component failure rate, Navy sailor interview data for insight of indications of maintainability and troubleshooting issues, and system SME questionnaire data to regarding existing system capability and criticality, with the goal of identifying components and subsystems that

would benefit from CBM+. Two systems identified during the analysis and were subsequently selected based on potential for return on investment (ROI) by implementing CBM+: (1) the high-pressure air compressors (HPAC) and (2) the advanced carbon dioxide removal unit (ACRU), a new system being developed to replace the old “CO_2 Scrubber” systems.

For both systems, the design process for insertion of PHM sensor technology for selected system components included consideration of multiple factors to generate a solution. This included considering platform spatial arrangement, current maintenance methods, and Technical Readiness Level (TRL) of the health management technologies, with the goal of using advanced analyses to influence system design to achieve efficient scheduled maintenance and reduce operation and support (O&S) costs.

3. Machine learning for machine condition assessment and maintenance decision-making

Rapid advances in computing power, digital storage density, and network connectivity between assets have led to a data explosion and demand for big data analytics in CBM strategies. This wave of data availability combined with advanced statistical techniques drive demand in the fields of machine learning, predictive analytics, and artificial intelligence. By applying mathematical techniques to enormous datasets, highly accurate insights can be divulged from previously underutilized data in fields including defense, manufacturing, healthcare, financial forecasting, and automation. Advanced techniques can be applied to large datasets to provide early anomaly detection, accurate fault type classification, and actionable predictions of remaining useful life to enable condition monitoring and support condition based (rather than schedule-based) maintenance to provide operation optimization, maximal equipment uptime, and cost-efficiency [3].

Although these methods supplement and/or replace physically driven condition assessments for assets with moderate to advanced control systems, how and when they are used makes a difference in their potential for return on investment, as experienced with the two CBM+ applications.

3.1. Barriers to Machine Learning Implementation in CBM

Healthy data machine learning training: (e.g. Digital Twin Modeling) uses data from a wide range of operating conditions during normal healthy condition state to train the machine learning techniques. The advantage of this approach is that it does not require fault data that typically is unavailable for new systems, such as the ACRU. However, it can be difficult to develop a fault identification/isolation and Remaining Useful Life (RUL) estimates with only the utilization of health condition data. In contrast, using fault/failure data to train the machine learning techniques can provide a prognostic capability (includes RUL) with fault identification/isolation capability. In addition, with this technique, maintenance records and/or log books are used to identify failure occurrences with associated sensor data to train the machine learning techniques. However this approach requires fault/failure data for each failure mode, which is not always available or may be lacking in the quantity/quality necessary to perform the desired analyses, as seen with the HPAC application.

Creating machine learning models that are accurate and reliable enough to provide useful predictions of machine health condition at any given point in time is non-trivial work. For all efforts involving machine learning, multiple models should be tested fairly to determine the most effective strategies, but often data density, available data collection rates, and accurate data labeling information cause issues even when data sources are enormous. While the model building and evaluation has not finished for the ACRU datasets, comparisons of data availabilities will be drawn between the data provided for the ACRU efforts with the data that was provided from the HPAC efforts.

Table 1. Data Quality Statistics

Data Sources	25^{th} Percentile of Time Gap	Mean Time Gap	Median Time Gap	75^{th} Percentile of Time Gap
HPAC	2 minutes	188.7 minutes	21 minutes	60 minutes
ACRU	1 second	7.1 seconds	1 second	1 second

The time gaps between concurrent measurements in the data provided for the HPAC datasets are on the order of minutes, while at least 75% of all observations in the ACRU dataset are only separated by 1 second. This enormous difference in sample rate significantly changes the maximum amount of information that can be contained in the data. In disconnected environments, data transfer from asset to a centralized data warehouse is often the step in which data is decimated down.

On top of this difference in sampling rate, roughly 15% of all values received for the HPAC data were missing values, most likely as a result of the data collection and exportation scheme. These missing values are scattered throughout the datasets, meaning many observations are not necessarily complete and need to be either dropped or have their missing values inputted. For comparison, the ACRU dataset contains 0.02% missing values.

3.2. Circumventing Challenges for Machine Learning Implementation

Data-driven techniques like data mining or machine learning are essential to detecting anomalous behavior in systems displaying complex, nonlinear behavior due to high dimensionality and multiple operating conditions that are often too difficult to design a reliable, analytical system model, yet present interesting challenges for mitigating unfavorable machine learning circumstances [3]. In some circumstances, characterization of deviance from stakeholders' reliability requirements and normal system behavior for novelty detection to indicate system faults may be limited to unsupervised/self-supervised learning. Reliability problems stem from lack of involvement leading to poor definition of reliability requirements, a lack of understanding by the system developers on how to operate and maintain the fielded system, lack of reliability incentives in contracting, and poor tracking of reliability growth during system development. A costly mitigation for when limited or no fault data exists involves running systems to failure to enable supervised learning to train for detection of anomalous behavior requires the existence of targeted fault data.

A proactive approach is vital to CBM+ and ROI, with early involvement in establishing requirements and reliability investment (ideally, early in the design process), with industry being a key in this area [14]. With DoD guidance for reliability growth, the Navy reliability, availability, and maintainability (RAM) program, as an integral part of design and development, demonstrated credible reliability assessment in its technical review process by instituting a failure review board for its ACRU R&D program. Early on, the program office sponsored and formally managed the reliability aspect of development by instituting disciplined systems engineering processes during prototyping to categorize failure with formal and regular reviews of failure data to establish higher quality maintenance data that will potentially enable CBM+ and supervised machine learning implementation.

The quality of sensor data and maintenance record log books is essential to the effort to develop predictive algorithms, which allowed for controlled conditions to provide for improved data quality in the case for ACRU. For candidate systems of supervised learning, performing time series representations are possible with advanced machine learning techniques, such as remaining useful life (RUL) estimation techniques (e.g. Embed-RUL utilizing sequence-to-sequence model based on Recurrent Neural Networks) to generate embeddings for multivariate time series sub-sequences to accommodate noisy conditions [6].

To overcome data availability challenges in the future, reasonable care should be taken when designing data acquisition and transportation schemes to potentially preserve relatively high sample rate data and full data density. Considering potential future data science and machine learning projects during the design phase of complex systems provides the most cost effective way to avoid these challenges. If the programmable logic controller (PLC) of a complex system is accessible, retrofit data collection systems can be added which read data traffic across the communication port and store data of a high enough sample rate and quality to facilitate machine learning implementation of CBM. This is one of the primary goals behind the health management system (HMS) under development for the HPAC.

4. Health Monitoring System development and implementation process

The HMS was developed with a concurrent, iterative approach of simultaneously designing the data-driven HMS and model-driven HMS for a holistic hardware and software design solution with an information interface shown in Figure 2.

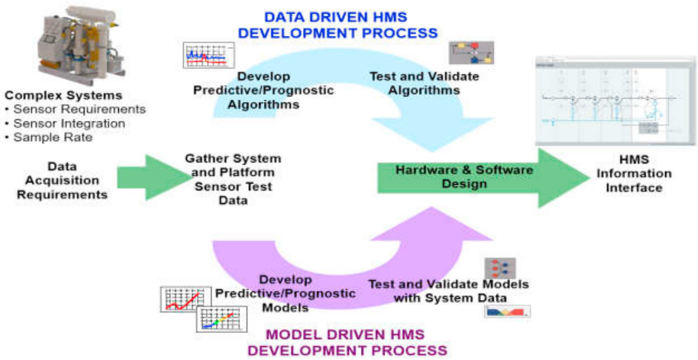

Figure 2. Health Management System Design Process

The first step in the HMS development process involves data gathering from the existing embedded sensors and any additional required sensors located on the critical asset in focus. Signal processing is then conducted to extract health features from the data, which provides the capability to diagnose fault severity and isolate the fault location. The signal processing is conducted by two methods: the data driven and the model driven approaches, which provided greater capability to diagnose and prognose faults with a higher confidence in the health assessment. The final step is the automated reasoning that allows the HMS to operate autonomously and provide health assessments to the operators and maintainers.

4.1. Selection of the Appropriate Predictive and Prognostics Approach

Research in CBM approaches involves identifying applicable characteristics of the system of interest and datasets to build an appropriate predictive and prognostics model. In each application, insight is provided with respect to dataset quality and other contextual factors to inform selection of the appropriate approach, which may be experience-based, physics-based, or data-driven, or some combination to form a hybrid approach. Each of the categories of approaches is described in Table 2, with their respective strengths and weaknesses outlined in [15].

Table 2. Predictive and Prognostics Approach Overview

Approach	Description	Strength	Weakness
Experience Based	• Uses expert knowledge and engineering experience to create logic and rules (i.e. If-Then statements) that correlate with the observed situation to infer RUL from historic sensor measurement or events. • Widely used for diagnostic capability and predictive/prognostic.	Does not require historical data to develop the techniques; only an understanding of the system function is needed.	Approaches are highly dependent on the knowledge of the domain experts.
Physics Based	• Approaches require a knowledge of a systems failure mechanisms to build mathematical models/algorithms to estimate the degradation process for the RUL. • Experiments/empirical data are used to develop an understand of the degradation parameters of a complex system.	Highly effective for components with well understood failure modes.	Requires a strong correlation between the sensor data and the mechanism of failure over the range of operating conditions.
Data Driven	• Approaches rely only on historical data to predict the projection of a system failure or to match patterns of past failure evolutions to estimate RUL. • Statistic based models are widely used for these approaches.	Effective for a broad range of applications and does not require a deep understanding of the system operational/failure dynamics a priori.	Requires a significant number of sensor inputs and quantity of historical data to train the models.

For the ACRU, a hybrid approach combining a physics-based model and data-driven model was selected to leverage the strengths of each and improve prediction performance.

4.2. Predictive Algorithm Development

The CBM Features Toolbox within Mathworks Matlab contains a set of conventional, publicly available standard signal processing routines for development and selection of diagnostics and predictive techniques tools, supplemented by novel features developed at the ARL Penn State to build diagnostic and predictive fault detection algorithms for the system's functional failure modes using data-driven and model-driven approaches. This combination provided significant capability for diagnosis of faults and prediction of failures with higher confidence in the health assessment by utilizing data from a variety of signal processing techniques. The output of the analyses identified potential predictive algorithms that were tailored to results of the enhanced failure modes, effects, and criticality analysis. Following the testing and validation of the algorithms and techniques, data fusion techniques were applied to combine data from multiple sensors and related information to capture specific inferences of component and subsystem damage on measured parameters, as well as to reduce the incidence of false alarms.

4.3. Multi-Signal Sensor System Data

The sample rate of data collection from multiple sensors was standardized to provide data for the machine learning application over a common interval. The frequency of data, relational to the amount of data samples, provided input data from two sets of sensors. The goal was to isolate the earliest warning of predicted failure to a particular failure mode, by simultaneously monitoring signals indicating the early stages of variation using thresholds and rules. By monitoring multiple signals, the incidence of false alarms is dramatically reduced.

4.4. Machine Learning Training

Critical components at risk for degradation and failure were identified as good targets for CBM. In order to train and test the data driven machine learning techniques to develop a predictive maintenance capability for the ACRU, data was acquired from NSWC Philadelphia from the prototype ACRU. Data was collected from 45 existing control system sensors at a sample rate of 1 Hz during development testing. NSWC Philadelphia also provided well annotated log books that provided a description, date, and fault code for all available anomalous events during the ACRU testing over a several year period. The data analysis team transferred the log book data to a data table that was cross referenced to the data based that contained the associated sensor data. Similar anomalies/failure mode events were identified from the log books and the sensor data that preceded the event dates was extracted from the data based to provide training and test data for the machine learning. The data analysis team is applying the data to several machine learning techniques, listed in Table 3.

Table 3. Machine Learning Techniques

Method	Data Driven Approach Type	Computation Complexity/Implementation Complexity
Ordinary Least Squares Regression	Fault Data	Simple/Simple
Statistical Classifier: Linear Discriminant Analysis (LDA)-Bayes, Random-Forest, Support Vector Machine (SVM), etc.	Fault Data	Difficult/Moderate (already government-owned property and implemented in CMAS development server)
RNN Embedding Auto-encoder	Healthy Data	Difficult/Difficult
Survival Regression	Fault Data	Moderate/Moderate
Decision Tree	Fault Data	Moderate/Moderate
Mahalanobis Distance Clustering	Healthy Data	Simple/Moderate
Unsupervised learning (DBSCAN, k-means, k-nearest neighbor)	Fault Data	Unknown
General Linear Model auto-encoder	Healthy Data	Difficult/Difficult

The table lists the machine learning methods that are being used for this application, the type of data that is applied, and the relative computational and implementation complexity for each method.

As of the date of publication, the data analysis team applied the ordinary least squares regression method to the ACRU time series data from the 45 sensors for a selected component failure events. One training data set was used and the results of using one test set is shown in Figure 3. The figure indicates the predicted remaining useful life on the Y-axis and the actual remaining cycles on the X-axis. The preliminary results show a potential capability to predict failure at 50 remaining cycles. The team will continue to conduct more testing using this method and the other listed methods, to be reported in the future.

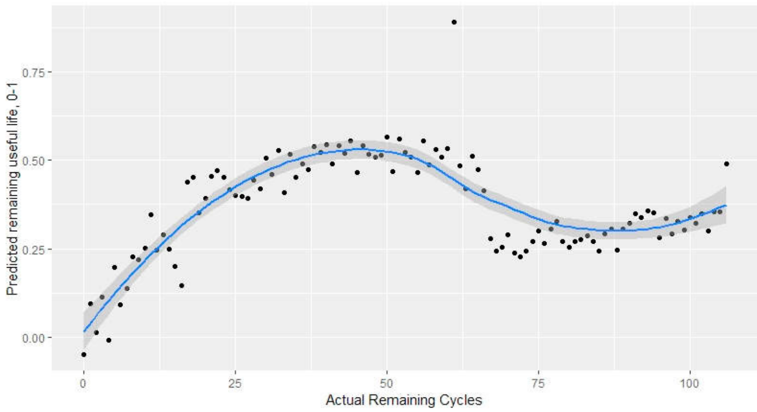

Figure 3. Ordinary Least Squares Regression Method Applied to ACRU Data

The focus of our analysis provides utility to users through continued development of an automated reasoning capability to provide system health assessments as a representation complex system while allowing the health management system to operate autonomously.

5. Conclusion

The goal of the research and development was to evaluate the potential of using existing control system sensors with machine learning techniques for the development of predictive maintenance for critical complex systems.

Degrader analysis revealed two sub systems that represented high value targets for the application of CBM, the HPAC and the ACRU. Detailed engineering analysis was used to determine physics based approaches likely to provide accurate information on the health status of both newly delivered and legacy HPACs. An integrated hardware and software solution is being developed, which not only supports the physics based approaches, it also increases the quality of data available for use in developing data driven approaches to HPAC. Both physics and data-driven approaches are in development for multiple critical components of the ACRU. These efforts have demonstrated the clear value of the reliability growth program, which in turn provided for good maintenance records to allow correlation of failures with sensor data. Key to be involved early in system development in order to collect usable machine learning data

The health management system design provides a prototype solution from which data collection and a hybrid approach supports evolutionary planning of a proactive maintenance strategy. The proposed integration of the onboard machinery monitoring system and the health management system is scheduled for implementation and demonstration on the ACRU in 2030.

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